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Detection of Twitter Fake News using Efficient Soft-Capsule and Improved BiGRU Architecture

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Abstract

Social media platforms, such as Twitter, are vulnerable to the spread of fake news, which can have significant consequences on people's daily lives. To combat this issue, various techniques have been developed to detect fake news, but they often have limitations, including low performance and high training times. To overcome these limitations, a new enhanced fake news detection technique is proposed, which utilizes an efficient soft-capsule and improved BiGRU model. This technique combines image and text data from the Twitter Fake News Detection (2ter-Fk-Nus) Model dataset, processing each modality separately with different pre-processing and feature extraction techniques. The extracted features are then optimized using the Binary Guided Whale–Dipper Throated Optimizer (BGW-DTO) method, and finally, the features from both text and image are fused using Cross-model Fusion (CmF) to predict whether a tweet is fake or real. The proposed model, Improved BiGRU efficient soft-capsule 2ter-Fk-Nus(IBiG-EcnTSCaps 2ter-Fk-Nusd), achieves an overall accuracy of 99.95%, outperforming other related techniques.

Keywords: Social Media, Fake News Detection, Wiener Filter, Autoencoder, WNet Process, Segmentation, BERT, BiGRU.

1. Introduction

The rapid growth of social media has transformed how information is shared. While platforms like Twitter facilitate easy news sharing, they also contribute significantly to the

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spread of fake news [1] [2]. With over 500 million users and 300 million active users generating approximately 170 million tweets daily, the potential for misinformation is high [3]. This ease of access allows for minimal scrutiny, making social media vulnerable to the intentional spread of false information for various motives [4]. Fake news poses serious risks to individuals, organizations, and governments, highlighting the need for effective strategies to identify and counter social media [5]. To address this, fact-checking organizations like Anti-Rumours Authority and Misbar have emerged, relying on experts to verify the news, though this process is often time-consuming [6] [7]. Thus, developing efficient methods for detecting and combating fake news is essential in today's digital landscape [8]. In recent years, various research has used machine learning (ML) techniques [9] such as support vector machine (SVM), logistic regression (LR), naive Bayes, random forest (RF), K-nearest Neighbour (KNN), maximum entropy, and conditional random forest (CRF) to find out fake news on Twitter [10]. While these methods produce promising results, they have disadvantages such as the need for manual labour, susceptibility to hyperparameter adjustment, and issues processing large amounts of data [22]. More accurate test models are now required to overcome this challenge.

Nowadays, the emergence of deep learning (DL) has transformed the task of detecting duplicate news on Twitter, providing a better and more effective way to identify and stop the propagation of duplicate information [11]. Unlike traditional machine learning methods that rely on manual features and are sensitive to hyperparameter tuning, DL models can learn complex patterns and features of information and easily process large files [12]. Researchers have developed a more powerful and effective method to detect fake news on Twitter by combining a convolutional neural network (CNN), long short-term neural network (LSTM), recurrent neural networks (RNN), and transformer, thus improving efficiency and reducing risk exposure [13]. As social media continues to shape public opinion, improving DL-based fake news detection can help preserve the integrity of online discourse [14].

1.1 Problem Statement and Motivation

The proliferation of duplicate news on social media platforms has become a major problem in recent years. The spread of false information can lead to serious consequences such as undermining domestic trust, manipulating public opinion, and even posing a national threat. Despite the importance of this problem, detecting fake news is still a difficult task, especially in multimedia content. The motivation behind this research is to develop effective solutions to control fake news on social media platforms, focusing on Twitter. The rapid spread of false information on Twitter can have a major impact, so it is important to create a system that can detect fake news according to various criteria. The proposed method, Twitter Fake News Detection (2ter-Fk-Nusd), aims to leverage ML and language optimization techniques to combat fake news and gain more insight into the online environment. This research leads to the following results for fake news detection:

- To identify tweets fake news, the novel enhanced multi-model fake news detection on Twitter using efficient soft-capsule and improved Bi-GRU architecture is introduced.
- **Image Processing**

  (i) To remove the unwanted noise and improve the image quality using a Probabilistic fused Wiener filter (Pb-FusWF).

  (ii) To extract image features using Deep Autoencoder (DAE).
- **Text Processing**

  (i) To pre-process the data gathered from the dataset, Stop Word Filtering (SWF), WordNet (WNet) processing, URL and hashtag removal, segmentation, and tokenization are performed to provide standardization and quality of the data, which is essential for accurate fake news detection.

  (ii) To extract the features of pre-processed data, the Robustly Optimized BERT – Whole Word Masking (ROBERT-WWM) model provides word embeddings with semantic information, which enhances detection accuracy.

  - **Feature Selection:** To select optimal features using the Binary Guided Whale-Dipper Throated Optimizer (BGW-DTO) algorithm.
  - **Feature Fusion and Prediction:** The feature from both text and image that are combined and fed into the deep learning model called Cross-model Fusion (CmF) based Improved BiGRU efficient soft-capsule 2ter-Fk-Nus (IBiG-EcnTSCaps 2ter-Fk-Nusd) model, which is used to predict whether the twitter news is a real and fake.

The remaining content of the paper is organized in the following manner: Section 2 includes a survey of various related techniques. In Section 3, the details and process of the overall proposed method are described in Figures. The Result analysis of the proposed methodology is briefly explained with Graphs in Section 4. The overall conclusion of the paper is described in Section 5.

