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Movie Review Based Sentiment Analysis

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Abstract:-_Sentiment analysis, an automated method for detecting emotions and opinions in text, has become a versatile tool applied across various domains, from assessing online customer feedback to monitoring sentiment trends on social media. While Bag of Words (BoW) has been the traditional method, more advanced techniques like Bidirectional Encoder Representations from Transformers (BERT) and Long Short-Term Memory (LSTM) have revolutionized sentiment analysis by elevating accuracy and context comprehension. This study conducts an extensive comparison between BERT, a hybrid model that combines CNN and LSTM in the realm of sentiment analysis within movie reviews. Through meticulous experimentation, the study strongly proves that both the hybrid model of CNN and LSTM models significantly outshine the techniques like BERT and BoW with noticeably higher accuracy in precisely categorizing sentiments expressed in movie reviews. These results highlight how deep learning methodologies remarkably refine the precision and effectiveness of sentiment analysis, allowing for more nuanced and context-aware sentiment classification. The study's significance goes beyond performance contrasts; it demonstrates the exceptional capacity of BERT along with the hybrid model of CNN and LSTM to comprehend the complexities of language and contextual nuances within movie reviews. This heightened contextual understanding is particularly crucial in sentiment analysis, enabling the models to discern subtle shifts in sentiment that simpler methods like BoW might overlook. By showcasing the supremacy of hybrid model that combines CNN and LSTM in movie review sentiment analysis, this research opens new avenues for the field's advancement. It emphasizes the potential of deep learning techniques in revolutionizing sentiment analysis across diverse domains, offering more accurate and contextually attuned sentiment classification for deeper insights and well-informed decision-making. This study stands as a valuable asset for researchers and practitioners aiming to leverage deep learning for sentiment analysis applications

I. INTRODUCTION

In the era of Web 2.0 platforms and the explosion of user-generated content online, businesses and organizations worldwide have embraced sentiment analysis and opinion mining as indispensable tools for extracting valuable insights from review posts across various web platforms. This data-driven approach has become increasingly crucial for informed organizational decision-making, enabling companies to gauge customer sentiment, identify trends, and gain a deeper understanding of their target audience [1]. Sentiment analysis, a branch of natural language processing, computational linguistics, and text mining, delves into the intricacies of human language to discern the polarity of opinions expressed in text and uncover the diverse emotions directed towards different aspects of a subject [2]. It encompasses the analysis of sentiments, which are private states encompassing opinions, attitudes, thoughts, judgments, and emotions, conveyed through language using subjective expressions [3]. The significance of sentiment analysis lies in its ability to transform unstructured text data, often littered with subjective opinions and emotional expressions, into structured and actionable information. By extracting meaningful insights from this vast reservoir of user-generated content, organizations can gain a competitive edge in various aspects of their operations.

Our investigation focuses on examining movie reviews due to the vast amount of user-generated content available online and the distinctive complexities these texts pose. Assessing sentiment in movie reviews proves more intricate than in other types, such as product reviews [4, 5]. In movie evaluations, negative elements like an evil character or a tragic plotline don't necessarily equate to a bad movie, in contrast to product reviews where multiple negative aspects often lead to branding a product as poor [4]. Our study doesn't just explore the overall sentiment conveyed in a movie review but also investigates sentiments directed at specific facets such as the cast, director, story, and music. This thorough exploration of diverse aspects facilitates a more refined analysis of sentiments. For instance, a statement like 'I love the story but not the music' encapsulates differing sentiments for distinct elements of the movie – the story and the music. Moreover, our research delves into sentiment intensity, indicated by sentiment scores assigned to clauses or sentences.

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For instance, 'this is superb' garners a higher sentiment score than 'this is good', revealing varying levels of positivity. These sentiment scores are pivotal in determining the sentiment polarity (positive, negative, or neutral) of clauses or sentences. They also enable comparisons between clauses or sentences, identification of the most positive or negative statements related to specific aspects, or ranking sentences based on their sentiment intensity in descending order.

Websites like carwale.com and imdb.com are now overflowing with user reviews, providing a wealth of information about cars and movies, respectively. These websites draw a diverse array of users, ranging from recent product purchasers or service users to regular patrons. The Internet Movie Database (www.imdb.com) stands as a prime example of a valuable resource for movie enthusiasts worldwide. Similarly, blog sites host a multitude of posts reflecting the opinions and experiences of numerous users. However, blog posts present unique challenges for sentiment analysis due to the often implicit nature of their content. Instead of explicitly stating opinions, blog posts frequently contain factual or episodic information. Despite this challenge, blog posts remain a valuable source of user opinions and perspectives, offering potential for sentiment-driven analyses and other insightful assessments.

While these reviews and posts provide valuable insights, navigating through them can be a daunting task for new users or potential customers. Thankfully, sentiment classifiers, integrated within modern Information Retrieval (IR) frameworks, offer a solution to this issue of information overload. These sentiment classifiers not only automatically categorize reviews as positive or negative but also extract and highlight the favourable and unfavourable aspects of a product or service. Sentiment analysis has become an indispensable component of IR-based frameworks across various domains. Initially, it was utilized to extract opinions about a product and summarize its positive or negative attributes. More recently, sentiment analysis has been employed for opinion-based clustering of textual documents and for enhancing recommendations within recommender systems. These advancements in sentiment analysis have enabled the generation of comprehensive summaries from extensive reviews, facilitating quicker access to relevant information for users. Consequently, this has significantly reduced information overload, leading to an improved user experience overall.

Machine learning-based text classifiers, operating within the supervised machine learning framework, require training using labelled training data before being applied to actual classification tasks. This training data typically consists of a subset of the original dataset, manually labelled to denote specific categories or classes. Once trained, these classifiers can be deployed for classification on real test data. Among these classifiers, Naïve Bayes (NB) stands out as a statistical classifier, while Support Vector Machine (SVM) serves as a vector space model-based classifier. For sentiment classification, Naïve Bayes is configured as a 2-class text classification problem, distinguishing between positive and negative classes. A detailed explanation of this adaptation can be found in [14]. SVM, on the other hand, requires transforming text documents into feature vectors, often utilizing multidimensional tf.idf vectors. The primary objective is to categorize each text document represented as a vector into a specific class, employing a large margin classifier. This approach aims to identify a decision boundary between two classes, maximizing the distance from any document in the training data. In our implementation, we have written the Naïve Bayes algorithm in python code and utilized the Sequential Minimal Optimizer (SMO) available in Weka [15] to implement SVM. This comparative analysis allows us to assess the effectiveness of these machine learning-based approaches for sentiment analysis.

The Naïve Bayes classifier operates based on Bayes' theorem, assuming the independence of features. It calculates the probability of each class given a document and selects the class with the highest probability. SVM, on the other hand, constructs a hyperplane that separates the training data into two classes, maximizing the margin between the hyperplane and the nearest data points. This approach ensures that the classifier can effectively generalize to unseen data. The choice of classifier depends on the specific task and dataset at hand. Naïve Bayes is known for its simplicity and efficiency, making it a suitable choice for large datasets. SVM, with its robust performance and ability to handle complex nonlinear relationships, is often preferred for tasks requiring high classification accuracy. Our comparative analysis, evaluating the performance of Naïve Bayes and SVM against our approach implementations, provides valuable insights into the effectiveness of these machine learning-based approaches for sentiment analysis. By understanding the strengths and limitations of each method, researchers and practitioners can make informed decisions when selecting an appropriate classifier for their specific needs.

Bidirectional Encoder Representations from Transformers (BERT), a groundbreaking innovation unveiled by Google Research in 2018, has propelled natural language processing (NLP) to new heights within the machine learning domain. Building upon the transformative foundation of deep learning models, BERT introduces a radical interconnection between inputs and outputs. This interconnectedness is established through automatically generated weightings that define their relational significance, a crucial aspect known as "attention" in NLP. Extensively trained on massive amounts of textual data, the BERT architecture gains a profound understanding of linguistic nuances and discerning various patterns inherent in NLP tasks. True to its name, BERT dynamically assimilates information from both the left and right sides of tokens during its training phase.

