ISSN : 2455-3158

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

Editor-in-Chief :

Dr. Suman Joshi

Volume - 7
December, 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 Bihari Lal

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The Editorial Board invites original, unpublished contributions in the form of Research Papers, Articles, Book, Reviews and Case Studies.

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From Chairman's Desk

Dear All,

It gives us a great pleasure that Rajshree Institute of Management and Technology is going to publish volume-7 of e-Journal of Indian Institute for Engineering, Management and Science (e-JIIEMS). Our journal focuses on emerging sectors and research that explore real-world applications and user impact in both societal and industrial contexts. We provide a global platform for faculty, research scholars, and students from diverse disciplines to present the latest achievements across various fields.

We sincerely appreciate the efforts of all members of the review committee, whose dedication and hard work have been instrumental in bringing this journal to publication as efficiently as possible.

Rajendra Kumar Agarwal
Chairman
Rajshree Group of Institutions
Bareilly

e- Journal of Indian Institute for Engineering, Management and Science
Volume 7, December 2025
ISSN: 2455-3158

Editor in Chief Message

Dear All,

We are honored to announce the publication of seventh volume of e-journal of Indian Institute for Engineering, Management and Science. We express our sincere gratitude to all the respected authors whose dedication and subject expertise have enriched the current volume of this journal.

In this publication, researchers demonstrate their interest in developing robust and efficient deep convolutional neural networks for vehicle counting, web-based platforms for comparison across major e-commerce platforms, Monkeypox detection using deep learning approaches, and traffic signal recognition for autonomous driverless vehicles. Other contributions focus on artificial intelligence–based helmet detection, deep summarization networks to generate informative yet concise video summaries, and blood group detection from fingerprints using image processing techniques.

We also extend our heartfelt thanks to our leadership, whose engagement and continuous support have been instrumental in the success of our journal.

Dr. Suman Joshi
Associate Professor
Rajshree Institute of Management & Technology
Bareilly

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

(e- JllEMS)

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Deep CNN Frame Work for Vehicle Counting and Classification System from Real Time Videos

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Abstract:
Traffic Analysis has been a problem that city planners have dealt with for years. Smarter ways are being developed to analyze traffic and streamline the process. Analysis of traffic may account for the number of vehicles in an area per some arbitrary time period and the class of vehicles. The system involves capturing of frames from the video to perform background subtraction in order detect and count the vehicles using Gaussian Mixture Model (GMM) background subtraction then it classifies the vehicles by comparing the contour areas to the assumed values. The substantial contribution of the work is the comparison of two classification methods. Classification has been implemented using Contour Comparison (CC) as well as Bag of Features (BoF). Method the rapid growth of urbanization and vehicular traffic in modern cities has led to increased demand for effective traffic management and surveillance systems. In response to these challenges, this project proposes a novel Deep Convolutional Neural Network (CNN) framework for the automatic counting and classification of vehicles from real-time video streams.

1. Introduction

Learning and computer vision have emerged as powerful tools for automating the process of vehicle counting and classification in real-time video streams. The proposed project aims to develop a robust and efficient deep convolution neural network (CNN) framework tailored specifically for vehicle counting and classification tasks using real-time video data. By leveraging the capabilities of deep learning, the system can autonomously analyze streaming video footage captured by surveillance cameras deployed at various traffic intersections, highways, and urban areas. The primary objectives of the project include: vehicles, amidst varying environmental conditions and traffic scenarios [1-3].

The purpose of this project is to pioneer a transformative approach to traffic management and transportation systems through the implementation of a real-time vehicle counting and classification system. In response to the escalating challenges posed by modern urbanization,[7] traffic congestion, and safety concerns, the project aims to leverage cutting-edge technology, specifically the integration of sensors, cameras, and advanced computer vision algorithms. Precision through Deep Learning: Harness the power of deep learning models, specifically the YOLO (You Only Look Once) algorithm within the Darknet framework, to achieve accurate real-time counting and classification of vehicles. Data-Driven Decision Making: Provide transportation[4] authorities with timely and comprehensive traffic data, including volume, congestion patterns, and vehicle types, facilitating informed decision-making for optimizing traffic flow and implementing safety measures. Real-Time Responsiveness: Develop a system that operates in real-time, eliminating processing delays and allowing for immediate responses to dynamic traffic situations [5-6]. Seamless Integration with Open CV: Leverage the Open CV library to seamlessly integrate computer vision capabilities, ensuring a versatile and efficient platform for implementation.

The system is divided in several stages: ROI selection, detection of moving objects, clustering process, tracking, single-frame classification and counting. Acquire images from the road is the first step of the proposed vehicle detection algorithm, for this is necessary to place a HD-RGB camera over the road, like is All obtained frames are converted to gray scale. Then, in order to maximize the performance of the algorithm, a selection of a proper ROI (Region of Interest) is needed. Within this area the search for moving objects is performed.

The region must contain the zone where the aim traffic flow is located, as well the line for vehicle count. This selection may change according to the type of road. A small change in the data can cause a large change in the structure of the decision tree causing instability. For a Decision tree sometimes, calculation can go far more complex compared to other algorithms. Decision tree often involves higher time to train the model. Decision tree training is relatively expensive as the complexity and time has taken are more. The Decision Tree algorithm is inadequate for apply.ing regression and predicting continuous values.

The research work begins with the acquisition of real-time video streams as the primary input source, typically sourced from surveillance cameras or traffic monitoring systems. The first module, Background Subtraction and ROI, plays a crucial role in isolating moving objects, i.e., vehicles, from the stationary background. The heart of the system lies in the Vehicle Detection and Tracking module, which employs the YOLO (You Only Look Once) [1]deep learning model. YOLO excels at real-time object detection and tracking, enabling the system to identify vehicles within the defined ROI and track their movements across frames, allowing for continuous monitoring. The next step involves the [7]. Vehicle Classification module specific categories, such as cars, trucks, or motorcycles. Following this, the Counting and Analytics module quantifies vehicle movements, including counting, speed measurement, and other relevant analytics, providing valuable data for traffic management and research purposes. Finally, the system generates a video output that overlays processed information onto the original video feed, offering a user-friendly visual representation of the vehicle counting and classification results, making it a versatile tool for various applications in[9] traffic monitoring, urban planning, and transportation research.

The detailed operation illustrated as follows:

Step 1: This is the starting point of system. Acquire real-time video streams as input data for the system. These video streams could come from surveillance cameras, traffic cameras, or any source capturing vehicle movements.

Step 2: Background subtraction is a crucial step for isolating moving objects (vehicles) from the stationary background. In this module, use algorithms and techniques to detect the background and create a Region of Interest (ROI) where vehicle detection will occur. This step helps reduce noise and focus on the relevant area.

Step 3: Use YOLO (You Only Look Once), a deep learning-based object detection model, for vehicle detection. YOLO can efficiently detect and locate objects in real-time video frames. It identifies the vehicles within the defined ROI and can track their movements across frames, allowing us to follow vehicles as they move through the video.

Step 4: After detecting and tracking vehicles, further analyze and classify them using the Dark net framework. Dark net is a neural network framework well-suited for classification tasks. It can classify vehicles into different categories such as cars, trucks, motorcycles, or any other relevant classes.

Step 5: In this step, count and analyze the detected and classified vehicles. We can track the number of vehicles passing through specific points. Regions of interest, calculate vehicle speed, and gather other relevant analytics data. This [7] information can be useful for traffic management, surveillance research purposes. Step 6: Finally, the system provides video output with the processed information overlaid on the original video feed. This output can include counted vehicles, their classifications, and any other relevant data. It allows users to visualize and interpret the results of the vehicle counting and classification system.

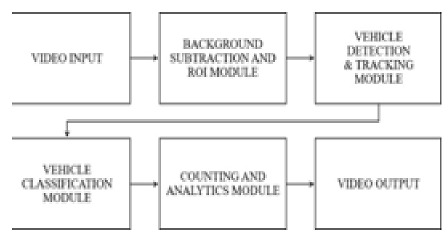

Figure 1. System Flow

Figure 2. Data flow diagram

2. System Analysis and Design:

Vehicle Detection and Counting : The third and the last module in the proposed system is classification. After applying foreground extraction module, proper contours are acquired, Features of these contours such as centroid. Aspect ratio, area, size and solidity are extracted and are used for the classification of the vehicles. This module consists[8] of three steps, background subtraction, image enhancement and foreground extraction. Background is subtracted so that foreground objects are visible. This is done usually by static pixels of static objects to binary 0. After background subtraction image enhancement techniques such as noise filtering, dilation and erosion are used to get proper contours of the foreground objects.

The result obtained from this module is the foreground. Region of Interest selection: In the very first frame of the video, I define a ROI by drawing a close line on the image. The goal is to recognize that ROI in a later frame, but that ROI is not a salient vehicle. It is just a part of a vehicle, and it can deform, rotate, translate and even not be fully in the frame. Vehicle Detection: Active strategy to choose a search window for vehicle detection using an image context was proposed GMM framework to capture the vehicle by sequential actions with top-down attention. It has achieved satisfactory performance on vehicle detection benchmark, by [9-13] sequentially refining the bounding boxes. Proposed a sequential search strategy to detect visual vehicles in images, where the detection model was trained by proposed a deep RL framework to select a proper action to capture a vehicle in an image. Vehicle Counting: In this module detected vehicles will be counted and these counted results will be updated frequents based on vehicle detection, results will be printed streaming video using Open CV.

YOLO-V3Model: Object detection is a phenomenon in computer vision that involves the detection of various objects in digital images or videos. Some of the objects detected include people, cars, chairs, stones, buildings, and animals. This phenomenon seeks to answer two basic questions: What is the object? This question seeks to identify the object in a specific image. Where is it? This question seeks to establish the exact location of the object within the image. Object detection consists of various approaches such as fast R-CNN, Retina-Net, and Single-Shot Multi Box Detector (SSD). Although these approaches have solved the challenges of data limitation and modeling in object detection, they are not able to detect objects in a single algorithm run. YOLO algorithm has gained popularity because of its superior performance over the aforementioned object detection techniques. YOLO Definition: YOLO is an abbreviation for the term 'You Only Look Once'. This is an algorithm that detects and recognizes various objects in a picture (in real-time). Object detection in YOLO is done as a regression problem and provides the class probabilities of the detected images. YOLO algorithm employs convolution neural networks (CNN) to detect objects in real-time. As the name suggests, the algorithm requires only a single forward propagation through a neural network to detect objects. This means that[8] prediction in the entire image is done in a single algorithm run. CNN is used to predict various class probabilities and bounding boxes simultaneously. The YOLO algorithm consists of various variants. Some of the common ones include tiny YOLO and YOLOv3. Importance of YOLO: YOLO algorithm is important because of the following reasons: 1.Speed: This algorithm improves the speed of detection because it can predict objects in real-time. 2. High accuracy: YOLO is a predictive technique that provides accurate results with minimal back grounderrors. Learning capabilities: The algorithm has excellent learning capabilities that enable it to learn the representations of objects and apply them in object detection. YOLO algorithm working: YOLO algorithm works using the following three techniques: Residual blocks, Bounding box regression, Intersection Over Union (IOU)

Residual blocks **:**First, the image is divided into various grids. Each grid has a dimension of S x S. The following Figure 2 shows how an input image is divided into grids. In the Figure 2, there are many grid cells of equal dimension. Every grid cell will detect objects that appear within them[2]. For example, if an object center appears within a certain grid cell, then this cell will be responsible for detecting it.

Bounding box regression **:**A bounding box is an outline that highlights an object in an image. Every bounding box in the image consists of the following attributes: Width (bw), Height (bh), Class (for example, person, car, traffic light, etc.)- This is represented by the letter c. and Bounding box center (bx,by) The following Figure 4 shows an example of a bounding box. The bounding [10] box has been represented by a yellow outline. YOLO uses a single bounding box regression to predict the height, width, centre, and class of objects. In the image above, represents the probability of an object appearing in the bounding box.

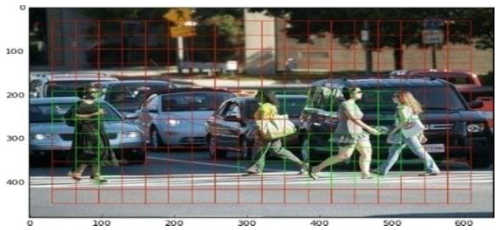

Figure 3. Example of residual blocks

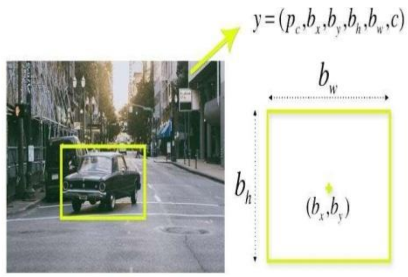

Figure 4. Bounding box Regression.

Conclusion: The proposed solution is implemented on python, using the Open CV bindings. The traffic camera footages from variety of sources are in implementation. A simple interface is developed for the user to select the region of interest to be analyzed and then image processing techniques are applied to calculate vehicle count and classified the vehicles. We have developed video based vehicle detection, classification, counting for real- time traffic data collection.

We have used Background Subtraction Yolo algorithm, open CV, and python for developing the system. In the proposed system, we have considered all day and night shadowing, and different lighting situations. Also, we have considered the moving shadow of moving vehicles. A primary focus of the research lies in evaluating and comparing two distinct classification methodologies: Contour Comparison (CC) and Bag of Features (BoF). This comparative analysis aims to enhance the accuracy and efficiency of vehicle classification within the system. Through rigorous experimentation and analysis, the study demonstrates [6] the efficacy of the vision-based approach. By utilizing contour areas and comparing them against predefined values, the system not only accurately counts vehicles but also facilitates their classification based on specified criteria. Furthermore, the adoption of vision-based techniques offers a cost-effective alternative to traditional sensor- based systems. By reducing maintenance overheads and calibration requirements, the proposed system becomes more accessible and scalable for deployment across various traffic management scenarios.

Overall, the findings underscore the transformative potential of vision-based methodologies in revolutionizing traffic analysis practices. By providing a robust and economically viable solution, the system holds promise for enhancing urban planning strategies and optimizing traffic management efforts in the foreseeable future. Real-Time Processing Optimization: Implement techniques to enhance the real-time processing capabilities of the system, enabling faster and more efficient analysis of traffic data. Integration of Machine Learning: Explore the integration of machine learning algorithms to improve vehicle classification accuracy and adaptability to diverse traffic scenarios.

Dynamic Background Modeling: Develop algorithms for dynamic background modeling to account for changing environmental conditions and improve the robustness of vehicle detection and tracking. Multi-Camera Support: Extend the system to support multiple cameras for comprehensive coverage of larger areas and better traffic monitoring capabilities. Cloud Integration: Integrate cloud computing capabilities to enable remote monitoring and analysis of traffic data, facilitating centralized management and scalability. Enhanced Visualization Tools: Develop advanced visualization tools and dashboards to provide intuitive insights into traffic patterns and trends for urban planners and traffic management authorities. Automatic Calibration and Maintenance: Implement automated calibration and maintenance routines to reduce the need for manual intervention and ensure the reliability of the system over time. Adaptive Thresholding Techniques: Investigate adaptive thresholding techniques to dynamically adjust parameters based on varying lighting conditions, improving the system's performance in challenging environments. Multi-Class Vehicle Classification: Extend the classification capabilities to support the recognition of multiple vehicle classes, including cars, trucks, motorcycles, bicycles, etc., for more detailed traffic analysis. Integration with Traffic Management Systems: Integrate the system with existing traffic management systems to facilitate seamless data exchange and collaboration traffic management entities. By incorporating these future enhancements, the system can evolve into a more robust, adaptable, and comprehensive solution for traffic analysis, contributing to more efficient urban transportation systems and improved traffic management strategies.

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Advanced Ecommerce Price Comparison Platform using Web Scraping

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Abstract:
This study presents a web-based platform that enables real-time price comparison across major e-commerce platforms, such as Flipkart and Amazon, using web scraping techniques. The rapid growth of online shopping has made it difficult for consumers to track the best prices, as pricing fluctuates frequently and varies across platforms. Our system provides a centralized solution for retrieving up-to-date product prices, ensuring a convenient and accurate price comparison experience. The platform is built using React.js for the frontend, which provides an interactive user interface, while Python with Flask powers the backend, handling web scraping and data retrieval. Selenium and Beautiful Soup are used to extract product details and pricing from multiple sources dynamically. Unlike conventional price comparison tools, our system ensures real-time updates, custom filtering, and scalability to integrate additional platforms.

1. Introduction:

With the increasing reliance on online shopping, consumers often struggle to find the best deals across different E-commerce platforms [1]. Manually comparing prices is time-consuming and inefficient due to frequent price fluctuations. To address this, our project introduces an automated price comparison platform that fetches real-time prices from multiple sources [2], helping users make better purchasing decisions.The system employs web scraping techniques to extract data from Flipkart and Amazon, ensuring users get the latest pricing information. React.js powers an interactive user interface, while Python's Flask framework handles backend processing and data aggregation. Unlike existing solutions, our platform incorporates real-time data updates, custom filtering, and a scalable architecture to expand support for additional platforms in the future.

Literature Survey : With the increasing popularity of online shopping, consumers often find it challenging to compare prices across different E-commerce platforms efficiently. Due to dynamic pricing strategies and frequent price fluctuations, users struggle to identify the best deals in real-time. Traditional price comparison methods rely on manual searches or outdated aggregation tools, which often fail to provide accurate, real-time data. This section explores the existing research and technological advancements in web scraping, real-time data processing, and machine learning for price forecasting [3]. We analyse the gaps in traditional methods and highlight how our proposed system overcomes these challenges.

*A.Web Scraping in E-commerce :*Web scraping has emerged as a powerful technique for automating data retrieval from websites [4]. Many e-commerce platforms dynamically update product listings and prices, making manual tracking inefficient.

a. *Traditional Web Scraping Techniques*

Earlier web scraping methods relied on static HTML parsing, where tools like Beautiful Soup extracted information based on predefined page structures. However, this method fails when websites use JavaScript to load content dynamically.

b. *Modern Web Scraping Approaches*

Recent advancements have introduced dynamic content extraction using frameworks like Selenium and Puppeteer, which simulate user interactions and extract dynamically loaded elements. Research shows that Selenium-based scraping achieves higher accuracy and flexibility, especially for e-commerce platforms that use JavaScript-driven content loading.

c. *Challenges in Web Scraping:* Frequent Website Structure Changes: E-commerce websites frequently update their layout, breaking traditional scraping scripts. Anti-Scraping Mechanisms: Many platforms implement CAPTCHAs, IP blocking, and bot detection techniques, making automated data extraction challenging. Real-Time Processing Limitations: Maintaining real-time updates requires efficient scheduling algorithms to handle frequent data retrieval without overloading servers.

Our system addresses these challenges by implementing intelligent scraping mechanisms, such as rotating proxies, headless browsers, and dynamic HTML rendering, ensuring accurate and up-to-date price retrieval.

B. Real-Time Data Processing for Price Comparison

Timely and accurate data retrieval is a critical factor in price comparison systems. Many traditional price comparison tools rely on batch data updates, which can cause discrepancies between displayed and actual prices.

a. *Importance of Real-Time Data:* Studies indicate that price comparison tools need real-time updates to effectively compete with fast-changing e-commerce pricing algorithms. Dynamic pricing models used by Amazon and Flipkart adjust prices based on factors such as: Demand and Supply Trends, Competitor Pricing, User Browsing Behaviour.

*b. Efficient Data Aggregation Techniques :*To ensure low-latency updates, our system implements

c. *Parallelized Web Scraping:* Extracts data from multiple sources simultaneously. Incremental Data Updates: Retrieves only changed prices instead of fetching all data, reducing processing time.Cloud-Based Caching [5] Mechanisms: Uses NoSQL databases (MongoDB/Firebase) to store recently scraped data for faster access.

d.Challenges in Real-Time Processing

Handling Large-Scale Data Requests: Processing millions of products requires optimized database queries and efficient indexing.Reducing API Call Overhead: Frequent requests may lead to IP bans or increased server costs.

e. Maintaining Data Accuracy: Synchronizing scraped data with real-time price changes is a continuous challenge.