2. Related Works

Koru et al. [20] created a pre-trained BERT model fine-tuned with Bi-LSTM and CNN layers to effectively detect fake news tweets in Turkish, achieving 94% accuracy on the TR_FaRe_News dataset. However, this model cannot detect fake news in other languages. Nair et al. [21] proposed a knowledge-based approach combining Information Retrieval, Natural Language Processing, and Graph Theory to tackle fake news on Twitter, reaching 99% accuracy. Its limitation is it focuses solely on Twitter, lacking generalizability to other platforms. Jadhav et al. [22] developed EDLM-ODA, an optimized deep attention network for detecting duplicate news on Twitter, achieving accuracies of 99%, 99.12%, and 99.2% on three datasets (PHEME, Liar, and FakeNewsNet). However, this method consumes a lot of time.

Hashmi et al. [23] introduced a method using FastText word embeddings with various machine learning and deep learning techniques to detect media-rich duplicate news, achieving 99%, 97%, and 99% accuracy on WELFake, FakeNewsNet, and FakeNewsPrediction datasets. Its limitation is that it does not adapt well to the rapidly changing online space. Abualigah et al. [24] combined deep learning algorithms (DNN, CNN, and LSTM) with GloVe embeddings to detect duplicate news, attaining 98.974% accuracy on the Curpos dataset. However, this method suffers from high complexity. Overall, existing research, including studies [20]-[24], has shortcomings such as being language or platform-specific, slow, complex, or outdated regarding the fast-evolving nature of the internet. To address these issues, a new model, such as the 2ter-Fk-Nusd, is needed for quick detection of false news and transforming it into valuable online information.

3. Proposed Methodology

Nowadays, the timely detection of duplicate news on Twitter has become a persistent concern, given the significant reach and influence of misinformation on the platform. Despite Twitter's ongoing efforts to combat this issue, the problem remains pervasive. The sophistication of false information further complicates the investigation process. Many works have consistently shown that duplicate news outperforms real news in terms of both audience reach and dissemination speed, emphasizing the need for effective countermeasures. To address this issue, a novel enhanced multimodal fake new detection on twitter using efficient soft-capsule and improved Bi-GRU model is proposed. The proposed model demonstrates robust fake news detection capabilities, with the methodology workflow illustrated in Figure 1.

Here, initially, the proposed model incorporated two modalities: image processing and text processing. In the image processing modality, the image is first pre-processed to remove the noise and improve the image quality using Pb-FusWF, followed by the extraction of image features using DAE. In the text processing modality, the data's standardization and quality is ensured using several preprocessing steps, including SWF, WNet processing, URL and hashtag removal, segmentation, and tokenization. Then the preprocessed text was fed into a feature extraction model, the ROBERT-WWM, which is pre-trained to provide word embeddings with semantic information. After extracting image and text features, BGW-DTO is used to select the optimal features. Following that, the selected features from both modalities are then fused and fed into the CmF-based IBiG-EcnTSCaps 2ter-Fk-Nusd for prediction.

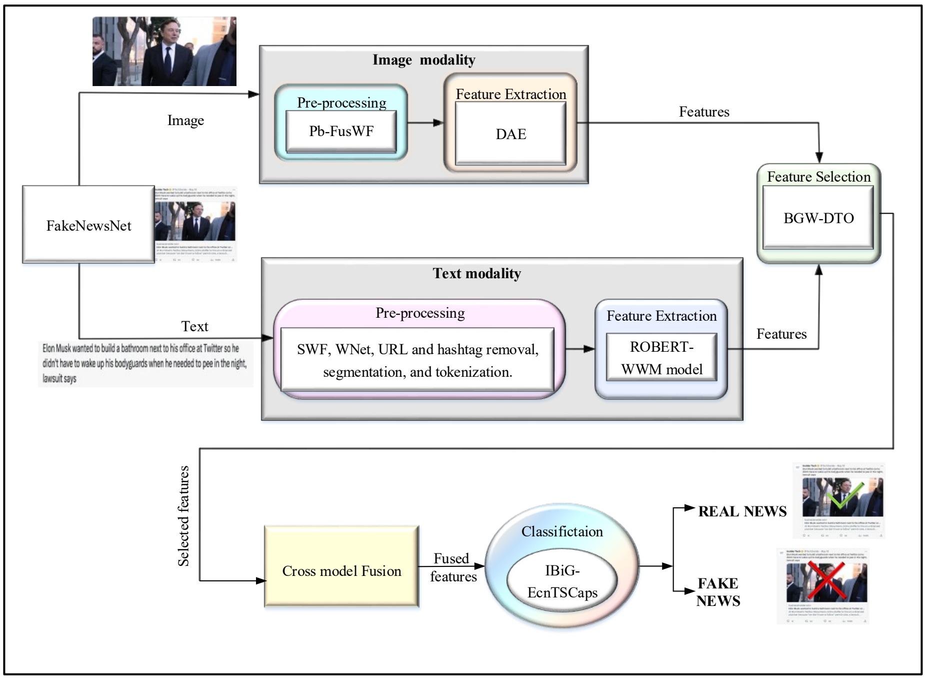

Figure 1. Workflow of Proposed Method

3.1 Image Processing Modality

In 2ter-Fk-Nusd, image processing is several steps as it helps in analysing and understanding the images. The image processing modality can be broken into several steps, including image pre-processing as well as feature extraction.

