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ORIGINAL

BERT-based two-channel neural network model text emotion analysis

Análisis de emociones en texto basado en un modelo de red neuronal de dos canales con BERT

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ABSTRACT

Introduction: text emotion analysis, or sentiment analysis, is a crucial area in natural language processing (NLP) focused on identifying emotions within textual data. Challenges in this field include disappearing gradients, information loss, and the lack of contextual semantics.
Method: to address these challenges, we propose a BERT-based model utilizing a two-channel neural network for enhanced emotion classification. The model transforms text into word vectors using BERT, which excels in capturing contextual information. The architecture includes Augmented Recurrent Neural Networks-mutated Unidirectional Long Short-Term Memory (ARNN-Uni-LSTM) to extract local semantic features and capture long-range dependencies. Preprocessing involved tokenization and Word2Vec on publicly available text emotion datasets. The first channel employs ARNN for local feature extraction, while the second uses Uni-LSTM for broader context.
Results: experiments conducted in Python demonstrated that our model outperformed traditional methods, achieving precision of 97,18 %, recall of 94,56 %, and an F1 score of 96,26 %.
Conclusions: the BERT-based model shows significant promise for applications such as customer feedback analysis, social media monitoring, and mental health diagnostics, offering a foundation for advanced emotion recognition systems.

Keywords: Bidirectional Encoder Representations from Transformers (BERT); Two-Channel Neural Network; Text Emotion; Augmented Recurrent Neural Networks-Mutated Unidirectional Long Short-Term Memory (ARNN-Uni-LSTM).

RESUMEN

Introducción: el análisis de emociones de texto, o análisis de sentimientos, es un área crucial en el procesamiento del lenguaje natural (PNL) centrado en la identificación de emociones dentro de los datos textu. Los desafíos en este campo incluyen la desaparición de gradi, pérdida de información, y la falta de semántica contextual.
Método: para abordar estos desafíos, proponemos un modelo basado en Bert que utiliza una red neuronal de dos canales para una mejor clasificación emocional. El modelo transforma el texto en vectores de palabras usando BERT, que sobresen en la captura de información contextual. La arquitectura incluye redes neuronrecurrentes aumentadas — memoria de corto plazo unidireccional mutada (ARNN-Uni-LSTM) para extraer características semánticas locales y capturar dependencias de largo alcance. El preprocesamiento involucrtokenización y Word2Vec en conjuntos de datos de emoción de texto disponibles públicamente. El primer canal emplea a ARNN para la extracción de características locales, mientras que el segundo utiliza Uni-LSTM para un contexto más amplio.

Resultados: los experimentos realizados en Python demostraron que nuestro modelo superó a los métodos tradicionales, logrando una precisión de 97,18 %, recuerdo de 94,56 %, y una puntuación F1 de 96,26 %.
Conclusiones: el modelo basado en Bert muestra una promesa significativa para aplicaciones como el análisis de retroalimentación del cliente, monitoreo de redes sociales y diagnósticos de salud mental, ofreciendo una base para sistemas avanzados de reconocimiento de emociones

Palabras clave: Representaciones de Codificación Bidireccional de Transformadores (BERT); Red Neuronal de dos Canales; Emoción Textual; Redes Neuronales Recurrentes Aumentadas - Memoria a Largo Plazo Unidireccional Mutada (ARNN-Uni-LSTM).

INTRODUCTION

BERT structure to classify emotional states expressed in text.[1] The technique combines different entry channels to establish the accuracy and robustness of emotion detection. The first channel techniques the raw textual input to extract semantic and syntactic functions, while the second channel carries auxiliary facts, which include contextual or sentiment-unique cues, which allows for refinement of the emotional class.[2] BERT, previously trained on a lot of textual data, captures deep bidirectional context, allowing to recognize nuanced language abilities, consisting of sarcasm, idiomatic expressions, and subtle emotional undertones. The two-channel format allows in the model to combine global and local data for a higher illustration of the emotional content.[3] The model structure normally consists of embedding layers, observed by means of transformer blocks, and culminates in absolutely linked layers that produce emotion labels (e.g., joy, unhappiness, anger, fear). The setup is suitable for various applications, together with social media sentiment evaluation, customer comments evaluation, or intellectual health monitoring.[4] The two-channel technique enhances the model's capability to discover complex emotional states, overcoming the restrictions of single-channel structures. Training such a model requires annotated datasets with numerous emotional labels, and fine-tuning is often employed to comply with the pre-trained BERT model to precise emotion-associated obligations. Overall, a BERT-based -channel neural community gives an effective and solutions for emotion evaluation, combining linguistic understanding with contextual refinement for accurate and insightful emotional interpretation in text.[5]