Unlike conventional transformers that employ both encoders for input reading and decoders for result prediction, BERT, solely focused on constructing a language representation model, exclusively utilizes the power of an encoder. This BERT encoder seamlessly processes input sequences as tokens, converting them into vectors that are essential for neural network operations. Among various transformer alternatives, such as Hugging Face's Distilled BERT, XLNet, and GPT-23, BERT distinguishes itself through its superior performance across a wide range of NLP tasks. The operational framework of the BERT model unfolds through two critical stages: pre-training and fine-tuning. In the pre-training phase, the model undergoes rigorous training using unlabelled datasets. Subsequently, during fine-tuning, the initial pre-trained parameters initialize BERT, which then hones and refines these parameters using labelled data from subsequent tasks.

II. EXISTING SYSTEMS

The Bag-of-Words (BoW) technique, widely employed in sentiment analysis, simplifies text by breaking it down into individual words, ignoring their sequence or grammatical structure. This method eases sentiment analysis by counting word frequencies in reviews, yet it does have limitations. BoW's disregard for the context between words can miss subtle emotional nuances within phrases or sentences. For instance, the phrase "painfully funny" combines words that individually might seem neutral or positive but together convey a blend of humour and discomfort. BoW's inability to grasp these subtleties might lead to misinterpretations in sentiment classification. To address these limitations, more advanced methods like n-grams and semantic analysis have emerged. N-grams consider consecutive word sequences, enabling a focus on local context and phrase-level sentiment. Semantic analysis incorporates linguistic knowledge and sentiment lexicons to offer a deeper understanding of text meaning and sentiment. While BoW offers simplicity and computational efficiency, its struggle with contextual nuances prompts the need for advanced techniques. By considering word order and relationships, these methods can better capture the complexities of language and provide a richer comprehension of sentiment in text

N-grams, an extension of the Bag-of-Words (BoW) method, address the limitations of BoW by capturing sequences of 'n' consecutive words, known as n-grams. This approach preserves word order and local context, enabling a more nuanced understanding of sentiments expressed within phrases and idioms. Compared to BoW, which considers individual words in isolation, n-grams can better capture the subtle emotional nuances conveyed by word combinations. For instance, the phrase "dead tired" has a distinct meaning and sentiment compared to simply considering the individual words "dead" and "tired." By incorporating word order, n-grams can identify and analyse such idiomatic expressions and phrases, providing a more comprehensive assessment of sentiment. However, despite its advantages, n-grams also face certain challenges. As the value of 'n' increases, capturing longer-range relationships between words becomes computationally demanding.

This can lead to increased processing time and memory requirements, especially when dealing with large datasets. Additionally, n-grams may struggle with handling long-range dependencies in text. While they can effectively capture local context, they may not adequately capture the sentiment conveyed by words further apart in the text. This limitation can lead to misinterpretations of sentiment, particularly in complex or lengthy texts.

Lexicon-based sentiment analysis methods employ predefined sentiment lexicons or dictionaries that assign sentiment scores (positive, negative, neutral) to individual words. These methods calculate the overall sentiment of a text by aggregating the sentiment scores of the lexicon words found in the text. Lexicon-based methods offer several advantages. They are computationally efficient and can be adapted to analyse text in various languages, making them versatile tools for sentiment analysis. Additionally, they do not require extensive training data, unlike machine learning-based approaches. The effectiveness of lexicon-based methods is heavily dependent on the comprehensiveness and accuracy of the underlying lexicon. If the lexicon lacks coverage of relevant words or contains inaccurate sentiment scores, the overall sentiment analysis may be affected. Despite these advancements, lexicon-based methods still face challenges in capturing the full complexity of human language and sentiment. To overcome these limitations, hybrid approaches that combine lexicon-based methods with machine learning or deep learning techniques have been proposed. These hybrid approaches aim to leverage the strengths of different methods and mitigate their weaknesses, potentially leading to more robust and accurate sentiment analysis.

Machine learning (ML) algorithms have emerged as powerful tools for sentiment analysis, enabling computers to learn from labelled data and identify patterns that associate words with specific sentiment classifications. Among these algorithms, Naive Bayes and Support Vector Machines (SVM) have gained prominence due to their effectiveness in handling large datasets. However, achieving optimal performance with these algorithms requires careful parameter tuning and meticulous feature selection, as these parameters significantly influence their ability to discern subtle sentiment cues. deep learning models, particularly Recurrent Neural Networks (RNNs) and sophisticated Transformers like BERT, have demonstrated remarkable capabilities in capturing intricate patterns and contextual nuances within text. These models excel at processing sequential data, allowing them to grasp the subtle emotional undertones conveyed by word order, phraseology, and contextual cues. This ability to handle long-range dependencies and contextual intricacies enables deep learning models to achieve a more profound understanding of sentiment expressions, particularly in complex or nuanced texts.

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While ML algorithms like Naive Bayes and SVM offer simplicity and computational efficiency, their reliance on carefully crafted features and parameter adjustments can limit their ability to capture the full complexity of human language and sentiment. Deep learning models, on the other hand, possess a greater capacity to learn from raw data and adapt to diverse linguistic contexts. This ability to extract intricate patterns and contextual information from text makes deep learning models well-suited for tasks that require a deep understanding of sentiment, such as analysing online reviews, social media posts, and customer feedback.

Aspect-based sentiment analysis delves deeper than overall sentiment classification, seeking to identify and analyse the sentiments associated with specific aspects or features of a movie, such as acting, plot, cinematography, or special effects. This granular approach aims to provide a more comprehensive understanding of how audiences perceive various aspects of a film, offering valuable insights into audience preferences and areas for improvement. Unlike overall sentiment analysis, which focuses on the overall emotional tone of a review, aspect-based sentiment analysis requires a more detailed and labour-intensive process. To accurately extract aspect-level sentiment, each review must be meticulously annotated, linking specific sentiments to the corresponding aspects under examination. This process demands a high degree of precision and attention to detail, as mislabelling or overlooking relevant aspects can significantly impact the accuracy of the analysis. aspect-based sentiment analysis often necessitates the development of specialized techniques tailored to the task. These techniques may involve natural language processing (NLP) methods to identify and extract aspect mentions within reviews, sentiment lexicons or dictionaries to assign sentiment scores to aspect mentions, and machine learning algorithms to classify sentiment at the aspect level. Despite the additional effort and complexity involved, aspect-based sentiment analysis offers several advantages over overall sentiment classification. By providing a more granular understanding of audience sentiment, it enables filmmakers, producers, and distributors to identify specific strengths and weaknesses of their work, allowing them to make informed decisions about future projects.

Sentiment analysis, particularly concerning movie reviews, encompasses a vast spectrum of techniques aimed at understanding the emotions and opinions conveyed within these textual evaluations. Each method brings its unique approach, strengths, and considerations to the table when attempting to categorize sentiments. Hybrid models combine various techniques—like merging lexicon-based analysis with machine learning or deep learning—to leverage their strengths and overcome individual limitations. These models aim to optimize sentiment classification performance. Ensemble methods aggregate predictions from multiple models, capitalizing on their diverse strengths to minimize errors and enhance overall accuracy and robustness in sentiment classification, especially when individual models exhibit different strengths and weaknesses.

➢ *Motivation*

Sentiment Analysis has emerged as a critical tool for both consumers and producers, enabling them to harness the power of customer opinions expressed across various platforms. Its growing significance has attracted substantial attention from both industry and academia, leading to the development of advanced techniques for extracting and analysing sentiment from textual data. The proliferation of online reviews and feedback has created a vast repository of opinions on a wide range of topics, from product evaluations to political viewpoints. This abundance of data necessitates robust sentiment engines capable of extracting sentiments pertaining to specific entities and aggregating diverse opinions from various platforms. Such engines can provide consolidated feedback or ratings on particular topics, offering valuable insights to both consumers and producers. sentiment analysis tools can facilitate informed decision-making by providing a comprehensive understanding of customer sentiment towards a product or service. By curating opinionated text from multiple sources and presenting a balanced polarity assessment, these tools empower consumers to make choices based on informed judgments rather than relying solely on personal preferences or limited information.

People benefit from sentiment analysis by gaining a deeper understanding of customer perceptions and preferences. By analysing the sentiment expressed in reviews and feedback, producers can identify areas for improvement, address customer concerns, and tailor their products or services to better meet customer needs. This information can also inform marketing and advertising strategies, allowing producers to effectively target specific customer segments and resonate with their preferences.

