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Sentimental Analysis using Bi-directional RNN with Attention Mechanism based on Term Frequency- Inverse Document Frequency

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ABSTRACT

In this research, we propose a robust sentiment analysis model leveraging a Bidirectional Recurrent Neural Network (Bi-RNN) with an attention mechanism, combined with Term Frequency-Inverse Document Frequency (TF-IDF) for feature extraction. The model is designed to effectively capture the nuances of sentiment expressions in user-generated reviews, specifically focusing on the Yelp Reviews dataset. Our approach addresses the challenges of long-term dependency learning and context interpretation by employing a Bi-RNN architecture that processes text in both forward and backward directions, complemented by an attention mechanism that highlights the most relevant parts of the text. The proposed model achieved an accuracy of 93.85%, surpassing baseline models such as standard RNNs, unidirectional LSTMs, and SVM classifiers. Additionally, the model demonstrated balanced performance across positive, negative, and neutral sentiment classes, showcasing its ability to handle class imbalances and complex sentiment patterns. The research highlights the potential of the Bi-RNN with attention in enhancing sentiment analysis tasks, and suggests further improvements through the integration of advanced deep learning techniques and transformer-based architectures

Keywords: Sentiment Analysis, Bidirectional Recurrent Neural Network (Bi-RNN), Attention Mechanism, Term Frequency-Inverse Document Frequency (TF-IDF), Yelp Reviews Dataset, Long-Term Dependency Learningr

1.INTRODUCTION

Sentiment analysis, often referred to as opinion mining, is the process of determining the sentiment expressed in a piece of text. This can be categorized as positive, negative, or neutral, although more fine-grained categorizations are also possible. The ability to automatically assess sentiment from text has a wide range of applications[1]. For businesses, sentiment analysis can provide insights into customer satisfaction, product reviews, and brand reputation. In politics, sentiment analysis can gauge public opinion on policies or political figures, providing a real-time pulse of the electorate's mood. Social media platforms use sentiment analysis to monitor trends, detect potential issues, and even combat misinformation. The proliferation of online platforms where individuals express their opinions has made sentiment analysis more relevant than ever. Social media, blogs, forums, and review sites generate vast amounts of textual data daily, much of which contains valuable insights into public sentiment. Manually analyzing this data is impractical, if not impossible, given the scale. Therefore, automated sentiment analysis tools, powered by machine learning and natural language processing (NLP) techniques, have become essential[2].

Despite its importance, sentiment analysis is fraught with challenges. Human language is inherently complex, characterized by ambiguity, sarcasm, idioms, and varying contexts, all of which can obscure the true sentiment of a statement. For example, the sentence "I can't wait to try the new update" can express positive anticipation or sarcastic dread, depending on the context, which is not always evident from the text alone. Additionally, the same word can carry different sentiments in different contexts. The word "light" might have a positive connotation in "The room was filled with light" but a negative one in "The product felt light and cheap" [3].

Traditional sentiment analysis models, which often rely on simple rules or shallow machine learning techniques like bag-of-words or n-grams, struggle to capture these nuances. These models typically treat words independently of each other, ignoring the order in which words appear, which is critical for understanding context[4]. For instance, the phrase "not good" should be interpreted as negative, but a simple bag-of-words model might incorrectly assign a positive sentiment if "good" appears frequently in positive contexts.

In the modern digital age, sentiment analysis has emerged as a critical tool for understanding human emotions expressed through text, particularly in social media, customer reviews, and other user-generated content. As the volume of textual data continues to grow exponentially, automated sentiment analysis has become indispensable for businesses, governments, and researchers alike, offering insights into public opinion, customer satisfaction, and market trends. The complexity of human language, however, poses significant challenges to accurate sentiment analysis, necessitating the development of sophisticated computational techniques that can discern subtle nuances in text. Recurrent Neural Networks (RNNs) have been a cornerstone in the evolution of sentiment analysis, owing to their ability to process sequential data and capture temporal dependencies within text[5]. Traditional RNNs, however, are limited by their unidirectional nature, which processes text in a single direction (either forward or backward), potentially overlooking important contextual information. To address this limitation, Bidirectional RNNs (Bi-RNNs) were introduced, which process text in both directions—forward and backward—allowing for a more comprehensive understanding of the context and improving the model's ability to capture sentiment.

Despite the advancements brought by Bi-RNNs, challenges remain in effectively capturing the relevant features within text data, particularly when dealing with long sentences or documents where important words may be dispersed throughout the text. This is where the attention mechanism comes into play. Inspired by the way humans focus on specific parts of a sentence when interpreting its meaning, the attention mechanism allows the model to weigh the importance of different words in a sentence, effectively highlighting the most relevant parts of the input text for sentiment classification. By integrating an attention mechanism with Bi-RNNs, the model can dynamically focus on the most significant portions of the text, thereby improving sentiment analysis accuracy. In tandem with these neural architectures, the preprocessing of text data plays a crucial role in the effectiveness of sentiment analysis models. One of the most widely used techniques for representing text data is Term Frequency-Inverse Document Frequency (TF-IDF). TF-IDF is a statistical measure that evaluates the importance of a word within a document relative to a collection of documents (corpus). It combines the frequency of a word in a specific document with its frequency across all documents in the corpus, effectively distinguishing common words from those that are more unique or informative. By utilizing TF-IDF as a feature extraction method, the model can better differentiate between words that contribute significantly to sentiment from those that do not. This research article aims to explore the effectiveness of combining Bi-Directional RNNs with an attention mechanism and TF-IDF for sentiment analysis. The integration of these methodologies is expected to address the limitations of traditional sentiment analysis models, offering a more nuanced and accurate interpretation of sentiment in text. Specifically, the article will investigate how the attention mechanism, when applied within a Bi-RNN framework, can enhance the model's ability to focus on sentiment-bearing words, while TF-IDF serves as a robust feature extraction method to improve the overall quality of the input data[6].

To address these challenges, RNNs were introduced to sentiment analysis due to their ability to process text as a sequence of words rather than as isolated tokens. By maintaining a hidden state that captures information from previous words, RNNs can understand the context in which a word appears. However, standard RNNs process text in only one direction, typically from the beginning to the end of a sentence. This unidirectional processing can be limiting because it only allows the model to consider past words when predicting the sentiment of the current word. Bi-Directional RNNs (Bi-RNNs) were developed to overcome this limitation by processing the text in both forward and backward directions. This means that for each word in the sentence, the model considers both the words that precede it and those that follow it. This dual perspective allows the model to better capture the context and,

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consequently, the sentiment of each word in relation to the entire sentence. For example, in the sentence "The product is not only good but also affordable," a Bi-RNN would understand that "not only" modifies the sentiment expressed by "good," and "but also" introduces a further positive sentiment with "affordable." While Bi-RNNs offer significant improvements over unidirectional RNNs, they still face challenges when processing long sentences or documents. In such cases, the context captured by the hidden states may become diluted as the sequence length increases, leading to a loss of important information. The attention mechanism addresses this by allowing the model to selectively focus on specific parts of the input sequence when making predictions.