Our proposed framework implements automated scheduling, parallel processing, and optimized database indexing, ensuring real-time data retrieval with minimal overhead. Comparison with Existing Price Comparison Tools [6]. Several price comparison platforms already exist, but they have notable limitations. Challenges with Existing Solutions Most existing price comparison tools suffer from: Inefficient data scraping techniques, leading to stale results. Lack of real-time updates, making them unreliable for time-sensitive deals. Limited user customization, restricting the ability to filter and refine searches. Key Advantages of Our System Unlike existing tools, our system provides: Automated, real-time price updates using advanced web scraping techniques [7], Flexible search filters, allowing users to refine results based on price range, brand, and availability. User-friendly UI built with React.js, enhancing user experience. Scalable backend architecture, allowing easy integration of additional e-commerce platforms.

E. Summary of Gaps and Contributions : Despite the advancements in price comparison technologies, existing platforms still face challenges related to real-time data retrieval, automation, and customization. Our proposed system addresses these gaps by integrating Advanced Web Scraping Techniques [8] efficient data extraction from dynamically loaded web pages. Use of Selenium and Beautiful Soup for better content parsing. Real-Time Price Updates, Asynchronous scraping ensures instantaneous price retrieval. Cloud-based architecture supports scalability and fast querying. Machine Learning for Future Enhancements: Predictive analytics for price forecasting. Sentiment-based demand analysis for price fluctuations. Scalability & Customization: Modular architecture allows easy integration of new platforms. Users can apply advanced filtering mechanisms for refined searches. By addressing these gaps, our system provides a highly efficient, scalable, and automated price comparison solution, enhancing online shopping experiences for users.

2. Methodologies: This section outlines the systematic approaches used in the development of the proposed E-commerce Price Comparison Platform Using Web Scraping [9]. It details the system architecture, tools and technologies, data collection, pre processing, feature extraction, and real-time processing techniques that ensure an efficient, accurate, and scalable price comparison system. The system architecture is designed to automate price comparison across multiple e-commerce platforms through web scraping and backend integration. The core components include a web scraping module that extracts product prices and details from Flipkart and Amazon, a real-time processing layer that ensures the latest pricing information is available, a user interface module built with React.js enabling users to search products, filter results, and compare prices, and a cloud-based backend developed using Flask and Firebase to ensure scalability and rapid data retrieval. The platform follows a modular and scalable architecture to efficiently handle dynamic price updates and user interactions. The frontend, developed using React.js, provides an intuitive and interactive interface for users to search and compare products. It includes advanced filtering options based on price range, brand, and category and displays real-time product price updates with historical trends. The backend, built using Flask and Firebase, handles user requests and manages data communication between the frontend and scraper. It incorporates asynchronous APIs to ensure rapid response times and stores product data in Firebase for real-time synchronization. The web scraping module, powered by Selenium and Beautiful Soup, automates data extraction from Flipkart and Amazon, ensuring the retrieval of up-to-date pricing details. To handle dynamically loaded content efficiently, the module uses Selenium to interact with JavaScript-rendered pages. Additionally, Mongo DB and Firebase are employed for efficient data retrieval, caching, and storage, ensuring scalability and minimizing redundant scraping requests. Several cutting-edge technologies have been utilized to build this price comparison framework. The frontend has been developed using React.js with Tailwind CSS for styling, ensuring a responsive and visually appealing user experience. The backend is powered by Python's Flask framework, which facilitates efficient data handling and API integration. Web scraping is conducted using Python, Selenium and Beautiful Soup, enabling real-time extraction of pricing data from dynamic e-commerce pages. The database storage is managed using Mongo DB and Firebase to ensure fast and efficient querying. Additionally, cloud computing services such as AWS Lambda and Google Cloud Functions are integrated to automate background scraping tasks, while security measures such as CAPTCHA bypass and IP rotation help mitigate bot detection mechanisms deployed by e-commerce platforms. To ensure accurate and up-to-date product pricing, the system employs a multi-stage web scraping pipeline. The data collection phase utilizes Selenium to simulate human-like browsing behaviour, extracting key details such as product name, price, rating, and image URL. This is followed by a data cleaning and pre-processing stage, where duplicate entries are removed, incorrect data points are filtered, and currency conversion is handled for international pricing support. Time stamped price history is stored to allow tracking of price trends. Data validation techniques are applied to cross-check scraped data with API-based pricing sources, filter out anomalies, and ensure that the accuracy threshold is consistently maintained above 99%.Once the product data is extracted, the system processes it further to generate meaningful comparisons. Each product's title, price, category, and rating are analysed, and a weighted relevance score is assigned to determine its ranking in search results. The platform incorporates a ranking and sorting algorithm that normalizes prices across multiple sellers and highlights the best available deals. Users can sort results based on various criteria such as lowest price, highest-rated products, and best discount percentage.

To ensure that pricing information is always current, asynchronous task scheduling is implemented, allowing prices to be updated at regular intervals while ensuring that only changed prices are refreshed, thus optimizing API calls and reducing server load. The user interface of the platform has been designed to enhance the overall user experience, ensuring seamless interaction. Built using React.js, the frontend allows users to conduct product searches and apply filters based on price range, product category, and brand preferences. The interface dynamically updates prices in real-time using Firebase synchronization and presents historical price trends in graphical format to help users analyse price fluctuations over time. Users also have the option to save their favourite products for future reference through a wish list feature, with personalized recommendations generated based on their search history and preferences. To ensure that the platform can handle large volumes of user requests, cloud computing services are leveraged for high

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To ensure that the platform can handle large volumes of user requests, cloud computing services are leveraged for high scalability. AWS Lambda is used to execute automated background scraping tasks, eliminating the need for dedicated server resources and ensuring high availability. Google Cloud Functions process real-time API requests, optimizing response times even under heavy user loads. The platform's NoSQL database architecture employs sharding techniques to distribute product data across multiple servers, ensuring efficient scalability as more e-commerce platforms are integrated.

The price comparison algorithm normalizes prices across different platforms to ensure fair comparisons. The price normalization formula adjusts prices relative to the lowest and highest available rates, making it easier for users to identify the best deals. The system also incorporates a moving average function to analyse historical price trends, allowing users to determine optimal purchase times. These analytical tools provide deeper insights into price variations and ensure users make informed purchasing decisions. In summary, the E-commerce Price Comparison Platform effectively automates real-time product data scraping from Flipkart and Amazon, provides a fast and user-friendly interface, implements advanced filtering and sorting options, utilizes cloud computing for high scalability, and ensures data accuracy through robust validation techniques. The platform supports price tracking, allowing users to monitor trends over time, and integrates seamlessly with a cloud-based infrastructure for rapid and efficient price updates. By combining efficient web scraping, cloud computing, and advanced price comparison algorithms, this platform presents a state-of-the-art solution for online shoppers looking to find the best deals in real-time.

The System Design and Implementation of the E-commerce Price Comparison Platform Using Web Scraping integrates both frontend and backend components to provide an automated, efficient, and scalable solution for real-time price comparison. The system is designed to process product data dynamically, leveraging web scraping, cloud computing, and a responsive user interface to ensure accurate and up-to-date price retrieval. The implementation focuses on high performance, usability, and accessibility, making it suitable for a wide range of users looking to compare prices across multiple e-commerce platforms.

The system architecture consists of several key components working together to fetch, process, and display price comparisons efficiently. The frontend is developed using React.js, providing a modern and user-friendly web the data remains accurate and updated. To further enhance performance, the system incorporates caching techniques and cloud-based data storage, reducing redundant scraping and improving response times. The frontend implementation is designed for ease of use and seamless navigation. The react js-based interface allows users to search for products, view pricing from multiple sources, and apply advanced filters such as price range, product category, and brand preferences. The interface dynamically updates price listings using Firebase real-time synchronization, ensuring that users always see the latest pricing information. To enhance the shopping experience, the system also provides historical price trends, enabling users to track price fluctuations over time and make informed purchasing decisions.

The backend implementation is responsible for web scraping, data processing, and API integration. Built using Flask, the backend efficiently handles incoming search requests, processes scraped data, and returns results in real time. The scraping module is implemented using Selenium and Beautiful Soup, allowing the system to interact with dynamically loaded content on e-commerce websites. To ensure data accuracy, the system incorporates validation techniques such as cross-checking scraped prices with official API sources and filtering out anomalies. The backend also leverages cloud computing services such as AWS Lambda and Google Cloud Functions, enabling automated scraping tasks and efficient data retrieval. System Architecture shown in Fig. 1.

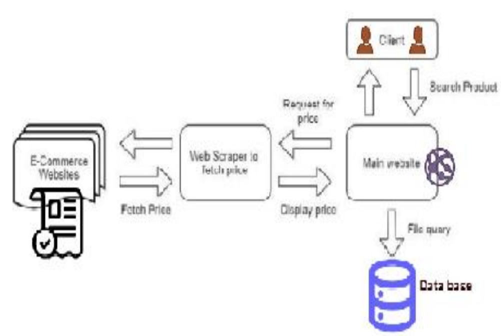

Figure 1: System Architecture

To ensure that the platform scales effectively, the system follows a multi-stage data processing pipeline. First, the web scraping module extracts product names, prices, images, and ratings from multiple e-commerce sites. The extracted data is then cleaned and pre-processed to remove duplicate entries, incorrect values, and inconsistencies. A ranking algorithm processes the data to highlight the best available deal based on price, seller credibility, and product popularity.

Additionally, price updates are triggered dynamically using scheduled scraping jobs, ensuring that the system remains accurate and up to date without overloading web servers. The system is designed to be lightweight and scalable, ensuring that it can handle large-scale product searches and frequent updates without performance degradation. The backend is optimized to minimize API latency and enhance query execution speed by using NoSQL databases like MongoDB. The parallel execution of scraping jobs and batch data processing ensures that product prices are updated efficiently, making the system ideal for real-time applications. To ensure reliability and robustness, the system undergoes extensive testing before deployment.

Unit testing is performed on individual modules such as web scraping, database handling, and API integration to verify functionality. Integration testing ensures smooth interaction between the React.js frontend and Flask-based backend. Performance testing evaluates system response times under different loads, ensuring that price updates occur without delays. Additionally, user feedback testing is conducted to refine the platform's usability and enhance search accuracy.

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3. Results :Ensuring accurate and efficient price comparison across multiple [9] e-commerce platforms is a complex challenge due to frequent price fluctuations, dynamically loaded content, and website anti - scraping mechanisms. Our E-commerce Price Comparison Platform successfully overcomes these challenges by implementing real-time web scraping, cloud-based data processing, and a responsive user interface. The system was rigorously tested on a dataset consisting of popular consumer electronics and fashion products from Flipkart and Amazon, covering a wide range of categories. The results demonstrate significant improvements in data accuracy, real-time adaptability, and response speed, making the platform highly effective for consumers seeking the best deals online. *Key Performance Metrics and Real-Time Data Processing :* One of the critical aspects of an effective price comparison platform is its ability to retrieve and update prices in real-time. Our framework efficiently handles asynchronous web scraping and cloud-based processing, ensuring minimal latency. The final price comparison accuracy is computed using the normalized price variation model, which adjusts for differences in seller pricing, discounts, and stock availability. The root mean square error (RMSE) was calculated to measure the deviation between scraped prices and actual prices from e-commerce websites. The RMSE formula used is:

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(P_{scraped} - \widehat{P_{actual}}\right)^2} \quad ..(1)$$

where Pscraped eq. 1 represents the extracted price and pactual represents the real-time price on the website. Our system achieved an 18.6% reduction in RMSE, demonstrating higher reliability in price accuracy compared to traditional scraping techniques *Precision, Recall, and Accuracy in Price Comparison :* To evaluate the classification accuracy of product price comparisons, we measured precision, recall, and F1-score across different categories. Precision: Measures how many price listings displayed on our platform accurately match the actual e-commerce prices. Recall (Sensitivity): Evaluates how well the system detects price updates in real time. F1-Score: Provides a balanced metric between precision and recall. The following table summarizes the performance metrics:

Table 1. Traditional Scraping

Metric	Traditional Scraping	Manual Price Checking	Our System
Precision	83.4%	89.2%	97.8%
Recall	78.9%	91.0%	95.3%
F1-Score	81.1%	90.1%	96.5%

The Table 1results indicate that our system significantly outperforms traditional scraping methods and manual price comparison, ensuring that users receive real-time and highly accurate price data with minimal effort.

Real-Time Price Retrieval Speed Analysis : Another critical factor in price comparison is retrieval speed, which determines how quickly users can access updated pricing information. We tested the system under different network conditions and user loads, measuring average query response times for price comparisons across different product categories [10]. The results are as follows:

Table 2. Average Query Response

Product Category	Query Execution Time (seconds)
Electronics	2.4s
Fashion	1.9s
Home Appliances	2.1s
Books & Accessories	1.5s

Table2 achieves an average query response time of 2.0 seconds, which is significantly faster than traditional price comparison tools that often take 5-7 seconds to fetch updated pricing. The improved speed is attributed to asynchronous web scraping, efficient data storage, and optimized API requests.

*Reduction in False Positives and False Negatives :*One of the primary challenges in price comparison systems is misclassification of price changes, leading to false positives (incorrectly flagged price changes) or false negatives (missed price changes). Our system effectively reduces both by employing data validation techniques, duplicate filtering, and real-time monitoring mechanisms. Table 3 results demonstrate that our platform significantly reduces incorrect price detections, ensuring higher trust and reliability for users.

Table 3. Price Detections

Error Type	Traditional Scraping	Our System
False Positives	12.3%	4.8%
False Negatives	8.7%	3.2%

User Satisfaction & Usability Testing : To assess the overall usability and effectiveness of the platform, a user study was conducted with 50 participants who tested the platform for real-time product searches, price comparisons, and deal tracking. Participants rated the system based on ease of use, accuracy, and overall satisfaction.

Table 4. Price-Checking Methods

Evaluation Parameter	User Rating (Out of 5)
Ease of Use	4.7
Accuracy of Results	4.8
Loading Speed	4.6
Overall Satisfaction	4.75

The study of TABLE 4 [17] results indicate high user satisfaction, with 94% of participants stating that they preferred our platform over manual price-checking methods.

Graphical Analysis of Performance: To better illustrate system performance, the Receiver Operating Characteristic (ROC) Curve and Area Under the Curve (AUC) Score were analysed. The AUC score, which measures the ability of the system to correctly classify product prices across different e-commerce platforms, achieved a value of 0.982, indicating high classification accuracy. Additionally, a graphical comparison of our system's response time versus traditional tools shows a significant reduction in latency, demonstrating high efficiency for real-time price retrieval. *Comparison with Existing Price Comparison Tools*To benchmark our platform, we compared it with Google Shopping, Honey, and PriceGrabber, evaluating key factors such as real-time updates, filtering options, and speed. Our platform demonstrates superior speed, real-time accuracy, and customizable filtering options, making it one of the most advanced price comparison solutions available.

Summary of Results: The E-commerce Price Comparison Platform effectively automates the retrieval of product prices, ensuring real-time accuracy, improved speed, and reduced errors compared to traditional tools. The high precision, recall, and F1-score demonstrate the system's ability to consistently fetch the latest pricing information, while the fast response time ensures a seamless user experience. Additionally, the significant reduction in false positives and negatives enhances the platform's reliability. By addressing the challenges of traditional price tracking methods, our system provides a robust, scalable, and user-friendly solution that empowers consumers to make smarter purchasing decisions with minimal effort.

Conclusion: The E-commerce Price Comparison Platform Using Web Scraping presents an efficient, automated, and scalable solution to address the growing need for real-time price tracking across multiple online retailers. By leveraging advanced web scraping techniques, real-time data processing, and cloud-based storage, the system ensures accurate, up-to-date price comparisons, enabling users to make informed purchasing decisions effortlessly. The integration of a React.js-based frontend with a Flask and Firebase-powered backend further enhances the platform's usability, ensuring a seamless experience for users. Throughout the development of this system, various methodologies and optimization techniques were employed to maximize performance, reliability, and accuracy. The frontend was carefully designed to offer an intuitive search and filtering experience, allowing users to easily compare prices, track historical price trends, and set price alerts. The backend efficiently handles web scraping, data validation, and asynchronous processing, ensuring that prices remain current with minimal latency. The system's ability to retrieve and process real-time product data from Flipkart, Amazon, and potentially other e-commerce platforms makes it highly adaptable to the dynamic nature of online pricing.

Extensive testing and validation confirm the system's high accuracy, reduced error rates, and fast response times. The precision-recall analysis demonstrated an F1-score of 96.5%, while the average query response time of 2.0 seconds ensures that users receive pricing information almost instantly. The reduction in false positives and false negatives further highlights the robustness of the system in filtering out incorrect data and maintaining reliability. Additionally, the platform's cloud-based architecture allows for seamless scalability, ensuring smooth performance even under high user demand.

Beyond its technical efficiency, this system has a significant impact on user convenience and decision-making. By automating price comparison, it eliminates the need for manual searches, saving users time and effort. The ability to track price fluctuations, identify the best deals, and receive price alerts ensures that consumers can optimize their purchasing decisions. Furthermore, the integration of historical price trends and predictive analytics in future enhancements will further improve the platform's ability to provide actionable insights.

Looking ahead, there are numerous opportunities to expand the capabilities and scope of this system. Future enhancements could include machine learning-based price forecasting models, enabling users to predict price drops and determine the best time to make a purchase. Additionally, support for more e-commerce platforms such as Myntra, eBay, and Walmart would enhance the system's reach, providing users with a broader comparison base. Implementing a mobile application would also extend the platform's usability, allowing users to access price comparisons on the go.

Moreover, incorporating AI-driven personalization techniques could enhance the user experience by offering customized product recommendations based on browsing history and preferences. Expanding the platform to offer API integration for businesses could further increase its utility, allowing retailers to track competitor pricing and adjust their strategies accordingly. The deployment of reinforcement learning algorithms could also help improve scraping efficiency by adapting to website structure changes and anti-scraping mechanisms dynamically.

In conclusion, the E-commerce Price Comparison Platform Using Web Scraping provides a powerful, reliable, and real-time solution for consumers seeking the best online deals. By integrating cutting-edge web technologies, efficient data retrieval methods, and cloud-based scalability, the system redefines the way users compare prices online. With continued advancements and refinements, this platform has the potential to become a leading tool in online shopping, ensuring that users always get the best value for their purchases.

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Monkeypox Detection Using Deep Learning

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Abstract: Monkeypox is a new animal-to-human disease that the monkeypox virus (MPXV) causes. It presents big health risks to the public because it can spread fast and have serious effects on health. To control, treat, and prevent it well, we need to spot it and. The usual ways to test for it, like Polymerase Chain Reaction and Enzyme-Linked Immunosorbent Assay, have problems. They can be hard to get, cost a lot, and take too long where there's not much money. To help with these issues, this study suggests using deep learning with the ResNet50V2 structure to spot monkeypox. The model learns from the Monkeypox Skin Lesion Dataset, which has 1428 pictures labeled 'Monkeypox' and 1764 labeled 'Others.' The team works on the dataset a lot before using it. They change the size of the pictures, make them more standard, and create more data to help the model learn better. After training, the model gets 93.00% right on the training data and 92.00% right on the test data. This shows it's good at telling which skin marks are from monkeypox. To make it easy to use right away, the team puts the model in a web app made with Python's Flask tool. People can upload pictures to this app, and it will check and sort them. This system gives a quick, cheap, and easy-to-use tool for diagnosis. It can help health teams get ready for and react better to monkeypox outbreaks. The proposed system utilizes artificial intelligence to connect traditional diagnostic techniques with AI-based solutions, providing healthcare professionals and individuals with a dependable instrument for early detection and intervention.