A BERT-based two-channel neural network for textual content emotion analysis consists of excessive computational cost, dependency on large annotated datasets, and potential overfitting with small datasets. It may struggle with domain-particular language, diffused emotions, and out-of-vocabulary words, and it requires careful fine-tuning to acquire optimal performance.

BERT's sentimental evaluation structure acts as the basis for the dual-channel HNN that is suggested by Zhang et al.[6]. The dual-channel HNN model was built using the BiLSTM and BiGRU channels to obtain the full and partial trait data of the chosen texts, while the BERT model vectorizes the text. The dual-channel's output features were horizontally fused to classify emotions. The SemEval 2014 dataset's results demonstrate that BERT was more effective at identifying semantic elements in the text.

Pre-BiLSTM, a multiple channel neural network framework with a pre-training mechanism was suggested by Liang et al.[7]. The model enhanced text sentiment analysis efficiency by extracting features from textual data, including travel notes and reviews, using an assortment of course and fine-granularity methods. The model used the SoftMax classifier to classify the three channels' text characteristics.

To examine Chinese texts' sentimental tendencies, Gan suggested an adaptable multi-channel dilation joint design of CNN and bidirectional LSTM (CNN–BiLSTM) framework that included a mechanism for attention.[8] Both the initial contextual features and the multiscale high-level circumstance features could be extracted by the model due to its multi-channel structure. Crucially, the actual corpus could be used to determine the greatest way to increase the number of model channels.

For NLP tasks, transformer-based models were covered in Acheampong et al.[9]. It lists the advantages and disadvantages of the selected models. BERT, Transformer-XL, Cross-lingual Language Models (XLM), and Generative Pre-training (GPT) and their variations were among the models that were covered. The effectiveness and widespread use of BERT in text-based identification of emotions, the individual examined recent research's where researchers put forth a variety of BERT-based models.

Chiorrini examined the application of BERT models to twitter data for sentiment analysis and recognizing emotions.[10] For the two tasks, specify two distinct classifiers and assess how well the resulting models perform on actual tweet datasets. According to experiments, the accuracy of the models on sentiment analysis and identifying emotions was 0,92 and 0,90, accordingly.

Abas aim to identify emotions in text by introducing a novel model called BERT-CNN. For the categorizing of texts, the model combines CNN with BERT.[11] The word semantically represented linguistic method was trained using BERT in the model. To predict the output, a conceptual vector was generated in real-time based on the word context and then fed into the CNN.

An innovative dual-channel technique has been suggested for multi-class text to identify emotions in Kumar and Raman, along with an innovative approach to elucidating its training and forecasts.[12] The explainability component the dual-channel element, the classification of emotions module, and the embedding module were all part of the suggested system's architecture. Using the pre-trained BERT model, the embedded module uses the input sentences' textual features and turns them into embedding vectors. Both channels produce embedding vectors as output, which were concatenated and supplied to the module for classifying emotions. The architecture of the suggested system has been established through extensive ablation studies and a framework for discussing its computational cost has been created.

To accomplish a fine-grained assessment of cross-domain text emotions, Liu and Zhao suggested a BERT-based sentiment analysis at the aspect level algorithm.[13] To create a pair, a sequence sentence, or the algorithm first extracted both at the phrase and aspect levels illustration vectors using the BERT structure, then used an enhanced CNN to extract local features and merged aspect-level and sentence-level corpora. To make the characteristic representations extracted from various fields as unrecognizable as possible, that was to increase the similarity between the characteristics obtained from both the source domain and the intended domain the algorithm employed a domain, adversarial neural network.

