“SENTIMENT ANALYSIS FOR MOVIEREVIEWS USING ARTIFICIAL NEURAL NETWORKS AND RECURRENT NEURAL NETWORKS”

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DECLARATION

I hereby declare that the work presented in this report entitled **"SENTIMENT ANALYSIS FOR MOVIE REVIEWS USING ARTIFICIAL NEURAL NETWORKS AND RECURRENT NEURAL NETWORKS",** was carried out by me. I have not submittedthe matter embodied in this report for the award of any other degree or diploma of any otherUniversityorInstitute.Ihavecreditedoriginalauthorswithallthatismyoriginalcontribution, including sentences, thoughts, diagrams, graphics, computer programs, tests,findings. I use quotation marks to distinguish literal phrases and to acknowledge the originalauthors/sources.

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CertifiedthatAqib Akhtar Zia(210479010016740)hascarriedouttheresearchworkpresented in this thesis entitled "SENTIMENT ANALYSIS FOR MOVIE REVIEWS USING ARTIFICIAL NEURAL NETWORKS AND RECURRENT NEURAL NETWORKS" confirm that the thesis submitted by the student under my supervision for the award of Master of Technology original work from Dr. APJ Abdul Kalam Technical University, Lucknow. The studies presented in the thesis were carried out solely by the student, and the information in the thesis has not been used by the candidate or anyone else from this or any other University/Institution to award any other degree.

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ABSTRACT

The ability to recognize and extract sentiments from text data depends heavily on sentiment analysis. We use the dataset of IMDb movie reviews in this work to investigate the use of machine learning and deep learning approaches for sentiment analysis. Using the sentiments indicated in the text, the goal is to categorize movie reviews as positive or negative. To extract pertinent features for the machine learning methodology from the movie reviews, we use conventional feature engineering techniques. These characteristics include sentiment lexicons, bag-of-words, and n-grams. Train well-known machine learning algorithms on these features to create sentiment classifiers, including Naive Bayes, Support Vector Machines, and Logistic Regression. The deep learning approach, in contrast, uses the strength of neural networks to automatically uncover representations from unprocessed text data. We employ a recurrent neural network (RNN), specifically an LSTM network, to track the flow of discourse and extract context information from movie reviews. The LSTM network is trained using the IMDb movie review dataset to learn how to represent sentiment. separated the data into training and testing sets to determine how well each technique worked. We also compare the results of the machine learning and deep learning models to determine the advantages and disadvantages of each approach. The performance of various machine learning models, including Linear SVM, Multinomial Naive Bayes, Linear SVM, and XGboost, is examined. Linear SVM exhibited the highest accuracy of the models tested, at 89.57%.

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CHAPTER 1

INTRODUCTION

1.1 SENTIMENTANALYSIS

A computational method called sentiment analysis, also called opinion mining, is used to figure out the sentiment or feeling in a piece of text. Sentiment analysis has become increasingly important in understanding public opinion and sentiment towards products, services, brands, events, and more as a result of the exponential growth of user-generated content on social media platforms, online reviews, and other textual data sources. The goal of sentiment analysis is to classify a piece of text as either positive, negative, or neutral. Machine learning algorithms that have been taught on labeled datasets, where human annotators give sentiment labels to the text, are typically used to perform this classification. Then, these algorithms use different linguistic and statistical features to automatically study and classify new text based on the patterns and traits they learned during the training phase. Sentiment analysis has many uses in many different fields. In marketing, it can help companies determine customer sentiment toward their products or campaigns, allowing them to make decisions based on the data to increase customer satisfaction and brand recognition. In the financial world, sentiment analysis can be used to look at stock market trends by keeping track of how the public feels about certain companies or industries. This gives investors useful information. In order to understand public opinion about their business, products, or services in real time, companies and organizations use sentiment analysis in social listening. This lets them address customer issues ahead of time, handle crises, and adjust their marketing plans accordingly.

Sentiment analysis encounters various challenges, such as handling sarcasm, cultural differences, and the presence of mixed emotions within a text. These complexities hinder the accurate interpretation of sentiments through algorithmic means. To enhance the precision and usefulness of mood analysis, researchers and developers in the fields of natural language processing (NLP) and machine learning are continually exploring novel approaches.Sentiment analysis forms an integral part of market research, utilizing techniques such as text analysis, biometrics, NLP, computational linguistics, and natural language understanding (NLUE). Its purpose is to discern the prevailing emotional tone—whether neutral, positive, or negative—of various forms of data, such as emails, social media posts, or stories. By employing these analytical tools, sentiment analysis enables a deeper understanding of people's sentiments towards the examined content.You may gauge public opinion and comprehend customer experiences using sentiment analysis. Why, then, should you even consider sentiment analysis? It's very beneficial for social media monitoring, to start. It offers a hugely effective way to measure public opinion on particular issues. Furthermore, it might be crucial in customer service and market research. You can find out what consumers think about your products or those of your rivals using sentiment analysis. Making judgments based on this increased understanding of customer views and tastes is possible.

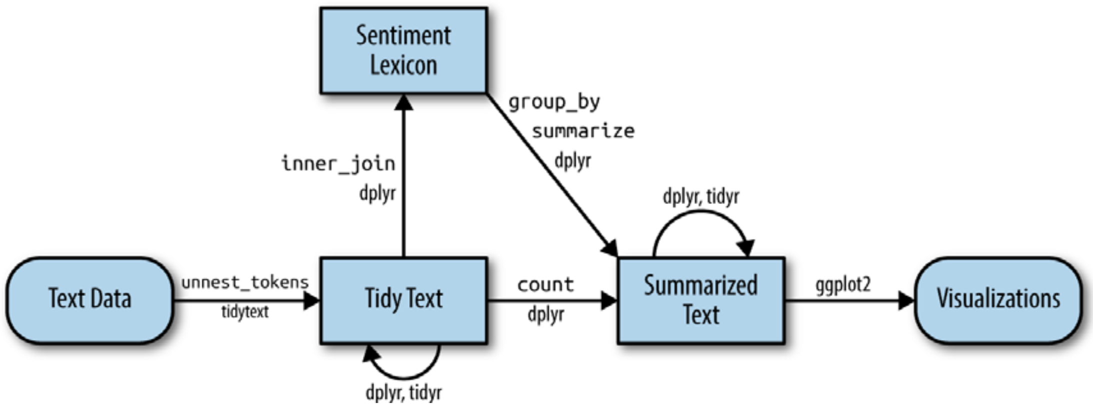


Figure 1.1 Sentiment analysis

1.1.1 SENTIMENTANALYSIS WORKS

Sentiment analysis typically takes the following actions:

1. **Assemble data:** The text under analysis is located and gathered. Utilizing a web scraping bot or application programming interface is required for this.
2. **Organize the data:** To remove background noise and voice fragments that don't contribute to the sentiment of the text, the data is processed and cleaned. This includes capitalization, punctuation, URLs, special characters, and contractions like I'm and words with minimal information like is and is. Standardising is what is meant by this.
3. **Select an ML model:**In the realm of sentiment analysis, different approaches such as rule-based, automated, or hybrid ML models are used to assess the sentiment expressed in text. In domains like law and health where precision and human oversight are paramount, rule-based systems are often utilized. These systems rely on established lexicon-based rules to perform sentiment analysis. On the other hand, automated systems leverage machine learning (ML) and deep learning algorithms to learn from datasets. Combining both strategies, hybrid models are considered to be the most accurate.

1.1.2TYPES OF SENTIMENT ANALYSIS

Sentiment analysis tools can be divided into numerous groups:

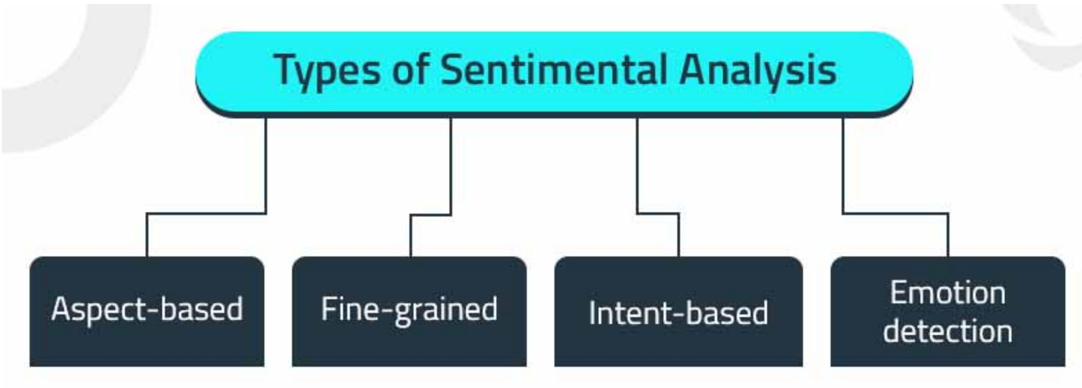


Figure 1.2 Types of sentiment analysis

Emotion Detection: Emotion detection, as its name suggests, aids in the identification of emotions. This can include rage, melancholy, joy, gratification, anxiety, worry, panic, etc. A list of phrases that express particular emotions is frequently used by emotion detection systems. Additionally, some sophisticated classifiers use powerful machine learning (ML) techniques. People convey their emotions in a variety of ways, making it preferable to employ ML over lexicons. Consider the following sentence: "This product is about to kill me." Fear and panic may be expressed in this line. A comparable phrase, "This product is killing it for me," has a very different and uplifting connotation. However, in the vocabulary, the term "kill" might be connected to anxiety or terror. This might make it harder to recognise emotions accurately.

Intent Analysis: Understanding customer preferences can enable companies to save both time and money. Often, businesses find themselves pursuing customers who have no immediate intention of making a purchase. However, this challenge can be addressed by effectively deciphering customer intent. Purpose analysis plays a crucial role in determining whether a potential buyer is actively seeking to make a purchase or simply exploring options. By accurately gauging customer intent, businesses can tailor their strategies accordingly. For instance, if a customer exhibits buying readiness, companies can strategically target them with relevant advertisements and personalized offers. By refraining from targeting individuals who are not yet prepared to make a purchase, valuable resources in terms of time and money can be conserved.

1.1.3 SENTIMENTANALYSIS PERFORMS

Sentiment analysis, which is also called "opinion mining," is a very important way to evaluate and understand how people feel in text data. It is a computer technique that uses different methods, like rule-based systems, automated machine learning (ML) models, or hybrid models, to study and categorize the tone of text. The main point of sentiment analysis is to figure out if a piece of text is good, negative, or neutral. This analysis can be used on a wide range of textual sources, such as social media posts, customer reviews, news stories, and surveys. Sentiment analysis gives valuable information about public opinion, customer feedback, company perception, and market trends by taking information about how people feel from these sources.One way that sentiment research is done is with rule-based systems. These systems rely on predefined rules and lexicons that contain sentiment-related words and phrases. By matching the text against these rules, sentiment labels are assigned to indicate the sentiment polarity. Rule-based systems are often employed in domains where precision and human control are crucial, such as legal or healthcare fields, as they provide a structured and interpretable approach. Automated ML models, on the other hand, leverage machine learning algorithms to learn from labeled datasets. These models can analyze textual features, linguistic patterns, and contextual information to automatically classify sentiment. ML models are capable of handling large volumes of data and can generalize patterns to new, unseen text. They offer the advantage of adaptability and scalability, making them suitable for applications where a significant amount of data needs to be processed

1.1.4 ASPECTS BASED SENTIMENT ANALYSIS (ABSA)

Sentiment analysis is particularly valuable when it focuses on specific attributes or aspects of the analyzed text. Aspect-based Sentiment Analysis (ABSA) is the technique employed to identify the emotions and qualities associated with these specific characteristics. Thematic refers to these aspects as "themes." For instance, when examining laptop reviews, one might be interested in the speed of the processor. By utilizing an aspect-based approach, it becomes possible to determine whether a statement regarding processor speed is neutral, positive, or negative.

- **ABSA for real-time monitoring:** Sentiment analysis is most beneficial when it is applied to a specific attribute or section of a text. ABSA, or Aspect-based Sentiment Analysis, is a technique for identifying emotions and traits associated with these features. These are referred to as "themes" by Thematic. When reading laptop reviews, you might be curious about the CPU speed. To determine whether a line describing processor speed is neutral, positive, or negative, an aspect-based technique can be utilized.
- **ABSA and Machine Learning:** Particularly helpful for real-time monitoring is aspect-based sentiment analysis. When customers raise problems on social media or in reviews, businesses can quickly find them. Response times could be sped up and customer satisfaction raised as a result. The main objectives of any business are to increase revenue and keep clients. Every additional star in a website review increases income by 5-9%, according to Apex Global Learning's research. Businesses with three-star or five-star ratings generate revenues that differ by 18%. You can use sentiment analysis to learn how many people are feeling about your brand or product. Simply said, there is usually too much data for this to be done manually. Businesses can now more easily acquire deeper insights into their text data thanks to specialised SaaS technologies. Everything from employee surveys and social media posts to consumer feedback could be included in this. Key business decisions can be influenced by the sentiment information from various sources.

1.1.5 BENEFITS OF SENTIMENT ANALYSIS

Let's examine the main advantages of sentiment analysis in more detail.

