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Sentimental Analysis Using RNN, CNN AND LSTM: A Comparative Study Of Accuracy And Computational Efficiency

Amanpreet Kaur[1] Pankaj Bhambri[2*] Sandeep Kumar Singla[2]

[1]Research Scholar, Department of Information Technology, Guru Nanak Dev Engineering College, Ludhiana
[2]Supervisor and Assistant Professor, Department of Information Technology, Guru Nanak Dev Engineering College, Ludhiana* pkbhambri@gmail.com

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ABSTRACT

With the growing trend of the social media, people express their emotions on the different platforms in the form of comments or reviews whether it is positive, negative or neutral. Social networking sites like Twitter, instagram, youtube etc. are gaining popularity very quickly as they allow people to express and share their thoughts on topics, communicate with different communities or spread it to the world. Many studies have been done in the field of data on social media. In political elections, it is used to track political views and detect inconsistencies and discrepancies between talk and action at the government level. It can also be used to predict election results. Now a days election polling is done to predict the winning party and which party's manifesto is grabbing the public interest.

In this paper, different models such as CNN, RNN and LSTM are used in order to compute accuracy and computation time. The work is done on the real-time data.

KEYWORDS

Sentiment analysis, Conventional Neutral Network(CNN), Recurrent Neural Network(RNN), Long Short-Term Memory(LSTM), Deep learning

INTRODUCTION

The information generated by online platforms such as social networking and research is increasing based on the expectation of electronic design. The large amount of data presents challenges and opportunities to researchers and companies in understanding people's experiences and preferences. As a leader in sentiment analysis, it has proven to be a powerful tool in conveying insights, information, thoughts and emotions in a data-driven format.

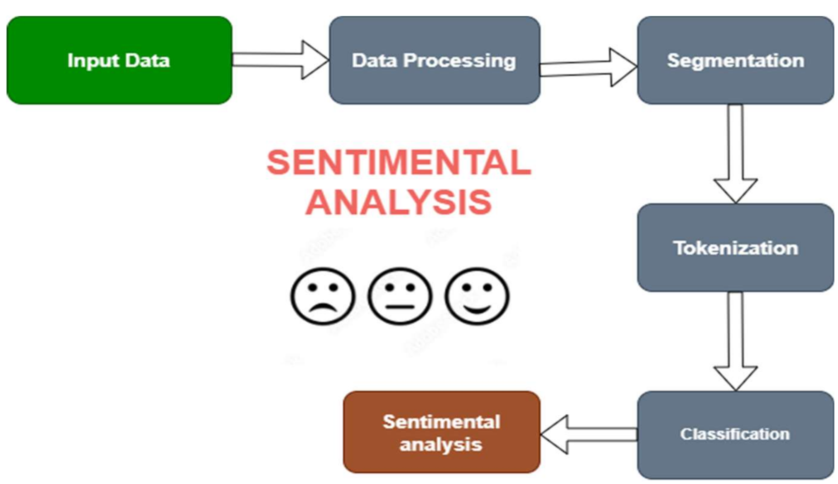

Fig 1.1: Sentimental analysis

We use survey data in the opinion analysis project of this study. Deep learning techniques have become a popular method for opinion analysis in recent years to analyze the opinions expressed in these documents [23], [24].

Deep learning is a branch of artificial intelligence that has shown great success in capturing the complexity and intricacy of human speech and emotions, making it the best candidate for a collection of election sentiment A. powerful tools [1], [35]. The core of our deep learning approach to the analysis of election data is a convolutional neural network that can learn hierarchical representations of political documents and extract content values and patterns, which are data for classification theory [26]. In particular, the models we use include convolutional neural networks (CNN), LSTM (RNN), and adaptive models, which have been effective in determining the sentiment mentioned in the election related literature [33]. By combining deep learning models with survey data, we can capture the positive and negative sentiments expressed in political discourse and provide insight into understanding emotional responses during elections.