The pre-processing is carried out using the Pb-FusWF filter [25]. Finally, the filter removes the noise from the image and improves the overall quality of tweet images. Then the filter image is fed into the feature extraction model using DAE [26]. The input, output, encoder, decoder, and representation layers make up the five layers of the DAE model. Together, these layers enable the extraction of new deep features from pre-processed images.

3.2 Text Processing Modality

In the context of fake news detection text processing is one of the essential step that involves the analysis and manipulation of text. The text processing modality can be broken down into several steps, including pre-processing, and feature extraction.

In the proposed technique, the pre-processing stage is performed initially to improve the data's quality. Here, five pre-processing techniques are utilized such as SWF [27], WNet processing [28], URL and hashtag removal [29], segmentation, and tokenization [27]. By using these pre-processing techniques, the proposed technique can increase the data's quality and make it additional suitable for analysis and modelling. Then the study uses a model called the ROBERT-WWM [30] model to extract features from pre-processed data for the task of fake news detection. This information is used to extract features for detecting the fake news.

3.3 Feature Selection

The BGW-DTO is a feature selection model designed to identify the most optimal features for selection by processing the extracted image and text features. This model aims to decrease the data's dimensionality, minimize overfitting, and enhance the overall performance. Top of Form

Inspiration from Dipper-throated Bird: The BGW-DTO algorithm takes inspiration from the Dipper-throated bird [31], a unique species belonging to the Cinclidae family. This bird's distinct bobbing motion and diving style enable it to hunt underwater, making it an ideal candidate for optimization scenarios.

GW Optimization Method: The GW optimization method [32], which underlies the BGW-DTO algorithm, has shown effectiveness in various optimization scenarios. The model's capacity to explore can sometimes be limited. The algorithm explores the search spaces, represented by the number of variables or dimensionality, and evolves the agents' positions to find the best solution.

$$\begin{aligned}\vec{K}(m+1) &= \vec{K}^*(m) - \vec{S}.\vec{A} \\ \vec{A} &= \left|\vec{L}.\vec{K}^*(m) - \vec{K}(m)\right|\end{aligned} \tag{1}$$

In this context, the discovered solution at iteration m is represented by $\vec{K}(m)$. The solution optimal position is denoted as $\vec{K}^*(m)$. The new position of the agents is represented by $\vec{K}(m+1)$. The vector $\vec{S}$ and $\vec{A}$ are computed as follows: $\vec{S} = 2\vec{s}.t_1 - \vec{s}$ and $\vec{L} = 2t_2$, Where $\vec{s}$ is a vector with values that linearly transition from 2 to 0. t_1, t_2 comprising randomly generated values ranging between 0 and 1.

Continuous to Binary Solution Conversion: The BGW-DTO algorithm employs a continuous optimizer output, which is subsequently transformed into a binary solution that indicates feature selection with the integers 0 and 1. The effectiveness of the optimizer's output is evaluated using fitness functions that account for the feature selected from the input data as well as the classification and regression error. The quality of the mentioned attributes is assessed using the following equation:

$$G_n = \alpha\, Err(O) + \beta \frac{|p|}{|q|} \tag{2}$$

In this equation, α is a value between 0 and 1, β is determined as $\beta = 1 - \alpha$, $|p|$ is denoted as the amount of selected features, and $|q|$ indicates the total amount of features on the dataset, and $Err(O)$ signifies the mistake of the optimizer(O).

BGW-DTO Algorithm for Feature Selection: The sigmoid function is used in this approach to transform the obtained solution into a binary solution. KNN is used to analyse the excellence of the chosen features that have been optimized for particular applications, such as the twitter fake news detection model.

$$\vec{K}^{(m+1)} = \begin{cases} 0 & f\ Sigmoid(K_{best}) < 0.5 \\ 1 & Otherwise \end{cases}$$

$$Sigmoid(K_{best}) = \frac{1}{1 + z^{-10(K_{best} - 0.5)}} \tag{3}$$

Finally, the BGW-DTO algorithm effectively identifies the optimal features of fake news in text and images.

3.4 Fusion Model using Cross-Model

The fusion modules combine information and insights from multiple modalities, including image, and text, to offer a thorough comprehension of detecting fake news on Twitter. The outputs of several 2ter-Fk-Nusd models applied to various modalities are integrated into this module, which then uses fusion techniques to efficiently gather and evaluate the resulting data.

To enhance learning outcomes, cross-modal fusion in deep learning is a developing field that deals with combining data from several data modalities (such as audio, and video). Figure 2 indicates the architecture of cross-modal fusion.

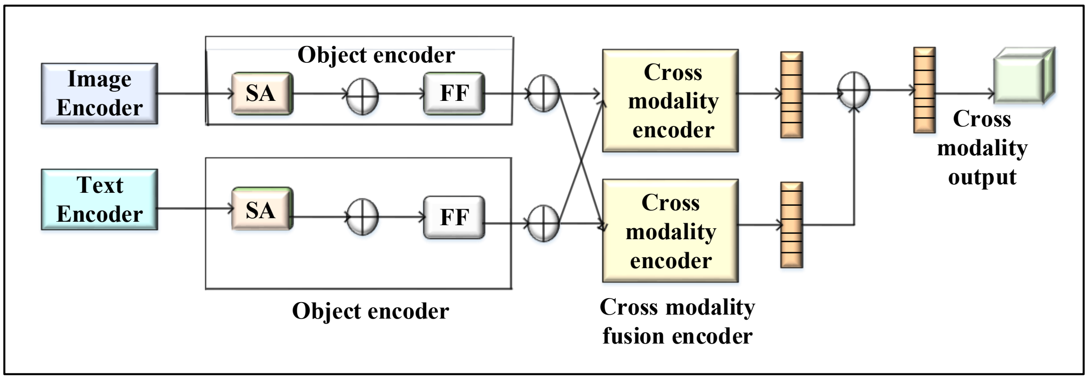

Figure 2. Architecture of Cross-Modal Fusion

The detailed cross-model fusion is utilized in [33].