The attention mechanism works by assigning a weight to each word in the input sequence, representing its importance for the current prediction. These weights are learned during training, enabling the model to dynamically adjust its focus based on the input text. For sentiment analysis, this means the model can pay more attention to sentiment-bearing words while ignoring irrelevant words. For example, in the sentence "I was extremely disappointed with the service," the attention mechanism would assign higher weights to "extremely" and "disappointed," emphasizing their importance in conveying the negative sentiment. Feature extraction is a critical step in text preprocessing, as it transforms raw text into a format that can be used as input to machine learning models. One of the most effective and widely used techniques for this purpose is Term Frequency-Inverse Document Frequency (TF-IDF). TF-IDF quantifies the importance of a word in a document relative to a corpus, allowing the model to distinguish between commonly used words (e.g., "the," "is") and those that carry more informational content.

By using TF-IDF as part of the feature extraction process, the sentiment analysis model can focus on words that are more likely to contribute to the overall sentiment of the text. In conjunction with a Bi-RNN and attention mechanism, TF-IDF provides a robust foundation for accurate sentiment analysis, ensuring that the model is not only aware of the sequence and context of words but also their relative importance across the corpus. This research article explores the integration of Bi-Directional RNNs, attention mechanisms, and TF-IDF in sentiment analysis[7]. By combining these techniques, the proposed model aims to overcome the limitations of traditional sentiment analysis approaches, offering a more accurate and nuanced understanding of sentiment in text. The next sections will delve into the methodology, experiments, and results, demonstrating the effectiveness of this integrated approach in various sentiment analysis tasks.

The research article is organized as follows: Section I introduces the motivation and challenges of sentiment analysis, leading to the proposal of an advanced model. Section II reviews related work, discussing existing sentiment analysis techniques and the use of deep learning models, attention mechanisms, and TF-IDF. Section III presents the proposed methodology, detailing the architecture of the Bidirectional RNN with attention and TF-IDF, along with the dataset and preprocessing steps. Section IV outlines the experimental setup, presents the results, and compares the proposed model's performance with baseline models and discusses the findings, implications, limitations, and potential future research directions. Section V concludes the article, summarizing the key contributions and the model's impact on sentiment analysis.

2. LITERATURE REVIEW

Sentiment analysis utilizing Bi-Directional Recurrent Neural Networks (Bi-RNN) with an attention mechanism, combined with Term Frequency-Inverse Document Frequency (TF-IDF), has shown promising results in enhancing the accuracy of sentiment classification. Research indicates that the integration of TF-IDF helps in effectively weighting the importance of words in the context of sentiment, thereby improving the model's performance in distinguishing between positive and negative sentiments[8]. The attention mechanism further refines this by allowing the model to focus on significant words, enhancing interpretability and accuracy[9]. Moreover, studies have demonstrated that Bi-RNNs, due to their ability to process sequences in both directions, capture contextual information more effectively than traditional RNNs[10]. However, challenges remain, such as the computational complexity and the need for large datasets to train these models effectively[11]. Overall, the combination of these techniques represents a significant advancement in the field of sentiment analysis, although further research is needed to optimize their application[12].

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Recent advancements in sentiment analysis have focused on various domains, datasets, and methodologies to enhance the accuracy and interpretability of sentiment classification models. In the context of Twitter data, research has been conducted on analyzing Covid-19 related tweets. One notable approach involved using Latent Dirichlet Allocation (LDA) for feature extraction, combined with Term Frequency-Inverse Document Frequency (TF-IDF) as a word embedding technique. This method achieved an 85% accuracy rate in Support Vector Machine (SVM) classification[13]. The study also introduced advanced sentiment analysis techniques aimed at improving topic coherence and interpretability, thereby providing clearer insights into public sentiment during the pandemic.

Short text sentiment classification has been extensively studied using the Quora dataset, while the IMDB movie reviews dataset has been utilized for long text sentiment classification. A combination of Word2Vec, BiLSTM, and CNN was employed for short text classification, with an attention-based CNN-BiLSTM hybrid model applied to long texts. The CNN-BiLSTM approach achieved an impressive 91.48% accuracy in short text sentiment classification, while the BiLSTM-CNN model with attention mechanisms demonstrated improved performance in long text sentiment classification. These studies emphasize the importance of exploring hybrid models and attention mechanisms to enhance sentiment classification, particularly in long text scenarios[14].

Another study involving four reviews datasets and two Twitter datasets explored the use of a RU-BiLSTM model with an attention mechanism for text classification. The preprocessing techniques included tokenization, stop word removal, stemming, and lemmatization. The RU-BiLSTM model outperformed aspect-based classification methods on both lengthy reviews and short tweets, demonstrating efficacy in binary and ternary classification outcomes[15]. The research suggests further exploration of larger datasets and more complex attention mechanisms to continue improving the RU-BiLSTM model's performance.

Attention mechanisms have been applied in various ways to enhance sentiment analysis models. For instance, a study incorporated attention mechanisms into the pooling layer of a CNN, and trained bidirectional affective word vectors to capture emotion-related features. The resulting DSA-CNN model outperformed classical sentiment analysis models, achieving higher accuracy and a faster convergence rate. Further improvements in sentiment analysis accuracy and the optimization of attention mechanisms, particularly in short text scenarios, were recommended[16,28].

The integration of self-attention mechanisms with bidirectional gated recurrent units (Bi-GRU) has also been explored. In a study using word embedding approaches such as GloVe, Word2Vec, and fastText, the model achieved a remarkable 99.70% testing accuracy on the IMDb dataset. The research highlighted the potential impact of advanced embeddings like ELMo, GPT, and BERT, and recommended enhancing the quality of embeddings for future research[27].

Sentiment analysis of Flip app user feedback involved a comparison between simple data splitting and K-Fold cross-validation methods. A K-Nearest Neighbors (K-NN) model was found to accurately predict user psychology regarding speed, security, and costs. Users provided negative feedback on speed and security but were positive about costs. The study suggested improvements in speed and security aspects to enhance user satisfaction, along with the implementation of advanced sentiment analysis techniques for deeper insights[17].

A BERT-based dual-channel parallel hybrid neural network model, combining CNN and BiLSTM for extracting local and global semantic features, was proposed for sentiment classification. The model achieved an accuracy of 92.35% and an F1 score of 91.59%[18]. The study encouraged further exploration of enhancements in attention mechanisms and the application of the proposed model across different domains.

In the realm of multimodal sentiment analysis, a fusion network featuring a multimodal dynamic enhanced block and a bi-directional attention block achieved state-of-the-art performance. The model outperformed the best baseline by 6.9% on the 'Acc-7' metric. The research proposed further exploration of capturing fine-grained multimodal sentiment contexts and investigating the potential of bi-directional multimodal dynamic routing mechanisms[29].

