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Original Article

Enhancing Social Media Fake News Detection Using PsychoLinguistic Multiplicative Attentive Net (PLiMA Net) with LIWC Features

B. Hemalatha[1], M. Soranamageswari[2]

[1]*Department of Computer science, Government arts and science college, Kaikaattiputhur(Post), Avinashi, TamilNadu, India.*
[2]*Department of Information technology, Government Arts College(Autonomous), Coimbatore, Tamil Nadu, India.*

[1]*Corresponding Author : sabahema99@gmail.com*

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Abstract *- Detecting fake news on social media platforms remains a critical challenge due to the rapid dissemination of information and the intricate nature of multimedia content. Traditional approaches inadequately capture the psycholinguistic features essential for understanding the social context, intent, and emotional undertones embedded in the text. To address these shortcomings, this study introduces a novel PsychoLinguistic Multiplicative Attentive Network (PLiMA Net) that incorporates psycholinguistic analysis and Luong attention mechanism into RNN for fake news detection systems, aiming to enhance the accuracy and reliability of identifying misleading content. Previous contributions: (a) The first work focused on text-based fake news detection through the "Integrated Hierarchical Granular Retentive XLNet with Fast Embedded Semantic Extraction" method. This approach utilized innovative components such as Structural Transition Enhanced Parsing (STEP), Multi-Granular Entity Resolution (MulGER), and Fast-X-Ref Semantic Feature Extraction, achieving a remarkable accuracy of 97.67%. (b) The second work extended this framework by incorporating emojis into sentiment analysis where the "Multi-Token Concatenated Embedding and SemantiXpert Probabilistic Classifier" method was proposed, featuring Multi-Run Byte Pair Encoding (MR-BPE) and a Concat-ViLT model for merging textual and visual representations and achieved an accuracy of 95.83%. By incorporating psycholinguistic analysis with Luong attention mechanism into those previous two works, this PLiMA Net model improves its precision and adaptability to the evolving linguistic area of social media, ensuring robust and trustworthy detection of fake news.*

Keywords *- Sentiment analysis, Fake news detection, Social media news, Psycholinguistic features, Recurrent neural network, Attention mechanism.*

1. Introduction

In the digital age, the proliferation of social media has dramatically transformed how information is disseminated and consumed. While this democratization of information has many benefits, it also poses significant challenges, particularly in the spread of fake news. Detecting false information swiftly and accurately is crucial to mitigate its impact on public opinion and societal stability. Sentiment analysis, a technique that evaluates and interprets emotional tones in textual data, has emerged as a powerful tool in the fight against fake news. By analyzing the sentiment expressed in social media posts, researchers can identify patterns and anomalies indicative of misinformation. This approach leverages the emotional content of the text, providing a nuanced layer of analysis that can enhance the accuracy of fake news detection systems. As social media continues to evolve, integrating sentiment analysis into these systems is becoming increasingly vital to ensure the reliability of information in the public sphere. Detecting fake news involves a series of critical stages aimed at effectively identifying and mitigating the impact of misinformation. Initially, content analysis scrutinizes text, images, or videos for inconsistencies, factual errors, and misleading information, assessing sources and coherence. Subsequently, source verification examines the credibility of information origins, evaluating publisher reputation, domain expertise, and history of misinformation dissemination [1-4].

Contextual analysis contextualizes information by assessing publication timing, geopolitical events, and alignment with known facts. Social network analysis follows, analyzing propagation patterns and identifying influential nodes to uncover potential misinformation sources and disrupt dissemination strategies. These stages collectively enhance the ability to combat misinformation, promoting informed decision-making and societal resilience against false information. Lastly, sentiment analysis can provide valuable insights into the emotional tone and reaction to the content. By analyzing public sentiment towards the information, analysts can gauge its impact on public opinion and identify emotional triggers that might indicate manipulation or bias. Sentiment analysis complements other stages by adding a behavioral dimension to the detection process, highlighting discrepancies between factual reporting and emotional manipulation. Several deep learning models have proven effective in detecting fake news on social media platforms by leveraging their ability to handle vast datasets and extract intricate patterns [5-8].

BERT (Bidirectional Encoder Representations from Transformers) stands out for its success in natural language processing tasks, including identifying misleading content. Its bidirectional training allows it to grasp contextual nuances in text, distinguishing between reliable information and misinformation based on language semantics and syntax. The GPT (Generative Pre-trained Transformer) series, notably GPT-3, excels in comprehending language structures and can be adapted to assess the coherence and factual consistency of text, detecting deviations that suggest potential misinformation. LSTM (Long Short-Term Memory) networks are utilized for their sequential data processing capabilities, ideal for analyzing temporal aspects of information dissemination on social media. They can detect irregularities in propagation patterns, such as sudden spikes in sharing or unusual engagement rates, indicative of fake news campaigns. CNN (Convolutional Neural Network) architectures are effective in scrutinizing multimedia content like images and videos, employing pattern recognition to identify manipulated visuals, thereby combating visual misinformation. These models collectively enhance the arsenal of tools for detecting and mitigating fake news, contributing to more informed and resilient digital environments [9-12].

Despite their effectiveness, deep learning models for fake news detection on social media encounter several challenges. BERT and GPT models rely heavily on the quality and diversity of training data, requiring extensive and representative datasets to generalize well across different types of misinformation. They may struggle with detecting subtle forms of misinformation that do not overtly violate grammatical or syntactic rules. LSTM networks face challenges in capturing the rapid evolution of information on social media platforms, as their sequential processing may not always adapt quickly to dynamic changes in content trends. Moreover, CNN architectures, while proficient in analyzing multimedia content, can be computationally intensive and require significant resources for real-time analysis, limiting their scalability [13-15]. Overall, integrating these models into robust detection systems requires addressing issues of data bias, model interpretability, real-time processing capabilities, and adaptation to emerging forms of misinformation, presenting ongoing challenges in the field of fake news detection.

Main Contribution of this work:

- A novel PsychoLinguistic Multiplicative Attentive Net (PLiMA Net) which integrates LIWC features with RNN and Luong attention mechanism to effectively capture psycholinguistic features and understand the context of text-emoji data, making it fit for social media sentiment analysis based fake news detection.
- This PLiMA Net is combined with the techniques used in the first and second work in appropriate stages to understand the effectiveness of this methodology by comparing the performance outcomes with and without this model.

The organization of the remaining content of this paper is as follows: Section 2 explains the literature survey, and a summary of previous contributions on sentiment analysis-based fake news detection is stated in Section 3. The proposed methodology and procedure for this work are discussed in Section 4. The datasets, experimental design, analytical findings, and comparison to earlier studies are all explained in Section 5, and Section 6 concludes the study.

2. Literature Survey

For the purpose of identifying bogus news, Rohit Kumar Kaliyar et al. [16] proposed the FakeBERT model, a deep convolutional approach based on BERT. Three parallel blocks of 1d-CNN with various convolutional layers and filters with variable kernel sizes were incorporated into the model, along with the BERT, for improved learning. The pre-trained word embedding model (BERT), which was based on a bidirectional transformer encoder, served as the foundation for the model. The classification findings show that results produced by FakeBERT were more accurate. This false news detection algorithm behaves differently when applied to news from different social media sources.

In order to prevent the spread of erroneous information, Nadeem et al. [17] provided an automated method for identifying incorrect information. The proposed multimodal EFND integrates contextual, social context, and visual data from news articles and social media to provide a multimodal feature vector with a high information density. Multimodal factorized bilinear pooling was used to combine the gathered data in order to improve their correlation and provide a more accurate shared representation. Finally, a Multilayer Perceptron was deployed to the shared representation to categorize fake news. EFND was evaluated using the "FakeNewsNet" collection of widely used fake news datasets. Nevertheless, it has challenges when attempting to extract different image qualities for the analysis of news articles and social media to identify false content.

