SSRG International Journal of Electronics and Communication Engineering
ISSN: 2348-8549/ https://doi.org/10.14445/23488549/IJECE-V12I6P112
Volume 12 Issue 6, 147-157, June 2025

Original Article

Intelligent Fake News Detection Model: An Attention-Driven Deep Learning with Improved Chimp Optimization Using YouTube Comments

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Received: 06 April 2025 Revised: 08 May 2025 Accepted: 09 June 2025 Published: 27 June 2025

Abstract *- In recent years, much information has been exchanged over the Internet, especially on social media platforms, which is developing rapidly. YouTube is the foremost social media network on which to share videos and comments. Lately, the rapid expansion of online platforms has resulted in a substantial increase in false information. Fake news has become pervasive, frustrating, and distracting across various sites. It has excellent effects on either society or individuals. However, developing an effective recognition method is crucial to categorize fake news, as it has become a crucial issue threatening the reliability of social networks. Consequently, Machine Learning (ML) and Deep Learning (DL) techniques have more precisely progressed in perceiving fake news. This study proposes an Attention-Driven Fake News Detection with Improved Chimp Optimization using YouTube Comments (ADFND-ICOYC) model. Initially, the text pre-processing stage cleans and transforms raw text into a structured format. Furthermore, the word2vec method is utilized for extraction. Moreover, the proposed ADFND-ICOYC model employs The Bidirectional Long Short-Term Memory and Attention Mechanism (BiLSTM-AM) method for classification. Finally, the Improved Chimp Optimization Algorithm (ICOA) optimally alters the hyperparameter value of the BiLSTM-AM method and results in higher classification performance. The efficacy of the ADFND-ICOYC method is examined under the Fake News Detection dataset. The performance analysis of the ADFND-ICOYC method demonstrated a superior accuracy value of 96.88% over existing models.*

Keywords *- Fake News Detection Improved Chimp Optimization Algorithm, YouTube comments, Text pre-processing, Feature extraction.*

1. Introduction

The digital transformation era has revolutionized daily human activities through digitalization. Individuals conventionally utilized Radio, news articles, or TV channels by the government sector [1]. Consequently, conventional multimedia channels are considered a more reliable resource of information. Therefore, in the initial stage of attention, to the start of the nineties, lesser concern was provided to online news articles. Owing to the internet speed, advancements, technology, and various newswires determined from social media accounts and websites [2].

A significant consideration is specified to online news articles in this period, while media platforms like YouTube are highly utilized [3]. The increasing popularity of YouTube and combined economic opportunities for content providers have triggered the promotion and creation of spam campaigns and fake videos on this platform. Unfortunately, multiple individuals use media platforms to broadcast rumours and fake news [4]. The global distribution of fake news can negatively affect society and individuals [5]. Propagandists generally utilize fake news to transfer political influence or messages. Fake news is deliberated an attack originating while utilizing media platforms [6].

It can cause danger and damage to several organizations and individuals. As a result, helping to reduce the harmful effects of fake news, whether for the public benefit or the news ecosystem. Developing effectual models to detect fake news on platforms like YouTube automatically is crucial [7]. Fake news recognition in media platforms is a broadly examined topic in the academic community. A huge number of real-world information is generated, shared, and commented on through online social media day by day, making online real-world fake news recognition more complex.

Nevertheless, multiple models are accepted to address this concern [8]. Several ML approaches are utilized to identify fake information spreading online regarding knowledge verification, Sentiment Analysis (SA), and Natural Language Processing (NLP) [9]. The earlier study used textual details from the article's content, like emotional data and arithmetic textual features. DL has become a developing technology in the investigation communities and has been verified to be more impactful in identifying fake news than conventional ML approaches [10]. The swift growth of online platforms has made social media a primary data source, enhancing the risk of spreading misinformation. Detecting fake news, particularly in user-generated content like YouTube comments, is crucial to ensure data credibility and protect public trust.

This study proposes an Attention-Driven Fake News Detection with Improved Chimp Optimization using YouTube Comments (ADFND-ICOYC) model. Initially, the text pre-processing stage cleans and transforms raw text into a structured format. Furthermore, the word2vec method is utilized for extraction. Moreover, the proposed ADFND-ICOYC model employs the Bidirectional Long Short-Term Memory and Attention Mechanism (BiLSTM-AM) method for classification. Finally, the improved Chimp Optimization Algorithm (ICOA) optimally alters the hyperparameter value of the BiLSTM-AM method and results in higher classification performance. The efficacy of the ADFND-ICOYC method is examined under the Fake News Detection dataset. The key contribution of the ADFND-ICOYC method is listed below.