- **MORE POWERFUL:** Sentiment analysis helps businesses make sense of massive amounts of unstructured data. When working with text, even 50 instances can feel overwhelming. Particularly when dealing with other people's opinions in product evaluations or on social media.Consider a corporation that has recently released a new product. Instead of sifting through hundreds of reviews, the company can enter the data into a comment management platform. To categorize the remarks, a sentiment analysis algorithm will be employed. The company can act correctly and learn more rapidly what buyers think of their new product. Customers' favorite portions and areas where things may be improved can be found.
- **SAVE TIME:** Sentimental analysis algorithms have the ability to quickly analyses hundreds of megabytes of text. You may now use your time on more worthwhile tasks rather than manually analysing data in spreadsheets. You can test the insight by asking, for instance, "Is it worthwhile acting on this?" Business context is also an option. Is there a problem, and if so, is it seasonal? Have we observed this in other areas of the company? Sentiment analysis merely offers a signal in the end. The right plan may be developed, nevertheless, if you receive this signal quickly and with little effort.Algorithms and methods for sentiment analysis are constantly improving. By providing higher-quality and more diverse training data, they are improved. Additionally, researchers create fresh algorithms that make better use of this data. Thematic keeps track of your results and evaluates any errors. We supplement existing training data with more, more precise information as necessary.
- **ACT FASTER:** Automating sentiment analysis is done using machine learning. This means that businesses can get information right away. This can be very helpful for finding problems that need to be fixed right away. For example, bad news that is growing on social media can be found right away and dealt with. If one customer has a problem with their account and tells the company about it, other customers may have the same problem. Companies can avoid bad things happening by telling the right people right away so they can fix the problem.

1.2 SENTIMENTANALYSIS OF MOVIE REVIEWS

Sentiment analysis of film reviews is essential for understanding how and what the movie audience thinks of the movies. Sentiment analysis is a technique that allows filmmakers, production companies, and moviegoers to understand more about how people feel about movies in general and specific parts of them by analyzing text data from various sources such as internet platforms, social media, and review websites. Movie reviews can reveal a lot about how the audience felt about the film, including what they loved and disliked about it, as well as how it made them feel. Using sentiment analysis tools, we may categorize these reviews into positive, negative, or neutral sentiments, giving us a greater understanding of how people feel about a movie in general. Aspect-based sentiment analysis (ABSA), which examines individual aspects of a movie such as the acting, script, visual effects, or music, might supplement this analysis. ABSA, which provides deep insights into audience sentiments linked with each facet, can help filmmakers and studios identify strengths, shortcomings, and opportunities for improvement in their films. The findings of a sentiment analysis of movie reviews can assist filmmakers in fine-tuning their marketing efforts, better understanding their target audience, and making informed decisions for future productions. Positive sentiment can be used to highlight a film's best aspects, whilst negative sentiment can be used to demonstrate where it needs to be improved or where marketing efforts should be directed. In addition, sentiment analysis can assist consumers in deciding which movies to watch based on what they know. By examining aggregated sentiments from many reviews, audiences can assess the general reception of a movie and alter their expectations appropriately. To do sentiment analysis, natural language processing (NLP) approaches, machine learning algorithms, and sentiment classification models are widely utilized in the context of movie reviews. These techniques examine linguistic patterns, words that communicate sentiment, and context hints to correctly identify sentiment polarity.

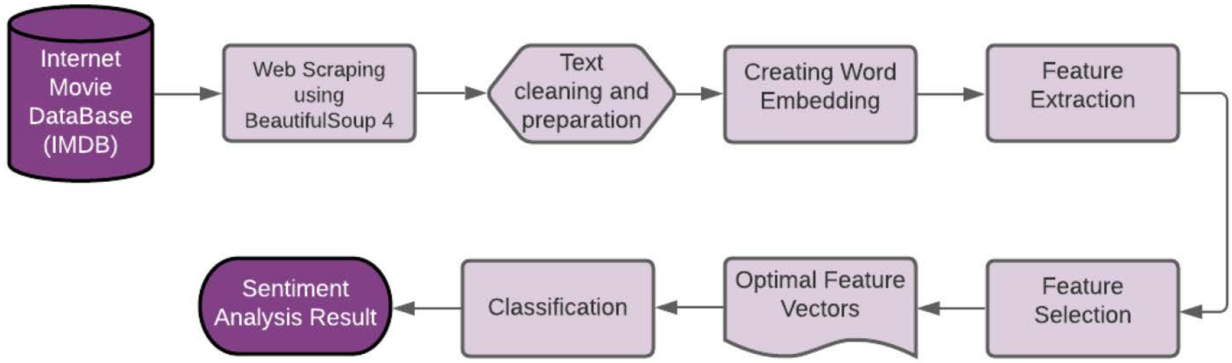


Figure 1.3 Sentiment analysis of movie reviews

Insights into audience sentiment and thoughts about films are provided by sentiment analysis of film reviews. Filmmakers and studios can better future projects by making educated decisions, enhancing marketing plans, and assessing the general sentiment and particular features of movies. The same is true for audiences, who can use sentiment analysis to inform their movie selections and control their expectations. In the always changing movie industry, sentiment analysis is a potent tool for understanding the impact and reception of films.

1.3 MACHINELEARNING SENTIMENT ANALYSIS

Automated sentiment analysis is done using machine learning (ML) methods. A machine learning system is trained to classify sentiment in this instance based on the words or their placement. How well this strategy performs depends on how good the algorithm is and how good the training data set is. ML and rule-based methods are combined in hybrid sentiment algorithms. Although much more challenging to build, they can offer more precision.

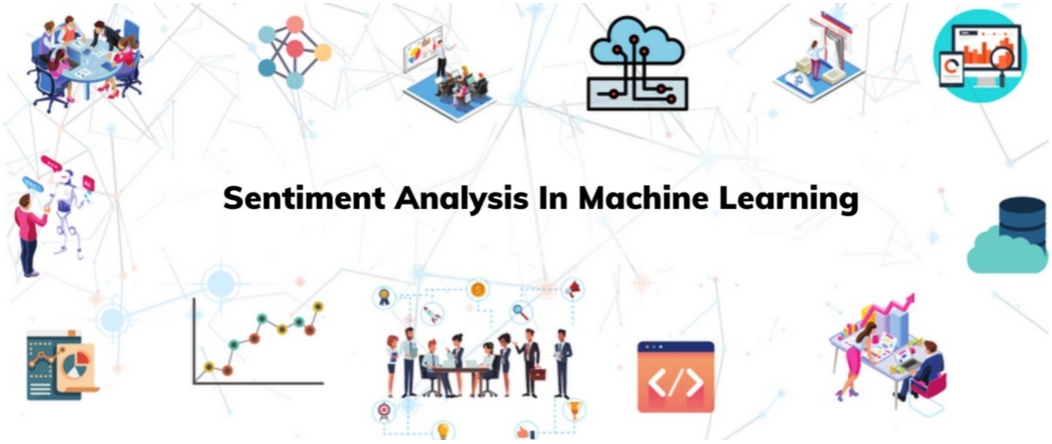


Figure 1.4 Machine learning sentiment analysis

1. **Feature extraction**

   The text must be prepared such that a computer can read it before the model can categorize it. Similar to rule-based techniques, this procedure can include tokenization, lemmatization, and stopword elimination. Additionally, a procedure known as vectorization is used to convert text into numbers. The term "features" refers to these numerical representations. The bag of words or bag-of-n-grams approaches are two typical ways to accomplish this. These vectorize text based on how frequently words appear.Deep learning has recently offered novel approaches to text vectorization. The word2vec algorithm, which makes use of a neural network model, is one instance. Word associations can be taught to the neural network by providing it with a lot of material. Each unique word is represented by a vector, or a collection of numbers, using Word2vec. This method has the benefit of giving words with comparable meanings equivalent numerical representations. This could help sentiment analysis become more accurate.

2. **Training and prediction**

   The algorithm is fed a training set with sentiment labels in the following step. The model then develops the ability to match input data with the best possible label. This input data can, for instance, consist of pairs of features (or text representations represented numerically) and the accompanying positive, negative, or neutral label. The reviews themselves or manually provided training data can both be used.

3. **Prediction**

   The final stage is where ML sentiment analysis outperforms rule-based methods the most. The model is updated with fresh text. Using the model developed from the training data, the model then predicts labels (also known as classes or tags) for this unobserved data. Thus, the sentiment of the data can be classified as either good, negative, or neutral. In rule-based sentiment analysis, a pre-defined lexicon is no longer necessary because of this.

1.4 DEEP LEARNING SENTIMENT ANALYSIS

Since deep learning yields the most precise sentiment analysis, it is worthwhile to investigate it further. Traditional ML techniques, which necessitate human effort to define classification features, have hitherto dominated the field. They frequently overlook the significance of word order as well. The field of natural language processing (NLP) has undergone significant transformations owing to the advancements in deep learning and artificial neural networks (ANNs). Drawing inspiration from the workings of the human brain, researchers have devised algorithms for deep learning, resulting in enhanced accuracy and utility in sentiment analysis. Deep learning empowers neural networks to autonomously rectify their own errors, a capability absent in traditional machine learning methods that require manual intervention for error correction. Machine learning is a component of deep learning, representing a neural network with multiple hierarchical layers. These neural networks strive to emulate the functioning of the human brain, enabling them to "learn" from vast amounts of information. However, despite their efforts, they still have substantial room for improvement. While even a single-layer neural network can yield close approximations, the addition of hidden layers assists in optimizing and fine-tuning accuracy. Deep learning techniques find extensive applications in various AI systems and services. This proliferation enables the automation of a wide range of mental and physical tasks. Notable applications of deep learning technology include well-known and cutting-edge goods and services such as digital assistants, voice-activated TV remote controls, and credit card fraud detection

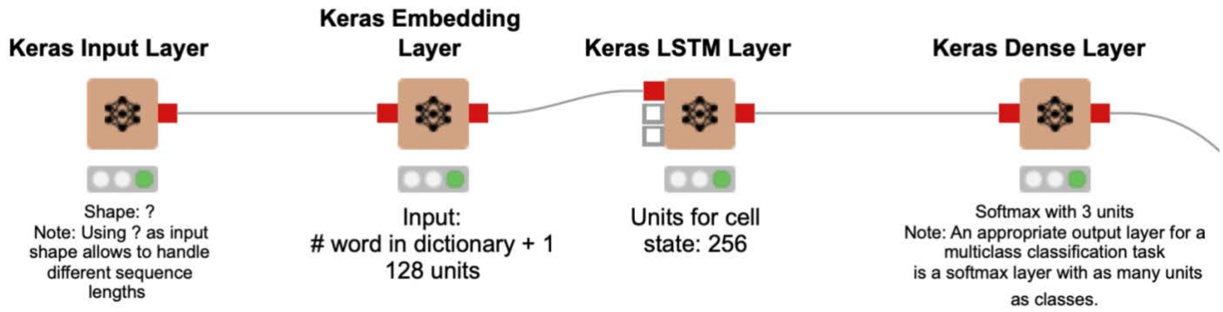


Figure 1.5 Deep learning sentiment analysis

1.4.1 ADVANTAGES OF DEEP LEARNING

- High Accuracy: Models for deep learning have displayed cutting-edge performance on a variety of challenging tasks. When compared to conventional machine learning techniques, their capacity to automatically build hierarchical representations from large datasets enables them to recognise subtle patterns and extract important information.
- Deep learning models are able to learn valuable features & representations directly from the raw data, doing away with the requirement for laborious feature engineering. Deep learning is ideally suited for jobs involving complex, high-dimensional input, such as images, audio, and text because it can automatically build hierarchical representations.
- The ability to handle enormous datasets with millions or even billions of samples is a strength of deep learning models. Deep learning's capacity for parallel processing, along with improvements in computational hardware like GPUs and TPUs, enable effective inference and training on enormous volumes of data.
- Deep learning models are excellent at extrapolating from the training set of data to new examples. They can discover underlying trends and connections in the data, which gives them the ability to forecast outcomes in novel, unforeseen situations with accuracy. This capacity for generalization is essential for real-world applications where the model must function well with a variety of data samples.

- End-to-End Learning: Deep learning models are capable of end-to-end learning, which entails training the entire system collectively to optimize a particular task.

1.4.2 APPLICTIONSOF DEEP LEARNING

In many fields, deep learning has had tremendous success. A few noteworthy applications are:

1. Computer vision: In tasks including image classification, object identification, picture segmentation, and facial recognition, deep learning models have shown ground-breaking results. Convolutional neural networks (CNNs) perform tasks requiring computer vision. are frequently utilised.
2. Natural Language Processing (NLP): Deep learning has transformed NLP by making it possible to perform tasks like question answering, sentiment analysis, text categorization, machine translation, and named entity recognition. NLP frequently uses transformer models and recurrent neural networks (RNNs).
3. Voice Recognition and Generation: Speech recognition and voice synthesis applications have substantially advanced thanks to long short-term memory networks and recurrent neural networks are examples of deep learning models. Deep learning methods are widely used in voice assistants and speech-to-text systems.
4. Deep learning has been effectively incorporated into recommendation systems to offer users personalised recommendations in e-commerce, media streaming, and other areas. Deep neural networks can record complicated interactions and preferences between users and items.

1.5 DEEP LEARNING VS. MACHINE LEARNING

If deep learning is a type of machine learning, then what sets it apart from its parent field? The nature of the data it uses and the ways in which it learns set deep learning apart from traditional machine learning. To create accurate forecasts, machine learning algorithms require "structured," or "labelled," data, in which individual features are specified from the input data for the model or tabulated accordingly. This doesn't rule out the possibility that it employs unstructured data; rather, it indicates that any such data is typically pre-processed in order to conform to a more conventional data structure. In contrast to traditional machine learning, deep learning does not require as much preparation of data. By ingesting and processing unstructured data like images and text, these algorithms reduce reliance on human specialists by automating feature extraction. Let's imagine we wanted to sort a collection of pet images into several categories, such as "cat," "dog," "hamster," etc. Algorithms trained with deep learning can figure out which characteristics (such ears) are crucial for distinguishing across species. This feature hierarchy is typically established in machine learning by a human expert.