In order to construct a multimodal feature vector with high information content for an automated fake news detection system, Balasubramanian Palani et al. [18] combined textual and visual data. This method preserved the semantic relationships between words while extracting textual attributes using the bidirectional encoder representations from the transformers (BERT) paradigm. The suggested Capsule neural Network (CapsNet) model, in contrast to the Convolutional Neural Network (CNN), retrieved the most illuminating visual information from an image. By combining these characteristics, a richer data representation was produced that aided in identifying if the news was authentic or fraudulent. In order for the algorithm to better reliably detect false news, it has to thoroughly understand the links between different modalities.

Using three concurrent Convolutional Neural Network (CNN) layers, Samadi and Momtazi [19] proposed a deep neural architecture that extracts semantic properties from contextual representation vectors. It sought to illustrate how content-based feature engineering enhances semantic models for challenging assignments such as identifying bogus news. The sequenced output of the text representation module was connected to three concurrent groups of convolutional and max-pooling layers. To extract features based on the tokens' collocation in news articles, two layers were inserted in each component: a convolutional layer and a max-pooling layer. It did not, however, look into other sources, including the social media users' graph, to comprehend user relationships and information distribution.

A novel hybrid method was presented by Ehab Essa et al. [20] to automatically detect bogus news. The LightGBM and BERT models were employed in this method to create a successful categorization scheme. The LightGBM model was built using an already-trained BERT word embedding model as a foundation. A few pre-processing methods were used for the input text in order to eliminate any extraneous content. Subsequently, tokenization was employed on the input text to generate distinct characters, subwords, and words that accurately represented the input data received by the "fine-tuned" BERT. From the distinct token of the final three buried layers of the BERT, it was able to get the text embedding. Nonetheless, some language patterns affected the model's decision-making abilities.

The affective resonance of Facebook posts regarding research articles was predicted by Murtuza Shahzad et al. [21]. When Facebook users' responses to research articles and postings were analyzed, it was shown that "Like" responses were the most prevalent. Facebook posts on scientific articles were predicted to have a certain tone by using machine learning algorithms. The Random Forest, Decision Tree, K-Nearest Neighbours, Logistic Regression, and Naïve Bayes classifiers were the five that were employed. Metrics like the F-1 score, recall, accuracy, and precision were used to assess the models. With values of 86% and 66% for two- and three-class labels, respectively, the Random Forest classifier was the most accurate model. Even when the outcomes precisely reflect users' genuine emotional responses, variations in sentiment interpretation have an impact on how accurate the model's predictions are.

The most recent multi-view deep learning method for sentiment analysis, which considered non-textual elements like emojis, was presented by Xu et al. [22]. The findings recognized the separate and combined contributions of textual and emoji perspectives to sentiment analysis. For the sentiment classification model, the suggested method treated textual and emoji viewpoints as separate views of emotional information. Three methods for managing emojis were proposed: Emoji Replacement, Emoji Scoring, and Emoji Embedding. Furthermore, the sentiment classifiers improved the performance of the classifiers when handling emoji features processed by the three techniques, either alone or in combination. However, in order for this model to identify textual patterns more accurately, more domain information has to be supplied.

Based on text linguistic patterns and emojis, Shelley Gupta et al. [23] introduced an emoji-based paradigm for the cognitive-conceptual-affective processing of emotion polarity. Voice segments were translated into n-gram patterns using a text-based parser that blended a range of emojis with recommended language features to portray emotions. Globally, 1,68,548 tweets from 650 famous individuals were downloaded. By extension, the CLDR name of each emoji was used to determine the proper polarity of emoji patterns and a lexicon of emotions was used to determine the polarity of text. However, in order for this model to identify textual patterns more accurately, more domain information has to be supplied.

Four deep learning models that integrate the BERT algorithm with the Bidirectional Long Short-Term Memory (BiLSTM) and Bidial Gated Recurrent Unit (BiGRU) algorithms were presented by Amira Samy Talaat [24]. The recommended approaches used pre-trained word embedding vectors to increase accuracy and examine BIGRU's impact on text sentiment categorization both with and without emojis. Model fine-tuning became significantly simpler as a result. The suggested techniques were contrasted with seven other models created using conventional machine learning for the same objective, as well as two pre-trained BERT models. However, efficient methods need to be used at every level of feature extraction and feature selection if overall performance is to be improved.

Chuchu Liu et al. [25] used well-known supervised and unsupervised learning techniques, such as neural network algorithms (LSTM) for supervised learning, rule-based algorithms for unsupervised learning, and classification algorithms (SVM), to assess the effects of emoji introduction and the ambiguity of emoji tags. It was demonstrated that supervised learning algorithms often yield superior accuracy when compared to unsupervised learning methods. Moreover, the best outcomes were consistently generated by deep learning systems.

Emoji usage has also been demonstrated to enhance the performance of SA algorithms, and emoji tag phrases were directly incorporated into the feature building process for classifier training. However, additional research is required to improve the strategy's robustness in terms of platform and scenario comparisons as well as usage patterns of more extensive emojis.

Overall, while FakeBERT [16] showed promising results, it faces challenges in adapting to different sources of social media news due to varying data characteristics, EFND [17] encounters difficulties in extracting diverse image attributes for accurate analysis of news articles and social media content, the model in [18] needs to better understand the relationships between different modalities to reliably detect false news, [19] didn't explore other sources like social media user connections for a comprehensive understanding of information dissemination, the model's [20] decision-making was influenced by specific linguistic patterns, variations in sentiment interpretation by [21] could impact prediction accuracy, the model proposed by [22] require more domain information for accurate pattern identification, [23] needs additional domain information for accurate pattern identification, efficient feature extraction and selection methods for [24] are needed for improved performance, and further research is needed on [25] to enhance the method's robustness across different platforms and scenarios.

3. A Summary of Previous Contributions to Sentiment Analysis-Based Fake News Detection

3.1. Work 1: Fake News Detection Using Only Text

A novel method called "Integrated Hierarchical Granular Retentive XLNet with Fast Embedded Semantic Extraction" was proposed to address the limitations of current NLP models, which fail to capture the evolving narrative structure of social media content. The method includes several innovative components, as discussed below:

3.1.1. Structural Transition Enhanced Parsing (STEP)

This pre-processing method uses dependency trees to capture hierarchical information and transitions between sections of an article, improving the model's comprehension of the text's structural flow.

3.1.2. Multi-Granular Entity Resolution (MulGER)

This algorithm follows the evolution of entities and knowledge throughout the article, employing temporal co-reference resolution to understand how entities are referenced and evolve, enhancing semantic understanding.

3.1.3. Fast-X-Ref Semantic Feature Extraction

This technique uses FastText to capture subword information and generate word embeddings outside the vocabulary, allowing the model to grasp the lexical diversity and tone of user narratives. It included a Cross Reference Semantic Weighting algorithm to assign more weight to word embeddings aligned with resolved entities, identifying rare words indicative of user intent and motivation.

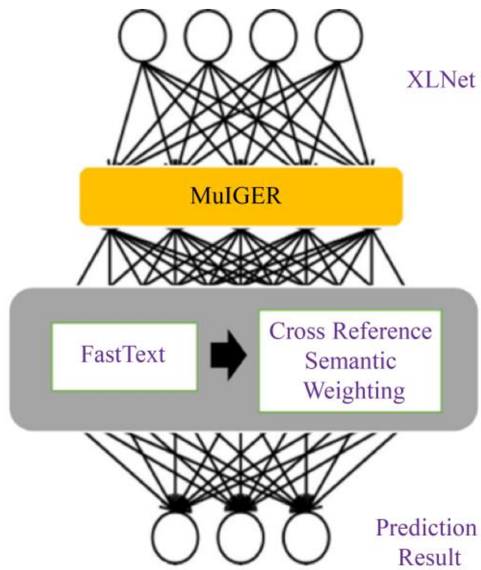

Fig. 1 Integrated hierarchical granular retentive XLNet with fast embedded semantic extraction

Figure 1 shows the methodology used in work 1. These components together enabled the XLNet model to detect fake news in social media content with text only by understanding the narrative structure, style, and semantics of social media content. This model has proven to be the most accurate and precise among all formerly developed models, achieving an accuracy of 97.67%.