- The ADFND-ICOYC model performs pre-processing to filter noise and inappropriate content and standardizes input data. This structured transformation enables a more accurate analysis of unstructured YouTube comments. It improves downstream tasks by preparing high-quality input.
- The ADFND-ICOYC method utilizes Word2Vec to extract meaningful semantic features from YouTube comments, capturing contextual word relationships. This improves the quality of textual representations.
- The ADFND-ICOYC approach employs the BiLSTM technique integrated with an AM model to capture sequential dependencies in text while emphasizing crucial segments. This improves the model's capability to comprehend context and improves classification accuracy.
- The ADFND-ICOYC methodology incorporates the ICOA model to fine-tune hyperparameters efficiently. This results in faster convergence and enhanced performance in detection tasks.
- The novel aspect of the ADFND-ICOYC model is its integration of BiLSTM with AM and the ICOA model within a unified framework. This integration allows for deep contextual analysis of YouTube comments while optimizing learning parameters efficiently. As a result, the model attains superior accuracy in fake news detection related to conventional approaches.

2. Related Works

Yan et al. [11] developed the Targeted Pareto (TPareto) optimizer model. This technique also employs the data attained from intermediate fusion to impact the overall process positively. Zeng et al. [12] projected a Multimodal Multi-View Debasing (MMVD) structure that creates the 1st attempt to reduce several multimodal biases for fake news video recognition. Stimulated by people's misleading situations by multimodal short videos, this method summarizes three cognitive biases: dynamic, social, and static biases. MMVD put forward a multi-view causal reasoning approach to learn unbiased dependences in the cognitive biases, improving the unbiased forecast of multimodal videos. In [13], a two-fold process is utilized: initially, a significant amount of marked fake novel information for the Arabic language from various resources is intended. The corpus is gathered from multiple resources to comprise diverse cultures and dialects. Then, this method develops fake recognition by creating ML techniques as model heads over the fine-tuned LLMs. Raghavendra and Niranjanamurthy [14] tackled these complications by advancing a process for identifying fake news utilizing DL models and techniques. To establish the novelty of news, longevity, and place of generation, dual DL methods are advanced ANN and a diverse classifier model of LSTM and CNN. This helps to identify bogus news and extract it from the server. It employs these dual models to improve the recognition of false information in media platforms.

Li et al. [15] developed a Heterogeneous Multimodal Latent network inference (HML) method. A refined social latent system is used for analysing news impact across similar events, using a heterogeneous graph built on social features and a self-supervised multimodal learning approach to align and fuse diverse content types. Dahou et al. [16] aimed to highlight lower-resource languages, specifically the Algerian dialect, over a stimulated analysis with dual objectives. Primarily confirming after the automated conversion from MSA to the Algerian might be deliberated as a method to improve the source in the Algerian dialect by the growth of LLMs. Shang et al. [17] advanced MultiTec, a multimodal detector that explores the visual and audio content in short videos to inspect the sequential relation of video elements or their inter-modality dependency to identify misinformation in medical care videos on TikTok collectively. MultiTec is a modality-aware dual-attentive short video recognition method for multimodal medical care misinformation on TikTok. Muqadas et al. [18] detected clickbait in Urdu news headlines utilizing DL with sentence embeddings, comparing its performance against conventional models.

TS and Sreeja [19] proposed an adaptive adam adadelta optimizer-based Deep Bi-LSTM methodology for fake news detection, using BERT for tokenization, feature extraction and selection via Singular Value Decomposition (SVD) with joint quantum entropy and Moving Principal Component Analysis (MPCA). Dellys, Mokeddem, and Sliman [20] utilized a 3D multimodal fusion method integrating text and images, attaining superior accuracy with a Vision-and-Language Transformer model. Hashmi et al. [21] presented a hybrid CNN-LSTM technique, utilizing FastText embeddings and optimized with regularization and hyperparameter tuning. Albtoush, Gan, and Alrababa [22] reviewed fake news detection utilizing ML/DL approaches and Arabic-specific methods while detecting gaps and future directions in the field. Abd El-Mageed et al. [23] introduced a technique using a hybrid African Vultures' Optimization (AVO) and Aquila Optimization (AO) models integrated with an extreme gradient boosting tree (Xgb-Tree) method. The approach comprises automatic data pre-processing, Relief algorithm feature selection, and classification. Choudhary, Chouhan, and Rathore [24] reviewed User-Generated Content (UGC), concentrating on multimodal features like text, audio, video, and images to detect fake news, suspicious profiles, and fake reviews. Al-Adwan et al. [25] implemented a hybrid Convolutional Neural Network (CNN) and Recurrent Neural Network (RNN) with Particle Swarm Optimization (PSO) models for detecting deepfake videos.