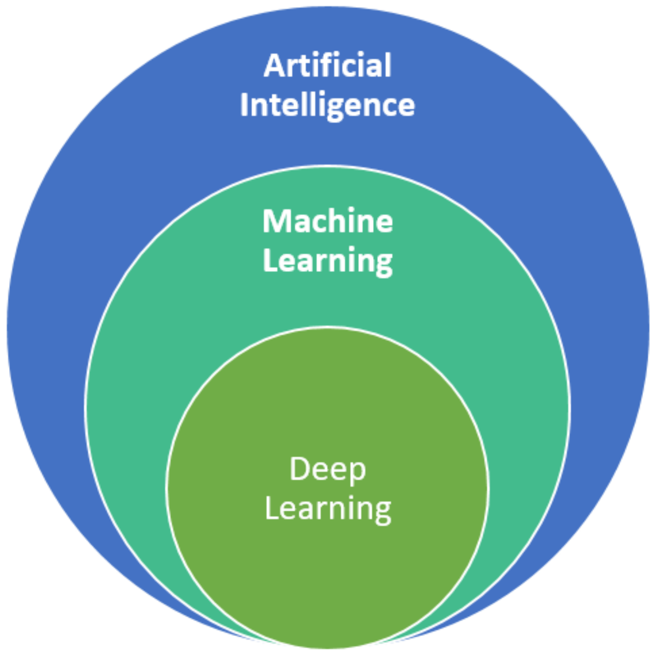


Figure 1.6 Deep learning vs. machine learning

The algorithm for deep learning then fine-tunes and "fits" itself to the data, enabling it to make more accurate predictions when presented with a new image of an animal. Both supervised and unsupervised learning, as well as reinforcement learning, are within the capabilities of machine learning as well as deep learning models. To correctly classify or forecast data, supervised learning relies on labelled datasets, which necessitates human interaction. While supervised learning relies on pre-labeled datasets, unsupervised learning can analyze raw data and group records together based on any differentiating features. The goal of reinforcement learning is to train a model to maximize its reward by improving its performance in a given environment.

1.6 DESIGNING MODELS AND ARCHITECTURE

The selection of architecture & model design is essential for accurate sentiment classification in the field of analysis of sentiment for movie reviews**.**

1. The Feed forward Neural Network (FNN)

- FNN is a fundamental ANN architecture in which data only travels in a single path, from input to output.
- This structure consists of an output layer and one or more hidden levels.
- The hidden layers may employ convolutional and attention layers in addition to complete connections or both.
- Gradient descent and back propagation algorithms can be used to train FNNs.

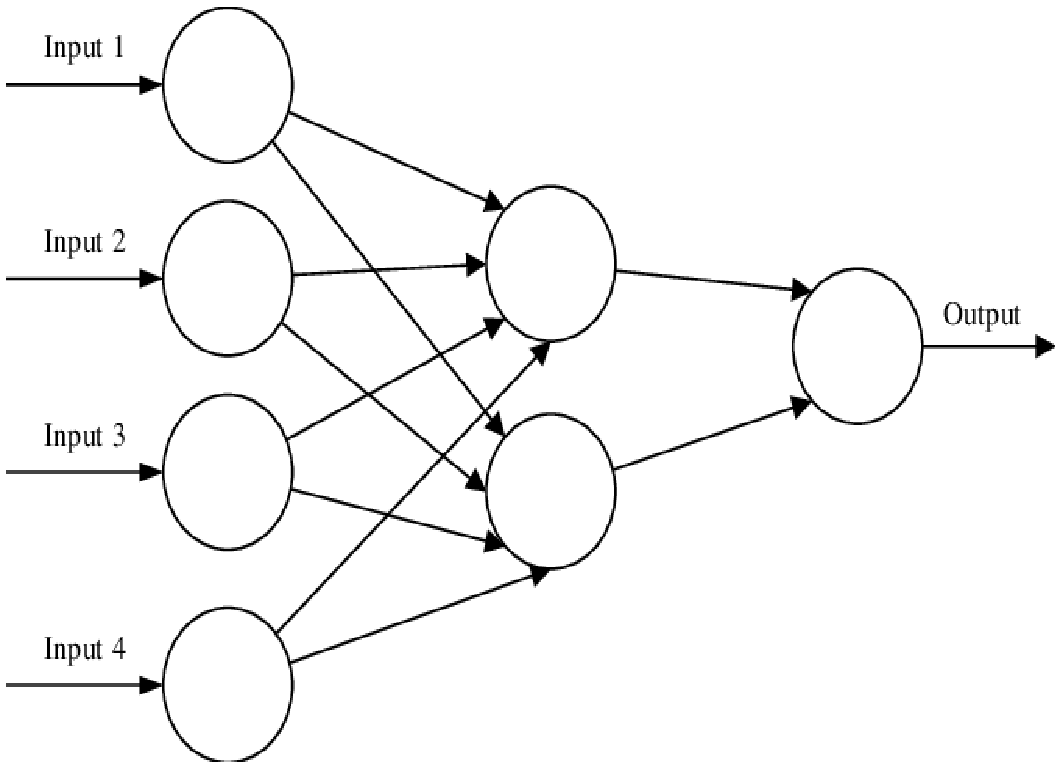


Figure 1.7Feed forward Neural Network (FNN)

2. RNN: Recurrent Neural Network

- RNNs are made to incorporate feedback links, which are intended to record sequential information.
- They perform iterative processing of input sequences, taking the prior hidden state and the current input into account at each stage.
- The network may preserve data from earlier phases thanks to the hidden state's function as memory.

- The issue of vanishing gradients is addressed by the common RNN variants Long Short-Term Memory (LSTM)& Gated Recurrent Unit (GRU), which also enhance information retention.

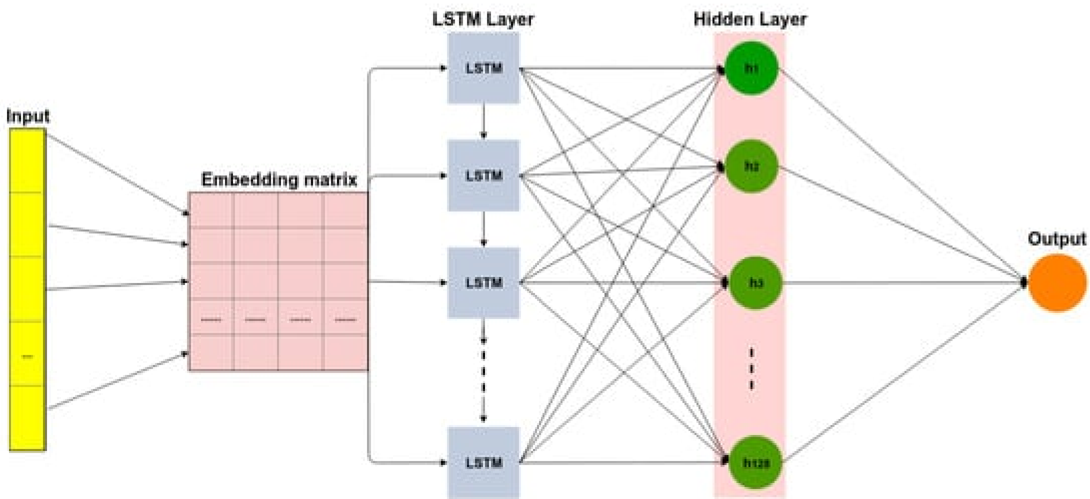


Figure 1.8 RNN: Recurrent Neural Network

3. Convolutional neural networks:

- CNNs are generally utilised for image analysis, but they may also be used for sentiment analysis and other text classification applications.
- CNNs use filters to identify regional trends while conducting sentiment analysis on text, treating it as a one-dimensional signal.
- As the filters read the input text, they extract pertinent information at various levels of abstraction.
- CNNs are able to recognise n-gram associations and learn textual hierarchy.

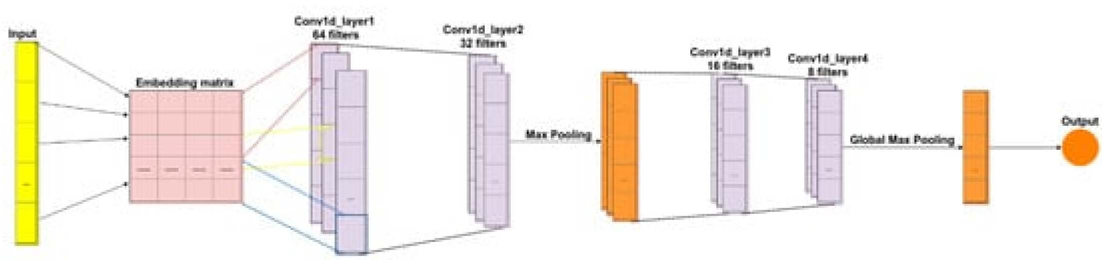


Figure 1.9 Convolutional neural networks

4. Hybrid Architectures:

- The advantages of several models are combined in hybrid architectures, such as when CNNs and RNNs are combined.
- An RNN can be used to analyse the extracted features & capture sequential dependencies, for example, when a CNN has been used as an extractor of features to collect local patterns.
- Utilising the benefits of many models will improve sentiment analysis's overall performance, according to hybrid designs.

1.7 PROCESSING OF DATA AND FEATURE REPRESENTATION

According to sentiment analysis for reviews of movies utilising artificial neural networks (ANNs) & recurrent neural networks (RNNs), data preparation and feature representation are essential processes. The methods and factors used to prepare the data and describe the features for accurate sentiment classification are the main topics of this subtopic.

1. Text Normalization and Cleaning

- Punctuation, special letters, and HTML tags are common sources of noise in raw text data that can affect how well sentiment analysis models perform.
- The text data may be cleaned and normalized using methods such as deleting punctuation, changing all text to lowercase, and managing special characters.
- You may also use text lemmatization and stemming to simplify words to their base forms and enhance feature representation.

2.Tokenization

- Tokenization is the process of separating text into tokens or words.
- It aids in dividing the material into digestible chunks for further examination.
- You may use simple approaches like whitespace tokenization as well as complex ones like leveraging libraries for natural language processing.

3.Stop Word Elimination

- Stop words are everyday words that lack feeling or substantial significance.
- Stop words like "and," "the," and "is" should be eliminated to decrease noise and increase the effectiveness of sentiment analysis models.
- But caution must be taken since in some situations, stop words may be used to express emotion.

4.Embedding Words

- Words are represented by word embeddings that are dense vectors in an ongoing space.
- Word embeddings can be created using methods such as Word2Vec, GloVe, or FastText.
- Word embeddings, which provide extensive contextual data for sentiment analysis, record the semantic links between words.

5.Sequence Padding

- Sequence padding is used to maintain consistent length since RNNs require input sequences with a set length.
- Padding increases the length of each sequence by zeros or a unique token.
- During model training, it ensures consistency and enables effective batch processing.

6.Feature Picking

- For the previously processed information to be fed into sentiment analysis models, suitable characteristics must be chosen.
- To capture significant aspects, methods such term frequency-inverse document frequency, or TF-IDF, or bag-of-words representations might be utilised.
- The use of more sophisticated techniques, such as attention mechanisms and transformer-based models, can help readers concentrate on the text's more valuable passages.

1.8 Recurrent Neural Network (RNN)

The output of one step serves as the input for the next in recurrent neural networks, or RNNs, a form of neural network. The inputs and outputs of conventional neural networks are independent of one another. However, you must keep in mind the words that occurred before the unknown word in order to determine the next word in a sentence. To address this issue, RNN, which employed a "Hidden Layer," was developed. The Hidden state, which preserves certain sequence-related information, is the RNN's most crucial and important feature. The state that keeps track of the most recent data supplied to the network is known as the memory state.

RNN-based training

- The network receives the input in a lone action.
- Then, given a set current inputs and the prior state, determine its present state.
- Depending on the problem, one can travel back to several steps and aggregate the data from all the earlier stages.
- The current time becomes time-1 for the next time step.
- After completing all essential stages, the output is calculated based on the current end state.
- After that, the output is compared to the desired output, which is the actual output, and the error is then produced.
- After the error is back-propagated to the neural network (RNN), training is given to it over time via backpropagation in order to update the weights.

Recurrent neural network benefits

- “Every piece of knowledge is retained by an RNN over time. Only the ability to recall past inputs makes it helpful for time series prediction. Long Short Term Memory is the term for this.
- Convolutional layers and recurrent networks of neurons are even combined to increase the effective pixel neighbourhood”.

Recurrent neural network drawbacks

- Issues with explosions and gradient fading.
- An RNN is extremely difficult to train.
- Tanh or relu cannot handle very long sequences when employed as the activation function.

RNN Types

According on the quantity of inputs as well as outputs in the network, there are four different types of RNNs

- **One to One**

It is sometimes referred to as a "vanilla neural network" and exhibits the same behaviour as a straightforward neural network. Just a single input and one output are present in this neural network.

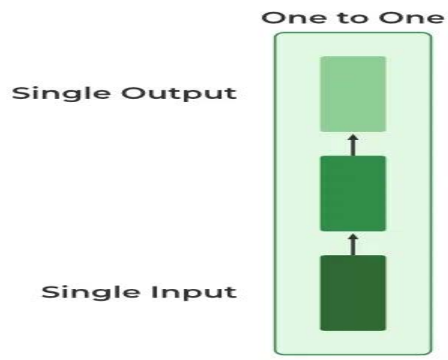


Figure 1.10 One to one RNN

- **One to many**

This kind of RNN has a single input and several related outputs. Image captioning, where we predict a phrase with many words given an image, is one of the most common applications of this network.

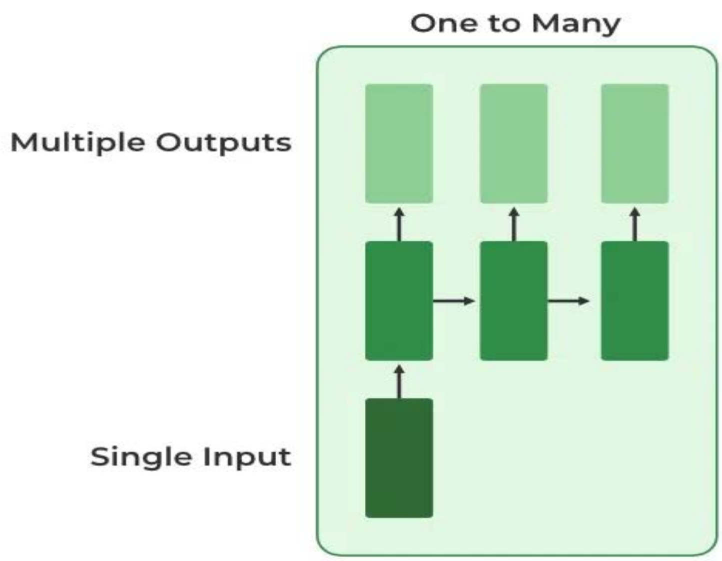


Figure 1.11 One to many RNN

- **Many to One**

In this kind of network, several inputs are delivered into the system at various network states, all of which result in a single output. Problems including sentimental analysis require this kind of network. Where just the emotion of the phrase is predicted as an output after receiving several words as input.