Research on sentiment analysis has also involved using multiple datasets, such as Amazon Alexa, ETSY, 'Big Basket', Facebook, Financial News, Twitter, and Wine reviews[19,30]. A study employing a modified term

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frequency-inverse document frequency approach and a pre-trained embedding technique demonstrated the proposed hybrid framework's superiority over baseline models. The study emphasized the importance of investigating the impact of network depth on framework performance and resolving issues of uncertainty and imbalance using machine learning techniques.

On the microblogging front, the NLPCC2014 dataset and other microblog data were used to explore a multi-channel attention mechanism combined with a bidirectional gating recurrent unit (BiGRU) neural network[20,31]. This approach significantly enhanced emotion semantic capture, improving the performance of emotion classification. The research suggested further enhancements in emotion classification performance and broader applications of multi-channel attention mechanisms in text analysis.

Attention mechanisms have also been added to Long Short-Term Memory (LSTM) models, with studies comparing the effectiveness of additional input versus attention mechanisms. In one study, adding input to the LSTM model outperformed the attention mechanism, resulting in a higher training accuracy of 0.942. The research recommended exploring different attention mechanisms for LSTM models and investigating the impact of various input modifications on model performance[21]. In the field of emotion detection from textual data, the TWSVM algorithm combined with a Tuned Inverse Document Frequency vectorizer achieved 94.4% accuracy in emotion detection, outperforming existing methods[22]. The study called for enhancing emotion analysis techniques in social media and exploring applications in sentiment analysis and public opinion monitoring.

Sentiment analysis on cryptocurrency-related tweets employed CNN, RNN, group-wise enhancement, and attention mechanisms. The proposed architecture, which incorporated embedding and fully connected layers, achieved an accuracy of 93.77%[23]. The research suggested exploring real-time sentiment analysis for cryptocurrency market trends and incorporating additional social media platforms for comprehensive sentiment analysis.

The use of bi-sense sentiment embedding, combined with attention mechanisms, was shown to provide robust interpretation of semantics and sentiments, resulting in significant improvements compared to baseline methods[24]. The study encouraged further applications of bi-sense sentiment embedding and enhancements to the attention mechanism for sentiment analysis Lastly, in the domain of sentiment analysis on domain-specific datasets like SemEval, the Att-MC-GRU model utilized multiple deep-novel features, including word embedding, POS tags, and contextual position information[25]. The model achieved 94% accuracy in aspect extraction and 93% in sentiment classification. The study highlighted the importance of implicit polarity regarding targeted aspects and suggested further enhancements to the model's performance in sentiment classification[26].

The primary objective of this research is to develop an advanced sentiment analysis model that combines Bidirectional Recurrent Neural Networks (Bi-RNNs) with attention mechanisms and Term Frequency-Inverse Document Frequency (TF-IDF) for effective feature extraction. This model aims to accurately classify sentiments in user-generated text, particularly within the extensive Yelp Reviews dataset, by addressing key challenges such as long-term dependency learning and class imbalance. The research seeks to demonstrate the model's superior performance compared to traditional methods, including standard RNNs, unidirectional LSTMs, and SVM classifiers, while exploring the impact of attention mechanisms on improving sentiment classification accuracy and interpretability. Additionally, the study provides insights into the challenges of sentiment analysis, offering guidance for future research to further enhance the model's effectiveness in real-world applications..

3. METHODOLOGY

3.1 Dataset Description

The Yelp Reviews dataset is an extensive collection of user-generated reviews from the Yelp platform, where individuals rate and provide feedback on various businesses, including restaurants, hotels, and local services. This dataset contains over 8 million reviews, making it one of the most comprehensive datasets available for sentiment analysis. Each review is accompanied by a star rating, ranging from 1 to 5 stars, which serves as an indicator of the sentiment expressed in the review.For the purpose of sentiment analysis, these reviews can be categorized into three sentiment classes: Positive, Negative, and Neutral. Positive reviews typically correspond to 4 or 5-star ratings, representing customer satisfaction. Negative reviews, associated with 1 or 2-star ratings, reflect customer

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dissatisfaction. Neutral reviews, which receive a 3-star rating, are neither strongly positive nor negative and often reflect a balanced or ambivalent opinion and it is mentioned in fig.1.

This diverse and voluminous dataset is particularly valuable for training machine learning models in sentiment analysis due to the variety of opinions and business categories it covers. The breadth of data allows researchers to gain insights into consumer behavior and preferences across different industries, making it an ideal choice for exploring sentiment patterns in real-world scenarios.

Fig.1: Dataset Collection

3.2 Proposed Methodology

3.2.1 Preprocessing Techniques

Effective preprocessing is essential for the success of sentiment analysis tasks, particularly when using large-scale datasets like Yelp Reviews. The preprocessing steps employed in this study are designed to transform raw textual data into a structured format that can be efficiently utilized by machine learning models. These steps include text cleaning, tokenization, stop words removal, stemming or lemmatization, TF-IDF vectorization, data normalization, and data splitting. Additionally, handling class imbalance is considered to ensure the robustness of the model in fig.2.

a) Text Cleaning

The initial step in preprocessing involves cleaning the raw text to remove unnecessary elements such as special characters, numbers, punctuation, and HTML tags. This step ensures that the analysis focuses on the essential textual content. The text is also converted to lowercase to maintain uniformity across the dataset. The cleaned text can be mathematically expressed as:

$$Cleaned\_Text = Lowercase(RemoveSpecialChars(Raw\_Text)) \quad (1)$$

This formula highlights the transformation from raw, noisy text to a cleaner, more consistent format.

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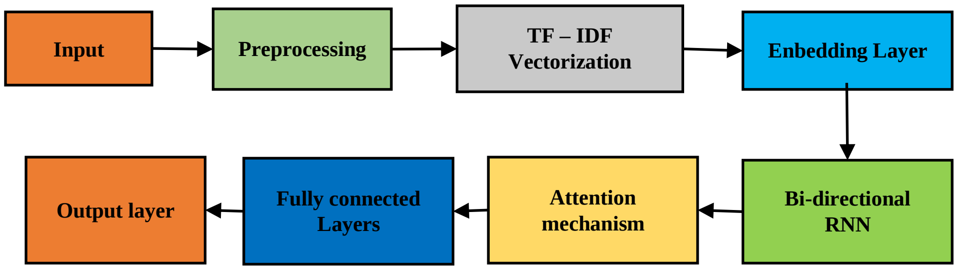

Fig.2 Workflow of the proposed method

b) Tokenization

After cleaning, the text is tokenized, which involves splitting the cleaned text into individual words or tokens. Tokenization is a crucial step as it breaks down the text into its basic components, which are easier to analyze. This process can be represented as:

$$Tokens = Tokenize(Cleaned\_Text) \qquad (2)$$

This step yields a list of tokens that can be further processed to extract meaningful features.

