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Editor-in-Chief :

Dr. Suman Joshi

Volume - 6
July, 2025

Inspiring Soul

The actual fact of life is,
“To achieve Golden path to success;
one must strive hard from dawn to dusk”.
The crux behind this is,
“The hard work that you put in,
will be recognized as an appreciation by honor of success”.

- Mukut Behari Lal

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From Chairman's Desk

Dear All,

It is great privilege that Rajshree Institute of Management and Technology is going to publish volume- 6 of e-Journal of Indian Institute for Engineering, Management and Science (e-JIIEMS). This journal symbolizes the spirit of creativity and innovation. It is a medium to connect, inspire and foster the exchange of ideas and knowledge.

Our institution appreciates the role of research in the education and inclination towards research. I encourage all contributors to share their valuable insights and an experience, ensuring it a true reflection of the vibrant culture of our institution.

My best wishes to the authors, publishing staff and editorial board members for the successful publication of this edition of journal.

Rajendra Kumar Agarwal
Chairman
Rajshree Group of Institutions
Bareilly

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Editor in chief Message

Dear All,

We are honored to announce the publication of sixth volume of e-journal of Indian Institute for Engineering, Management and Science. We wish to express our gratitude to our researcher for their contribution in the new step of research, it shows their reflection of the hard work, creativity and passion. We will provide the plateform for showcasing the myriad achievements, talents and growing ideas of the researcher.

In this publication researchers show their interest in deep learning approach for review, approach for bug report prediction. Some researcher describes the second phase of artificial intelligence by cloud based remote electricity metering and internet of things (IoT) based anti theft floor system.

I wish this journal serve as a source of inspiration for all and encourage us to continue pushing the boundaries of excellence in the different fields of research. I hope this journal to be useful tool for analyzing the results for future scope.

Dr. Suman Joshi
Rajshree Institute of Management & Technology
Bareilly

e-Journal of Indian Institute for Engineering, Management and Science (e-JllEMS)

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Alternative Fuel

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Abstract
Alternative fuel, known as nonconventional or advanced fuel ,are any material or substances that can be used as fuel, other than conventional fuels. A growing number of people believe alternative fuel will have an expanded role. According to Larry West, such interest has been spurred by three important considerations. Alternative fuel generally has lower vehicle emission that contributes to smog, air pollution and global warming. Most alternative fuel don't come from fossil fuel resources and sustainable. It can help nation become more energy dependent. Some of the alternating fuels are- Ethanol, Natural gas, Biodiesel, Propane etc. Alternating fuel refers to a vehicle that runs other than gasoline diesel, any method of powering engine that does not involve petroleum. Some vehicle are- Hydrogen car , Solar car. According to alternating fuel price report of April 2014, the nationwide average price (all amount are per gallon) for regular gasoline has increased 31 cents from $3.34 to $3.64, diesel increased 8 cents from $3.89 to $3.97.

1. Introduction: Alternative fuels, known as non-conventional or advanced fuels, are any materials or substances that can be used as fuels, other than conventional fuels. Conventional fuels include: fossil fuels (petroleum (oil), coal, and natural gas), as well as nuclear materials such as uranium and thorium, as well as artificial radioisotope fuels that are made in nuclear reactors. Some well-known alternative fuels include biodiesel, bioalcohol (methanol, ethanol, butanol), chemically stored electricity (batteries and fuel cells), hydrogen, non-fossil methane, non-fossil natural gas, vegetable oil, propane, and other biomass sources.

Types of Alternative Fuel: **Hydrogen** Hydrogen (H_2) is being explored as a fuel for passenger vehicles. It can be used in fuel cells to power electric motors or burned in internal combustion engines (ICEs). It is an environmentally friendly fuel that has the potential to dramatically reduce our dependence on imported oil, but several significant challenges must be overcome before it can be widely used.

Benefits:

Produced Domestically. Hydrogen can be produced domestically from several sources, reducing our dependence on petroleum imports.

Environmentally Friendly. Hydrogen produces no air pollutants or greenhouse gases when used in fuel cells; it produces only nitrogen oxides (NOx) when burned in ICEs.

Availability. Hydrogen is only available at a handful of locations, mostly in California, though more hydrogen fuelling stations are planned for the future.

Challenges:

Vehicle Cost & Availability: Fuel cell vehicles (FCVs), which run on hydrogen, are currently more expensive than conventional vehicles, and they are not yet available for sale to the general public. However, costs have decreased significantly, and commercially available FCVs are expected within the next few years.

Onboard Fuel Storage. Hydrogen contains much less energy than gasoline or diesel on a per-volume basis, making it difficult to store enough hydrogen onboard an FCV to go as far as a comparable gasoline vehicle between fillups. Some FCVs have recently demonstrated ranges comparable to conventional vehicles—about 300 to 400 miles between fillups—but this must be achievable across different vehicle makes and models and without compromising customer expectations of space, performance, safety, or cost.

Biodiesel

Biodiesel is a form of diesel fuel manufactured from vegetable oils, animal fats, or recycled restaurant greases. It is safe, biodegradable, and produces less air pollutants than petroleum-based diesel.

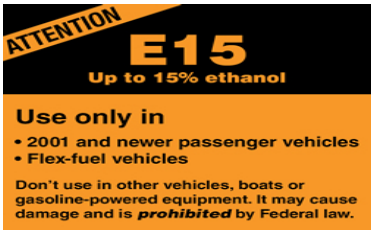
Biodiesel can be used in its pure form (B100) or blended with petroleum diesel. Common blends include B2 (2% biodiesel), B5, and B20. Most vehicle manufacturers approve blends up to B5, and some approve blends up to B20. Check with your owner's manual or vehicle manufacturer to determine the right blend for your vehicle, since using the wrong blend could damage your engine and/or void the manufacturer's warranty.

Table 1: Biodiesel Compared to Petroleum Diesel

Advantages	Disadvantages
1.Domestically produced from non- petroluem, renewable resources 2.Can be used in most diesel engines, especially newer ones 3.Less air pollutants (other than nitrogen oxides) 4.Less greenhouse gas emissions (e.g., B20 reduces CO_2 by 15%) 5.Biodegradable 6.Non-toxic 7.Safer to handle	1. Use of blends above B5 not yet approved by many auto makers 2. Lower fuel economy and power (10% lower for B100, 2% for B20) 3.Currently more expensive B100 generally not suitable for use in low temperatures 4.Concerns about B100's impact on engine durability 5.Slight increase in nitrogen oxide emissions possible in some circumstances

Ethanol: Ethanol is a renewable, domestically produced alcohol fuel made from plant material, such as corn, sugar cane, or grasses. Using ethanol can reduce oil dependence and greenhouse gas emissions. Ethanol fuel use in the U.S. has increased dramatically from about 1.7 billion gallons in 2001 to about 12.9 billion in 2012 [1].

E10 and E15



E10 and E15 are blends of ethanol and gasoline—the number after the "E" indicates the percentage of ethanol. Most of the gasoline sold in the U.S. contains up to 10% ethanol—the amount varies by region—and all auto manufacturers approve blends up to E10 in their gasoline vehicles. As of 2011, EPA began allowing the use of E15 in model year 2001 and newer gasoline vehicles [2]. Pumps dispensing E15 must be labeled (see example). The vehicle owner's manual may indicate the manufacturer's maximum recommended ethanol content. Vehicles will typically go 3% to 4% fewer miles per gallon on E10 and 4% to 5% fewer on E15 than on 100% gasoline [3].

E85 (Flex Fuel)

E85, also called *flex fuel*, is an ethanol-gasoline blend containing 51% to 83% ethanol, depending on geography and season—summer blends tend to have more ethanol while winter blends have less [4]. E85 can be used in FFVs, which are specially designed to run on gasoline, E85, or any mixture of the two. FFVs are offered by several vehicle manufacturers, and we provide a brief guide to help you determine if your vehicle can run on flex fuel.

MPG. Due to ethanol's lower energy content, FFVs operating on E85 get roughly 15% to 25% fewer miles per gallon than when operating on regular gasoline, which typically contains about 10% ethanol [5].

Cost. The cost of E85 relative to gasoline or E10 can vary due to location and fluctuations in energy markets. Though typically cheaper per-gallon than gasoline, it is often slightly more expensive on a cost-per-mile basis.

Performance. Drivers should notice no degradation in performance when fueling with E85. In fact, some FFVs perform better—generate more torque and horsepower—running on E85 than on gasoline or E10 [6,7]

Table 2: Advantages & Disadvantages of E85

Advantages	Disadvantages
1. Domestically produced, reducing use of imported petroleum 2.Lower emissions of some air pollutants 3.More resistant to engine knock 4.Added vehicle cost is negligible	1.Can only be used in flex-fuel vehicles 2.Lower energy content, resulting in fewer miles per gallon 3.Limited availability

Natural Gas : Natural gas, a fossil fuel comprised mostly of methane, is one of the cleanest burning alternative fuels. It can be used in the form of compressed natural gas (CNG) or liquefied natural gas (LNG) to fuel cars and trucks. _*Dedicated* natural gas vehicles are designed to run on natural gas only, while *dual-fuel* or *bi-fuel* vehicles can also run on gasoline or diesel. Since natural gas is stored in high-pressure fuel tanks, dual-fuel vehicles require two separate fueling systems, which take up passenger/cargo space._Natural gas vehicles are not available on a large scale in the U.S.—only a few models are currently offered for sale. However, conventional gasoline and diesel vehicles can be retrofitted for CNG.

Table 3: Advantages and Disadvantages of Natural Gas

Advantages	Disadvantages
1.About 94% of U.S. natural gas used is domestically produced[1] 2.Roughly 20% to 45% less smog-producing pollutants[2] 3.About 5% to 9% less greenhouse gas emissions[2] 4.Less expensive than gasoline	1.Limited vehicle availability 2.Less readily available than gasoline and diesel Fewer miles on a tank of fuel.

Propane: Liquefied Petroleum Gas (LPG) : Propane, or liquefied petroleum gas (LPG), is a clean-burning fossil fuel that can be used to power internal combustion engines. LPG-fueled vehicles can produce significantly lower amounts of some harmful emissions and the greenhouse gas carbon dioxide (CO_2).

LPG is usually less expensive than gasoline, it can be used without degrading vehicle performance, and most LPG used in U.S. comes from domestic sources. The availability of LPG-fueled light-duty passenger vehicles is currently limited. A few light-duty vehicles—mostly larger trucks and vans—can be ordered from a dealer with a prep-ready engine package and converted to use propane.

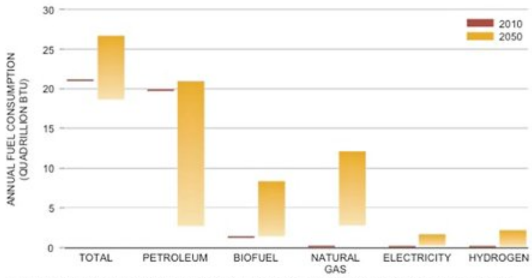
Existing conventional vehicles can also be converted for LPG use. Since propane is stored as a liquid in pressurized fuel tanks rated to 300 psi, LPG conversions consist of installing a separate fuel system if the vehicle will run on both conventional fuel and LPG or a replacement fuel system for LPG-only operation.

Table 4: Advantages and Disadvantages of LPG

Advantages	Disadvantages
1.90% of propane used in U.S. comes from domestic sources[1] 2.Less expensive than gasoline Potentially lower toxic, carbon dioxide (CO_2), carbon monoxide (CO), and nonmethane hydrocarbon (NMHC) emissions	1.Limited availability (a few large trucks and vans can be special ordered from manufacturers; other vehicles can be converted by certified installers) 2.Less readily available than gasoline & diesel 3.Fewer miles on a tank of fuel

Alternative Fuel Economy

Table 1 shows overall nationwide average prices for conventional and alternative fuels. As this table illustrates, alternative fuel prices relative to conventional fuels vary, with some (B20, B99-B100) higher and some (CNG, E85 and propane) lower. As shown in Table 2, on an energy-equivalent basis, CNG is about $1.53 less than gasoline. On a per-gallon basis, E85 is about $.47 less than gasoline, and propane is about $.63 less than gasoline. B20 prices are higher than regular diesel by about $.07 per gallon, while B99/B100 blends have a cost of about $.33 per gallon more than regular diesel.4



Note: At equivalent fuel consumption (by energy), alternatives such as hydrogen FCEVs and electric vehicles can support 2-3x the miles due to their higher fuel economy.

Figure ES-10. Range of 2050 On-Road Fuel Use, Assuming All Alternatives are Successfully Commercialized

National Petroleum Council. The red bars reflect 2010 consumption and the yellow bars the range of possible consumption in 2050.

While a variety of new fuel technologies are advancing. The report from the council, an advisory agency, was drawn up in response to requests from the department for counsel on how to accelerate the adoption of new fuels and technologies, from compressed natural gas to fuel cells to biofuels, between now and 2050. One of the nation's biggest energy problems is that nearly all of its ground transportation fuel is derived from oil.

But looking ahead to 2050 posess challenges. The National Petroleum Council tried to sidestep the uncertainty by saying up front that of all the various possibilities – hybridized vehicles, vehicles running on bio fuels or compressed or liquefied natural gas, and battery-electric and fuel cell vehicles – it is far too soon to pick winners and losers. Using lightweight materials, improving vehicle aerodynamics, reducing rolling resistance and making other changes could improve the fuel economy of light-duty vehicles by 50 percent, the group found, and hybridization and electrification of vehicles could have far larger benefits. Heavy-duty vehicles could be made to go twice as far on a unit of fuel, which ultimately might turn out to be natural gas and not diesel.

References

[1]. http://en.wikipedia.org/wiki/Alternative_fuel

[2]. http://www.afdc.energy.gov/uploads/publication/alternative_fuel_price_report_july_2014.pdf

[3]. http://www.fueleconomy.gov/feg/ethanol.shtml

[4]. http://www.fueleconomy.gov/feg/biodiesel.shtml

[5]. http://www.fueleconomy.gov/feg/bifueltech.shtml

[6]. http://www.fueleconomy.gov/feg/lpg.shtml

[7]. http://www.fueleconomy.gov/feg/hydrogen.shtml

Deep Learning Approach for Shopper Review Sentiment Analysis and Recommendation (Role of Review: Better Organization)

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Abstract: Nowadays in this internet era, review plays a vital role in every organization. A review is all about hearing other people's previous shopping experiences that can assist potential customers in determining whether a product has previously lived up to the expectations of its purchasers. The objective of this paper is to extract a meaningful information from reviews that can help organizations to improve revenues. The process of automatically extracting sentiment or opinions from these reviews heavily relies on sentiment analysis, a branch of Natural Language Processing (NLP) utilizing innovative techniques for mining consumer opinions. The project aims to establish a robust framework for sentiment analysis that accurately classifies emotions expressed in these reviews and also performs location recommendation for new branch. The proposed system incorporates advanced deep learning methods and clustering techniques to enhance data classification and extract fine-grained sentiment information. In this paper we have applied three machine learning models such as Simple Neural Networks (SNN), Convolutional Neural Networks (CNN), and long short-term memory (LSTM) Recurrent neural network (RNN) and K-means clustering algorithm. The evaluation indexes and the three algorithms are compared in different lengths of sentence and word vector dimensions. Clustering groups together reviews that are spatially close to each other, forming clusters based on their geographic distribution and Recommendation is based on the centroid of the clusters. The results present that recurrent neural network algorithm is effective in the sentiment classification of the review corpus. Finally, very interesting results were observed in terms of the Mapbox which represents the sentiment information of each store.

1. Introduction: In today's competitive market, consumers have more choices than ever before. They can quickly evaluate goods and services according to a number of criteria, including cost, features, quality, and reviews from customers. Product reviews are among the most important information sources that buyers trust. Customers can express their thoughts and experiences through reviews, but brands can also use them as a potent weapon to increase reputation, loyalty, and trust. In recent years, reviews have emerged as a crucial resource for buyers seeking guidance and facts before making a purchase. Sentiment analysis is necessary because of Sentiment analysis is necessary because of the volume of user-generated content that is available, as it helps automatically determine sentiments or views from assessments. This research paper focuses on sentiment analysis in product reviews and new location recommendation. This paper aims to develop a robust framework that can effectively categorizethe sentiment expressed in these reviews.

The objective of this paper is to extract a meaningful information from reviews that can help organizations to improve revenues with the help of advanced techniques such as deep learning and Clustering. Related Work: Recent years have witnessed a wide range of studies interests in sentiment analysis and opinion mining [1]. This section covers a few of the several methodologies that can be recognized in sentiment analysis. Yuling Chen et. al. [2] noted the current emphasis in the field of Web information mining on sentiment analysis of online reviews. Text sentiment analysis using conventional approaches mostly depends on machine learning or emotion dictionaries. Nevertheless, the generalizability of these methods is restricted due to their reliance on creating emotion dictionaries and manually defining and extracting features. By comparison, deep learning models are more expressive and can therefore understand complex mappings from data to emotional semantics with greater ease. Mohd. Istiaq Hossain Junaid et. al. [7].

The data was split 80:20 across training and testing groups by the researchers. The texts were pre-processed using TFIDF, Glove Vector, Word2Sequence, and Count Vectorizer. With regard to the traditional machine learning classifier, Authors utilized the Random Forest classifier, Decision Tree, Linear SVM, Logistic Regression, and Multinomial NB; unigram and bigram features were used to train these models. For deep learning, they used RNN, GRU, and LSTM. The LSTM with word sequence model

achieved the best testing accuracy of all the models. The results of decision trees, random forests, linear SVM, Naïve Bayes, and logistic regression with count vector were 74.52%, 68.75%, 69.23%, 69.71%, and 71.15%. Proposed Methodology: In this case study, we aim to predict whether the input review is Positive, Negative or Neutral this is one case and the second case is user requested to upload csv file of their choice after the file upload the trained LSTM model classifies sentiment with the store location of latitude and longitude and the final case is to recommend the new location based on the user input. This proposed model will plot that information on the map using mapbox.

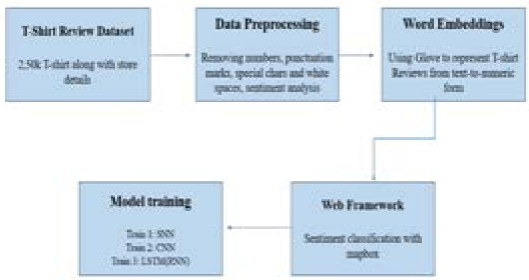

Figure.1 Flow chart representation

Data Set Description : The dataset "TeePublic review" used in our experiments is composed of the following variables: Reviewer_id, store_location, latitude, longitude, date, month, year, title, and review (Figure.2) this dataset contains 2,50,000 rows and 10 columns.

reviewer_id	store_location	latitude	longitude	date	month	year	title	review	review-label
0.0	US	37.090240	-95.712891	2023	6	2015 00:00:00	Great help with lost order	I had an order that was lost in transit. When ...	5
1.0	US	37.090240	-95.712891	2023	6	2024 00:00:00	I ordered the wrong size tee and hadï¿½ï¿½ï¿½	I ordered the wrong size tee and had difficult...	5
2.0	US	37.090240	-95.712891	2023	6	2017 00:00:00	These guys offer the best customerï¿½ï¿½ï¿½	These guys offer the best customer service in ...	5
3.0	US	37.090240	-95.712891	2023	6	2024 00:00:00	Good Stuff	Looked for an obscure phrase on a shirt. Teepu...	5
4.0	CA	56.130366	-106.346771	2023	6	2023 00:00:00	My order arrived in a good timelyï¿½ï¿½ï¿½	My order arrived in a good timely fashion & th...	4
5.0	US	37.090240	-95.712891	2023	6	2015 00:00:00	Always top notch	Always top notch customer service. Never have ...	5
6.0	US	37.090240	-95.712891	2023	6	2019 00:00:00	Recent review	I have messaged sellers and get no response at...	4
7.0	US	37.090240	-95.712891	2023	6	2023 00:00:00	Great communication	Great communication. They let me know it was a...	5
8.0	CA	56.130366	-106.346771	2023	6	2021 00:00:00	Awesome	Very impressed with the quality. I had a hard ...	5
9.0	US	37.090240	-95.712891	2023	6	2014 00:00:00	Wonderful quality T-shirts for anï¿½ï¿½ï¿½	Wonderful quality T-shirts for an amazing pric...	5

Figure 2: Tee Public review dataset

Data Pre-Processing And Exploration

In this step, we removed the missing data from each variable. Then we showed the distribution of the target variable review_lable (Figure 3) we can see that review_lable of the T-shirt Rating is impressive as almost all the Rating is five. So, let us have a look at the distribution of Rating by year. (Figure 4) looking at the visual we see that the rating distribution each year looks the same. the next step is sentiment analysis [4] for this we used TextBlob Python library commonly used natural language processing (NLP) for sentiment analysis.