Despite crucial improvements in fake news detection, the utilized studies have various limitations and research gaps. Several techniques majorly concentrate on specific languages, namely English or Arabic, with restricted exploration of low-resource languages or dialects. Furthermore, incorporating multimodal aspects such as text, video, and audio often lacks fusion and dependency modelling, resulting in suboptimal performance. Another research gap is in the restricted adaptation of models to real-time environments, particularly in social media platforms where news grows rapidly. Moreover, the dependence on labelled datasets for training limits the scalability and generalization of these models.

3. Proposed Methodology

This manuscript proposes the ADFND-ICOYC model. The ADFND-ICOYC method comprises distinct methods such as text pre-processing, feature extractor, BiLSTM-AM detection, and parameter selection. Figure 1 signifies the structure of the ADFND-ICOYC method.

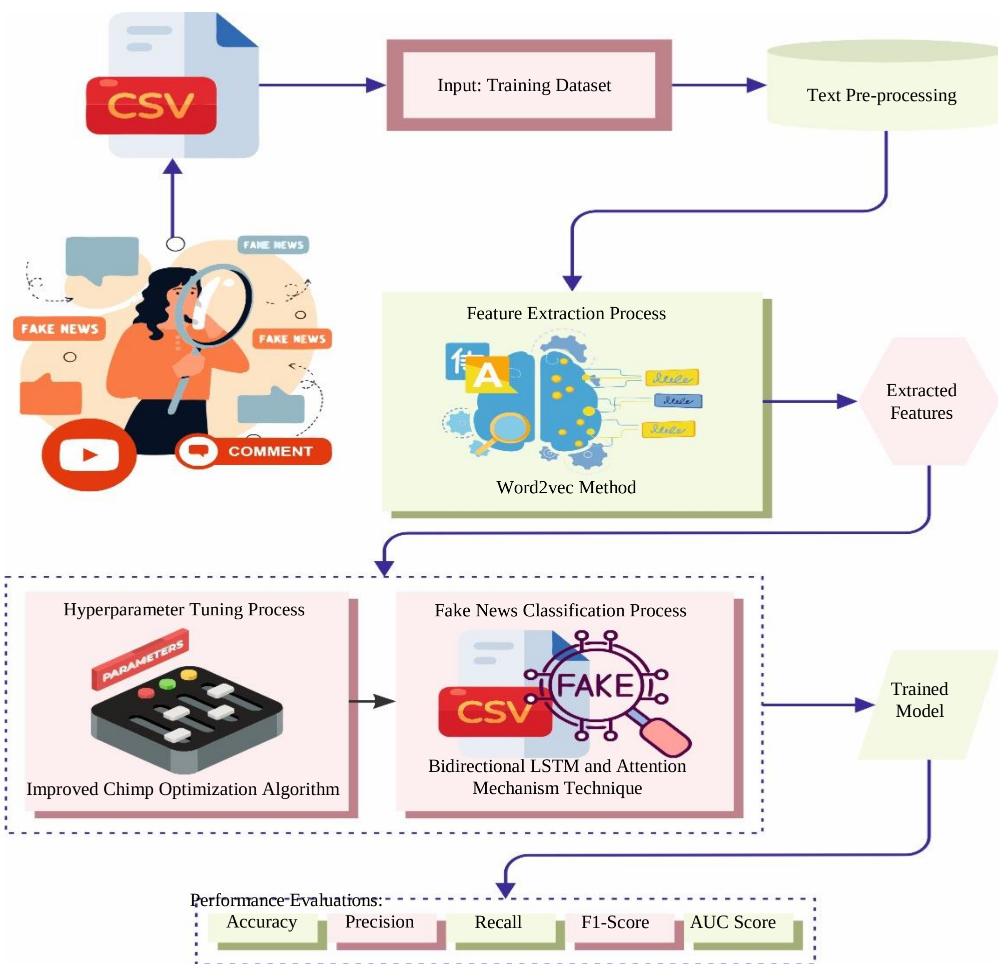

Fig. 1 Overall structure of ADFND-ICOYC method

3.1. Text Pre-Processing

Initially, the pre-processing is utilized to clean and transform raw text into a structured format. This is an essential stage in NLP to improve the quality of textual data before investigation [26]. The following pre-processing methods enhance the model's performance by decreasing noise and normalizing text representation.