3.2. Work 2: Fake News Detection Using Text and Emojis

In the field of fake news detection, incorporating emojis into sentiment analysis significantly enhances the detection of misinformation. Emojis add critical context and emotional tone that text alone cannot convey, improving the accuracy of identifying fake news. To address the challenges of integrating text and emojis, a novel method called "Multi-Token Concatenated Embedding and SemantiXpert Probabilistic Classifier" was proposed. This method aimed to improve sarcasm detection, polarity prediction, and overall sentiment analysis accuracy with the following techniques:

3.2.1. Multi-Token Concatenated Embedding

Utilizes Multi-Run Byte Pair Encoding (MR-BPE) to capture common sub-words and specialized text patterns iteratively. The Concat-ViLT model merges textual and visual representations of emojis, enhancing the understanding of text-emoji pairs and improving the detection of sarcasm or deception.

3.2.2. SemantiXpert Probabilistic Classifier

Enhances semantic classification by accurately interpreting the emotional tone within text data. It includes:

Contrastive Semantic Clause Filter Network

Uses CLIP to capture semantic connections and a Clause Separator Algorithm to break user comments into clauses for precise semantic analysis, improving polarity prediction accuracy.

Polarized Probabilistic Classifier

Utilizes ELECTRA to identify important semantic representations and determine polarity accurately. The Naive Bayes classifier further enhances sentiment classification by considering semantic relationships and polarization scores.

Figure 2 illustrates the fake news detection model used in work 2. These mechanisms work together to reduce misclassifications and improve the overall accuracy of sentiment prediction, enhancing the detection of fake news by capturing the intricate interplay between text and emojis. Through comparative investigation, the suggested model outperforms the state-of-the-art techniques with the greatest accuracy of 95.83%.

3.1. Motivation for the Evolving Research Work

In social media, fake news often leverages emotional manipulation to influence readers. Traditional lexical analysis methods overly depend on superficial text features (e.g., word frequency, n-grams) and focus on the presence and frequency of words but lack the depth to understand the social context or relational dynamics embedded in the text. This is because the previous models do not effectively capture the psycholinguistic features that provide deeper insights into the context of language use, such as intent, motivation, and emotional state. Without these features, the model's comprehension of context is limited, affecting its ability to discern fake news accurately. Also, psycholinguistic features help models adapt to evolving language and communication patterns, including new slang, memes, or shifting emotional tones in fake news. Misinterpreting the psychological intent leads to a higher rate of false positives (real news classified as fake) and false negatives (fake news classified as real), undermining trust in the detection system. Without the understanding of psycholinguistic features, the models become outdated more quickly.

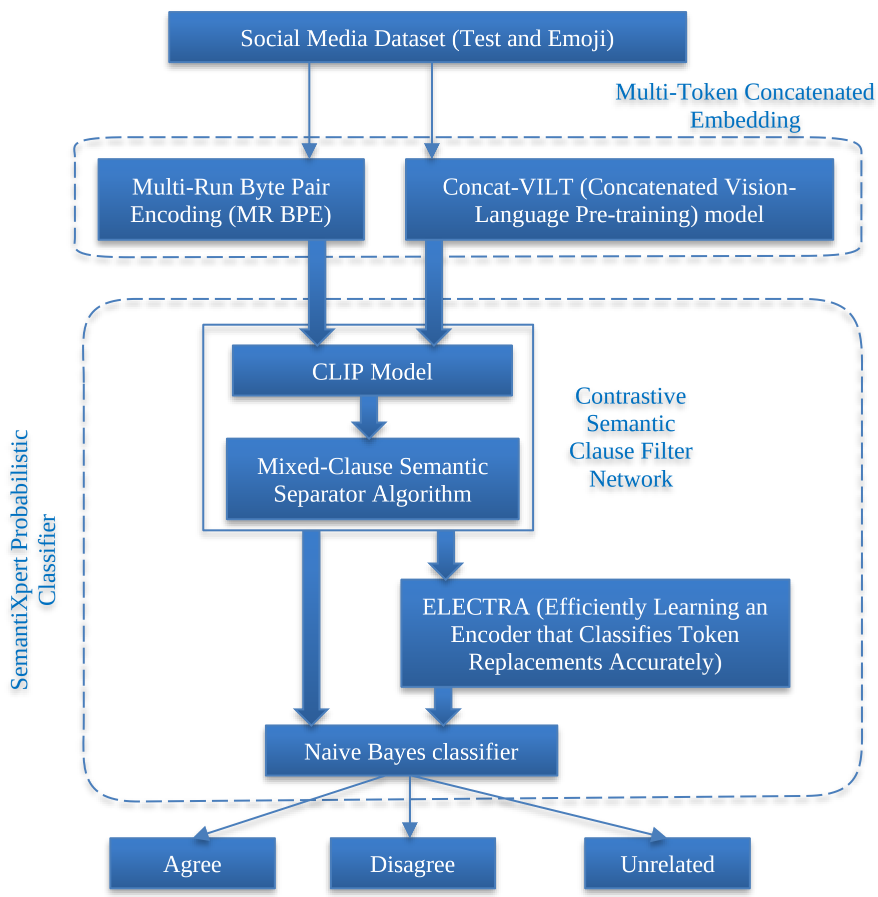

Fig. 2 Multi-token concatenated embedding and semantiXpert probabilistic classifier

Given these limitations, there is a demanding need for novel methodologies that incorporate psycholinguistic analysis into fake news detection systems. Such methods would enhance the model's ability to interpret the underlying psychological intent and emotional manipulation strategies used in fake news, leading to more accurate and reliable detection. These advanced models would not only improve the precision of identifying fake news but also adapt more rapidly to the evolving linguistic landscape, thereby maintaining their effectiveness and trustworthiness over time. Incorporating psycholinguistic features is, therefore, essential for developing robust, adaptive, and reliable fake news detection systems in the ever-changing domain of social media.

4. The Proposed Fake News Detection Methodology and Procedure

The proposed PsychoLinguistic Multiplicative Attentive Net (PLiMA Net) is designed by integrating psycholinguistic features with advanced sequential modeling and attention mechanisms, thereby enhancing the fake news detection capabilities with improved accuracy and reduced misclassification addressing the problems in the previous models. This section provides a detailed technical overview of the PLiMA Net architecture, highlighting its components and their roles in improving the accuracy and robustness of fake news detection.

4.1. Proposed Architecture of PsychoLinguistic Multiplicative Attentive Net (PLiMA Net)

The PLiMA Net integrates LIWC features with Recurrent Neural Networks (RNNs) and Luong's attention mechanism to create a powerful model that captures both the psycholinguistic and sequential dependencies in the text.

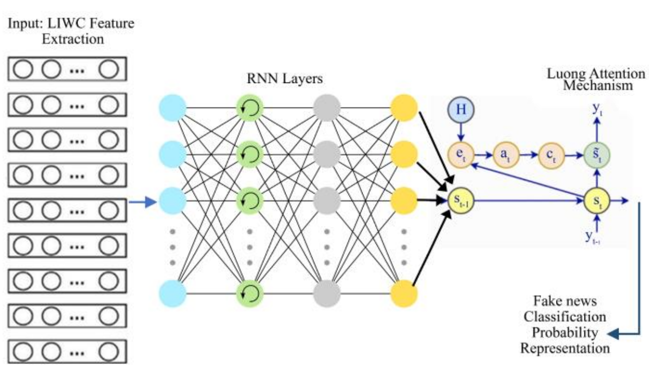

Fig. 3 Architecture of the proposed psycholinguistic multiplicative attentive net

The proposed PLiMA Net architecture is shown in Figure 3. The architecture consists of the following key components:

- LIWC Feature Extraction
- RNN Layers
- Luong Attention Mechanism
- Output Layer

4.1.1. LIWC Feature Extraction

Linguistic Inquiry and Word Count (LIWC) is a text analysis tool that extracts psycholinguistic features from written content, providing a detailed view of psychological and emotional cues embedded in the text. The process begins with pre-processed text or text with emoji, which is fed into the LIWC software to generate a variety of features that fall into several categories:

Emotional Tone

This includes metrics for positive and negative emotions. Positive emotion features capture words that convey happiness, optimism, and positive sentiment, while negative emotion features identify words associated with sadness, anger, and negative sentiment. These features are critical in discerning the emotional undertone of the text, which can be a strong indicator of manipulative or misleading content.