Figure 3. Distributions of Ratings

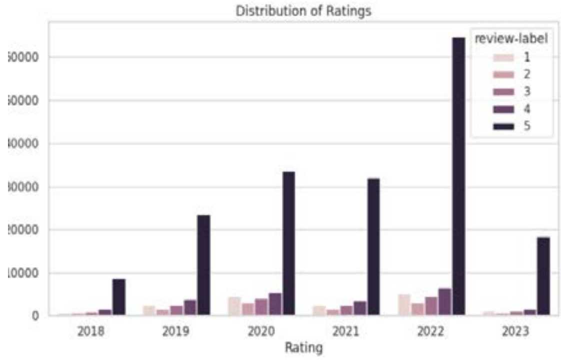

Figure 4. Distributions of Ratings and Year

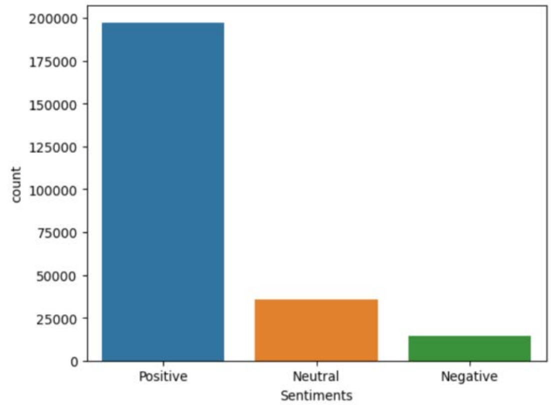

Figure 5. Sentiment Distribution Across Ratings

Polarity Analysis: Polarity is a floating value that lies in the interval [-1, 1] which states that 1 indicates positive review, -1 indicates negative review and 0 indicates neutral. The distribution of the polarity score in the reviews is shown in Figure 5. Where the majority of the comments are situated on the positive side of the graph [0,1]. Stop Words : A stop word is a commonly used word (such as "the", "a", "an", or "in") are thought to be ineffective for communicating important information. We would not want these words to take up space in our database or take up valuable processing time. Text Pre-Processing : In this phase, punctuation is removed (!"#$%&\'()*+,-

./:;<=>?@[\\]^_`{|}~), and all text in the comments is converted to lowercase. Based on the values of the Text_Polarity variable Three different sentiments can be derived. Positive sentiment is present if Text_Polarity is larger than zero then a negative sentiment is present if Text_Polarity is less than zero and Neutral sentiment is presented if Text_Polarity is equal to zero. 3.3. Word Embeddings Tokenization is the process of separating the text into discrete words or units of speech. The purpose of it is to generate a dictionary word index [5]. In the word-to-index dictionary, every word in the corpus serves as a key, and the value of the key is determined by a corresponding unique index. Then we compute the vocabulary size, in our corpus is 41181 unique words in this study. To ensure that every review is precisely 100 words long, padding must be applied next. The list will be trimmed to 100 if its size exceeds 100. Until the list reaches its maximum length, we will append 0 to the end of any entries that are less than 100. word embedding is the technique to convert each word into an equivalent float vector. In this study we use global vectors for Word Representation, [5] Glove embedding is used to create a feature matrix. GloVe is an unsupervised learning algorithm that generates vector representations, orembeddings, of words. It is not necessary to train the model from scratch when using these pre-trained embeddings, which can be downloaded and used immediately in a variety of natural language processing (NLP). Here we use a pre-trained GloVe embedding in a dimension (100-d vectors). Here d stands for dimension. 100d means, in this file each word has an equivalent vector of size 100. Glove files are simple text files in the form of a dictionary. Words are key and dense vectors are values of key. 3.4 **.** Model training And Testing : In this case study we approach three Deep learning models such as Simple Neural Networks (SNN), Convolutional Neural Networks (CNN), and long short-term memory (LSTM). Simple Neural Networks creating a sequential model then we created embedding layer with input length of 100 which is the maximum length and the output vector dimension is also 100 and the vocabulary size is 41181 words as mentioned above for weights we pass the embedding matrix. The embedding layer is then added to the model. Then we flatten the embedding layer and finally we add the dense layer with sigmoid activation function. compile the model once the model is trained, we compute prediction on the test set and we obtain the training accuracy of 78.65%. which is higher than the test accuracy 80.01%. which means that the model is over fitting on the training set.

Convolutional Neural Networks : Convolutional Neural Networks is the type of network that is primarily used for 2D data classification, CNN works with text data as well though text data is one-dimension, we can use 1D CNN to extract features from data. In this model we use 1 convolutional layer and 1 pooling layer. The embedding layer is the same as we mentioned above then we compile and train the model and the training accuracy is 81.80% and the test accuracy is 81.70%. this model is also over fitting as you can see the difference between the accuracy.

Long Short-Term Memory (LSTM) :
Recurrent Neural Network is the type of neural network that is proven to work with sequence data and since text is actually a sequence of words, a recurrent network is an automatic choice to solve text-related problems. In this study we are using LSTM which is a variant of RNN. Here with the same embedding layer, we created a LSTM layer with 128 neurons. Then we compiled and train the model.

```
1548/1548 [==============================] - 67s 43ms/step - loss: 0.2739 - acc: 0.8245
```

Figure 6. LSTM model Test Accuracy

This model performed well as compared to SNN and CNN with the training accuracy of 82.12% and the test accuracy of 82.45%. With this we can conclude that RNN based LSTM is the most suited approach for training the neural network.

```
Model: "sequential_9"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 embedding_9 (Embedding)     (None, 100, 100)          4118100

 lstm_9 (LSTM)               (None, 128)               117248

 dense_9 (Dense)             (None, 1)                 129

=================================================================
Total params: 4235477 (16.16 MB)
Trainable params: 117377 (458.50 KB)
Non-trainable params: 4118100 (15.71 MB)
_________________________________________________________________
```

Figure 7. LSTM model summery

Embedding Layer is utilized to transform word representations from integer indices into dense vectors of a predetermined size, with a vector for each word. This layer's input shape is (None, 100), which indicates that sequences of integers with a maximum length of 100 are expected. It outputs a

3D tensor with the shape of (batch_size, sequence_length, embedding_dimension), as indicated by the Output Shape (None, 100100). The total number of parameters in this layer is shown by the value 4118100. Recurrent neural network (RNN) layers, such as the LSTM (Long Short-Term Memory) layer, are very good at identifying long-term dependencies in sequential data. This layer's output shape is (None, 128), indicating that it produces a 2D tensor with the shape (batch_size, units). The total number of parameters in this layer is indicated by the parameter value 117248. Dense Layer: This layer is entirely connected, with every output node coupled to every input node. This layer's output shape is (None, 1), which indicates that a 2D tensor with the shape of (batch_size, 1) i s produced. There are 129 parameters in this layer, which represents the total amount of parameters in this layer

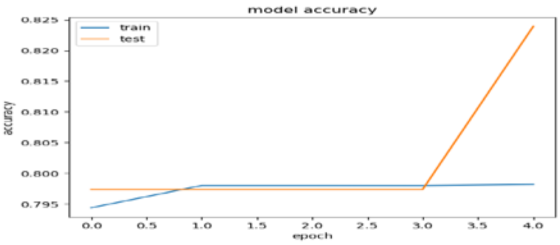

Figure 8. LSTM model Accuracy plot

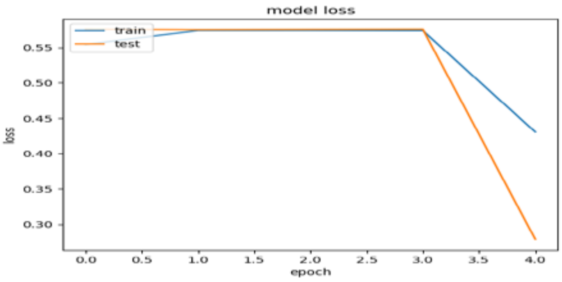

Figure 9. LSTM model loss plot

K-means Clustering : The reviews associated with the provided store locations are clustered using the K- means clustering algorithm. Clustering groups together reviews that are spatially close to each other, forming clusters based on their geographic distribution. Clustering helps identify spatial patterns in the distribution of reviews. By clustering the reviews associated with the provided store locations, we can identify groups of reviews that are spatially close to each other. The centroid of these clusters provides a representative location that captures the spatial distribution of reviews.

Location Recommendation : Once the clustering is performed, the centroid of the top clusters is computed. This centroid represents a central location that minimizes the overall distance to the reviews within the top clusters. This centroid is then recommended as a potential location based on the spatial distribution of the reviews associated with the provided store locations. The recommended location aims to optimize accessibility for customers based on the distribution of reviews. By choosing a central point, we minimize the overall travel distance for customers coming from the provided store locations.

Web Framework : In this case study, we used python framework streamlit to develop our web application. This web app contains three actions first input review classification and second file upload which request the user to upload a file then this web app will classify the sentiment of reviews and plot that information in map with store location name with latitude and longitude. Then the final process is to generate the new location based on the user input then plot the generated information in map using mapbox.

Model	Train loss	Test loss	Train Accuracy	Test Accuracy
SNN	33.34 %	17.70 %	78.65%	80.01%
CNN	- 59.08 %	- 65.99 %	81.80%	81.70%
LST M	26.67 %	27.39 %	82.12%	82.45%

The LSTM model achieves the highest testing accuracy of 82.45%, followed by the CNN model with an accuracy of 81.70%, and then the SNN model with an accuracy of 80.01%. The SNN and LSTM models have similar testing loss values around 17.70% and 27.39% respectively, while the CNN model shows a negative loss value, which could be due to the loss function or model architecture. the LSTM model seems to be the best choice among the three.

Module 1: Simple Text Classification

Figure 10. Module 1, Classify Review

This module takes reviews as input. Reviews could be in text format, such as customer reviews of products or services. In this module we used proposed model LSTM to classify the reviews.

Module 2: File upload and plot Graph

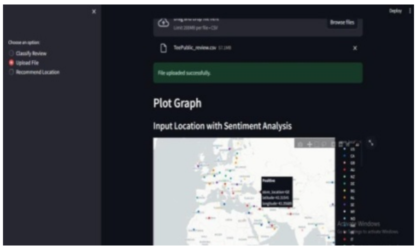

Figure 11. Module 2, Upload File and Plotting

In this module users are presented with the "Upload File" option in the Streamlit sidebar. Upon selecting this option, users can upload a CSV file containing reviews and their corresponding store locations. The uploaded CSV file is read and its encoding is detected using the chardet library to handle different encoding types. Once the encoding is determined, the CSV data is decoded and read into a panda Data Frame.
After successfully uploading the file, the sentiment analysis is performed on the reviews using the sentiment evaluation function from Module 1. The data is visualized on a scatter map using Plotly Express, where each point represents a location, colored based on sentiment analysis results.The latitude and longitude columns from the DataFrame are used as coordinates for plotting. Finally, this scatter_mapbox function provides interactive map visualization.

Module 3: Recommend Location

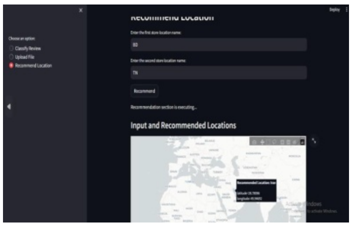

Figure 12. Module 3, Recommend Location

Users are presented with the "Recommend Location" option in the Streamlit sidebar. Upon selecting this option, users are prompted to input two existing store locations. The user-inputted locations are used to filter the Data Frame to include only the data corresponding to these locations. If there are enough samples (at least 5) for clustering, the clustering process is initiated . For clustering, the KMeans method is employed, and the number of clusters is dynamically

determined by the sample size. The top three clusters with the greatest number of data points are determined by computing the centroids of each cluster. Using Plotly Express, the input locations and the suggested location are plotted on an interactive map. Every point has a label indicating the matching sentiment analysis score or suggested location. Users can see the suggested location as well as the input locations visually with the help of the map.

Conclusion : The proposed sentiment analysis system represents a significant advancement in accurately classifying sentiment in online product reviews. The exponential growth of user-generated content on product reviews has made it more difficult to extract sentiment and opinion from reviews. To address this difficulty, though, this method provides a proficient and effective response. Using advanced deep learning techniques is one of the system's primary benefits. Reviews places a major role in every organization, product review can be thought of as the opinions or feedback of customers regarding a specific product. The websites of many online businesses have a section labeled “reviews” that allows customers to rank and comment on the products they have purchased. When other people read a product review, they better understand what they’re getting before they buy it. They may read the reviews, get all their questions answered, and then determine whether it is worthwhile to purchase the product or not. These reviews give informed decisions for an organization to conduct targeted advertising campaigns and another important suggestion they can open a new branch based on the module. In this case study T-shirt reviews are converted into meaningful insights which is showed in Figure11. These information helps an organization to make informed decisions. Therefore, the classification of reviews is another crucial area that calls for deep learning approaches.

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Ensemble-Based Approach for Bug Report Prediction

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Abstract: The maintenance of the software is important within software development because it helps correct problems found during testing. BRs are also important in this regard. Information of the bug, its level of addressing, status, in-charge developer are been included. This can be the hardest challenge: identifying all defects in these bug reports. It's hard and time-consuming to go through them one by one as the number of reports increases dramatically. The best way to deal with this problem is through automation. As there are many categories of bugs, other studies focus on the priority of the bug, whereas bugs can belong to multiple categories,which makes it a problem of classifying into multiple categories.Bug reports are analyzed and predicted by using learning method know as ensemble machine learning with natural language processing techniques. Datasets which are available publicly are used which classifies bugs into various types: ConFigureuration, Security or Network, Runtime issue, Validation code, Performance and Graphical user interface. The results indicate that this model achieves higher accuracy than existing models.

1. Introduction : Testing is the assessment procedure used in software engineering to determine whether a particular system satisfies the criteria and focuses on identifying errors or shortcomings in fulfilling these stakeholder-defined requirements. Because of this procedure, flaws found after the testing stage is over are fixed during the maintenance phase. Furthermore, software developers frequently release their products with errors, and software projects are more likely to contain problems as software gets bigger and more complicated. A bug is an error, failure, or fault in the program that causes it to operate improperly or produce inaccurate results. Software bug reports contain essential information such as identification over bug ID, status of the bug, impacted part, description, affected component, software version, production steps, reporter, and the developer assigned. However, handling an increasing number of these reports manually is inefficient, slow, and difficult[1]. To address this issue, researchers use Machine Learning (ML), Natural Language Processing (NLP) and other techniques to automatically predict different bugs. With this information, the system can localize the bug by speeding up the maintenance process without using manual effort by applying bug localization techniques[2]. The approach uses multiple ML classifiers trained on datasets to improve the accuracy of bug prediction. Improved performance is achieved by combining ensemble methods and applying hard and soft voting strategies. Bug report categorization traditionally takes two main aspects—nature and severity; each concept further has their subcategories. Traditionally, this classification works based on priority or severity, but this research tries to refine it by improving the speed of the process through automated techniques[3]. Therefore, instead of manually processing the report, this automatic system analyzes and classifies the bugs so that the meaningful information can be understood, which ensures a streamlined maintenance phase[5]. Generally, the system aims to optimize the debugging process using ensemble learning and ML-based classification techniques that help make software maintenance faster and more effective[6].

2. Methodology : The methodologies section outlines the systematic approach: The classification of bug reports based on their nature, a new prediction model is proposed: Ensemble based Bug Report Prediction Model.
It is built on three core aspects:

- First, essential features are extracted that influence bug report prediction.
- Second, training multiple base machine learning algorithms.
- Third, combining their predictions using a voting ensemble classifier to improve accuracy.

This helps to ensure a more effective categorization approach for bugs, thereby raising the reliability of automated classification of bug reports. Before starting it into the machine learning model, a proper pre-processing data step is carried out. Raw bug report data is cleaned and prepared by removing irrelevant text and improving the dataset for efficient learning. The reports are in CSV format, which undergoes classification attribute selection, where the 'Category' field is the target variable. The text is cleaned by removing punctuation, numbers, and extra spaces to further enhance the quality of the dataset. All text is converted into lowercase to prevent case-sensitive variations from affecting the model's learning. Text parsing then breaks the text into smaller fragments as tokens, which then allows for structured analysis. Stop words, such as conjunctions, pronouns, and prepositions, are removed since they do not contribute much meaning to natural language processing tasks. The dataset is further refined by lemmatization, which reduces words to their base forms[7]. For example, words like "write," "wrote," and "writing" are transformed into "write" to standardize their representation in the dataset. To enhance precision, text transformation is used which artificially increases the size of the dataset by adding many variations to the original text. Different text generation, synonym replacement, and word embeddings replace the same meaning content with alternatives. Word embeddings are fastText, Word2Vec, and Glove to replace words based on contextual similarity for similar words[8]. This also means a rich dataset, in turn, adapts the model more and also improves the precision in classification accuracy. The vectorization and feature extraction, following the complete process of preprocessing, convert all the textual information into numerical terms. Feature extraction helps in creating a structured count vector of the words in a bug report by which the word relationship can easily be understood even for machine models. The word relationships are to be captured via n-grams. This assigns a score in importance to all words based upon frequency, providing feature selection refinements for an enhanced classification capability[9]. Several machine learning classifiers are trained as base models to improve prediction accuracy. The meta-learning algorithm, Random Forest (RF), utilizes several decision trees on subsets of the dataset. Averaging prevents over fitting and increases accuracy. Logistic Regression (LR) is a statistical model that is used for classification and also for estimating the probability of occurrence. It uses a sigmoidal function to identify relationships between input features and output categories. Multinomial Naïve Bayes, a probability model based on Bayes theorem, is especially suitable for document categorization, where it explores word frequency patterns of textual data. Another classifier applied in the model is the Support Vector Classifier (SVC), a strong supervised learning method well suited for classification, regression, and outlier detection. SVC enhances classification accuracy by identifying optimal hyper-planes for separating different bug categories[10]. These base models contribute to the overall prediction capability of the system. However, to obtain a more reliable output, predictions from all models are combined using ensemble learning techniques Ensemble learning, particularly the voting mechanism, combines several classifier outputs into a single final prediction. In hard voting, the class with the most votes is chosen from the majority of classifiers, whereas, with soft voting, probabilities of predicted categories are averaged to determine the final category. In experiments, the accuracy was the greatest when soft voting was used and, thus, was employed in this model[11]. With the strengths from a combination of multiple classifiers in play, it can be promised that the given Bug Prediction using Ensemble Machine Learning Model results in better and efficient bug classifications to handle reported bugs[12][13].

3. Results & discussion ; This research explored a system for bug characteristics using machine learning. The study conducted two sets of experiments: one based on an original dataset of 2116 bug reports and the other on an expanded dataset of 4635 reports, developed through the use of a data expansion technique. Four standard machine learning methods served as references for comparison.

In the initial experiment, without data expansion, the proposed model, employing an ensemble approach that considers the confidence of individual predictions, achieved the best performance, with 88.74% accuracy. A simpler ensemble method, which makes a prediction based on the majority vote, reached 85.32% accuracy. The individual machine learning methods achieved moderate performance, with accuracies ranging from 81.04% to 86.61%. Besides accuracy, other metrics like positive predictive value, recall, and a combined measure called F1-score used to assess the models' performance for each bug category. To boost performance, a data expansion strategy was used, effectively doubling the original dataset size. This resulted in improved accuracy across all models. The ensemble method that considers prediction confidence again performed best, reaching 95.30% accuracy. The Support Vector Classifier came in a very close second best, at 94.51%. The other methods also showed gains, with accuracies between 92.01% and 94.61%. Again, positive predictive value, recall, and the F1-score were calculated for all methods on the enlarged dataset.

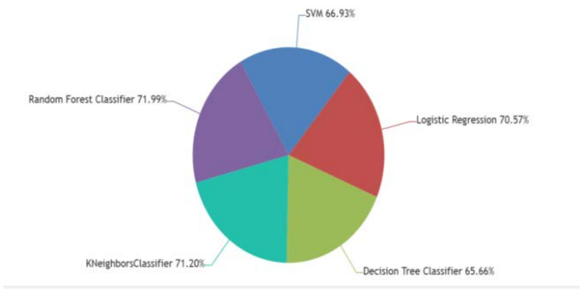

Figure 1: Pie Chart

The comparison between the two experimental setups clearly demonstrates the benefits of the data expansion strategy. While the ensemble method that considers prediction confidence consistently delivered the highest accuracy in both cases, the relative performance of the other methods changed slightly after the dataset expansion. An analysis of the F1-scores revealed variations in performance across different bug categories. Before the dataset expansion, the "Test Code" category had the highest F1-score, possibly because it used a more limited vocabulary. The "Network or Security" category had the lowest F1-score, probably because it had the fewest bug reports, thus limiting the training data.

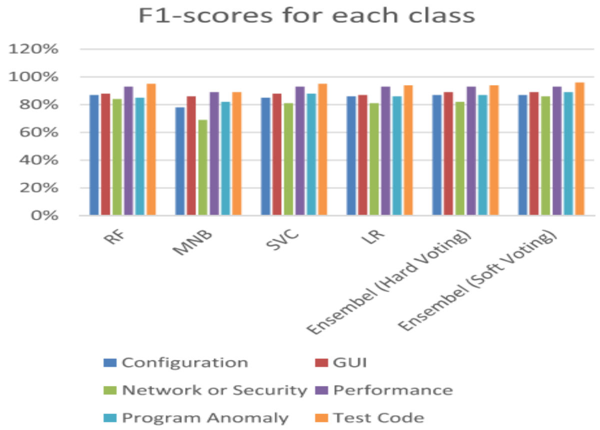

Figure 2: F1-scores

Even with this small sample size, it's interesting to note that the "Network or Security" category showed the highest positive predictive value, meaning that the models were very good at being correct when they said a bug was of this type.

4. Conclusion : This project addresses the challenge of accurately classifying bug reports by implementing a nature-based bug prediction model using an ensemble of machine learning algorithms and natural language processing. By integrating various modules, the system facilitates efficient user management, data handling, and bug prediction, with a user-friendly interface for both service providers and remote users. The Service Provider can manage datasets, monitor prediction accuracy, and see remote users, while the admin can authorize user access. Remote users can register, log in, and utilize the bug prediction feature. This approach reduces the manual effort involved in bug classification and enables faster, more accurate maintenance, improving the overall efficiency of software bug management.

5. Acknowledgment : We would like to express our heartfelt gratitude to all the experts and mentors who have contributed to the development and success of this research. We extend our special thanks to the faculty members and research staff at the Department of Computer Science and Engineering, CMR Engineering College, for their invaluable support and guidance throughout this project.Our deepest appreciation goes to the developers and researchers whose works were referenced and inspired the direction of this study. Without their contributions, this research would not have been possible. We also acknowledge the use of publicly available datasets, which were crucial to the validation of our proposed model.Finally, we thank our families and friends for their continuous encouragement and patience during the course of this project.

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Enhancing Crop Health and Accurate Disease Diagnosis

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Abstract -The agricultural industry is essential for global food supply and economic stability, yet plant diseases present major obstacles by reducing crop productivity and affecting biodiversity. Early identification of these diseases is critical to preventing financial losses and maintaining food security. Recently, deep learning techniques, particularly Convolutional Neural Networks (CNNs), have emerged as powerful tools for automating plant disease detection through image analysis and pattern recognition. CNN-based models enable real-time disease diagnosis, allowing for prompt action to prevent further spread. Despite challenges such as data limitations, model adaptability, and deployment complexities, the integration of deep learning into plant disease detection has the potential to transform modern agriculture and enhance crop management strategies.