3.5 IBiG-EcnTSCaps 2ter-Fk-Nusd model

The fused features are fed into IBiG-EcnTSCaps 2ter-Fk-Nusd model, though the model accurately identifies Twitter fake news. This model integrates various components including Bi-GRU, EfficientNet B3, CapsNet, and soft capsule layer. Figure 3 in the research paper provides a visual representation of the IBiG-EcnTSCaps 2ter-Fk-Nusd model and its architecture.

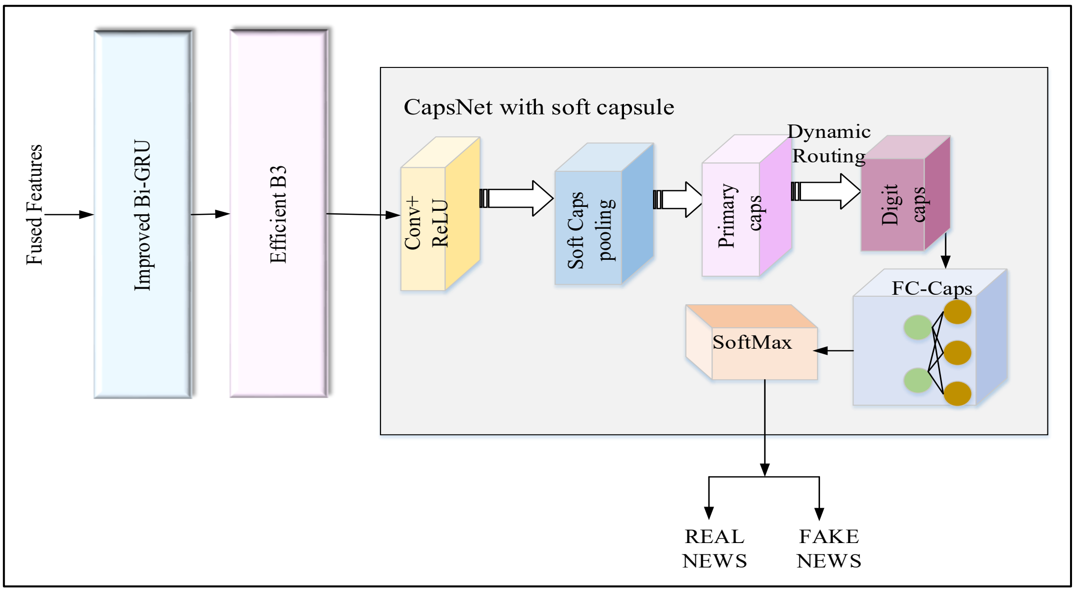

Figure 3. Structure of IBiG-EcnTSCaps 2ter-Fk-Nusd Model

Initially, the IBiG-EcnTSCaps 2ter-Fk-Nusd model has a BiGRU [34] layer, which is a form of RNN that can detect physical patterns. Using BiGRU, the model can examine the physical relationship between different sleep stages to better understand their gradual changes, leading to better predictions. The BiGRU model is defined by the following equation:

Given an input A_i and the previous state R_{i-1} at position i, R_i can be computed as follows.

$$c_i = \sigma(Y_o A_i + U_o R_i - 1) \tag{4}$$

$$U_i = \sigma(Y_u A_i + U_u R_{i-1}) \tag{5}$$

$$\bar{R}_i = \tanh(Y_t A_i + U(o_i \oplus R_i - 1)) \tag{6}$$

$$R_i = (1 - U_i) \oplus R_{i-1} + U_i \oplus \bar{R}_i \tag{7}$$

Here, R_i, o_i and $U_i \in R^t$ are t-dimensional hidden state, reset gate, and update gate, respectively; $Y_o, Y_u, Y_t \in R^{de*d}$ and $U_o, U_u, U \in R^{d\times d}$ are the parameters of the GRU; σ is the sigmoid function, and $\oplus$ indicates element-wise production. For the i^{th} word in sequence, in these hidden states $\vec{R}_i$ and $\bar{R}_i$, which are encoded through the forward GRU, to represent the preceding and following context of A_i, respectively. The concatenation $R_i = [\vec{R}_i ; \bar{R}_i]$ is the output of the Bi-GRU layer at i. Finally, the BiGRU model provides an output sequence of vectors that represent the input text and image.

BiGRU output sequence vectors are included in the EfficientNet B3 [35] model. EfficientNet B3 is a member of the EfficientNet family, which comprises B0 through B7 and is widely regarded as one of the most efficient ImageNet-based deep learning systems. EfficientNet is a CNN design that measures all dimensions with integrated coefficients (depth, breadth, and resolution). Scaling techniques use scaling techniques to balance width, depth, and resolution; this is not a practice of scaling different dimensions. CNN uses connections to build maps and kernels as filters to extract features from the data. The EfficientNetB3 architecture consists of a convolutional layer of large kernels (3 × 3) with batch normalization and Swish activation, based on 26 MB convolutional blocks. The sizes of these blocks are different (3×3) and (5×5) respectively. The last MB convolution block is based on the convolution process. Global mean pooling is used at the end of the convolution layer to make feature maps less dimensional.