➢ *Software Description*

Python 3.8 stands out as a widely used programming language renowned for its simplicity and ease of understanding. It encompasses an extensive standard library and supports multiple programming paradigms, making it adaptable to a diverse range of applications. Version 3.8 introduced several significant enhancements, including assignment expressions, positional-only parameters, and runtime audit hooks.

Jupyter Notebook provides an interactive environment for creating and sharing documents that seamlessly integrate live code, visualizations, explanatory text, and equations. Its ability to combine code execution with rich text elements has propelled it to prominence as a valuable tool for data analysis, machine learning, and scientific computing. Anaconda Navigator, a graphical user interface (GUI) included with the Anaconda distribution, specifically caters to data science applications. It offers a user-friendly interface for managing packages, environments, and applications related to data analysis, machine learning, and scientific computing. This includes Jupyter Notebooks, JupyterLab, Spyder, and other tools. Anaconda Navigator streamlines the process of installing, updating, and organizing libraries and environments for Python programming.

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III. PROPOSED SYSTEM

Traditional classification analysis has primarily focused on structured data, but the recent explosion of unstructured data, including text, images, and audio, has driven a surge of interest in analysing this type of data. Within this domain, Natural Language Processing (NLP) research, particularly sentiment analysis, has flourished. NLP sentiment analysis involves identifying emotions, subjective thoughts, and sentiments from online text. Essentially, it involves gauging sentiment about services by categorizing text sequences into predefined sentiments—positive, negative, or neutral. Analysing the polarity of unstructured data, such as movie reviews, requires more sophisticated techniques than those used for structured data. Methods that consider the sentence structure within reviews become essential. Previous studies have primarily relied on basic machine learning techniques like artificial neural networks and SVM, which often fall short in classification accuracy due to their inherent limitations.

This study aims to overcome these limitations by proposing a fused model of CNN and LSTM, two extensively researched deep learning techniques in machine learning. CNN, commonly used in facial recognition and image classification, also finds application in NLP, akin to Bag of Words. On the other hand, LSTM's strength lies in applications like chatbots and text translation, as it arranges words sequentially to predict upcoming words. Integrating a CNN-LSTM model can harness the merits of both techniques and enhance sentiment analysis accuracy on review data. Deep learning-based models have exhibited superior performance in various domains compared to traditional machine learning methods. However, ensuring robustness to prevent overfitting is crucial in practical applications. Despite the widespread use of deep learning in image recognition, its application in text analysis, such as movie reviews, remains limited. Thus, this study endeavours to address the polarity classification challenge in movie review data to evaluate the performance of the CNN-LSTM model. The proposed model combines the strengths of CNN and LSTM to effectively extract positive and negative sentiment features from text data. Unlike traditional machine learning algorithms, CNN employs convolution layers for automated feature extraction, enabling extensive parallel processing and efficient handling of large datasets. This parallel processing capability sets CNN apart from RNNs, which process text sequentially and can suffer from vanishing gradients.

LSTM, while lacking CNN's parallel processing capabilities, possesses unique advantages in handling long-term dependencies in text sequences. LSTM's gate mechanism, consisting of input, output, and forget gates, provides precise control over processing moments, enabling it to strategically position memory blocks within hidden nodes. This feature allows LSTM to effectively resolve the long-term dependency issues that can arise in CNN-based sentiment analysis. By integrating LSTM into CNN's pooling layer, the proposed model creates an end-to-end structure that simultaneously considers both spatial and temporal features. LSTM's uniform modelling of sequence vectors during word prediction further enhances the overall accuracy of the model. The sentiment analysis process begins with word embedding, an NLP technique that represents words as vectors. In this context, word embedding is trained to capture labels for sentence similarities and positive and negative sentiments. CNN then takes over, creating text matrix vectors from the word embedding output. The convolution layer in CNN adjusts its kernel size, allowing it to effectively combine words and extract local features. ReLU, a non-linear activation function, is employed in CNN to address the vanishing gradient problem that can arise in deep neural networks.

After applying ReLU, CNN processes the entire word dataset and conducts pooling using a max pooling method. Max pooling condenses multiple values into a single output, effectively aggregating designated area values. This pooling operation reduces the dimensionality of the convolution layer's results, ultimately extracting features essential for sentiment analysis. To prevent overfitting and reduce the model's focus on specific inputs, a dropout process is applied post-max pooling. Dropout randomly configures part of the layer's input, encouraging the model to learn more robust features. LSTM layers complement CNN by handling sequential data and storing memory as cell states, effectively addressing CNN's long-term dependency issue. LSTM's input, output, and forget gates offer adaptable control across different data scenarios. Finally, in the fully connected Dense layer, a sigmoid function generates a single value, representing the overall sentiment of the input text.

To assess the effectiveness of the proposed model, a comparison methodology was meticulously selected after a comprehensive review of past research. Initially, machine learning algorithms like Naive Bayes (NB) and Support Vector Machines (SVM) were chosen as benchmarks. These algorithms are renowned for their robust text classification capabilities, making them well-suited for tasks like sentiment analysis. Random Forests (RF) and Gradient Boosting were also integrated into the comparison due to their established success across various classification challenges.

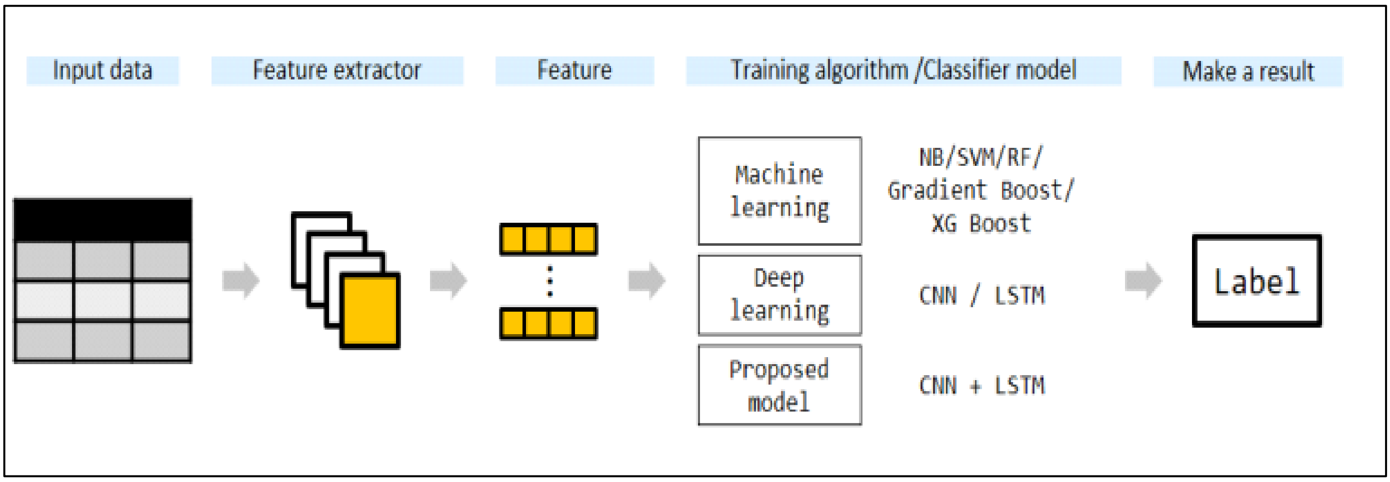

Fig 1 : Flow Chart of Classifier Model

In the domain of deep learning, text data often undergoes processing via Convolutional Neural Networks (CNN) for classification, eliminating the need for separate vectorization. However, conventional machine learning demands the conversion of textual data into numerical format before processing. Bag of Words (BoW) and TF-IDF (Term Frequency-Inverse Document Frequency) emerge as notable vectorization techniques. BoW, disregarding grammar and word order, constructs a vocabulary list based on the corpus, represented as numerical vectors. This approach proves efficient across diverse domains, encompassing data scalability, time series classification, text processing, and research in image-related fields. Presently, these vectorization methods are being utilized to propose novel strategies for classification tasks involving unstructured data, employing both machine learning and deep learning methodologies.