Cognitive Processes

This category includes features such as insight and causality. Insight words reflect cognitive engagement and the depth of processing, indicating the presence of analytical thinking and reflective thought. Causality words indicate the presence of causal relationships and logical reasoning in the text. These cognitive markers help in understanding the thought patterns and logical structures present in the narrative, which are essential for detecting inconsistencies and manipulations typical in fake news.

Social Aspects

LIWC identifies references to family, friends, and other social groups, providing a measure of the social context within the text. Words that refer to social relationships can reveal the text's appeal to communal ties and emotional bonds, which are often exploited in fake news to create a sense of trust and credibility.

The LIWC tool uses a comprehensive dictionary of words associated with various psychological constructs and social dimensions. Each word in the text is compared against this dictionary, and counts are generated for each category. These counts are then normalized to account for text length, providing a set of features that represent the psychological and emotional profile of the text. By extracting these LIWC features, the model gains insight into the fine psychological and emotional aspects of the text, enhancing its ability to detect the indirect cues that differentiate fake news from legitimate content. This psycholinguistic analysis is a crucial step in the data pipeline, as it provides the foundation for the subsequent integration of the PLiMA Net, which further refines and leverages these features using advanced neural network techniques and attention mechanisms.

4.1.2. RNN Layers

Recurrent Neural Networks (RNNs) are employed to capture the sequential dependencies and temporal patterns in the text data. The RNN layers are designed to process the input sequentially, maintaining a hidden state that captures the context from previous tokens. The mathematical representation for each time step in the hidden layer is given by Equation (1);

$$h_t = f(W_x x_t + W_h h_{t-1} + b) \tag{1}$$

Where h_t is the hidden state at time t, x_t is the input at time t, W_x and W_h are weight matrices, b is the bias term, and f is the activation function. The RNN layers are crucial for understanding the context over long sequences, which is essential for detecting fake news that often relies on the sequential narrative structure. The RNN processes the text sequentially and outputs a context-aware representation for each time step, encapsulating the structural flow and transitions of the text, thereby capturing the narrative and evolving nature of social media content.

4.1.3. Luong Attention Mechanism

The attention mechanism allows the model to weigh different parts of the input text differently, giving more importance to relevant sections. It computes attention scores by comparing the current hidden state of the RNN with all previous hidden states.

The Luong attention mechanism is applied to the output of the RNN layers in PLiMA Net to enhance the focus on relevant psycholinguistic features captured by LIWC. The RNN encoder processes the input sequence $X=(x_1,x_2,\dots,x_T)$ to produce a set of hidden states (annotations) $H=(h_1,h_2,\dots,h_T)$. The alignment model computes the alignment scores $e_{t,i}$ by measuring the similarity between the current decoder hidden state s_t and each encoder hidden state h_i. This is done using a multiplicative approach, and the alignment scores are normalized using a softmax function to obtain the attention weights $\alpha_{t,i}$. These are represented mathematically in Equations (2) and (3).

$$e_{t,i} = s_t^T W_a H_i \tag{2}$$

$$\alpha_{t,i} = \frac{\exp(e_{t,i})}{\sum_{j=1}^{T} \exp(e_{t,j})} \tag{3}$$

An attentional hidden state $\hat{s}_t$ is computed based on a concatenation of the context vector c_t, which is a weighted sum of the hidden states, capturing the most relevant information based on the attention weights, and the current decoder hidden state is represented by s_t. The mathematical representation of this context vector and the additional hidden state are given in Equations (4) and (5).

$$c_t = \sum_{i=1}^{T} \alpha_{t,i} h_i \tag{4}$$

$$\hat{s}_t = \tanh(W_c\,[c_t;\ s_t] \tag{5}$$

Hence, this Luong attention mechanism enhances the RNN outputs by dynamically assigning weights to different parts of the input sequence, effectively allowing the model to focus on the most relevant sections for the final prediction. This mechanism operates on the principle of calculating alignment scores between the current decoder's hidden state and each encoder's hidden state using a multiplicative approach. These alignment scores are then normalized using a softmax function to produce attention weights.

The attention weights determine the importance of each hidden state, allowing the model to create a context vector that is a weighted sum of these hidden states. By integrating this context vector with the current decoder hidden state, the Luong attention mechanism ensures that the model emphasizes the most salient parts of the input sequence.

In the context of fake news detection, this technical significance is crucial. It allows the model to prioritize inputs that carry significant psycholinguistic features, such as emotional tone, cognitive processes, and social aspects extracted by LIWC.

This prioritization improves the model's ability to discern manipulative language, identify misleading content, and capture subtle cues embedded in the text, ultimately enhancing the accuracy and robustness of fake news detection. By focusing on the most informative parts of the text, the model makes contextually aware predictions, leading to better performance compared to models without such attention mechanisms.

4.1.4. Output Layer

The output layer of PLiMA Net is responsible for classifying the text as fake news or real news based on the enhanced representation from the RNN and attention layers. This layer typically consists of a fully connected neural network followed by a softmax activation function to produce the final classification probabilities as represented by Equation (6).

$$y_t = softmax\,(W_o \hat{s}_t + b_o) \tag{6}$$

Overall, the LIWC features offer deep insights into the psychological and emotional aspects of the text, enhancing the model's ability to detect manipulative language and intentions behind fake news. The integration of context vectors and hidden states creates a rich representation of the input, capturing both local and global dependencies in the text.

The Luong attention mechanism ensures that the model focuses on the most relevant parts of the input, particularly those with significant psycholinguistic cues. This improves the accuracy and robustness of fake news detection.

4.2. Overall Execution Plan for the Proposed PLiMA Net Application

The primary objective of this work is to improve the existing fake news detection models by integrating the PsychoLinguistic Multiplicative Attentive Net (PLiMA Net) into two previous works, enhancing their ability to capture psycholinguistic features, and then comparing the performance of the upgraded models.

4.2.1. Phase 1: Integration of PLiMA Net into Work 1

Incorporating PLiMA Net into the first work, "Integrated Hierarchical Granular Retentive XLNet with Fast Embedded Semantic Extraction", begins with data pre-processing. Ensuring that the data is cleaned and pre-processed using the Structural Transition Enhanced Parsing (STEP) method is the initial step. Subsequently, LIWC features will be extracted from the pre-processed data. The integration of PLiMA Net occurs after the STEP method, where the data is fed into the PLiMA Net, processed by RNN layers, and enhanced using the Luong attention mechanism to focus on important psycholinguistic features. Following this, the usual steps of Multi-Granular Entity Resolution (MulGER) and Fast-X-Ref Semantic Feature Extraction will proceed. The updated model will then be trained and evaluated, with performance metrics such as accuracy, precision, recall, and F1 score compared to the original model's performance.

Fig. 4 Overall execution idea for the proposed developmental work

4.2.2. Phase 2: Integration of PLiMA Net into Work 2

For the second phase, data pre-processing involves using Multi-Run Byte Pair Encoding (MR-BPE) to capture common sub-words and specialized text patterns. LIWC features will be extracted from both text and emojis in the pre-processed data. PLiMA Net will be integrated into the data pipeline after the MR-BPE step, where RNN layers will process both text and emoji sequences. The Luong attention mechanism will be applied to enhance the understanding of emotional and psycholinguistic features. The subsequent steps will involve the Concat-ViLT model and the SemantiXpert Probabilistic Classifier. The enhanced model will then undergo training and evaluation, with its performance metrics compared to the original model's results.