The resulting feature map is then fed into the CapsNet [36] model. The capsule network (CapsNet) was created to address the spatial context problems inherent in CNNs. CapsNet can learn both the classification of features and the distances between identified features by "encapsulating" the spatial information between variables using vectors. In the CapsNet design, the original capsule and the capsule classification model are closely related. However, this may lead to duplicates and reduced representation opportunities. To solve this problem, a new method called Caps-Soft pooling is developed. Using this method, it is necessary to build a key capsule machine that can reduce all capsules in the network and improve the power representation in detecting fake news. CapsNet and Caps-Soft pooling techniques will improve the overall accuracy and performance of proposed.

The Soft Pool method offers a balanced approach by employing softmax weighting, to sum up each part of a region. In traditional CapsNet, the typical pooling technique functions element-wise in every area, which can disrupt capsule direction and create learning difficulties. This can result in unwanted changes to the characteristics of the entity represented by the capsule. To overcome this limitation, this study proposes the Caps-SoftPool method, designed to be used between primary capsules. Caps-SoftPool employs a softmax weighting approach, which effectively preserves the essential characteristics of the capsule layers while amplifying primary capsules with higher intensity. The capsule response A_i, also referred to as the activation energy value of the capsule vector, serves as an indicator of the level of capsule activation.

$$A_i = \sqrt{\sum_u (\upsilon_{iu})^2} \tag{8}$$

Here, υ_{iu} denotes the element values of a capsule vector in the same pixel position in the capsule deck.

The natural exponent (n) is used to ensure that the energy value of activation has a greater impact on the output, with higher values exerting more influence. The caps-soft pool operation employs a smooth maximum approximation of the primary capsule, where all primary capsules within a pooling kernel neighborhood L in a capsule deck are assigned a unique proportional coefficient, calculated as:

$$\omega_u = \frac{n^{V_{iu}}}{\sum_{d \in O} n^{V_{iu}}} \tag{9}$$

Here, u is the u^{th} primary capsule with a kernel region, O is the weight that denotes the n capsule's ratio to the amount of n of all primary capsules. The non-linear transforms in capsule networks suggest that larger activation values are more beneficial than smaller ones. This is because each element of a primary capsule shares the same weight, and the output of the caps-soft pool is a capsule vector. Furthermore, each element of a capsule vector is calculated as:

$$\upsilon_u = \sum_{r \in n} \omega_r * \upsilon_{uiu} \tag{10}$$

In Caps-SoftPool, each parent capsule acts as a point and is normalized by softmax. The resulting distribution depends on the value of each master capsule compared to adjacent master capsules in the docking area. This is important to create more impact, thus improving knowledge of the job. Additionally, Caps-SoftPool develops a powerful and focused encoding class. Adding Caps-SoftPool before FC Caps layer can reduce network inconsistencies since

FC CapsL usually takes up too much space. In a capsule network, each FC Caps layer represents a specific category or class. The length of the capsule vector, typically a 16-dimensional vector, encodes the probability of the input vector belonging to that particular category. The dynamic routing algorithm plays a crucial role in this layer, as it enables the capsules to communicate with each other and determine the strength of the connections between them. Finally, the softmax layer effectively detects Twitter fake news.

4. Result & Discussion

This section presents a comprehensive experimental analysis of both proposed and existing models, evaluating their performance on the FakeNewsNet dataset for 2ter-Fk-Nusd. The performance of each model is assessed using a range of metrics, including F1-Score, Root Mean Squared Error (RMSE), accuracy, Mean Squared Error (MSE), precision, Mean Absolute Error (MAE), recall, kappa, math coefficient correlation (MCC). The proposed model's accuracy is then compared to that of established models, including improved Bi-GRU, Efficient Net B3, ResNet 121, CapsNet, and Efficient CapsNet. This section provides a thorough comparison of the performance metrics across various models, offering valuable insights into their advantages and disadvantages. Table 1 offers the hyperparameter values used in the experiments.

Table 1. Analysis of Proposed Model Hyperparameter Value

Parameter	Value	Parameter	Value
Activation	“softmax”	Learning rate	0.0002
Optimizer	“Adam”	Batch size	64
Loss	“MSE, RMSE, MAE”	Dropout	0.5

4.1 Dataset Description

In this study used the FakeNewsNet dataset downloaded link from https://www.kaggle.com/datasets/mdepak/fakenewsnet?select=PolitiFact_fake_news_content .csv. Specifically, the PolitiFact_fake_news_content.csv file is utilized, which contains news articles from PolitiFact, a reputable fact-checking organization. Each article is labeled as either "fake" or "real", allowing for the creation and assessment of models for detecting false news.

4.2 Performance Metrics

The suggested model's efficacy is evaluated using several performance metrics. These metrics and their calculations are detailed in below Table 2.