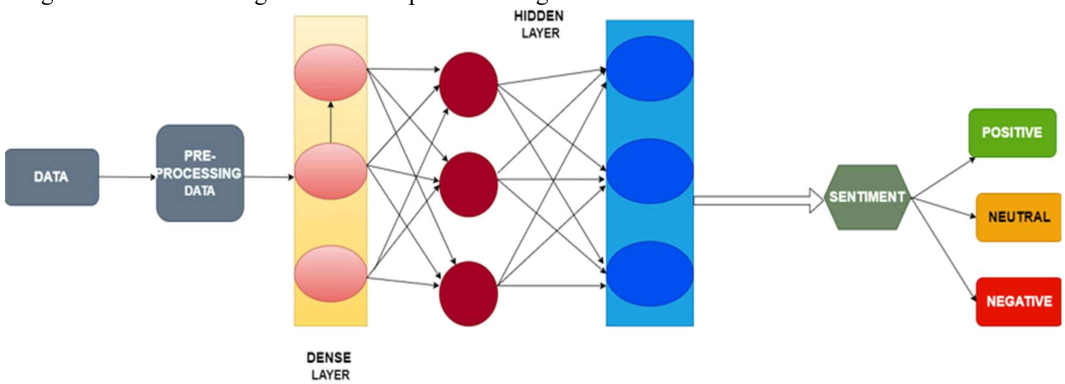

Fig 1.2: Deep Learning

1. Model Architecture

Deep learning models are models that include the configuration of processes, connections between neurons, and activation. The architecture of the model determines its complexity and expressiveness.

- **Convolutional Neural Networks (CNN) for Sentiment Analysis:** Convolutional Neural Networks (CNN) are widely used due to their ability to capture local behavior and context in the case of analytical thinking [16], [37]. By utilizing convolutional filters and pooling mechanisms, CNNs can extract n-gram features and learn meaningful representations of sentiments and sentences, thus enabling the classification of attributes from data, sentence, or specific level. The basic principle of CNN for sentiment analysis is to learn high-level features, lower-level to capture local patterns such as n-grams, and outer layers to layer more of these patterns to generate more sentiments. This hierarchical learning process makes CNNs a good model in terms of the relationships between words and their support for the needs presented in the text [17], [40]

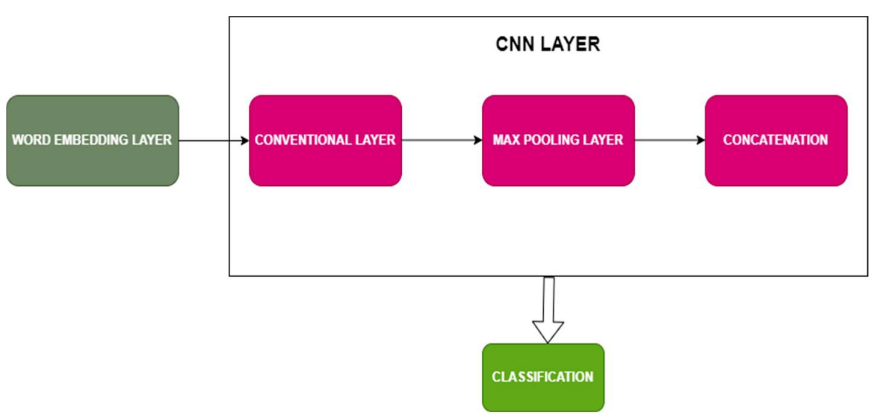

Fig 1.3: CNN Model

- **Recurrent neural networks (RNN) Model:** Recurrent neural networks (RNN), especially short-term (LSTM) and gated recurrent units (GRU), are also widely used in sentiment analysis [8], [33]. These models are good at capturing the connection between sentences and the content of words, allowing them to model interest across the text and take into account all the needs to be taught. Sequentially, one word (or token) is found at a time and holds a hidden state that encodes the contextual content from the previous input. It allows models to understand long-term expectations and how sentiments evolve across the text, leading to a more comprehensive distribution of sentiments [18], [38].