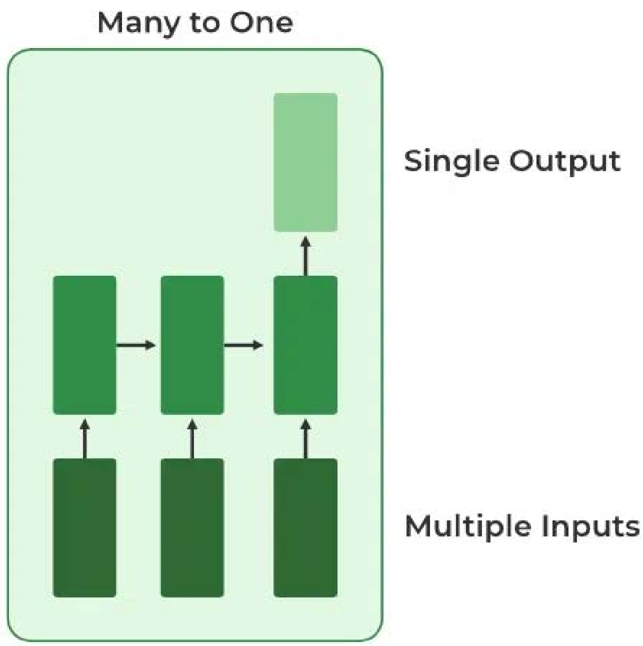


Figure 1.12 Many to One RNN

- **Many to Many**

Several inputs and several outputs that are related to an issue are included in this kind of neural network. The translation of languages will be a single instance of this issue. In translation, we offer several words from a single tongue as input and anticipate numerous words in the additional language as output.

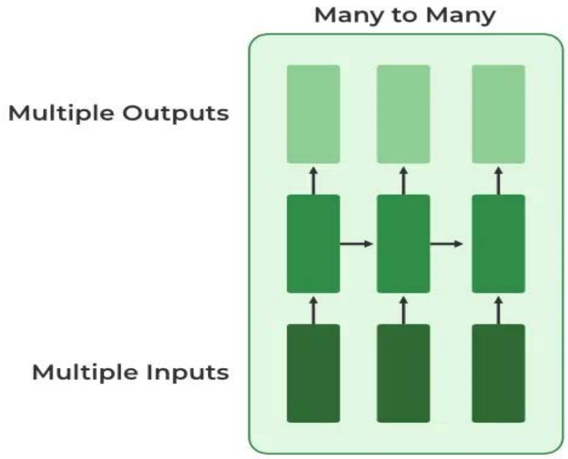


Figure 1.13 Many to Many RNN

1.9 ARTIFICIAL NEURAL NETWORKS

Algorithms called Artificial Neural Networks (ANN) are used to model complex patterns and predict problems. They are modelled after how the brain operates. A deep learning technique called an Artificial Neural Network (ANN) was developed from biological neural networks theory seen in the human brain. In an attempt to replicate how the human mind works, artificial neural networks (ANN) were created. Biological neural networks and ANNs function in very similar ways, however they do not function in the same way. Only numerical and structured data are accepted by the ANN algorithm.

1.9.1 ARTIFICIAL NEURAL NETWORKS ARCHITECTURE

1. The input layer, hidden layer (there is more than one), and output layer are the three layers that make up the network architecture. They are frequently referred to as MLPs (Multi-Layer Perceptrons) due to their many layers.
2. The hidden layer in a neural network can be envisioned as a "distillation layer" that extracts and transmits key patterns and trends from the input sources to the subsequent layers for deeper analysis. This layer plays a vital role in enhancing the efficiency and effectiveness of the network by identifying and eliminating redundant data from the sources. By performing this task, it accelerates the processing speed of the network and optimizes its performance, ensuring that the subsequent layers focus on essential

information for improved analysis.For two reasons, enabling the feature is essential. It first allows you to turn on your computer.

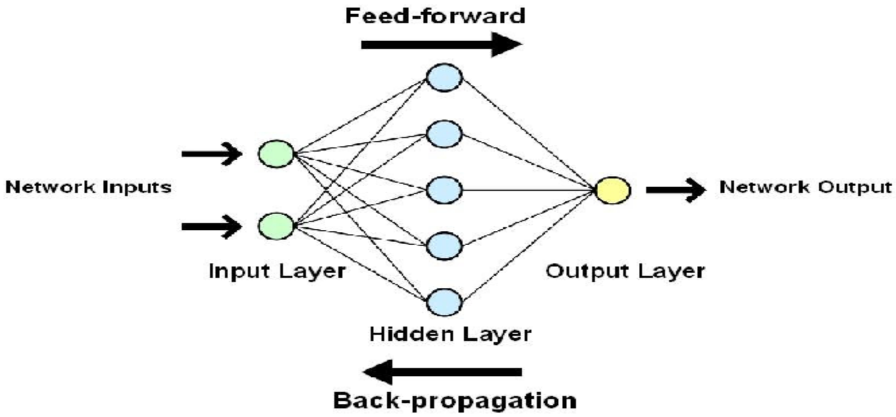


Figure 1.14 Artificial neural network architecture

1.9.2 FEATURES OF ARTIFICIAL NEURAL NETWORKS

Artificial neural networks (ANNs) have a number of crucial traits that increase their efficiency in a variety of applications.

1. Nonlinearity: ANNs use nonlinear activation processes for specific neurons, which enables them to model complicated connections and detect nonlinear patterns in the data.ANNs can tackle extremely complex and nonlinear situations thanks to their nonlinearity.
2. Learning and Adaptability: ANNs may adjust their internal parameters (weights and biases) to optimise performance by learning from data. The parameters are changed throughout this training phase depending on the input-output patterns seen in the training data. ANNs have the ability to extrapolate from training data and generate predictions about new data.

3. Parallel Processing: ANNs are capable of doing calculations simultaneously. Because the neurons in a layer may analyse incoming data concurrently, ANNs can handle big datasets and do calculations quickly by using the capabilities of contemporary parallel computing systems.

4. Distributed Representation: ANNs use distributed representation, which means that data is not stored in a single unit of neurons but rather in the activation patterns of numerous neurons. By mixing and modifying signals from several sources, ANNs are able to gather and analyse complicated information thanks to this distributed representation.
5. Robustness and fault tolerance: ANNs are naturally robust and fault-tolerant to noisy or missing data. ANNs can still produce appropriate outputs even when certain neurons or links are damaged or missing because of the dispersed nature of information representation & redundant nature in connectivity.
6. ANNs are designed to generalise from training data in order to generate precise predictions on unknown or test data. ANNs may generalise and make predictions about similar but previously unobserved cases by learning patterns & underlying relationships from training data.
7. Representation Learning and Feature Extraction: ANNs are capable of automatically learning and extracting useful features from unprocessed or highly dimensional input data. ANNs are capable of recording abstract and higher-level information because they can gradually acquire hierarchical representations for the data through the use of numerous layers of neurons.
8. Adaptability to Different Data Types: ANNs are capable of handling a variety of data types, including categorical, textual, and numerical data. To efficiently accept particular data formats and extract pertinent characteristics, a variety of designs and methods for preprocessing can be used.
9. Scalability: To handle datasets of different sizes, ANNs can be scaled up or scaled down. Depending on the intricacy of the issue at hand and the available computer resources, the network's size and complexity can be changed.

1.9.3 ARTIFICIAL NEURAL NETWORK APPLICATIONS

The diverse range of uses for ANNs is due to their special characteristics. Several significant uses for ANNs include:

1. Image processing or character recognition: ANNs are widely used in image processing highly character identification because to their ability to handle a large number of inputs and uncover complex, hidden non-linear relationships. Character recognition, like

handwriting recognition, is useful for a variety of tasks, including conducting national security analyses and spotting fraud (like bank fraud). Image recognition is a fast developing field that has a variety of uses, including as facial recognition on social media, cancer detection in the medical field, and satellite processing of images for agricultural and defence purposes.

2. Forecasting: Economic & monetary policy, finance, the stock market, and daily business choices (sales, financial allocation of resources among items, and capacity utilisation) all heavily rely on forecasting. Complex forecasting problems are common; for instance, projecting stock prices is difficult due to a number of underlying variables (some known, some unknown).

1.9.4ARTIFICIAL NEURAL NETWORKS HAVE SEVERAL BENEFITS

- In ANN, issues are represented as pairs of attributes and values.
- ANN output must be either real-valued or a vector of real or discrete-valued features, whereas the target function could be discrete-valued, genuine-valued, or a vector of different real or discrete-valued qualities.
- Noise from the first training data does not provide a problem for ANN learning methods. Even if the training samples have mistakes, the results will still be accurate.
- It is employed when a rapid assessment of the taught target function is required.
- Longer training periods for ANNs may be caused by a greater amount of network the weights, the quantity of test cases processed, or the configurations of different learning algorithm parameters.

1.9.5ARTIFICIAL NEURAL NETWORKS NEGATIVE ASPECTS

1. Hardware Dependence: Parallel processors are required for the development of Artificial Neural Networks.Therealisation of the device is therefore dependent.
2. Understanding how the network functions is the most significant problem with ANN. When ANN responds to a challenging question, it doesn't say why or the way it was selected. As a consequence, the network loses faith in itself.

3. Guaranteed network structure: The structure of computerised neural networks is not predetermined by any precise rules.To create a proper network structure, expertise and experimentation are utilised.
4. Difficulty in communicating the problem to the network: ANNs can process numerical data. Problems must be transformed into numerical values prior being introduced to ANN.

CHAPTER 2

LITERATURE REVIEW

Iddrisu 2023 et al. develops a framework with three operators—Assemble + Deft, Edify + Authenticate, and Forecast—to identify if an opinion instance is being sarcastic or not. A Twitter dataset is used to evaluate the framework employing a recurrent neural network (RNN) along using Gated Recurrent Unit & Support Vector Machines (SVM), two important state-of-the-art methods. Opinions of how the COVID-19 epidemic has affected air travel are included in the dataset. Precision, accuracy, recall, and F1-score are some of the evaluation criteria employed. The experimental research revealed a considerable rise from 10.1% optimised sentiment analysis to 9.28% under a normal sentiment review. The findings indicate a significant enhancement in the predictive capability of the optimized Support Vector Machine (SVM) compared to Recurrent Neural Networks (RNN). These research outcomes hold great potential for the aviation industry, enabling airlines to gain deeper insights into customer dissatisfaction and complaints. Consequently, this understanding will empower them to make informed decisions on how to improve their services and offerings. Moreover, the proposed framework serves as a valuable benchmark for sentiment analysis, not limited to the aviation sector alone. Its applicability extends to various industries where capturing and analyzing consumer feedback and opinions are crucial for delivering exceptional services. By establishing a standardized approach, this framework facilitates accurate sentiment analysis across diverse domains, thereby promoting better decision-making and enhanced customer experiences..[1]

Chan 2023 et al. Deep Learning has changed the field of natural language processing, making it possible to extract and analyze feelings in Chinese and other languages in a more accurate and complex way. This paper is about how deep learning methods can be used to analyze how people feel about things in the Chinese language. The first part of the study talks about the difficulties and complexities of analyzing sentiment in Chinese, such as the use of homophones, idioms, and the lack of clear sentiment indicators. Because of these differences, it's important to come up with specific ways to pull out and analyze the feelings in Chinese writing. The study then looks at how different deep learning models, such as recurrent neural networks (RNNs), convolutional neural networks (CNNs), and transformer models, are used to analyze Chinese sentiment. These models have done a good job of capturing the semantic and contextual information that is needed for correct classification of sentiment. Also, the study looks into techniques, like word embeddings and attention mechanisms, that make it easier to understand and describe Chinese text for sentiment analysis tasks. It also talks about how to use pre-trained language models, like BERT (Bidirectional Encoder Representations from Transformers), to pull out and analyze mood in Chinese.[2]

Paliwal 2023 et al. A landslip is a rapid downward movement of the geomaterial along slopes of mountains that may be made up of rock, soil, or a combination of both owing to various natural or manmade processes. The Himalayan Mountain sides are made up of both rocks and old dirt. Most of the dirt left behind is made by the weathering of bedrock on gentle to moderate slopes. On the other hand, steep slopes tend to be rocky and bare of dirt. There isn't a stable prediction method that can look at the slope in terms of both the soil and the rock surface. In this study, artificial neural network technology was used to make predictions about the stability of the joined rock with residual dirt slope in the Himalayas. The library for an artificial neural network was made by running a lot of numerical simulations of models of residual soils or rock slopes. With the help of artificial neural networks and computing, nonlinear equations have been made. Using an Android app, you can also quickly predict how stable a rock and dirt slope will be. It was found that the newly made Android app has potential for predicting the stability and safety of hills.[3]

Yu 2022 et al. Fine-grained, aspect-based mood analysis has become a valuable approach to examine people's emotions in greater depth, particularly in the economic and financial domains. This paper discusses how to apply this strategy to an economic and financial lexicon. The study begins by discussing the importance of fine-grained sentiment analysis in the economic and financial fields, where having a clear understanding of how people feel about specific things like market trends, economic indicators, financial products, or company performance is critical for making decisions and determining risks. The paper then discusses the concept of "aspect-based sentiment analysis," which is a method of discovering and analyzing how individuals feel about specific features or aspects. This can include topics like interest rates, stock performance, inflation, government policies, or firm earnings in the economic and financial realm. The paper discusses how to create and use an economic and financial vocabulary designed for mood analysis. This dictionary contains terms, phrases, and mood indicators related to economic and financial issues. It is a useful tool for determining how individuals feel in this sector.[4]