To comprehensively assess the CNN-LSTM model proposed, we opted for two well-established deep learning models, CNN and LSTM, as standalone comparison models. Alongside, we introduce the CNN-LSTM combination model designed to harness the strengths of both CNN and LSTM, aiming to address their limitations. In our deep learning analysis, we reprocessed the lemmatized text and conducted word-level tokenization anew. This approach assists in numerical transformation akin to data vectorization and creates sequential data suitable for CNN and LSTM processing in deep learning. In the case of using CNN independently, the word embedding values representing the one-hot vectors transition into a one-dimensional format. Here, the size of the embedding vector relies on the sentence length. The convolution process involves the count of words within the pattern, dictating the embedding vector size and facilitating the formation of a max-pooling layer.

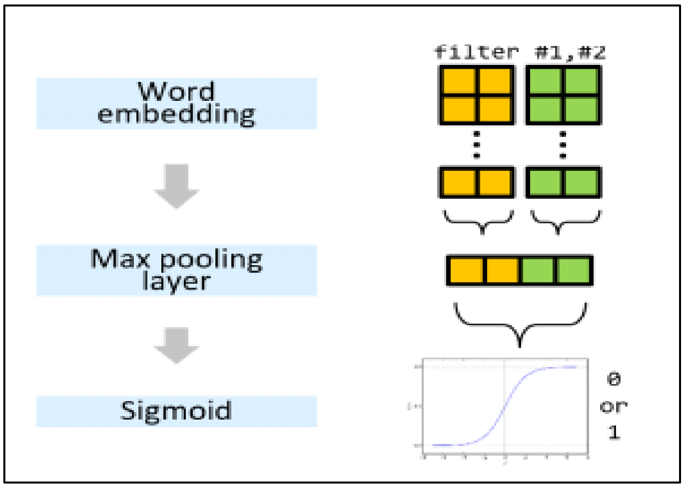

Fig 2 : Word Embedding Flow Chart

To adapt to the various sentence lengths within the dataset, we established a maximum length of 1191 for sentences processed into morphemes. To accommodate this variability, we adjusted the maximum length of word vectors to 1200 during the word embedding process. We also set the dimension of these word vectors to 100, mindful of the GPU's performance constraints.

Utilizing the resulting 100 x 1200 word embedding matrix, we constructed a one-dimensional (1D) convolution layer. This layer consisted of 256 filters, each with a kernel size of 2, utilizing the ReLU activation function and a stride of 1. Following this, a global max-pooling layer was applied to capture the highest value among the kernel nodes. To produce feature maps, the ReLU activation function was

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employed across the 256 filters, followed by the application of the Sigmoid activation function to each filter, approximating values for the classifier function. For training the model, we used the Adam (Adaptive moment) optimization algorithm. This algorithm calculates velocity and gradient accumulation vectors to gauge accuracy during subsequent steps. When employing only LSTM for comparison with CNN, we maintained identical word embedding parameters. The maximum length was fixed at 1200 with a dimension of 100, and we set up a bidirectional LSTM layer. This layer processed input sequences in both forward and backward directions, capturing contextual information from both ends of the input.

To optimize model performance in sequence classification tasks, the LSTM layer configuration employed a bidirectional approach. This involved setting the input gate to "forward" and the output gate to "backward," enabling the LSTM to capture contextual information from both sides of the input sequence. Bidirectional gates are preferred over unidirectional ones due to their ability to facilitate quicker and more comprehensive learning throughout sequence progression. To implement this bidirectional approach, a bidirectional LSTM layer was constructed, containing 128 neurons. A 25% dropout layer was introduced following the LSTM layer to maintain iterative learning within the LSTM. This dropout layer prevents overfitting by randomly dropping out a certain percentage of neurons during training, encouraging the model to learn more robust features. Sentiments were then modelled as binary values (0 or 1) using the sigmoid activation function. This approach mirrors the CNN's approach and enables effective classification. For the proposed CNN-LSTM combination model, the parameters for word embedding were maintained consistent with those of the individual CNN and LSTM models. This involved setting a maximum length of 1200 and a dimension of 100. When configuring CNN, 128 filters were deployed with a kernel size of 5. A pool size of 4 was designated for feature map construction, and a 25% dropout layer was integrated after the CNN layer. The Adam optimizer was then utilized to further refine the model.

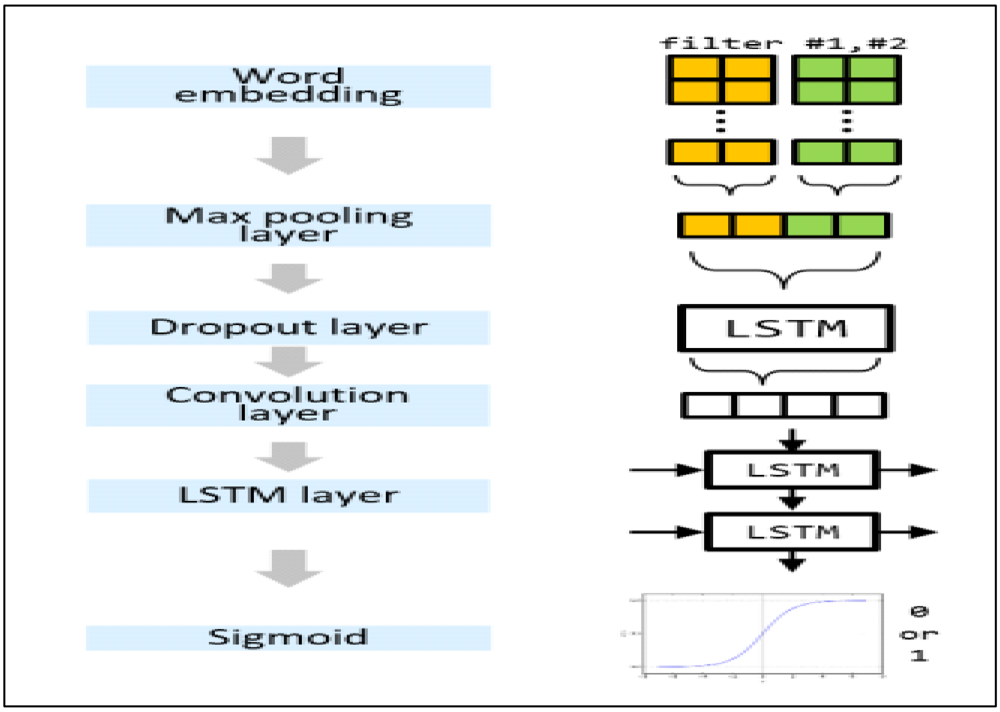

Fig : 3 Flow Chart of Long-Short Term Memory

BERT (Bidirectional Encoder Representations from Transformers) has emerged as a powerful tool for sentiment analysis, particularly in the domain of movie reviews. With its ability to capture contextual nuances and understand the relationships between words, BERT has revolutionized sentiment analysis tasks. In the context of movie reviews, BERT excels at comprehending the subtleties of language, considering the context and tone of phrases within the review text. Its bidirectional nature allows it to analyse a word while taking into account its surrounding words, resulting in a deeper understanding of sentiment. By leveraging pre-trained language representations, BERT can efficiently process movie review texts and predict sentiment with a high degree of accuracy. Its capability to contextualize words within a sentence or a paragraph contributes significantly to more nuanced sentiment analysis, enabling it to discern various sentiments expressed in movie reviews accurately. practitioners widely employ BERT in sentiment analysis tasks involving movie reviews due to its ability to capture intricate linguistic patterns, thereby enhancing the accuracy and depth of sentiment classification in this domain.

The synergistic combination of Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks in a hybrid model has proven to be a formidable rival to Bidirectional Encoder Representations from Transformers (BERT) in the realm of natural language

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processing (NLP) tasks, particularly in the areas of sentiment analysis and sequential data processing. While BERT has garnered widespread recognition for its exceptional ability to capture intricate contextual nuances and relationships between words, the hybrid CNN-LSTM model exhibits remarkable accuracy and effectiveness in a variety of NLP tasks. CNNs excel at extracting local features and patterns from textual data, making them well-suited for identifying subtle language cues and sentiment indicators. LSTMs, on the other hand, are adept at modelling sequential data and capturing long-range dependencies, allowing them to grasp the context and overall sentiment expressed within a text. The fusion of CNNs and LSTMs in the hybrid model capitalizes on the strengths of both architectures, leading to a more comprehensive and nuanced understanding of sentiment within textual data. CNNs provide the initial feature extraction, while LSTMs delve into the contextual and sequential intricacies within the text. This collaborative approach enables the model to capture both localized and overarching patterns, culminating in a more refined grasp of sentiment nuances. The CNN-LSTM model often requires less computational resources compared to BERT, making it more suitable for deployment on resource-constrained environments.