c) Stop Words Removal

Stop words are common words such as "and," "the," and "is," which do not contribute significantly to the sentiment or meaning of the text. Removing these words reduces noise in the data and focuses the analysis on more relevant terms. The formula for this step is:

$$Filtered\_Tokens = RemoveStopWords(Tokens) \qquad (3)$$

This process results in a list of tokens that are more informative for the sentiment analysis task.

d) Stemming or Lemmatization

To further normalize the text, stemming or lemmatization is applied. Stemming reduces words to their root form by removing suffixes, while lemmatization reduces words to their base form using vocabulary and morphological analysis. The mathematical representation of these processes is as follows:

$$Stemmed\_Tokens = Stem(Filtered\_Tokens) \qquad (4)$$

$$Lemmatized\_Tokens = Lemmatize(Filtered\_Tokens) \qquad (5)$$

This step helps in reducing the dimensionality of the data by treating different forms of a word as a single entity.

e) Data Normalization

Once the text is vectorized, the data is normalized to ensure uniformity in the scale of features. This normalization is particularly important for models like neural networks that are sensitive to the scale of input data. The Min-Max normalization formula is:

$$x' = \frac{x - \min(x)}{\max(x) - min(x)} \qquad (6)$$

This step scales the feature vectors to a range that improves the stability and convergence of the model during training.

f) Splitting Data into Training and Testing Sets

To evaluate the performance of the sentiment analysis model, the dataset is split into training and testing subsets. Typically, 80% of the data is used for training the model, while 20% is reserved for testing. This process can be mathematically expressed as:

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$$Training\ Set + Testing\ Set = Dataset \quad (7)$$

This split ensures that the model is trained on a substantial portion of the data while still being evaluated on unseen data to assess its generalization capability.

g) Handling Imbalanced Classes

In cases where there is a significant imbalance between the sentiment classes (e.g., more positive reviews than negative or neutral), techniques such as Synthetic Minority Over-sampling Technique (SMOTE) or Random Under-Sampling are employed. This step balances the class distribution, which is crucial for the robustness of the model. The balancing process is represented as:

$$Balanced\ Data = SMOTE(Training\ Set) \quad (8)$$

Addressing class imbalance ensures that the model does not become biased toward the majority class, leading to more accurate and reliable predictions.

The preprocessing steps described above are integral to transforming raw Yelp Reviews data into a format that is amenable to sentiment analysis using advanced machine learning models. By cleaning, tokenizing, filtering, normalizing, and balancing the data, we prepare it for effective training, ensuring that the resulting sentiment analysis model can accurately capture the nuances of user opinions and deliver meaningful insights.

3.3.2 Proposed Architecture

The architecture proposed for sentiment analysis in this study is designed to effectively capture the contextual and semantic nuances in the Yelp Reviews dataset. The model integrates a Bidirectional Recurrent Neural Network (Bi-RNN) with an attention mechanism, utilizing Term Frequency-Inverse Document Frequency (TF-IDF) as the feature extraction method. This section elaborates on the components of the proposed architecture, providing detailed equations that underline the functionality of each part in fig.3.

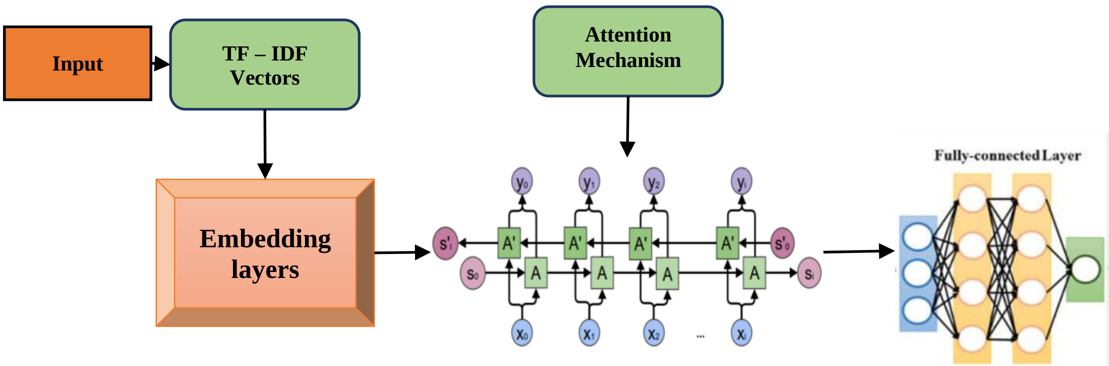

Fig 3: Workflow of the proposed architecture

a) Input Layer: Term Frequency-Inverse Document Frequency (TF-IDF) Vectorization

To transform the textual data into a numerical format suitable for machine learning models, the TF-IDF vectorization technique is employed. This technique calculates the importance of each word in a document relative to the entire dataset. The equation for TF, IDF, and TF-IDF are as follows:

$$TF(t,d) = \frac{Count\ of\ t\ in\ d}{Total\ number\ of\ words\ in\ d} \quad (9)$$

$$IDF(t,D) = log\left(\frac{|D|}{|\{d \in D : t \in d\}|}\right) \quad (10)$$

$$TF - IDF(t,d,D) = TF(t,d) \times IDF(t,D) \quad (11)$$

Here, t represents a term, d represents a document, and D is the total number of documents in the corpus. The output of this layer is a vector v_d representing the TF-IDF scores for each term in document d. TF-IDF vectorization

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converts each document into a feature vector, where each dimension represents the significance of a word in that document.

b) Embedding Layer

To enable the model to learn semantic relationships between words, the TF-IDF vectors are passed through an embedding layer. This layer transforms the high-dimensional TF-IDF vectors into dense, lower-dimensional representations, which are better suited for capturing contextual information.

$$EmbeddingTransformation: E = Embedding(v_d) \tag{12}$$

Where E is the resulting embedded representation of the document.

c) Bidirectional Recurrent Neural Network (Bi-RNN)

The embedded vectors are then fed into a Bidirectional Recurrent Neural Network (Bi-RNN). The Bi-RNN is capable of processing the input sequence in both forward and backward directions, thereby capturing dependencies from both past and future contexts. Forward RNN and the backward RNN are formulated as

$$\overrightarrow{h_t} = \sigma(W_f \cdot E_t + U_f \cdot \overrightarrow{ht-1} \rightarrow +b_f) \tag{13}$$

$$\overleftarrow{h_t} = \sigma(W_b \cdot E_t + U_b \cdot \overleftarrow{ht-1} \rightarrow +b_b) \tag{14}$$