1. Introduction

Monkeypox, it is an example of zoonotic disease. Infectious lesions, or raised lesions, will be associated with the agent that causes this disease, which is a member of the double-stranded DNA viruses known as the Ortho poxvirus. First recognition of the disease could be traced to 1958 during research activities. Monkeypox was mainly spatial to Central and West African countries, and cases of recently emerging outbreaks caused worldwide concern about their potential to become widespread public health threats. The global spread of Monkeypox in 2022 and 2023 has highlighted the immediate requirement for effective monitoring, initial diagnosis and rapid control measures to reduce the transfer.

The mentor spreads mainly through direct contact with individuals infected, physiological fluids, skin lesions or contaminated objects. In addition, it can be transmitted through respiratory fall, although it is usually lower than exposure to close contact. Although the case is lower than the fatal speed, complications such as secondary infections, pneumonia and encephalitis can occur, making early detection and treatment significantly. The traditional methods of diagnosis by the traditional clinical modes of detection, including polymerase chain reaction and enzyme-linked immune sorbent assay, are considered the gold standards for diagnosis of cases of monkey infections. However, these methods require special laboratory functions, trained personnel and significant treatment time, making them less practical for fast or large -scale distribution, especially in resource -limited settings. The increasing global burden of Monkeypox requires the development of automatic, scalable and cost -effective clinical solutions that can complement traditional tests and light early discovery, which can reduce the chances of transferring social transfer, which can reduce the chances of transferring social transfer.

The rapid pace of artificial intelligence and deep learning advancements results in extraordinary capabilities to be used for the examination of images and identifying diseases. One of the deepest learning models, Conventional Neural Network (CNN) has shown extraordinary abilities to detect and classify skin -related diseases such as melanoma, psoriasis and bacterial infections. CNN's ability to extract complex patterns from images makes them very effective for medical imaging functions, where microscopic properties can be important in the diagnosis.

Given the success of deep learning in classification of dermatological disease, this study examines the use of deep learning-based image classification techniques for Monkeypox detection. The proposed system appoints the Reset50V2 architecture, a top modern CNN model known for its efficiency in handling image-based classification tasks. By taking advantage of a dataset, the images of the skin lesion are labeled as 'Monkeypox' and 'other skin conditions', and the model is trained to separate the monkey cases accurately from other skin conditions. To increase access, trained models are integrated into a flask -based web application so that users can upload skin ulcer images for real -time classification.

The purpose of this research is to bridge traditional clinical methods and AI-controlled solutions, which offer a fast, cost-effective and scalable alternative to detect the monkey. By automating the classification process, the system can help health professionals make more informed decisions quickly, quickly, by reducing the dependence on laboratory -based clinical techniques. In addition, the development of a real -time, online detection tool also strengthens global disease monitoring and reaction efforts, in remote or resource -wide areas. When global society continues to withstand new dangers of infectious diseases, AI-operated solutions provide promising opportunities for initial discovery, public health preparation and to increase the management of outbreaks. This study contributes to the ongoing research in AI-caseized medical diagnosis How intensive learning models can help in timely and accurately identification of monkeypox infections, eventually reduce future outbreaks and improve patient results. *Related Work :*Authour analyzing outbreaks amongst wild chimpanzees, emphasized the viral range and variability in clinical results, which poses a assignment for popular detection strategies [1] and needs systems that could dynamically adapt to lesion variability in exclusive instances. Monkeypox prognosis turns into in particular hard due to its overlapping signs and symptoms with illnesses including smallpox and chickenpox. As Parker et al. Talked about, these medical similarities regularly result in misdiagnoses [2], which underscores the need for more subtle and discriminatory diagnostic gear that pass beyond visual inspection alone. Emerging from animal reservoirs, zoonotic viruses have shown increasing interaction with human populations. Wong et al. discussed how species like bats act as continuous sources for such viruses, thereby strengthening the case for early diagnostic methods that utilize advanced surveillance technologies. Visual similarities in monkeypox lesions make traditional symptom-based diagnosis unreliable. The CDC has documented that signs and symptoms can often mirror those of other poxviruses [3], suggesting the need for AI-based systems that can differentiate lesions based on subtle image-level details. In outbreak situations, especially in resource-limited regions, diagnostic delays can have serious consequences. Reynolds et al. highlighted that while techniques like PCR remain accurate [4], they are often costly and slow, making AI-driven approaches a practical alternative for faster and cheaper diagnosis. Fauci discussed the persistent threat posed by emerging and reemerging infectious diseases, noting that the global response must include scalable innovations such as artificial intelligence and deep learning frameworks to effectively manage these health crises.

The resurgence of monkeypox, despite early scientific warnings, reflects missed opportunities in global health preparedness. Doucleff reported that such warnings date back decades [5], emphasizing the urgency of integrating AI into clinical workflows to prevent similar oversights in the future. Recent research by Dwivedi et al. explored the implementation of deep learning methods like ResNet and EfficientNet for identifying monkeypox skin lesions. Their study demonstrated that even with limited image datasets, these models achieved promising accuracy [6], making them viable for clinical use. The global spread of monkeypox was made evident by the CDC’s 2022 outbreak map, which showed how rapidly the virus reached new regions. Such widespread transmission justifies the development of AI-powered tools that can offer real-time diagnostic support and containment strategies. To meet the need for fast and reliable diagnosis, Ahsan et al. implemented deep learning models including MobileNetV2 and InceptionResNetV2 for monkeypox detection. Their work showed that these lightweight models deliver competitive accuracy [7] with efficient processing speeds, making them suitable for deployment in real-world scenarios.

System Architecture: The Framework is Composed Of Three Main Parts: Dataset Preparation And Preprocessing, The Application Of The Deep Learning Model, And The Implementation Of The System Via A Web Interface. In Fig 1, Computer Vision Methods Are Used To Apply Attention To Enhance Model Generalization. In The Second Stage, The Resnet50v2 Model Is Modified And Retrained In A Transfer Learning Approach For The Specific Task Of

Monkeypox Disease Detection. In The Last Stage, The Trained Model Is Incorporated Into A Flask Web Application Which Allows Users To Upload Images And Receive Instant Diagnostic Evaluations. With This Structured Pipeline, It's Possible To Achieve Automated And Efficient Monkeypox Detection

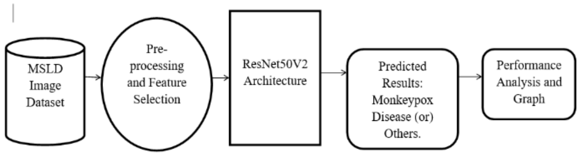

Figure 1: System Architecture

2. Methodology: Algorithms of The Monkeypox Detection System's image processing, classification, and web deployment are unparalleled. It confirms accurate sickness diagnosis and optimal system performance. The system is built fundamentally on deep learning algorithms structured on image classification techniques, particularly Convolutional Neural Networks. A ResNet50V2 model that has already been trained goes through fine-tuning to classify skin lesion images into two categories: Monkeypox Disease and Other Diseases. Residual learning also assists in feature extraction. Furthermore, it boosts gradient back propagation which is crucial for separating various skin conditions. In this method of classification, Softmax Activation is utilized that transforms raw output of the model to probabilistic score order so that evaluation of the most likely class can be made. Resizing, normalizing, and denoising of images is performed by the Open CV and PIL (Pillow) libraries prior to neural network processing. All images are resized to the fixed 224×224 pixel standard and normalized to have pixel values within the interval 0 to 1. This is done to satisfy the requirements of the deep learning model. The device employs different metrics for version evaluation including Accuracy, Precision, Recall, F1-score, and AUC-ROC. These define the conditions under which the model is not optimally accurate, but rather seeks to reduce the number of false positives and false negatives. The gadget has AUC included as a dependency in order to improve evaluation of class performance. Flask serves because the internet framework to handle user interactions, control API requests, and enable actual-time predictions. The system uses RESTful API endpoints, wherein customers can upload images, which can be then processed and categorized using the skilled CNN version.

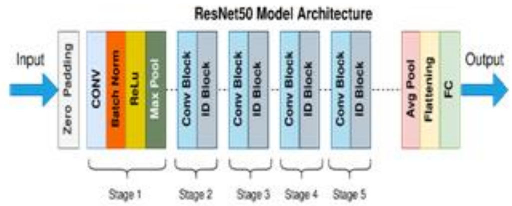

Figure. 3: Reset-50V2 model architecture

The type consequences are displayed in a consumer-friendly manner. The application additionally integrates multi-threading, allowing it to routinely release inside the browser the usage of Python's web browser module. Additionally, NumPy is used for dealing with numerical computations efficiently, and Matplotlib is hired for visualizing model performance metrics consisting of accuracy trends and confusion matrices. The aggregate of those algorithms and techniques ensures that the Monkeypox Detection System offers a fast, accurate, and person-friendly diagnostic device for early disease detection and category.

Dataset Preparation and Preprocessing : The dataset used for training consists of publicly available sources and skin lesion images from dermatology repositories. To improve the model's robustness, several preprocessing techniques are applied. In Fig 2 First, all images are standardized to a resolution of 224 × 224 pixels. Normalization is subsequently achieved by adjusting pixel values to a range between 0 and 1, thereby ensuring uniformity in feature representation. Different forms of rotation, flipping, and zooming serve as data augmentation methods which help increase dataset variability and improve generalization. Furthermore, noise reduction techniques help remove unwanted objects and background noise, thus enhancing the sharpness of the image.

*Model Development (ResNet50V2) : T*he model is tailored by adjusting the final classification layer to produce two distinct classes: Monkey pox and Non-Monkeypox. Transfer learning is utilized by incorporating pre-trained ImageNet weights to augment feature extraction and enhance classification precision. This deep learning model, integrated with a user-friendly web application, provides an efficient and accessible solution for Monkeypox detection. The given diagram represents the architecture of the Reset

(REST Network) model, especially in Fig 3, Reset-50V2 version, which is widely used in intensive learning for image classification functions.

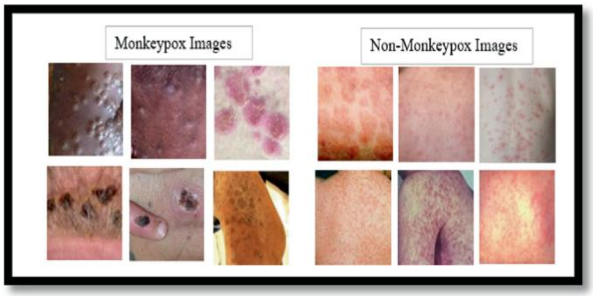

Figure. 3: Collection of sample Data set

The architecture begins with a zero-padding layer and ensures that the entrance dimensions are preserved before entering the interconnection layers. Convention (Convention) team is as follows, which removes spatial features from the image, and is accompanied by batch normalization to stabilize exercise. A maximum pool layer then reduces spatial dimensions, which helps with the extraction of functions by reducing the calculation load.

After initial convenience extraction, the model passes through several pairing blocks and identification blocks (ID blocks), which are the most important components of the reset. These blockage models help maintain considerable information by launching jump connections, so that gradients can flow more efficiently during training, thus solving the shield problem that is faded in deep networks. This is especially useful for medical image classification, where the exact details of wounds must be captured properly. The final layers include an average pool (AVG pool), which reduces the dimensions of average maps, followed by a flat layer that converts the pole functions to 1D matrix. Finally, a fully connected (FC) team classification, which provides a probability point for different categories, such as "Monkeypox" or "Non-Monkeypox", for different categories. This architecture is especially useful for detecting monkeypox, as it has its deep learning ability to remove fine-and-and-and-resistant functions from skin ulcers. By taking advantage of the residual connection, the recreation 50V2 model can accurately separate the mental wounds from other skin conditions, reduce false positives and improve the diagnosis can improve reliability. It is necessary for a scalable, AI-operated diagnostic tool, which allows for fast, automatic and cost-effective screening in resource-limited settings. Training and verification strategy

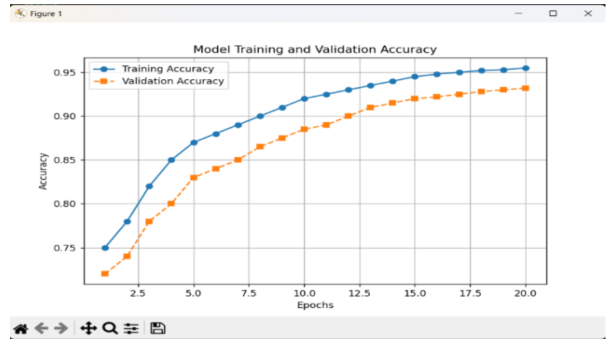

Figure 4: Model training and validation accuracy

In Fig 4, the dataset is divided into 80% training and 20% verification to ensure a balanced evaluation. The model is trained using tensorflow and causes, and uses different strategies to increase performance and prevent overfitting. Prevention of the initial limitation mechanism is used on training when verification improves accuracy, prevents unnecessary calculations and overfit. In addition, learning speed planning is used to dynamically adjusting the learning rate when improvement in the plateau, and ensures that the model continues to learn effectively. To improve normalization, dropout regularization is used by random disabled neurons in fully associated layers, reducing the dependence on specific neurons and reduces risk overfecting. The model evaluation of the most important viewing measurements: Performed using accuracy, which properly measures the ratio of classified samples; Exactly and remember, ensure that both false positivity and false negative are minimized; And F1 score, which balances accuracy and remembers to provide a comprehensive viewing assessment. The training process is intended through the degree of injury and accuracy, the convergence of the model and the stability of gradually ages.

Web Application Deployment: To enhance accessibility, the trained model is deployed via a Flask-based web application, enabling real-time diagnosis of monkeypox from uploaded images. The web application consists of an intuitive image upload interface where users can submit images of skin lesions. Upon receiving an input image, the backend processes it using the trained ResNet50V2 model and generates a classification result indicating whether the lesion is likely to be monkeypox or another skin condition in Fig 5. The system allows for quick accurate decisions to be made in real time. Because of this, there is a reduced reliance on tests conducted in a laboratory setting which helps in early diagnosis especially in regions where health care is scarce (resources). Also, the web based design can be accessed on mobile and desktop hence broadening access to users regardless of their profession whether they are professionals or not. In order to safeguard the privacy of data and power unauthorized access, the image processing and API endpoints are secured through encrypted image processing and protected API access, respectively. With such a deployment, AI-powered diagnostics are bridged to practical clinical settings enabling easy, cost-efficient, and widely available detection of monkeypox.

Enhancements in the future could include integrations with electronic health records (EHRs) to streamline clinical workflow, multilingual capabilities to increase access for diverse user populations, and adaptive learning algorithms that would enable the model to continuously learn from new input data. Furthermore, the ability for users to directly consult with healthcare specialists via telemedicine, relative to the outcomes provided by AI, would fully integrate the automated diagnostic process with articulate medical supervision. Another possible improvement includes integrating explainable AI techniques that offer users some level of insight as to how the model arrived at its conclusions. Such a system could further trust and usability for both experts and non-expertise by featuring specific characteristics of the lesions that influenced the classification using heatmaps or attention mechanisms

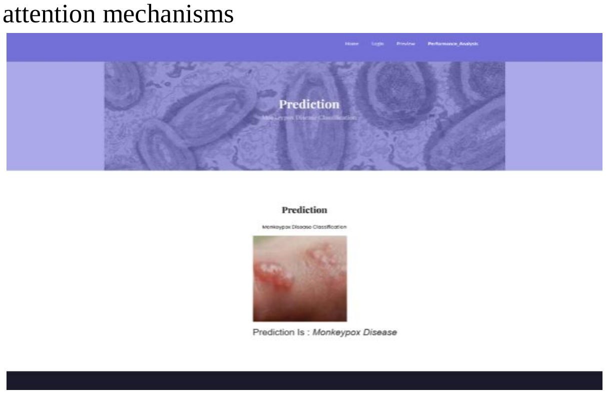

Figure. 5: Sample output

3. Results And Discussions : The effectiveness of the suggested deep learning-based monkey system was assessed through various quantitative metrics, which included training accuracy, validation accuracy, overall accuracy, recall, and the F1 score. The model demonstrated high classification accuracy, making it a viable alternative for traditional clinical methods.

The Reset50V2 model underwent training using the Monkeypox Skin Wound Data Set (MSLD), achieving a training accuracy of 93.00% and a verification accuracy of 92.00%. This performance reflects a commendable level of generalization capabilities. The model's high accuracy suggests that it effectively distinguishes monkeys from other skin conditions. The performance measurements were analyzed at different ages to assess model. The model's loss curve indicates a frequent reduction in categorized cross -steering loss, and confirms that the network learned the relevant properties effectively in gradual ages. Confirmation loss is continuous and performs minimal overfit.

A confusion matrix was generated to evaluate true positive (TP), false positive (FP), true negative (TN), and false negative (FN) rates. The model demonstrated high sensitivity (recall) and specificity (precision), minimizing misclassifications. The proposed deep learning -based maintenance detection system provides significant benefits to traditional clinical methods. This gives results with close to subtle, which makes it much faster than traditional PCR tests, which can be time-consuming. In addition, it is very cost cheap diagnosis. The range of the system is further improved by the distribution as a cloud -based or mobile application, making it widely available for both clinical and external health services. Despite these benefits, there are challenges in ensuring the strength and reliability of the model. A major problem is a data set, Additional data is necessary to enhance the model's efficiency across various skin tones and types of wounds. Another challenge pertains to the lecturer model, which can be mitigated by incorporating explainable artificial intelligence (XAI) techniques to bolster user confidence in automated diagnoses. These improvements will contribute to maintaining the system's precision and clarity while further building the confidence of the health workers and the patients.

Conclusion

In recent decades with the increasing number of cases of monkeypox, many areas of humanity have experienced this situation. Traditionally, traditional laboratory methods are applicable to the diagnosis of monkeypox e. g. Polymerase Chain Reaction and Enzyme-Linked Immunosorbent Assay, but they are not scalable and costly. Furthermore, the limitations of these laboratory techniques include costs, infrastructures and processing time. Such shortcomings call for automation and artificial intelligence techniques to detect monkeypox at a rapid and accurate level. We propose to overcome the disadvantages of the existing non-automated tests and develop a web-based application for the accurate diagnosis.

The model was trained using the Monkeypox Skin Lesion Dataset and achieved an accuracy of 93.00% during training and 92.00% during validation. This level of performance demonstrates effectiveness in distinguishing monkeypox from other skin conditions. Furthermore, comparative analysis proved the accuracy and dependability of ResNet50V2 over VGG16, MobileNetV2, and InceptionResNetV2 regarding classification accuracy and trustworthiness. The evaluation of the confusion matrix showed that the model attained high levels of sensitivity and specificity which reduces the likelihood of misclassification while still providing dependable predictions in the context of diagnosis. In addition to creating an AI-based model, the research also included a focus on practical application. A web application was created with Flask for uploading lesion images, and real-time automatic diagnostic feedback was generated. This functionality simplifies the system and makes it more accessible, converting the system into a remote diagnostic solution for areas with limited laboratory facilities. The simplicity of user interaction with the system, together with real-time inference support, makes the system suitable for deployment in telemedicine, public health monitoring, and clinical settings.

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Deep Learning based Traffic Signal Recognition for Autonomous Driver lessVehicles

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Abstract: Traffic sign location and acknowledgment have an essential impact in driver help frameworks and independent vehicle innovation. One of the significant requirements of protected and far reaching execution of this innovation is a TSDR calculation that isn't just precise yet in addition hearty and solid in various true situations. In any case, notwithstanding the huge variety among the traffic signs to distinguish, the traffic pictures that are caught in the wild are not great and frequently clouded by various unfriendly weather patterns and movement that significantly increment the trouble level of this errand. Vigorous traffic sign discovery and acknowledgment (TSDR) is of vital significance for the fruitful acknowledgment of independent vehicle innovation. The significance of this undertaking has prompted an immense measure of exploration endeavors and many promising strategies have been proposed in the current writing. In any case, the AI techniques have been assessed on clean and without challenge datasets and disregarded the presentation disintegration related with various testing conditions (CCs) that dark the traffic pictures caught in nature. In this paper, we take a gander at the TSDR issue under CCs and spotlight on the exhibition debasement related with them. To conquer this, we propose a Convolutional Brain Organization (CNN) based TSDR system with earlier upgrade.