The hybrid architecture can be readily adapted to various NLP tasks by adjusting the network parameters and configurations, providing greater flexibility compared to BERT's pre-trained nature. The CNN-LSTM model offers improved interpretability compared to BERT. By analysing the activation values of the gates and memory cells, it is possible to gain insights into the model's decision-making process and better understand how it is capturing and utilizing long-term dependencies. This interpretability can be valuable for debugging, improving model performance, and gaining a deeper understanding of the data being analysed. The choice between the CNN-LSTM hybrid model and BERT hinges on the specific nature of the data, the task at hand, and the computational resources available. In certain contexts, BERT might outperform the CNN-LSTM hybrid, especially when dealing with a broad range of complex linguistic patterns or when leveraging pre-trained language representations. However, the CNN-LSTM hybrid model's ability to process data with substantial accuracy, particularly in sentiment analysis tasks, underscores its significance as a robust alternative to BERT in certain applications. The CNN-LSTM hybrid model emerges as a compelling choice for NLP tasks that demand a deeper understanding of sequential data and context, particularly in sentiment analysis.

➢ *Advantages*

Movie reviews offer a treasure trove of information about audience opinions, emotions, and reactions to films. By applying sentiment analysis, we can uncover these insights, allowing filmmakers, producers, and distributors to better grasp audience preferences and tailor their work accordingly. Sentiment analysis empowers moviegoers to make informed decisions when choosing which films to watch. By delving into reviews, individuals can gain a sense of the overall reception and sentiment towards a particular film, assisting them in selecting movies that align with their preferences and tastes. Sentiment analysis furnishes filmmakers with valuable feedback about their work. By comprehending how audiences respond to their films, filmmakers can identify areas for improvement and make informed decisions regarding future projects. Sentiment analysis plays a pivotal role in improving user experience on movie recommendation platforms and streaming services. By analysing reviews, these platforms can tailor recommendations based on individual users' preferences and sentiments, providing a more personalized and enjoyable movie-watching experience. Sentiment analysis of movie reviews serves as an invaluable tool for market research in the film industry. Studios and distributors can leverage this data to gain insights into market demands and trends, shaping their marketing strategies and content creation decisions. Sentiment analysis can be employed to assess the overall quality of a film. By analysing the tone and sentiment conveyed in reviews, viewers can make informed choices about which films to watch, filtering through the vast array of options available. The widespread adoption of social media has amplified the influence of movie-related sentiments. Sentiment analysis of discussions on platforms like Twitter or Facebook can provide insights into public perceptions and trends, shaping broader discussions and perceptions surrounding films.

➢ *Feasibility Study*

The fusion of CNN and LSTM in the model for sentiment analysis within movie reviews marks a groundbreaking approach. To maximize its transformative capacity, further adjustments and adaptations are crucial. By refining the fusion mechanism between CNN and LSTM, optimizing the model's architecture, and exploring hybrid models leveraging their complementary strengths, we can unlock more intricate and sophisticated sentiment analysis capabilities.

Expanding the model's scope to real-time applications and domain-specific adaptations holds the promise of substantial impact. Integrating real-time sentiment analysis into market research, for instance, can offer invaluable insights into consumer sentiment and market trends, empowering businesses to make well-informed decisions aligned with consumer preferences. Likewise, incorporating the model into recommendation systems can elevate personalized suggestions based on user preferences and sentiment, enhancing user experiences. Additionally, utilizing the model for customer feedback analysis can yield actionable insights for product development and customer satisfaction initiatives, fostering robust customer relationships and fuelling business growth. Continuously refining and adapting the fused CNN-LSTM model is the key to unleashing its full potential in revolutionizing sentiment analysis across diverse industries and real-world scenarios. This evolution promises a future that is more informed, tailored, and driven by data insights.

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IV. LITERATURE SURVEY

In the domain of sentiment analysis, Joscha and colleagues [1] made significant contributions by introducing and comparing various methodologies, including Bag of Words models and n-grams. Their work focused on incorporating semantic information into sentiment analysis to enhance its performance. This approach addressed the limitations of earlier methods that failed to consider the semantic connections between segments within sentences or documents. Subsequently, A. Hogenboom et al. [2] delved deeper into the methodological aspects of sentiment analysis and explored strategies for optimizing the amalgamation of disclosure units. They proposed utilizing Rhetoric Structure Theory (RST), a framework for hierarchical document-level representation, to refine sentiment analysis. To extract sentiment scores from RST trees, they employed a combination of grid search and weighting techniques. Additionally, they introduced a feature engineering approach that encoded binary data into random forests, effectively reducing the complexity of the original RST tree. Their findings demonstrated the effectiveness of machine learning techniques in enhancing sentiment analysis. Their proposed approach yielded a notable improvement in balanced accuracy and achieved a remarkable F1 score of 71.9%. This outcome underscores the potential of these methodologies to significantly improve the performance of sentiment analysis tasks. Both Joscha and colleagues [1] and A. Hogenboom et al. [2] made significant contributions to the field of sentiment analysis by introducing novel methodologies and exploring optimization strategies. Their work has paved the way for further advancements in sentiment analysis techniques, enabling more accurate and nuanced sentiment classification.

Amir Hossein Yazdavar and his team [3] presented a novel approach to address sentiment analysis in drug reviews, specifically focusing on sentences containing numerical data. Their primary goal was to classify these sentences as either opinionated or non-opinionated while simultaneously identifying the expressed sentiment polarity. To achieve this, they employed fuzzy set theory, a framework particularly well-suited for handling imprecise and ambiguous information prevalent in drug reviews. Their methodology cantered on the development of a fuzzy knowledge base, enriched with insights gleaned from interviews with multiple doctors from diverse medical centres. This knowledge base served as the foundation for classifying sentences based on their numerical content and sentiment polarity. Prior research in this domain, such as the work of Bhatia et al. [4], had largely overlooked the significance of numerical data within drug reviews when determining sentiment polarity. Additionally, the training data employed in these studies often exhibited a high degree of domain dependency, limiting their applicability across diverse domains.

Yazdavar and his team's innovative approach, grounded in knowledge engineering with fuzzy sets, addressed these limitations by providing a simpler, more efficient, and highly accurate method for sentiment analysis in drug reviews. Their proposed approach achieved an F1 value exceeding 72%, demonstrating its effectiveness in capturing the nuances of sentiment expressed in drug reviews. Their findings underscore the potential of fuzzy set theory in enhancing sentiment analysis and offer a promising avenue for further advancements in this field. By effectively incorporating numerical data and reducing domain dependency, their work paves the way for more comprehensive and accurate sentiment analysis of drug reviews, ultimately contributing to improved patient care and drug development.

Dhiraj Murthy's paper [5] extensively explored the multifaceted role of tweets in political elections, addressing a gap in previous research that hadn't delved into whether these tweets predominantly held Predictive or Reactive characteristics. His comprehensive analysis yielded a crucial finding: tweets tend to exhibit a more reactive nature rather than being predictive in shaping political outcomes. Contrary to common assumptions linking Twitter success with electoral triumphs, Murthy's research emphasized that the surge in a candidate's popularity across social media platforms was often a strategic tactic aimed at generating attention and visibility, rather than a direct predictor of electoral success. This revelation illuminated the intricate relationship between social media engagement and actual political results, underscoring Twitter's role as a reactive platform that amplifies existing sentiments rather than a crystal ball predicting electoral victories. Murthy's work provided valuable insight into how social media dynamics influence public perception during elections, showcasing that online popularity doesn't necessarily translate into electoral success.

Akshay Amolik and his team [9] made significant contributions to the field of sentiment analysis by developing a novel approach for classifying movie reviews extracted from Twitter posts. Their methodology consisted of three phases: data pre-processing, feature extraction, and classification. During the data pre-processing phase, they employed various techniques to clean and standardize the data, ensuring its suitability for further analysis. This included removing irrelevant information such as URLs and hashtags, and correcting spelling errors and grammatical mistakes. In the feature extraction phase, they generated a comprehensive feature vector that captured the salient characteristics of each tweet, including words, sentiment lexicons, and linguistic features. These features provided valuable insights into the sentiment expressed in the tweets. Finally, they applied a range of classifiers to categorize the tweets into positive, negative, and neutral classes. Among the classifiers evaluated were Naïve Bayes, Support Vector Machine (SVM), Ensemble classifier, k-means clustering, and Artificial Neural Networks.