3.1.1. Handle Negations

Accurately handling negations is the key challenge encountered. A hassle-free response such as "$not\ good$" is misclassified as positive and deprived of accurate negation handling. To deal with this, a rule-based method connects negation terms with the observed words, therefore converting expressions such as "$not\ happy$" into "not_happy," guaranteeing that the technique can precisely take the negative sentiment.

3.1.2. Removing Punctuation

In best NLP applications, punctuation symbols such as question marks, commas, and periods are not involved in textual meaning. Eliminating them guarantees reliability and prevents redundant tokens from prompting the method.

3.1.3. Removing Numbers

Numbers might not have substantial information in particular NLP tasks (for example, SA). Removing numeric values streamlines the text while preserving its essential meaning.

3.1.4. Handling Emoticons

Despite their applicability to sentiment and their status on online platforms, particularly social media web pages, the works on graphic emojis and their word-based precursor's emoticons-, are restricted. An emoticon, an abbreviated form of $an\ emotion\ icon$, is the incorporation of numbers, letters, and punctuation marks that characterize a facial appearance :-) For a smile or :-(For a frown, it transfers the intended tone or feelings of the writer. Recently, emojis (☺) have been combined with conventional text-based emoticons. Emojis and emoticons are vital in interconnecting emotions, which are challenging to communicate over words only, like sarcasm, which is transferred by utilizing exaggerated or ironic emoticons. Nevertheless, handling emojis is mainly challenging owing to their composite nature. Hence, precisely analyzing and identifying the sentiment of the tweet, which has emojis, needs advanced methods that can explain the complexities and nuances of these visual signs. The Western-style collection of emoticons substituted all with consistent meaning by utilizing regular expressions. For instance, :) It is substituted with the word $smiley$.

3.1.5. Removing Single Letter Words

Separated single-letter words, such as a and I, might not offer significant Value in NLP tasks. They are generally eliminated until they transfer significant meaning in particular contexts.

3.1.6. Removing Extra Blank Spaces

Numerous spaces among words or at the start/ending of sentences can make discrepancies in tokenization. Eliminating additional spaces guarantees a structured and clean text design.

3.1.7. Removing Stopwords

Removing and identifying general stopwords, namely the, is, and of, did not contribute to the sentiment. Nevertheless, particular domain-specific stopwords related to banking, like $loan$s, $branch$es, and $transaction$s, should be preserved to guarantee that the main features of customer skills were taken.

3.1.8. Lemmatization

Lemmatization involves mapping words to their root form (lemma) according to their dictionary meaning and part of speech by utilizing vocabulary and the morphologic study of words. For instance, the words $sang$ and $sung$ are lemmatized to $sing$.

3.1.9. Convert to Lower Case

Text is frequently converted to lowercase to prevent case sensitivity problems. For instance, Apple and Apple must be preserved as identical words in maximum NLP methods.

3.2. Word2vec-based Feature Extraction

Word2Vec is a neural network-based word-embedded approach mainly concentrating on removing textual features [27]. Before delving into Word2Vec, observing the significant principles of NLP is essential. During NLP, the best granularity is words that express documents, sentences, and paragraphs. It is necessary to convert words into a computer to facilitate machines in knowing human language. The transformation procedure from symbolic representation (words in different languages) to numeric method is essential. Word embedding, further named word vectors, is a method for mapping words to the vector area, possibly summarizing semantical relationships between words. Primarily, simple one-hot encoders have been applied to attain these transformations; nevertheless, they absent semantical information and lead to higher-dimensional vectors. To overwhelm these limits, the Word2Vec method provided an effective model for calculating word vectors, which reduced complexity and compressed semantical relationships between words. Word2Vec relies on the notion that words that appear in related contexts must have equal word vectors. This notion is applied in Skip-gram and Continuous Bag of Words (CBOW), which forecasts the targeted word derived from its context; however, the Skipgram method forecasts the context depending on the targeted word. This CBOW method forecasts a targeted word depending on its adjacent contextual words. The model includes three layers (hidden, output, and input) and utilizes dual methods: CBOW and skip-gram. In skip-grams, all neurons understand the context near the single targeted word, whereas CBOW forecasts the targeted word from context. The activation function is linear Equation (1), and the Hidden Layer (HL) encodes semantical associations among words Equation (2). The output layer uses softmax to transform outputs into likelihoods for precise prediction Equation (3).