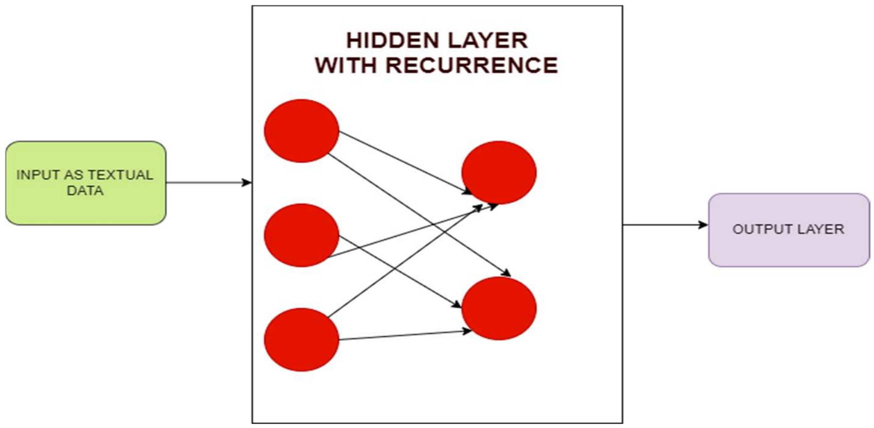

Fig 1.4: RNN Model

- **Long Short-Term Memory (LSTM) Model:** LSTM (Long Short-Term Memory) is a neural network (RNN) widely used in deep learning. It is good at capturing long-term dependencies, which makes it ideal for ranking. This makes it useful for understanding and predicting patterns in physical data such as time, text, and speech.

Datasets are important for analyzing voting behavior and public opinion. This study focuses on data that includes tweets related to elections in India, where voting is an important part of the democratic process with millions of participants. The electoral process in India is characterized by public participation and discussions on social media such as Twitter. Analyzing tweets in this context allows us to understand voters' opinions, preferences, and key issues affecting the election.

Real time dataset is taken from the different social media platform such as Instagram, facebook and twitter. Dataset on election tweets show positive trends in public opinion. The sentiment distribution, as shown in the pie and count charts, shows that the majority of tweets are neutral (48.1%), with almost equal amounts of positive and negative sentiment (37.6% positive and 14.3% negative). This classification shows the public's attitudes towards the elections, which are balanced or controversial, with varying degrees of approval or criticism.

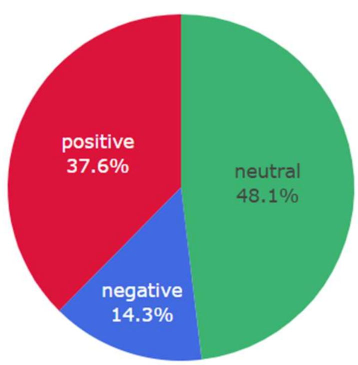

Fig 1.5: Pie Chart

2. METHODOLOGY

Many websites and blogs generate thousands of comments each day, making it difficult for large companies to track and analyze user input. To be effective, text must be structured to clearly convey underlying ideas. However, the brevity and informality of online language, often including special characters and slang, pose a serious problem for sentiment analysis. This problem is further complicated by the fact that words can have multiple interpretations depending on the organization's context and interests. In addition, observers' opinions can add another layer of complexity to the sentiment process. . The main challenge is to interpret and understand the thoughts in the text correctly. Successful classification depends on identifying relevant features that reflect the subtleties of individual words in a sentence. The main goal is to achieve accuracy in emotional assessment using as few dimensions as possible.