The emotion cause pairs extraction (ECPE) model, which pre-processed the text data using clause-level detection algorithms was employed by Kumar et al.[14]. A collection of a document's emotions and cause pairs was produced by sorting and combining the separated cause and sentiment clauses. The BERT was fed the pre-processed data as input. On a standard emotion analysis corpus, the classifier model yields results that were at the cutting edge of the field. When performance on English phrases was compared to the existing models, the ECPE-BERT sentiment classifier outperformed.

The research introduces a BERT-based two-channel neural network model for text emotional analysis, enhancing comprehension and classification of emotions using ARNN-Uni-LSTM.

METHOD

Social media tweets were used as datasets to pre-process and extract the data tokenization and the word2vec technique was used accordingly. The dual-channel architecture uses ARNN-Uni-LSTM to improve the model's understanding and classification of emotions. Both local and global semantic data are extracted from the text using ARNN and Uni-LSTM. The process of analyzing text emotion is shown in figure 1.

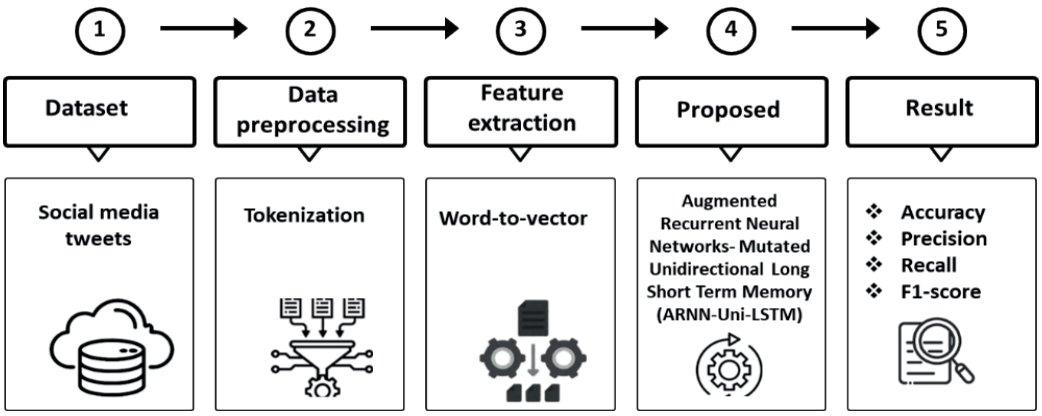

Figure 1. Process of text classification

Dataset

Identifying emotions in the text is one of the most difficult issues in NLP. The lack of labeled datasets and the problem's multi-class nature are the causes. Because humans experience a wide range of emotions and it is challenging to gather sufficient data for each emotion, class imbalance becomes an issue. In this case, the goal is to develop an effective model for emotion detection using labeled data. The information is essentially a set of tweets with their corresponding emotions noted. Content, sentiment, and tweet_id are three columns. "content" contains the unfiltered tweet. "Sentiment" denotes the sentiment underlying the tweet.

Data source: https://kaggle.com/datasets/pashupatigupta/emotion-detection-from-text.

Using Tokenization for pre-processing

Tokenization of the emotion analysis data involves splitting case titles and text into individual words or phrases for analysis and processing. It for textual content emotion information involves splitting text into phrases or sub-words with the use of libraries like NLTK, spaCy, or Hugging Face Tokenizers, enabling preprocessing for sentiment evaluation or emotion classification tasks. Tokenization is usually referred to as any form of natural language text preparation. Tokenization is also the process of replacing sensitive data with individual identification symbols while retaining critical information and ensuring security. Separated strings are divided into basic units of processing in extended tokenization, while isolated tokens are grouped to create higher-level attributes. Raw texts were processed and separated into text units.