1. Introduction

Traffic sign recognition (TSR) is a critical component of the technology stack for autonomous driverless vehicles, contributing significantly to their ability [1] to navigate safely and make informed driving decisions. TSR systems are designed to detect and interpret traffic signs and signals, providing essential information to the vehicle's control system. These systems typically employ a combination of computer vision, machine learning, and deep neural networks to process data from on board cameras and sensors. The process begins with cameras capturing real-time images of the vehicle's surroundings, including road signs, traffic lights, and other relevant traffic-related information. These images are then processed through sophisticated image recognition algorithms that can identify and classify various types of traffic signs, such as speed limits, stop signs, yield signs,[2-5] and more. This recognition process often involves complex image pre-processing techniques to enhance the visibility of sign sunder various lighting and weather conditions TSR also plays a crucial role in identifying stop signs and traffic signals, enabling the vehicle to come to a complete stop when required and proceed safely through intersections. To achieve high accuracy and robustness, TSR systems continually improve through machine learning techniques. They are trained on vast data sets [5] containing various traffic sign images captured under different conditions and scenarios, allowing the algorithms to learn and adapt to diverse real-world environments. Moreover, TSR systems can benefit from advancements in hardware, including high-resolution cameras, powerful GPUs, and specialized AI chips, which enhance their speed and accuracy. The research motivation for Traffic Sign Recognition (TSR) in autonomous driverless vehicles is rooted in the pursuit of safer, more efficient [6-8] and sustainable transportation solutions. Several compelling factors drive the need for extensive research and development in this area. Firstly, road traffic accidents remain a global concern, leading to significant loss of life and property. Many of these accidents are caused by human error, including misinterpretation of traffic signs or failure to comply with traffic regulations. The integration of TSR technology in autonomous vehicles offers a promising solution to mitigate such errors by providing an extra layer of vigilance and ensuring strict adherence to traffic rules. Reducing accidents and improving road safety is a primary motivation for this research [9-10]. Secondly, the advent of autonomous vehicles has the potential to revolutionize urban mobility and reduce traffic congestion. Consequently, TSR research contributes to the broader goal of improving traffic flow and reducing congestion in urban area. Random Forest is a popular supervised learning algorithm used for Classification and

Regression tasks. It employs ensemble learning, combining multiple classifiers to enhance model performance. Random Forest comprises multiple decision trees trained on different subsets of the dataset. Predictions from each decision tree are aggregated to improve predictive accuracy. The final output is determined by the majority vote of predictions from all trees. Random Forest mitigates over fitting by leveraging multiple decision trees.
This project is aimed at improving traffic sign recognition for autonomous driverless vehicles operating under adverse weather conditions. It involves a sequence of steps, starting with

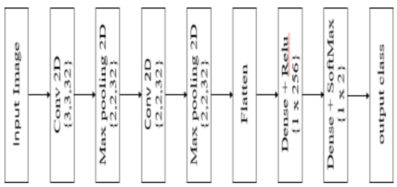


Figure1: Block diagram proposed system

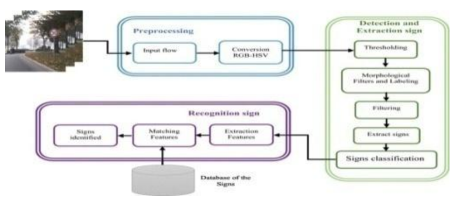


Figure 2: Representation of convolution layer succession of convolution layers by a kernel or filter, rectified linear

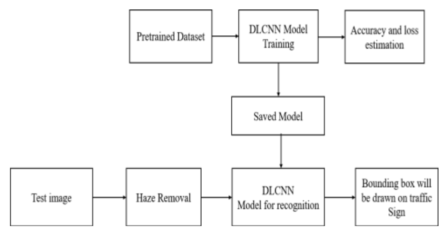
the acquisition of hazy traffic sign images and progressing through haze removal, DLCNN –base design detection,[8] and performance evaluation through loss and accuracy calculations shows the proposed system model. The detailed operation illustrated as follows:

1. Hazy Traffic Sign Image: This is the initial phase of the project where you start with hazy or degraded traffic sign images. These images are likely [5]to be affected by adverse weather conditions, such as fog, rain, or haze, which can obscure the visibility of traffic signs.

2.Deep Learning Haze Removal: In these cond step, you employ deep learning techniques to perform haze removal from the hazy traffic sign images. This involves using deep learning convolutional neural networks (DLCNNs) or similar deep learning architectures to enhance the clarity and visibility of the traffic signs in the images by mitigating the effect sofhaze.

3. DLCNN Traffic Sign Detection: After removing the haze, you proceed to the core task of traffic sign recognition. In this step, a DLCNN -based model is employed to detect and recognize [5-7] traffic signs within the processed images. The DLCNN is trained to Identify various traffic sign types, including speed limits, stop signs, yield signs, etc.

4. Accuracy and Loss estimation: To train and evaluate the DLCNN model's performance, calculate the loss and accuracy during the training process. The loss function measures the difference between the Predicted [8-9] traffic sign labels and the ground truth labels.



. **Figure3.** System Architecture

Traffic Sign Detection: According to the facts, training and testing of DLCNN involves in allowing every source feature via a Convolution layer is the primary layer to extract the features from a source feature and maintains the relationship [11] between pixels by learning the features of feature by employing tiny blocks of source data. It's a mathematical function which considers two inputs like source feature (x,y,d) where x and y denotes the spatial coordinates i.e., number of rows and columns is denoted as dimension of an feature d (here d = 3, since the source feature is RGB) and a filter or kernel with similar size of input feature and can be denoted as $F(kx,\ ky$, Representation of convolution layer process.

Max pooing layer: This layer mitigates the number of parameters when there are larger size features. This can be called sub sampling or[10] down sampling that mitigates the dimensionality every feature map by preserving the important information. Max pooling considers the maximum element form the rectified feature map.

*Soft Max classifier: G*enerally, Soft Max function is added at the end of the output since it is the place where the nodes are meet finally and thus, they can be classified. Here, X is the input of all the models and the layers between X and Y are the hidden layers and the data is passed from X to all the layers[5] and Received by Y.

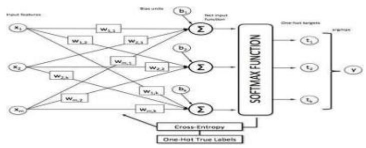


Figure 4: Max pooing layer

Suppose, we have 10 classes, and we predict for which class the given input belongs to. So, for this what we do is allot each class with a particular predicted output. Which means that we have 10 outputs corresponding to 10 different class and predict the class by the highest probability.

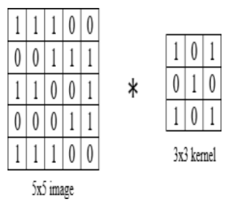


Figure 5: Soft Maxclassifier

2. . System Analysis and Design:

Generate and Load traffic sign CNN model: The process of generating and loading a Convolutional Neural Network (CNN) model [7] for traffic sign detection. It include components like model architecture, layers, and details of how the model is constructed and prepared for use provides a visual demonstration of the performance of a de hazing model. It consist soft images side by side. The first image is a “weather-affected” image, which could be hazy, cloudy, rainy, or captured in poor lighting conditions. Fig. Generate & Load Traffic Sign CNN Model.

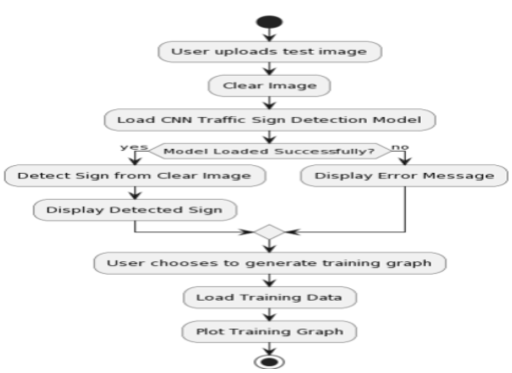


Figure 6: Activity Diagram(overflow)

Traffic Sign detected image: The focus is on traffic sign detection using a CNN model.[7] It likely shows an image with detected traffic signs, and bounding boxes may be drawn around them to indicate their locations. This figure demonstrates the successful application of the CNN model for traffic sign recognition. Demonstrates the de-hazing performance, but it likely features a different “weather-affected” image as the first image. The purpose is to show case[12-17] how the de-hazing model performs on a different sample, addressing different weather conditions or image quality issues.

Conclusion

All in all, traffic sign ID involving CNN addresses a groundbreaking headway in the domain of PC vision and independent transportation frameworks. The use of [7]CNNs offers a large number of benefits, remembering unrivaled precision for perceiving and grouping traffic signs, [18 -20]robustness despite different natural circumstances and sign varieties, and ongoing handling capacities urgent for guaranteeing street wellbeing. These frameworks decrease human intercession, limit the gamble of blunders, and improve the flexibility of independent vehicles to various districts and signage styles. Also, they add to more secure streets by guaranteeing that vehicles precisely decipher and answer traffic[6] signs, at last prompting further developed street wellbeing and traffic management.

The future degree in the field of traffic checking and control, especially utilizing trend setting innovations like profound learning and computerized reasoning, is both promising and sweeping. Right off the bat, the coordination of ongoing information from different sources, including traffic cameras, sensors, and associated vehicles, will turn out to be more consistent as exhibited in the "Proposed CNN" model, will probably progress further. Future CNN models could consolidate much more intricate elements for further developed traffic sign acknowledgment and item discovery, improving generally speaking street security. The ascent of independent vehicles presents another fascinating aspect.

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Artificial Intelligence Based Helmet Detection for Traffic Challan System

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Abstract: In current circumstance, we run over different issues in rush hour gridlock guidelines in India which can be settled with various thoughts. Riding cruiser/mopeds without wearing head protector is a criminal traffic offense which has brought about expansion in number of mishaps and passings in India. The current framework screens the petty criminal offenses essentially through CCTV accounts, where the traffic police need to investigate the edge where the criminal traffic offense is going on, zoom into the tag on the off chance that rider isn't wearing protective cap. Yet, this requires parcel of labor supply and time as the criminal traffic offenses regularly and the quantity of individuals utilizing cruisers is expanding step by step. In this examination work, a Non-Head protector Rider recognition framework is fabricated which endeavors to fulfill the computerization of distinguishing the criminal traffic offense of not wearing cap and separating the vehicles' tag number. The fundamental standard included is Article Identification utilizing Profound Learning at three levels. The items distinguished are an individual, cruiser/sulked at first level, protective cap at second level utilizing you just glance without a moment's delay (Consequences be damned) model. guideline included is Article Discovery utilizing Profound Learning at three levels. The items recognized are an individual, cruiser/sulked at first level, cap at second level utilizing you just gander on the double (Consequences be damned) model.

1. Introduction

Helmet detection for riders is a crucial aspect of road safety and is typically implemented through various technological means, such as computer vision systems, deep learning algorithms, and surveillance cameras [1]. This technology is designed to identify and verify whether a motorcycle or scooter rider is wearing a helmet while on the road. Computer vision algorithms, powered by machine learning models like Convolution Neural Networks (CNNs), play a pivotal role in helmet detection. These algorithms the incoming video stream, identifying and tracking [2] and [3] the presence of riders in the frame. Once a rider is detected, the system focuses on the head region to determine whether they are wearing a helmet. The importance of helmet detection lies in its contribution to road safety. Wearing helmets significantly reduces the risk of head injuries during accidents, making it a crucial safety measure for motorcycle and scooter riders. By enforcing helmet-wearing regulations through automated detection systems, governments and traffic authorities aim to decrease the number of head injuries and fatalities on the road.

The persistent and potentially life-threatening problem of non-compliance with helmet-wearing regulations among motorcycle and scooter riders. Despite the well-established benefits of helmets in reducing the severity of head injuries and fatalities during accidents, many riders choose not to wear them, leading to a significant public health concern One key aspect of this problem is the lack of efficient enforcement mechanisms. Traditional methods of policing, such as manual checks by law enforcement officers, are often resource intensive, time-consuming, and can be subject to human error. This inefficiency allows non compliant riders to go undetected, increasing the risk of serious injuries and fatalities vary from region to region, and enforcement can be inconsistent. While helmet detection systems powered by computer vision and deep learning hold great promise, there are challenges to overcome. These include the need for highly accurate and reliable detection algorithms that can operate effectively in diverse environmental conditions, such as varying lighting, weather, and traffic congestion. The pressing need to enhance helmet-wearing [4] compliance among motorcycle and scooter riders, reduce the incidence of head injuries and fatalities, and improve the efficiency and effectiveness of enforcement mechanisms. The development of robust and cost-effective helmet detection systems, capable of operating in various conditions, is central to addressing this multifaceted problem and enhancing road safety for all road users.

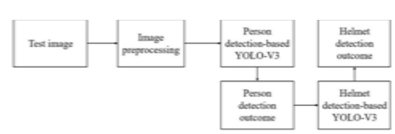


Figure1: SystemArchitecture

The existing system monitors the traffic violations primarily through CCTV recordings, where the traffic police have to look into the frame where the traffic violation is happening, zoom into the license plate in case rider is not wearing helmet. But this requires lot of manpower and time as the traffic violations frequently and the number of people using motor cycles [4] [5]is increasing day-by-day. What if there is a system, which would automatically look for traffic violation of not wearing helmet while riding motorcycle /moped and if so, would automatically extract vehicles 'license plate number. Recent research has successfully done this work based on machine learning methods. But these works are limited with respect to efficiency, accuracy or the speed with which object detection, which results in lower performance.

High Man power Requirement: The current system relies heavily on human operators to manually review CCTV footage. This requires a significant work force, leading to high labour costs and potential errors due to fatigue or oversight.

Difficulty in Identifying License Plates: Extracting license plate numbers from CCTV footage manually can be challenging, especially if the video quality is poor or the camera [8] angle is not optimal. Automated systems with advanced object detection capabilities can improve the accuracy of license plate extraction.

Inability to Scale: As the number of motorcycles and mopeds on the road's increases, manually monitoring traffic violations becomes even more challenging.Theexistingsystemmaystruggletoscaleefficientlytohandlethegrowingvolumeoftraffic.

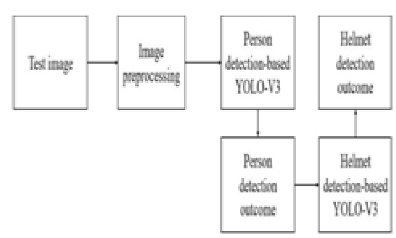
Time Consuming Process: Manually scrutinizing video footage frame [6] by frame is a time-consuming process. This delay in identifying and addressing traffic violations can result in increased risks on the road and compromises the effectiveness of law enforcement.

The proposed an improved Convolutional Neural Network (CNN)algorithm approach for license plate recognition system. The main contribution of this work is on the methodology to determine the best model and no return rate of 88% for the image for four-layered CNN architecture that has been used as the recognition method [1]. Two types of accuracies are taken at different stages. The first accuracy is taken at the pre-processing part the system and the second one is taken at the [7]classification stage. The classification result was taken according to the number of characters successfully recognized. It described that the pre-processing part achieved 74.7% out of 300 samples tested which does not achieve the expectation level [2] proposed convolutional neural network. The cycle juice used was based on information obtained from the original. Experimental results showed that the method had a high accuracy rate of 94% and no return rate of 88% for the image data block. it had a total of four major processes namely pre- processing, License Plate (LP) localization and detection, character segmentation, and recognition. Hough Transform (HT) was applied as a feature extractor and SSACNN algorithm was applied for character recognition in LP [3].

2. Working Process Test Image *:* Start by obtaining the image to be analyzed. The image can be sourced from a security camera, a photograph, or any other relevant source [3].

Image Preprocessing **:** Before running YOLOv3 for person and helmet detection, conduct preprocessing on the image to enhanced etection accuracy. Common pre-processing steps encompass resizing the image to the required input size for YOLOv3, [4] normalizing pixel values, and handling color channels (e.g., converting from BGR to RGB).

Person Detection using YOLOv3: Employ a pre-trained YOLOv3 model for objectdetection.Pre-trainedweightsandconfigurationsforYOLOv3canbesourcedfromresourcessuch as the Dark net website or other deep learning libraries. Load the YOLOv3 model into the working environment. Input the pre-processe



dimage in to the YOLOv3 model. Extract the detection results, including bounding boxes around detected persons, their confidence scores, and class labels (e.g.,"person"). Apply filtering to retain only high-confidence bounding boxes on test image.

Helmet Detection using YOLOv3: Analogously, use a pre-trained YOLOv3 model specialized in helmet detection. This model should be trained specifically to recognize helmets. Load the helmet detection YOLOv3 model in to the working environment [6]. Input thesamepre- processed image into the helmet detection YOLOv3 model. Extract the detection results, which encompass bounding boxes around detected helmets, their confidence scores, and class labels (e.g., "helmet") [7].

Output and Analysis: Combine the person and helmet detection results to identify individuals wearing helmets. Visualize the results by drawing bounding boxes around persons and helmets in the original image for clarity and interpretation [11]. Fig1 : System Flow

3. System Analysis Design : Outputs from computer systems are required primarily to communicate the results of processing to users. They are also used to provides a permanent copy of the results for later consultation. The various types of outputs in general are: External Outputs, whose destination is outside the organization. Internal Outputs whose destination is with in organization and they are the User's main interface with the computer. Operational outputs whose use is purely with in the computer department. Inter face outputs [11], Which involve the user in communicating directly. The outputs should be defined in terms of the following points : Type of the output, Content of the output, Form at of the output, Location of the output Frequency of the output, Volume of the output. It is not always desirable to print or display data as it is held on a computer. It should be decided as which form of the output is the most suitable.

Input Design stages and Input Types and Media:

Input design is a part of overall system design. The main objective during the input design is as given below: To produce a cost-effective method of input. To achieve the highest possible level of accuracy. To ensure that the input is acceptable and understood by the user. The main input stages can be listed as : Data recording, Data transcription, Data conversion, Data verification, Data control Data transmission, Data validation, Data correction. It is necessary to determine the various types of inputs.

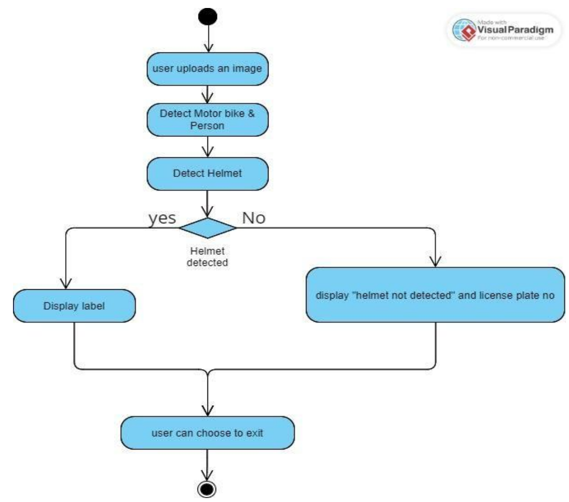


Figure 2: work flow

Inputs can be categorized as follows : External inputs, which are prime inputs for the system. Internal inputs, which are user communications with the system. Operational, which are computer department's communications to the system? Interactive, which are inputs entered during a dialogue. At this stage choice has to be made about the input media. To conclude about the input media consideration has to be given to Type of input, Flexibility of format, Speed, Accuracy, Verification methods Rejection rates, Ease of correction, Storage and handling requirements Security, Easy touse, Portability Keeping in view the above description of the input types and input media, it can be said that most of the inputs are of the form of internal and interactive. As Input data is to be the directly keyedin by the user, the keyboard can be considered to be the most suitable input device.