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Their findings revealed that the SVM classifier achieved the highest accuracy, reaching an impressive 75%. This outcome challenged the conclusions of a previous study by Wu et al. [10], which suggested that the presence of '@username' in tweets influenced user behaviour and affected sentiment classification probabilities. Interestingly, Amolik and his team opted to replace '@username' with 'AT_USER' and remove hashtags from the tweets. This modification led to a significant improvement in sentiment classification accuracy, with SVM outperforming Naïve Bayes by a remarkable 10%. This alteration in their approach highlights the importance of careful data preprocessing and feature selection in achieving optimal sentiment classification performance. Amolik and his team's work provides valuable insights into sentiment analysis of movie reviews extracted from Twitter posts. Their proposed methodology, encompassing data pre-processing, feature extraction, and classification, demonstrates the effectiveness of SVM as a classifier for this task. Additionally, their findings underscore the impact of data preprocessing and feature selection on sentiment classification accuracy, emphasizing the importance of these steps in achieving optimal performance.

Humera Shaziya and team, in their published work [8], investigated the realm of sentiment analysis applied to movie reviews employing the WEKA Tool. Their study built upon prior attempts in sentiment classification by aiming to identify diverse opinions that encompass both positive and negative sentiments within individual reviews. They were attentive to the complexity inherent in reviews where multiple individuals might express differing sentiments within a single critique. Conducting a comprehensive experiment using the WEKA platform, they arrived at a notable finding: Naïve Bayes surpassed Support Vector Machine (SVM) in analysing both movie reviews and general text content. With an impressive accuracy rate of 85.1%, Naïve Bayes stood out as the more effective classifier for discerning sentiment within movie reviews, highlighting its efficacy in this specific domain.

➢ *Objective*

The proposed CNN-LSTM fusion model seeks to transcend the limitations of individual models by merging their capabilities, ultimately leading to enhanced sentiment analysis for unstructured text data. This hybrid approach addresses the shortcomings of standalone CNNs and LSTMs by leveraging their complementary strengths. Convolutional Neural Networks (CNNs) possess a remarkable ability to extract local features from textual data, making them well-suited for identifying subtle language nuances and patterns within words and phrases. This capability empowers CNNs to capture the essence of the text and provide a valuable representation of its meaning.

However, CNNs struggle to handle long-term dependencies and contextual information, which are crucial for understanding the overall sentiment of a text. This is where Long Short-Term Memory (LSTM) networks come into play. LSTMs excel at modelling sequential data, enabling them to effectively capture the context and long-range dependencies within text. Their ability to grasp the order and relationships between words in a sentence facilitates a deeper comprehension of the text's sentiment. By combining CNNs and LSTMs, the proposed hybrid model harnesses the strengths of both architectures to achieve a more nuanced and comprehensive sentiment analysis. CNNs provide the initial feature extraction, while LSTMs capture the contextual and sequential information within the text. This collaborative approach allows the model to capture both localized and overarching patterns, leading to a more refined understanding of sentiment nuances.

➢ *Architecture*

Convolutional neural networks (CNNs) represent a potent tool in machine learning, especially in domains like image recognition and pattern detection. Their end-to-end learning architecture, combined with the gradient descent algorithm, enables automatic extraction of essential features from raw data and optimization of model parameters without manual feature engineering. This streamlines the machine learning process, boosting efficiency in intricate tasks. CNNs excel in capturing local data patterns and relationships, making them ideal for image classification and object recognition. They use filters (kernels) to slide across input data, pinpointing and extracting crucial features that signify inherent patterns and relationships. This eliminates the need for manual feature extraction, a time-consuming step in traditional machine learning.

Their end-to-end learning framework heightens effectiveness. By concurrently optimizing all model parameters, CNNs align extracted features and classification decisions, enhancing performance. This differs from traditional methods where feature extraction and classification are often disjointed, potentially causing inconsistencies. The gradient descent algorithm's role is pivotal. Through iterative parameter adjustments based on predicted vs. actual outputs, CNNs continually refine their feature extraction and classification, known as backpropagation. This iterative process aids CNNs in gradually enhancing performance, achieving high accuracy and generalization. CNNs have transformed machine learning by automating feature extraction and optimizing parameters through the gradient descent algorithm. This breakthrough has significantly advanced image recognition, pattern detection, and tasks involving valuable information extraction from raw data

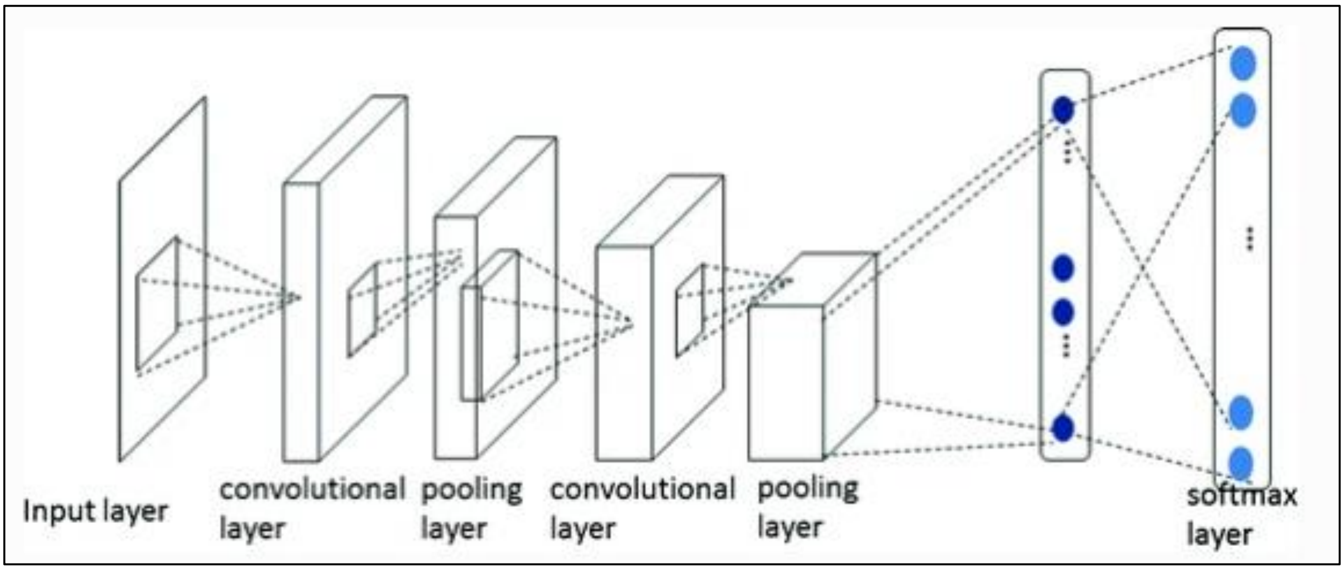

Fig 4 Integration Process of Softmax Layer

Long Short-Term Memory (LSTM) networks, a specialized type of recurrent neural network (RNN), have gained prominence for their remarkable ability to handle long-term dependencies in sequential data. Unlike traditional RNNs that struggle with vanishing gradients, LSTMs effectively preserve and utilize information from distant points in the sequence. This capability makes them particularly well-suited for tasks involving natural language processing (NLP) and other applications where understanding the context of a sequence is crucial. The heart of an LSTM unit lies in an elaborate gating mechanism, consisting of three gates: input, forget, and output. These gates meticulously regulate the flow of information through the memory cell, a key component of the LSTM architecture. The input gate determines which new information to add to the cell, while the forget gate decides which existing information to discard. The output gate controls what information is exposed to the rest of the network.

This intricate gating system allows LSTMs to selectively retain and utilize long-term dependencies, making them ideal for processing sequential data like text. In the context of NLP, LSTM networks can effectively capture the nuances of language, such as grammatical structure and long-range dependencies, enabling them to perform tasks like machine translation, text summarization, and sentiment analysis with remarkable accuracy. One of the key advantages of LSTMs over traditional RNNs is their ability to overcome the vanishing gradient problem. This problem arises in RNNs when the gradients of the error function become very small or zero during backpropagation, making it difficult for the network to learn long-term dependencies. LSTMs, with their clever gating mechanism, effectively mitigate this issue, allowing them to learn and utilize information from distant points in the sequence.