Feature extraction using Word2Vec

To extract Word2Vec features from emotion analysis data, preprocess the case text by tokenizing and cleaning, then train a Word2Vec model on the corpus to generate dense vector representations for each word or sentence. This method discovers word representation using the Word2Vec model. It uses the Skip-gram model to calculate the probability distribution of unique terms in a corpus. This method discovers semantic relationships among terms but is inefficient for sentiment analysis. Instead, it discovers vectors representing the set of terms in the vocabulary S in equation (1).

$$S = \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_i \end{bmatrix} \Rightarrow \vec{U}_S = \begin{bmatrix} \vec{U}_1 \\ \vec{U}_2 \\ \vdots \\ \vec{U}_j \end{bmatrix} \qquad (1)$$

Word2Vec is a two-layer neural system that represents words as vectors based on their similarity. It effectively implements a constant bag of words and Skip-Gram to calculate vectors of words from text input.

Using Augmented Recurrent neural network as the first channel for text emotion analysis

The BERT-based two-channel neural network model for textual content emotion analysis can comprise an ARNN as Channel 1. In this configuration, Channel 1 (ARNN) methods sequential information with more enhanced memory, capturing long-term dependencies in text. Channel 2 (Uni-LSTM) focuses on contextual understanding through pre-trained embeddings, combining both for nuanced emotion detection in textual information. A recurrent hidden unit is used to sort long-term dependence in long-term terrible memory. In a traditional recurrent layer, the inputs are weighted linearly and averaged before a nonlinear function is applied. Additionally, a recurrent layer with long short-term memory forms a memory cell. For the purpose of classifying text data, the input layer was given the text sequence $W=(W^1,W^2,\ldots,W^L)$. The LSTM-based recurrent layer d_s creates a memory cell at step s. It is possible to compute equation (2) for activation during processing layers.

$$g_s = p_s tanh(d_s) \qquad (2)$$

In this case, the output gate that chooses which section of the memory content will be displayed is $p_s$tanh (•), which is the function of the hyperbolic tangent. The equation (3) modifies the output layer.

$$p_s = \sigma\left(X_{pjw_s} + X_{pg}g_{s-1} + X_{OCC_S}\right) \qquad (3)$$

X implies weight matrices in this context: e.g. weight matrix between memory by X_{OC}, while the input-output weight matrix is represented by X_{pg}. The logistic signal function is σ. By deleting some of the existing memory material and adding new memory (d_s) content, memory cell ct can be changed.

$$d_s = j_s \odot \overline{d_s} + e_s \otimes d_{s-1} \qquad (4)$$

Element- wise multiplication in this case and the new memory cell content (d_s) is obtained by equation (5).

$$\overline{d_s} = \tanh(X_{djw_s} + X_{dg}g_{s-1}) \qquad (5)$$

Using Unidirectional Long Short-term Memory as a second channel for text emotion analysis

A unidirectional LSTM technique processes textual content sequentially, capturing past context for every word. In a BERT-primarily based two-channel neural community for textual emotion analysis, it enhances BERT's bidirectional embeddings through improving temporal dependencies, improving emotion popularity accuracy throughout sequential inputs. Unidirectional LSTM methods input sequences with one-directional reminiscence, extracting emotional context from text information. It complements BERT's pre-trained embeddings, allowing effective sentiment classification across two input channels. An RNN that has been improved to compute the hidden state is called an LSTM. Using the idea of gating, this cell chooses which data to ignore and which to retain in memory, transferring necessary information. The LSTM cell is comprised of three gates, input, forget, and output. Figure 2 shows the structure of unidirectional LSTM.