Xu 2022 et al. This article introduces the concept of sports picture sequence analysis and feature extraction, highlighting the significance of sports in this context. The application of template matching technology for identifying human motion has shown a detection rate ranging from 15% to 47%, as evidenced by the testing results. In contrast, the accuracy of the image sequence analysis approach has significantly improved from 17% to approximately 65%. While initially, the image sequence analysis approach surpassed template matching technology in terms of popularity, over time, the popularity of the image sequence analysis approach has notably increased compared to template matching technology. Therefore, it is crucial to employ cyclic neural networks for the analysis and feature extraction of sports images through sequence analysis..[5]

Wu 2022 et al. BP (backpropagation) This study focuses on analyzing the weldability of metals using a network-based approach. Tensile tests are conducted on welded joints using testing samples as training data. The results reveal that metallic materials exhibit tensile strengths around 500 MPa and yield strengths of approximately 400 MPa. To further investigate the impact of welder current, electrode pressure, and power-on duration on the tensile and shear strengths of metal materials, both shear tests and tension tests are conducted. The findings indicate that the shear strength of spot welding increases steadily with higher welding currents. However, when the weld current reaches 10,000 Amperes, the shear strength experiences a sharp decline from 24.25 MPa to 18.84 MPa.[6]

Alshuwaier 2022 et al. In order to identify various features in the text, we aim to offer a systematic overview of the literature on deep learning techniques for document-based sentiment evaluation in this work. A brief overview of recent advancements in sentiment analysis techniques and applications for deep learning is also provided in this systematic review of the literature. Starting with the convolutional neural network, it moves on to cover the recurrent neural network, which has several features including long short-term memory as well as gated repetitive units. The implementation and use of recursive neural networks, deep belief networks, domain-adversarial network models, and hybrid neural networks are also covered in this paper. The majority of articles released when the development of deep learning began are taken into account in this study, specifically the sentimental evaluation of the documents.[7]

Arora 2022 et al. The paper investigates fine-grained sentiment analysis techniques such as supervised learning, deep learning models, and rule-based methods, as well as other machine learning and natural language processing techniques. These techniques use economic and financial language to categorize sentiment toward certain themes, allowing for a more comprehensive grasp of sentiment in economic and financial information. The paper addresses difficulties connected to fine-grained sentiment analysis in the economic and financial sectors, such as the necessity for domain knowledge, term clarification, handling context-dependent sentiment, and dealing with language variances across diverse financial markets and locations. This paper also discusses the potential applications and benefits of fine-grained, aspect-based sentiment analysis in economics and finance. It underlines how this strategy can assist financial institutions, investors, decision-makers, and analysts in making sound decisions, identifying market trends, weighing risks, and efficiently managing portfolios. It shows how to build and use a financial and economic lexicon for sentiment analysis, as well as how to use a range of techniques for performing fine-grained sentiment analysis. The work enhances sentiment analysis research in economic and financial contexts by identifying its applications and resolving the challenges that occur.[8]

Miao 2022 et al. This article focuses on analyzing time-series data (TSD) related to movies and developing a movie recommendation system. The proposed system incorporates recurrent neural networks (RNN) and the multifractaldetrended mobile cross-correlation analysis (MF-DCCA) technique within an Internet of Things (IoT) framework. Several modifications are made to the standard RNN model to improve its performance in capturing spatial-temporal transformations. This includes replacing the conventional convolution operation with spatial adaptive convolution and introducing an additional convolution layer to obtain position parameters for adaptive convolution. Additionally, the MF-DCCA approach is optimized to minimize noise signal interference during the analysis and processing of TSD from movies. Extensive testing of the TSD analytics system demonstrates its stability and flawless functionality. When using long short-term memory (LSTM) as the prediction method, the LSTM network achieves a high one-frame similarity of 0.977 and a nine-frame similarity of 0.727. This unique approach combining the MF-DCCA method and RNN model provides an effective means of analyzing TSD from movies.[9]

Surendiran 2022 et al. With modified recurrent neural networks (mRNN), we create a method for extracting and segmenting the optic disc and cup from an input image of the eye. In order to take use of the intra- and interslice contexts, the mRNN combines recurrent neural networks (RNN) and fully convolutional networks (FCN). By creating a feature mapping for the intraslice and interslice contexts, the FCN can determine what is in a picture. RNN pays more attention to the backdrop between slices in order to extract relevant information. The test is performed to determine how well the model that uses context data to determine the optimal approach to separate an optical disc from a cup performs. The test results reveal that the proposed method, dubbed mRNN, outperforms existing deep learning models such as Drive, STARE, MESSIDOR, ORIGA, and DIARETDB in terms of improving segmentation rate.[10]

Lakshmipathy 2022 et al. The flat plate collectors (FPC) utilised in solar thermal applications might need some design improvements to perform better. Retaining the available heat energy inside the collector is one technique to enhance the FPC's performance characteristics. This means that a collector must be able to provide a working fluid with greater heat energy for a longer period of time. The solar cavity collector (SCC) is the result of its implementation in this manner in an upgraded and entertained model. It has five different cavity counts and is fitted with intake and output tubes. Construction and testing of the same system with an enclosure were done to determine its best performance. Generally speaking, the collector's physical attributes have a greater impact on how SCC behaves when it is operating. The comparison of five to seven number of cavities and the impact of aperture entrance are the performance variables taken into account for the current investigation. Other performance factors taken into account include water mass flow rates, two different types of flow modes, and collector tilt angles. The artificial neural network (ANN) assists in training, testing, and validating the experimentation data. The model's accuracy is 96%, and the final findings showed that both experimental & ANN simulation results followed the same general pattern. Additionally, there are 4% differences between ANN and tested findings.[11]

Ali Al-Abyadh 2022 et al. evaluates the dependability of various hybrid methods on various datasets. We contrast single models with hybrid models across domains and datasets. Our techniques for deep sentiment analysis and learning take into account text from tweets and reviews. The hybrid model is created by combining the support vector machines (SVM), long short-term memory (LSTM), and ghost model convolution neural network (CNN). Each method's reliability and calculation time were assessed. When the techniques of deep learning & SVM are coupled, hybrid models perform better than single models on all datasets. While the latest deep learning techniques have lately demonstrated their great promise in sentiment analysis, older models were less reliable. Feature maps employ linear transformations to get rid of redundant or related features. The ghost unit creates ghost features by removing from each fundamental feature elements that are identical and redundant. CNN requires less hyperparameter changing and monitoring whereas LSTM requires more processing time but yields better results. Depending on the job, the integrated model's efficacy varies, and some performed better than others. LSTM networks, CNNs, & SVMs are required for the learning of hybrid deep emotional models of learning. We examined the accuracy and errors of SVM, LSTM, and CNN using hybrid models and compared their performance. Models combining deep learning and SVM increase the precision of sentiment analysis. Experimental findings have demonstrated the suggested model's accuracy, which was 91.3 percent for datasets of type 1 and 8 while 91.5 percent for type 8.[12]

Fu 2022 et al. Due to high traffic and unique data, traditional intrusion detection will have issues with accuracy, false hits, and reliance on reduction of dimensionality techniques. For the purpose of navigating the complicated network environment of today, it is crucial to build up a quick and effective network assault anomaly detection system. In this paper, a recurrent neural network is employed to create a computer network intrusion detection model. This is done to investigate a fresh method of detecting invasions. The following are some of the main objectives of this article: 1) Design a network security rescue system based on the recurrent neural network paradigm. The management center module, knowledge database module, data collecting module, risk detecting tool module, risk analysis and handling module, data security module, and connection from distance auxiliary module are all components of this system. The system functions well because all of its components operate together. (2) A network intrusion detection model is created that combines a deep neural network (DNN) and a bidirectional long short-term memory (BiLSTM) to handle the intrusion analysis and processing module.BiLSTM is suggested as a way to find the significance between features, and DNN is suggested as a way to find deeper features, since current models don't take into account the before-and-after relevance of intrusion data features and the multifeature problem. It is suggested that an attention mechanism be added to the network in order to increase consideration for the significance of features in order to address the problem that the model doesn't take into account the significance of characteristics. (3) Extensive tests have shown that the method suggested in this study is reliable and effective.[13]

Madhiarasan 2022 et al. demonstrates the many artificial neural network topologies, kinds, benefits, and drawbacks, as well as their uses. As a result, this study offers useful information to learners and investigators so they may learn more about artificial neural networks and do research on them. Additionally, this study suggested models for forecasting solar irradiance using multilayer perceptron neural networks, rainfall using enhanced backpropagation neural networks, and temperature using Elman neural networks. A variety of hidden neurons are used to analyseand test the efficacy of the suggested neural network-based models for forecasting using real-time meteorological data. The suggested neural network-based forecasting models provide accurate outcomes with lower error rates for the applications under consideration and promote sustainability.[14]

Ghosh 2022 et al. is to provide a subsampled and balancing recurrent neuron lossless data compression (SB-RNLDC) method for boosting compression rate while lowering compression time. This is achieved by creating two models, one for BRN-LDC and the other for subsampled averaged telemetry data preprocessing. At the preprocessing stage, subsampling & averaging are done with the aid of a variable sampling factor. Depending on the probability assessment made at the LDC step, the data is encoded using an appropriate balanced compression interval (BCI). This study compares differential compression methods head-to-head. The final product shows how the balancing-based LDC may speed up compression while also enhancing reliability. Final experimental findings demonstrate that, in comparison to current approaches, the model suggested can improve computational capabilities in data compression.[15]

Ullah 2022 et al. The input layer is referred to as the embedding layer, and it encodes the dataset as a series of integers called vectors. Dimensions are decreased using a global max-pooling layer. Additionally, a dropout layer and a dense classification layer are utilised in the neural network's model to enhance generalisation error and lessen overfitting. The last layer to forecast between two classes is one that is totally linked. The research community uses two datasets that are well-liked by movie reviewers. The first dataset has 25,000 samples, half of which are positive and half of which are negative, while the second dataset has 50,000 samples of movie reviews. Binary classification, a function of our neural network model, determines whether a movie review is good or negative. On both datasets, the model achieves 92% accuracy, which is superior than conventional machine learning models in terms of efficiency.[16]

Wang 2022 et al. aims to investigate the subject of self-driving vehicle route planning and to advocate the development of a route planning model. This study employs a model of recurrent neural networks to construct a self-driving vehicle route planning model. The driving route is planned using a high-speed priority system, and the challenge of choosing the best route takes into account both the amount and quality of attractive sights. The created model is applied to enhance self-driving journey routes, and the outcomes are encouraging.[17]

Yao 2022 et al. presents the ideas of two different types of neural networks before building a cell recognition model using the convolution neural network theory and staining principle. The best cell identification model put forward in this study was evaluated in the experimental section utilising three sets of experiments created using the same equations as the experiment.[18]

Ning 2022 et al. Avoid the issue of manually picking characteristics by using artificial neural networks to identify folk music genres and convert audio information into a sound spectrum. In addition, we mix a number in music data enhancement techniques with the properties of the music signal to improve the music data. The suggested approach can isolate sound spectrum components that have been more closely related to a specific musical genre. The efficiency of our model is confirmed by experimental findings, which show that the suggested strategy achieves an excellent rate of accuracy.[19]

Zhang 2021 et al. LDA is used to pull out the topics of comments about movies, and it can also figure out how people feel about those themes. In order to make content-based suggestion algorithms better, we add emotional tendencies to user interest models and product feature models. When applying sentiment categorization to recommendation systems, previous research mostly focused on how to use sentiment dictionaries to figure out polarity and pattern matching techniques to find features. In this work, LDA is used to find themes, and BERT is used to train sentiment classification models. The algorithm is used on the collection of movie reviews from Douban, and the trial showed that the number of suggested reading lists increased significantly.[20]

Abid 2021 et al. based on material from social media, a contextualised concatenated word representation (CCWRs) is created and used to identify misspelt and out-of-vocabulary words (OOV). Upon the sequence of input, many word representation models used in CCWRs, such as Word2Vec, its optimised counterpart FastText, Global Vectors, &GloVe, combine to provide contextualised representations. Second, it is suggested to use dilated convolution kernels rather than traditional CNN kernels in a three-layered dilated convolutional neural networks (3D-

CNN). With various dilation rates, the detail loss problem is successfully solved and long-term context information is obtained by including the extension into the size of the receptive field. The suggested framework provides trustworthy results through the selection of multiple hyperparameter settings and configurations for enhanced optimisation, which results in a reduction in processing resources and dependable accuracy, according to experiments on datasets.[21]

Uba 2021 et al. The University of Energy & Natural Resources, Ghana, administration block was chosen and modelled in SketchUp for energy analysis. EnergyPlus was used to calculate the facility's daily energy use for the year 2018, with equipment in the building using 68.7% of the power consumed, cooling using 26.78%, and lights using the remaining percentage. The artificial neural network model was created in MATLAB and used meteorological variables and days as input neurons and output neurons for equipment, lighting, cooling, and overall building power use. The model's R values for training, testing, and validation were all 0.999 after training, and its validation performance was 1.7 10-4. It was able to make predictions about how much energy will be used for equipment, lighting, and cooling that were very accurate. EnergyPlus simulations were contrasted with the outcomes of the ANN model prediction. Lighting, cooling down and equipment all have maximum deviation profiles that are 13%, 8%, and 4%, respectively. The difficulty in forecasting people's conduct and weather conditions is the cause of the lighting & cooling differences. Due to its independence from outside circumstances, the equipment's value is listed as being the lowest.[22]