Furthermore, LSTMs offer a higher level of interpretability compared to other deep learning models. By analysing the activation values of the gates and memory cells, it is possible to gain insights into the model's decision-making process and better understand how it is capturing and utilizing long-term dependencies. This interpretability can be valuable for debugging, improving model performance, and gaining a deeper understanding of the data being analysed. LSTM networks have revolutionized the field of NLP and other sequential data analysis tasks. Their ability to handle long-term dependencies makes them a powerful tool for understanding and extracting meaning from complex sequential data. Their interpretability and ability to overcome the vanishing gradient problem further enhance their value as a versatile tool for a wide range of applications.

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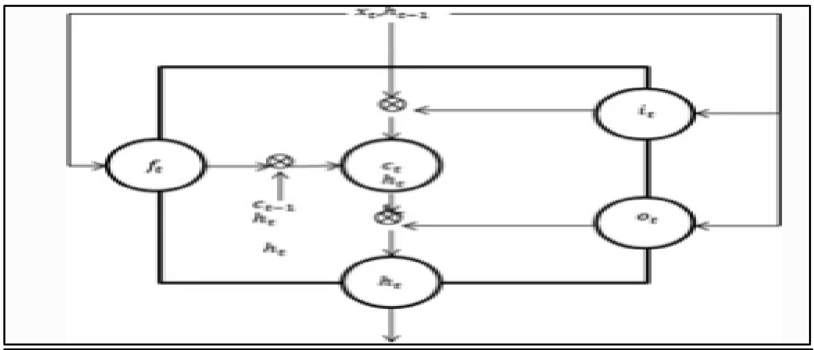

$$i_t = \sigma\left(W_{xi} x_t + W_{hi} h_{t-1} + W_{ci} c_{t-1} + b_i\right)$$

$$f_t = \sigma\left(W_{xf} x_t + W_{hf} h_{t-1} + W_{cf} c_{t-1} + b_f\right)$$

$$o_t = \sigma\left(W_{xo} x_t + W_{ho} h_{t-1} + W_{co} c_{t-1} + b_o\right)$$

Fig 5 Algorithms to Derive I, F And O

Word embedding holds a crucial role in NLP when integrating deep learning techniques, converting individual words into feature embeddings that encapsulate semantic information. In our model, the pretrained words in the dataset were converted into word vectors within the input phase. Subsequently, we implemented a sequence involving a convolution layer, a max pooling layer, a dropout layer, and a BLSTM layer. The input segment accommodated a maximum of 1000 word vectors, each containing 50 dimensions. To counter potential model overfitting, a dropout layer was introduced following the final max pooling layer. The model culminated with a BLSTM layer and two dense layers.

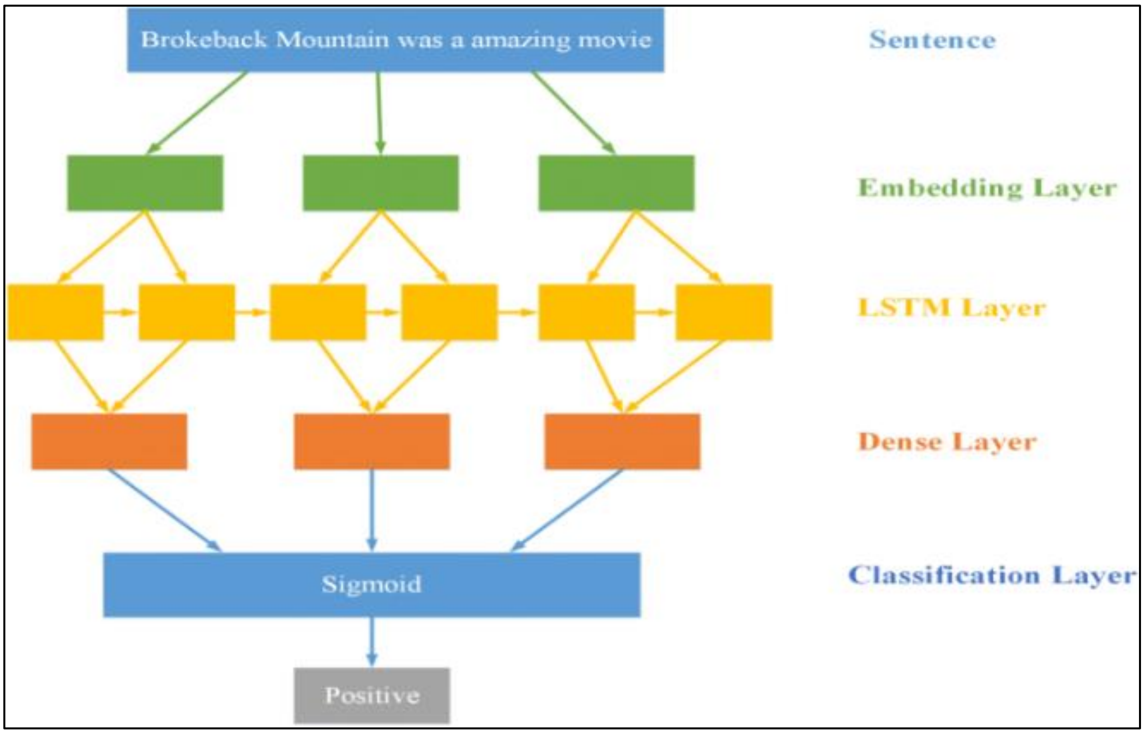

Fig 6 Embedding and Classification of LSTM Layer

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V. RESULTS AND DISCUSSION

The integration of Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks for sentiment analysis in this study yielded a remarkable enhancement in accuracy, surpassing the performance of other methods and standalone models. This synergistic fusion of two powerful deep learning architectures resulted in a significant improvement in the accuracy rate, marking a substantial advancement in sentiment analysis specifically for evaluating movie reviews. The superior accuracy achieved by the hybrid CNN-LSTM approach underscores its effectiveness and potential superiority in comprehending and classifying sentiment within textual data.

The robustness of this fusion model lies in its ability to capture the intricate complexities and subtle nuances present in movie reviews. This capability stems from the complementary strengths of CNNs and LSTMs. CNNs excel at extracting local features and patterns from text, enabling them to identify subtle language cues and sentiment indicators. LSTMs, on the other hand, are adept at modelling sequential data and capturing long-range dependencies, allowing them to grasp the context and overall sentiment expressed within a review.