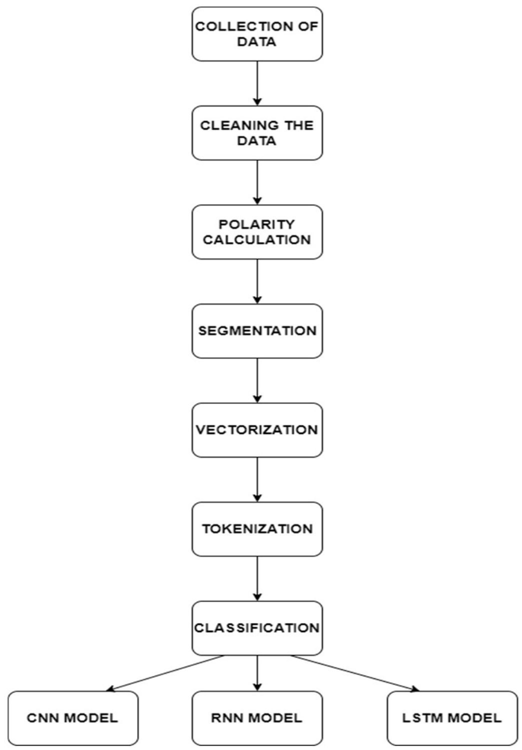

Fig 1.6: Methodology

- Data collection: Data collected from different platforms are compiled into a CSV file containing votes on tweets and sent to the appropriate data analysis environment for further study.
- Data cleaning: After collecting data, the next step is to pre-process it by cleaning it. This includes removing irrelevant content such as links, hashtags, phrases, and labels that cannot be used for sentiment analysis.
- Polarity calculation: In this step, we calculate the polarity of the text. Polarity measures the opinion expressed in the text by measuring it on a scale of -1 to 1: -1 represents negative opinion, 0 represents negative opinion, and 1 represents positive opinion. All opinions in the collected data are categorized to clarify public opinion.
- Vectorization: Convert text into digital form through the process of vectorization. Vectorization converts a word or phrase into numerical vectors for quantitative analysis. Techniques used in vectorization include Word2Vec, TF-IDF, and embedding
- Sequence padding: It is used to handle sequences of different length, Keras pad_sequences function is used. This function normalizes the length of a segment by padding it to normal size. Parameters like maximum length control the length of the padding sequence.
- Modeling: The last step is to apply CNN, RNN and LSTM models to evaluate their performance in sentiment analysis. Accuracy and efficiency in distributing sentiments. CNNs are mainly used to capture spatial hierarchies in data, while RNNs are suitable for continuous data analysis due to their memory and content storage. LSTM can collect long-term data series.

3. RESULTS AND DISCUSSIONS

The analysis investigates the distribution, patterns and patterns of opinion over time, as well as the effectiveness of various models and methods used to process and classify information. This section aims to better understand public opinion during elections by analyzing the results of Convolutional Neural Networks (CNN) and Recurrent Neural Networks (RNN). The findings from this analysis provide good information not only about the accuracy and reliability of the opinion distribution model, but also about the opinions of voters and their impact on important election events.