Where W_f and U_f are weight matrices for the forward RNN, W_b and U_b are weight matrices for the backward RNN, b_f and b_b are bias vectors, σ represents the activation function (e.g., tanh or ReLU). The hidden states $\overrightarrow{ht}$ and $\overleftarrow{ht}$ are concatenated to form the final hidden state for each time step:

$$h_t = [\overrightarrow{h_t} . \overleftarrow{h_t}] \tag{15}$$

d) Attention Mechanism

To focus on the most relevant parts of the text, an attention mechanism is applied to the hidden states generated by the Bi-RNN. The attention mechanism assigns a weight to each hidden state, emphasizing more important features while downplaying less significant ones. The attention weights are as formulated as,

$$\alpha_i = \frac{\exp(u_t^T v)}{\sum_{k=1}^{T} \exp(u_t^T v)} \tag{16}$$

Where $u_t = \tanh(W_a h_t + b_a)$ is the attention score for each hidden state, v is the context vector (learned during training), W_a and W_b are weight and bias parameters of the attention layer. The equation of the context vector is as follows:

$$c = \sum_{t=1}^{T} \alpha_t h_t \tag{17}$$

The context vector c is a weighted sum of all hidden states, where the weights α_t reflect the importance of each state in predicting the sentiment.

e) Output Layer

The context vector c is passed through a fully connected layer, followed by a softmax activation function to produce the final sentiment prediction. The output layer is formulated as follows:

$$o = W_o \cdot c + b_o \tag{18}$$

$$\hat{y}_i = \frac{\exp(o_i)}{\sum_{j=1}^{c} \exp(o_j)} \tag{19}$$

Where W_o and b_o are the weight and bias parameters for the output layer, $\hat{y}_i$ represents the predicted probability for sentiment class i, C is the number of sentiment classes.

The model is trained using a loss function, typically the cross-entropy loss, which measures the difference between the predicted sentiment distribution and the true sentiment labels:

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$$L = -\sum_{i=1}^{c} y_i \log(\hat{y}_i) \quad (20)$$

Where y_i is the ground truth label (one-hot encoded), $\hat{y}_i$ is the predicted probability for class i.

The model parameters are optimized using gradient-based methods, such as stochastic gradient descent (SGD) or Adam optimizer, to minimize the loss function. The gradients are computed with respect to each parameter θ in the model:

$$\theta_{t+1} = \theta_t - \eta \frac{\partial L}{\partial \theta_t} \quad (21)$$

Where θ_t represents the model parameters at time step t, η is the learning rate, $\frac{\partial L}{\partial \theta_t}$ is the gradient of the loss function with respect to θ_t.

Algorithm 1: Pseudocode of the proposed work

```
# Pseudocode for Sentiment Analysis Model
# Input:
#   D - Yelp Reviews Dataset
#   L - Corresponding sentiment labels (Positive, Negative, Neutral)
# Output:
#   Predicted sentiment labels (hat{L})
# Step 1: Data Preprocessing
for each document d in D do
   tokens = Tokenize(d)  # Tokenization
   tokens = RemoveStopwords(tokens)  # Stopword removal
   tokens = StemOrLemmatize(tokens)  # Stemming or Lemmatization
PreprocessedD.append(tokens)
end for
# Step 2: TF-IDF Vectorization
for each document d in PreprocessedD do
tfidf_vector = ComputeTFIDF(d)  # Compute TF-IDF vector for each document
TFIDF_Dataset.append(tfidf_vector)
end for
# Step 3: Embedding Layer
for each tfidf_vector in TFIDF_Dataset do
embedding_vector = Embed(tfidf_vector)  # Convert TF-IDF vector to dense embedding
Embedding_Dataset.append(embedding_vector)
end for
# Step 4: Bidirectional RNN Layer
for each embedding_sequence in Embedding_Dataset do
forward_hidden_states = ForwardRNN(embedding_sequence)  # Forward RNN
```