Table 2. Performance Metrics

$Accuracy = \frac{tp+tn}{tp+tn+fp+fn}$	$\Pr ecision = \frac{tp}{tp+fp}$	$Kappa = 1 - \frac{1-P_o}{1-P_e}$
$F\,meacure = \frac{2 * \Pr ecision * \operatorname{Re} call}{\Pr ecision + \operatorname{Re} call}$	$\operatorname{Re} call = \frac{T_P}{T_P + F_N}$	$MAE = \frac{\sum_{i=1}^{n} \lvert y_i - \hat{y}_i}{n}$
$RMSE = \sqrt{\frac{\sum_{i=1}^{n} (y_i - \hat{y}_i)^2}{n}}$	$RMSE = \sqrt{\frac{\sum_{i=1}^{n} (y_i - \hat{y}_i)^2}{n}}$	

Here, tp and tn is represented as the true positives and negatives, fn and fp is denoted as the false negatives and positives, $\hat{y}_i$ -true value, y_i-prediction, n-total amount of data points, and P_o- predict value.

4.3 Performance Evaluation of 2ter-Fk-Nusd

This study evaluated the proposed strategy using the FakeNewsNet dataset and compared its performance to existing classifier models. The outcomes of this comparison are presented in the following section. The introduction of the IBiG-EcnTSCaps 2ter-Fk-Nusd model led to a significant improvement in the classification stage, resulting in more accurate classification of duplicate news or original news on twitter. The performance of the IBiG-EcnTSCaps 2ter-Fk-Nusd model and existing models on the FakeNewsNet dataset is visually compared in Figures 4 (a) and 4(b), demonstrating the enhanced accuracy of the IBiG-EcnTSCaps 2ter-Fk-Nusd model.

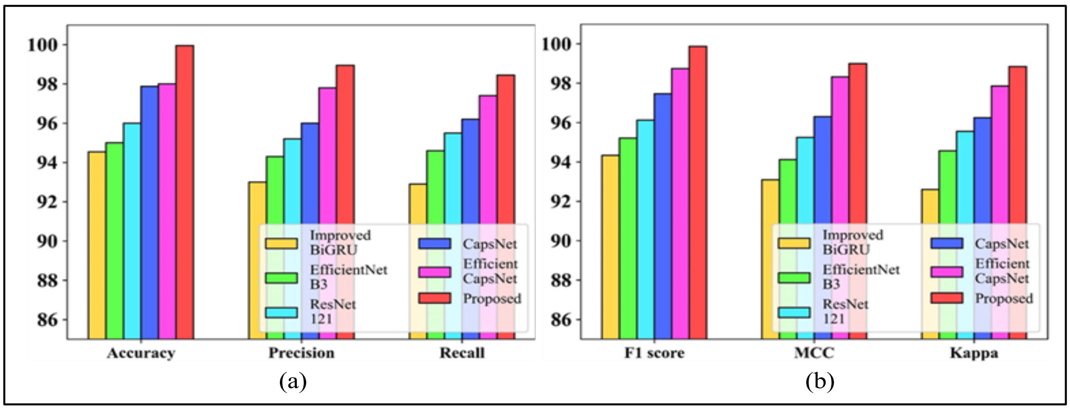

Figure 4 (a) and 4 (b). Analysis of the IBiG-EcnTSCaps 2ter-Fk-Nusd Model and other Model Performance

The performance of the IBiG-EcnTSCaps 2ter-Fk-Nusd model is compared to other classification models in Figures 4(a) and 4(b), which illustrate the accuracy, precision, F1-score, recall, MCC, and kappa of each model. With an overall accuracy of 99.95%, precision of 98.95%, recall of 98.45%, F1-score of 98.87%, MCC of 98.99%, and kappa of 98.85%, the result demonstrates that the IBiG-EcnTSCaps 2ter-Fk-Nusd model performs significantly better than the other models. The existing models struggled with limitations such as high computational times, low recall values, and reduced accuracy in identifying Twitter fake news, resulting in poor performance. However, the proposed classification strategy effectively addresses these limitations, leading to a more accurate and precise classification of real and fake news, surpassing previous methodologies. The confusion matrix for the IBiG-EcnTSCaps 2ter-Fk-Nusd model is shown in Figure 5.

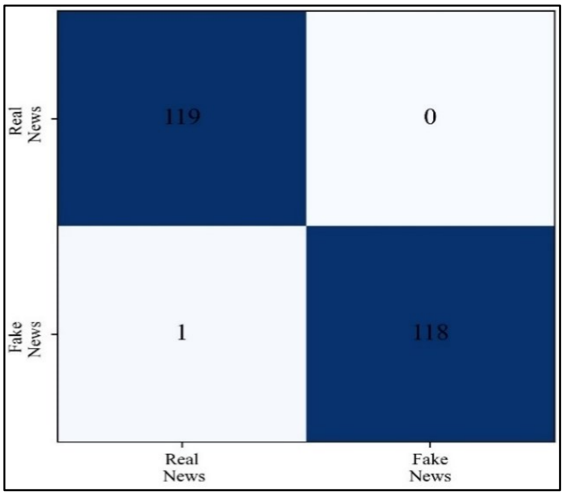

Figure 5. Analysis of IBiG-EcnTSCaps 2ter-Fk-Nusd Model Confusion Matrix

Figure 5 illustrates the evaluation of the confusion matrix for various classes present in the FakeNewsNet dataset, including real news and fake news classes. The IBiG-EcnTSCaps 2ter-Fk-Nusd model demonstrates a greater level of accuracy in predictions associated with other existing models. By predicting the classes represented as numbers based on FakeNewsNet the proposed model can achieve a more efficient Twitter fake news detection. Figure 6 compares the error performance of the suggested and current models.