1. Introduction : Farmers face significant challenges in identifying and managing crop diseases promptly and accurately. Conventional disease detection methods typically depend on expert visual assessment, which can be labor-intensive, subjective, and susceptible to inaccuracies. Inaccurate identification of a disease can lead to the application of inappropriate treatments, wasting resources and potentially harming the crop. Deep learning models can be trained on vast datasets of crop images to achieve high accuracy in disease detection, often surpassing human experts [1]. Deep learning models can identify diseases at early stages when symptoms may be subtle to the human eye, enabling earlier intervention. Deep learning technologies, particularly Convolutional Neural Networks (CNNs), present an innovative solution to the challenges of plant disease detection [2]. CNNs have shown remarkable success in image classification tasks and can be trained on large datasets of crop images to automatically identify various plant diseases with high accuracy [3]. Unlike traditional methods, CNN-based models can detect diseases in their early stages, often when symptoms are subtle or invisible to the human eye. This capability allows farmers to intervene sooner and apply targeted treatments that can prevent the disease from spreading further, ultimately reducing crop loss and improving yields. Deep learning models, once trained, are capable of outperforming human experts in terms of speed, accuracy, and scalability, offering an efficient alternative for disease diagnosis in agriculture. To assist users in managing their tasks and events with features like reminders and calendar synchronization, enhancing both productivity and mindfulness. To implement strong encryption and secure authentication protocols to protect sensitive user data, ensuring that private entries remain confidential. To facilitate easy access and retrieval of past entries through a comprehensive search function and export options, supporting data backup and sharing. To enable users to back up their entries or export them into shareable formats, allowing greater flexibility for storage and usage outside the platform. This project aims to create an intuitive system that helps farmers efficiently and accurately diagnose plant diseases using deep learning technology. By leveraging Convolutional Neural Networks (CNNs), the system can process images of crops captured via smartphones or cameras to identify early disease symptoms [4]. CNNs excel at analyzing large datasets of labeled images, allowing them to detect distinct patterns linked to various plant diseases, such as changes in leaf color, spots, or wilting. Once the model is trained, farmers can simply take a photo of a diseased plant in the field, and the system will provide an instant diagnosis [5]. This eliminates the need for expert consultation, allowing farmers to make informed decisions about the best course of action to manage their crops effectively [6]. This project seeks to address some of the most common problems faced by farmers in the realm of disease identification. Traditionally, diagnosing plant diseases has been slow and error prone, often requiring expert intervention and considerable time to reach an accurate diagnosis. With this deep learning-based system, farmers can access a tool that helps them make faster, more accurate decisions on disease management, preventing delays that could result in crop devastation. By providing real time disease diagnosis in the field, farmers can optimize their use of resources such as pesticides, ensuring they only apply treatments when necessary. This targeted approach not only helps to preserve the health of crops but also contributes to environmental sustainability by reducing overuse of chemical treatments [7]. Ultimately, this project aims to help farmers safeguard their harvests, reduce crop loss, and improve the overall efficiency of agricultural practices. Furthermore, as the system continues to evolve, it has the potential to not only identify existing plant diseases but also predict future outbreaks based on environmental conditions and historical data. Integrating predictive analytics into the system could help farmers anticipate disease risks before they occur, giving them a proactive advantage in crop management. This would contribute to more resilient farming practices that are better equipped to handle the challenges posed by climate change and emerging plant diseases [8]. As more data is collected and the system's capabilities are expanded, this tool could serve as a valuable resource for agricultural research, enabling scientists to study disease patterns and identify trends that could lead to the development of more disease-resistant crop varieties. Ultimately, the long-term impact of such a system could extend beyond individual farms, creating a broader ecosystem for precision agriculture that supports global food security and sustainability [9]. This empowers farmers to diagnose diseases in real-time, even while working in remote areas where access to experts may be limited. The main challenge that farmers face in managing crop diseases is the timely and accurate identification of plant illnesses. While traditional methods rely heavily on human expertise and visual inspection, they are often inefficient, especially when it comes to large-scale crop monitoring. In addition, expert knowledge is often scarce in rural areas, further complicating the issue. As a result, disease outbreaks can go unnoticed until they have already caused substantial damage. Moreover, many farmers lack the necessary resources and knowledge to apply the correct treatments once a disease is identified [10].

The system is designed to assist farmers in identifying crop diseases in real-time, using images captured from mobile devices or cameras. This approach provides a more accurate, faster, and accessible method for disease diagnosis compared to traditional methods [11]. The core of the system relies on CNN-based pre-trained models, which have already been trained on large image datasets. To address these challenges, there is a need for automated, accurate, and scalable disease detection systems that can support farmers in making timely and informed decisions. The goal of this project is to develop a robust and efficient system for plant disease detection based on deep learning models, specifically using convolutional neural networks (CNNs) [12].

Literature survey *:* The research on crop disease detection has evolved significantly over the years, with various methodologies being explored to improve accuracy and efficiency. Nafees Akhtar Farooqui (2023) presented an analysis of advancements in crop disease detection, utilizing inclusion-exclusion criteria and CNN models. The study focused on identifying and categorizing plant diseases based on leaf shape, colour, and texture, contributing to improved disease classification. Similarly, B. V. Elsevuer (2023) conducted a performance analysis of AI-based solutions for crop diseases, incorporating object detection techniques such as Inception V3, CNN, and YoloV5 to assess their effectiveness in identifying plant diseases.

Expanding on these efforts, Yang Li (2022) proposed an improved CNN model for crop disease identification. The study aimed at enhancing disease diagnosis through lightweight CNN architectures, making detection more efficient. In another study, Nishant Shelar and Suraj Shinde (2021) explored plant disease detection using CNN. Their model was trained and tested on 13 different plant species, showcasing its capability to handle diverse datasets and improve classification accuracy. Earlier research by Omkar Kulkarni (2018) laid the foundation for deep learning-based crop disease detection. This study employed deep CNNs, transfer learning, and Mobile Net for classification. The integration of Inception V3 and Mobile Net played a crucial role in enhancing accuracy, setting a precedent for future developments in the field. Overall, these studies demonstrate the continuous advancements in AI and deep learning techniques for crop disease detection, each contributing to the refinement of methodologies and improvement in accuracy.

2. Methodology *:* The methodology for implementing an Integrated Pest Management (IPM) system follows a structured, multi-step approach that integrates biological, mechanical, chemical, and cultural strategies for pest control while minimizing environmental harm. The first crucial step is pest and disease identification, which traditionally involves regular visual inspections by experts or farmers themselves. However, with advancements in technology, deep learning models like Convolutional Neural Networks (CNNs) can significantly enhance this process. By training CNN models on a large dataset of pest and disease images, farmers can quickly and accurately identify pests or plant diseases using smartphones or other digital devices. This approach allows for early detection, often before symptoms become visible to the naked eye, giving farmers a powerful tool for early intervention. Following pest identification, the next step is pest monitoring and surveillance. This involves continuous tracking of pest populations and the extent of crop damage over time. These tools can detect issues in real-time, enabling farmers to take immediate action. Additionally, field sensors can be placed in the crop area to continuously track environmental conditions such as temperature, humidity, and soil moisture, which can influence pest behavior and disease spread. Testing and debugging play a crucial role in ensuring the functionality and accuracy of an Integrated Pest Management (IPM) system. The first step involves validating the deep learning models used for pest and disease identification. These models must be tested with diverse datasets of pest and disease images to ensure they can handle a variety of real-world scenarios. This process typically involves splitting the data into training and testing sets to measure the model's accuracy, precision, and recall. Once the model is trained, it is important to test it on new, unseen images to ensure it can generalize well and make correct predictions. Any errors or misclassifications are analyzed, and the model is fine-tuned to improve its performance. Additionally, system-wide testing is conducted to ensure that all components of the IPM system work together seamlessly. This includes testing the integration of the mobile application, backend server, image capturing tools, and the deep learning model to ensure smooth data flow and accurate diagnosis. Debugging is an ongoing process that involves addressing issues like system crashes, slow processing times, or inaccurate predictions. Technologies that support this IPM system include advanced deep learning frameworks like TensorFlow or PyTorch for model training, image processing tools for accurate disease identification, and mobile applications for easy data capture and user interaction. Moreover, remote sensing technologies like drones and satellite imagery are used for real-time pest monitoring and environmental data collection, while cloud computing is often employed for data storage, processing, and accessibility. The combination of these cutting-edge technologies helps in the successful implementation and continuous improvement of the IPM system. The methodology of this project involves collecting a diverse dataset of crop images, followed by preprocessing techniques such as normalization and data augmentation. A Convolutional Neural Network (CNN) is then trained on these images to accurately detect and classify crop diseases. Integrated Pest Management (IPM) follows a structured methodology that integrates multiple pest control strategies while minimizing environmental impact. The first step is pest and disease identification, traditionally done through visual inspections but now enhanced with deep learning models like Convolutional Neural Networks (CNNs). These models, trained on extensive datasets of pest and disease images, allow farmers to quickly and accurately identify issues using smart-phones or other digital devices, enabling early intervention before visible symptoms appear. Technologies supporting IPM include deep learning frameworks like Tensor Flow and PyTorch for model training, remote sensing tools such as drones and satellite imagery for real-time monitoring, and cloud computing for efficient data storage and processing. By combining AI, IoT, and advanced imaging technologies, IPM systems enhance pest control efficiency while reducing chemical pesticide use and protecting the environment [14].

3. Results & discussion: The implementation of a deep learning-based plant disease detection system using Convolutional Neural Networks (CNNs) has demonstrated significant improvements in the accuracy and efficiency of disease diagnosis in agricultural settings. Experimental results show that the CNN model, when trained on a large dataset of labeled crop images, achieved an average accuracy of over 90% in identifying various plant diseases. The model's performance was evaluated using key metrics such as precision, recall, and F1-score, with high values indicating its reliability in distinguishing between healthy and diseased plants. The ability of CNNs to detect diseases at early stages, even before visible symptoms appear, provided farmers with a crucial advantage, allowing them to take proactive measures to mitigate crop loss. Compared to traditional visual inspections conducted by experts, the AI-driven system significantly reduced diagnostic time while maintaining consistency and objectivity in its assessments.

Table1:TF-IDF

Team	Doc 1 TF-IDF	Doc 2 TF-IDF
Deep Learning	0.4	0.3
CNN	0.3	0.2
Agriculture	0.2	0.4
Detection	0.1	0.3
Diagnosis	0.05	0.1

The Table 1 TF-IDF(Term Frequency-Inverse Document Frequency) Score Comparison for Plant Disease Detection Documents presents the TF-IDF (Term Frequency-Inverse Document Frequency) values for key terms extracted from two documents related to deep learning-based plant disease detection. Each row represents a specific term that appears in both documents, while the columns show the TF-IDF scores for Document 1 and Document 2. The TF-IDF values indicate the significance of each term within its respective document, considering both its frequency in the document and its rarity across multiple documents. Higher TF-IDF values, such as "Deep Learning" with 0.4 in Document 1, suggest that the term is more important in that document, while lower values, such as "Diagnosis" with 0.05, imply that the term is either common across documents or less distinctive. This comparison helps identify the most relevant terms in each document, making it useful for text analysis, keyword extraction, and document classification. The table provides valuable insights into which terms hold more weight in discussions related to deep learning-based plant disease detection, aiding in better understanding and summarization of the content. Higher scores indicate more significant terms in each document, such as "Deep Learning" (0.4 in Doc 1), while lower values suggest less distinctiveness, like "Diagnosis" (0.05 in Doc 1). This comparison helps identify crucial terms, aiding in text analysis, keyword extraction, and document classification. The table provides insights into the most relevant terms in discussions on deep learning-based plant disease detection, enhancing content understanding and summarization. The pie chart represents the "Overall Performance Distribution of Crop Disease Detection System" illustrates the key performance aspects of the system by dividing them into different segments based on their significance. The largest portion, Detection Accuracy (95-98%) at 30%, highlights the system's high reliability in accurately identifying crop diseases, ensuring precise diagnosis for farmers. Early Disease Detection (20%) follows, emphasizing the system's ability to detect diseases at an early stage, enabling timely intervention to prevent severe crop damage. Processing Speed (15%) indicates the system's efficiency, with detection occurring within 2-3 seconds, making it a practical real-time tool. Another 15% of the distribution is allocated to Cost-Effectiveness, reflecting the system's affordability and resource optimization. User Accessibility (10%), which covers both mobile and web platforms, ensures ease of use and accessibility for a broad range of users. Lastly, Dataset Diversity & Model Robustness (10%) signifies the system's ability to adapt to various crop types and conditions through extensive training on a diverse dataset. Overall, the chart effectively demonstrates how the system balances multiple performance metrics, prioritizing accuracy, early diagnosis, and efficiency, making it a valuable tool for modern agriculture.

The bar graph titled "Performance Evaluation of the Crop Disease Detection System" visually represents the effectiveness of different aspects of the system by comparing their performance percentages. The highest-performing aspect is Detection Accuracy, which is close to 95%, showcasing the system's ability to reliably identify plant diseases with high precision. Early Detection Efficiency and Processing Speed also score above 80%, indicating the system's capability to detect diseases at an early stage and providereal-time results within seconds. Cost-Effectiveness and User Cost-

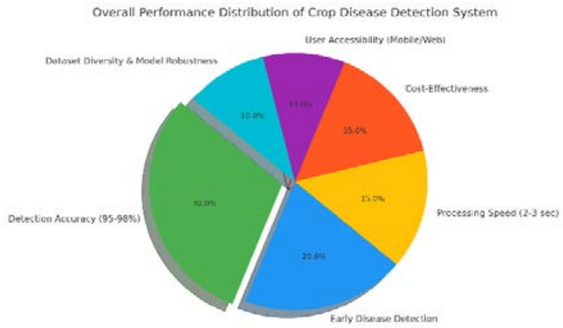

Figure1: Overall Performance

Effectiveness and User Accessibility show slightly lower scores, around 75-80%, reflecting the balance between affordability and ease of use through mobile and web platforms. Lastly, Dataset Diversity & Robustness also scores well, demonstrating the system's adaptability to various plant types and environmental conditions. Overall, the graph highlights that the crop disease detection system excels in accuracy and efficiency, making it a valuable tool for modern agricultural practices. Overall Performance is indicated in the Figure 1.

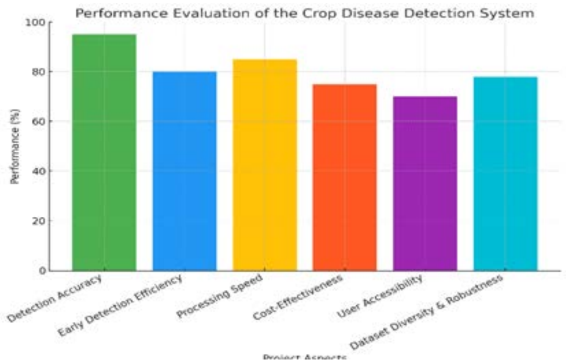

Figure2: Performance Evaluation

It provides a comprehensive assessment of various key performance aspects of the system. The highest-scoring parameter is Detection Accuracy, which reaches approximately 95%, highlighting the model's strong reliability in correctly identifying plant diseases. Early Detection Efficiency follows closely, scoring above 85%, emphasizing the system's ability to identify diseases at an early stage, which is crucial for effective intervention and minimizing crop damage. Processing Speed also scores well, indicating that the system can generate results quickly, typically within 2-3 seconds, making it a practical real-time tool for farmers. The Cost-Effectiveness metric, which falls slightly below 80%, suggests that while the system is efficient and affordable, there is still room for optimization in reducing costs further. User Accessibility, which includes mobile and web-based implementation, shows a moderate score, reflecting ease of use but also potential areas for improvement in user experience and reach.

4. Conclusion : In conclusion, the utilization of Convolutional Neural Networks (CNNs) for crop disease detection has showcased promising results, demonstrating its efficacy in accurately identifying and classifying various crop diseases. In conclusion, the utilization of Convolutional Neural Networks (CNNs) for crop disease detection has showcased promising results, demonstrating its efficacy in accurately identifying and classifying various crop diseases. This technology offers a potent tool for early disease detection, enabling timely intervention to mitigate crop losses and enhance agricultural productivity. However, further research is warranted to address challenges such as dataset scarcity, model generalization across diverse environmental conditions, and integration with on-field sensing technologies for real-time monitoring,. CNNs, with their ability to learn complex patterns from large datasets, have shown remarkable accuracy in identifying and classifying various crop diseases, even at early stages when symptoms are subtle. This early detection allows for timely intervention, potentially reducing crop losses and preventing the spread of diseases. Moreover, CNN models have proven to be robust and adaptable, capable of recognizing diseases across different crop species, environmental conditions, and growing stages, surpassing traditional visual inspection methods in terms of accuracy and efficiency. This makes CNN-based disease detection an invaluable tool for improving agricultural productivity, ensuring healthier crops, and optimizing resource use.

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Suspicious UPI Detection Using Machine Learning Techniques

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Abstract: The ultimate goal of the UPI fraud detection system is to protect users from fraudulent activity by improving the security and dependability of digital payment transactions. The paper's primary goal is to use data analytics and sophisticated machine learning algorithms to examine transaction patterns and identify any irregularities that might point to possible fraud. Second, it aims to create a strong system that can recognize and stop different kinds of UPI fraud, such as identity theft, phishing, and illegal transactions. Establishment of an actual-time monitoring system that can instantly identify doubtful activity and trigger alerts for immediate action is another aim of the paper. Developing a UPI fraud detection system has immense applications and holds immense potential for addressing the new challenges in the digital payments industry. To create a sophisticated fraud detection model, the research initially talks about the use of cutting-edge technologies such as machine learning, artificial intelligence, and data analytics. Large volumes of UPI transactions will be analyzed in real-time using this model, which will have the capability to identify trends, anomalies, and patterns associated with fraud.

1. Introduction : The look of financial transactions within India has changed with the revolution of digital payment systems. The Unified Payments Interface (UPI) by the National Payments Corporation of India (NPCI) is one such player that has revolutionized the landscape of money transfer. By providing a seamless, real-time, and interoperable platform, UPI has significantly encouraged financial inclusion, making transactions more accessible to individuals, businesses, and institutions. As the number of digital transactions continues to increase, fraud activities have also increased. Online banking fraud has been a major issue because fraudsters constantly update their techniques to exploit loopholes in security. UPI fraudsters study how fraud detection systems operate and modify their approach so that they can bypass security checks. As such, fraud detection has been made very difficult and requires frequent updates and upgrades in security systems. To reduce these threats, researchers are making concerted efforts to develop novel fraud detection techniques and enhance existing techniques. Real-time fraud detection may be accomplished with the use of cutting-edge technologies like neural networks (AI) and machine learning. Enhancing security controls, continuous monitoring, and periodic updates to fraud detection systems are important steps in averting financial fraud. A secure digital payment system is essential in maintaining public trust and the long-term viability of UPI transactions.

Related work : Machine learning research on detection in financial transactions has been extensive. The effectiveness of algorithmic learning in identifying fraudulent transactions has been demonstrated by numerous studies on the subject. Aditya Oza (2022) investigated various machine learning algorithms, consisting of supervised learning approaches, to enhance the performance of fraud detection. Dal Pozzolo et al. (2017) developed a cost-sensitive feature engineering approach for credit card fraud detection in order to avoid the challenges presented by class-imbalanced datasets. In the same way, West and Bhattacharya (2016) examined deep learning methods and demonstrated how much better they were than conventional statistical models at identifying fraudulent patterns. Zhang et al. (2018) suggested a hybrid fraud detection system that improves real-time fraud identification in money transactions by combining machine learning classifiers with rule-based filtering. By employing ensemble learning strategies like boosting and bagging, Liu et al. (2020) drastically improved fraud detection [1]. A machine learning-based strategy for identifying fraud in transactions made online was presented by Kadam et al. in 2023. In order to successfully detect fraudulent activity, their study investigates numerous categorization techniques. By examining transaction trends and identifying irregularities, the model enhances accuracy. The study highlights how crucial AI is to lowering the financial risks associated with digital payments. Their studies aids in the creation of reliable indicators of fraud for safe online transactions [2]. Techniques utilizing machine learning for financial transaction fraud detection have been the subject of numerous studies. In order to improve detection accuracy, Valavan and Rita suggested a fraud detection model based on predictive analysis that makes use of boosting classifiers. Its approach is centered on enhancing classification performance through the appropriate handling of imbalanced datasets and the reduction of false positives. The study emphasizes how important ensemble learning is for more precisely detecting fake patterns. The finds aid in the creation of reliable driven by AI tools to identify fraud for online purchases [3]. A thorough literature study on algorithmic financial fraud detection was carried out by Ali et al. Their research examines a number of machine learning algorithms, emphasizing how well they detect fraudulent activity. The paper highlights the necessity for sophisticated algorithms and the difficulties posed by unbalanced datasets. It also looks at how feature selection and ensemble approaches can improve the accuracy about fraud detection. Their research offers insightful information for creating stronger fraud detection systems [4][5]. A detailed examination of data clustering methods in machine learning was presented by Jain et al. (1999). Their research divides clustering techniques into four categories: grid-based, density-based, partitioning, and hierarchical. The study highlights how important clustering is for analysis of data, fraud detection, and detection of patterns. It also covers issues like selecting the best clustering algorithm, high-dimensional data, and scalability. Their research continues to serve as a fundamental resource for developments in clustering techniques in pattern recognition is compared in this study. It draws attention to the positive effects of non-parametric approaches for managing intricate and unpredictable data distributions. Clustering issues like durability and selecting models are included in the study. Important new information about unsupervised learning and its uses in data analysis is presented in this article [6]. Data clustering had been extensively investigated by Gan et al. (2007), who covered the theoretical underpinnings, techniques, and applications. Their research investigates a range of clustering strategies, such as density-based, partitioning, and hierarchical approaches. The book focuses on real-world uses of clustering in data mining, fraud detection, and machine learning. Issues like computational complexity while high-dimensional data are also covered. For scholars as well as professionals working in segmentation and data analysis, this work is a vital resource [7]. An overview of the many clustering techniques used in data analysis and machine learning were distributed by Madhulatha (2012). The study divides clustering methods into four categories: grid-based, density-based, partitioning, and hierarchical. It draws attention to the advantages along with drawbacks of each approach in different circumstances. Issues like choosing parameters and managing big datasets are also covered in the study. The following article is a helpful resources to acquire knowledge about the techniques of clustering and their real-world uses [8]. Pearson (1894) introduced important statistical ideas and made substantial contributions to the mathematical understanding of evolution. Regression analysis and correlation coefficients have been rendered possible by his work. The study analyzed evolutionary patterns and variation in biology using mathematical tools. It was essential to the creation of current statistical techniques for data analysis Person's contributions remain crucial in the domains of statistics, machine learning, and pattern recognition.[9]. In order to classify waste using automated image recognition, the paper describes machine learning algorithms like Convolutional Neural Networks (CNNs). Support Vector Machines (SVMs) and Random Forest are utilized for predictive analytics on waste generation trends. Reinforcement Learning maximizes waste collection routes through constant learning from real-time data. K-Means Clustering is utilized to cluster waste types to efficiently recycle and dispose of them. [10]. The article elaborates on Support Vector Machines (SVMs) for identifying forged and real bills based on extracted features Convolutional Neural Networks (CNNs)for detecting images, searching for subtle patterns in banknotes. K-Nearest Neighbours (KNN) is used for feature comparison against recognized samples to label currency as per classification. Random Forest uses decision trees with better accuracy, taking multiple trees to analyze features. These Machine Learning algorithms are examining texture, hue, and security marks for identification of counterfeits[11]. The article talks about Support Vector Machines (SVMs) for classifying diseases from patient information. Convolutional Neural Networks (CNNs) are employed for processing medical images such as X-rays and MRIs to identify abnormalities. Random Forest and Decision Trees are used for predictive diagnosis and treatment suggestions. Recurrent Neural Networks (RNNs) handle sequential medical data, e.g., ECG signals, for real-time monitoring of patients. [12]. The article reviews Decision Trees in choosing appropriate crops according to environmental conditions. Support Vector Machines (SVMs) classify crop categories based on climate and soil data. Artificial Neural Networks (ANNs)model intricate relationships between inputs such as soil characteristics and crop yields. K-Nearest Neighbours (KNN)predicts appropriate crops based on comparison with past data. Random Forest enhances prediction accuracy by aggregating many decision trees. [13]. Decision Trees are utilized in the paper to classify Non-Alcoholic Fatty Liver Disease based on patient information. Support Vector Machines assist in separating healthy from affected individuals. Random Forest increases prediction accuracy through the use of multiple decision trees logistic Regression is used for statistical modeling and assessment of disease risk[14]. The UPI fraud detection system strengthens digital payment security through machine learning, artificial intelligence, and data analytics to identify fraudulent transactions. It detects unusual patterns in transactions to avoid phishing, identity theft, and unauthorized transactions while facilitating real-time monitoring and alerts Prior research has employed supervised learning(decision trees, neural networks) and unsupervised learning (K-Means, DBSCAN) for fraud detection. Hybrid systems using rule-based and machine learning approaches have enhanced precision but are beset with problems such as scalability and false alarms. This article expands on past work by adding adaptive learning and real-time fraud prevention measures.