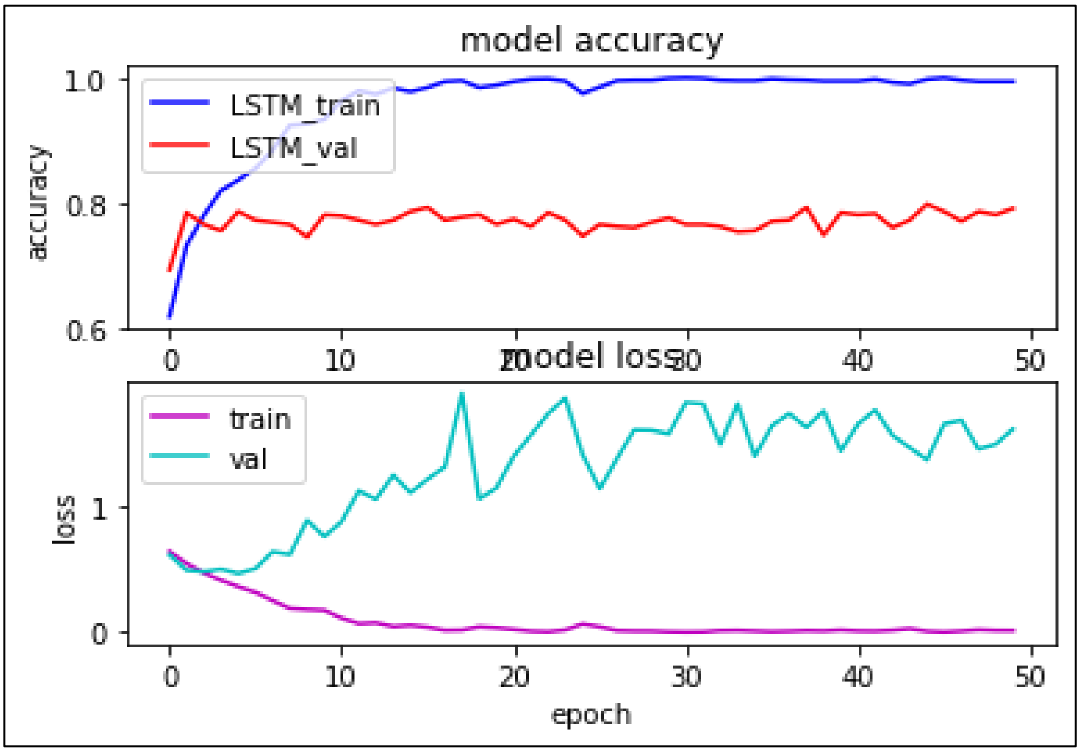

Fig 7 Trained LSTM vs Ideal LSTM Value Graph

By combining these two complementary architectures, the CNN-LSTM fusion model effectively captures both local and global patterns, leading to a more refined and nuanced understanding of sentiment. This comprehensive approach enables the model to discern subtle variations in sentiment that would otherwise be overlooked by simpler methods.

The notable improvement in accuracy achieved by the CNN-LSTM fusion model highlights the remarkable impact and efficacy of employing this combined approach for sentiment analysis in the context of movie reviews. Its ability to capture the complexities and nuances of language, coupled with its robustness and adaptability, makes it a promising tool for various sentiment analysis applications beyond movie reviews.

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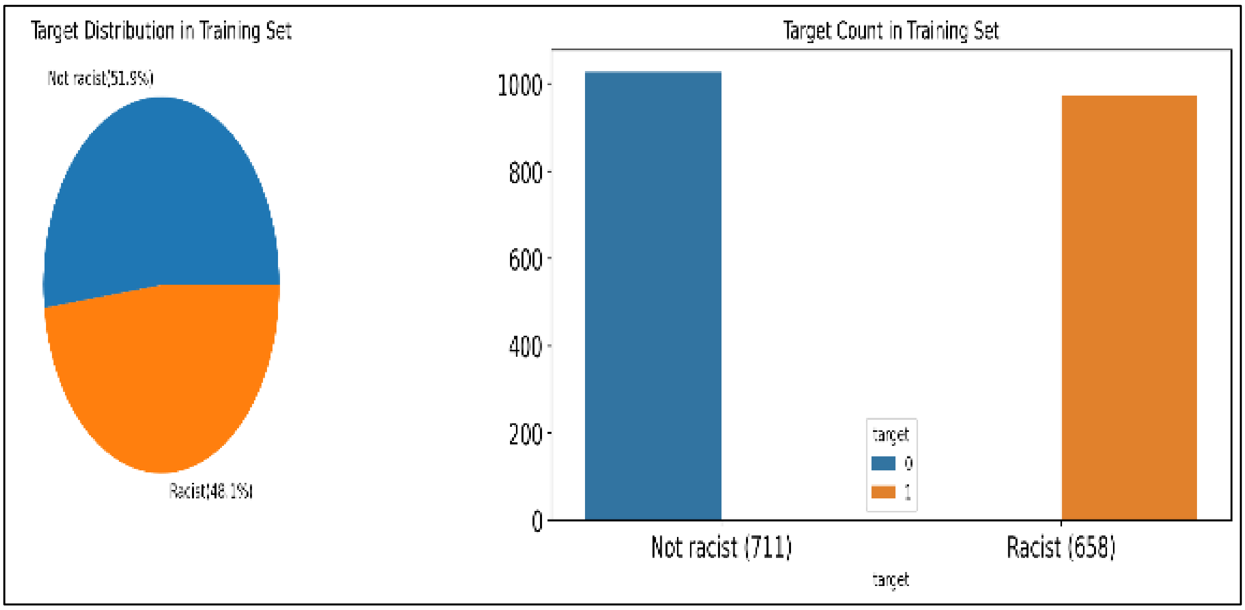

Fig 8 Graphical Representation of Train LSTM and Val LSTM

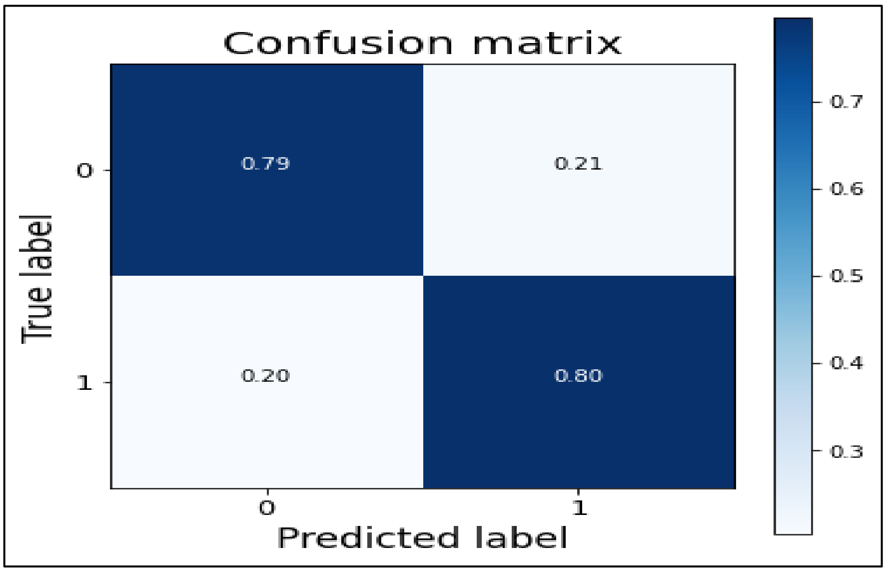

Fig 9 Confusion Matrix of LSTM Value

VI. CONCLUSION AND FUTURE WORK

This study proposes a novel approach to sentiment analysis in movie reviews by combining two powerful deep learning algorithms: Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks. The proposed CNN-LSTM fusion model demonstrates superior performance compared to traditional machine learning methods and standalone deep learning models, exhibiting greater consistency and accuracy in sentiment classification.

The use of vector models, which represent words as numerical vectors, can lead to the "curse of dimensionality" when word occurrence-based feature vectors result in excessively high dimensionality, potentially causing information loss. This issue is addressed by the CNN-LSTM model through the careful selection of network sequence lengths and convolutional kernel sizes tailored to specific word embeddings. This approach not only mitigates dimensionality concerns but also enables flexible segmentation and parallel corpus training of specific sentences, enhancing the overall efficiency of the model. Moreover, the sequential nature of the CNN-LSTM model allows for the application of max-pooling, a technique that effectively captures document relevance by selecting the most significant features from each sequence. Within the composite model, LSTMs are employed to leverage their unique gating mechanism, which regulates input and output timings. This capability enables the model to predict subsequent words ahead when encountering new sentences, thereby augmenting the learning process. During training, LSTM's predictive ability extends beyond probability distribution, incorporating positive or negative sentiment into the predicted next word, leading to more refined sentiment classifications compared to other models.

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Online reviews, including movie critiques, serve as valuable sources of information but pose challenges due to their nuanced and subjective nature. To streamline review classification, this study employs machine learning methods like Bag of Words and TF-IDF for vectorization, while leveraging deep learning to convert text into sequenced data via word embedding for analysis. While this study did not produce significant accuracy improvements compared to certain machine learning methods, future research incorporating feature selection techniques may further enhance the model's performance. This could involve analysing the impact of different parameter settings on training data vectorization and identifying the most informative features for sentiment classification. The practical implications of this research are significant, highlighting the potential of deep learning-based sentiment analysis to refine sentiment predictions. This holds promise for analysing success factors, particularly in the film industry, offering valuable insights for industry advancement. Additionally, integrating sentiment analysis into movie recommendation systems could provide more personalized and effective recommendations, diversifying from systems solely reliant on user ratings. This study presents a novel CNN-LSTM fusion model that demonstrates superior performance in sentiment analysis of movie reviews compared to traditional methods. The model's ability to address the "curse of dimensionality" and effectively capture nuanced sentiment through LSTM's predictive capabilities holds promise for further improvements in sentiment analysis and its application in various domains.

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