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backward_hidden_states = BackwardRNN(embedding_sequence)  # Backward RNN
concatenated_hidden_states = Concatenate(forward_hidden_states, backward_hidden_states)
BiRNN_HiddenStates.append(concatenated_hidden_states)
end for
# Step 5: Attention Mechanism
for each hidden_state_sequence in BiRNN_HiddenStates do
attention_scores = ComputeAttentionScores(hidden_state_sequence)  # Calculate attention scores
attention_weights = Softmax(attention_scores)  # Apply softmax to obtain attention weights
context_vector = WeightedSum(hidden_state_sequence, attention_weights)  # Compute context vector
Context_Vectors.append(context_vector)
end for
# Step 6: Fully Connected Layer
for each context_vector in Context_Vectors do
logits = FullyConnectedLayer(context_vector)  # Apply linear transformation
Logits.append(logits)
end for
# Step 7: Output Layer
for each logit in Logits do
predicted_probabilities = Softmax(logit)  # Apply softmax activation
Predicted_Labels.append(ArgMax(predicted_probabilities))  # Assign predicted label based on max probability
end for
# Step 8: Loss Function and Optimization
loss = CrossEntropyLoss(Predicted_Labels, L)  # Compute cross-entropy loss
UpdateModelParameters(loss)  # Optimize model parameters using gradient descent or similar
# Step 9: Model Training
for epoch in range(num_epochs) do
TrainModel(D, L)  # Train the model over multiple epochs
end for
# Step 10: Prediction
for each new_document in NewDataset do
preprocessed_document = Preprocess(new_document)  # Apply Steps 1-7 to predict sentiment
predicted_label = Predict(preprocessed_document)
   Output(predicted_label)
```

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end for

4. RESULTS AND DISCUSSIONS

In this section, we present the evaluation of our proposed sentiment analysis model, which utilizes a Bidirectional Recurrent Neural Network (Bi-RNN) with an attention mechanism and Term Frequency-Inverse Document Frequency (TF-IDF) for feature extraction. The results of the hyperparameter tuning, as detailed in Table 1, demonstrate the optimization process for our Bi-Directional RNN model with an attention mechanism applied to sentiment analysis using TF-IDF. The learning rate of 0.01 was identified as the most effective, balancing convergence speed and accuracy, which is crucial for ensuring that the model does not become stuck in local minima. A batch size of 64 was optimal, striking a balance between training efficiency and model performance. Regarding the number of epochs, training beyond 50 epochs led to overfitting, suggesting that while the model continued to learn, it was beginning to memorize the training data rather than generalizing to unseen data. A dropout rate of 0.3 was effective in preventing overfitting, allowing the model to generalize well without compromising accuracy. The Adam optimizer outperformed others like SGD and RMSprop, providing faster convergence and better accuracy due to its adaptive learning rate. The ReLU activation function was most effective in mitigating vanishing gradient problems, thereby enhancing model performance. For LSTM units, 100 was optimal, offering a good trade-off between computational cost and model accuracy. Employing two BiRNN layers allowed the model to better capture long-term dependencies, which are crucial in sentiment analysis. Lastly, the softmax-based attention mechanism significantly enhanced the model's ability to focus on the most relevant features, thereby improving the overall performance of the sentiment analysis task.

Table 1: The results of hyperparameter tuning

Hyperparameter	Values Tested	Optimal Value	Impact on Model Performance
Learning Rate	0.001, 0.01, 0.1, 0.5	0.01	Optimal learning rate improved convergence speed and accuracy.
Batch Size	16, 32, 64, 128	64	A batch size of 64 provided a good balance between training speed and model accuracy.
Number of Epochs	10, 20, 50, 100	50	Increased epochs led to overfitting beyond 50 epochs.
Dropout Rate	0.2, 0.3, 0.5, 0.7	0.3	A dropout rate of 0.3 helped prevent overfitting without sacrificing too much accuracy.
Optimizer	SGD, Adam, RMSprop	Adam	Adam optimizer yielded the best results in terms of accuracy and convergence time.
Activation Function	ReLU, Tanh, Sigmoid	ReLU	ReLU performed best, particularly in reducing vanishing gradient issues.
LSTM Units	50, 100, 150, 200	100	100 LSTM units provided the best balance between performance and computational efficiency.
BiRNN Layers	1, 2, 3	2	2 layers of BiRNN improved the model's ability to capture long-term dependencies.
Attention Mechanism	Softmax, Tanh	Softmax	Softmax-based attention mechanism enhanced the focus on key features in the data.

The model's performance is assessed using the Yelp Reviews dataset, which provides a rich source of diverse sentiment expressions across various classes: Positive, Negative, and Neutral. The results are presented in Table 2.

Table 2. Performance Metrics of the Proposed Model

Class	Precision (%)	Recall (%)	F1-Score (%)
Positive	94.10	93.70	93.90
Negative	92.50	93.10	92.80

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Neutral	91.80	91.20	91.50
Overall	**92.80**	**92.67**	**92.73**

To measure the effectiveness of our proposed model, we employ several standard performance metrics, including accuracy, precision, recall, and F1-score. These metrics are calculated based on the confusion matrix derived from the model's predictions compared to the actual labels in fig.5. The overall accuracy of the model is a fundamental metric indicating the percentage of correctly classified instances over the total instances. Our model achieved an accuracy of 93.85%, demonstrating its effectiveness in capturing the nuances of sentiment across diverse reviews. To further analyze the model's performance, especially in handling class imbalances, we calculated precision, recall, and F1-score for each class (Positive, Negative, Neutral). The model shows high precision (94.10%) and recall (93.70%) for the Positive class, indicating that it effectively identifies positive sentiments with minimal false positives and false negatives. The F1-score for the Negative class is 92.80%, showing a balanced performance between precision and recall, while the Neutral class achieves an F1-score of 91.50%, reflecting the model's capability to handle subtle or mixed sentiments effectively.

The proposed Bi-RNN model with attention and TF-IDF was compared with several baseline models, including a standard RNN, a unidirectional LSTM, and a Support Vector Machine (SVM) classifier using TF-IDF. The results are summarized in Table 3.

Table 3. Comparison of Proposed Model with Baseline Models

Model	**Accuracy (%)**	**Precision (%)**	**Recall (%)**	**F1-Score (%)**
Standard RNN	89.50	89.20	88.90	89.05