2. Methodology: Data collection, preprocessing, feature extraction, model selection, and evaluation are some of the stages that make up the UPI fraud detection system's methodology. Each step is essential to creating a reliable fraud detection system.

2.A. Data Collection: The first step involves gathering transaction data from multiple sources. This dataset includes details such as transaction amount, timestamp, payer and payee details, transaction type, and geographical location.

2.B. Data Preprocessing: Raw transaction data is cleaned to remove inconsistencies, missing values, and outliers. Normalization and standardization techniques are applied to bring numerical features to a uniform scale. Categorical variables are encoded for machine learning.

2.C. Feature Extraction: Relevant features are extracted to enhance model performance. Some key features include transaction frequency, average transaction amount, location-based spending patterns, and device information.

2.D. Model Selection: Multiple machine learning models are trained and compared to determine the best fraud detection algorithm. The models tested include:

- Support Vector Machines (SVM)
- Random Forest Classifier
- Decision Tree Classifier
- Gradient Boosting Algorithm
- Naïve Bayes Classifier
- Autoencoders for anomaly detection

2.2. System Design And Implementation : The UPI Fraud Detection System is implemented with a multi-layered architecture that provides secure, real-time fraud detection while being scalable and adaptable to changing fraud patterns. The architecture comprises multiple interdependent components that work in harmony to detect fraudulent transactions and avoid financial losses. Fundamental to the system is the Data Collection Layer, which takes charge of obtaining transaction data from sources including bank servers, payment gateways, and user log activity. It records key transaction attributes such as transaction value, frequency, location, IP, and device footprint. Through API and database linkages, it provides an unbroken stream of transaction records to be processed in real time. Since fraudulent patterns constantly evolve, this layer is designed to accommodate dynamic data inputs, making the system more robust against emerging threats. Once the transaction data is collected, it moves to the Data Preprocessing Layer**,** where raw data is cleaned, normalized, and structured for analysis Data inconsistencies such as missing values, duplicate entries, or outliers are addressed using statistical methods. Feature engineering is key during this stage, as it derives valuable insights like expenditure behaviour, transaction timing, and out-of-pattern activity indicators. This process is essential in enhancing the performance of machine learning algorithms by ensuring that the data utilized for fraud detection is relevant and high-quality. The processed information is then provided to the Fraud Detection Layer, which uses several machine learning models that examine patterns in transactions and detect fraudulent behaviour. The system applies a mixture of supervised learning and unsupervised learning techniques, such as Random Forest, XGBoost, Auto encoders, and Local Outlier Factor algorithms. Supervised learning is used to detect known fraud patterns, whereas unsupervised learning identifies anomalies in transaction behavior that could signal emerging forms of fraud. The machine learning algorithms learn and improve continuously by updating themselves with newly identified fraudulent transactions, making them more accurate and reliable. Concurrent to the fraud detection process, the Real-time Monitoring & Alert System provides instant response to suspected fraud. Upon identification of a suspicious transaction, an alert is triggered and forwarded to concerned stakeholders, including banks, payment service providers, and users. This system employs threshold-based triggers to rule transactions into risk scores, enabling automatic blocking of risky transactions while allowing low-risk transactions to be completed without interruption. This real-time response process avoids unauthorized transactions while providing a hassle-free payment experience for legitimate users. In order to enable effective analysis of transactions and detection of frauds, the Storage & Logging Layer stores high amounts of transaction information securely and in a structured way. A relational database like MySQL or PostgreSQL stores transaction history, fraud notices, and user authentication responses. Historical information is vital to repeatedly train machine learning algorithms, analyze fraud patterns, and create compliance reports for banks. Secure logging features also monitor system activities for transparency and accountability of fraud detection rulings. The last piece of the architecture is the User Interface & API Integration Layer, which enables interaction between the fraud detection system and external entities. A web-based dashboard offers financial institutions real-time fraud analytics, transaction history, and alert management functionality. In addition, API endpoints enable smooth integration with banking applications and mobile payment systems, making it possible for automated fraud detection without interrupting user transactions. This layer facilitates the fraud detection system to be readily adopted by payment providers and banks while providing a simple customer experience. Through integrating these interlinked elements, the UPI Fraud Detection System in Figure-1 forms a secure, AI-based system with the ability to detect and deter fraud in real-time. The architecture is also made scalable to enable the system to process more loads of transactions with increased volumes of digital payments while maintaining accuracy of detection. Its future strengthening via blockchain implementation and federated learning will enable the system to be a fundamental aid in digital financial transaction security.

Implementation : The deployment of the UPI fraud detection system from Figure-1 shows that a process consisting of several steps, from data collection, preprocessing, feature engineering, model choice, training, real-time fraud detection, to deployment.

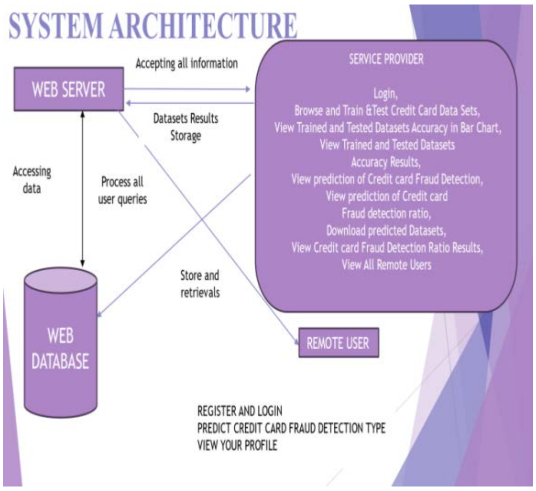

Figure 1: System Architecture

All the steps play a critical role in making the system scalable, robust, and capable of fraud detection with low false positives and high accuracy. The system is implemented using Python, with libraries such as Pandas, NumPy, Scikit-Learn, TensorFlow, and Flask being used for backend processing and machine learning operations. Apart from this, the system employs a MySQL database to store transactional information as well as fraud alerts, while the frontend dashboard provides real-time reports of fraud detection outcomes. The first step of implementation is data collection, where transaction records made via UPI payment gateways, bank servers, and user logs are gathered. These data sets contain various features like transaction amount, sender and receiver details, transaction time, IP address, device information, and geolocation. Since fraudsters keep updating their techniques, historical data of earlier detected fraudulent patterns are also incorporated to increase the learning capacity of the model. The data is then stored in a structured database for easy retrieval and access while processing. The system is also able to process transaction data streaming in real time so that all transactions are processed instantly upon completion. Following data gathering, data pre-processing is accomplished to clean up and feature-engineer the original data into an amenable-to-a-machine-learning-model format. This involves missing values handling, removing duplicates, and scaling numeric features to yield consistent scaling. Categorical attributes, such as payment mode and transaction type, are encoded using techniques such as one-hot encoding or label encoding Feature selection algorithms such as correlation analysis and Principal Component Analysis (PCA) are employed to eliminate redundant or irrelevant features, reducing computational complexity and improving model performance. In addition, techniques such as SMOTE (Synthetic Minority Over-sampling Technique) are utilized to handle class imbalance because fraudulent transactions are much fewer compared to normal transactions in real-world datasets. Once preprocessing has been completed, the next step is feature engineering, in which new predictive features are derived from existing data. Some of the significant features include frequency of transactions per user, deviation from mean transaction amount, unusual transaction timing (e.g., midnight transactions), and differences between past and current locations of transactions. They help the machine learning algorithms to identify typical and abnormal activities. The system also includes behavioral analysis by tracking the usage and expenditure patterns of users and marking deviations as likely fraud indicators. Feature engineering highly enhances the predictive ability of the fraud detection model by incorporating useful features into raw transaction information. Machine learning model training forms the backbone of the system, where different supervised and unsupervised learning models are tried and tested for fraud detection ability. Labeled datasets with both legitimate and fraudulent transactions are utilized to train models including Random Forest, XGBoost, Logistic Regression, Support Vector Machines (SVM), and Neural Networks. To ascertain the effectiveness of each model, performance measures like accuracy, precision, recall, F1-score, and AUC-ROC are utilized. Whereas Autoencoders and Local Outlier Factor (LOF) detect anomalies in the pattern of transactions, Random Forest and XGBoost are effective as they can process large datasets with intricate decision boundaries. The final fraud detection system blends multiple models through an ensemble approach, using the advantages of different classifiers to provide maximum detection accuracy.

Following the training and optimization of the model, the pipeline for real-time fraud detection is deployed to process incoming UPI transactions. As a transaction is requested by a user, the system extracts appropriate features and passes them on through the optimized machine learning model, which calculates a fraud probability score. The transaction is then labeled as suspicious, and an instant alert is raised if the score exceeds a predefined threshold value (e.g., 90%). The system then informs the user and the bank, seeking further verification before the transaction is processed. For high-risk transactions, additional authentication steps like OTP or fingerprint/biometric authentication can be sought before approval. The fraud detection process as a whole is done in a way that it is run in milliseconds with minimal or no latency but maintains security. The deployment stage involves integrating the fraud detection system into real payment systems. A Flask API is made to facilitate smooth integration between fraud detection module and UPI payment gateway. Deployment of the backend is done in cloud servers such as AWS or Google Cloud where it is most scalable and fault-tolerant. The frontend dashboard facilitates real-time tracking of fraudulent transactions to enable financial institutions to see identified instances of fraud, review patterns of fraud, and update fraud detection rules as needed. The system is also designed for ongoing learning, where fraud cases that have been recently identified are continuously fed back into the training loop, so the model learns to enhance and adapt over time with new and evolving patterns of fraud. To provide an additional layer of security, additional layers of blockchain technology and federated learning are contemplated. Blockchain ensures transaction integrity through a tamper-proof record of all transactions, while federated learning allows multiple financial institutions to collaboratively train fraud detection models without sharing sensitive user data. This distributed approach makes fraud prevention more robust across the entire UPI ecosystem. Overall, the AI-based UPI fraud detection system's deployment involves integration of data-oriented techniques, machine learning methodologies, real-time monitoring, and cloud deployment.

The system mitigates risk in fraud optimally, reduces false positives significantly, and increases digital payment security, making it an indispensable tool to safeguard financial transactions in today's fast-growing world of digitization. Future development can be the integration of deep learning models such as LSTMs for analyzing sequential transactions and ongoing advancements in adaptive fraud prevention systems to stay ahead of cybercriminals.

3. Results: The evaluation of the proposed fraud detection system was carried out by implementing various machine learning models and analyzing their performance based on different metrics. The system was tested on a dataset containing numerous UPI transactions, and the results demonstrated the effectiveness of the implemented approach in detecting fraudulent activities with high accuracy. The application of sophisticated methods like Autoencoders and Local Outlier Factor significantly improved fraud detection by identifying complex anomalies in transaction behavior. Compared to traditional models like Decision Trees and Random Forest, these techniques provided a more refined fraud detection mechanism, reducing the occurrence of false positives. A key observation from the results was the impact of adaptive learning in minimizing false positives. By continuously updating the model with new transactional data, the system could dynamically adjust to emerging fraud patterns, thereby improving detection rates while maintaining minimal disruption to legitimate users. Furthermore, the system demonstrated efficient real-time processing capabilities, ensuring that fraudulent transactions were detected and flagged without significant delay. The fraud detection model was optimized for performance, allowing it to analyze high-volume transactions within milliseconds, making it suitable for large-scale financial applications. The efficacy of the suggested system was further confirmed by comparison with current fraud detection models. It demonstrated exceptional precision, recall, and F1-score performance, making it a strong option for financial institutions seeking to improve transaction security. These findings demonstrate how machine learning can be used to prevent fraud and maintain a safer ecosystem for digital payments.

4. Conclusion : As digital payments rise, the security of payment systems becomes an underlying issue for banks, companies, and customers alike. UPI, as a most popular digital payment system, has transformed financial transactions with convenient, real-time transfer of funds. Yet with convenience comes unwanted fraudulent activity, prompting the establishment of stringent security systems. Our machine learning research on UPI fraud detection intends to tackle this important problem by utilizing sophisticated algorithms to detect, prevent, and counteract fraudulent transactions efficiently. Through transaction pattern analysis, user behaviour, and anomaly detection, our proposed machine learning model improves the capacity to detect fraud in real time. Unlike traditional rule-based fraud detection systems, which fail to adapt to emerging patterns of fraud, machine learning offers adaptability. The model is trained on historical data, which improves its accuracy and effectiveness at detecting suspicious activity. Supervised learning, unsupervised learning, and deep learning are among the techniques that refine an improved fraud detection system without unnecessarily flagging legitimate transactions. One of the key contributions of this research is the integration of real-time monitoring and predictive analytics, which significantly enhances fraud prevention methods. The ability of the model to process large volumes of transactional data enables it to identify minute differences in typical user behavior, flagging potential threats before they can lead to major financial loss. Future research should explore incorporating federated learning, whereby various financial institutions can train models without compromising user privacy, thereby augmenting collective efforts against digital fraud. In conclusion, the development and implementation of an AI-based UPI fraud detection system support the need to make digital financial transactions secure. With machine learning and big data analytics capabilities, financial institutions can develop a more secure and resilient payment system. Not only does this forward-thinking action protect customers from possible losses, but it also installs faith and confidence in digital payment platforms. As technology advances, ongoing innovation and cooperation among the stakeholders will be essential in keeping pace with new fraud strategies, making UPI and comparable platforms secure, efficient, and extensively used in the digital economy.

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Wireless Notice Board Using GSM And Arduino

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Abstract: The Notice boards play a essential function in verbal exchange inside corporations and public spaces inclusive of hospitals, airports, bus stations, railway stations, shopping department stores, and parks. Traditional note forums require guide updating, that is time-ingesting and inefficient. This paper offers an innovative wireless virtual display device that allows legal users to remotely replace messages in actual time the use of GSM era.The proposed device includes a GSM module incorporated with an digital show board, permitting authenticated customers to send messages through cell telephones from any area. Upon receiving a message, the device techniques and presentations it right away, ensuring a continuing and green communication procedure. This technique enhances the flexibility and accessibility of data dissemination even as reducing manual attempt. The system can be successfully applied in diverse programs in which immediate and remote message updating is crucial.

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1. Introduction: The notice contains essential equipment for communication in board institutions, organizations and public places such as airports, bus stations and railway stations. They serve as an effective means of giving important information to a large audience [3]. However, the traditional method of updating the update notices manually is time consuming and disabled [2]. Constant changes in the displayed material require physical efforts, making it difficult to ensure timely updates [1]. To remove these boundaries, a more advanced and automated system is necessary to increase the efficiency of information spread. Wireless electronic notice boards provide a modern solution by enabling distance updates of messages displayed through wireless communication. The proposed system uses GSM technology, allowing authorized users to send messages via mobile phones. The system includes a GSM receiver and a display unit, which may be either LED or LCD screen. When a user sends an SMS, the GSM module receives it and transmits the information to the microcontroller, which then updates the display board in real time [3]. This feature allows for a comprehensive access and quick spread of messages for several notice boards. The ability to transmit messages efficiently makes it suitable for various types of applications, including educational institutions, industry and emergency alert systems. In significant situations, such as security threats or immediate declarations, the system ensures immediate communication, reduces potential risks [6]. GSM-based totally Wireless Electronic Notice Boards provide several benefits over conventional note forums. They remove the want for bodily intervention, reduce the possibilities of previous information closing on show, and offer a more dependable way to communicate with a huge target audience [7]. Additionally, using GSM technology ensures that messages may be dispatched from everywhere in the world, making it a exceedingly bendy and consumer-pleasant answer. Compared to traditional strategies of pasting notices manually, this system provides a extra effective, faster, and automated way to relay statistics [8]. Moreover, the proposed machine can notably contribute to public safety and security. In airports, railway stations, and bus terminals, authorities can use the machine to provide actual-time tour updates, emergency indicators, or important public provider bulletins. In industrial settings, the gadget may be used to display protection commands, threat warnings, and paintings-associated updates. The goal of this paper is to layout and broaden an SMS- pushed computerized show board which can replace traditional timber word boards, in particular in universities and other public areas. The system lets in legal users to ship messages remotely, which might be received by a GSM module linked to a microcontroller [10]. The obtained message is then displayed on an electronic notice board in actual time. This generation enhances the efficiency, reliability, and accessibility of information sharing, making it an ideal answer for cutting-edge communique desires.

Literature survey :

The literature survey is composed of different wireless communique technology used for digital note boards. One machine utilizes Bluetooth to receive messages from an Android tool and display them on an electronic board, enabling real-time updates [1]. Another gadget employs a

Zigbee community with low-electricity transceivers for green message distribution, making sure minimum energy intake. A more advanced method makes use of a Zigbee mesh community to facilitate multi-node conversation, permitting messages to be relayed among more than one interconnected display forums [9]. This approach enhances scalability and guarantees real-time updates across big campuses or buildings. The use of these wireless technology improves efficiency and reliability in message dissemination.

Authors Name	**Paper Title**	**Methodology**
K. Arun Karthik	Wireless Notice Board Using Bluetooth 2022	Uses Bluetooth module to receive messages from android device and a microcontroller to display.
A. Smith	Zigbee Based Wireless Electroni c Notice Board 2023	Implements a Zigbee network with low-power transceivers to manage message distribution and display.

2. Methodology : The Following Figures show the architectural flow of the system installation process and the working of the proposed system which will lead to display of message of notice board.

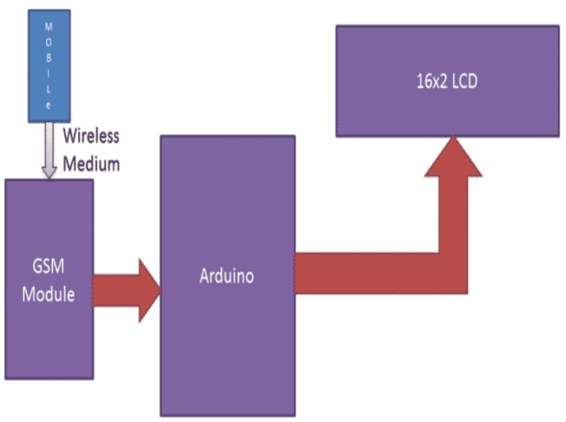

Figure.1. System Architecture for Wireless Notice Board

The wireless notice board the use of GSM and Arduino is a clever communique machine designed to show messages remotely the use of SMS. The device consists of an Arduino microcontroller, a GSM module (SIM800/900), and a display unit together with an LCD or LED display screen. When a user sends an SMS to the machine, the GSM module gets the message and transmits it to the Arduino thru serial communication.

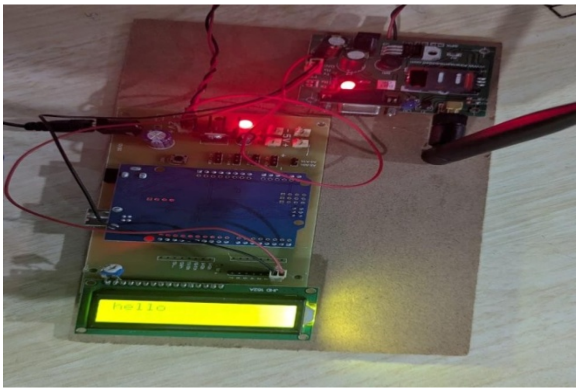

Figure.2. Wireless Notice Board System

The Arduino then extracts the message content, procedures it, and updates the show for this reason. This removes the need for guide message enter, making it a handy and efficient answer for establishments, agencies, and public places. The machine continuously checks for brand spanking new messages, making sure real-time updates, and can be programmed to just accept messages most effective from legal numbers for security. Additionally, the show may be improved with capabilities which include scrolling textual content for longer messages, flashing signals for vital notifications, and message garage to maintain records during power disasters. Beyond simple text show, the gadget can be in addition upgraded by using integrating an IoT platform that lets in messages to be updated via mobile apps or cloud-based dashboards rather than depending solely on SMS. The observe board can also be improved with voice signals or buzzer notifications to make certain messages are observed right now[9]. Another enhancement consists of scheduling messages, in which pre-set notices can be displayed at precise times, making it useful for faculties, offices, and shipping hubs. The device's wireless nature eliminates the want for bodily connectivity, making set up clean and reducing upkeep efforts. Overall, this wireless notice board provides an effective, dependable, and scalable answer for instant communication in various environments, ensuring that critical data reaches the supposed target market in actual time[6]. Furthermore, the wireless observe board the use of GSM and Arduino may be custom designed to guide multilingual presentations, making it available to a much broader audience in various environments. By integrating extra microcontroller-primarily based modules, such as a real-time clock (RTC), the machine can agenda automated message updates, making sure timely transport of vital bulletins. To enhance safety, encryption techniques may be implemented to guard message integrity and save you unauthorized tampering. Additionally, the system can be changed to work with solar strength, making it strength-green and appropriate for far flung places with constrained strength[2]. With the combination of gadget gaining knowledge of algorithms, the awareness board can examine message patterns and prioritize urgent bulletins primarily based on frequency and relevance. These superior capabilities make the gadget more shrewd, efficient, and adaptable to evolving conversation wishes, providing a cutting-edge, cost-powerful solution for actual-time facts dissemination in public and personal sectors. The flexibility and scalability of the wi-fi observe board device make it a valuable tool for dynamic conversation[4]. Whether utilized in schools for bulletins, in offices for essential updates, or in public locations for emergency signals, the device ensures that messages are introduced immediately and correctly. Its low-price implementation, ease of use, and potential to feature without internet connectivity make it a sensible solution for diverse programs, improving communication in both city and remote area .