Manoharan 2021 et al. the significance of using internet of things (IoT)-based intelligent monitoring devices to keep track of how much each household's various appliances are being charged. In India, it has been shown that commercial appliances that receive significantly more charge than the similar appliances do squander 20% of the energy they consume. The implementation of an intelligent device to monitor charge flow requires a reliable method of gathering accurate information. Wireless sensor networks (WSNs) offer a solution by enabling precise data collection on charge flow. While many researchers have developed intelligent devices for charge tracking, these solutions often suffer from high implementation costs, energy consumption, and delays. To reduce packet transmission latency in a network, it is crucial to extract precise information at the right moments. One approach to achieving real-time data extraction from the network layer is by consolidating multiple network regions into a single cluster. Additionally, a binary coded artificial neural network (BCANN) can be utilized to learn about hidden layers, aiding in the extraction process. To assess the effectiveness of this integration approach, several tests have been conducted using both online and offline analyses. The results demonstrate that this simulation-based method outperforms existing approaches in various scenarios, achieving a success rate of 52.4%..[23]

Ali 2017 et al. A study conducted in the Northern Area and Khyber Pakhtunkhwa (KPK) regions of Pakistan utilized the MLPNN algorithm to analyze monthly time series data of the Standardized Precipitation Evapotranspiration Index (SPEI) at seventeen climatological sites. The researchers evaluated the performance of the MLPNN model using various metrics such as Mean Average Error (MAE), coefficient of correlation (R), and Root Mean Square Error (RMSE). The results indicated that MLPNN has the potential to be an effective tool for forecasting drought conditions based on SPEI. This finding suggests that water resource managers and decision-makers can employ the MLPNN model to anticipate and prepare for water scarcity issues in advance, particularly in areas facing water shortages. This can enable them to make informed decisions regarding water management and take timely actions to address water-related challenges.[24]

Wei 2021et al. to create a traffic behaviour modelling technique for mobile malware detection using a one-dimensional convolutional neural network (CNN) with autoencoder and an independent recurrent neural network (1DCAE-IndRNN). The design addresses the issue that the majority of current methods for detecting mobile malware traffic have trouble capturing the dynamics of the network traffic and the sequential patterns of abnormalities in the traffic. To extract local information from various network flows, we recreate and use the a one-dimensional convolutional neural network. In order to emphasise the sequential link between the most relevant characteristics, the autoencoder is used to digest the main traffic characteristics of the neural network and is included into an independent recurrent neural networks design. In order to successfully address the issue of unstable training, the Softmax function with the LReLU function of activation is also modified and integrated to the neurons of the independently recurrent neural network. In order to assess the performance of the suggested technique for the 1DCAE-IndRNN-integrated detection procedure, we run a number of tests. The suggested technique yields up to 98% detection precision and recall rates, clearly outperforming previous benchmark methods, according on the detection findings of the open Android malware dataset

CICAndMal2017.[25]

Bian 2021 et al. To examine sentimental analysis of Chinese artworks, they integrate their aesthetic features with an improved SqueezeNet model. They perform two SqueezeNet-based optimisations so that the benefits of lightweight convolutional neural networks may be fully utilised. Chinese paintings acquired from the Internet to assess the efficacy of the optimisedSqueezeNet model employed in the sentiment evaluation of Chinese paintings. The optimisedSqueezeNet model utilised in this work may increase classification accuracy and has superior generalisation ability, according to the findings of comparison trials. Finally, the research findings presented in this paper can be used to advance the preservation of traditional culture, the understanding of traditional Chinese creating art, and art training and education, all of which support the growth and prosperity of traditional art and culture.[26]

Xiang 2021 et al. Several suggestive terms that communicate emotional meanings and elicit a reader's collective feelings are typically used to indicate the sentiment of a text. However, the majority of existing sentiment evaluation models have mostly used neural network designs with end-to-end training methods and little awareness of affective information. As a result, these models frequently fail to identify the crucial characteristics for sentiment prediction. In this paper, they describe a unique neural network-based method for sentiment analysis that incorporates external emotional knowledge. The Affect Control Theory and word attachments in terms of Valence, Arousal, & Dominance are two sentiment lexicons that serve as the foundation for the affective knowledge. We carry out cross-dataset and cross-model experiments as well as a thorough ablation analysis to investigate the influence of emotional knowledge over sentiment analysis. The results demonstrate that our suggested approach beats fashionable neural networks in all five benchmarks with constant and considerable improvement (1.4% accuracy on average). Further talks show that our model is resilient to changes in lexicon size and that all emotional qualities display favourable impacts on model improvement[27].

Research Gap

The research gap in the context of sentiment analysis for movie reviews using artificial neural networks (ANN) and recurrent neural networks (RNN) lies in the need for further exploration and improvement in the following areas:

Model performance and accuracy: While ANN and RNN have been widely applied for sentiment analysis, there is still room for enhancing the performance and accuracy of these models. This could involve investigating novel architectures, optimizing hyperparameters, or incorporating advanced techniques such as attention mechanisms or transformers to improve sentiment classification accuracy.

Handling of contextual information: A greater understanding of the context is frequently required to understand the complex sentiments inherent in movie reviews. Contextual information may be challenging to gather and incorporate for existing ANN and RNN models. Exploring approaches to improve the contextualization of sentiment analysis, such as using contextual embeddings or pre-training models on large movie-related corpora, could be a lucrative research field.

Domain-specific sentiment analysis: Movies exist in a variety of genres and types, each with its own distinct characteristics and ways of making people feel. If ANN and RNN models were created for movie reviews and could be applied to different sorts of movies, the sentiment analysis results may be more accurate. Also, for a complete picture of how someone feels, consider things like humor, irony, or shifts in attitude within a single review.

Dealing with noisy or unstructured data: Movie review databases frequently contain noisy data, such as misspelled words, acronyms, or non-official language. It requires additional study to develop ANN and RNN models that are robust to noise and can handle unstructured data. Methods such as "data augmentation," "pre-processing strategies," and "unsupervised learning" may be useful in addressing these issues.

Interpretability and explainability: As ANN and RNN models are typically considered black-box models, it can be challenging to interpret and understand the reasoning behind their sentiment predictions. Incorporating interpretability techniques, such as attention visualization, saliency maps, or feature importance analysis, can provide insights into how the models make sentiment decisions, increasing transparency and trust in the predictions.

Addressing these research gaps will contribute to the advancement of sentiment analysis for movie reviews using ANN and RNN models, leading to more accurate, robust, and context-aware sentiment classification systems for movie recommendation systems and other related applications.

CHAPTER 3

SIMULATION TOOLS

3.1 PYTHON

A prominent programming language is Python. In 1991, Guido van Rossum was the one responsible for its production and publication. This programming language is of the greatest level, exhibiting exceptional knowledge as well as excellent interactivity and artefacts. Python is designed to be a simple and straightforward language. While other examples make use of punctuation, this example makes extensive use of English keywords. It has a relatively small number of syntactic structures in comparison to other languages.

• Interpreted: The Python interpreter is responsible for carrying out execution at runtime. There is no requirement for you to design your software until you actually launch it. There is a connection between PHP and PERL.

• Interactive: A Python prompt gives you the option to interact with a program-writing interpreter by speaking directly to it.

• Object-oriented: Python encourages the usage of modules that encapsulate object-oriented applications. This feature is one of Python's most notable strengths.

• Software for Novices Python allows novice programmers a wide range of queries that can be used for simple text processing for sports applications on the World Wide Web.

Python is a programming language that, in contrast to many other programming languages such as Fortran or Java, enables the user to concentrate more quickly on solving domain problems rather than stumbling over the complexities of how a machine operates. Other programming languages include Fortran and Java. Python is able to accomplish this objective because it possesses the following characteristics:

• Python is a high level language, which means that it abstracts the specifics of the knowledge that is technical regarding computers. Python, for example, ensures that users understand what the developer is trying to say without giving them undue concern about the accuracy of variable definitions or computer storage without forcing them to understand what the developer is trying to say. There is also the possibility of using a high-level language to communicate in order to approach English prosthetics or mathematics. The "small ceremony" simplicity that Python possesses makes it an excellent choice for literary programming.

•Python is not a language that is specialised in a certain discipline, such as statistical analysis; rather, it is a language that can be used for any purpose and may be applied to any situation. As the UCAR scientist indicated earlier, Python can be used for a wide number of other tasks, including artificial and statistical studies.

• The primary goal of the Python programming language was to facilitate immediate code examination rather than a time-consuming compilation and execution loop, which sped up the process of both experimentation and thought. The programming language Python, created by Fernando Perez, also comes in an interactive version known as IPython.

• Python contains the major library, but there are so many third-party implementations that it allows users a wide variety of popular codebases and models for problem-solving. These configurations work wonderfully for quickly testing new ideas or generating brief code prototypes.

• Programmers may quickly obtain answers to their problems, as well as examples of code that is known to be functional, with the assistance of Google and Stackoverflow.

The number of people who utilise Python is significant.

Let me give you an example:

"print()" is an optimised Python function that prints console text. Its arguments include "Ferrari," "Honda," "Porsche," and "Toyota." The expression "for each car in Garage," followed by "each car," is called "each car."

The output of system information is referred to as "printing to the screen," and when someone says this, they are referring to the process. There is a possibility that the interaction prompt in IDLE or the terminals for Mac and Linux users (CMD.exe) will contain a command prompt. Here is an example of the term "console performance."

Examining the automobile code at the garage, are you able to make any predictions about what will occur? Maybe you have a core concept. Every time we see a car parked inside a garage, we will take appropriate action. What are the next steps to take? What are the next steps to take? Every automobile is written about by our company.

It could appear to be common sense that a "Ferrari, Honda, Porsche, or Toyota" console might reveal information because "printing" sends text to the "console."

What kinds of jobs can Python take on? Python is a strong programming language that can compete effectively with virtually any other language and has a speed that is comparable to those other languages.

Python is no different from any other language in that it can process GPUs or run threads. In addition to this, the majority of C/C++ code is encapsulated in Python by data processing modules.

Python is a modern computer programming language that is known for its speed. Even though it is far more powerful than Fortran, it has certain similarities with one of the original programming languages. These similarities include specific syntax and semantic parallels. Python's use of indentation as a control mechanism makes it possible to make use of variables without explicitly declaring them. This is accomplished by implicitly stating the forms of the variables. Python does not compel you to develop classes like Java does; nonetheless, you have the option to do so whenever you like.

Python is a free and open-source programme. The individual responsible for its conception is Guido van Rossum. Python is available at no cost, in a manner analogous to "free beer." Python, on the other hand, does not cost anything in a number of important respects. For instance, you have the ability to make as many copies of it as you like, as well as to inspect and change the source code. In 1983, Richard Stallman presented the idea of free software, which sparked a movement that spread around the world.

Even though it is easy to build, quick to check, and has a syntax that is compatible with how mathematical concepts are given in the literature, Python is an excellent choice for performing mathematical calculations. This is despite the fact that it is basic. Learning Python will provide you with access to a tool that is helpful for many software engineers. Python has been implemented in the real world in the following ways:

- Desktop Applications With A GUI
- Web applications and web frameworks
- Applications for Businesses & Enterprises
- Running Systems
- Language Development
- Prototyping

3.1.1 PYTHON ENIVIRONMENT VARIABLES

• PYTHONPATH: It performs a role that is analogous to that of PATH. This variable provides the Python interpreter with information regarding where to look for files that are associated with import modules. There will be either the Python source code directories or the source library directories. Python has the ability to sometimes predetermine the PYTHONPATH variable.

An import declaration in Window panes contains the first case-insensitive match. This is because Python is case-insensitive. Simply entering a value into this variable will make its use acceptable.

• PYTHONHOME: This quest line leads to a separate module. It is located in the PYTHONSTARTUP folder as well as the PYTHONPATH folder so that changing the module libraries may be done more easily.

3.1.2 RUNNING PYTHON

Python can be started using one of three different interpreters: the participative one, the interactive one, or both. Python can be launched from a Unix, DOS, or other environment that provides a command line & shell window for the interpreter. Another option is to launch Python directly from the Python interpreter.

Python connect line.

You should proceed with the coding immediately using the interactive interpreter.

$python # Unix/Linux Or python% # Unix/Linux Or C:>python # Windows/DOS $python # Windows/DOS

Table 3.1 - Available command-line options.

Option	Description
-d	Perform debug
-O	More efficient bytecode creation (resulting in files with.pyo)
-S	Do not run the import website to search for startup Python paths
-V	Comprehensive import monitor output (verbose output)
-X	Unable built-in class (just usage strings) exceptions; obsolete from version 1.6
-c cmd	Execute the script Python sent as cmd string
File	Execute Python file script

The following statement explains how to run a Python script from the command line interface by invoking the proper interpreters for your application. This may be done by typing "python script" followed by the script's name.

$python script.py # Operating Systems: Unix and Linux

Alternatively, python% script.py can be run on Unix or Linux, while C:>python script.py can be run on Windows or DOS.

Note: Make sure file enables execution in permission mode

Python code can be run after the Graphical User Interface environment (GUI) if an appropriate GUI framework is available to support the Python application. Integrated Development Environment.

• Unix: IDLE was the first Python integrated development environment (IDE) for Unix.

• Windows: PythonWin is the first Windows client and GUI integrated development environment for Python.

• Macintosh: MacBinary and BinHex files for the Macintosh & IDLE-IDE Python versions can be downloaded from the main website. In the event that we are unable to correctly configure the framework, you should make use of your machine administrator. Make that the Python framework is configured appropriately and that it runs smoothly.

3.2 JUPYTER

The Jupyter Notebook is a popular tool for developing data science projects in an interactive manner and for visualising the results of those projects. Text, photos, mathematical calculations, and other forms of media together with the results of the code's execution are all combined into a single document known as a notebook. Notebooks are extremely likely to be candidates for the heart of modern data science, technological development, and innovation. This is due to the fact that intuitive systems enable incremental yet quick increase. The fact that this Jupyter open source procedure is entirely free is the most disappointing aspect.