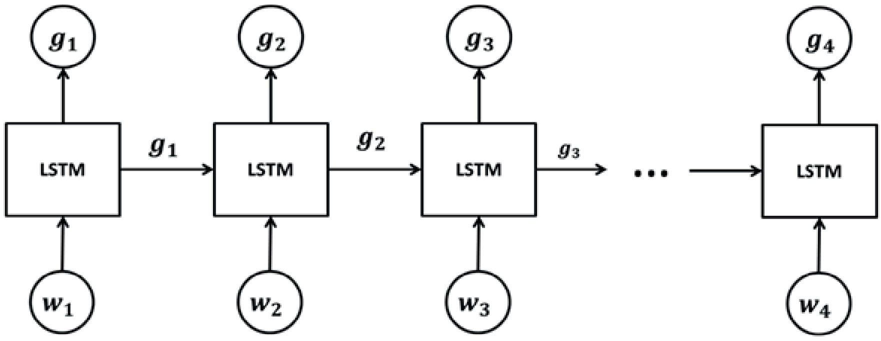

Figure 2. Structure of Unidirectional LSTM

The forget gate is in charge of deciding which information should be erased and which should be remembered. Equation (6) indicates that the sigmoid layer is in charge of making this choice.

$$e_s = \sigma(w_s V^e + g_{s-1} X^e) \qquad (6)$$

The result is either 0 or 1, where 1 denotes keeping and 0 denotes forgetting. The input gate is the second gate. Equation (7) illustrates how this gate employs a second sigmoid layer to decide which values to update.

$$j_s = \sigma(w_s V^j + g_{s-1} X^j) \qquad (7)$$

Equation (8) illustrates how the tanh function generates a vector of fresh candidate values that could be included in the cell state.

$$\widehat{D}_s = tang(w_s V^h + g_{s-1} X^h) \qquad (8)$$

Concatenating both ˜t and $\hat{D}_s$ then prepares the cell state for the update. According to equation (9), the LSTM modifies the previous cell state (D_{s-1}) to be (D_s).

$$D_s = \sigma\left(e_s \times D_{s-1} + j_s \times \widehat{D}_s\right) \qquad (9)$$

The sigmoid gate's output is determined by equation (10).

$$p_s = \sigma(w_s V^p + g_{s-1} X^p) \qquad (10)$$

Equation (11) shows that when we multiply p_s by tanh (D_s), automatically decide which part to remove.

$$g_s = tanh(D_s) \times p_s \qquad (11)$$

tanh of the cell state is used to create values between -1 and 1, and the end result gate uses the function of sigmoid to decide which portion of the condition of the cell will emerge.

Classification of emotions using ARNN-Uni-LSTM

ARNN-Uni- LSTM networks in a two-channel BERT-primarily based structure offer several advantages for textual emotion analysis. ARNNs enhance the model's potential to deal with complex sequential data by augmenting the standard LSTM with additional mechanisms, together with attention or adaptive memory, to improve long-term dependency capturing. This is particularly beneficial in understanding intricate emotional nuances that emerge over long textual contexts, where simple LSTMs might struggle. The ARNN's augmented structure allows the model to maintain a better memory of advanced emotional indications, which is crucial in identifying emotions tied to occasions described later within the text.

Unidirectional LSTMs excel at modeling sequential data; however, they processing long-range dependencies can be challenging. By integrating LSTM with ARNN, the model can better adapt to the text's emotional context, and ensure more accurate emotion identification across various levels of abstraction. The BERT-based second channel leverages pre-trained contextual embeddings, capturing deep semantics that mean from text and supplying a rich understanding of the linguistic and emotional context. Combining each channel, ARNN for long-term dependencies and BERT for contextual semantics, ensures robust emotion analysis, ensuing in a more precise and effective text emotion recognition system.

RESULTS

The results obtained by the research using specific performance indicators are discussed. Experimental setup components and their descriptions are listed in table 1.

Table 1. Experimental setup

Component	Details
Operating system	Windows
Python version	Python 3.12.6
Processor	Intel core i7(12th Gen)
RAM	32GB
Device type	Contemporary laptop
Purpose	Performance measurements for intensive multitasking and development workloads

To analyze the emotion through text for that, social media tweets were used as data. Table 2 and figure 3 provide emotion intensity scores derived from data, reflecting the emotional content of the text. Happiness (0,91) indicates strong positivity, at the same time as Sadness (0,65) suggests moderate depression. Anger (0,77) represents a relatively high level of frustration, Fear (0,72) indicates substantial anxiety, and Surprise (0,84) signals unexpected or surprising factors. The textual content appears to contain a balance of positive emotions like joy and surprise, with some negative tones like anger and fear. This evaluation can be useful in understanding the emotional context of used data.