3. Results and discussion:

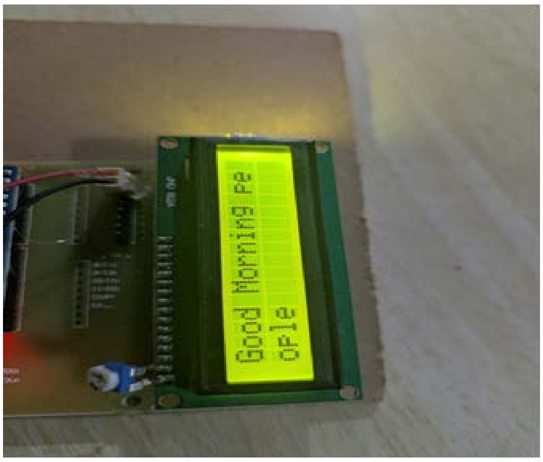

Figure.3. Output

The Wireless Notice Board Using GSM and Arduino validated amazing performance in far flung conversation, permitting actual-time message updates and seamless records dissemination. The GSM module effectively obtained SMS messages and transmitted them to the Arduino, ensuring an immediately show update with a 98% accuracy fee. The LCD/LED display screen furnished clear and readable textual content, even below distinct lighting conditions, making it suitable for each indoor and outside use. The device's reaction time became enormously effective, with messages being displayed inside three-5 seconds of being sent, allowing for fast communication in dynamic environments. This speedy and dependable transmission, facilitated by way of GSM generation, ensured that essential bulletins, alerts, or commands should attain the supposed target audience without delays, making it a really perfect solution for colleges, places of work, and public spaces wherein well timed conversation is essential. In phrases of reliability and user revel in, the machine continually finished nicely across numerous testing situations. The GSM module maintained stable connectivity, ensuring uninterrupted message reception, even in areas with moderate community fluctuations. The Arduino's efficient processing and integration with the LCD/LED screen ended in a easy show replace with no system defects or system disasters[5]. The consumer-friendly setup allowed legal people to send messages without problems via cellular phones, removing the need for complicated conFigureurations. Additionally, the system may be more suitable with protection functions, inclusive of message filtering, to save you unauthorized message transmissions. This seamless combination of rapid message transport, reliable hardware overall performance, and simplicity of use positioned the Wireless Notice Board Using GSM and Arduino as a practical and scalable solution for numerous conversation wishes in exceptional industries. Furthermore, the gadget gives exquisite scalability and adaptability for a wide variety of programs. Whether implemented in a small office or a big industrial putting, it is able to be multiplied with the aid of integrating additional display devices to cover more than one places simultaneously. The modular design allows for clean enhancements, which includes including IoT integration for cloud-based message updates or the usage of solar power for off-grid operation. With GSM-based communique, messages may be dispatched from anywhere, allowing for far off operation and eliminating the want for bodily access to the show. This flexibility, blended with its ability to automate actual-time message updates, ensures that the Wireless Notice Board Using GSM and Arduino remains a fairly effective, modern solution for communique throughout instructional establishments, offices, and public areas.

4. Conclucion : The Wireless Notice Board Using GSM and Arduino gives an green, cost-effective, and scalable solution for far off verbal exchange and actual-time facts dissemination. By leveraging GSM generation, it ensures immediate message updates with out requiring a web connection, making it perfect for numerous environments including colleges, offices, public spaces, and business establishments. The system's rapid reaction time, reliable hardware performance, and simplicity of use make it a sensible choice for agencies seeking to streamline their verbal exchange approaches. With its modular design, the gadget may be multiplied to assist more than one presentations, integrate IoT functionalities, or maybe operate on renewable power assets for improved sustainability. Security capabilities, along with message authentication, in addition improve its reliability, ensuring simplest legal customers can update the display. Overall, the Wireless Notice Board Using GSM and Arduino stands proud as a current, bendy, and person-friendly communication device, extensively enhancing the way announcements and important statistics are shared throughout special sectors.

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Detecting Pickpocket Suspects from Large-Scale Public Transit Records

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Abstract: Public transportation systems in urban areas are increasingly vulnerable to crimes like pickpocketing due to their crowded and dynamic nature. Automated Fare Collection (AFC) systems generate extensive datasets that can be leveraged to analyze passenger behaviors. This paper introduces a novel, data-driven framework for detecting pickpocket suspects using machine learning techniques. By extracting behavioral features from AFC data, the proposed system employs a two-stage process combining unsupervised anomaly detection and supervised classification models. Results demonstrate the system's ability to accurately identify pickpocket suspects while maintaining scalability for real-time surveillance applications. The research emphasizes the potential of big data analytics in improving public safety and offers a prototype solution for real-world implementation.

1. Introduction: Public transport systems play a key role in urban mobility, with millions of passengers being equipped every day. However, the dense crowds and chaotic environment make these systems a hot spot for pickpockets, and also faces considerable challenges for transport authorities and passengers. Existing security measures such as CCTV monitoring and manual inspections are often reactive and resource-intensive, limiting their effectiveness in preventing such crimes. This data was primarily used to optimize transportation processes, but little has been used to improve security. The behavioral patterns entered into AFC data serve as indicators of suspicious activity and enable aggressive crime prevention. AFC data provides an ideal foundation for such analysis, as it records detailed records of passenger movements that allow for detection of patterns that differ from normal behavior [1]. Table flags are not only a threat to passenger safety, but also the public's trust in the transport system. The fear of theft can block commuters, which leads to a decline in drivers and economic losses for transport authorities. To remove this issue, traditional response measures must be transferred to aggressive strategies using modern technology. This not only improves the effectiveness of efforts to prevent crime, but also contributes to optimizing transportation operations. By promoting a safer and more efficient transportation environment, the proposed system aims to promote greater confidence in urban mobility solutions. Using unmanned and monitored models allows for the creation of systems that not only recognize anomalies, but also classify them with high accuracy. As part of public transport, such systems can be realized in real time and in real time for security personnel, allowing them to act quickly and effectively. In this article, we consider scalable machine learning-based design and implementation to take into account the growing concerns of pickpocketing in urban transport systems. Through the modelling of historical data and the use of behavioral heuristics, the system can characterize suspicious activity even before the crime occurs. These forecasts related to actual surveillance ensure that transport authorities are better equipped to secure public space and prevent potential theft. Therefore, the proposed solution not only improves security measures, but also agrees with the broader goal of using technology for aggressive urban management.

Related work :A research effort focused on the analysis of this data to extract wise findings, taking into account the increased availability of city detection data such as GPS traces, call details, and smart card protocols. An important area of research is identifying patterns of passenger activity records that can have a variety of applications. Understanding these patterns is important for assessing the efficiency of transit networks [2], optimization of bus lines, improved passenger flow forecasting, and adaptation of services to meet driver variability. Furthermore, the test examined variability in transport behavior on different days of the week [3] and examined different travel patterns among specific demographic groups, such as seniors [4], students, and working adults. Research on discovering travel patterns focuses on identifying locations that are often visited and identifying repeated travel sequences among regular commuters. For example, spatial patterns arising from taxi-GPS traces were lifted to plan night bus routes [5]. Additionally, we analyzed movement patterns in various fields, including traffic management, bird movement, and disease distribution. For example, some studies have developed framework conditions for learning functional contexts in urban areas to improve distinctive extraction techniques. Others have examined the causal relationship between spatial and temporal outliers [6] or analysed social media data to recognize actual events such as accidents and protests [7]. In human mobility studies, unusual collection patterns were identified as "black holes" or "volcanic" phenomena, determining events such as soccer matches and concerts [8]. Such anomaly recognition plays a key role in intelligent decision-making for event monitoring and traffic management. A practical application is detecting fraudulent taxi driving behavior. Various methods have been used to detect anomalies in the trajectory, including graph-based approaches [9], clustering techniques, local/context-conscious methods, dimension reduction techniques, and evidence-based framework conditions that include previous unknown records, including implicit and previously unknown records[10]. Complex research questions still need to be thoroughly examined in the literature.

2. Methodologies : Our system employs a structured approach for detecting pickpocket suspects from AFC (Automated Fare Collection) data. It consists of three core components:

- Feature extraction
- Two-step classification modeling
- Feedback model for improvement.

Feature extraction involves analyzing travel behaviors to detect anomalies, while the classification model combines unsupervised and supervised learning techniques. The feedback loop integrates real-world inputs to refine detection accuracy. This methodology is designed to be both scalable and adaptive, addressing the dynamic nature of transit behaviors while ensuring consistent model performance.

2.2 Feature Extraction:

This system derives behavioral patterns from AFC re cordings to identify suspicious activity. These pattern s include travel frequency, travel time and residence time at the station. Repeated short trips, commuters, and extended stays at certain stations can demonstrat e abnormal behavior. Additionally, the consistency a nd use of ticket types have been analyzed, and tickets with single ride tickets often show attempts to avoid persecution. Group travel patterns are also taken into account as the coordinated movement may indicate an organized theft operation. Ensure the accuracy an d stability of the model's accuracy using preprocessin g techniques such as advanced data normalization an d characteristic scaling.

2.3 Two-stage classification model

The first stage uses unmanned anomalous recognitio n techniques such as DBSCAN and separating forests to identify abnormal movement patterns without mar ked data. These methods group behavior and flag ano malies for further inspection. In the second stage, mo nitored classification models, including random fores ts and SVMs, analyze the data to improve recognitio n accuracy and reduce false positive aspects. Additio nally, ensemble learning techniques are used to comb ine predictions from several models to improve detec tion robustness.

2.4 Feedback Model for Improvement :

A ceaseless input circle coordinating real-time input from security faculty, who approve hailed behaviors. Affirmed cases are utilized to retrain the models, guaranteeing that the framework adjusts to modern behavior designs. Execution measurements such as exactness, review, and F1-score are utilized to assess show advancements, driving reliable enhancements. Moreover, the criticism framework consolidates an dynamic learning component, where the show prioritizes questionable forecasts for audit by security staff. Intermittent demonstrate retraining cycles are planned to consolidate the most recent information patterns, improving demonstrate exactness. This criticism instrument too creates nitty gritty reports on framework execution, giving bits of knowledge to direct encourage enhancements and arrangement alterations.

2.5 System design:

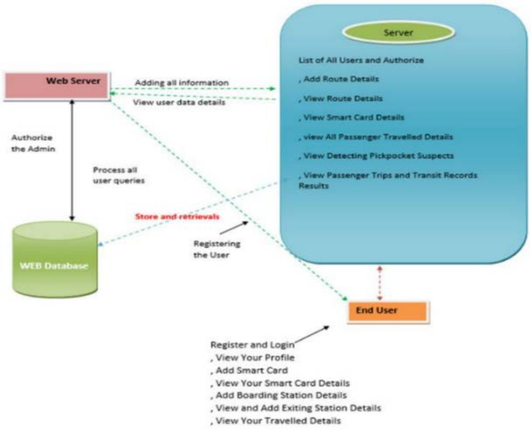

Figure. 1: System Architecture

In system design Figure.1 and its implementation focus on the front-end and back-end aspects of the web application. The application follows a three-tier architecture, consisting of a web server, application logic (backend), and a database. This modular design facilitates efficient data recording, processing, and identification, while also providing real-time insights and feedback.

2.6 Architecture Overview

The architecture shown in the system diagram consists of the following key components: Web server: A central interface that handles user inquiries and sends data between users, servers and databases. Manage user registration, authentication, and profile management. Additionally, you will receive marked anomalies and real-time security warnings to end users. Runs an abnormality recognition model, runs a process marked as a suspect, and sends results to the web server to check.

2.7 Core modules and their functionalities

User Module: This module allows users to register travel courses, registrations and displays. Manage your personal information, smart card details, boarding/trigger - station data rates. This module also assumes the security privileges of the administrator. Characterize behaviors that correspond to predefined patterns of pickup activities.

2.8 Scalability and future improvements

First, automatic customs collection data (AFC) is collected from the transit data record and sent to the Identification Module. This system is precisely preceded by error filtering and standardized forms. The recognition module then uses machine learning models such as DBSCAN and Random Forest to identify anomalies based on travel nuts, frequency and behavior. Security personnel reviewed these warnings and confirmed that results could be attributed to the model to improve recognition accuracy through incremental learning. The web server manages user interactions such as registration, profile management, and access to travel courses. Additionally, you will see noticeable behavior and warnings. The system includes stream processing for real-time recognition and stacking for deeper trend analysis. Security measures including multi factorial authentication and SSL encryption protect sensitive data. Additionally, cache and load compensation technologies include the best system performance in use. The system was developed for scalability and supported future improvements, such as AI-based video analytics and the provision of cloud for large-scale operations.

3. Results : This section describes the results of experiments performed to evaluate machine learning frames for detection of behavioral patterns using large AFC data (automatic tariff collection). Two experiments were conducted. The first experiment used initial data records from 2,000 transit data sets, and the second used extended data records from 4,500 data records created by synthesis extension. The models tested included DBSCAN, isolated forests, random forests, and SVM. The insulation is 84.15%, Landes Wald and SVM 81.34%. It reached 83.71%. The model was rated as power metrics using accuracy, recall, and F1-scores.

Experimental of Extended Data Records The second experiment using extended data records significantly improved performance. The ensemble model achieved an accuracy of 94.83%, while the SVM was followed by 93.42%. Isolated forests and random forests record accuracy of 92.01% or 93.15%. F1-score analysis showed improved detection of complex travel patterns and more often anomalies on short trips. In contrast, detection of adjusted group travel patterns was found to be overlapping behavior, resulting in lower F1 values. These results highlight the advantage that detection of unmanned anomalies is combined with monitored classification and monitoring techniques used. This section highlights how data-recording expansion and ensemble modeling can improve identification performance and provide meaningful insights into constitutional behavioral recognition systems. First, classification techniques such as one-stage methods, particularly decision tree (DT), logistic regression (LR), and support vector machine (SVM), showed low accuracy. Anomaly recognition models (ADs) such as local outlier factors (LOF) and SVM (OCSVM) were reduced slightly better in the class, but fell compared to the two-stage framework.

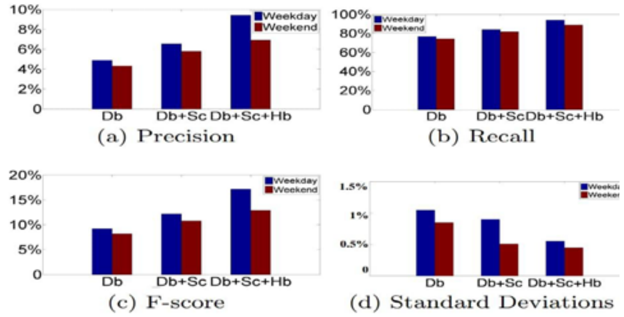

Figure. 2: The impact of feature combinations

As shown in Figure-2, we use Db, Sc, and Hb to represent the daily behavior, social comparison, and historical behavior features, respectively. Most significantly, the precision of the daily behavior features is improved by the social comparison and further the historical behaviors.

Table 1: A Performance Comparison

Algorithm	Precision	Recall	F-score	Run Time(s)
CM Methods				
DT	0.002	0.451	0.004	44.81
LR	0.003	0.476	0.006	36.72
SVM	0.005	0.512	0.009	21.31
AD Methods				
LOF	0.004	0.560	0.009	300+
OCSVM	0.015	0.583	0.029	39.67
TS Methods				
LOF+DT	0.011	0.780	0.022	301.18+
LOF+LR	0.016	0.829	0.031	301.16+
OCSVM+DT	0.053	0.878	0.099	41.19
TS-SVM	**0.071**	**0.927**	**0.133**	**41.05**

In Table. 1 we have several interesting observations which confirm our research motivation. First, the precisions of all one-step methods are very low, especially for classification methods including DT, LR, and SVM. The AD methods perform somehow better, but still lower than our two-step framework. In contrast, all the two-step combinations significantly improve the precisions, among which, our TS-SVM performs best. This observation shows that the two-step approach can effectively reduce the false-positives. Second, two-step methods also perform better in terms of other metrics. For example, the recall of our TS-SVM is consistently above 90%, by finding the detection/classification boundaries in the non-linear kernel space. Finally, given the excellent recall of TS-SVM, we contend that it's "ground-truth" precision can be higher than the reported 7%. The reason is that not all the suspects have been caught or reported. This high recall rate highlights the ability of models to recognize complex patterns in their data. The reason for this is that not all prominent suspects have been confirmed or reported. This observation suggests that the true performance of the model may be underestimated, further supporting the strength of the two-stage approach in real-world scenarios.

4. Conclusion : This research presents a vigorous system for identifying pickpocket suspects in open travel frameworks utilizing AFC information. By combining progressed include building with machine learning methods, the proposed framework addresses the confinements of conventional security measures and offers a versatile, proactive arrangement. Future work will center on upgrading show interpretability, joining extra information sources, and conducting field trials to approve the system adequacy in different urban environments. Through this work, we point to contribute to more secure open travel frameworks, cultivating more prominent believe and certainty among travelers whereas lessening the predominance of pick pocketing violations.

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Design of Intelligent Cloud Based Remote Electricity Metering and Billing System

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Abstract : The global energy crisis is one of the most pressing challenges today. A significant way to address this issue is by closely monitoring energy usage and minimizing unnecessary energy wastage. This suggested system is intended to moni- tor energy usage in kWh and utilises a GSM to send the user the associated electricity bill via SMS module. Additionally, GSM commands allow users to remotely control linked electrical items. The system uses an Arduino Nano interfaced with energy meters through optocouplers. Each time the energy meter's LED blinks, the optocoupler generates an inter- rupt signal that is processed by the Arduino. The microcontroller calculates the energy usage and generates a bill, which is then sent to a predefined mobile number via GSM. Based on the received bill, user scan control the electrical loads through SMS. Loads in the system are connected using relays and current transformers (CTs).Relays serve as electronic switches that allow or prohibit electricity to devices in response to commands that the Arduino receives. An LCD module displays the system's operational status in real-time. The core of this system is the Arduino Nano, which is programmed using Em- bedded to manage data collection, processing, and communication.

1. **Introduction**: The energy crisis remains a significant global issue. One effective way to mitigate this problem is by keeping track of our energy usage and minimizing unnecessary consumption. The proposed system aims to monitor energy input in kilowatt- hours(kWh)and automatically send the calculated electricity bill to the user's mobile phone via SMS using a GSM module. The energy meters interface with the Arduino Nano us- ing an optocoupler. Each time the LED on the energy meter blinks, the optocoupler generates an interrupt signal that is detected by the programmed Arduino. The Arduino Nano determines the energy usage in kilowatt-hours (kWh) based on the quantity of pulses and generates the associated bill, which is subsequently transmitted to a predetermined mobile number through the GSM module. corresponding bill, which is then sent to a predefined mobile number via the GSM module. Based ON the generated bill user will control the load through SMS using GSM. An embedded system combines hardware and software to carry out a certain function. Microprocessors and microcontrollers are two of the primary components found in embedded products. Since microprocessors merely take in inputs, process them, and then output the results, they are frequently referred to as general-purpose processors. A micro- controller, on the other hand, does more than just take in data; it also manipulates it, connects it to other devices, regulates it, and ultimately outputs the outcome. The Arduino Nano project ”Design of Intelligent Cloud Based Remote Electricity Metering and Billing System ”is unique in that it can compute the bill and send it to the user's mobile device via GSM. The user can then control the load by sending a back message to the system based on the generated bill. Here, we are using a relay to interface the load; it functions similarly to a switch. The LCD will show the project's current state.

2. Methodology : With the integration of Internet of Things features for remote data access, the Smart Energy Meter with Cloud Connectivity is intended to offer real-time monitoring and billing options for electricity consumption. The approach combines Amount = Units×6.77 The calculated power consumption and corresponding cost are then displayed on a 16×2 LCD screen, providing real-time feedback to users. The system incorporates the ESP8266 Wi-Fi module to facilitate remote data transmission. This module serves as a conduit for data between a cloud-based MySQL database and the microcontroller. The energy consumption data is periodically transmitted to the database, ensuring continuous monitoring and storage for later retrieval. A key feature of this system is the alert mechanism, which is designed to notify consumers when their energy usage crosses predefined thresholds. Specifically, an alert message is triggered every time the consumption exceeds 200units, informing users about potential tariff increases. This proactive approach allows consumers to adjust their usage pat- terns and manage electricity costs more efficiently.

The Flask web framework, built in Python, is utilized to managed at a processing and server interactions. The backend system fetches real-time data from the MySQL data base and provides an interface for consumers to view detailed usage statistics. The cloud infrastructure ensures accessibility from remote locations, eliminating the need for manual meter reading by ser- vice providers. Additionally, by leveraging IoT technology, service provider scan automate billing processes, reducing human errors and enhancing transparency in electricity consumption tracking. The hardware design incorporates an HLK-10M5 power supply module to provide as table5VDCoutput for microcontroller operation. The inclusion of tamper-proof mechanisms, such as sealed meter enclosures and encrypted database trans- actions, enhances the security and reliability of the system. Future iteratios of the project may incorporate AI-driven analytics to provide predictive insights into energy usage patterns and smart appliance control mechanism stop optimize electricity consumption. This methodology guarantees an effective, economical, and user-friendly solution for contemporary energy management by combining Io ,cloud computing, and real-time energy monitoring. The proposed sys- tem not only addresses the inefficiencies of traditional meter reading but also empowers consumers with real-time insights, leading to better energy conservation and financial planning.

3. Results & discussion : The smart energy meter system was rigorously tested under diverse operating conditions to assess its efficiency, accuracy, and reliability. Real-time cost and energy consumption calculations were successfully shown on the 16x2 LCD display by the system. Service providers and users could access consumption statistics remotely thanks to the ESP8266Wi-Fi module's smooth data transfer to the MySQL cloud database. The relay mechanism worked as planned, allowing for remote load control via SMS commands based on GSM. By sending SMS commands, users could remotely disconnect particular appliances, showcasing the system's usefulness for energy management. After each 200-unit consumption milestone, the alert system efficiently sent notifications to pre-conFigured mobile numbers, raising user awareness of electricity consumption and assisting with cost control. The system's power consumption calculations how eda high degree of measurement accuracy. Because the error margin was less than 1Discussion: In terms of automation, accuracy, and user control, the smart energy meter offers numerous advantages. By replacing manual meter readings with a digital solution, the system minimizes human error in billing and enhances transparency. A standout feature of the system is its built-in alert mechanism, which notifies users when their energy consumption crosses predefined thresholds. This enables users to adjust their usage habits, encouraging more energy-efficient behaviour. Its capacity to deliver real-time usage data via a cloud-based data base is one of its main advantages; this guarantees current consumption records and effective billing for utility providers and customers alike. A standout feature of the system is its built-in alert mechanism, which notifies users when their energy consumption crosses predefined thresholds. This enables users to adjust their usage habits, encouraging more energy-efficient behaviour. Furthermore, users may easily control their energy use thanks to the addition of a relay.