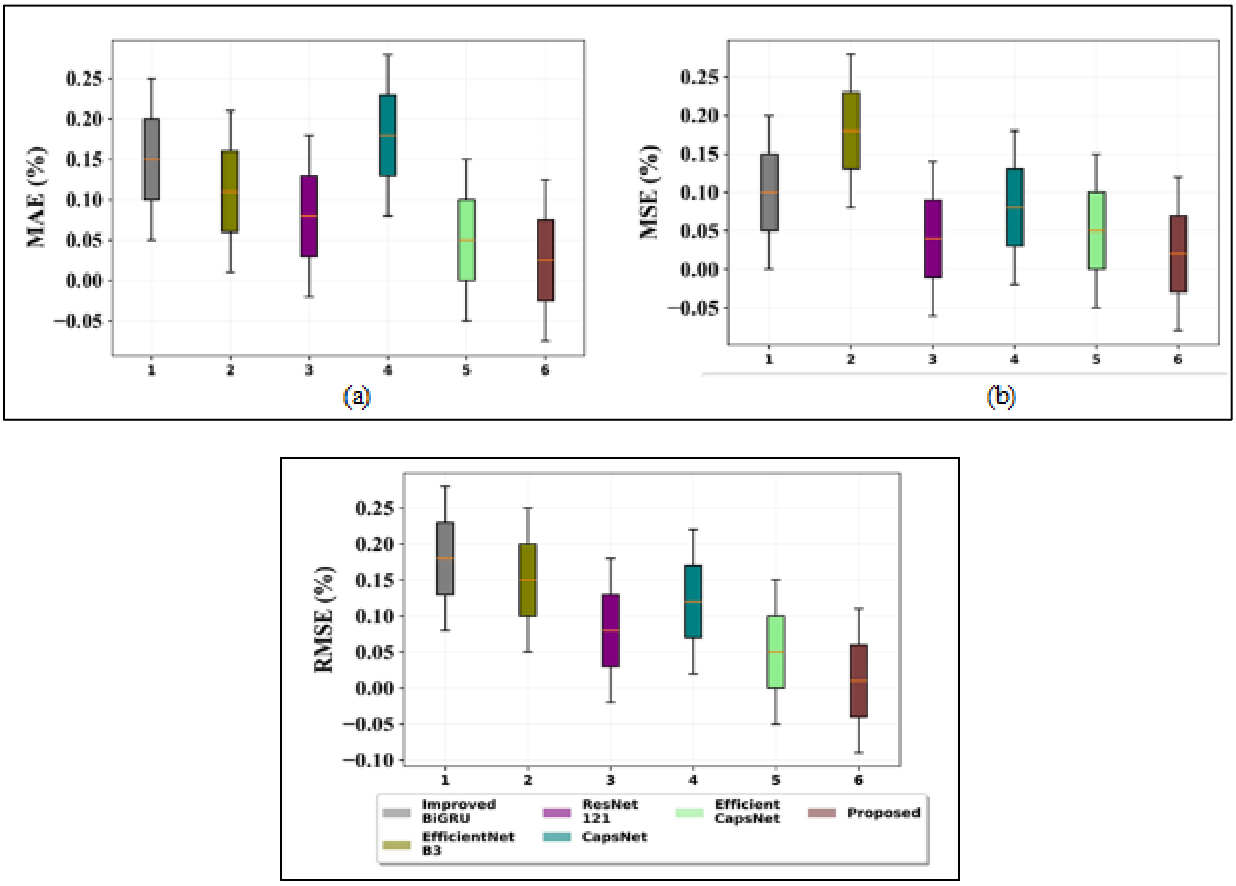

Figure 6. Analysis of Error Performance

In Figure 6, the proposed model can be analysed through three error matrices: RMSE, MSE, and MAE, with values of 0.01, 0.02, and 0.0025, respectively. The measurements demonstrate that the proposed model surpassed existing strategies in terms of performance, as the existing methods achieved greater error values. Hence, the proposed approach demonstrates a reduction in error rates when compared to current models, resulting in improved error performance. Figures 7(a) and 7(b) show the training and testing of the accuracy and loss curve for the suggested technique.