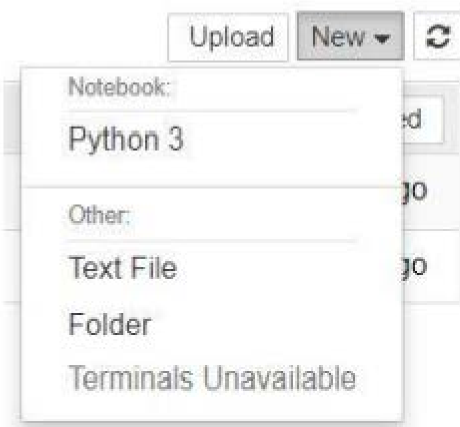
The work that is being done with Jupyter is a descendant of the IPython Notebook, which was initially made accessible as a reference in the year 2010. Jupyter Notebooks, on the other hand, support a wide variety of programming languages; nonetheless, Python is the language that is utilised the majority of the time in the aforementioned article. You can use pip as an alternative to manual package management if you are an experienced Python user or if you choose to handle packages manually.

```
pip3 install jupyter
```

3.2.1 RUNNING JUPYTER

Launch Jupyter by utilising the Anaconda add-ons that are available in your start menus. This will cause your default option on Windows to open a new tab that looks like a snapshot.

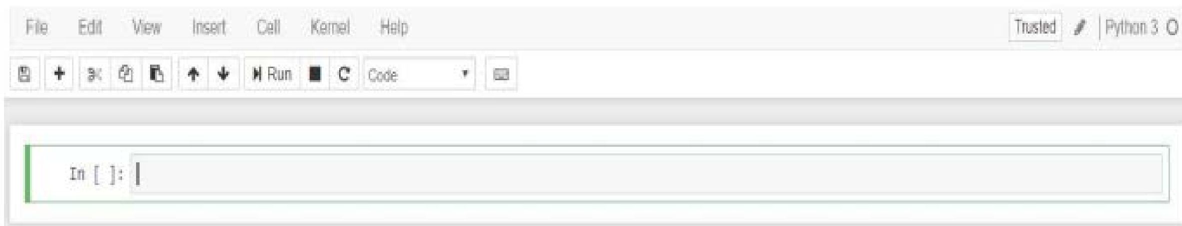
This dashboard provides access to your Jupyter Journals and displays their content. This was crafted with you in mind. You might think of this as the beginning of the process of searching, editing, or constructing your journals. Choose "Python 3" from the drop-down menu that appears when you tap the "New" option in the page's upper right corner.



When you return to the dashboard, you'll notice Untitled. ipynb and a green word indicating that your notebook is about to execute.

3.2.2 THE NOTEBOOK INTERFACE

Given that you currently have an open notebook in front of you, I really hope that the interface doesn't look completely unfamiliar to you. Actually, Jupyter can perform adequately as a word processor. Why are you avoiding looking? You can display the list of commands that are available in a short amount of time by using the menus (or by pressing Ctrl + Shift + P), and the instructions are represented by the tiny buttons that have either symbol.



Cells and kernels are two fairly typical notions that you will encounter that you are most likely not familiar with. In the same way that understanding the output of a word processor is essential for understanding Jupyter, so too is understanding both. Thankfully, gaining a knowledge of these concepts is not a challenging endeavour.

- Notebook code is executed by a kernel that is also known as a “programme processor”.
- The display for a notebook’s transcript and the code that the kernel of the notebook executes is referred to as a cell.

3.2.3 CELLS

First things first, however, let's get the situation with the cell under control. We'll go back to the kernels in a little while. The primary component of a notepad is its cells. In the snapshot of a notebook that was shown in the earlier part of this chapter, an empty cell is depicted as a box with a green border around it. In this section, we will discuss the following two primary types of cells:

• The contents of a code cell may provide instructions for the kernel to carry out, or the cell's output may be displayed in the following section.

• The text that is created in a Markdown cell is immediately shown when it has been formatted in the Markdown style.

A coding cell is always placed in the first available space in a brand-new notebook. Let's give it a shot by utilising some of the most commonplace examples of a hello world. Tap the run button that's located in the toolbar up top, or hit Ctrl and Enter on your keyboard. The conclusion should look like this.

```
print('Hello World!')
Hello World!
```

The output of a cell can be seen down below, and the labelling on the left has been updated to reflect the change. Due to the fact that the output of the code cell has been merged into the text of this item, it is visible to you. It is always possible to differentiate between the two types of cells; this is due to the fact that markdown cells do not have the label that is located on the right of coding cells. When the label number is on a kernel, the word "in" in the label refers to "data," but the initial cell is running when the label number is on a label. After another round of running the cell, the label will reflect that this cell is the second-most important one in the kernel. When we go through kernels in greater depth, you will have a better understanding of why this is beneficial. To generate your very first brand-new code cell, please use the following code:

```
importtime
time.sleep(3)
```

This cell is active for three seconds but does not produce any output throughout that time. Keep in mind that when the label of a cell changes to [*], Jupyter is indicating that the associated code is running in that cell. The content of the last line in a cell, whether it be a single attribute, a function call, or something else, controls the outputs of a cell type as well as all textual information that is specifically recorded during cell execution. This is true whether the content is a single attribute, a function call, or something else.

```
defsay_hello(recipient):
return'Hello, {}!'.format(recipient)
say_hello('Tim')
'Hello, Tim!'
```

3.2.4 DATA TYPE CONVERSION:

It's possible that often converting between the many built-in forms will be required. Simply using the category names as a way to differentiate between them is sufficient. Converting between the various data types can be done with any one of a large number of built-in methods. The modified value is reflected in a brand new object that is created by these operations. The list of the few can be found below.

Table 3.2 - Functions & Descriptions

S.no.	Functions & Descriptions
1.	int(x [,base]); Conversion of x to an integer, base stipulates that x is string.
2.	float(x); Transforms x into set of floating points.
3.	complex(real [,imag]); Produces an interesting no.
4.	str(x); Conversion of object x to a string file.
5.	repr(x); Turns object x to a string expression.
6.	eval(str); Returns an object to evaluate a string.
7.	tuple(s); Turns s into tuple.
8.	list(s); Turns s into list.
9.	set(s); Turns s into set
10.	dict(d); Make dictionary. d shall be tuple (key, value) sequence.

CHAPTER 4

PROPOSED METHODOLOGY

4.1 HYPER PARAMETERS USED FOR EVALUATION

In order to conduct the evaluation, the following hyperparameters were utilized: model = LSTM, input shape = maxlen, maxpooling layer = (2)(x), batchnormalization = x, activation function = relu and sigmoid, metrics = loss and accuracy, and epochs = 20.

4.2 PROPOSED METHODOLOGY

The methodology that has been developed for conducting sentiment analysis on IMDb reviews consists of a number of essential phases that are meant to examine and categorize the sentiment that is conveyed in the reviews. The following is a condensed explanation of the research methodology:

4.2.1 DATA COLLECTION

The IMDB dataset contains 50,000 different movie reviews, making it useful for natural language processing and text analytics. When compared to earlier benchmark datasets, this one for classifying binary attitudes contains a substantial amount of additional information. There are 25,000 highly polar critiques of movies offered for instruction, and another 25,000 are provided for testing. Make a decision between using categorization methods or machine learning techniques to make a forecast regarding the amount of positive and negative reviews. For additional information regarding this dataset, please visit the following URL: http://ai.stanford.edu/amaas/data/sentiment/.

4.2.2 DATA PROCESSING

In the process of data mining, one of the most important steps is known as "data preprocessing," which can mean either the alteration of data or the deleting of data before it is used to ensure or improve efficiency. Projects involving data mining and machine learning are excellent illustrations of how the proverb "garbage in, garbage out" might be applicable. Remove any more punctuation, put a stop to the birds, activate the limiter and tokenizer, or remove any data that isn't necessary.

4.2.3 PERFORM EDA

Exploratory data analysis, often known as EDA, is a process that needs to be carried out before one can completely analyze and investigate a dataset. The process of analyzing data comprises summarizing the most important aspects, locating correlations, and identifying outliers. The steps involved in the EDA process are outlined in this section.

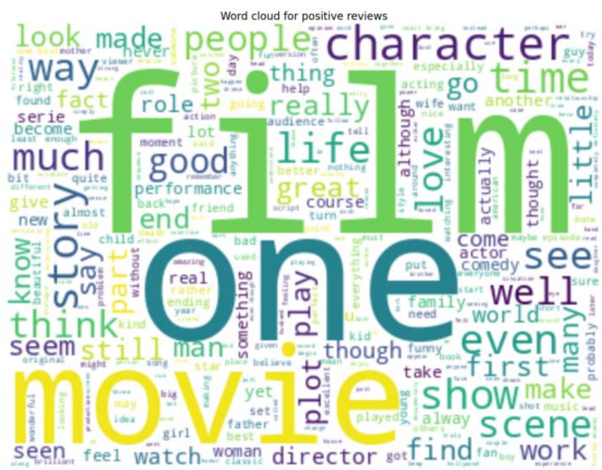


Figure 4.1 shows the word clouds of positive reviews

Figure 4.2Shows the word clouds of Negative reviews

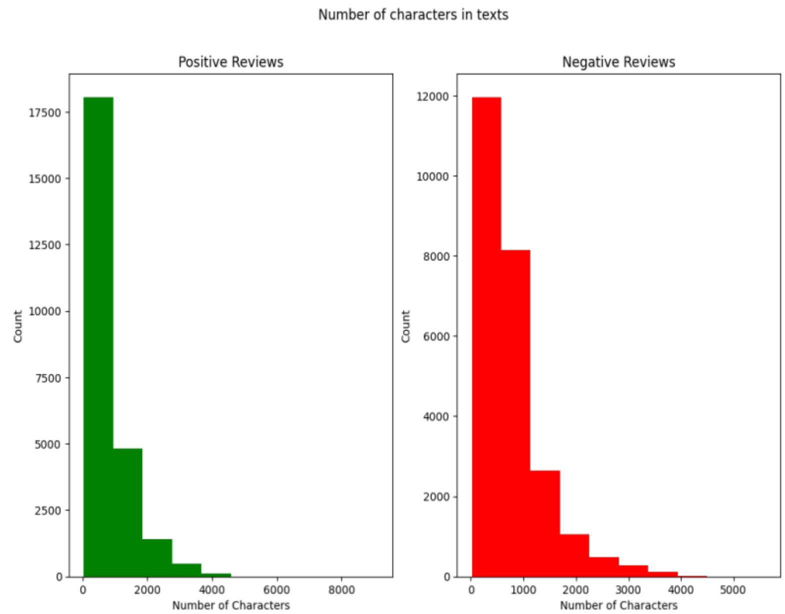


Figure 4.3 Shows the count and number of character in positive and negative reviews

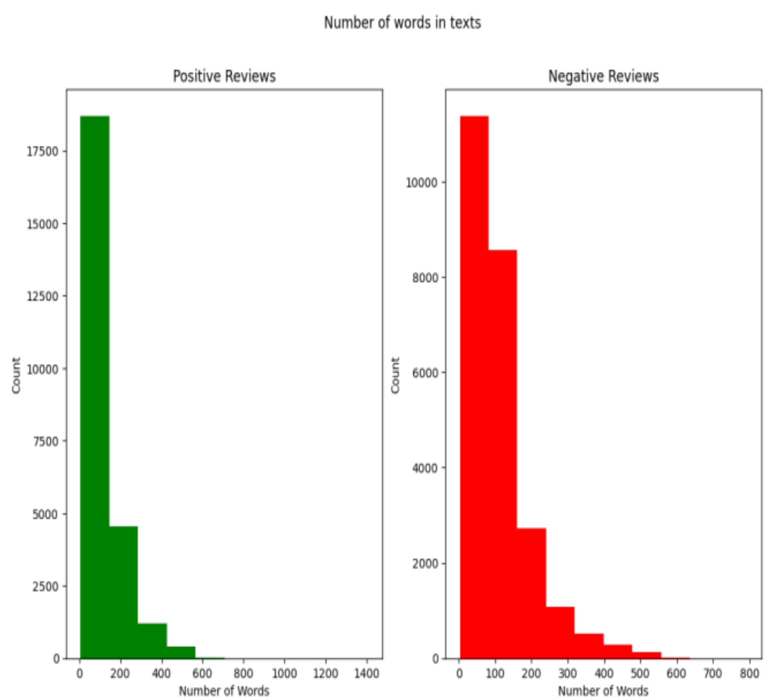


Figure 4.4 shows the count and number of words in texts based on positive and negative reviews