$$h = W^{T}x \tag{1}$$

$$u_j = W'^{T}h \tag{2}$$

$$y = \frac{\exp(u_j)}{\Sigma_{j=1}^{V}\exp(u_j')} \tag{3}$$

The h refers to HL, and W^T denotes the transpose of the weight vector (x), whereas W' signifies the column. u_j stands for output route to the HL. The Softmax (yi) activation function utilizes the output value of u_j based on the vocabulary word counts (V).

3.3. Detection using BiLSTM-AM Model

Besides, the proposed ADFND-ICOYC model implements a BiLSTM-AM method for the fake news classification process. Bi-LSTM has dual collections of stacked LSTM units [28]. The forward LSTM studies the semantical information in regular order, and the backward LSTM handles the input vectors in reverse order. Assuming the higher input feature E_t.The forward and backward information calculation processes are exposed in Equation (4) and (5).

$$\overrightarrow{H_t^f} = LSTM\left(E_t, \overrightarrow{H_{t-1}^f}\right) \tag{4}$$

$$\overleftarrow{H_t^b} = LSTM\left(E_t, \overleftarrow{H_{t-1}^b}\right) \tag{5}$$

Whereas the subscript t signifies the time step, the arrows specify the flow of information direction. $\overrightarrow{H_t^f}$ and $\overleftarrow{H_t^b}$ are the forward and backward outputs at instant t, correspondingly, whereas their output sizes are half of the input vector. Then, the features in the dual directions are joined to get the output H_t of the Bi-LSTM layer at instant t. The calculation procedure is presented in Equation (6).

$$H_t = w_t\overrightarrow{H_t^f} + v_t\overleftarrow{H_t^b} + b_t \tag{6}$$

Here, u_t and w_t Individually represent the weights of the reverse and forward output matrices. It indicates the offset state value at the tth moment. This experiment set the LSTM HL size to 64, leading to the output feature, which joins basic context information, having a size of (200 and 128). Following the semantical feature sequence output from the preceding layer, numerous hierarchical feature representations are gained utilizing three convolution processes of dissimilar dimensions. This experiment uses an incorporation of 512 convolutional kernel sequences of dimensions (2, 3, 4) to get a convolutional feature mapping of 1536 vectors. The $ReLU$ (rectification Linear Unit) improves the representation model. Considering that the output matrix from the top layer is depicted as H, the convolution process is implemented to remove the local feature C. This procedure is exemplified in Equation (7).

$$C = f(wH_{i:i+h-1} + b) \tag{7}$$

In this case, f denotes the process of ReLU; $w \in R^{d\times h}$ indicates the weighted matrix of the convolution kernel; $H_{i:i+h-1}$ depicts the matrix window from row I to row $i + h - 1$, and b represents the matrix offset. Afterwards, it is sampled by max-pooling to remove the non-maximum value effects, maintaining main characteristics while joining the information of dissimilar convolutional kernel vectors in the top layers. Therefore, feature T is gained after convolutional pooling, and the calculation procedure is presented in Equation (8) and (9).

$$T_i = \max\{C_1, C_2, \ldots, C_{n-h+1}\} \tag{8}$$

$$T = \{T_1, T_2, T_3, \ldots, T_{n-h+1}\} \tag{9}$$

In this analysis, the feature vectors managed by the pooling layer are fused and spliced to get output features of dimensions (200, 1536). Furthermore, batch normalization is applied to process the data and steady the model training procedure before progressing to the classification and feature combination phase.