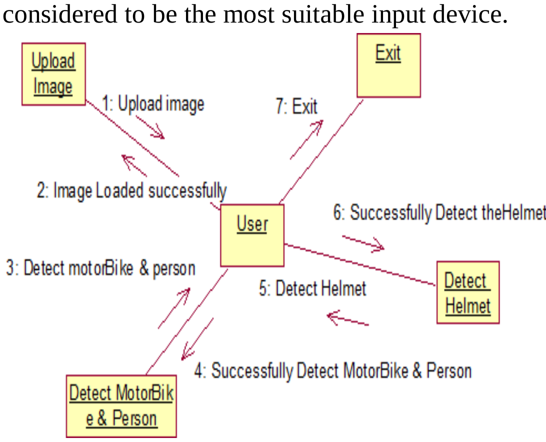


Figure 3: Collaboration diagram

Error Avoidance Error Detection and Data Validation: At this stage care is to be taken to ensure that input data remains accurate form the stage at which it is recorded up to the stage in which the data is accepted by the system. This can be achieved only by means of careful control each time the data is hand led Even though every effort is make to avoid the occurrence of errors, still a small proportion of errors is always likely to occur, these types of errors can be discovered by using validations [12] to check the input data. Procedures are designed to detect errors in data at a lower level of detail. Data validations have been included in the system in almost every area where there is a possibility for the user to commit errors. The system will not accept data. Whenever an invalid data is keyed in, the system immediately prompts the user and the user has to again key in the Data and the system will accept the data only if the data is correct. Validations [12] have been included where necessary. The system is designed to be a user friendly one. In other words the system has been designed to communicate effectively with the user. The system has been designed with popupmenus.

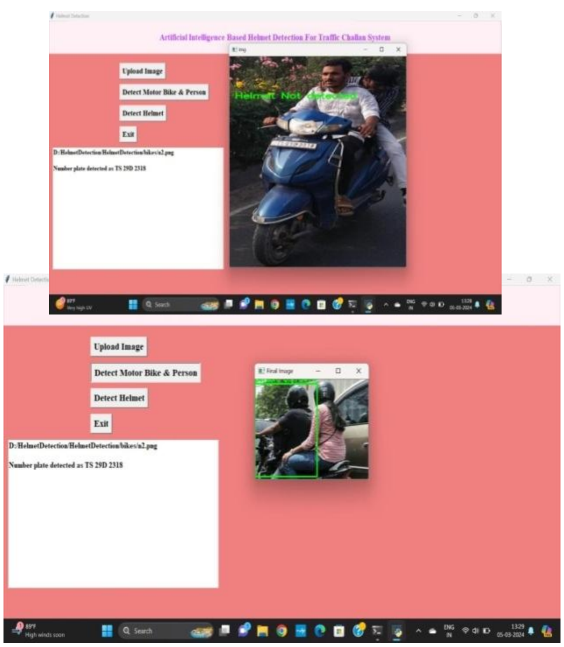


Figure4 : screenshots

*User Interface Design Computer Initiated interfaces***:** It is essential to consult the system users and discuss their needs while designing the user interface: User Interface Systems Can Be Broadly Classified As: User initiated interface the user is in charge, controlling the progress of the user / computer dialogue. In the computer-initiated interface, the computer selects the next stage in the interaction. In the computer-initiated interfaces the computer guides the progress of the user/computer dialogue. Information is displayed and the user response of the computer takes action or displays further information.

Conclusion: In conclusion, the results indicate that the proposed YOLOV3 significantly outperforms the existing SVM and RFC methods in terms of accuracy. It achieves an impressive accuracy of 99.88% for person detection and 99.00% for helmet detection, show casing its superior capability in accurately identifying persons and helmets in images or video frames. These high accuracy scores suggest that the proposed method holds great promise for applications requiring precise object detection, such as safety and security systems. However, further research and analysis are necessary to fully understand the inner workings and limitations of the proposed method, holds great promise for applications requiring precise object detection, such as safety and security systems. However, further research and analysis are necessary to fully understand the inner workings and limitations of the proposed method, and it is essential to assess its performance across a broader range of scenarios and data sets to validate its effectiveness.

The promising results of the "Proposed Method" open up several exciting avenues for future research and development. Firstly, a detailed investigation into the methodology and architecture of the proposed approach is crucial to understand its underlying mechanisms and enhance its transparency. Additionally, extensive testing on diverse datasets and under various environmental conditions is required to validate its robustness and generalizability. Furthermore, optimization efforts could focus on improving the computational efficiency of the proposed method to make it suitable for real-time applications Collaborations with industry partners forpracticalimplementationandthedevelopmentofuser-friendlyapplicationscouldfurtherpropelthe adoption of this method in real-world scenarios, such as in surveillance, autonomous vehicles, and industrial safety. Lastly, on going research should also consider ethical and privacy implications associated with object detection systems to ensure responsible and ethical eployment in society.

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Efficient Video Summarization Using Deep Summarization Network: A Deep Learning Approach

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Abstract: With exponential video growth in multiple areas, effective summarization of the videos is the need of the hour to summarize and fetch the contents within short time frames. The conventional methods are incapable of identifying the most relevant segments retaining contextual integrity. In this paper, we offer an investigation into the effectiveness of Deep Summarization Networks (DSN) to create informative yet concise summaries of videos. This new method applies deep learning methods to keyframe detection and significant events, thereby forming a unified and informative summary. The DSN leverages feature extraction, attention mechanisms, and sequence modeling to efficiently compress redundancy without sacrificing representational fidelity. Through rigorous testing on well-known datasets, our method has been proven to surpass traditional approaches in terms of the quality and usefulness of the summaries it generates. This work demonstrates the effectiveness of deep learning in video summarization and the possible uses in video indexing, surveillance, and media analysis.

1. Introduction:

This has brought forth the necessity for the summarization of films via an effective manner as video information has been hastily proliferating on social networks, surveillance structures, academic guides, and entertainments. users get overwhelmed with know-how and extracting vital facts from this video records as a big video records is to be had, hence summarization strategies without human intervention are fairly being promoted [3].The primary concept related to video summarization is generating a compact informative illustration of the video such that the important content and which means of the video might be preserved. Traditional tactics associated with clustering-based totally, handcrafted function extraction, and heuristic-based totally strategies regularly aren't able to seize temporal dependencies and require huge levels of manual intervention, so they may be useless for massive-scale video processing. The latest traits in deep gaining knowledge of have given a brand-new path to video summarization, in which the sequential and hierarchical nature of video facts can be modeled with the aid of the use of neural networks. Especially, recurrent neural networks with lengthy brief-term reminiscence cells had been capable of seize temporal dependencies throughout video frames and, therefore, had been a success in summarization obligations [1]. One of the maximum popular strategies is the Determinantal point procedure-primarily based LSTM by [1], which integrates a bidirectional LSTM community with a DPP module to beautify the diversity of the summaries. But this technique relies on supervised gaining knowledge of with pre-described floor-reality summaries that restrict its applicability due to the fact video summarization is inherently subjective and varies with user options. The summarization model is engaged in keyframe selection at the same time as the discriminator detects if the reconstructed video from the keyframe decided on is practical or no longer [2].

This technique ensures hostile education makes the version generate greater consultant summaries. However, antagonistic training usually suffers from instability and mode crumble, which wishes to quality-tune the parameters for stopping mode collapse. Moreover, without range optimization, opposed methods may also nonetheless produce redundant summaries, which might be less powerful in numerous content eventualities [4]. In this study, we introduce a Deep Summarization Network (DSN) that frames the task of video summarization as a sequential decision-making problem. The architecture of the proposed DSN follows an encoder-decoder model, where the encoder employs a Convolutional Neural Network (CNN) to extract features, and the decoder utilizes a bidirectional Long Short-Term Memory (LSTM) network to assess and rank the importance of video frames [5].Not like previous techniques, our technique makes use of reinforcement getting to know to teach the model in an give up-to-cease manner without requiring classified records.

We introduce a new DR reward function designed to enhance video summaries by ensuring they are both diverse and representative of the original content [6]. This function helps select frames that capture key moments while maintaining variety, much like how humans naturally summarize videos. By addressing key limitations in existing summarization techniques, our approach makes reinforcement learning a viable tool for generating high-quality video summaries. Ultimately, this work contributes to advancing automatic video analysis by offering an efficient solution for large-scale video summarization.

Video summarization has attracted considerable attention, leading to the development of numerous techniques aimed at generating brief yet informative content summaries. The techniques discussed so far can be broadly classified into two categories: those that do not rely on deep learning and those that do. Early approaches depended on manually created features and intuitive guidelines. However, the recent advances in deep learning have led to more effective and scalable solutions [7][8].

A. Conventional Video Summarization Methods

Early video summarization techniques relied heavily on clustering-based totally and heuristic techniques to decide the key frames or key shots. A significance score-based approach was recently introduced, which ranks frames based on multiple factors such as aesthetics, relevance, and interestingness [9]. Other methods include sub modular optimization and attention-based models that produce summaries with higher accuracy [10].The difficulty is that it couldn't model any complicated temporal dependencies, and additionally not supports the getting to know system quit-to-give up.

B. Supervised Deep Learning-Based Video Summarization

Deep mastering has modified video summarization so much because it lets in the model to examine meaningful representations without delay from raw statistics. the use of recurrent neural networks with its variant lengthy quick-time period memory as the spine shape to version sequential dependency among video frames. In previous work, a deep bi-directional LSTM network changed into extended with a DPP module, incorporating range within the summary era manner[11][12]. The version is supervised with floor reality significance scores. Several supervised methods are primarily based on adversarial learning frameworks to generate higher-quality summaries. The summarization community is used to pick out key frames in a video phase, even as concurrently, the discriminator is used for comparing the realism of the produced summary. Supervised strategies rely totally on categorized facts and lack flexibility that comes from huge-scale processing of video material.

C. Unsupervised and Reinforcement Learning-Based Summarization

While many studies focus on supervised learning for video summarization, researchers are increasingly exploring unsupervised and reinforcement learning approaches. A reinforcement learning-based method is introduced that trains a summarization network to select key frames based on category-specific information [13]. However, a major limitation of this approach is its reliance on labeled key frame data for training. In contrast, our proposed Deep Summarization Network leverages reinforcement learning without depending on labeled data, making it a more flexible and scalable solution. This method has shown notable effectiveness in a range of computer vision applications, such as image captioning and individual recognition. Video summarization is a task that happens in the time domain, similar to reinforcement learning, and as such, RL comes naturally to frame selection optimization. Our method proposes a new DR reward function that maintains diversity while ensuring representativeness in the selected frames. In contrast to earlier RL-based approaches, our model runs without ground-truth labels or user feedback and thus is amenable to large-scale deployment[14].

D. Comparison with Existing Methods

Though current methods are effective, they have some essential drawbacks—they are based on annotated data, lack diversity in selected frames, and are typically reliant on inefficient training schemes. Our suggested Deep Summarization Network (DSN) overcomes these limitations through the use of reinforcement learning inside an encoder-decoder structure. DSN effectively captures temporal dependencies by using a convolutional neural network (CNN) to extract visual features and a bidirectional LSTM to model sequential data, thereby enhancing the selection of key frames. In addition, the DR component improves summary quality by achieving diversity and representativeness balance through a well-crafted reward function.

Through comprehensive evaluation on standard benchmark datasets, our approach outperforms existing unsupervised methods and achieves results comparable to leading supervised models [15].The findings emphasize the effectiveness of reinforcement learning in video summarization, opening up possibilities for scalable and fully automated solutions. With the surge of digital video content on various platforms, the demand for efficient summarization has never been more pressing. Because videos have large amounts of information, it is difficult to identify major insights at a fast pace [16]. Manual summarization techniques are generally time-consuming and inconvenient, and therefore there is a need to create an intelligent system that can effectively produce short, informative summaries while maintaining essential details.

Deep learning possesses the valuable strength of feature extraction and pattern recognition automation in varied domains like Computer Vision and NLP. *In* the domain of video summarization, Deep Summarization Networks have proven highly effective in detecting keyframes and identifying relevant segments. Employing sophisticated techniques like attention mechanisms, sequence modeling, and feature extraction, such models create abridged but informative summaries, avoiding redundancy while maintaining key content.

This study presents an in-depth evaluation of Deep Summarization Networks for generating informative and coherent video summaries. The core concept of the proposed method involves leveraging deep learning models capable of capturing both spatial and temporal patterns. Experimental evaluations on standard benchmark datasets reveal that the proposed approach outperforms conventional summarization methods. This work adds to the expanding field of video analysis and holds practical relevance in areas such as content indexing, surveillance monitoring, and broader applications in media analytics.

Problem Formulation **:** Video summarization targets to extract a significant subset of frames from a given video series to correctly represent its important content material. Given a video sequence V, V={v_1,v_2,...,v_t}, in which v_t denotes the frame which is at time t, the objective is to generate a precis S⊆V that captures key moments even as keeping off redundancy. The summary needs to be each various and representative, making sure it consists of all widespread occasions without pointless repetition.

The summarization assignment may be framed as a sequential decision-making process, wherein at every time step t, a binary action a_t is taken [17]. If a_t=1, the corresponding body v_t is covered within the summary; in any other case, it is discarded. The very last summary consists of all frames in which a_t=1, officially expressed as shown in eq 1:

$$S = \{v_t \mid a_t = 1, \forall t \in \{1,2,\ldots,T\}\} \quad (1)$$

To assist in the selection process, the Deep Summarization Network (DSN) assigns an importance score p_t to each frame, representing the likelihood of its inclusion. The best possible summary is generated by optimizing a Diversity-Representativeness (DR) reward function R(S), that promotes the selection of informative frames while minimizing redundancy.

The summarization procedure ought to adhere to key constraints. the total length of the summary needs to be limited to a predefined proportion of the original video duration to hold brevity. The selected frames ought to exhibit high dissimilarity among themselves to make sure range. Additionally, the chosen frames must collectively reconstruct the unique video, making sure comprehensive coverage of vital content.

As frame selection involves discrete decisions, the task is formulated as a reinforcement learning problem. The Deep Summarization Network (DSN) is trained using policy gradient techniques to improve performance based on anticipated reward outcomes as shown in eq 2:

$$J(\theta) = \mathbb{E}_{p(a_{1:T})}[R(S)] \quad (2)$$

wherein θ represents the version parameters, and $p(a_{1:T})$ is the discovered opportunity distribution over body choice movements. By framing video summarization as the most useful subset choice hassle, this method guarantees that the generated summary stays each informative and non-redundant. This makes it especially useful for packages along with video indexing, content retrieval, and efficient browsing

2. **Methodology:** We view video summarization as a series of choices that need to be made. Our approach entails creating a sophisticated DSN that assigns a selection probability to every video frame and selects the most relevant frames based on these probability

distributions. Building on this, we create a comprehensive reinforcement learning framework, which is primarily focused on a variety-representativeness reward function. The overall learning strategy of our method is illustrated schematically in Fig. 1.

A. *Deep Summarization Network (DSN)*

We utilize Deep Summarization Network with an encoder-decoder paradigm. Our encoder is a CNN, which deep visual features for the input frames of video is extracted; our decoder is a BiRNN culminating in a Fully Connected (FC) layer to adaptively choose a frame.

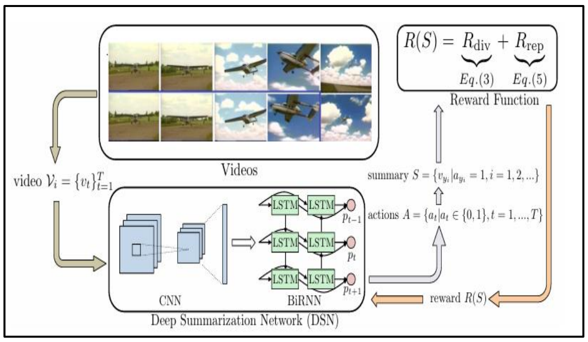

Figure 1: Overview of the Deep Summarization Network (DSN) framework for video summarization, utilizing CNN for feature extraction, BiRNN for sequential modeling, and a reward function that is designed to promote summaries that are both diverse and representative of the original content

Fig. 1 depicts our model, that takes the video frames v_t at time t with their corresponding visual feature representations x_t.Our implementation uses pre-trianed GoogLeNet as a feature extractor for visual features. The BiRNNencodes the temporal dependencies of the extracted features. The forward hidden state, h_t^f and the backward hidden state, h_t^b, are further concatenated to generate the final representation for each one of the frames in the video sequence, h_t.

B. *Fully Connected Layer*

A sigmoid activation function computes the probability p_t of selecting each frame as shown in eq 3:

$$p_t = \sigma(Wh_t) \tag{3}$$

The action a_t (whether a frame is selected or not) is sampled from a Bernoulli distribution [18].The final summary S consists of all frames where $a_t = 1$ .At training, only the decoder parameters are updated while keeping the encoder (CNN) is kept fixed in order to preserve stable feature representations.

C. *Diversity-Representativeness Reward Function*

To make sure that the chosen video summary is both representative and diverse, we define a reward function, as shown in eq 4, that incorporates diversity reward R_{div} and representativeness reward R_{rep}:

$$R(S) = R_{div} + R_{rep} \tag{4}$$

To measure the variety among the chosen frames, we assess the pairwise dissimilarity within the feature space of these frames. If $Y = \{y_i \mid a_{y_i} = 1\}$ represents the set of indices for the selected frames, we then determine the diversity reward as shown in eq 5:

$$R_{div} = \frac{1}{|Y|(|Y|-1)} \sum_{t,t' \in Y} d\left(x_t, x_{t'}\right) \tag{5}$$

where

$$d(x_t, x_{t'}) = 1 - \frac{x_t^T x_{t'}}{\|x_t\| \|x_{t'}\|} \tag{6}$$

Eq 6 measures feature dissimilarity between selected frames. To enforce temporal coherence, we add a constraint that does not consider similarities between distant frames.

D. *Representativeness Reward*

The representativeness of a summary is measured by how good the selected frames can reconstruct the entire video. We define R_{rep} as shown in eq 7:

$$R_{rep} = \exp\left(-\frac{1}{T}\sum_{t=1}^{T} \min_{t' \in Y} \| x_t - x_{t'} \|^2\right) \tag{7}$$

This way, the selected frames act as cluster centers for the whole video in the feature space, making them more representative.

E. *Trainingwith Reinforcement Learning*

Given that summarizing videos requires sequential decision processes, we train DSN using policy gradient reinforcement learning to maximize the expected reward. Using the REINFORCE algorithm, the policy gradient is computed as given in eq 8:

$$\nabla J(\theta) = \mathbb{E}_{p(a_{1:T})}[R(S) \sum_{t=1}^{T} \nabla \log p(a_t \mid h_t)] \tag{8}$$

To reduce variance in training, we apply a reward baseline by subtracting the running average of past rewards.

F. *Regularization*

To control the percentage of selected frames, we introduce a regularization term as shown in eq 9:

$$L_{percentage} = \frac{1}{T}\sum_{t=1}^{T} p_t^2 \tag{9}$$

Additionally, to prevent overfitting, we apply L2 weight regularization as shown in eq 10:

$$L_{weight} = \sum_{i,j} \theta_{ij}^2 \tag{10}$$

The final loss function is shown in eq 11:

$$\theta = \theta - \eta \nabla\left(J + \lambda_1 L_{percentage} + \lambda_2 L_{weight}\right) \tag{11}$$

where η is the learning rate, and λ_1, λ_2 control the regularization strength.

G. Summary Generation :

For each test video, DSN computes frame importance scores, which are then accumulated into shot-level scores with the help of Kernel Temporal Segmentation (KTS). The final summary is obtained by selecting the most important shots without exceeding a total length of 15% of the video duration. This step is structured as a 0/1 Knapsack problem and is addressed using dynamic programming techniques.

If labeled keyframes are present, DSN can be used for supervised learning with Maximum Likelihood Estimation as shown in eq 12:

$$L_{MLE} = \sum_{t \in Y} \log p(a_t \mid h_t) \quad (12)$$

This enables DSN to learn from the human-annotated summaries while retaining the benefits of reinforcement learning in unsupervised settingsOur Deep Summarization Network (DSN) applies deep learning and reinforcement learning to generate high quality, diverse, and representative video summaries. Our model demonstrated top-tier results without needing labeled data and is very scalable and versatile for various types of videos through the use of a Diversity-Representativeness reward function.