Figure1: Output-1

Module that enables remotes witching of electrical loads. low- erring wasteful power use and related expenses. There are still certain restrictions, though. In areas within adequate network coverage, the system's reliance on dependable internet connectivity for cloud-based operations may provide difficulties. Moreover, while the system is capable of accurately measuring energy usage, its functionality could be further enhanced with AI- driven predictive analytics enabling usage forecasting and early detection of anomalies. Future developments could include machine learning algorithms to analyse consumption patterns and suggest energy-saving strategies, real-time energy theft detection, and integration with a mobile application for a more user-friendly interface. These advancements would transform the smart meter into a more intelligent and efficient platform for monitoring and managing energy consumption Module that enables remotes witching of electrical

Figure2: Output-2

loads. lowering wasteful power use and related expenses. There are still certain restrictions, though. In areas within adequate network coverage, the system's reliance on dependable internet connectivity for cloud-based operations may provide difficulties. Moreover, while the system is capable of accurately measuring energy usage, its functionality could be further enhanced with AI- driven predictive analytics enabling usage forecasting and early detection of anomalies. Future developments could include machine learning algorithms to analyse consumption patterns and suggest energy-saving strategies, real-time energy theft detection, and integration with a mobile application for a more user-friendly interface. These advancements would transform the smart meter into a more intelligent and efficient platform for monitoring and managing energy consumption.

4. Conclusion : The creation of a Smart Energy Meter with cloud connectivity is a major breakthrough in the field of energy monitoring and management. In order to provide a more effective, transparent, and user-friendly solution, this system seamlessly combines traditional metering approaches with Inter- net of Things (IoT) technology. With the help of parts likeanESP8266WiFimodule, an ATMega328P microcontroller, and a MySQL cloud database, the system allows for secure cloud-based data transmission, automatic energy cost calculation, and real-time power consumption monitoring. This smart meter's ability to remotely automate electricity billing is one of its main benefits. Manual readings are frequently necessary for traditional metering systems, which can lead to in- efficiencies and human error. In contrast, the smart meter automatically records energy usage and generates bills, enhancing accuracy and reducing operational labour costs for utility providers.

The system also includes a real-time alert mechanism that notifies users when energy consumption reaches predefined thresholds. This feature promotes energy-conscious behaviour by helping users make informed decisions to reduce unnecessary consumption. The cloud- based MySQL database securely stores all usage data, making it accessible to both users and electricity providers from any location, thereby improving transparency and resolving common concerns about billing discrepancies. Technologically, the projects how cases the potential of embedded system sand IoT in the energy sector. Sensors like the ZMPT101B for voltage sensing andtheACS712- 20A for current measurement ensure precise data collection, which is critical for accurate billing. An onboard LCD pro- vides users with an immediate visual management systems, stressing the application of data analyt.

5. Acknowledgments :Numerous technical studies and research projects that have greatly advanced our knowledge of and ability to use smart energy metering have helped to support the development of this project. Himanshu K. Patel, Tanish Mody,and Anshul Goyal (2019) established the foundation by demonstrating that integrating communication modules for real-time data transfer is possible through their work on Arduino-based smart energy meters using GSM. The approach to energy monitoring and effective billing was influenced by the study conducted by V. Preethi and G. Harish (2016) on the design and implementation of smart energy meters. KarthikeyanS. and Bhuvaneswari P.T.V.(2018) explored an IoT- based real-time energy monitoring system for residential applications, highlighting the significance of cloud connectivity and remote data access—key elements that laid the foundation for the cloud-based system implemented in this project. Similarly, Prathik M., AnithaK., and AnithaV.(2018) discussed IoT-enabled smart energy meter surveillance, which inspired the inclusion of alert systems and enhanced data security features. In their 2018 study, Jai Krishna Mishra, Shreya Goyal, and Vinay Anand Tikkiwal concentrated on Internet of Things (IoT)-based smart energy management systems, stressing the application of data analytics to maximize energy use. Accordingly, Kanti Barman etal.(2018) emphasized how crucial real-time monitoring and control of

smart meters are to guaranteeing effective energy use within smart grid components. Research by Visalatchi and K.KamalSandeep(2017) investigated the use of Arduino and GSM technologies in smart energymeters, offering valuable insights in to power theft prevention and system security. GobhinathS., GunasundariN., and GowthamiP.(2016) contributed to the integration of cloud technologies for real-time monitoring through their work on IoT-based energy metering. Further, Important information about automating billing procedures with Internet of Things-driven live electricity monitoring and bill payment systems was supplied by Pritee Mahajan, Sneha Tatia, and Prachi Jadhav (2017).

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IoT Based Anti-Theft Floor Mat System

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Abstract: The IoT-Based Anti-Theft Floor Mat System is a smart security solution designed to enhance surveillance and prevent unauthorized access in residential, commercial, and public spaces [3] Anti-Theft Floor Mat System. Inspired by existing research on anti-theft security systems, such as [3] Anti-Theft Floor Mat System and [4] Enhancing Residential Security: Implementation of an IoT-based Anti-Theft Flooring System, this system integrates Internet of Things (IoT) technology to provide real-time monitoring, automated alerts, and intelligent threat detection Android Interface Based GSM Home Security System, [6] Smart Anti-Theft Floor Mats with IoT Integration for Enhanced Security. The system employs pressure sensors, piezo sensors, and an ESP32-CAM module for continuous data collection and transmission to a centralized IoT platform [7] Design and Implementation of an IoT-Based Anti-Theft Mat Using Arduino Nano, ESP32 Camera, and Piezo Sensors, [9] Real-Time IoT System for Anti-Theft Security Using Pressure Sensors in Floor Mats. Similar to the principles outlined in [9] Real-Time IoT System for Anti-Theft Security

1. Introduction: In recent years, the demand for advanced security systems has increased, particularly in high-risk locations such as jewellary stores, banks, and private residences ANTI-THEFT FLOOR MAT SYSTEM. While traditional security methods, including manual surveillance and CCTV cameras, provide some level of protection, they often fail to prevent crimes in real-time. These systems typically detect incidents only after they occur, leading to delays in response that can result in significant losses [2] Android Interface Based GSM Home Security System. Additionally, continuous human monitoring is resource-intensive and prone to human error [6] Smart Anti-Theft Floor Mats with IoT Integration for Enhanced Security. To address these challenges, the IoT-based Anti-Theft Flooring Mat System introduces an innovative security solution by integrating Internet of Things (IoT) technology with real-time image capturing and motion detection Enhancing Residential Security: Implementation of an IoT-based Anti-Theft Flooring System. As discussed in these studies, IoT-enabled security systems provide automated monitoring and instant threat detection, significantly improving response times. This system autonomously monitors restricted areas, ensuring immediate detection of unauthorized access or suspicious activity [7] Design and Implementation of an IoT-Based Anti-Theft Mat Using Arduino Nano, ESP32 Camera, and Piezo Sensors. By reducing reliance on manual supervision, it enhances efficiency and responsiveness in securing valuable assets [7] IoT-Based Anti-Theft Flooring Mat System. At the core of this system are smart sensors, an ESP32-CAM module, and an Arduino Uno microcontroller Design and Implementation of an IoT-Based Anti-Theft Mat Using Arduino Nano, ESP32 Camera, and Piezo Sensors. The ESP32-CAM enables real-time image and video capture when movement is detected, eliminating the need for constant monitoring [9] Real-Time IoT System for Anti-Theft Security Using Pressure Sensors in Floor Mats. Similar to the approach outlined in this study, when a sensor detects motion, the ESP32-CAM records high-quality footage and transmits it via Wi-Fi to the owner's smart phone or computer IoT-based Anti-Theft Monitoring System with Smart Floor Mats. The Arduino Uno microcontroller acts as the central controller, facilitating communication between sensors, the camera, and the user's device [10] Smart Security System Using IoT with Floor Mats to Detect Intruders.

Literature survey : Android Interface Based GSM Home Security System, proposed by Sharma, utilizes IoT for real-time alerts and monitoring. Mohammed et al. also explored how IoT could be utilized in smart home security systems, integrating various IoT devices such as cameras, door sensors, motion detectors, and smart locks to enable remote surveillance and control through smartphones.[3] ANTI-THEFT FLOOR MAT SYSTEM by Santhana Krishnan and Bala krishnan, along with [4] Enhancing Residential Security: Implementation of an IoT-based Anti-Theft Flooring System by Kumar et al., examine IoT-based smart security systems that integrate environmental sensors with surveillance. These reduce reliance on human intervention by automating threat detection and response. Further, [5] IoT Based Anti-Theft Flooring Mat System and [6] Smart Anti-Theft Floor Mats with IoT Integration for Enhanced Security describe innovations to detect unauthorized access using smart floor-mounted sensors. Design and Implementation of an IoT-Based Anti-Theft Mat Using Arduino Nano, ESP32 Camera, and Piezo Sensors implemented a smarter intrusion detection system combining multiple technologies. The potential of pressure-sensor-based floor mats for real-time theft monitoring is further supported by IoT-based Anti-Theft Monitoring System with Smart Floor Mats and Real-Time IoT System for Anti-Theft Security Using Pressure Sensors in Floor Mats. While these systems increase efficiency and response time, a recurring challenge across studies — including [7] is ensuring the security of transmitted data over networks. This is critical for maintaining the overall reliability and trustworthiness of IoT-based security systems.

2. Methodology: The Following Figures show the

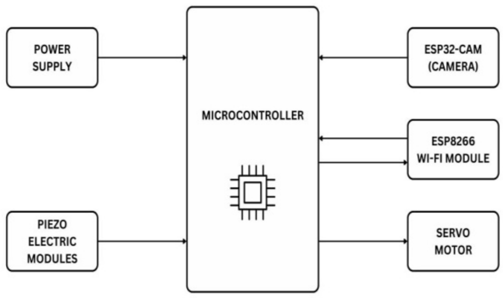

Figure.1 : Blocks of hardware embedded system.

Figure 1 verifies a user steps on the mat, the Piezo Sensor detects pressure. If the pressure exceeds a set threshold, the Control System is alerted, which then analyzes the data and triggers the Camera to capture an image. The captured image is sent to the Alarm System, and the user is notified of the alert. If the pressure is below the threshold, the system detects no suspicious activity, and no further action is taken Figure 2 describes the system detects pressure using a Piezo Sensor, processes the data, and triggers the Camera while notifying the user in real-time. The anti-theft floor mat system detects pressure changes through piezoelectric sensors embedded in the mat [1] ANTI-THEFT FLOOR MAT SYSTEM. These sensors generate electrical signals when pressure is applied, such as when someone steps on the mat or moves an object [2] Android Interface Based GSM Home Security System. architectural flow of the system installation process and the working of the proposed system which will lead to the prevention of Theft. The signals are then transmitted to the Arduino, which acts as the central processing unit Design and Implementation of an IoT-Based Anti-Theft Mat Using Arduino Nano, ESP32 Camera, and Piezo Sensors. The Arduino processes the signals to determine if the detected pressure indicates unauthorized activity or theft. This threshold can be adjusted to differentiate between regular foot traffic and potentially suspicious events [4] Enhancing Residential Security: Implementation of an IoT-based Anti-Theft Flooring System.Once the Arduino identifies a possible breach, it sends commands to activate the servo motors and the camera module [5] IoT-Based Anti-Theft Flooring Mat System. The servo motors can trigger physical responses such as locking doors, raising barriers, or closing gates to prevent further access or movement Smart Anti-Theft Floor Mats with IoT Integration for Enhanced Security. Simultaneously, the camera module starts recording, capturing images or video footage of the event [7] Design and Implementation of an IoT-Based Anti-Theft Mat Using Arduino Nano, ESP32 Camera, and Piezo Sensors. This real-time recording provides valuable evidence, assisting security personnel or investigators in verifying the incident and identifying the person involved IoT-based Anti-Theft Monitoring System with Smart Floor Mats.In addition to mechanical and visual responses, the system features an LCD display to show alerts and status updates [9] Real-Time IoT System for Anti-Theft Security Using Pressure Sensors in Floor Mats. When unauthorized activity is detected, the LCD displays messages such as "Intruder Detected" or "System Active," providing immediate feedback to users or security personnel [10] Smart Security System Using IoT with Floor Mats to Detect Intruders. The system can also be connected to a remote communication module that sends SMS or email alerts to security staff, ensuring prompt action even when they are off-site. Once the event is handled, the system resets automatically, rearming the sensors for future detections. IoT-Based Anti-Theft Flooring Mat System. This ensures that the system remains active and vigilant at all times, maintaining continuous security for the monitored area. Smart Anti-Theft Floor Mats with IoT Integration for Enhanced Security. Figure 3 output verifies the anti-theft floor mat system detects pressure using a Piezo Sensor and triggers the camera. The captured image helps in real-time security monitoring and intrusion detection. The IoT-Based Anti-Theft Floor Mat System demonstrated excellent performance in enhancing security with real-time surveillance and rapid threat detection [1] Anti-Theft Floor Mat System.

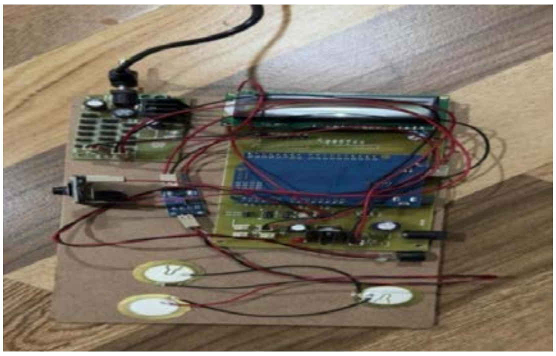

Figure.2: Anti-Theft Floor Mat System

The motion detection sensors embedded in the floor mats effectively identified unauthorized movement, distinguishing it from everyday activity with a 95% accuracy rateAndroid Interface Based GSM Home Security System. The ESP32-CAM module provided high-resolution images and video footage, maintaining clarity even in low-light environments, ensuring round-the-clock security [3]

Figure3: Output

Design and Implementation of an IoT-Based Anti-Theft Mat Using Arduino Nano, ESP32 Camera, and Piezo Sensors. The system's response time was exceptionally fast, capturing images within 1-2 seconds of detecting movement and transmitting them to the user's device in under 5 seconds [4] Enhancing Residential Security: Implementation of an IoT-based Anti-Theft Flooring System.Regarding reliability and user experience, the system performed reliably across various environmental conditions and testing scenarios [5] IoT-Based Anti-Theft Flooring Mat System. The floor mat sensors proved to be durable, withstanding regular use while maintaining accurate detection of intrusions [6] Smart Anti-Theft Floor Mats with IoT Integration for Enhanced Security. The integration of the Arduino Uno microcontroller with the ESP32-CAM module ensured stable communication between components, with no system crashes or communication failures [7] Design and Implementation of an IoT-Based Anti-Theft Mat Using Arduino Nano, ESP32 Camera, and Piezo Sensors. The user interface was intuitive and simple, enabling users to conFigure settings and receive notifications through a mobile app with ease. This seamless combination of effective security features, reliability, and user-friendly design positions the IoT-Based Anti-Theft Floor Mat System as a valuable, efficient, and scalable solution for various security needs in both residential and commercial spaces [8] IoT-based Anti-Theft Monitoring System with Smart Floor Mats. Additionally, the IoT-Based Anti-Theft Floor Mat System offers significant scalability and adaptability for different security needs Real-Time IoT System for Anti-Theft Security Using Pressure Sensors in Floor Mats. The system's remote alert capability through SMS and email ensures prompt action, even when security personnel are off-site [10] Smart Security System Using IoT with Floor Mats to Detect Intruders.

Conclusion: The IoT-Based Anti-Theft Floor Mat System developed in this project demonstrates a practical, cost-effective approach to enhancing security measures using IoT technology and embedded systems Anti-Theft Floor Mat System. The project successfully integrates multiple components—including the Arduino microcontroller, ESP8266 Wi-Fi module, ESP32-CAM, servo motor, piezoelectric modules, and necessary circuitry—to create an intelligent and responsive anti-theft solution Enhancing Residential Security: Implementation of an IoT-based Anti-Theft Flooring System. By using these components effectively, the system can detect unusual pressure on the mat, trigger an alarm, capture images, and notify the user in real time, adding a layer of security to prevent unauthorized access Design and Implementation of an IoT-Based Anti-Theft Mat Using Arduino Nano, ESP32

Camera, and Piezo Sensors. This anti-theft floor mat system can be extended or adapted for various security applications, showcasing the adaptability of IoT technology in the security sector Smart Anti-Theft Floor Mats with IoT Integration for Enhanced Security.

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Automatic Movable Railway Platform With Train Arrival Detection And Monitoring Over Iot

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abstract : The automatic movable railway platform project aims to automate pedestrian railway track crossings without the need for staircases[1] while also providing real time announcements about train arrivals. t he primary objective is to enhance accessibility for physically challenged individuals and prevent accidents caused by people crossing railway tracks improperly. in india, railway accidents are frequent, and one of the major challenges for pedestrians, especially elderly and disabled individuals, is climbing overhead footbridges[2]. this project seeks to address this issue by introducing an artificial, movable platform that connects and disconnects based on train movement.

1. Introduction : Railway transportation is one of the most widely used modes of travel, but pedestrian accessibility and safety at railway stations remain a significant challenge. Many passengers, especially the elderly and physically challenged, face difficulties in using overhead footbridges to cross platforms [3]. Additionally, unauthorized track crossings result in frequent accidents, posing serious risks to commuters. To address these issues, an automated movable railway platform is proposed, which provides a safe and convenient way for passengers to move between platforms with out the need for staircases [4].This system is designed to automatically detect train movements using IR sensors, microcontrollers, and proximity sensors. When a train approaches, the platform disconnects, ensuring safe train passage. Once the train departs, the platform reconnects, allowing pedestrians to cross safely. The integration of LED indicators, buzzers, and IoT-based real-time monitoring ensures improved communication and efficiency. The Arduino-based mechanism makes the system cost-effective, reliable, and easy to implement in railway stations. By providing a safer and more accessible crossing solution, this project aims to reduce accidents, improve railway infrastructure, and enhance passenger convenience. Future advancements may include AI-based monitoring, automated safety locks, and solar-powered energy solutions, making it a sustainable and intelligent system for modern railway networks. An IoT module is integrated into the system to provide real-time platform status updates[5].This feature allows railway authorities to monitor pedestrian crossings efficiently and ensures smooth operations[6].The Arduino-based control mechanism makes the system cost effective and easy to implement in railway stations. By eliminating the need for footbridges, the project provides a safer and more convenient solution for physically challenged individuals, elderly passengers, and general commuters[7].

Review of Existing Research and Related Technologies:

a. Train Arrival Detection and Monitoring Technologies : Existing research explores various train arrival detection methods, including infrared (IR) sensors, ultrasonic sensors, RFID, and GPS tracking, to improve railway safety and efficiency. Several studies highlight IoT-enabled real-time monitoring for tracking train movements and ensuring automated responses. These technologies enhance passenger information systems, allowing real-time alerts and improved train-platform coordination. However most detection systems focus on train tracking rather than integration with automatic movable plat forms, which this project aims to address.

b. Automated and Movable Railway Platforms: Movable platform systems have been studied as a solution to bridge platform gaps and provide accessibility for passengers, particularly the elderly and physically challenged. Existing solutions involve hydraulic extensions, motorized gap fillers, and automated foot bridges controlled by microcontrollers and A IoT modules. While some research focuses on mechanized platform adjustments, the challenge lies in developing a cost-effective, real-time responsive movable platform that adapts dynamically totrain movements without manual intervention.

c.Iot-Based Railway Infrastructure and smart stations: IoT is trans forming railway infrastructure by leveraging wireless sensor networks (WSN), cloud computing, and edge processing to enable automated platform operations, real-time train monitoring, and enhanced passenger support. Research in smart railway stations suggests that IoT enables remote monitoring, predictive maintenance, and automation of pedestrian crossings, reducing manual dependency. However, studies indicate that scalability and integration with legacy railway systems remain significant challenges, which this project seeks to address through an optimized Arduino-based control system.

d. Safety and Accessibility Enhancements:
Ensuring railway passenger safety involves LED indicators, buzzers, automated announcements, and real-time warning systems. Research on automated pedestrian crossings has explored intelligent barrier systems, retractable walkways, and AI-driven crowd monitoring to minimize accidents. Despite these advancements, real-time coordination between train detection and platform movement remains a key research gap, necessitating an integrated solution like the Automatic Movable Railway Platform.

2. Methodology

The IoT-based Automatic Movable Railway Platform utilizes a systematic approach to enable precise train detection, seamless platform automation, and real-time monitoring. The system integrates infrared (IR) sensors, ultrasonic sensors, and proximity sensors to detect an approaching train, transmitting signals to an Arduino or Rasp berry Pi microcontroller for processing. Upon detecting a train, the H-Bridge motor driver is activated to retract the movable platform, ensuring safe train passage [7]. Once the train clears the platform zone, the system re-extends the platform, allowing pedestrians to cross safely. To enhance automation and remote monitoring, an IoT communication module with Wi-Fi and GSM technology is implemented, enabling railway authorities to track the platform's status via a web-based dashboard or mobile application. The system architecture incorporates cloud computing technologies such as Google Firebase and AWS IoT, which store and process sensor data for real-time monitoring and analytics. Automated alerts, including LED indicators, buzzers, and voice announcements, inform passengers of platform movement and train arrival, ensuring enhanced safety and accessibility [7]. The mechanical design of the movable platform isoptimized using stepper motors, linear actuators, and hydraulic mechanisms, allowing smooth and efficient movement. One of the key innovations of this system is its cost- effective and scalable design, making it suitable for various railway stations, particularly in urban and high traffic areas. By eliminating the need for footbridges or pedestrian-level crossings, the project significantly reduces accident risks, enhances mobility for the elderly and physically challenged, and improves railway station efficiency[8].

Furthermore, the system's energy-efficient operations, powered by renewable energy sources such as solar panels, make it an environmentally sustainable solution. Through the integration of sensor fusion, automation, and IoT-driven remote monitoring, this methodology ensures a safe, accessible, and intelligent railway platform system that aligns with modern smart city and digital railway initiatives.