Table 2. Evaluation of emotion intensity score

Emotion	Score (Intensity)
Happiness	0,91
Sadness	0,65
Anger	0,77
Fear	0,72
Surprise	0,84

Figure 3. Emotion scores for text data

To compare the methods, several parameters are used, including accuracy, recall, f1 score, and precision, this contrasts the suggested approach with other current techniques. Based on these criteria, the results demonstrated that the recommended approach performed better than other traditional techniques. The proposed ARNN-Uni-LSTM method was compared with the BERT + CNN + BiLSTM, BERT + CNN + BiLSTM + (Attention) Att, Multi-stage Comparative Benchmarking Analysis (MsCBA), traditional methods for analyzing the text emotion.[15,16]

Accuracy
The accuracy metric quantifies the proportion of correctly predicted examples among the instances. By splitting up all of the observations by the proportion of correctly anticipated observations, it may be calculated. Figure 4 (A) and table 3 compare the accuracy of three models, BERT + CNN + BiLSTM (91,15 %), BERT + CNN + BiLSTM + Att (92,35 %), are obtained and the proposed ARNN-Uni-LSTM for analyzing the text emotion analysis achieved an accuracy of (97,18 %) consistently outperforms other methods.

Precision
Precision measures how well a model predicts positive outcomes and is a performance in classification metrics. The calculation involves dividing the entire quantity of false positives and true positives by the forecasting percentage that is truly positive. Figure 4 (B) and table 3 show the precision of traditional models. They obtained BERT + CNN + BiLSTM (89,65 %), BERT + CNN + BiLSTM + Att (92,05 %), MsCBA (92,24 %), and the proposed ARNN-Uni-LSTM for analyzing the text emotion analysis achieved a precision of (94,56 %) consistently outperforms other methods.

Table 3. Overall comparison of suggested methods with traditional methods

Methods	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)
BERT+CNN+BiLSTM (Chen et al.,2023)	91,5	89,65	91,04	90,34
BERT+CNN+BiLSTM+Att (Chen et al.,2023)	92,35	92,05	91,13	91,59
MsCBA (Na et al.,2024)	-	92,24	92,37	92,31
ARNN-Uni-LSTM (Proposed)	97,18	94,56	95,21	96,26