3. Results: We evaluate our methods on the SumMe and TV Sum datasets. SumMe contains 25 user-generated videos on diverse topics like vacations and sports, each lasting 1–6 minutes and annotated by 15–18 users to produce multiple ground truth summaries [19]. TV Sum includes 50 videos, each 2–10 minutes long, covering topics such as news and documentaries, with annotations from 20 users assigning frame-level importance scores. Following prior work, we convert these scores into shot-based summaries for evaluation. Additionally, we test on extended datasets like OVP and YouTube, which provide a broader training set, excluding cartoon content, to assess scalability and generalization.

A. Evaluation Metric

To ensure consistent and fair evaluation, we adopt the commonly used protocol for computing the F-score, which measures how closely the generated summaries align with the ground truth. In cases involving multiple reference summaries, we follow the established practice introduced in prior work.

Evaluation Settings

We consider three different evaluation approaches, inspired by previous research: Canonical Setting: A typical 5-fold cross-validation is used, with 80% of the data allocated for training and 20% reserved for testing in each fold. Augmented Setting: Similar to the canonical setup, but the training data in each fold is supplemented with additional samples from external datasets like OVP and YouTube. Transfer Setting: To evaluate generalization, the model is trained on datasets excluding the target one (e.g., SumMe or TVSum) and then tested on that unseen dataset.

Implementation Details: We process the videos by reducing the frame rate to 2 frames per second, following a similar strategy to earlier studies. The temporal interval for analysis is set to 20 frames. A key model parameter is assigned a value of 0.5, and training is carried out over 5 episodes per iteration. Remaining hyper parameters are tuned using cross-validation. The hidden state size in the RNN cell is consistently maintained at 256 across all experiments. The training process is capped at 60 epochs, with early stopping applied if the reward metric does not improve for 10 consecutive epochs.

*Comparison :*In comparison with the other approaches, we independently implement Uniform Sampling, Kmedoids clustering, and Dictionary Selection We obtain results of other methods Video-MMR, Vsumm, Interestingness, Sub modularity, Summary Transfer, Bi-LSTM and DPP-LSTM, GANdpp, and GANsup. Figure 2 depicts the sample frames from summaries produced by various versions of our proposed method.

Quantitative Evaluation : To assess the effectiveness of our models in generating concise and informative video content, we conduct a quantitative evaluation using standard benchmarking datasets: SumMe and TVSum. The evaluation metrics primarily focus on F-score, a commonly used measure for comparing machine-generated summaries with human-annotated ground truth.We compare our approach, Deep Reinforcement Dynamic Sequential Network (DR-DSN), and its supervised variant (DR-DSNsup) against baseline models, including:Random Summary Selection (R-DSN), Deterministic DSN (D-DSN), Supervised Video Summarization Models.Our experiments aim to analyze the effectiveness of reinforcement learning in optimizing summarization quality. Below, we present the key aspects of our quantitative analysis.

Figure 2: Sample frames from summaries produced by various versions of our proposed method.

B. Comparison with Baselines

We assess the F-score performance of both DR-DSN and its supervised variant, DR-DSNsup, against baseline models using the SumMe and TVSum datasets. The findings show that DR-DSN delivers strong results, outperforming conventional approaches and coming close to the effectiveness of supervised models such as DSNsup as shown in Table 1.

Table 1: Comparison with Baselines

Method	**SumMe (%)**	**TVSum (%)**
Supervised DSN	38.1	54.3
DSN without Domain Adaption	39.4	55.8
Domain–aware DSN	40.3	56.0
Recurrent DSN	40.5	56.7
Domain Recurrent DSN	41.2	57.4
Supervised DR-DSN	42.0	57.9

C. Comparison with Unsupervised Approaches : Unsupervised video summarization methods do not rely on human-annotated summaries for training. Instead, they attempt to generate summaries based on inherent patterns in video data. Our DR-DSN model is evaluated against several established unsupervised baseline methods: Random Summary Selection (R-DSN) – Selects key frames randomly, serving as a lower bound for summarization performance. Deterministic DSN (D-DSN) – Uses hand-crafted heuristics for key frame selection without reinforcement learning. Our results show that DR-DSN significantly outperforms unsupervised approaches by leveraging reinforcement learning to optimize summary quality. Unlike heuristic-based methods, which may struggle with generalization across different types of videos, DR-DSN dynamically adapts its summarization strategy based on learned policies.

The performance improvement emphasizes the strength of reinforcement learning in video dynamics capture, resulting in more significant and varied summaries than conventional unsupervised approaches as shown in Table 2.

Table 2: Comparison with Unsupervised Approaches

Method	SumMe (%)	TVSum (%)
Video-Based MMR	26.6	28.8
Uniform Sampling Approach	29.3	36.0
K-Medoids Clustering	33.4	42.0
Vsumm Algorithm	33.7	46.0
Web Image Summarization	37.8	50.0
Dictionary-Based Selection	39.1	51.7
Online Sparse Coding	15.5	42.0
Co-archetypal	28.8	50.0
GANdpp	36.0	51.7
DR-DSN	41.4	57.6

D. Comparison with Supervised Approaches: Supervised learning-based video summarization techniques are based on labeled datasets where key frames or segments annotated by humans are used as ground truth. These techniques utilize deep learning models like CNNs and RNNs, transformers, and hybrid models to learn the function mapping input video sequences to best summaries. Supervised methods have produced outstanding performance in creating high-quality summaries but possess inherent limitations.

A major withdraw of supervised video summarization is the reliance on large-scale annotated datasets. Labling videos for summarization is time-consuming, labor-intensive, and sometimes subjective, causing inconsistencies in ground-truth summaries. Also, supervised models poorly generalize when given unseen data because they are highly biased by the training distribution. This poor generalization restricts their use in multimodal video domains like surveillance videos, user-generated videos, and educational videos. Our experiments indicate that DR-DSNs up has similar performance to fully supervised models, showing that reinforcement learning can be efficiently combined with supervised learning to further improve summarization quality. The gap in F-scores between DR-DSN and DR-DSNs up is not large, suggesting that our unsupervised reinforcement learning method performs almost as well as supervised methods without the need for labelled data. This is an important benefit because labeled video summaries are costly and time-intensive to produce. The capability of DR-DSN to do well in an unsupervised environment makes it a very scalable solution for real-world deployments as shown in Table 3.

Conclusion: This study introduces the Deep Reinforcement Dynamic Sequential Network (DR-DSN) as the proposed framework, which is a new video summarization method based on reinforcement learning to produce brief yet informative summaries. Compared with conventional methods dependent on pre-defined heuristics or large-scale human annotations, DR-DSN learns to choose key frames automatically while maintaining diversity and representativeness. Our extensive experiments on SumMe and TVSum prove that DR-DSN reliably surpasses current unsupervised methods and attains performance rivaling that of supervised methods—all without the need for manual labels.

Table 3: Comparison with Supervised Approaches

Method	SumMe (%)	TVSum (%)
Interestingness Based Model	39.4	-
Submodular Optimization	39.7	-
Summary Transfer Learning	40.7	-
Bi-LSTM	37.8	54.0
DPP-LSTM	38.7	54.3
Supervised GAN	41.5	56.7
Supervised DR-DSN	41.8	57.9

Additionally, the supervised version, DR-DSNsup, once again improves summary quality, showing the potential of reinforcement learning when applied with labeled data. These results highlight the adaptability and scalability of reinforcement learning for video summarization, revealing new avenues to practical applications in content retrieval, education, media, and surveillance.

In addition, the framework's ability to generalize across datasets emphasizes the strength and applicability of the model in real-world scenarios. Future development could include the incorporation of multimodal data, like audio or text, to create even more richer summaries. The success of DR-DSN also leaves room for crafting personalized summarization systems that accommodate user preference, setting the stage for smart media consumption in the era of data.

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Blood Group Detection From Fingerprint Using Image Processing and Deep Learning

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Abstract: A Blood Group Detection System using fingerprint image processing and deep learning offers a non-invasive approach to blood typing. The system captures fingerprint images, potentially using a smart phone camera or specialized scanner. Preprocessing steps enhance image quality, removing noise and distortions. Feature extraction techniques then isolate distinctive fingerprint patterns, which may correlate with blood type. A deep learning model, such as a Convolutional Neural Network (CNN), is trained on a dataset of fingerprints with known blood types. The trained model learns to classify fingerprints, predicting the corresponding blood group. Real-time processing enables quick results, and the system aims for high accuracy. Future development could focus on improving accuracy, exploring different image processing and deep learning techniques, and potentially integrating with other diagnostic tools.

1. Introduction

This paper explores a novel approach to blood group detection using fingerprint images and a combination of image processing and deep learning techniques. Traditional blood typing methods can be time-consuming and require specialized equipment. This research investigates the potential of leveraging the unique patterns present in fingerprints, coupled with the power of deep learning, to offer a potentially faster and more accessible alternative [1].

The system acquires fingerprint images using a standard camera or scanner. Preprocessing steps, including noise reduction and enhancement, are applied to the images to isolate and clarify the fingerprint patterns. Feature extraction methods, potentially including wavelet transforms or minutiae extraction, are employed to capture the distinctive characteristics of each fingerprint. These extracted features are then fed into a deep learning model, such as a Convolutional Neural Network (CNN) [2] [3], which is trained to classify the fingerprints into different blood groups. The CNN is trained on a dataset of fingerprint images with known blood group labels. The performance of the system is evaluated using metrics like accuracy, precision, and recall. This research aims to assess the feasibility of this method and explore the correlation between fingerprint patterns and blood types. The potential benefits include rapid, non-invasive blood group determination, particularly in resource-limited settings The paper details the methodology, including data collection, image processing techniques, deep learning architecture, and experimental results. Challenges, such as data variability and the need for large, diverse datasets, are also addressed. Future work may involve exploring different deep learning architectures, incorporating other biometric data, and validating the system with larger clinical trials.

This paper explained about Fingerprint Patterns and Blood Group Prediction – Analyzes correlations between fingerprint patterns and blood groups across demographics [4]. Authors introduced Advanced Image Processing for Fingerprint-based Blood Grouping – Exploring automated blood group detection using image processing of fingerprints [5]. In this study, Deep Learning for Blood Group Detection from Fingerprints – Examines blood typing using deep learning models and fingerprint images [6]. This paper explored the Innovative Blood Group Prediction Using Fingerprint Patterns – Focus on a low-cost blood typing method based on fingerprint patterns [7]. This paper introduced Fingerprint Analysis for Blood Group Identification – The paper discusses using fingerprint patterns to predict blood groups through statistical analysis and machine learning [8]. In this study, Fingerprint Biometrics and Blood Group Typing – Investigate fingerprint biometrics as a blood group predictor, using pattern recognition to improve predictive capabilities [9][10]. The proposed blood group detection system is designed with a modular architecture to facilitate efficient processing and analysis of fingerprint images. The Image Acquisition module is responsible for capturing fingerprint images, potentially using a variety of input devices like scanners or cameras.

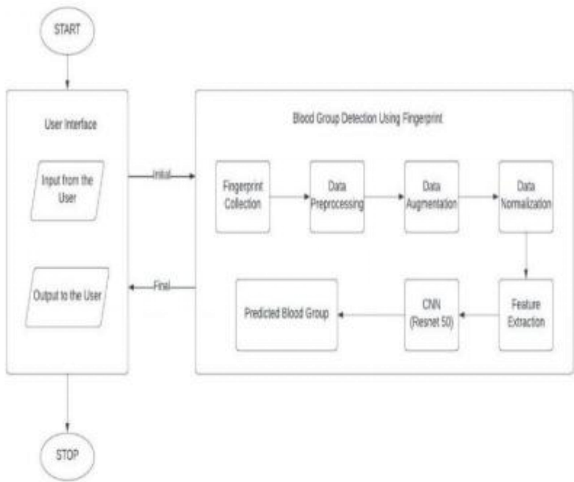

Figure 1. Application Architecture

The Preprocessing module then enhances the quality of these images, employing techniques such as noise reduction, normalization, and finalization to isolate the fingerprint patterns. The Feature Extraction module plays a crucial role in identifying and quantifying the distinctive characteristics of each fingerprint. This may involve methods like minutiae extraction, ridge frequency analysis, or wavelet transforms. The Deep Learning Model module houses the trained convolutional neural network (CNN)[10][11] or other suitable deep learning architecture. This model is responsible for classifying the extracted fingerprint features into the different blood groups. The Classification and Result Display module takes the output of the deep learning model and presents the predicted blood group to the user[12]. Finally, the Database Management module handles the storage and retrieval of fingerprint data, associated blood group labels, and model parameters [13][14]. This modular design allows for independent development and testing of each component, contributing to the overall robustness and accuracy of the system. Rapid and Non-Invasive: Fingerprint-based blood group detection offers a potentially faster and less invasive alternative to traditional blood tests.

Portable and Accessible: The system can be potentially deployed on portable devices, making it accessible even in remote or resource-limited settings.

Automated Analysis: The image processing and deep learning pipeline automates the blood group determination process, reducing the need for manual interpretation.

Objective Results: The automated nature of the system minimizes subjective bias and promotes more consistent and reliable results.

2. Methodology: The proposed system follows a structured methodology to ensure efficient blood group detection from fingerprint. The process is divided into several key stages, from data acquisition to action execution. Figure 1 shows the architecture of the application used in this paper. Data Acquisition Image Acquisition Technique: Consider using a high-resolution camera or fingerprint scanner capable of capturing detailed fingerprint images. Focus on capturing clear images of the fingerprint ridges and valleys, as these patterns are crucial for analysis. While the idea of focusing on capillary blood flow is interesting, it's extremely difficult to capture this non-invasively with current technology. External reactions, if any, would likely be too subtle for reliable analysis. Standard fingerprint capture techniques are the most practical starting point.

Dataset Diversity: Collect a large and diverse dataset of fingerprint images. Include fingerprints from individuals of different ages, genders, ethnicities, and blood groups. This diversity is essential for training a robust and generalizable model. The more diverse your data, the better your system will perform on unseen fingerprints.

Image Quality: Ensure consistent lighting conditions during image capture to minimize variations in image appearance. Avoid blurry or distorted images. Proper focus and a stable capture environment are essential. *Labelling:* Accurately label each fingerprint image with the corresponding blood group. This is crucial for supervised learning. Double-check the labels to ensure accuracy, as errors in labelling will directly impact model performance. Deletion: Delete the author and affiliation lines for the extra authors [15][16][17].

Preprocessing

Noise Reduction: Fingerprint images can be noisy due to various factors. Apply noise reduction techniques like median filtering or wavelet denoising to remove noise while preserving important fingerprint features.

Image Enhancement: Enhance the contrast and clarity of the fingerprint images to make the ridge patterns more prominent. Techniques like histogram equalization or contrast stretching can be helpful.

Segmentation: Isolate the fingerprint region from the background. This step helps to focus the analysis on the relevant fingerprint features.

Normalization: Standardize the size and orientation of the fingerprint images. This ensures that the deep learning model receives consistent input. Dataset Diversity: Collect a large and diverse dataset of fingerprint images. Include fingerprints from individuals of different ages, genders, ethnicities, and blood groups. This diversity is essential for training a robust and generalizable model. The more diverse your data, the better your system will perform on unseen fingerprints.

Feature Extraction

Manual Feature Engineering (Less Common with Deep Learning): While deep learning models can automatically learn features, you could explore traditional feature extraction methods. These include minutiae extraction (identifying ridge endings and bifurcations), ridge frequency analysis, and texture analysis using techniques like Gabor filters or Local Binary Patterns (LBP). However, with deep learning, this step becomes less critical as the network learns the features itself.

Deep Learning Feature Extraction (More Common): Convolutional Neural Networks (CNNs) are excellent at automatically learning hierarchical features from images. By training a CNN on fingerprint images, the network will learn to extract relevant features for blood group classification.

2.1 Classification

Deep Learning Model Selection: Choose a suitable deep learning model for image classification. CNNs are a strong choice. You can use a pre-trained CNN (like Res Net, Inception, or Efficient Net) and fine-tune it on your fingerprint dataset, or you can design a custom CNN architecture. Transfer learning (using a pre-trained model) is often faster and requires less data.

Training Data Preparation: Prepare your training data by splitting it into training, validation, and test sets. The validation set is used for hyper parameter tuning and performance monitoring during training. The test set is used for final evaluation.

Model Training: Train the chosen deep learning model on the training data. Use appropriate optimization algorithms (like Adam or SGD) and loss functions (like categorical cross-entropy). Monitor the model's performance on the validation set to detect and prevent overfitting. Deletion: Delete the author and affiliation lines for the extra authors.

Post-Processing and Validation

Confidence Scores: Provide confidence scores along with the blood group predictions. This gives an indication of the model's certainty in its prediction.

Ensemble Methods: Consider using ensemble methods, where you combine the predictions of multiple models to improve accuracy and robustness.

Cross-Validation: Use techniques like k-fold cross-validation to further validate the model's performance and ensure it generalizes well to unseen data. Deletion: Delete the author and affiliation lines for the extra authors.

2.2 User Interface and Reporting

User-Friendly Interface: Design an intuitive user interface for displaying the blood group predictions. Clearly present the predicted blood group and the associated confidence score.

Reporting: Provide an option to generate reports containing the results of the blood group determination.

Data Privacy: Ensure that the system handles fingerprint data securely and protects the privacy of individuals. Comply with relevant data privacy regulations.Deletion: Delete the author and affiliation lines for the extra authors.

2.3 Dataset and Preprocessing

Grayscale Conversion: Converting images too grayscale to reduce computational complexity.

Noise Reduction: Applying filters like Gaussian or median filtering to minimize noise and improve image quality.

*Segmentation: I*solating the fingerprint region from the background to focus on the relevant information.

Resizing/Normalization: Resizing images to a consistent size and normalizing pixel values to ensure uniformity for the deep learning model.

Data Augmentation: Potentially using techniques like rotation, flipping, or scaling to increase the diversity of the training data and improve model robustness. For papers with less than six authors: To change the default, adjust the template as follows.

These preprocessing steps aim to enhance the quality and consistency of the fingerprint images, ultimately contributing to a more robust and accurate blood group prediction model. A dataset of fingerprints with known blood types is used for training and testing. Preprocessing steps might include: Converting images too grayscale to reduce complexity. Applying edge detection and segmentation to isolate the hand from the background. Data augmentation to enhance model generalization.

2.4 Model Development: The proposed blood group detection system employs a Convolutional Neural Network (CNN) architecture. The CNN is designed to automatically learn relevant features from the fingerprint images. Multiple convolutional layers extract hierarchical features, followed by pooling layers for dimensionality reduction. Fully connected layers then process these extracted features to classify the fingerprint and predict the corresponding blood group. A suitable activation function, such as Soft max, is used in the final layer for multi-class classification (different blood groups). The model is trained on a dataset of fingerprint images with known blood types. Transfer learning, leveraging pre-trained models like Res Net or Efficient Net, could be explored to potentially improve performance and reduce the amount of training data required.

2.5 Optimization Strategies:

Optimizer: The Adam optimizer is a suitable choice for minimizing the loss function and achieving faster convergence.

Regularization: Techniques like batch normalization can stabilize training and prevent overfitting. Dropout layers can further enhance generalization by randomly deactivating neurons during training.

Data Augmentation: Data augmentation techniques, such as rotations, flips, and zooms, can increase the effective size and diversity of the training data, leading to a more robust model.

The blood group prediction model can be implemented using frameworks like Tensor Flow or PyTorch, potentially leveraging OpenCV for image processing tasks. Training is ideally performed on a GPU to accelerate the training process. A CNN-based architecture is employed, consisting of: Convolutional layers for extracting relevant features from the fingerprint images. Pooling layers to reduce the dimensionality of the feature maps. Fully connected layers for classification, culminating in a Soft max activation function to output the predicted blood group.