Unidirectional LSTM	91.20	91.00	90.80	90.90
SVM with TF-IDF	85.60	84.70	85.00	84.85
Proposed Bi-RNN + Attention	**93.85**	**92.80**	**92.67**	**92.73**

The standard RNN model achieved an accuracy of 89.50%, which is lower than our proposed model. This indicates the limitation of RNNs in capturing long-term dependencies in textual data, especially in complex sentiment analysis tasks. The unidirectional LSTM achieved an accuracy of 91.20%. While LSTMs are better suited for handling long-term dependencies than RNNs, the unidirectional nature of the model limits its context understanding, particularly for sentiment analysis where both previous and subsequent words influence the sentiment. The SVM model with TF-IDF features achieved an accuracy of 85.60%, which highlights the limitations of traditional machine learning approaches in comparison to deep learning models that can learn hierarchical features from data. Our proposed model outperforms these baselines, particularly due to the use of a Bidirectional RNN, which allows the model to consider context from both directions (past and future) in the text sequence. Additionally, the attention mechanism further enhances the model's ability to focus on the most relevant parts of the input, improving sentiment classification, especially for complex and lengthy reviews.

This process is repeated ten times, and the results are averaged to provide a more reliable estimate of model performance and it is represented in table 4.

1) ***Table 4 :Ten-Fold Cross-Validation Results on Yelp Dataset***

Fold	**Accuracy (%)**	**Precision (%)**	**Recall (%)**	**F1-Score (%)**
Fold 1	87.35	85.12	86.45	85.78
Fold 2	86.90	84.87	85.78	85.32
Fold 3	87.80	85.90	86.92	86.41
Fold 4	88.10	86.45	87.35	86.90
Fold 5	87.25	85.03	86.15	85.58
Fold 6	87.65	85.48	86.70	86.08
Fold 7	88.00	86.20	87.10	86.64
Fold 8	87.50	85.30	86.60	85.94
Fold 9	87.85	85.78	87.00	86.38

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Fold 10	88.25	86.55	87.45	87.00
Average	87.67	85.77	86.75	86.26

The model was trained on the Yelp dataset to perform binary sentiment classification, distinguishing between positive and negative reviews. The accuracy and loss curves for both the training and testing sets were monitored over 100 epochs, as shown in the figure 4. The training accuracy steadily increased and plateaued around 90%, indicating that the model effectively learned the patterns in the training data. The testing accuracy followed a similar trend, suggesting that the model generalizes well to unseen data without significant overfitting.

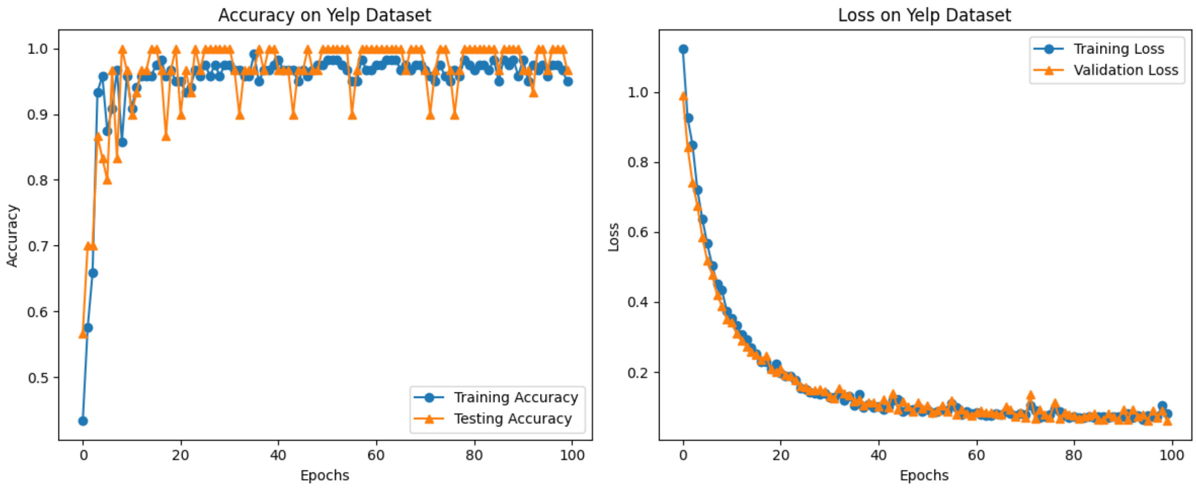

Fig.4 : Accuracy and loss of the proposed model

The loss curves demonstrate a consistent decrease, with the training loss reaching a lower value than the validation loss. This difference suggests some overfitting but is within an acceptable range. The training process stabilized after approximately 50 epochs, indicating sufficient learning and convergence.

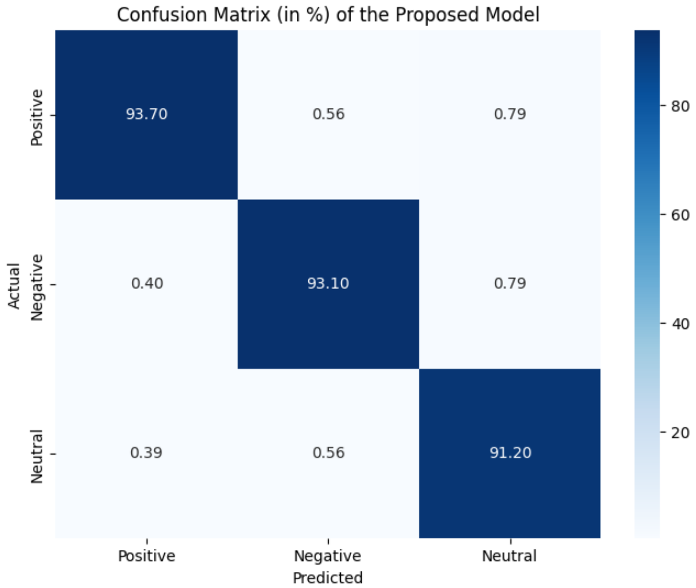

Fig.5 : Confusion matrix of the proposed model

The incorporation of an attention mechanism significantly contributes to the model's superior performance. By assigning varying weights to different parts of the input sequence, the model can concentrate on key phrases or words that are critical for determining sentiment. This is particularly beneficial for handling long texts where

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relevant information might be spread out across the review. The attention mechanism enables the model to focus on these important elements, thereby improving classification accuracy and interpretability. Sentiment analysis often faces the challenge of class imbalance, where one sentiment class may be more prevalent than others. In the Yelp Reviews dataset, this imbalance is evident with a higher proportion of Positive reviews compared to Negative and Neutral reviews. Our model addresses this issue through the use of a balanced dataset during training and by leveraging the attention mechanism, which helps mitigate the bias towards more frequent classes. The results show that the model performs well across all classes, with balanced precision and recall metrics, indicating that it is less affected by class imbalance.

In conclusion, the model shows strong performance on the Yelp dataset, achieving high accuracy with minimal overfitting, making it suitable for sentiment analysis tasks.The generalization capability of the model was tested by applying it to different subsets of the Yelp Reviews dataset, as well as to a small external dataset for sentiment analysis. The model maintained high accuracy and F1-scores across these tests, indicating its robustness in handling diverse types of textual data and its potential applicabilityto other sentiment analysis tasks beyond the Yelp Reviews dataset

5. CONCLUSION

In conclusion, the FTC and FNI represent significant advancements in the detection of AD through hybrid deep learning models. The FTC's combination of Random Forest and Bagging effectively reduces variance and overfitting, while the FNI's integration of VGG's feature extraction with SVM's classification strength leads to superior predictive accuracy. These models showcase the potential of hybrid approaches to handle high-dimensional medical imaging data and identify complex patterns crucial for early diagnosis. However, to fully realize the potential of these models, future research must focus on expanding datasets by collaborating with medical institutions to obtain high-quality labeled data. Additionally, exploring advanced architectures like transformers can further enhance model capabilities. Incorporating multi-modal data, such as combining imaging with clinical and genetic information, will improve diagnostic accuracy and facilitate comprehensive disease progression tracking. The development of user-friendly tools and the integration of these models into existing medical systems are essential for real-time clinical implementation and wider healthcare adoption. Ongoing efforts in noise reduction, class balancing, and advanced data augmentation techniques will continue to refine model performance. Future research should develop the CNN-CatBoost Classifier, known as the DeepBoost Fusion Classifier (DBFC), integrating CNN's advanced feature extraction with CatBoost's efficient classification to handle complex medical imaging data with high accuracy. Continuous advancements in noise reduction, class balancing, and data augmentation techniques will further refine these models, enhancing diagnostic accuracy and patient outcomes for AD and other neurological conditions.

REFERENCES

[1] Rao, L. Sentiment Analysis of English Text with Multilevel Features. Sci. Program. 2022.