4.2.3. Phase 3: Comparative Analysis

In this phase, a comparative performance analysis will be conducted. The performance of the two upgraded models (integrated with PLiMA Net) will be compared against the original models. Standard performance metrics such as accuracy, precision, recall, and F1 score will be used. The analysis will focus on the impact of integrating PLiMA Net on each model, identifying improvements in capturing psycholinguistic features and their contribution to the overall performance. These findings will be documented comprehensively, highlighting significant improvements.

Figure 4 shows the overall execution plan for the proposed approach. The primary objective of this work is to enhance existing fake news detection models by integrating the PsychoLinguistic Multiplicative Attentive Net (PLiMA Net) to better capture psycholinguistic features. Phase 1 involves incorporating PLiMA Net into "Integrated Hierarchical Granular Retentive XLNet with Fast Embedded Semantic Extraction," with steps including data pre-processing, LIWC feature extraction, and integration with PLiMA Net followed by model training and evaluation. Phase 2 integrates PLiMA Net into another model using Multi-Run Byte Pair Encoding (MR-BPE), focusing on both text and emoji sequences, and follows similar steps for enhancement and evaluation. Finally, Phase 3 compares the performance of these upgraded models against the originals using standard metrics to document improvements in capturing psycholinguistic features. The next section discusses the outcomes of the proposed fake news detection architecture after applying it to the two previous works.

5. Results and Discussion

This section provides a comprehensive analysis of the performance of the proposed PsychoLinguistic Multiplicative Attentive Network (PLiMA Net) integrated into both the text-only and text-and-emoji fake news detection models. By comparing the enhanced models with their original versions, the improvements in accuracy, precision, recall, and F1 score are evaluated. The software tool and system configuration used for this analysis are provided below;

Software	:	MATLAB
OS	:	Windows 10 (64-bit)
Processor	:	Intel i5
RAM	:	8GB RAM

5.1. Description of Datasets Used in this Analysis

In this work, two distinct datasets from the first and second works are utilized to evaluate the performance of the proposed PsychoLinguistic Multiplicative Attentive Network (PLiMA Net). For text-only fake news detection, the FNC-1 (Fake News Challenge) dataset used in work 1 is taken. This dataset comprises a combination of real news articles from reputable sources and fake news articles generated for the challenge. Each article is labeled with one of four categories indicating its stance concerning a particular headline: "agree," "disagree," "discuss," or "unrelated." The objective is to determine whether the article agrees with, disagrees with, discusses, or is unrelated to the headline. For text-and-emoji fake news detection, the Fake News Detection (XLMRoberta) dataset used in work 2 is employed. This dataset includes a diverse range of textual data, such as news stories, social media posts, and online content, gathered from various sources and domains. Each sample is labeled with a binary classification indicating whether the content is real or fake. The dataset consists of 1000 samples, with 90% used for training and 10% for testing. The data is available at https://huggingface.co/Sajib-006/fake_news_detection_xlmRoberta.

5.2. Performance Analysis of the Proposed PLiMA Net Model

The performance of the proposed fake news detection model is evaluated with parameters such as accuracy, precision, recall, F1-score, sensitivity, specificity, MSE (Mean Squared Error), loss and area under the ROC curve.

The accuracies of the proposed PLiMA Net model, when integrated into the first and second work, are depicted in Figure 5. At 50 epochs, the accuracy of work 1 with PLiMA Net achieves 99.13%, while work 2 with PLiMA Net achieves 98.87%. Both models attain almost equal values of accuracy with slight differences.

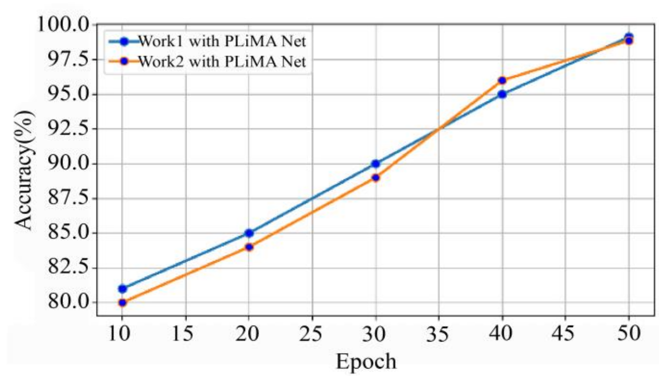

Fig. 5 Accuracy of the proposed PLiMA Net model

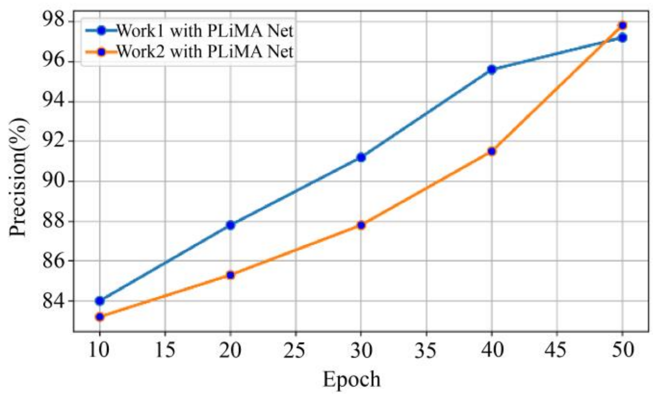

Fig. 6 Precision of the proposed PLiMA Net model

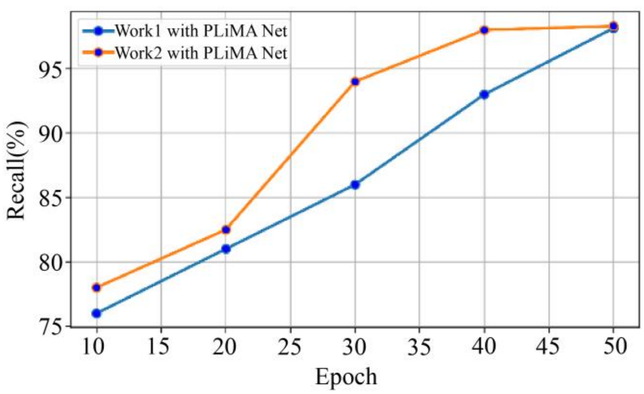

Fig. 7 Recall of the proposed PLiMA Net model

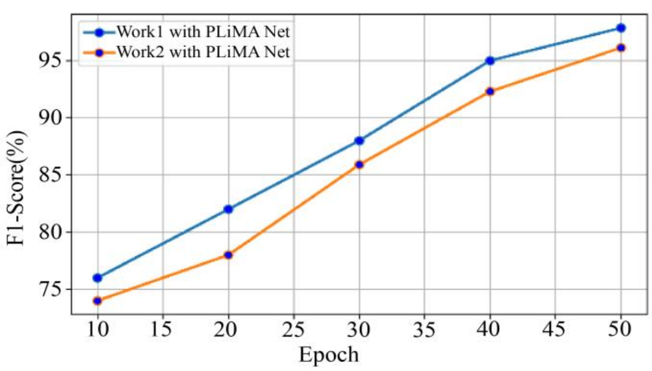

Fig. 8 F1-Score of the proposed PLiMA Net model

Figure 6 illustrates the enhancement of precision of the proposed PLiMA Net model and shows that there is a significant improvement in the precision with an increase in epochs. At 50 epochs, work 1 with PLiMA Net achieves an accuracy of 97.21% and work 2 with PLiMA Net achieves comparatively a higher accuracy of 97.82%.

The recall of the proposed PLiMA Net with work 1 and work 2 are compared and presented in Figure 7. At 30 epochs, there is a significant difference in the values of recall for both models, but at 50 epochs, work 1 with PLiMA Net and work 2 with PLiMA Net achieve recall values of 98.85% and 98.31%, respectively.

The F1 score, which is the harmonic mean of precision and recall, benefits from the improvements in both these metrics. The graph shown in Figure 8 compares the F1-score values of the proposed PLiMA Net model integrated with work 1 and work 2, and it shows that there is a markable difference in the F1 Score values of both models. At 50 epochs, work1 with the PLiMA Net model achieves an F1 score of 97.86%, and work2 with PLiMA Net achieves 96.13%.