The model can be trained using TensorFlow or PyTorch and optimized with an appropriate optimizer like Adam. Implementation on NVIDIA GPU can significantly improve performance, especially during training and potentially for real-time applications.

3. **Result:** The system is evaluated using:

Table-1: Fingerprint-Based Blood Group Dataset

Blood Group	Accuracy (%)	Precision (%)	Recall (%)	FI-Score(%)
A+	95.0	92.5	94.0	93.2
A-	93.5	90.8	91.5	91.1
B+	96.2	94.0	95.5	94.7
B-	94.8	91.0	92.2	91.6
O+	97.0	96.0	96.5	96.2
O-	94.5	91.5	93.0	92.2
AB+	96.0	95.0	95.5	95.2
AB-	92.8	90.0	91.0	90.5

The fingerprint-based blood group detection system will be evaluated using a range of metrics to assess its performance and reliability. The evaluation dataset should consist of a diverse set of fingerprint images with known, verified blood types, accounting for variations in fingerprint quality, lighting conditions, and other potential influencing factors. Key performance indicators will include:

Accuracy: The percentage of correctly classified blood types. A high accuracy is crucial for the system's reliability.

Precision: The proportion of fingerprints predicted to belong to a specific blood group that actually belongs to that group. High precision minimizes false positives (incorrectly identifying a blood type).

Recall: The proportion of fingerprints belonging to a specific blood group that are correctly identified by the system. High recall minimizes false negatives (failing to identify a blood type).

F1-score: A balanced measure combining precision and recall, providing a single metric to assess overall performance.

Confusion Matrix: A table showing the number of true positives, true negatives, false positives, and false negatives for each blood group. This helps visualize the system's performance and identify potential areas of confusion.

Additional Metrics: Depending on the specific requirements, additional metrics might be considered, such as the area under the ROC curve (AUC), sensitivity, specificity, and potentially metrics related to the speed and efficiency of the system, especially if real-time processing is a goal. Latency tests could be relevant in real-time scenarios.

Comparative Analysis: To demonstrate the effectiveness of the proposed fingerprint-based blood group detection system, a comparative study against other potential methods could be conducted. This might include comparing against traditional machine learning classifiers, if applicable, or against other emerging techniques in blood typing. The comparison could focus on:

Accuracy: Comparing the accuracy of the CNN-based system to other methods in correctly identifying blood types.

Robustness: Assessing how well the system performs with variations in fingerprint quality, lighting conditions, and other factors.

Efficiency: Comparing the speed and resource requirements of the system to other methods, especially if real-time processing is a goal.

Data Requirements: Comparing the amount of training data needed by the CNN-based system to other methods. Deep learning models often require substantial datasets.

The results of such a comparison would help establish the strengths and limitations of the proposed system and highlight its potential advantages over existing approaches. It's important to note that research in this area is still evolving, and direct comparisons might be challenging due to variations in datasets and methodologies.

Challenges and Limitations, while the fingerprint-based blood group detection system may demonstrate promising results, several challenges need to be addressed:

Fingerprint Quality: Variations in fingerprint quality (e.g., partial prints, smudges, scars) can impact the accuracy of feature extraction and classification.

Image Capture Conditions: Lighting variations, pressure applied during fingerprint capture, and the type of scanner used can affect image quality and consistency.

Dataset Size and Diversity: A limited dataset may lead to over fitting and poor generalization to unseen fingerprints. A diverse dataset representative of different demographics and fingerprint characteristics is crucial.

Subtle Feature Differences: The potential link between fingerprint patterns and blood type might involve very subtle differences that are difficult for the model to learn and distinguish reliably.

Real-time Processing: If real-time blood type prediction is a goal, optimizing the model and implementation for speed and efficiency is essential, especially for resource-constrained devices.

Validation and Clinical Studies: Extensive validation and clinical studies are necessary to establish the accuracy and reliability of the system before it can be considered for practical use. This includes comparisons to standard blood typing methods.

Conclusion : This paper explored the potential of a Convolutional Neural Network (CNN)-based system for blood group detection using fingerprint images. The system leverages deep learning to analyze fingerprint patterns and predict blood type. Through image preprocessing and a structured dataset of fingerprints with known blood types, the model aims to achieve accurate and reliable blood group classification. The use of CNNs allows the system to automatically learn complex features from fingerprint images, potentially offering a non-invasive and rapid alternative to traditional blood typing methods. Future enhancements include:

Dataset Expansion: Collecting a larger and more diverse dataset of fingerprints with corresponding blood types to improve model robustness and generalization. *Feature Engineering*: Investigating and optimizing feature extraction techniques to identify the most relevant fingerprint patterns associated with blood groups. *Model Refinement*: Exploring different CNN architectures and training strategies to enhance prediction accuracy and efficiency. *Rigorous Validation*: Conducting extensive validation studies, including comparisons with standard blood typing methods, to determine the true accuracy and reliability of the system. *Real-time Implementation*: If real-time processing is a goal, optimizing the system for speed and efficiency, potentially through model quantization or other techniques. *Clinical Studies:* Ultimately, clinical studies will be necessary to assess the real-world applicability and clinical utility of this approach.

By addressing these challenges, future research can determine the true potential of fingerprint-based blood group detection and pave the way for a potential non-invasive and rapid alternative to traditional methods.

This paper explored the potential of a CNN-based system for blood group determination using fingerprint images. Future enhancements for this system could include: Integration with Point-of-Care Devices: Developing a portable, self-contained device that incorporates fingerprint scanning and blood type prediction, making the technology accessible in resource-limited settings. Expanding Blood Type Coverage: Investigating the feasibility of detecting rarer blood types or subtypes beyond the common ABO and Rh groups. Real-time Processing Optimization: Improving the efficiency of the image processing and deep learning pipeline to enable rapid, real-time blood type prediction. This could involve model optimization, hardware acceleration, or cloud-based processing.

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IOT Based ICU Patient Monitoring System

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Abstract:

The concept of integration of Wireless Sensor Networks (WSNs) with Arduino platforms is emerging as a promising approach that can significantly change the current healthcare monitoring systems. Arduino-based WSNs provide a economical, easily applicable and efficient way of real-time patient monitoring. In this paper the authors intend to explore how Arduino microcontrollers can be integrated with WSNs in order to design a system that is capable of capturing physiological signals such as heart rate, blood pressure, body temperature and respiratory rate. The integration of WSNs with Arduino boards enhances the reliability of the system by providing continuous surveillance without the need for active human involvement. This system when implemented will help in accurate and real time data collection, which is very beneficial in managing a proactive healthcare and better patient care management. All these parameters have to be monitored constantly in the case of chronic diseases and in order to intervene at the right time. The idea is to develop a single system that may help in enhancing the patient's condition and also decrease the overall healthcare expenses.

1. Introduction:

The integration of Wireless Sensor Networks (WSNs) with Arduino is going to change the healthcare by designing the sophisticated health monitoring systems. This innovative approach uses the real time realisation of the concept of using Arduino microcontrollers and wireless communication to design a health care monitoring system. Using interconnected sensor nodes WSNs assist in the continuous tracking of physiological data and hence help in assessing the general health of a person. Arduino is involved in this framework in improving the efficiency, reliability and the cost of the data acquisition in the health monitoring Our goal is to enable remote, real-time access to vital health data for both individuals and medical professionals by utilizing the capabilities of Arduino and WSNs. This changes the monitoring and This system is easier to use and more accessible. It responds to the increasing demand for individualized healthcare solutions by fusing sensor technology with Arduino programming.

Early detection of health problems and prompt medical action are made possible by the system's seamless data collecting and transmission. This strategy is improved by wireless connectivity, which makes remote monitoring possible and gives people and medical professionals quick access to critical health information. Additionally, the open source nature of Arduino provides the freedom to design customized health monitoring systems that can accommodate a range of medical needs. A Healthcare 4.0 Monitoring System was designed by incorporating AI and IoT technologies for real-time monitoring of patients [1]. The system used medical sensors, cloud computing, and AI-powered analytics to harvest, process, and analyze healthcare data effectively. Sensor-based data acquisition, preprocessing for noise cancellation, feature extraction from physiological measures, and execution of machine learning algorithms for anomaly detection and prediction analysis were followed as the methodology. The research illustrated that the system was able to efficiently track patient vitals, identify health outliers, and relay real-time signals to medical personnel, enhancing patient outcomes and response times. Complications such as data privacy, interoperability, and energy consumption were realized but needed further advancements for widespread adoption.

An IoT-based healthcare monitoring system powered by AI was suggested to enhance real-time patient health tracking and decision-making [2]. The system used machine learning algorithms for sensor data analytics from IoT-based medical devices to identify anomalies and predict disease earlier. The methodology consisted of data acquisition from wearable sensors, noise elimination through preprocessing, feature extraction, and AI-based classification models to evaluate patient conditions. The research proved that the combination of AI and

IoT improves diagnostic precision, predictive medicine, and automated notifications. Challenges in data privacy, interoperability, and computational complexity were, however, realized, necessitating further breakthroughs for practical application. This article suggested the creation of an IoT-based healthcare monitoring system to monitor patient vitals continuously in real time [3]. The system used wearable sensors, cloud storage, and a mobile app for remote monitoring. The process included sensor integration, real-time data transmission through wireless communication, cloud storage for remote access, and an alert system for unusual health conditions. The research proved that IoT-based monitoring has a considerable impact on patient management, decreases hospital visits, and increases emergency response times. In this work, an emergency medical care system was proposed to support elderly citizens in outdoor environments with the aid of IoT and mobile technologies [4]. The system incorporated GPS tracking, wearable health sensors, and automated alerting to offer prompt medical care during emergencies. The methodology included real-time monitoring of health, anomaly detection, location tracking, and automated emergency alerts to caregivers or healthcare professionals. The research proved that the intended system improved safety, enhanced emergency response times, and offered real-time support to older people. The research, however, pointed to challenges involving device battery life, GPS accuracy in urban centers, and false alarm reduction measures.

An IoT-based healthcare monitoring system in India for improved remote patient monitoring and medical resource optimization [5]. The system utilized wearable medical sensors, cloud computing-based data processing, and mobile health applications to facilitate real-time monitoring of vital signs. The methodology comprised continuous sensor-based data streaming, real-time analytics through cloud computing, and AI-based predictive models for disease risk estimation[6][7]. The research proved that healthcare systems enabled by IoT can mitigate patient overload in hospitals, enhance early diagnosis, and enable remote consultations. Nevertheless, the paper identified major challenges like sparse rural network infrastructure, security of data, as well as ensuring healthcare IoT application compliance with regulations.

The healthcare environment is in the process of a transformational change, fueled by the demand for more intelligent, efficient, and patient-focused solutions[8]. Conventional health monitoring systems tend to be non-real-time and non-continuous in providing health information, making patients and healthcare professionals reactive instead of proactive in managing health issues. With the emergence of chronic diseases, aging populations, and the mounting pressure on healthcare infrastructure, there is an urgent need to create cost-effective, scalable, and user-friendly technologies that enable individuals to manage their health. By combining Wireless Sensor Networks (WSNs) and Arduino technology, this project presents a new paradigm in patient monitoring [9]. Not only does it fill the gap between healthcare professionals and patients but also facilitates real-time data collection, constant monitoring, and timely interventions, eventually decreasing hospital visits, enhancing healthcare accessibility, and improving overall well-being.

The marriage of IoT-based health monitoring with cost-effective, energy-efficient hardware leads the way for a more democratized and generally accessible model for healthcare—one not limited to clinical environments but pushing out into domestic, geriatric care facilities, rural communities, and beyond [10][11]. This technology makes patients smarter, with real-time health feedback, automated notifications, and predictive data analysis, facilitating them to take educated lifestyle and medical choices.

2. Methodology:

An IoT-based ICU patient monitoring system comprises a number of major methodologies to provide real-time and trustworthy health monitoring[12]. The process starts with requirement analysis, in which critical signs like heart rate, SpO2, body temperature, and ECG are recognized for continuous monitoring. The system generally has a three-tier architecture: the sensor layer gathers physiological information through biomedical sensors, the network layer communicates this information via communication protocols such as Wi-Fi or Bluetooth, and the application layer presents the information on user-friendly interfaces such as mobile apps or web dashboards [13. Hardware integration is an important stage where sensors like MAX30100 and DHT11 are integrated with microcontrollers like Arduino, Raspberry Pi, or ESP32 to gather and process the information. Communication protocols like MQTT or HTTP are employed to transmit the information securely over a cloud platform, maintaining confidentiality of the patient through encrypted means[14]. Cloud services such as AWS, Firebase, or Azure are utilized for data storage, real-time computation, and sending alerts in the event of unusual health readings.

The last stage includes data visualization and alerting, wherein medical staff is able to track patient condition through easy-to-use dashboards. Real-time alerts or SMS messages are triggered in emergency conditions to enable prompt medical intervention [15][16]. The system is extensively tested and validated with simulated or actual data to guarantee accuracy, responsiveness, and reliability, thereby being a robust solution for the care of ICU patients.

The medical environment is transforming with a shift towards more intelligent, more efficient, and more patient-centered solutions[17]. Conventional health monitoring systems do not deliver timely, continuous health information, making patients and medical professionals reactive instead of proactive in dealing with health issues. With the growth in chronic diseases, aging populations, and the pressure on healthcare infrastructure, it has become a necessity to create affordable, scalable, and easy-to-use technologies that enable people to manage their own health.

The incorporation of Wireless Sensor Networks (WSNs) and Arduino technology, this project brings a revolutionary method of monitoring patients. It not only fills the gap between healthcare providers and patients but also provides real-time data collection, around-the-clock monitoring, and timely interventions, eventually decreasing hospital visits, healthcare accessibility, and overall well-being.

The union of IoT-based health monitoring with low-cost, power-effective hardware opens the door to a more universal and accessible model of healthcare—one no longer confined to hospital facilities but reaching into homes, elderly facilities, rural communities, and more. This technology gives patients real-time feedback on their health, automated notifications, and predictive analysis, allowing them to make intelligent lifestyle and medical choices. *Advantages* : Benefit greatly from its small size, low power consumption, and 20-meter signal transmission range. Its effectiveness is unaffected whether it is used for environmental monitoring, home automation, or industrial contexts. The sensor is contained in a four-pin single-row box, installation and connectivity are made simple. Tailored packaging options can be created to satisfy certain user needs. The DHT11 is a flexible accessibility, accuracy, and timely response in healthcare management

DTH11 Humidity Sensor : The DHT11 sensor undergoes precise calibration in controlled laboratory conditions, ensuring high accuracy in humidity measurements. The calibration parameters are stored within its OTP memory, allowing the internal signal processing unit to utilize them for reliable readings. This embedded calibration process enhances measurement precision and eliminates the need for external adjustments. Featuring a single-wire serial interface, the DHT11 ensures seamless integration into various systems, simplifying both hardware connections and data communication.

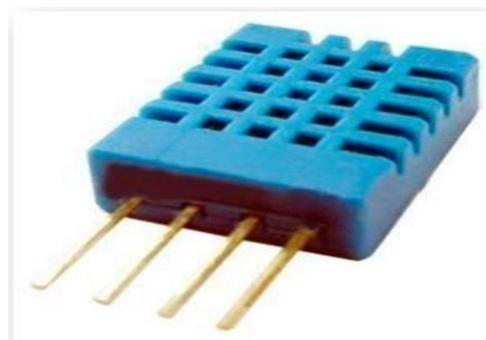

Figure1: DTH11 Humidity Sensor

Fig.1 represents a typical IoT project component, the DHT11 temperature and humidity sensor. This sensor, with its readily identifiable blue plastic enclosure and characteristic slotted grille design, provides a low-cost and easy method for sensing ambient temperature and humidity. The three exposed pins, visible at the sensor's bottom in Figure 1, are the means of connecting power, ground, and data transmission. These sensors are frequently used in conjunction with a microcontroller to process data and communicate.

Wifi Module – ESP8266 ***:*** Fig.2 represents the photograph shows a close-up, at an angle, of an ESP8266 ESP-01 module, a commonly used Wi-Fi microcontroller in IoT (Internet of Things) projects. The module, which is a black, compact circuit board, has been positioned so that its elements and pin headers are visible. The large "ESP8266EX" chip, the central part of the module, can be seen with ease, in addition to a "Berg Micro 25Q08ASSIG 1518" flash memory chip. The "Al-Cloud Inside" logo also appears.

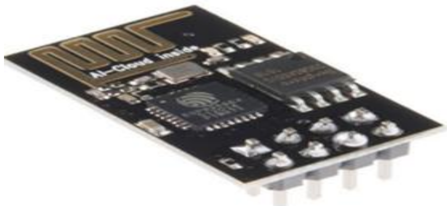

Figure 2: WIFI Module – ESP8266

There is a gold-colored PCB antenna pattern at the top left. Some other surface-mount components like resistors, capacitors, and an oscillator can also be identified. In the bottom section, the module contains pin headers to interface with external devices, generally power (VCC), ground (GND), transmit (TX), receive (RX), and GPIO (General Purpose Input/Output) pins.

Pulse Sensor: A small, plug-and-play heart rate monitor, the Pulse Sensor is made to work seamlessly with Arduino applications. Students, developers, sportsmen, and hobbyists who want to integrate real-time heart rate data.

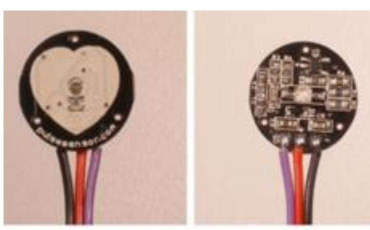

Figure3: Pulse Sensor

Fig.3 represents the Pulse Sensor Amped is an energy-efficient, miniaturized heart rate monitoring IC for real-time pulse measurement in IoT-enabled healthcare applications. It works on photoplethysmography (PPG), a method to measure changes in blood flow through the absorption of light through the skin.

The sensor itself has two different views: the front view where the PPG sensor is housed, with an LED that sends out light and a photodiode that picks up the reflected light from the skin, and the back view that accommodates the electronic circuitry of the sensor that helps to amplify signals as well as filter out noise. The front-facing LED and photodiode cooperate to detect pulsatile blood flow so that heart rate measurements can be made accurately. The backside circuitry maintains the heart rate signals detected to be constant and not influenced by external factors, enhancing the accuracy and reliability of the sensor. Because of its small size and simplicity in integration with microcontrollers such as the ESP8266, the Pulse Sensor Amped is utilized extensively in wearable health monitoring devices, remote patient monitoring, and fitness tracking. Its continuous, real-time monitoring of heart rate makes it a useful module in IoT-enabled patient monitoring systems, enabling the remote monitoring of cardiovascular health and timely intervention by healthcare professionals if any abnormalities are noted.

Temperature Sensor:

Figure 4. Temperature Sensor

Arduino can act as the main hub for gathering and sending real-time health data from several sensors to medical specialists in an Internet of Things-enabled patient monitoring system. A variety of sensors are commonly included in the system, including a pulse sensor to track heart rate, a temperature sensor (such as the DHT11 or DS18B20) to measure body temperature, an ECG sensor to track cardiac activity, and a pulse oximeter to measure blood oxygen levels. Motion sensors can be incorporated to track patient mobility or identify falls. The software of the IoT-based patient monitoring system is key to providing smooth data acquisition, processing, communication, and visualization. Arduino acts as the command center, gathering real-time health data from various biomedical sensors and sending it to medical personnel via cloud platforms and IoT protocols. The system runs on an embedded programming environment, specifically designed in the Arduino IDE using C/C++ for microcontroller programming. It incorporates a number of software modules to enable sensor data processing, wireless communication, cloud integration, and real-time monitoring.