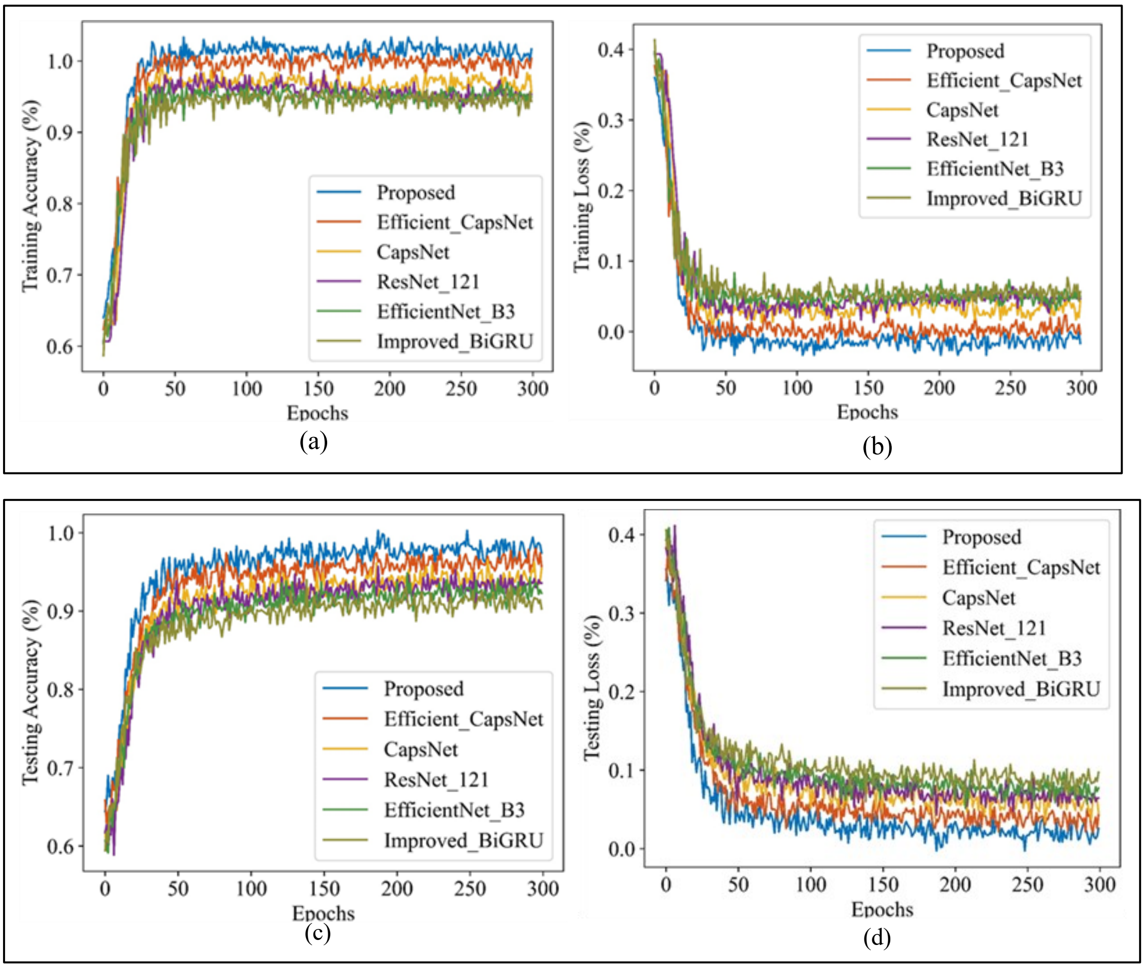

Figure 7 (a) and 7 (b). Analysis during Training and Testing [Accuracy and Loss]

Figure 7 (a) associates the test and train accuracy of existing and proposed models, each trained for 300 epochs. The proposed model achieves higher accuracy with train and test values of 0.92 and 0.9672, due to extensive training iterations. Figure 7 (b) demonstrates the train and testing loss for the same models. The proposed model attains lower loss values of 0.89 (training) and 0.156 (testing), indicating better generalization and learning efficiency. These results demonstrate the proposed model's superior performance over existing models. Table 3 presents an overall comparison of the proposed model (IBiG-EcnTSCaps 2ter-Fk-Nusd)and existing model performance.

Table 3. Overall Performance in the IBiG-EcnTSCaps 2ter-Fk-Nusd Model and other Model

Performance (%)	Improved_ Bi-GRU	EfficientNet-B3	ResNet-121	CapsNet	Efficient_ CapsNet	Proposed
Accuracy	94.54	95	96	97.87	98	99.95
Precision	93	94.3	95.2	96	97.8	98.95
Recall	92.9	94.6	95.5	96.2	97.4	98.45
F1-Score	94.34	95.21	96.12	97.47	98.74	99.87
MCC	93.1	94.12	95.25	96.3	98.32	98.99
Kappa	92.6	93.74	95.5	96.74	97.2	98.85
MAE	0.15	0.11	0.08	0.18	0.05	0.025
MSE	0.1	0.18	0.04	0.08	0.05	0.02
RMSE	0.18	0.15	0.08	0.12	0.05	0.01

5. Conclusion

The text and image datasets for the Twitter false news detection algorithm were initially used to collect the text and image data. DAE is used for feature extraction, and Pb-FusWF is used to reduce noise in photos. The text is then preprocessed using techniques including segmentation, tokenization, URL and hashtag removal, WNet processing, and SWF to improve the data's quality. The features were extracted using the ROBERT-WWM model. After that, BGW-DTO was applied to identify the best features. Finally, the CmF-based IBiG-EcnTSCaps 2ter-Fk-Nusd model fuses all of the features from the text and image to predict whether the data is real or fake. The accuracy of the IBiG-EcnTSCaps 2ter-Fk-Nusd technique is obtained to be 99.95% which is higher than other related techniques. The proposed technique achieves 98.95% precision, 98.45% recall, 99.87% F1-score, 98.99% MCC and 98.85% Kappa score. The error metrics such as MAE, MSE, and RMSE of the IBiG-EcnTSCaps 2ter-Fk-Nusd technique are obtained to be 0.025, 0.02 and 0.01 which lower than the existing models. In Future, the proposed technique will analyze the fake news detection for image, text and audio.

Efficient DL-based technique will be explored to attain efficient fake news detection. Hybrid dataset of image text and audio will be utilized to perform the fake news detection.

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