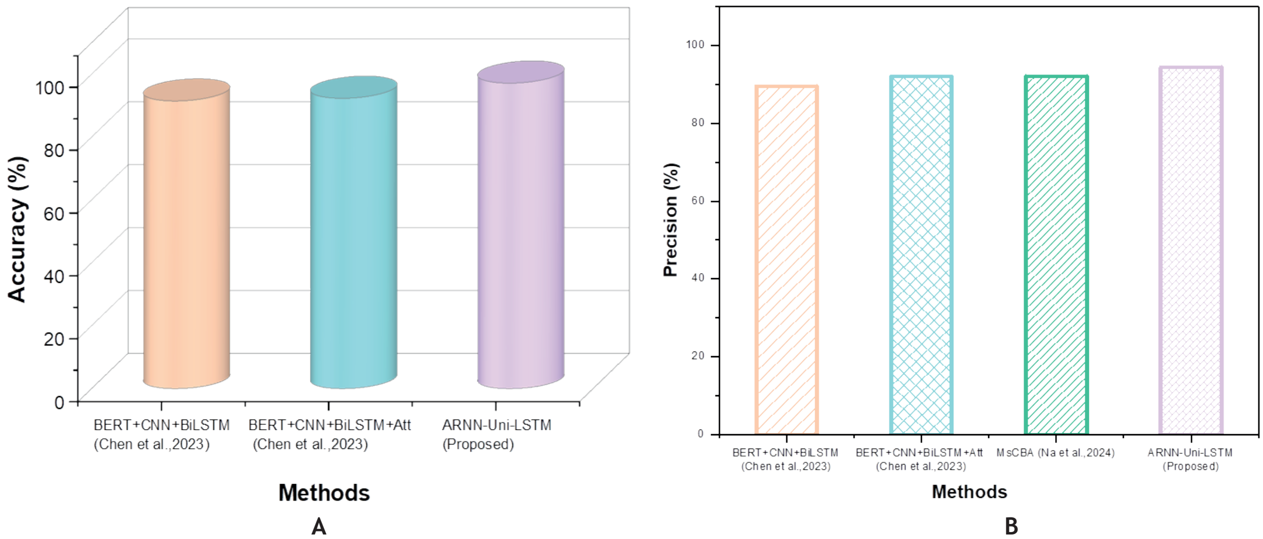

Figure 4. Performance of (A) accuracy and (B) Precision

Recall
Recall is a performance metric for classification models that assesses a model's accuracy in identifying the relevant examples that belong to a particular class. Figure 5 (A) and table 3 compare recall throughout four models, BERT + CNN + BiLSTM (91,04 %), BERT + CNN + BiLSTM + Att (91,13 %), MsCBA (92,37 %) are obtained and the proposed ARNN-Uni-LSTM for analyzing the text emotion analysis achieved Recall of (95,21 %) consistently outperforms other methods.

F1 Score
This combines recall and precision, which are well-studied to provide a good indicator of their relationship. It determines if there are any appreciable differences between the means of various groups. Figure 5 (B) and table 3 compare the F1-score evaluation of the obtained BERT + CNN + BiLSTM (90,34 %), BERT + CNN + BiLSTM + Att (91,59 %), MsCBA (92,31 %), and the proposed ARNN-Uni-LSTM for analyzing the text emotion analysis, achieving an F1 score of (96,26 %) consistently outperforms other methods.

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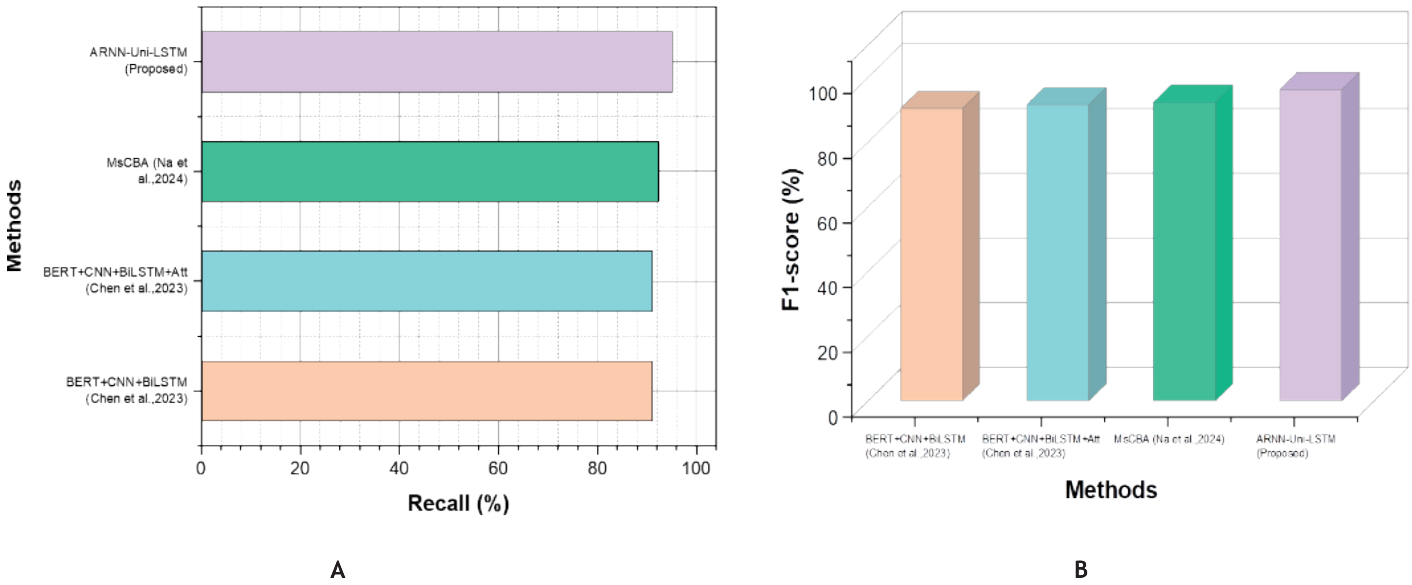