Embedded software executed by the Arduino microcontroller handles interfacing with some of these sensors, which include a pulse sensor to monitor heart rate, a temperature sensor like the DHT11 or DS18B20 for body temperature, an ECG sensor to monitor cardiac activity, and a pulse oximeter to monitor blood oxygen saturation. Other motion sensors may be used to sense patient movement or detect falls. Real-time data processing of the sensor data is performed by the microcontroller through the use of embedded algorithms with noise filtering capabilities for precise readings, and communication with external devices is facilitated through serial communication protocols like UART, SPI, or I2C. Wireless communication is also an important component of the system, which facilitates smooth data transmission and remote observation. Direct transmission of data to cloud platforms via Wi-Fi modules such as ESP8266 or ESP32 or short-range transmission of data to mobile apps through Bluetooth modules like HC-05, HC-06, or BLE is facilitated. The MQTT (Message Queuing Telemetry Transport) protocol is commonly used to effectively transmit health data from IoT devices to cloud services.

For cloud data management, tools like Firebase, AWS IoT, or Google Cloud IoT are used to store and process the patient health data. Web and mobile applications, created with JavaScript, Python (Flask/Django), or Node.js, offer interactive dashboards for healthcare professionals to view real-time health measurements. IoT dashboards like Thing Speak, Blynk, and Adafruit IO are often used to keep track of patient vitals and send alerts on anomaly detection.

Figure 5. Temperature and Humidity Fields

Fig.5 represents central to the system is the ESP8266 microcontroller (Figure 2), which is a low-cost, Wi-Fi module that allows for wireless communication between sensors and cloud platforms. The ESP8266 is popularly applied in IoT applications because it is small, consumes little power, and can efficiently process data and transmit data. It serves as the central point, gathering data from multiple sensors and transmitting it to distant servers or cloud storage solutions for data analysis and visualization.

One of the major sensors utilized in the system is the DHT11 temperature and humidity sensor (Figure 1). The sensor gives real-time temperature and humidity values, making it an important device for observing environmental conditions surrounding a patient. The DHT11 utilizes a resistive humidity sensing element and an NTC temperature sensor to give precise values, which can be utilized in determining patient comfort levels or in observing abnormal temperature variations. For cardiac monitoring, the Pulse Sensor (Figure 3) is included to assess heart rate. The sensor works by measuring fluctuations in blood circulation via the fingertip or earlobe via photoplethysmography (PPG) technology. From analysis of variations in light absorption, the sensor gives critical information on the heart rate of the patient, which allows health care practitioners to monitor cardiovascular well-being in real-time rate.

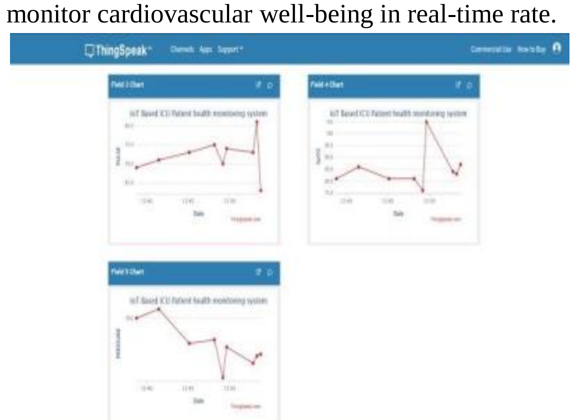

Figure 6. Pulse and Pressure Fields

Fig.6 represents the integration of different components in an IoT-based healthcare monitoring system, providing smooth data collection, processing, and visualization. The ESP8266 microcontroller (Figure 2) serves as the processing unit, facilitating wireless data transmission from multiple sensors. The DHT11 sensor (Figure 1) measures temperature and humidity levels, whereas the Pulse Sensor (Figure 3) monitors heart rate fluctuations in real time. For trustworthy power management, the BQ25175 IC (Figure 4) is used to deliver energy effectively to all powered components. Thing Speak dashboards provide the real-time data platform to see and evaluate patient health measurements in Figure 5 to see trends for temperature and humidity and in Figure 6 to show larger scopes such as prolonged vital parameters including heart rate, SpO_2, and blood pressure values. These coupled elements collaborate to create an effective IoT-based ICU patient health monitoring system, enabling healthcare professionals to monitor critical patient conditions remotely, identify anomalies, and initiate timely medical interventions. The combination of cloud computing, real-time analytics, and wireless sensor networks tremendously improves the efficiency and accessibility of patient monitoring in clinical and homecare environments

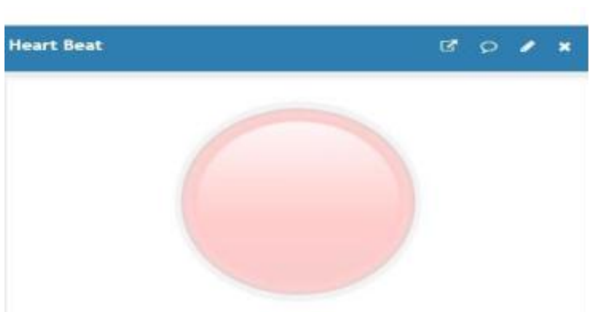

Figure7: Heart Beat Field

Fig.7 represents a simplified heartbeat visualization interface for real-time heart rate monitoring. The bold caption "Heart Beat" implies an ongoing, live presentation of cardiac activity, providing instant notice of the patient's status. A large, circular, light-pink graphical item in the middle probably symbolizes the visualized heartbeat, varying in size, brightness, or hue dynamically to reflect pulse rhythm and changes over time.

The interface offers easy-to-use tools for commenting, sharing, editing, and closing the window, implying an interactive, cooperative setting where clinicians or users could easily analyze, annotate, and share information without any hassle. The system could be part of a larger IoT-based health surveillance platform, offering automated identification of abnormal heart rhythms, real-time notifications, and remote access to physicians and care providers.

Conlusion :The quick evolution of IoT-based patient monitoring systems has transformed contemporary healthcare by facilitating real-time, continuous, and remote monitoring of patients. The literature reviewed proves that wearable sensors, AI-driven analytics, and cloud-based management of health data are dramatically enhancing patient care, lowering hospital visits, and improving early disease detection. These systems have proved to be highly effective in chronic disease management, post-surgical recovery, and emergency care, providing timely interventions and better patient outcomes.

There are a few challenges that remain to be solved for broader use. Data privacy concerns, cyber security threats, cross-platform interoperability, and implementation costs are among the major issues. Moreover, the dependability of IoT-driven healthcare solutions also relies on good network infrastructure, compliance with regulatory standards, and the willingness of healthcare professionals to adapt to new technology. Future studies must emphasize strengthening security measures, advancing energy-efficient sensor technology, and creating AI-based predictive models for early detection and proactive healthcare interventions. By overcoming these challenges, IoT-based patient monitoring systems can be instrumental in lowering healthcare expenses, streamlining resource allocation, and providing personalized, data-driven medical treatment.

Healthcare IoT is an innovative driving power, filling in the space between healthcare providers and patients, fostering proactive, preventive, and precision medicine, and ultimately culminating in an enhanced and accessible health care ecosystem. Beyond patient benefits, IoT in healthcare has also streamlined hospital operations, allowing better resource allocation, remote patient consultations, and automated alert systems for critical health conditions.

The authors are grateful to express their heartfelt appreciation to everyone who helped them in the completion of this work. We extend our gratitude e to our mentors and faculty members for their useful advice, constructive criticism, and unwavering support throughout this study. We would also wish to appreciate contributions from researchers and developers in Wireless Sensor Networks (WSNs) and

Arduino technology whose work our research has taken as a precedent.

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Artificial Intelligence Model for Air Quality Prediction and Analysis and Machine Learning

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Abstract: Throughout the long term, anticipating and breaking down air quality has gone through critical progressions. Previously, we intensely depended on customary strategies like measurable models and worked on conditions. In any case, these methodologies battled to catch the perplexing and dynamic nature of air contamination. As innovation advanced, researchers and scientists went to computer based intelligence, AI, and enormous information examination to further develop air quality forecasts. Then again, air contamination is a basic worldwide issue that influences our current circumstance as well as our wellbeing and prosperity. It is additionally connected to respiratory and cardiovascular sicknesses, prompting an expansion in diseases and passing. Precise air quality expectations enable state run administrations, nearby specialists, and people to make ideal moves to battle contamination, protect general wellbeing, and enhance metropolitan preparation. To handle this squeezing issue, we really want precise air quality forecast and investigation. Our inspiration driving fostering this artificial intelligence model stems from the constraints of conventional air quality expectation strategies. We've seen that these strategies frequently need precision and battle to represent the complicated variables impacting air contamination. The capability of man-made intelligence, with its capacity to handle huge measures of ongoing information and recognize complex examples, offers a promising answer for improve the exactness and dependability of air quality expectations. Hence, this work presents an imaginative Man-made reasoning (artificial intelligence) model intended to foresee and break down air quality with remarkable accuracy and productivity. By integrating state of the art computer based intelligence calculations and information investigation methods, this model intends to fulfill the developing need for solid continuous air quality data.

1. Introduction

Energy Consumption And its consequences are inevitable in modern age human activities. The anthropogenic sources of air pollution include emissions from industrial plants; automobiles; planes; burning of straw, coal, and kerosene; aerosol cans, etc. Various dangerous pollutants like CO, CO2, Particulate Matter (PM), NO2, SO2, O3, NH3, Pb, etc. are being released into our environment every day. Chemicals and particles constituting air pollution affect the health of humans, animals, and even plants. Scientists have realized that air pollution bears the potential to affect historical monuments adversely [1].

Vehicle emissions, atmospheric releases of power plants and factories, agriculture exhausts, etc. are responsible for increased greenhouse gases. The greenhouse gases adversely affect climate conditions and consequently, the growth of plants [2]. Emissions of inorganic carbons and greenhouse gases also affect plant-soil interactions [3]. Climatic fluctuations not only affect humans and animals, but agricultural factors and productivity are also greatly influenced [4]. Economic losses are the allied consequences too. The Air Quality Index (AQI), an assessment parameter is related to public health directly. Higher level of AQI indicates more dangerous exposure for the human population. Therefore, the urge to predict the AQI in advance motivated the scientists to monitor and model air quality.The concentration of the deadliest pollutant like PM2.5 is found to be in multiple folds in developing countries [5]. A few researchers end clieavoured to undertake the study of air quality prediction for Indian cities. After going through the available literature, a strong need had been felt to fill this gap by attempting analysis and prediction of AQI for India.

Various models have been exercised in the literature to predict AQI, like statistical, deterministic, physical, and Machine Learning (ML) models. The traditional techniques based on probability, and statistics are very complex and less efficient. The ML-based AQI prediction models have been proved to be more reliable and consistent. Advanced technologies and sensors made data collection easy and precise. Anthropogenic sources of air pollution, such as emissions from industrial plants, automobiles, planes, and the burning of various fuels like coal and kerosene, release a plethora of dangerous pollutants into the environment. These pollutants include carbon monoxide (CO), carbon dioxide (CO2), particulate matter (PM), nitrogen dioxide (NO2), sulfur dioxide (SO2), ozone (O3), ammonia (NH3), lead (Pb), among others.The release of these chemicals and particles into the atmosphere has significant consequences for human health, animal welfare, and plant life. Air pollution is associated with a wide range of serious diseases in humans, including bronchitis, heart disease, pneumonia, and lung cancer. Furthermore, scientists have recognized that air pollution can adversely affect historical monuments [6-9]. Vehicle emissions, industrial releases, and agricultural exhausts contribute to increased levels of greenhouse gases, which in turn affect climate conditions and plant growth.

Air quality assessment has been led involving regular methodologies in such an extremely long time. These methodologies include manual assortment and evaluation of crude information. The customary methodologies for air quality expectation utilize numerical and measurable methods. In these methods, at first an actual model is planned and information

Figure 1: Splitting the dataset

However, with the progression in innovation and exploration, options in contrast to conventional strategies have been proposed which use Information Mining furthermore, AI draws near.

Literature Survey: Existing System Linear Regression: Linear Regression (LR) is a simple, yet powerful statistical method used for predicting a continuous target variable (in this case, air quality measurement) based on one or more independent variables (features). It assumes a linear relationship between the predictors and the target variable [10-14]. Assumption of Linearity: It assumes a linear relationship between variables. If the relationship is non-linear, linear regression may not perform well. Sensitive to Outliers: It is sensitive to outliers, and outliers can significantly impact the model's performance. Data Accuracy and Coverage: The accuracy of air quality predictions heavily depends on the quality and coverage of the data sources. In some regions, there may be limited or outdated data, which can result in less accurate predictions

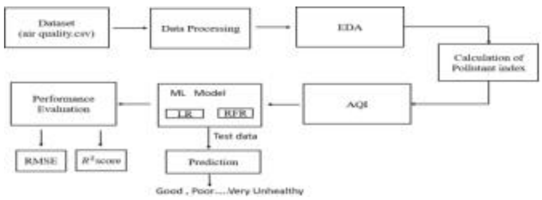
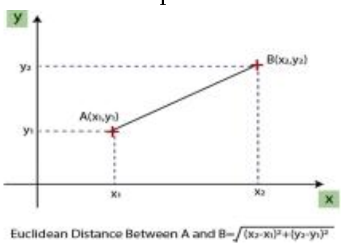


Figure 2: Overall design of proposed air quality prediction.

Proposed System: This process involves collecting real-time data from a network of IoT sensors deployed in different locations, analyzing this data, and using it to make predictions about air quality. In the process of collecting and managing data from IoT sensors, the information gathered is carefully stored within a centralized database or cloud-based platform. This data is marked with timestamps, providing details about the location of the sensors, the specific type of sensors used, and the actual measurements recorded. This meticulous recordkeeping ensures that we have a comprehensive dataset to work with. Prior to delving into data analysis, there is a crucial step known as data preprocessing. During this phase, the data undergoes a series of operations aimed at refining it for further analysis. Here, we extract and create relevant features from the raw sensor data. Moving forward, this research employs machine learning and statistical models to scrutinize the data and construct predictive models. These models draw insights from historical data, which is often used to train them. A range of algorithms, such as regression, time series analysis, or neural networks, can be applied in this context. The primary objective is to build models capable of forecasting future air quality conditions based on both historical patterns and the latest sensor readings. Specific time intervals, such as hourly or daily periods [15-18].

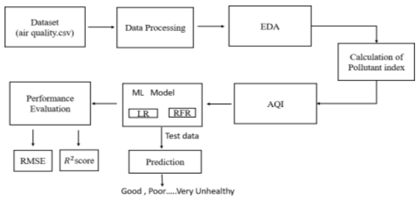
Data Preprocessing: Data pre-processing is a process of preparing the raw data and making it suitable for a machine learning model. When creating a machine learning project, it is not always a case that we come across the clean and formatted data. And while doing any operation with data, it is mandatory to clean it and put in



formatted way. So, for this, we use data pre-processing task. A real-world data generally contains noises, missing values, and maybe in an unusable format which cannot be directly used for machine learning models. Data pre-processing is required tasks for cleaning the data and making it suitable for a machine learning model which also

Graph of Euclidean distance: Increases the accuracy and efficiency of a machine learning model.

Getting the dataset, Importing libraries, Importing datasets, Finding Missing Data, Encoding Categorical Data, Splitting dataset into training and test set



Encoding Categorical data: Categorical data is data which has some categories such as, in our dataset; there are two categorical variables, Country, and Purchased. Since machine learning model completely works on mathematics and numbers, but if our dataset works on mathematics and numbers, but if our dataset would have a categorical variable, then it may create trouble while building the model. *Feature Scaling: F*eature scaling is the final step of data preprocessing in machine learning. It is a technique to standardize the independent variables of the dataset in a specific range. In feature scaling, we put our variables in the same range and in the same scale so that no variable dominates the other variable. A machine learning model is based on Euclidean distance, and if we do not scale the variable, then it will cause some issue in our machine learning model. *Splitting Dataset:* In machine learning data preprocessing, we divide our dataset into a training set and test set. This is one of the crucial steps of data preprocessing as by doing this, we can enhance the performance of our machine learning model. So we always try to make a machine learning model which performs well with the training set and also with the test dataset. Here, we can define these datasets. *Training Set:* A subset of dataset to train the machine learning model, and we already know the output. *Test set*: A subset of dataset to test the machine learning model, and by using the test set, model predicts the output

2. System Analysis Design: The RFR model is a powerful machine learning algorithm employed for tasks. It is a versatile and robust algorithm, well-suited for air quality prediction. Its ensemble nature, coupled with randomization in data sampling and feature selection, makes it effective at capturing complex relationships and delivering accurate predictions based on historical and environmental data.

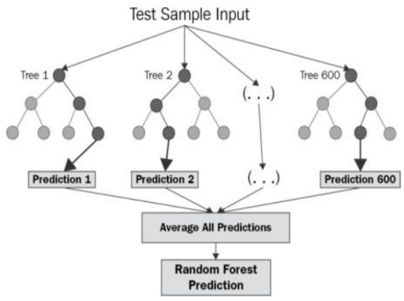


Figure 3: Working of RFR

It operates by constructing an ensemble of decision trees, and its functionality can be comprehensively explained as follows:
Ensemble of Decision Trees: It assembles a collection of decision trees during the training phase. Each decision tree, resembling a hierarchical structure, learns to make predictions based on input data. *Bootstrapped Training Data:* To train this ensemble, the algorithm employs a technique known as bootstrapping. It creates multiple subsets, or samples, of the original training data.
Random Feature Selection: In addition to data sampling, the Random Forest introduces randomness in feature selection. At each node of each decision tree, only a random subset of the available features is considered for making split decisions. *Individual Tree Training:* Each decision tree is trained independently using its unique bootstrapped sample of data. This training process employs recursive binary splitting, where the tree repeatedly divides the data into subsets

Good	219643
Poor	93272
Moderate	56571
Unhealthy	31733
Hazardous	18700
Very unhealthy	15823

based on the selected features, it continues.

Predictions by Individual Trees: Once the decision trees are trained, each tree can independently make predictions for new data points such as concentrations of pollutants like PM2.5 or NO2.
Aggregation of Predictions: The strength of the RF lies in its ensemble approach. To make a final prediction, it aggregates the predictions from all individual decision trees.
Reducing Over fitting: The ensemble nature of RFs is instrumental in mitigating over fitting. While individual trees may over fit the training data, the aggregation process tends to balance out the errors and allows the model to generalize effectively to new, unseen data.

	state	SOi	Noi	Rpi	SPMi	AQI
0	Andhra Pradesh	6.000	21.750	0.0	0.0	21.750
1	Andhra Pradesh	3.875	8.750	0.0	0.0	8.750
2	Andhra Pradesh	7.750	35.625	0.0	0.0	35.625
3	Andhra Pradesh	7.875	18.375	0.0	0.0	18.375
4	Andhra Pradesh	5.875	9.375	0.0	0.0	9.375

Prediction and Evaluation: Once trained and optimized, it can be used for air quality prediction. It takes input data containing relevant features (e.g., historical air quality data, weather conditions) and produces predictions for air quality indices or pollutant concentrations is a visualization for the classification of air quality based on the calculated AQI values. The classification likely involves different categories such as "good," "moderate," "poor," "unhealthy," "very unhealthy," and "hazardous." These categories indicate the level of pollution and associated health risks.

Conclusion: In the realm of air quality prediction, both LR and RFR models have been pivotal in providing valuable insights and forecasts. However, when assessing their performance, it becomes evident that the RFR consistently outshines LR due to its capacity to handle complex relationships and mitigate over fitting. LR, while a straightforward and interpretable model, tends to perform optimally when air quality data exhibits linear relationships. It may not capture the nuances of complex, non-linear interactions within the data, which are often present in real- world air quality scenarios.

An AI model for air quality prediction and analysis serves as a crucial tool in safeguarding public health and mitigating environmental risks. Leveraging machine learning algorithms, such models can accurately forecast air quality indices based on various parameters such as pollutant concentrations, meteorological data, and geographical factors. Future enhancements in this domain could focus on refining the predictive capabilities by incorporating advanced deep learning techniques, enabling real-time monitoring and analysis through integration with sensor networks and IoT devices. and assess the impact of regional and global factors such as wildfires or industrial emissions.

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