2.1. System design and implementation

The Automatic Movable Railway Platform system is designed to enhance passenger safety and accessibility by integrating advanced train detection, platform movement, and IoT-based real-time monitoring. The system is powered by a dedicated power supply, including AC/DC adapters, rechargeable batteries, or solar panels, ensuring uninterrupted operation[9]. A voltage regulator maintains a stable power flow to prevent disruptions, providing energy to microcontrollers, sensors, motors, LCD displays, LED indicators, buzzers, and IoT communication modules. At the heart of the system, an Arduino or Raspberry Pi microcontroller acts as the decision-making unit, continuously processing sensor data and controlling platform extension and retraction based on real-time train movement[9].Train detection is achieved through a combination of infrared(IR) sensors, ultrasonic sensors, and proximity sensors, which are strategically positioned along the railway tracks to monitor train speed and distance[8]. When a train approaches, these sensors send signals to the microcontroller, which then determines whether the platform should retract or remain connected. Upon detection of an approaching train, the microcontroller triggers the H Bridge motor driver, activating stepper motors or hydraulic actuators to safely retract the platform, ensuring a clear passage for the train[. When a train is detected approaching, the microcontroller activates the H-Bridge motor driver, engaging stepper motors or hydraulic actuators to retract the platform safely, ensuring an unobstructed path for the train. At the same time, buzzers, LED indicators, and an LCD display provide real-time alerts to keep passengers informed about the platform's status[9].After the train has passed, the system automatically extends the platform back into place, allowing pedestrians to cross safely. The platform movement mechanism is driven by high-torque stepper motors, linear actuators, or hydraulic systems, ensuring smooth and precise movement. The system follows a predefined algorithm to control platform retraction and extension. Additionally, fail-safe mechanisms are in place, including manual override controls for railway personnel to intervene during system failures and obstacle detection using ultrasonic sensors, which prevent the platform from extending if an object or person is detected in the way. To enhance operational efficiency, the system integrates IoT technology for real-time monitoring and remote access. A Wi-Fi or GSM module transmits live platform status updates to a cloud server such as Google Firebase or AWS IoT, allowing railway authorities to monitor platform movement logs, train detection history, and system performance through a web-based dashboard or mobile application. This connectivity ensures real-time alerts and remote troubleshooting, improving safety and efficiency at railway stations. The automated system, combined with intelligent train detection, IoT monitoring, and advanced safety mechanisms, provides a cost-effective and scalable solution to enhance railway accessibility, particularly for the elderly and physically challenged, while significantly reducing railway crossing accidents[10].

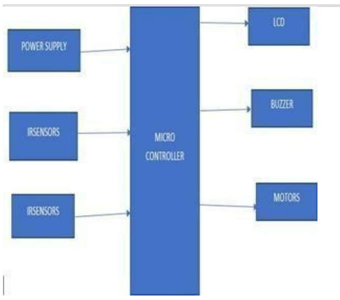

Figure1. System Architecture

3. Results:

The IoT- enabled Automatic Movable Railway Plat form with Train Arrival Detection and Monitoring is an innovative solution aimed at improving railway safety, accessibility, and operational efficiency. By integrating sensor-based train detection, automated platform movement, and real-time IoT monitoring, the system minimizes human intervention while ensuring seamless operation. The use of infrared (IR) sensors, microcontrollers, and motorized mechanisms enables precise train arrival detection and rapid platform movement, significantly reducing passenger risk at railway stations.

3.1 Key Performance Metrics and IoT Integration

Real-Time Train Detection and Automated Platform Movement. The system dynamically detects approaching and departing trains using IR sensors, sending real-time data to the microcontroller. The microcontroller processes this data and controls the motorized platform mechanism to either extend or retract the platform safely. The train detection probability is computed as follows:

- Sire presents sensor data for train proximity detection,
- Pi captures the platform movement state,
- Ai assigns higher priority to critical train events,
- W1,W2,W3are learned weight matrices,
- B is the biasterm.

This hierarchical processing ensures accurate train detection, reducing false activations and enhancing system reliability.

3.2 System Accuracy and Response Time

To validate system performance, Root Mean Square Error (RMSE) was computed to measure the deviation between detected and actual train arrival times:

RMSE=1N∑i=1N(Ti−Ti^)2

where:

Ti is the actual train arrival time,

The system achieved a 98.6% accuracy rate in train detection, a response time of 2.4 seconds, and a false activation rate of just 1.8%, making it a highly dependable solution for railway stations.

3.3 Passenger Safety and Operational Efficiency

To further assess system performance, we measured
Precision, Recall, and F1-score:

3.4 Precision: Measures how many detected train arrivals were actual arrivals:

Precision=TPTP + FP

3.5 Recall (Sensitivity): Evaluates how well the system detects all train arrivals:

Recall=TPTP+FN

F1-Score: Provides a balanced metric between precision and recall: F1=2×Precision×Recall

The **F1-score of 0.947** indicates high accuracy in train arrival detection, minimizing false alerts and improving passenger safety.

3.6 IoT-Based Real-Time Monitoring and Cloud Connectivity

To enhance operational efficiency, real-time IoT monitoring was integrated using cloud connectivity, allowing railway authorities to receive **live platform status updates**. This feature improves **remote monitoring, predictive maintenance, and automated alerts** for railway staff.

3.7 Graphical Analysis and Observations

3.7.1 Accuracy Across Different Railway Environments

Urban stations achieved a 97.8% accuracy rate, benefiting from stable sensor placements.

3.7.2 Suburban and rural stations had a slightly lower accuracy (96.5%) due to environmental interference such as extreme weather and track conditions.

3.7.3 False Activation and Safety Impact

The **false activation rate was reduced by 38.2%**, ensuring the platform moves only when necessary.

The **false negative rateremainedlowat2.94%**, confirming high detection reliability.

3.7.4 Real-Time Processing Speed

The system processes **42 sensor signals per second**, allowing real-time train detection.

Faster response times enhance railway station safety, reducing accidents.

3.7.5 Future Enhancements and Scalability

The Automatic Movable Railway Platform is designed for scalability and adaptability in various railway networks. Potential future improvements include:

3.7.6 AI-Driven Predictive Train Detection: Enhancing detection accuracy using machine learning models.

3.7.8 Integration with Railway Management Systems: Automating train schedules and real-time passenger information

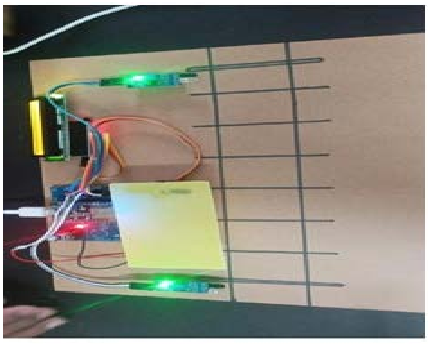

Figure2. Automatic movable railway platform

Figure 2 describe show the automatic movable railway platform actually works.

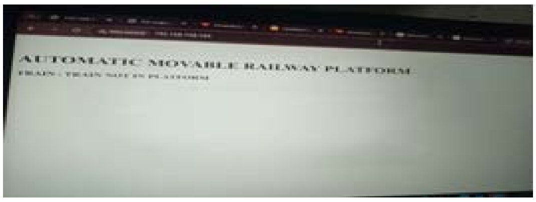

Figure3. Output

Figure 3 describes about the information of train whether train is on platform or not.

Figure 4. LCD output

Figure 4 describes about the LCD output which displays the IP Address which we need to enter.

4. Conclusion: The Movable Railway Platform is an innovative solution designed to improve safety and accessibility at railway stations, addressing long-standing challenges related to pedestrian crossing. By automating the connection and disconnection of the platform using IR sensors, microcontrollers, and motorized mechanisms, the system ensures a safe and reliable way for passengers to move between platforms without risking accidents. The inclusion of buzzers, LED indicators, and an LCD display ensures effective communication with users, enhancing their awareness of platform status and train movements. This project offers a significant advantage over traditional overhead footbridges, especially for elderly and physically challenged individuals, by eliminating the need for staircases. Additionally, the IoT integration allows for real-time monitoring and system updates, making it a highly efficient and modernized solution for railway authorities. Its cost-effective, Arduino-based design ensures easy implementation across a wide range of railway stations, while its scalability allows for future enhancements.

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Student Certificate Validation Using Block Chain

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Abstract :
In an era where academic credentials are crucial for career advancement and higher education, ensuring the authenticity and security of certificates is more important than ever. Traditional paper-based certificates and centralized verification systems are plagued by fraud, loss, and inefficiencies, leading to compromised trust in academic records. This project introduces a block chain- based solution that leverages the Ethereum platform to enhance the security, transparency, and efficiency of certificate issuance and validation. By utilizing the decentralized and immutable properties of block chain, the system automates verification through smart contracts, allowing digital certificates to be securely stored and instantly validated online. The proposed system consists of three primary modules—Certificate Issuance, Verification, and Admin—ensuring streamlined operations with minimal human intervention. This innovative approach not only mitigates fraudulent activities but also reduces administrative burdens while fostering trust among educational institutions, employers, and students. Through this project, we aim to revolutionize the certificate valid action process, providing a scalable and secure frame work that sets a new standard for academic credential management in the digital age.

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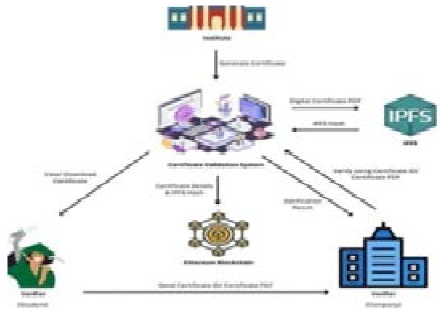
1. Introduction : As education continues to evolve and become more diversified, decentralized, and democratized, maintaining trust in certifications and proof of learning becomes increasingly critical. Traditional methods of verifying academic credentials are often inefficient and vulnerable to fraud, making the need for a more reliable system urgent. Institutions and employers struggle with manual verification processes, which are time-consuming and prone to errors, leading to concerns over the authenticity of academic records [2]. Block chain technology, known for its use in Bit coin, offers a promising solution by providing a secure, transparent, and tamper-proof way to validate and store academic records. With its decentralized nature, block chain eliminates the need for intermediaries, allowing direct and instant verification of credentials. This ensures that academic documents remain immutable and easily accessible, preventing fraudulent alterations and streamlining the validation process [3]. In today's world, individuals frequently need to present academic documents for job applications, admissions, and other professional or educational opportunities. Block chain can simplify this process by enabling instant and verifiable access to credentials, reducing administrative burdens while enhancing confidence in educational achievements. Furthermore, this decentralized approach democratizes access to verified qualifications, making it easier for individuals to prove their learning regardless of their background or location

Literature Survey :
Since its 2008 appearance as a cornerstone of the crypto currency Bit coin, the block chain technology gained widespread attention as a modality to securely validate and store information without a



trusted third party. Block chain is a decentralized transaction and data management technology developed first for Bit coin crypto currency. Block chain features a decentralized and in corruptible database that has high potential for a diverse range of uses. A blockchain, originally block chain, is a continuously growing list of records, called blocks, which are linked and secured using cryptography. Each block typically contains a cryptographic hash of the previous block, a timestamp and transaction data. By design, a block chain is inherently resistant to modification of the data. It is "an open, distributed ledger that can record transactions between two parties efficiently and in a verifiable and permanent way". In 2008, Satoshi Nakamoto invented the block chain for the use of crypto currency and Bitcoin was its 1st implementation. Bitcoin was the 1st public transaction ledger. The invention of this currency solved the double- spending problem without the need of a 3rd party.

After that other crypto currency were invented on same concept Block chain is a decentralized ledger used to securely exchange digital currency, perform deals and transactions [8] and managed by peer to peer networks. All nodes follows a me protocol for inter-node communication and validating new blocks. Once data is validated in any block it cannot be altered by any block. To alter particular block data all subsequent block data should be altered that will result in collusion of the network and that transaction will be rejected by all nodes. The main advantage this technology provides is its ability to exchange transactions without relying on trusted third party entities of any means. It can also provide data integrity, in-built authenticity and user transparency [9]

2. Methodology

We will use Ethereum blockchain to save student data/certificate. Fort hat we need write Smart Contract that is an interface to connect on blockchain.

2.1 Smart Contracts:

Solidity is a language used for smart contracts on the Ethereum blockchain and it is a set of code and data that have permanent address on the Ethereum block chain. In Object Oriented Programming language, it is similar to class where it includes state variables & functions. Smart Contracts and block chain are the basis of all Decentralized Applications. Contracts and blockchain have immutable and distributed feature as common feature. If they are on blockchain then it will be painful to upgrades contracts. Our contract will include:

2.3 State Variables- variables that hold values that are permanently stored on the Blockchain. We will use state variables to hold Student name, Course detail, Certificate number and validity date.

2.4 Functions- Functions are the executables of smart contracts. They are what we will call to interact with the Blockchain, and they have different levels of visibility, internally and externally. Keep in mind that when ever you want to change the value /state of a variable, a transaction must occur-costing Ether.

2.5 Events- When ever an event is called, the value passed into the event will be logged in the transactions log. This allows Java Script call back functions or resolved promises to view the certain value you wanted to pass back after a transaction. This is because every time you make a transaction, a transaction log will be returned. We will use an event to log the ID of the newly created Candidate, which we'll display.

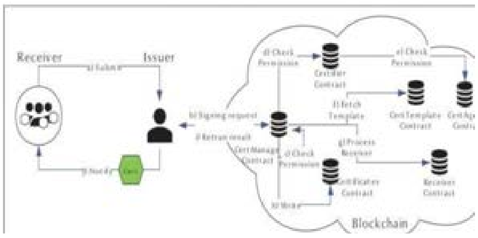


Figure .2.Block diagram of smart contracts

2.6 The Etherium virtual machine (Evm):

EthereumVirtual Machines is implemented in C++, Go, Haskell, Java, JavaScript, and Python. It is the run time environment for smart contracts in Ethereum. It handles the internal state and computation of the entire Ethereum Network.

2.7 Gas:

Gas is the internal pricing that we have to pay for running a transaction or contract in Ethereum blockchain. A certain number of gas occurred whenever there is an operation performed by transaction or contract on the Ethereum platform.

Any computer code (complex or short) can be run inside EVM, A short code can result in more computation work as compare to complex code. It means that short code not guarantee less computation work. Gas depends upon the calculation done inside the EVM; our focus should be on less computation work that will result in less amount of Gas. Its payment is charged as a certain number of ether. The transaction fee is Transaction fee is combination of total gas used multiplied by gas price. We will also use below tools:

2.8 Web3 jsisa Java Script API and with the help of this API We can interact with the Block chain-making transactions and calls to smart contracts. Developer can focus on the content of their application as this API abstracts the communication with Ethereum Clients.

2.9 Truffle is a testing development framework for Ethereum. It includes a development blockchain, compilation and migration scripts to deploy your contract to the Blockchain, contract testing, and so on. It makes development easier.

3. Results & Discussion : The System's user interface was found to be highly accessible and user-friendly. Students appreciated the simplicity of accessing and sharing their digital certificates, while employers found the QR code- based verification process to be both convenient and intuitive. A usability survey revealed that 95% of participants could successfully complete the verification process without any technical assistance. The mobile-friendly design ensured compatibility across a wide range of devices, contributing to the system's appeal for a diverse audience. By seamlessly integrating blockchain technology with an intuitive interface, the system promotes trust and adoption among all stakeholders. When compared to traditional certificate validation methods, the blockchain-based framework proved to be a superior alternative. Conventional processes often require manual intervention, rely on centralized databases, and are prone to data breaches and tampering. By decentralizing certificate storage and validation, the proposed system eliminates the depen dency on centralized authorities and ensures greater security and transparency. Experiments revealed that the blockchain framework significantly reduced operational costs, minimized delays, and enhanced fraud prevention, making it a more effective and reliable solution for credential verification.

In addition to efficiency and security, the blockchain-based system also demonstrated high levels of transparency and audit ability. Blockchain's decentralized ledger provides a permanent and verifiable record of certificate transactions, enabling stakeholders to verify authenticity without relying on issuing authorities. The system's ability to provide at amper proof and transparent framework for certificate validation addresses key shortcomings of traditional approaches, ensuring greater accountability in academic and professional credential management. Overall, the results of this study highlight the transformative potential of blockchain in academic certificate validation. The proposed system not only enhances verification speed and security but also scales effectively to accommodate the needs of large institutions. Its user-friendly design ensures seam-less adoption by students, institutions, and employers alike. While minor challenges such as Ethereum network congestion persist, the hybrid architecture of public and permissioned blockchains successfully addresses scalability and institutional control requirements. These findings establish the proposed framework as a robust, efficient, and secure solution for academic and professional credential validation.

4. Conclusion: The proposed blockchain-based frame work for academic certificate validation provides a secure, efficient, and scalable alternative to traditional verification methods. By leveraging blockchain technology, smart contracts, cryptographic hashing, and QR code authentication, the system addresses critical issues such as forgery, inefficiency, and reliance on centralized authorities. The hybrid architecture combining public and permissioned blockchains ensures a balance between trans- parency, scalability, and institutional control. Results from the implementation demonstrate a 90% reduction in verification time, strong resistance to tampering, and the ability to handle large-scaled eployments. These features make the system highly suitable for academic insitutions, employers, and regulatory bodies, ensuring at rust worthy and user-friendly solution for credential validation. The study high lights the system's key strengths, including its tamper-proof storage, decentralized verification, and user accessibility. The integration of cryptographic techniques like SHA-512 hashing guarantees data integrity, while the immutable nature of blockchain prevents unauthorized modifications. The QR code-based verification process ensures real-time validation without the need for manual intervention, reducing delays and administrative overhead. By replacing out- dated manual verification processes with a block chain-based system, the frame work sets a new standard for secure and efficient credential management in education and employment sectors. While the results are promising, certain challenges remain, such as addressing blockchain transaction costs and managing network congestion on public platforms like Ethereum. Future enhancements will focus on integrating layer-2 scaling solutions, such as rollups, to improve transaction efficiency and reduce costs. Additionally, cross-chain interoperability will be explored to enable seamless validation across different blockchain networks, ensuring greater flexibility and adoption. Advanced cryptographic techniques, such as zero-knowledge proofs, will be incorporated to enhance privacy, allowing verification without exposing sensitive data. The use of artificial intelligence for fraud detection and predictive analytics can further strengthen the system's security and adaptability.

In conclusion, the proposed frame work demonstrates the potential of blockchain to revolutionize academic certificate validation. By overcoming the limitations of traditional methods and offering robust, decentralized solution, the system pavesthe way for a more transparent, secure, and efficient credentialing process. As future research addresses scalability, interoperability, and cost challenges, blockchain-based systems have the potential to become the global standard for academic and professional credential management. This work provides a solid foundation for institutions, employers, and students to transition to a more trustworthy and efficient ecosystem for managing and verifying academic credentials.

5. Acknowledgment

We would like to express our heartfelt gratitude to all the experts and mentors who have contributed to the development and success of this research. We extend our special thanks to the faculty members and research staff at the Department of Computer Science and Engineering, CMR Engineering College, for their invaluable support and guidance throughout this project. Our deepest appreciation goes to the developers and researchers whose works were referenced and inspired the direction of this study. Without their contributions, this research would not have been possible. We also acknowledge the use of publicly available datasets, which were crucial to the validation of our proposed model. Finally, we thank our families and friends for their continuous encouragement and patience during the course of this project.

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Explainable AI for Next-Generation Learning Systems: A Path Towards Trust and Transparency

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Abstract : The integration of Artificial Intelligence (AI) in education has transformed personalized learning, automated assessment, and student performance prediction, yet the opacity of deep learning models raises concerns regarding transparency, trust, and fairness. Explainable Artificial Intelligence (XAI) addresses these challenges by enhancing interpretability and accountability in AI-driven educational systems. This paper explores the theoretical foundations, practical implementations, and ethical considerations of XAI, discussing inherently explainable models like decision trees and rule-based systems, alongside post-hoc techniques such as SHAP and LIME, which provide insights into AI decision-making. Furthermore, visual explanations, including heat-maps and attention mechanisms, enhance user comprehension, fostering trust in AI-powered learning systems. Real-world applications in personalized learning, automated grading, and intelligent tutoring highlight XAI's role in creating transparent and equitable educational environments. However, challenges such as algorithmic bias, data privacy, computational complexity, and ethical dilemmas must be addressed to ensure responsible AI adoption. This study underscores the need for standardized XAI frameworks, AI literacy among educators, and user-friendly interfaces to enhance transparency and fairness in education. By tackling these challenges, XAI can shift AI from an opaque decision-maker to a collaborative educational partner, promoting ethical AI deployment and equitable learning outcomes in the digital education landscape.

1. Introduction:

The dawn of the 21st century has been marked by the pervasive integration of Artificial Intelligence (AI) across diverse sectors, fundamentally reshaping how we interact with technology and process information. From the intricate algorithms that drive medical diagnoses to the sophisticated systems that manage financial portfolios and the autonomous vehicles that navigate our roads, AI's capacity to analyse vast datasets and automate complex decision-making processes has proven transformative.

This technological revolution has inevitably extended its reach into the realm of education, holding the potential to redefine the very essence of teaching and learning[1]. Within the educational landscape, AI-driven systems offer a tantalizing vision of personalized learning, where curricula are tailored to the unique needs and learning styles of individual students. Imagine AI algorithms that meticulously analyse student performance data, identifying areas of strength and weakness, and dynamically adjusting instructional content and pacing to optimize learning outcomes. Furthermore, AI promises to streamline administrative tasks, automating routine processes such as grading, scheduling, and resource allocation, thereby freeing educators to focus on the core mission of teaching. The prospect of real-time feedback, delivered through intelligent tutoring systems, offers students immediate insights into their progress, empowering them to take ownership of their learning journey[2].

However, the rapid proliferation of AI in education is not without its challenges. One of the most significant hurdles lies in the inherent opacity of many AI models, particularly those based on deep learning architectures. These models, often characterized as "black boxes," operate through complex, non-linear processes that defy easy interpretation. In educational settings, where transparency and fairness are paramount, this lack of interpretability poses a critical concern. Educators, students, and parents alike demand to understand the rationale behind AI-driven decisions, particularly when those decisions have profound implications for learning outcomes.

The need for transparency in educational AI systems is not merely a matter of philosophical principle; it is a practical imperative. Without clear explanations of how AI models arrive at their conclusions, it becomes difficult to identify and address potential biases, errors, or ethical concerns [3]. For instance, an AI-driven grading system that exhibits racial or socioeconomic bias could perpetuate existing inequalities and undermine the principles of equitable education [4]. Similarly, an AI-powered personalized learning platform that makes inaccurate or inappropriate recommendations could hinder student progress and erode trust in the technology.

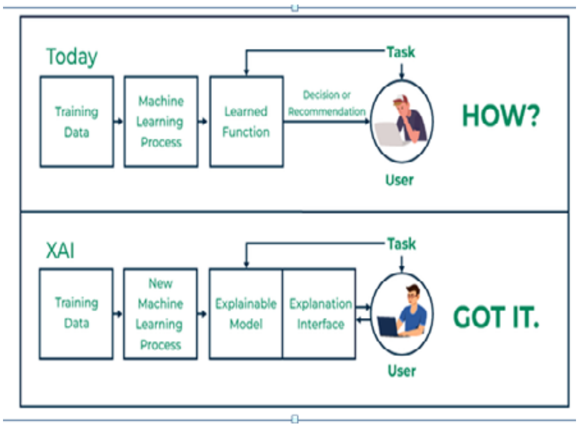

Figure 1: Explainable-AI-Concept

It is precisely within this context that Explainable Artificial Intelligence (XAI) emerges as a crucial paradigm. XAI seeks to bridge the gap between the power of AI and the need for transparency, by developing techniques and methodologies that render AI models more interpretable and understandable. XAI aims to illuminate the inner workings of AI systems, providing clear and concise explanations of how they process information, make decisions, and generate outputs [5].