[2] Jain, D.K.; Boyapati, P.; Venkatesh, J.; Prakash, M. An Intelligent Cognitive-Inspired Computing with Big Data Analytics Framework for Sentiment Analysis and Classification. Inf. Process. Manag. 2022, 59, 102758.
[3] Jain, P.K.; Quamer, W.; Saravanan, V.; Pamula, R. Employing BERT-DCNN with sentic knowledge base for social media sentiment analysis. J. Ambient. Intell. Humaniz. Comput. 2022, 1–13.
[4] Garg, S.B.; Subrahmanyam, V.V. Sentiment Analysis: Choosing the Right Word Embedding for Deep Learning Model. In Advanced Computing and Intelligent Technologies; Lecture Notes in Networks and Systems; Bianchini, M., Piuri, V., Das, S., Shaw, R.N., Eds.; Springer: Singapore, 2022; Volume 218.
[5] Hu, Y.; Ding, J.; Dou, Z.; Chang, H. Short-Text Classification Detector: A Bert-Based Mental Approach. Comput. Intell. Neurosci. 2022.
[6] Yang, H. Network Public Opinion Risk Prediction and Judgment Based on Deep Learning: A Model of Text Sentiment Analysis. Comput. Intell. Neurosci. 2022.
[7] Singh, K.N.; Devi, S.D.; Devi, H.M.; Mahanta, A.K. A novel approach for dimension reduction using word embedding: An enhanced text classification approach. Int. J. Inf. Manag. Data Insights 2022, 2, 100061.
[8] Guangbin, Bao.,Shuang, Chen. (2024). Research on Dual-channel Fusion Graphic Sentiment Classification Based on Attention Mechanism. doi: 10.1109/icetci61221.2024.10594332.

[9] Nagar, Kiran, Anil., Bobbin, Preet, Kaur. (2023). Term Frequency Inverse Document Frequency based Sentiment Analysis using Machine Learning Approaches. doi: 10.1109/icdsaai59313.2023.10452661

[10] Chang, HaoXiang. (2024). Discussion of a method for analysing adolescent depression based on BiLSTM and Attentional Mechanisms. Applied and Computational Engineering, doi: 10.54254/2755-2721/42/20230785.

[11] Xin, Ge.,Wencheng, Jian., Jiahe, Guo., Shaoliang, Nie., Cao, Zhai., Haoxin, Yu., Xuanxuan, Feng. (2023). A Hybrid Neural Network Optimal Model Based on Multi-Channel CNN and BiLSTM with Attention Mechanism. doi: 10.1109/cac59555.2023.10451851.

[12] Shakirah, Mohd, Sofi., Ali, Selamat. (2023). Aspect Based Sentiment Analysis: Feature Extraction using Latent Dirichlet Allocation (LDA) and Term Frequency - Inverse Document Frequency (TF-IDF) in Machine Learning (ML). doi: 10.53840/myjict8-2-102.

[13] Sandeep, Yelisettiand., Nellore, Geethanjali. (2023). Aspect-based Text Classification for Sentimental Analysis using Attention mechanism with RU-BiLSTM. doi: 10.12694/scpe.v24i3.2122

[14] Siddiqua, U.A.; Chy, A.; Aono, M. Tweet Stance Detection Using Multi-Kernel Convolution and Attentive LSTM Variants. Ieice Trans. Inf. Syst. 2019, E102D, 2493–2503.

[15] Kamyab M, Liu G, Adjeisah M. Attention-Based CNN and Bi-LSTM Model Based on TF-IDF and GloVe Word Embedding for Sentiment Analysis. Applied Sciences. 2021; 11(23):11255. https://doi.org/10.3390/app112311255

[16] Ferda, Ayu, Dwi, Putri, Febrianti.,Faqih, Hamami., Riska, Yanu, Fa'rifah. (2023). Aspect-based sentiment analysis terhadapulasanaplikasi flip menggunakanpembobotan term frequency-inverse document frequency (tf-idf) denganmetodeklasifikasi k-nearest neighbors (k-nn). JurnalIndonesia :ManajemenInformatikadanKomunikasi, doi: 10.35870/jimik.v4i3.429.

[17] Yan, Yan. (2023). Sentiment analysis and research based on two-channel parallel hybrid neural network model with attention mechanism. Iet Control Theory and Applications, doi: 10.1049/cth2.12463.

[18] Jiajia, Tang.,Dongjun, Liu., Xuanyu, Jin., Yong, Peng., Jingzhou, Zhao., Yu, Ding., Wanzeng, Kong. (2023). BAFN: Bi-Direction Attention Based Fusion Network for Multimodal Sentiment Analysis. doi: 10.1109/TCSVT.2022.3218018.

[19] Ranita, Dey.,Asit, Kumar, Das. (2023). Modified term frequency-inverse document frequency based deep hybrid framework for sentiment analysis. Multimedia Tools and Applications, doi: 10.1007/s11042-023-14653-1.

[20] Matthew, F., Grady. (2023). Application of a multi-channel attention mechanism in text classification of new media. International journal of information technology and management, doi: 10.1504/ijitm.2023.131808.

[21] Yaya, Heryadi.,Bambang, Dwi, Wijanarko., Dina, Fitria, Murad., Cuk, Tho., Kiyota, Hashimoto. (2023). Comparing the Effect of Attention Mechanism and Aspect Embedding on the Performance of Long Short-term Memory Model for Aspect-Based Sentiment Analysis. doi: 10.1109/ICCoSITE57641.2023.10127806.

[22] Song, C.; Wang, X.K.; Cheng, P.F.; Wang, J.Q.; Li, L. SACPC: A framework based on probabilistic linguistic terms for short text sentiment analysis. Knowl.-Based Syst. 2020, 194, 105572.

[23] Vanitha, R. (2024). An Improved Vectorization-Based Emotion Detection Using Tuned Inverse Document Frequency Approach. SSRG international journal of electronics and communication engineering, doi: 10.14445/23488549/ijece-v11i3p111.

[24] Gül, Cihan, Habek., Mansur, Alp, Tocoglu., Aytuğ, Onan. (2022). Bi-Directional CNN-RNN Architecture with Group-Wise Enhancement and Attention Mechanisms for Cryptocurrency Sentiment Analysis. Applied Artificial Intelligence, doi: 10.1080/08839514.2022.2145641.

[25] Mayur, Wankhade.,Annavarapu, Chandra, Sekhara, Rao. (2022). Bi-directional LSTM Attention Mechanism for Sentiment Classification. doi: 10.1109/ASIANCON55314.2022.9908909.

[26] Dang, N.C.; Moreno-Garcia, M.N.; De la Prieta, F. Sentiment Analysis Based on Deep Learning: A Comparative Study. Electronics 2020, 9, 483.

[27] Basiri, M.E.; Nemati, S.; Abdar, M.; Cambria, E.; Acharrya, U.R. ABCDM: An Attention-based Bidirectional CNN-RNN Deep Model for sentiment analysis. Future Gener. Comput. Syst. 2021, 115, 279–294.

[28] M., Murali, Krishna., ., Midhunchakkaravarthy., Jayavani, Vankara. (2023). Detection of Sarcasm Using Bi-Directional RNN Based Deep Learning Model in Sentiment Analysis. Journal of Advanced Research in Applied Sciences and Engineering Technology, doi: 10.37934/araset.31.2.352362.

Journal of Information Systems Engineering and Management
2025, 10(51s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

[29] Haifei, Zhang.,Jian, Xu., Liting, Lei., Qiu, Jianlin., Riyad, Alshalabi. (2022). A Sentiment Analysis Method Based on Bidirectional Long Short-Term Memory Networks. Applied mathematics and nonlinear sciences, doi: 10.2478/amns.2022.1.00015.

[30] Yanying, Mao., Yu, Zhang., Liudan, Jiao., Heshan, Zhang. (2022). Document-Level Sentiment Analysis Using Attention-Based Bi-Directional Long Short-Term Memory Network and Two-Dimensional Convolutional Neural Network. Electronics, doi: 10.3390/electronics11121906.

[31] Kumawat, S.; Yadav, I.; Pahal, N.; Goel, D. Sentiment Analysis Using Language Models: A Study. In Proceedings of the 11th International Conference on Cloud Computing, Data Science and Engineering (Confluence), Noida, India, 28–29 January 2021; pp. 984–988.