Figure 5. Outcome of (A) Recall and (B) F1-score

DISCUSSION

A BERT-based two-channel neural network processes text through dual pathways, enhancing contextual understanding and feature extraction for improved natural language processing tasks. The BERT+CNN+BiLSTM model for a BERT-based two-channel neural network faces limitations such as high computational cost, overfitting risk, complex parameter tuning, potential redundancy in feature extraction, and difficulty in capturing long-range dependencies efficiently due to convolution constraints. The BERT+CNN+BiLSTM model achieved 91,5 % accuracy, 89,65 % precision, 91,04 % recall, and a 90,34 % F1-score, demonstrating strong performance in classification tasks by effectively capturing contextual and sequential dependencies. The BERT+CNN+BiLSTM+Att model for a BERT-based two-channel neural network faces limitations such as high computational cost, increased complexity, risk of overfitting, difficulty in real-time processing, and potential redundancy in feature extraction, affecting efficiency and interpretability. The BERT+CNN+BiLSTM+Attention model achieved 92,35 % accuracy, 92,05 % precision, 91,13 % recall, and a 91,59 % F1-score, demonstrating its strong performance in classification tasks with high reliability and effectiveness. The MsCBA method for the BERT-based two-channel neural network may suffer from computational overhead, limited generalization to unseen data, sensitivity to hyperparameters, potential overfitting, and inefficiency in handling long-range dependencies, affecting performance in complex natural language understanding tasks. The MsCBA method achieved 92,24 % precision, 92,37 % recall, and a 92,31 % F1-score. Accuracy is unspecified. These metrics indicate strong performance in balancing precision and recall for the evaluated task. To overcome these limitations, ARNN, specifically those utilizing mutated unidirectional LSTM, provide a more efficient alternative for text emotion analysis. By augmenting the LSTM with mutations which include non-linear activation capabilities or novel gating mechanisms, the model can capture each short and long-range dependency more efficiently than traditional LSTMs. The unidirectional nature ensures that computations are streamlined, decreasing useful resource usage compared to bidirectional counterparts. Furthermore, ARNNs are less prone to overfitting, as their flexibility permits better generalization to unseen data. This makes more efficient and effective for emotion analysis responsibilities, especially while dealing with large-scale text corpora.

CONCLUSIONS

A BERT-based two-channel neural network processes input through two separate BERT encoders, capturing different contextual representations, which are then fused for enhanced understanding in tasks like text matching, classification, or sentiment analysis. The dataset utilized social media tweets for text emotion analysis. Data preprocessing involved tokenization, while feature extraction was performed using Word2Vec. The proposed ARNN-Uni-LSTM model leveraged BERT-based word vectors, with ARNN capturing local features and Uni-LSTM extracting global context. The fusion of both channels improved classification accuracy. Experimental results showed superior performance, achieving 97,18 % precision, 94,56 % recall, 96,26 % F1 score. This model enhances sentiment analysis applications in customer feedback, social media monitoring, and mental health diagnostics. The observation used publicly available datasets, which had been pre-processed through tokenization and word2vec as feature extraction. Local and global semantic feature classification analysis usage of ARNN-Uni-LSTM, respectively. The proposed dual-channel model verified advanced performance, attaining an accuracy of 97,18 %, precision of 94,56 %, recall of 95,21 %, and F1 score of 96,26 %, and accuracy of 97,18

% in the classification of text emotion analysis. Despite those promising results, it faced obstacles regarding the computational complexity and scalability of the BERT model, especially while managing larger datasets. Future development ought to concentrate on enhancing the functionality of the model and investigating its applications in real-time emotion analysis for client remarks, social media, and mental health diagnostics.

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FINANCING

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CONFLICT OF INTEREST

The authors declare that there is no conflict of interest.

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