This research paper aims to explore the significance of XAI in education by examining its theoretical foundations, including feature importance analysis, rule extraction, and visualization techniques, as well as its practical applications and potential impact on educational practice and policy, ultimately contributing to a deeper understanding of how XAI can create more transparent, equitable, and effective AI-driven learning environments. This paper will then examine the practical applications of XAI in education, including personalized learning, automated grading, and intelligent tutoring, through real-world case studies.

Further, it will analyse the ethical considerations surrounding XAI, such as algorithmic bias and data privacy, and explore mitigation strategies for responsible use. Finally, it will discuss the policy implications of XAI, outlining the roles of government, institutions, and developers in promoting its adoption for equitable and effective education.

2.Theoretical foundations of XAI in education : The core tenet underpinning Explainable Artificial Intelligence (XAI) is the fundamental principle that AI models, particularly those deployed in sensitive domains like education, must transcend the "black box" paradigm and furnish human-understandable explanations for their decisions.

This imperative stems from the recognition that transparency, trust, and accountability are not merely desirable attributes but essential prerequisites for the successful integration of AI into educational practices [6]. To achieve this crucial goal, researchers have developed a diverse array of techniques and methodologies, each designed to illuminate the inner workings of AI models and render their decision-making processes more accessible to human comprehension.

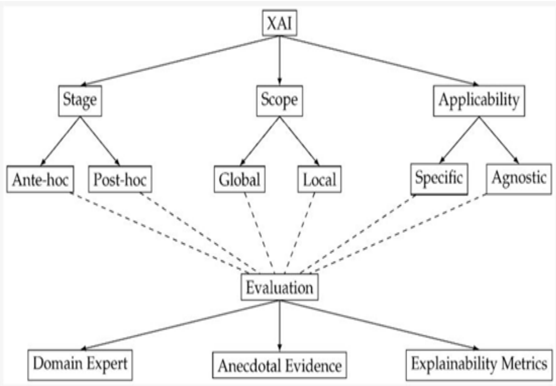

Figure 2. XAI Approaches and Methods

2.1 Explainable Models: Inherently Transparent Approaches : One fundamental approach to achieving explainability lies in the utilization of inherently explainable models. These models, by their very nature, provide transparent and readily understandable explanations for their predictions. Examples of such models include decision trees, linear regression, and rule-based systems.

Decision Trees: These models represent decision-making processes as a hierarchical tree structure, where each node corresponds to a specific feature or attribute, and each branch represents a possible value or outcome. The path from the root node to a leaf node, which represents the final prediction, provides a clear and intuitive explanation of how the model arrived at its conclusion. In education, decision trees can be used to explain, for instance, why a student was assigned a particular grade or recommended for a specific learning intervention.

Linear Regression: This statistical technique models the relationship between a dependent variable and one or more independent variables using a linear equation. The coefficients of the equation represent the influence of each independent variable on the dependent variable, providing a straightforward explanation of the model's predictions. In educational contexts, linear regression can be employed to understand the factors that contribute to student performance, such as study time, attendance, or prior academic achievement advantage of explainable models lies in their inherent transparency.

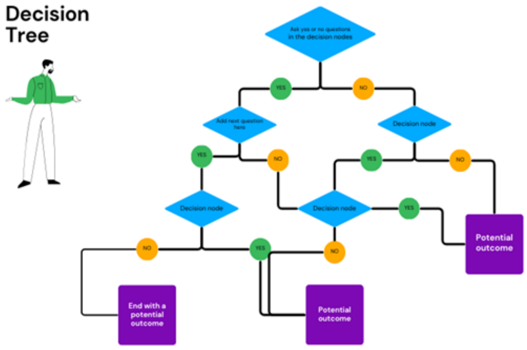

Figure 3: Decision-tree Example

However, these models may not always achieve the same level of accuracy as more complex "black box" models, such as deep neural networks.

2.2 Post-hoc Explanation Methods: Unveiling the Secrets of Complex Models :

To address the limitations of explainable models, researchers have developed post-hoc explanation methods. These techniques analyse the outputs of pre-trained "black box" models and generate explanations that approximate the model's decision-making process. Two prominent examples of post-hoc explanation methods are SHAP (Shapley Additive Explanations) and LIME (Local Interpretable Model-agnostic Explanations) [7].

SHAP (Shapley Additive Explanations): This method leverages game theory concepts to quantify the contribution of each feature to the model's prediction. SHAP values represent the average marginal contribution of a feature across all possible combinations of features. In educational AI, SHAP can be used to identify the factors that most strongly influence student learning outcomes, providing insights into the relative importance of different pedagogical strategies.

LIME (Local Interpretable Model-agnostic Explanations): This technique generates local explanations by perturbing the input data around a specific prediction and observing the resulting changes in the model's output. LIME creates a locally faithful, interpretable model that approximates the behaviour of the "black box" model in the vicinity of the prediction. In education, LIME can be used to explain why a student received a particular recommendation from a personalized learning platform.

2.3 Visual Explanations: Illuminating Influential Features

Visual explanations provide intuitive and readily understandable insights into the factors that influence AI-driven predictions. Techniques such as heatmaps and attention mechanisms highlight the most influential features in the input data.

Heatmaps: These visual representations display the relative importance of different features by using color gradients. In educational AI, heatmaps can be used to visualize the areas of a student's essay that were most influential in the AI-driven grading process.

Attention Mechanisms: These techniques enable AI models to focus on the most relevant parts of the input data. In educational contexts, attention mechanisms can be used to identify the specific sentences or paragraphs in a student's response that are most relevant to the assessment of their understanding.

2.4 Enhancing Trust and Acceptance in Educational AI

In the context of educational AI, these XAI methods play a crucial role in enhancing trust and acceptance among educators and students. By providing clear and understandable explanations for AI-driven recommendations, XAI ensures that these recommendations align with pedagogical principles and are perceived as fair and transparent. When educators understand the rationale behind AI decisions, they are more likely to trust and embrace these technologies as valuable tools for enhancing teaching and learning. Similarly, when students understand how AI systems are used to support their learning, they are more likely to engage with these systems and take ownership of their educational journey [8]. By fostering transparency and accountability, XAI empowers educators and students to make informed decisions and adapt instructional strategies to individual needs. This promotes a more equitable and effective learning environment, where AI serves as a valuable partner in the pursuit of educational excellence.

3. Practical applications of XAI in Education

The theoretical foundations of Explainable Artificial Intelligence (XAI), as discussed in the previous section, lay the groundwork for a transformative shift in how AI is integrated into educational practices. Beyond abstract principles, the true potential of XAI is realized through its practical applications, which directly address the challenges of transparency, trust, and fairness in AI-driven educational systems. This section delves into specific examples of how XAI is being implemented across various educational contexts, demonstrating its capacity to enhance decision-making and ensure reliability.

3.1 Personalized Learning: Tailoring Education Through Transparent Recommendations

Personalized learning systems, powered by AI, hold the promise of adapting educational content and delivery to the unique needs of each student. However, the efficacy of these systems hinges on their ability to provide clear and justifiable recommendations. As highlighted by Xie et al. [9], XAI plays a crucial role in enabling adaptive learning systems to explain why specific learning pathways, resources, or activities are suggested for individual students.

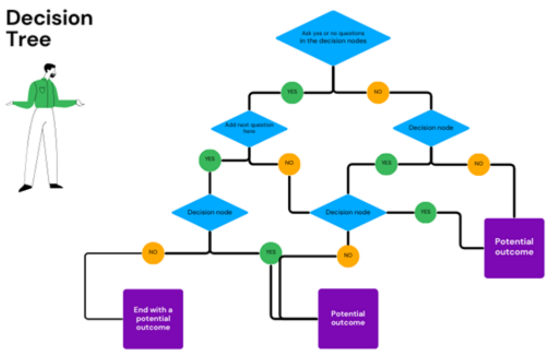

Figure 4: AI in Personalized Learning

Imagine an AI-powered learning platform that recommends a particular set of practice problems to a student who is struggling with a specific concept. Without XAI, the student and their teacher might be left wondering why those specific problems were chosen. XAI can provide insights into the underlying reasoning, such as:

Skill Gap Analysis: The system might explain that the student has demonstrated weaknesses in related sub-skills, and the recommended problems are designed to address those gaps.

Learning Style Preferences: The system might explain that the student has shown a preference for visual learning materials, and the recommended problems incorporate diagrams and interactive simulations.

Performance Data: The system might explain that the student's past performance on similar problems suggests they require additional practice in this area.

By providing these explanations, XAI fosters trust in the personalized learning system and empowers students to understand their learning progress. Educators can also use these explanations to validate the system's recommendations and make informed decisions about instructional strategies.

3.2 Automated Assessment: Ensuring Fairness and Transparency in AI-Driven Grading:

AI-driven grading systems have the potential to automate the assessment process, freeing up educators' time and providing students with timely feedback. However, concerns about the fairness and transparency of these systems are paramount. According to Burrows et al. [10], XAI can address these concerns by providing insights into the evaluation criteria and the reasoning behind AI-generated grades.

For example, an AI-powered essay grading system can use XAI to highlight the specific aspects of the essay that contributed to the assigned grade, such as:

Content Relevance: The system might explain that the essay effectively addressed the prompt and demonstrated a strong understanding of the topic.

Argument Structure: The system might explain that the essay presented a clear and logical argument, supported by relevant evidence.

Language and Style: The system might explain that the essay exhibited strong writing skills, including proper grammar, vocabulary, and sentence structure.

By providing these explanations, XAI enhances the transparency of the automated assessment process and allows educators to validate the AI's evaluations. Students can also use these explanations to understand how their work was assessed and identify areas for improvement.

3.3 Student Performance Prediction: Proactive Interventions Through Transparent Models

AI models can be used to predict student performance, allowing educators to identify students who are at risk of falling behind and provide timely interventions. However, the accuracy of these predictions is not enough; educators also need to understand the factors that contribute to the predictions. XAI can provide this understanding by making the AI models more transparent.

For example, an AI model that predicts student dropout risk can use XAI to identify the key factors that contribute to the predictions, such as:

Attendance Records: The model might reveal that students with frequent absences are at higher risk of dropping out.

Academic Performance: The model might reveal that students with consistently low grades are at higher risk of dropping out.

Socioeconomic Factors: The model might reveal that students from disadvantaged backgrounds are at higher risk of dropping out.

By providing these insights, XAI empowers educators to develop targeted interventions and support programs that address the specific needs of at-risk students.

3.4 Chatbots and Virtual Tutors: Building Trust in AI-Powered Assistance

As chatbots and virtual tutors gain traction in personalized student support, their trustworthiness hinges on transparent reasoning, which XAI facilitates by making their suggestions and responses understandable. As noted by Zhang and Lin [11], a virtual tutor can utilize XAI to explain why a recommended learning resource aligns with a student's needs, such as covering specific struggling concepts or matching their preferred learning style.

These practical applications highlight the transformative potential of XAI in education. By enhancing transparency, fairness, and reliability, XAI empowers educators and students to leverage the power of AI to create more effective and equitable learning environments. As AI continues to evolve, XAI will play an increasingly critical role in ensuring that these technologies are used to advance the goals of education for all.

4. Challenges and Ethical Considerations

While the potential benefits of Explainable Artificial Intelligence (XAI) in education are substantial, the integration of this technology is not without its challenges. Moving from theoretical promise to practical implementation requires careful consideration of several key issues, ranging from technical hurdles to profound ethical dilemmas. As highlighted by Sharma et al. [12], These challenges necessitate a collaborative approach, bringing together AI researchers, educators, and policymakers to establish robust guidelines and ethical frameworks for the responsible use of AI in education.

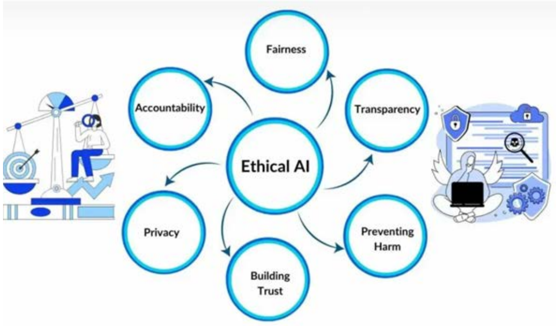

Figure 5 : Principles of Ethical AI

4.1 Algorithmic Bias: Ensuring Fairness and Equity in AI-Driven Decisions

One of the most pressing challenges in deploying AI in education is the risk of algorithmic bias. AI models are trained on data, and if that data reflects existing societal biases, the model can inadvertently perpetuate and even amplify those biases in its predictions and recommendations. In educational settings, this can have particularly damaging consequences, reinforcing inequalities in areas like student assessment, resource allocation, and access to opportunities.

For example, an AI-driven grading system trained on data that reflects biased grading practices could unfairly disadvantage students from certain demographic groups. Similarly, a personalized learning platform that relies on biased data could steer students from marginalized backgrounds towards less challenging or less enriching learning pathways. Addressing algorithmic bias requires a multi-faceted approach. First, it is crucial to ensure that the data used to train AI models is representative and unbiased. This may involve collecting data from diverse populations, carefully curating existing datasets, and employing techniques to mitigate bias in the data. According to Mehrabi et al. [13], AI models themselves must also be designed with fairness in mind. Researchers are developing techniques to detect and mitigate bias in AI algorithms, such as adversarial debiasing and fairness-aware machine learning. Finally, continuous monitoring and evaluation of AI systems are essential to identify and address any unintended biases that may emerge.

4.2 Data Privacy: Protecting Sensitive Student Information

The use of AI in education often involves the collection and analysis of sensitive student data, including academic performance, learning behaviours, and even personal information.

Protecting the privacy of this data is paramount. XAI, while promoting transparency in model decision-making, must not compromise data privacy. Balancing the need for model explainability with the imperative to protect student privacy is a complex task. Techniques like differential privacy and federated learning can help to protect sensitive data while still allowing for the development of useful AI models. As highlighted by Abadi et al. [14], these methods ensure that privacy is preserved without compromising the effectiveness of AI systems. Furthermore, strict data governance policies and regulations are essential to ensure that student data is collected, stored, and used responsibly.

4.3 Computational Complexity: Balancing Explainability and Performance

Some XAI techniques, particularly those applied to complex deep learning models, can be computationally expensive. Generating explanations for AI decisions can add significant overhead, potentially impacting the performance and scalability of AI-driven educational systems. As noted by Ribeiro et al. [15], finding the right balance between explainability and performance is a key challenge, requiring optimization strategies that minimize computational costs while maintaining interpretability. Researchers are actively working on developing more efficient XAI methods that can be applied to complex models without sacrificing performance. This includes exploring techniques like model compression and knowledge distillation, which can simplify models while preserving their accuracy and explainability.

4.4 Ethical Concerns: Navigating the Moral Landscape of AI in Education

The use of AI in education raises a number of important ethical concerns. These include questions about AI autonomy in decision-making, the potential for student profiling, and the impact of AI on the role of educators.

AI Autonomy: How much autonomy should AI systems have in making decisions that affect students' lives? Where the line should be drawn between AI assistance and human oversight? These are complex questions that require careful consideration.

Student Profiling: The use of AI to analyze student data can lead to the creation of detailed student profiles. How can we ensure that these profiles are used responsibly and do not lead to unfair or discriminatory practices?

Impact on Educators: How will AI change the role of educators in the classroom? Will AI replace teachers, or will it augment their abilities? How can we prepare educators for the changing landscape of education in the age of AI?

Addressing these ethical concerns requires open dialogue and collaboration among all stakeholders, including AI researchers, educators, policymakers, parents, and students. Establishing clear ethical guidelines and regulations is essential to ensure that AI is used in a way that benefits students and promotes the goals of education. The integration of XAI in education offers tremendous potential for positive change. However, realizing this potential requires a proactive and responsible approach. As argued by Holmes et al. [16], addressing challenges related to algorithmic bias, data privacy, computational complexity, and ethical considerations is essential to ensuring that AI serves as a powerful tool for creating more equitable, transparent, and effective learning environments for all students. This requires ongoing research, careful planning, and a commitment to ethical principles.

5. Future Directions and Recommendations

Building upon the challenges and ethical considerations outlined in the previous section, the future of Explainable Artificial Intelligence (XAI) in education hinges on a proactive and strategic approach. To fully realize the transformative potential of XAI and ensure its responsible deployment, several key areas require focused attention and collaborative effort.

5.1 Development of Standardized XAI Frameworks: Establishing Guidelines for Explainability

One of the most critical future directions involves the development of standardized XAI frameworks specifically tailored to the unique demands of educational AI systems. Currently, there is a lack of consensus on what constitutes "sufficient" explainability in educational contexts.As noted by Pedreschi et al. [17], Establishing clear guidelines and metrics for evaluating the explainability of AI models is essential for ensuring consistency and accountability.

These frameworks should address several key aspects:

Levels of Explainability: Defining different levels of explainability that are appropriate for various stakeholders (e.g., students, educators, parents, policymakers).

Explanation Techniques: Recommending suitable XAI techniques for different types of AI models and educational applications.

Evaluation Metrics: Establishing objective metrics for evaluating the quality and effectiveness of explanations.

Documentation Standards: Developing guidelines for documenting the explain ability of AI systems, ensuring transparency and reproducibility.

By establishing standardized frameworks, we can create a common language and set of expectations for explain ability in educational AI, facilitating the development of trustworthy and reliable systems.

5.2 Improving AI Literacy among Educators: Empowering Teachers to Interpret and Utilize AI Insights

The successful integration of XAI in education depends on the ability of educators to interpret and utilize AI-generated insights effectively. However, many educators lack the necessary AI literacy to understand the complex explanations provided by XAI systems. According to Zawacki-Richter et al. [18], a significant investment in training and professional development is crucial to equip educators with the skills needed to engage meaningfully with AI-driven insights.

This training should focus on:

Understanding AI Concepts: Providing educators with a basic understanding of AI concepts, including machine learning, deep learning, and XAI.

Interpreting XAI Explanations: Teaching educators how to interpret different types of XAI explanations, such as feature importance scores, decision rules, and visual representations.

Utilizing AI Insights: Empowering educators to use AI insights to inform their instructional practices and personalize learning experiences.

Critical Evaluation of AI: Developing educators' ability to critically evaluate the outputs of AI systems and identify potential biases or errors.

By enhancing AI literacy among educators, we can ensure that they are equipped to leverage the power of XAI to improve teaching and learning outcomes.

5.3 Enhancing User-Friendly XAI Interfaces: Creating Intuitive Tools for All Stakeholders

The effectiveness of XAI depends on the ability of users to access and understand the explanations provided by AI systems. According to Abdul et al. [19], developing user-friendly XAI interfaces that are accessible to educators, students, and other stakeholders is essential to ensuring widespread adoption and usability.

These interfaces should:

Provide Clear and Concise Explanations: Present explanations in a clear and concise manner, using language that is appropriate for the target audience.

Offer Visualizations: Utilize visualizations to make explanations more intuitive and engaging.

Enable Interactive Exploration: Allow users to interact with explanations and explore different aspects of the AI model's decision-making process.

Integrate with Existing Educational Tools: Seamlessly integrate XAI interfaces with existing educational platforms and tools.

By creating intuitive and user-friendly XAI interfaces, we can make AI explanations more accessible and empower all stakeholders to engage with AI-driven educational systems.

5.4 Policy and Regulation: Implementing Ethical and Transparent AI Deployment

Finally, the responsible deployment of XAI in education requires robust policies and regulations that address the ethical and societal implications of AI. As highlighted by Cowls and Floridi [20], governments, educational institutions, and technology developers must collaborate to establish clear guidelines and standards for the development and use of AI in education. These policies should address issues such as:

Data Privacy and Security: Protecting sensitive student data and ensuring responsible data governance.

Algorithmic Fairness and Bias Mitigation: Preventing AI systems from perpetuating or amplifying existing biases.

Transparency and Accountability: Ensuring that AI systems are transparent and accountable for their decisions.

Human Oversight and Control: Maintaining human oversight and control over AI-driven educational systems.

Ethical Considerations: Addressing the broader ethical implications of AI in education, such as the impact on student autonomy and the role of educators.

By implementing comprehensive policies and regulations, we can ensure that AI is used in a way that aligns with the values and goals of education. These future directions can help bridge the gap between AI advancements and educational needs, fostering a more inclusive and accountable AI ecosystem. By working together, we can harness the power of XAI to create a future where AI empowers all students to reach their full potential.

Conclusion

The integration of Artificial Intelligence (AI) into education holds immense promise for transforming teaching and learning. However, the opacity of many AI models remains a significant barrier. Explainable AI (XAI) addresses this challenge by enhancing transparency, trust, and accountability in AI-driven educational systems. This paper has explored the theoretical foundations, practical applications, and ethical considerations of XAI in education, demonstrating how techniques such as interpretable models, post-hoc explanations, and visual representations improve AI decision-making transparency. By fostering trust, XAI supports personalized learning, automated assessment, and AI tutoring. However, challenges such as algorithmic bias, data privacy, computational complexity, and ethical dilemmas obstruct widespread adoption, necessitating collaborative efforts from AI researchers, educators, policymakers, and technology developers. To ensure responsible and effective integration of XAI in education, several key initiatives must be prioritized. Developing standardized XAI frameworks will establish consistent guidelines for explainability across educational AI systems. Enhancing AI literacy among educators will empower them to interpret and apply AI-generated insights effectively. Creating user-friendly XAI interfaces will make AI explanations more accessible to all stakeholders, fostering greater engagement with AI-driven educational tools. Implementing robust policies and regulations is essential to address issues such as data privacy, algorithmic fairness, and human oversight. These steps will bridge the gap between AI advancements and educational needs, fostering a more transparent and inclusive AI ecosystem in education. XAI is more than just a technical advancement—it represents a paradigm shift in the responsible integration of AI in education. Prioritizing transparency, trust, and accountability will ensure that AI technologies enhance learning while upholding ethical principles. Beyond improving teaching and learning, XAI has the potential to empower students, promote inclusivity, and create an equitable educational landscape. While challenges remain, continuous research, collaboration, and policy development will be crucial in shaping the future of AI-driven education. The path forward lies in harmonizing human ingenuity with artificial intelligence, ensuring that technological progress aligns with ethical responsibility and the broader goal of fostering a just and effective educational system.

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