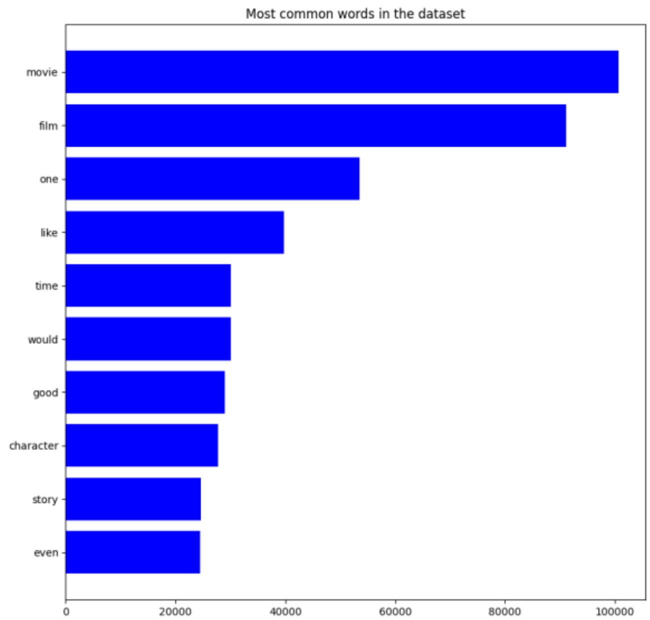


Figure 4.5 shows the most common words in the dataset

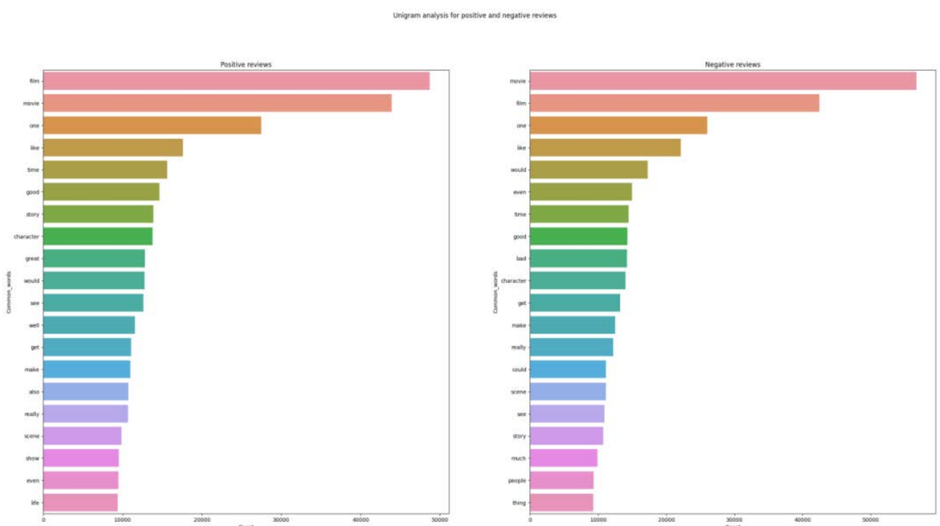


Figure 4.6Shows the unigram analysis for a positive and negative review

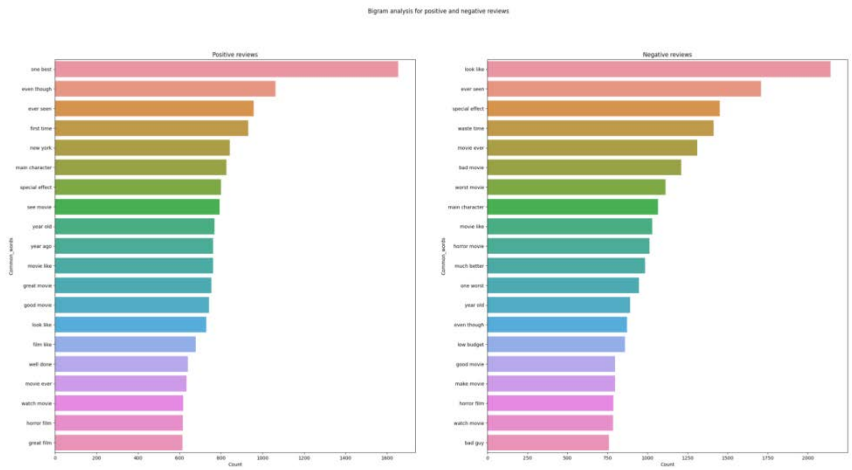


Figure 4.7 shows a diagram analysis of a positive and negative review

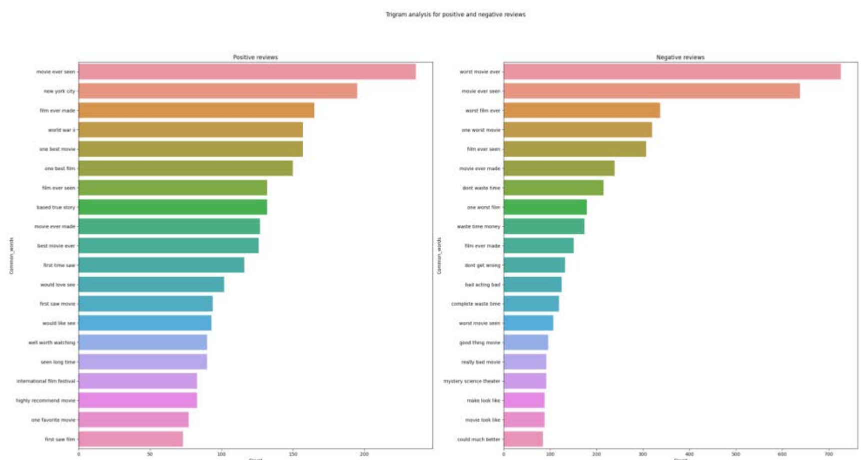


Figure 4.8 shows the trigram of analysis of negative and positive reviews

4.2.4 MODEL IMPLEMENTATION

Long Short-Term Memory (LSTM) is a sort of recurrent neural network (RNN) architecture that has become quite popular in the deep learning and machine learning fields. Because of how LSTMs are built, they can handle time-dependent and sequential data, which makes them ideal for applications like time series analysis, speech recognition, and natural language processing.LSTMs, as opposed to conventional feed-forward neural networks, feature an exclusive memory cell structure that enables them to capture and store information over extended periods. This makes them useful for modeling long-term dependency sequences, which is a typical difficulty in many real-world applications. An LSTM's memory cell, which consists of different gates responsible for regulating the information flow, is its essential part. Input, forget, and output gates are a few of the gates. These gates control the information flow into and out of the memory cell, allowing the LSTM to keep or discard information selectively depending on its usefulness.LSTMs have demonstrated their effectiveness in time series prediction applications, where the preceding context and dependencies between data points are essential for precise forecasting. Using past data, the model can produce precise predictions thanks to the LSTM architecture's capacity to recognize and learn complex patterns and connections. Overall, LSTM models have proven to be successful at managing sequential data, making them a potent tool in machine learning and deep learning. They are excellent for a variety of applications, including natural language processing, time series analysis, and beyond, due to their capacity to represent long-term dependencies and store information across time.

CHAPTER 5

RESULT AND DISCUSSION

You can determine how well your taught machine learning models performed by using performance evaluation measures. This makes it easier to assess the likelihood that your machine learning and deep learning model will work with new data sets. The ideas that should be often specified include the following:

1) TN/TP/FN/FP

- True Positive - It was anticipated to be successful, and it did succeed.
- False Positive -It was supposed to be uplifting, but the outcome was depressing.
- True Negative - Unfavourable outcomes were predicted to occur, and they have now happened.
- False Negative - Despite negative projections, the outcome was favorable.

2) Confusion Matrix

A confusion matrix is a performance measurement tool used in statistical analysis and machine learning to assess the accuracy of a classification model. It shows a tabular comparison of the model's projected labels and the test data's actual labels. The matrix clearly delineates true positives, true negatives, false positives, and false negatives.

3) Accuracy

The percentage of data instances that have been correctly classified relative to the total number of data instances is known as accuracy.

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (1)$$

4) Loss

If your prediction is off, you'll lose money. In these other contexts, loss is used to quantify the model's failure to accurately anticipate a given instance. If a model's prediction is incorrect, losses will be higher than if the prediction is accurate. Models need to be trained in order to discover a balanced collection of biases and weights.

$$Loss = -\frac{1}{m}\sum_{i=1}^{m} \mathcal{Y}i . \log(\mathcal{Y}i) \qquad (2)$$

5) Precision

A good predictor should have a precision of 1, indicating that it is extremely accurate. When the numerator and denominator are the same, as in the formula TP = TP + FP, the precision increases to one and the FP decreases to zero. When FP increases, the value of the denominator increases while the value of accuracy decreases. This is the polar opposite of what we want.

$$Precision = \frac{TP}{TP+FP} \qquad (3)$$

6) Recall

In addition to the denominator's value rising as FN rises, recall's value falls, which is the exact opposite of what we desire. Its capacity to discern between negative and positive examples serves as a gauge of a machine learning model's sensitivity. Depending on the situation, it may also go by the names recall and true positive rate (TPR). Sensitivity is one aspect that is taken into account when assessing the performance of a model since it allows us to observe how many successful detections the system was able to make.

$$Recall = \frac{TP}{TP+FN} \qquad (4)$$

7) F1 Score

Both the precision and memory scores must be one for the F1 Score to be one. The F1 score will only rise if the recall and accuracy are exceptional. The harmonic mean of recall and precision is the ideal measure to utilize to maximize the F1 score.

$$F1 - score = \frac{2}{\frac{1}{precision}+\frac{1}{recall}} \qquad (5)$$

Table 5.1 Performance Evaluation of Models

Model	Accuracy	Precision	recall	F1-score
LR	89.03%	87.86%	90.68%	89.24%
Multinomial Naive Bayes	86.79%	87.29%	86.24%	86.76%
Linear SVM	89.57%	88.56%	90.98%	89.75%
XGboost	84.63%	82.93%	87.36%	85.09%

Table 5.1 shows how well different machine learning models work, including LR, Multinomial Naive Bayes, Linear SVM, and XGboost. Linear SVM outperforms the competition with a test accuracy of 89.57%. In a comparison study, Linear SVM was better than XGboost by 5% and better than Multinomial Naive Bayes by 3%.

Table.5.2 Shows LSTM model Accuracy, Loss, Validation accuracy, and Validation loss.

Model	Accuracy	Loss	Val Acc	Val Loss
Hybrid LSTM	0.879	0.676	87.98	0.676

Table.5.2 exhibits LSTM Loss is 0.676, Accuracy is 0.879, Validation Accuracy is 87.98, and Validation Loss is 0.676.

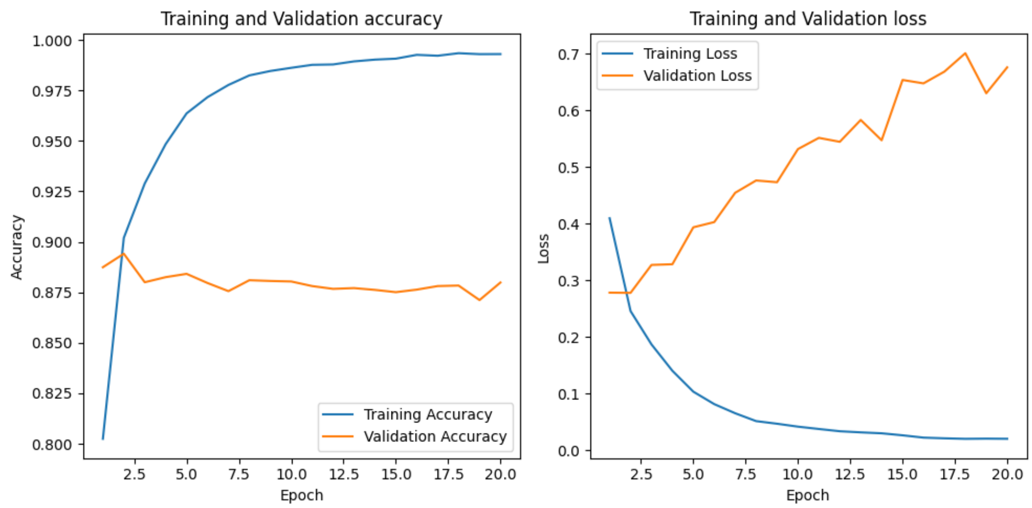


Figure 5.1 shows the training and validation accuracy and loss graph

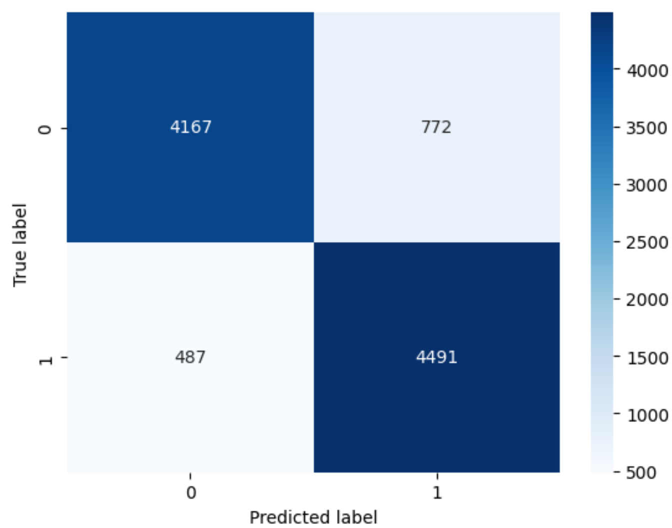


Figure 5.2 shows the confusion matrix of true and predicted labels of LSTM

Figure 5.1 and 5.2 shows the loss and accuracy of the LSTM model and Figure 5.2 shows the confusion matrix of the true and predicted label.

CHAPTER 6

CONCLUSION

The IMDb movie reviews served as the research project's dataset, and the potential of machine learning and deep learning techniques for sentiment analysis was investigated. Both methods demonstrated some potential for determining if a movie review was good or terrible based on the opinions provided in the review's text. The machine learning method was built on feature engineering techniques such as bag-of-words, n-grams, and sentiment lexicons. These characteristics were utilized to train machine learning methods such as Naive Bayes, SVMs, and Xgboost, which were then used to create sentiment classifiers. These models were quite accurate, but they couldn't detect the subtle ways in which the text expressed distinct types of emotion. The deep learning method, on the other hand, uses a recurrent neural network (RNN), or more precisely an LSTM network, to automatically generate models from raw text input. The LSTM network was able to successfully extract the contextual information from the movie reviews while also successfully capturing the sequential character of the language. Because of this, it performed significantly better than traditional machine learning algorithms in terms of precision and its ability to recognize complex patterns of emotion. In conclusion, the research demonstrates that sentiment analysis using IMDb movie reviews may be conducted using either machine learning or deep learning methods. The findings contribute to our understanding of different methods for classifying emotions and offer insights into the benefits and drawbacks of various approaches. The findings of the study pave the way for further advancements in sentiment analysis and its application in a wide variety of industries. Analysis examined the performance of several different machine learning models, including Linear SVM, Multinomial Naive Bayes, Linear SVM, &XGboost, with Linear SVM achieving the greatest accuracy of 89.57% when compared to the other models in the study. Deep learning finds that the validation loss for hybrid cars is 0.676, the accuracy is 0.879, the validation accuracy for hybrid cars is 87.98, and the validation loss for hybrid cars is 0.676 for the comparison research. Linear SVM improves by 5% over XGboost and by 3% over Multinomial Naive Bayes.

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