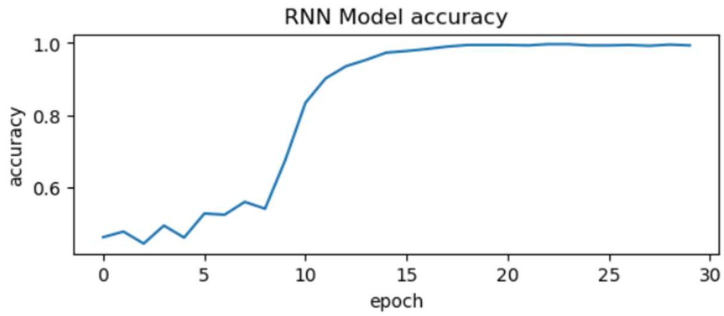

Fig 1.7: RNN Model Accuracy

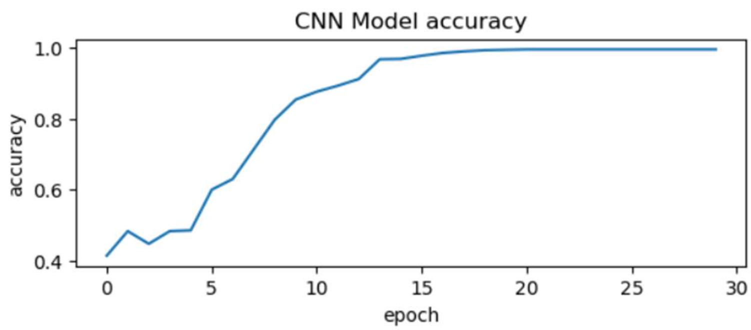

Fig 1.8: CNN Model Accuracy

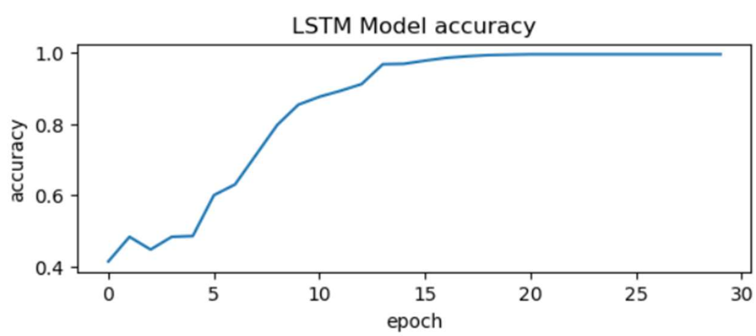

Fig 1.9: LSTM Model Accuracy

Typical graphs for RNN, LSTM and CNN models illustrate the nature of deep learning models. In both cases, there were discussions about the problems and learning processes in training neural networks for sentiment analysis. The RNN model was found to be excellent with some modifications, while the accuracy of the CNN model increased after initially decreasing. These observations highlight the importance of extensive and careful training to achieve the best performance in cognitive tasks. The results highlight the ability of LSTM, RNN and CNN models to identify and classify the sentiment of social media profiles.

Table 1.1: Results of Accuracy

MODELS	ACCURACY

CNN MODEL	89%
RNN MODEL	90%
LSTM MODEL	94%

Table 1.2: Computational Efficiency

)DELS	)MPUTATION TIME
CNN MODEL	53ms/step
RNN MODEL	81ms/step
LSTM MODEL	368ms/step

The performance evaluation of the model shows that the RNN, LSTM, and CNN models all teach different learning patterns. The accuracy of the RNN model shows that the total increases over time and shows improvement after tinued training. In contrast, the accuracy of the CNN model experienced a decrease before the increase, indicating that the model adapts and corrects its prediction with less computational time during the learning curve. The accuracy of the LSTM model is higher but the computational time is longer.

4. CONCLUSION AND FUTURE SCOPE

In this paper, we describe the implementation and evaluation of deep learning models used for sentiment analysis of social network data, focusing specifically on survey tweets. Using predefined methods (such as TF-IDF), we transform the input data to improve the performance of the model. We adopt and compare the design of CNN, LSTM, and RNN models, taking advantage of their advantages in processing data connections and extracting complex patterns in text. Our experiments evaluate the effectiveness of these models in the distribution of sentiments and provide insight into their results and performance.

The results show that CNN and RNN models can classify sentiment on social media profiles when combined with TF-IDF. The CNN model shows a good balance between accuracy and time performance, while the RNN model shows better accuracy, especially in LSTM, which shows more confidence on accuracy in using more time. These results highlight the importance of choosing the right model according to the specific needs of the sentiment analysis task.

In future work, the aim to explore a hybrid model that combines the advantages of various deep learning methods to improve classification accuracy and reduce computational cost. Data can be taken on large scale and analyze opinion-based insights to gain deeper insight into specific topics or features in the data. This is especially important for organizations that want to obtain detailed feedback from users.

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