The sensitivity values of the proposed PLiMA Net with work 1 and PLiMA Net with work 2 are plotted in Figure 9. At 50 epochs, the sensitivity of work 1 with PLiMA Net is obtained as 98.28%, and that of work 2 with PLiMA Net is found to be 98.86%, which is slightly more than that of work 1 with PLiMA Net. Sensitivity, or the true positive rate, is improved by the model's ability to detect fine psychological and emotional cues embedded in the text.

Specificity, or the true negative rate, benefits from the model's precision in identifying real news. Figure 10 depicts the variation of specificity of the proposed models with epochs from 10 to 50, and it is found that there is a huge difference in the specificity values at the beginning of the 10 epoch. However, it converges to a small difference when epochs are increased. The specificity values at 50 epochs for work 1 with PLiMA Net is found to be 97.92% and for work 2 with PLiMA Net is recorded to be 98.58%.

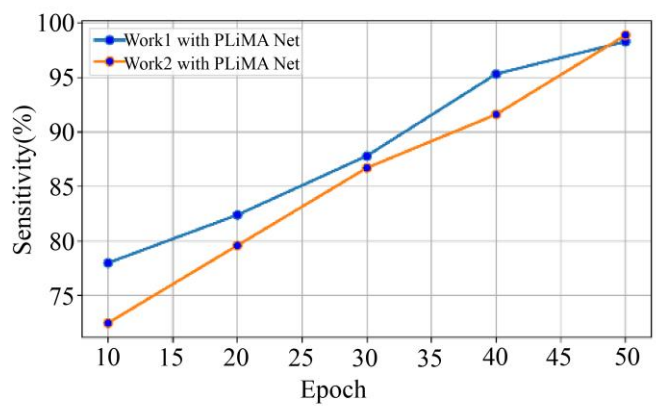

Fig. 9 Sensitivity of the proposed PLiMA Net model

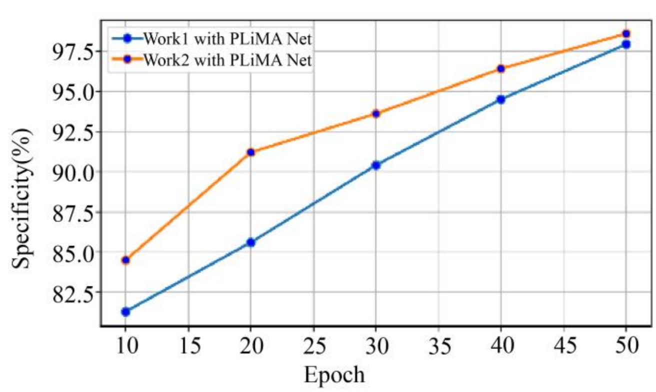

Fig. 10 Specificity of the proposed PLiMA Net model

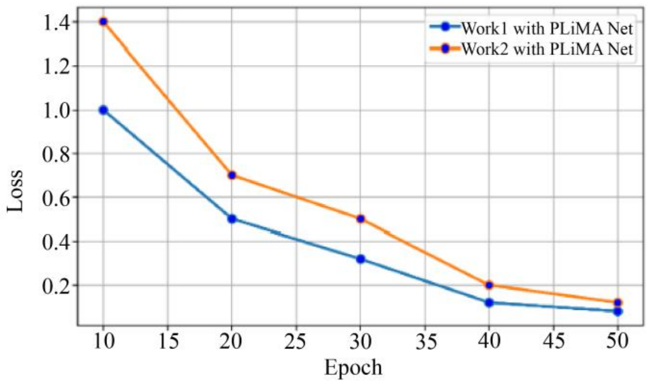

Fig. 11 Loss of the proposed PLiMA Net model

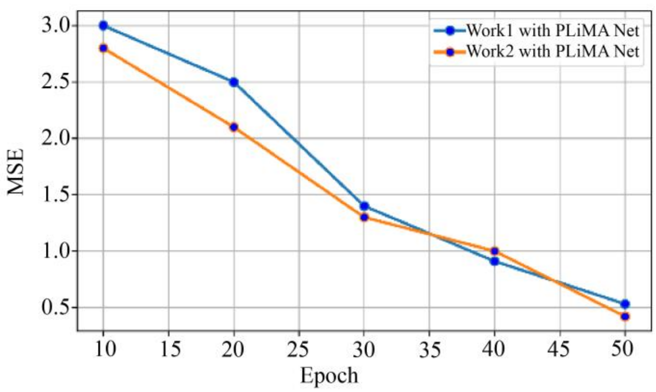

Fig. 12 MSE of the proposed PLiMA Net model

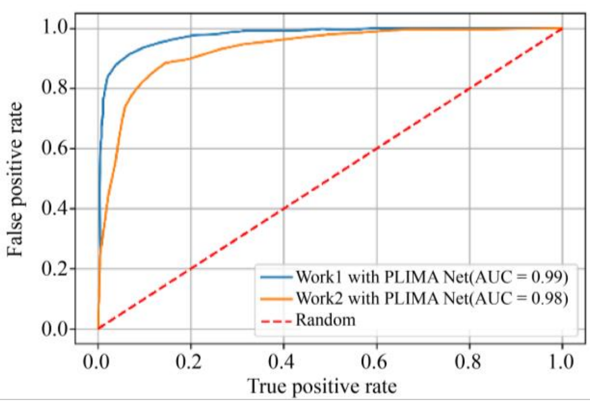

Fig. 13 Area under the ROC of the proposed PLiMA Net model

The losses of the proposed PLiMA Net models integrated into work 1 and work 2 are illustrated in Figure 11. The loss is found to be decreasing with an increase in epochs for both models, and it is recorded to be 0.08 for work 1 with PLiMA Net and 0.12 for work 2 with PLiMA Net. The reduction in loss indicates improved training efficiency and generalization capability of the PLiMA Net model.

The MSE of the proposed PLiMA Net with work 1 and work 2 are compared and depicted in Figure 12. This MSE continues to reduce with an increase in epochs. At 50 epochs, work 1 with PLiMA Net attains MSE 0.53 and work 2 with PLiMA Net attains 0.42.

The area under the ROC curve (AUC) reflects the model's overall ability to discriminate between fake and real news across various thresholds. Figure 13 shows the comparison of the proposed model's AUC when integrated with work 1 and work 2. From this graph, it is understood that work 1 with PLiMA Net achieves an AUC equal to 0.99 and work 2 with PLiMA Net achieves an AUC equal to 0.98.

5.3. Comparison of Performance of the Proposed PLiMA Net with Other State-of-the-Art Methods

In this section, the performance of the proposed PLiMA Net with other existing approaches [26], [27], and [28] such as ANN, CNN, DNN and LRA-DNN are compared using the performance parameters such as accuracy, precision, recall, F1 score, sensitivity, specificity and MSE. Additionally, some state-of-the-art methods [27] and [28], such as LDAVAE, MVAE and Hybrid CNN, have also been compared with the proposed PLiMA Net model.

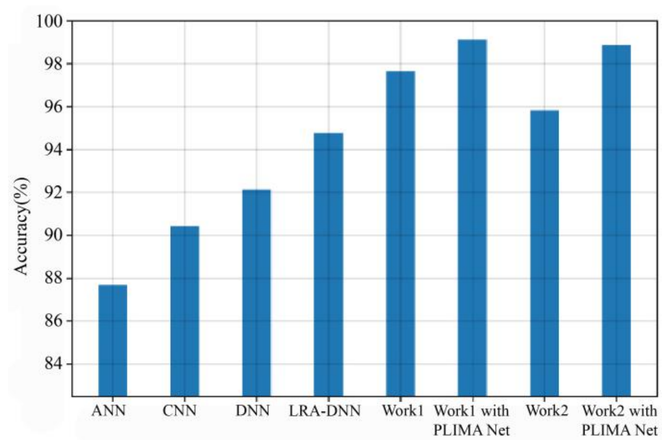

Fig. 14 Comparison of accuracy

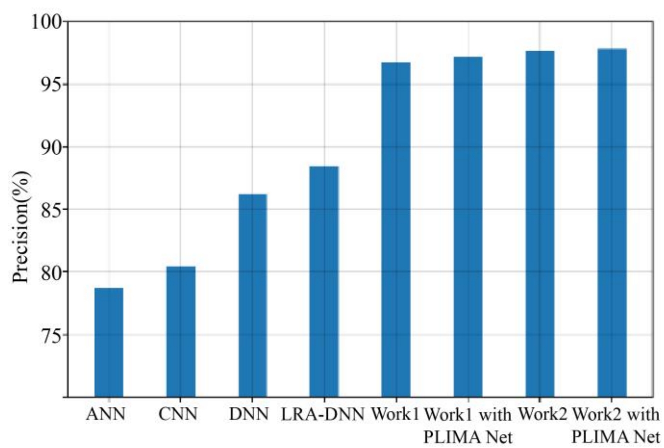

Fig. 15 Comparison of precision

The accuracy of different existing methods is compared with that of the proposed PLiMA Net integration, and it is shown in Figure 14. Compared to other methods, the proposed model achieves higher accuracy both in work 1 with PLiMA

Net case (99.13%) and work 2 with PLiMA Net case (98.87%). The integration of psycholinguistic features through LIWC and the advanced sequential modelling capabilities of RNNs, combined with the Luong attention mechanism, ensures that the PLiMA Net model captures intricate details and dependencies in the text. This comprehensive understanding enables the model to distinguish between fake and real news more accurately, leading to a significant improvement in overall accuracy.

Figure 15 depicts the comparison of the precision of the proposed model with other existing approaches. After integrating PLiMA Net, work 1 and work 2 show improvement in their precision, being 97.21 % for work 1 with PLiMA Net and 97.82% for work 2 with PLiMA Net. Compared to all other existing models, the proposed approach attains better precision. By leveraging the Luong attention mechanism, PLiMA Net focuses on the most relevant parts of the text that are rich in psycholinguistic cues. This selective attention reduces the number of false positives, as the model is better at identifying true indicators of fake news, thereby enhancing precision.

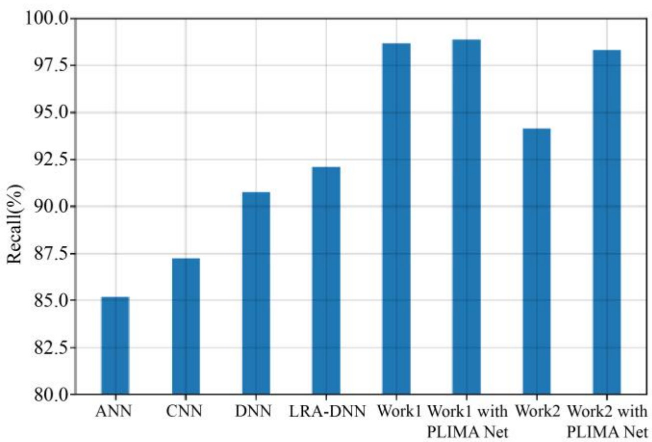

Fig. 16 Comparison of recall

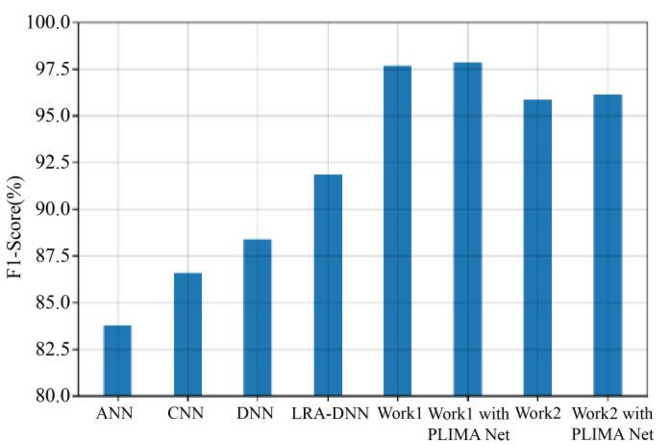

Fig. 17 Comparison of F1-score

The recall of the proposed PLiMA Net model is compared with that of other models, and the results are shown in Figure 16. The proposed method achieves higher recall when compared to other models, such that work 1 with PLiMA Net achieves 98.85 % recall, and work 2 with PLiMA Net achieves 98.31% recall. The use of RNNs to capture sequential dependencies ensures that the model retains context over long sequences, which is crucial for identifying subtle cues that indicate fake news. This thorough analysis reduces the number of false negatives, thereby improving recall.

The bar chart in Figure 17 displays the comparison of F1-Score (in percentage) for various neural network models and methodologies. The performance, measured by the F1-Score, shows a progression from 83% for ANN to over 97% for the models integrated with PLiMA Net. Notably, Work1 and Work1 with PLiMA Net achieve the highest F1-Scores, 97.86% and 97.13%, both exceeding 97%, indicating the effectiveness of the PLiMA Net integration in enhancing model performance. The PLiMA Net's ability to accurately capture and prioritize important features results in a balanced performance where both precision and recall are optimized, leading to a higher F1 score.

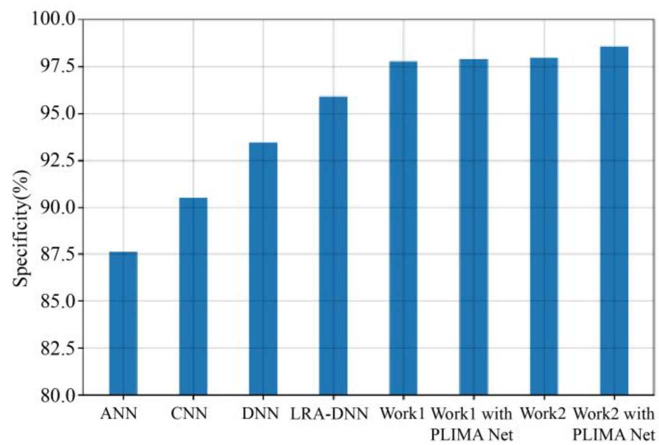

Fig. 18 Comparison of specificity

Figure 18 illustrates the specificity (in percentage) of various neural network models and methodologies. The specificity values indicate a rising trend from approximately 88% for the ANN model to over 97% for the models that incorporate the PLiMA Net. Both Work1 and Work2, when enhanced with the PLiMA Net, achieve the highest specificity scores of 97.92% and 98.58%, respectively, showcasing the significant improvement in model performance with the integration of the PLiMA Net.

The attention mechanism in PLiMA Net helps reduce false positives by ensuring that only the most relevant and indicative parts of the text influence the final decision, thereby increasing specificity.

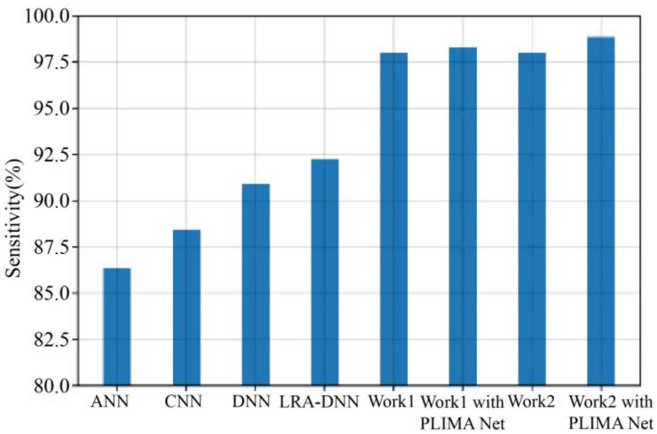

Fig. 19 Comparison of sensitivity

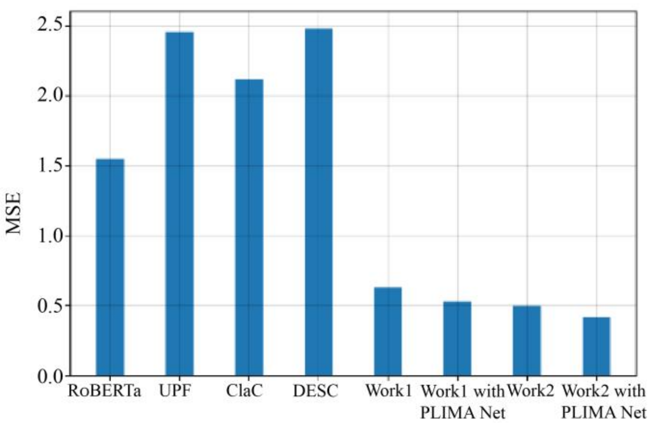

Fig. 20 Comparison of MSE

The sensitivity of the proposed PLiMA Net models with other existing models is compared in Figure 19. It is obvious from the graph that the proposed work 1 with PLiMA Net and proposed work 2 with PLiMA Net are performing with better sensitivity compared to other models, with 98.28% and 98.86%, respectively. The integration of LIWC features allows PLiMA Net to identify more instances of fake news correctly, enhancing its sensitivity.

The comparison of the MSE of the proposed PLiMA Net with other models is depicted in Figure 20. When compared to other existing models, the proposed work 1 with PLiMA Net and work 2 with PLiMA Net are found to have very low MSE values of 0.53 and 0.42, respectively. By accurately capturing and leveraging psycholinguistic and sequential features, the model converges more effectively during training, leading to lower values of MSE.

The bar graph in Figure 21 illustrates the loss values of various fake news detection models [27] and [28], including LDAVAE, MVAE, Hybrid CNN, RNN, and two proposed enhanced models incorporating the PLiMA Net architecture into previous works Work1 and Work2. It is evident from the graph that the models integrated with PLiMA Net demonstrate significantly lower loss values of 0.008 and 0.012 compared to the other models. This substantial reduction in loss is due to the enhanced capabilities of PLiMA Net, which combines psycholinguistic analysis and Luong attention mechanisms with Recurrent Neural Networks (RNNs).

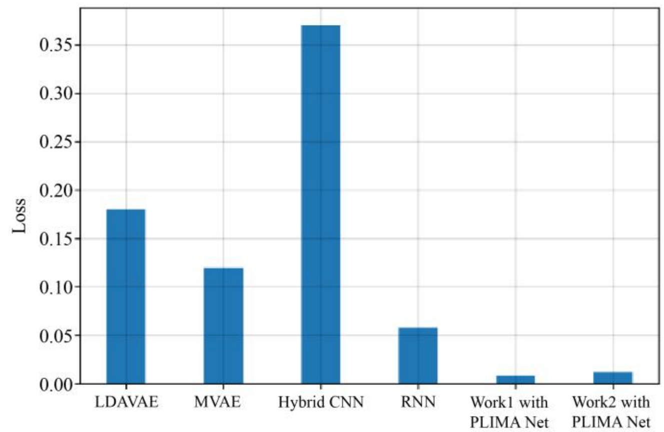

Fig. 21 Comparison of loss

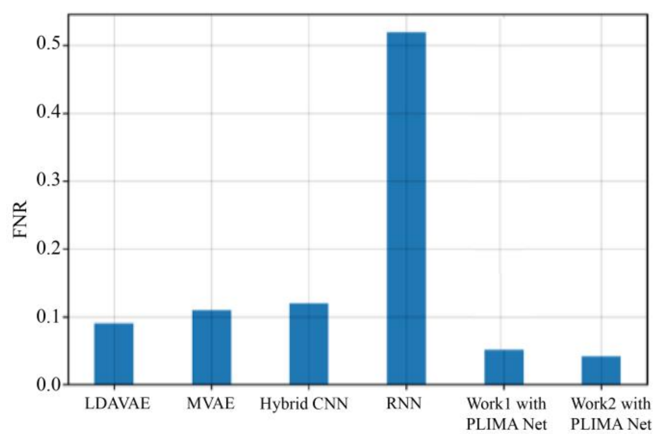

Fig. 22 Comparison of FNR

Figure 22 illustrates the False Negative Rate (FNR) of various fake news detection models, and the graph clearly shows that the models incorporating PLiMA Net exhibit significantly lower FNR values of 0.05 and 0.042 compared to the other models. This reduction in FNR is primarily due to the advanced capabilities of PLiMA Net, which combines psycholinguistic analysis with the Luong attention mechanism and RNNs. The inclusion of LIWC features enables the model to capture nuanced psychological and emotional aspects of the text, while the attention mechanism ensures that critical parts of the input receive more focus.

The bar graph in Figure 23 compares the False Positive Rate (FPR) of the existing fake news detection models. It clearly demonstrates that the models incorporating PLiMA Net achieve significantly lower FPR values compared to the other models. This reduction in FPR can be attributed to the sophisticated integration of psycholinguistic analysis and Luong attention mechanisms within PLiMA Net, which enhances the model's ability to discern indirect psychological and emotional cues embedded in the text.

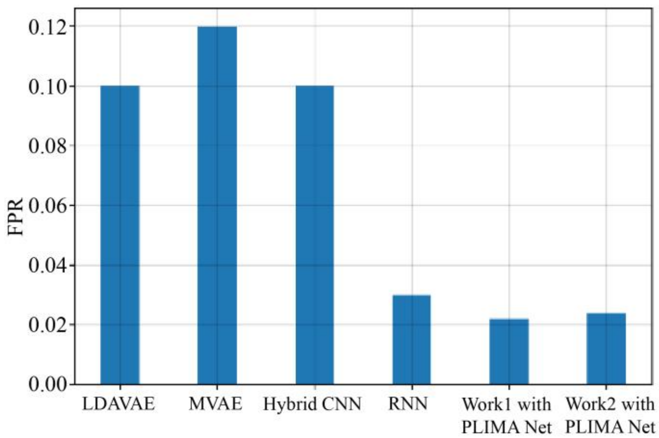

Fig. 23 Comparison of FPR

Overall, the proposed PLiMA Net model significantly outperforms existing neural network methodologies in various performance metrics, including accuracy, precision, recall, F1-Score, specificity, sensitivity, and Mean Squared Error (MSE). By integrating psycholinguistic features through LIWC and employing advanced sequential modeling with RNNs and the Luong attention mechanism, the PLiMA Net captures intricate details and dependencies in the text. This comprehensive approach enables superior detection of fake news, with Work1 and Work2 models incorporating PLiMA Net achieving the highest scores across all metrics, such as 99.13% accuracy, 97.82% precision, 98.85% recall, 97.86% F1-Score, 98.58% specificity, 98.86% sensitivity, and the lowest MSE values of 0.53 and 0.42. This demonstrates the model's ability to accurately capture and prioritize relevant features, resulting in a balanced and enhanced performance.

6. Conclusion

In conclusion, the PLiMA Net model represents a significant breakthrough in the domain of fake news detection, showcasing substantial improvements over existing neural network methodologies. By proficiently integrating psycholinguistic features extracted through the LIWC framework with advanced sequential modeling techniques, including RNNs and the Luong attention mechanism, PLiMA Net is able to capture and interpret intricate details and dependencies within textual data with remarkable precision. This holistic and sophisticated approach enables the model to excel across a comprehensive set of performance metrics. Empirical evidence from the studies, particularly the exemplary performance of the Work1 and Work2 models incorporating PLiMA Net, demonstrates the model's superiority, achieving an impressive 99.13% and 98.87 % accuracy and notably low Mean Squared Error (MSE) values of 0.53 and 0.42 respectively. These results underscore PLiMA Net's ability to accurately capture and prioritize the most relevant features, leading to a balanced and enhanced performance. This robust capability not only highlights the model's proficiency in fake news detection but also sets a new standard in the field, promising far-reaching implications for natural language processing applications. The attainment of PLiMA Net in achieving such high levels of accuracy and reliability in detecting deceptive content suggests its potential for broader applications in other domains requiring sophisticated text analysis and verification, marking a significant step forward in the ongoing battle against misinformation and disinformation in the digital age.

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