The benefit of the Attention Mechanism (AM) is that it permits the method to calculate the positional feature weights for all sequence elements, making it conceivable to concentrate on the connection between the input and the output result after the outcome was forecast. The computation process is demonstrated in Equation (10).

$$S = Dropout\Big(\tanh\big(Att(T)\big)\Big) \tag{10}$$

In this case, Att signifies the process of the AM component, which, once continuous activation functions tanh and Dropout process, outputs the consistent feature vector S. The AM mapping the feature T into three vector matrices: the Value (V), the Query (Q), and the Key (K) to query the present sequence connection with other sequences. The dissimilar position comparisons among Q and transpose K are initially computed based on the dot product method, thus making the technique concentrate on related information inside the present input. The matrix is scaled according to the dimension to prevent weakening the model training by making the dot product outcome too high. d_k of vector K. Then, it is regularized by Softmax and multiplied with the value vector to obtain the last output, A. Therefore, the calculation procedure is defined in Equation (11). Figure 2 depicts the infrastructure of BiLSTM-AM.

$$A = Attention(Q, K, V) = softmap\left(\frac{QK^T}{\sqrt{d_k}}\right)V \quad (11)$$

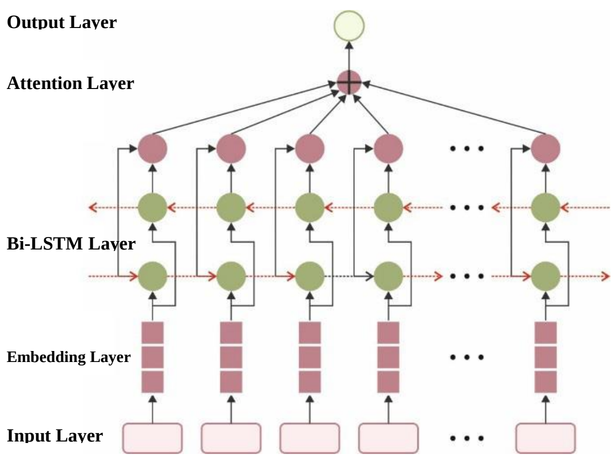

Fig. 2 Structure of BiLSTM-AM

3.4. Hyperparameter Selection using ICOA

Finally, the ICOA optimally alters the hyperparameter value of the BiLSTM-AM system, resulting in higher classification performance. CHOA is the intelligent optimizer model presented due to the social behaviour of chimpanzees, comprising four stages of chasing, repelling, attacking, and surrounding [29]. Targeting the difficulties of unequal primary distribution of the population and easier to drop into local optimal in CHOA, ICHOA is enhanced by presenting cosine dynamic feature and Sobol sequence, and the particular codes are offered as demonstrated:

- Describe the promising interval of the global solution, present the randomly generated variable produced by the Sobol sequence, and specify the population's initialization location as illustrated in Equation (12):

$$X_n = lb + S_i \cdot (ub - lb) \quad (12)$$

Whereas lb and ub represent the left and right limits of the range and S_i refers to ith random variable produced by the sequence of Sobol, $S_i \subseteq [0,1]$.

Assume that the searching region is 2D, and the lower and upper limits are (0,1) correspondingly. The population size is 50, comparing the Sobol sequence adjusted and the arbitrarily initialized population spatial distributions. (2) Subsequently, chimpanzees are separated into four types: Barrier, Attacker, Driver, and Chaser. The attackers cause the population to seek prey, while the other three types assist in this process. The attacker's location is adjusted based on the victim's position. Consequently, its location is upgraded as presented in Equation (13), and all location vectors are computed in Equation (14)-(17):

$$X_{chimp}(t+1) = X_{prey}(t) - a \cdot d \quad (13)$$

$$a = 2 \cdot f \cdot r_1 - f \quad (14)$$

$$d = \left|c \cdot X_{prey}(t) - m \cdot X_{chimp}(t)\right| \quad (15)$$

$$c = 2 \cdot r_2 \quad (16)$$

$$m = Chaotic.value \quad (17)$$

Whereas X_{chimp} represents a coordinated vector of the recent chimpanzee troop; X_{prey} Signifies the coordinate location of the present targeted prey; t denotes present iteration counts; a denotes randomly generated vector applied for measuring the comparable distance among the prey and the chimpanzee group; f means convergence feature, whose size declines non-linearly from 2.5 to 0 by the iteration counts; r_1 denote randomly generated number by the Value of [0,1]; d denotes the distance between the prey and the chimpanzee; c refers to the distance in the searching procedure problem influence feature on chimpanzee searching; r_2 denote randomly formed number in [0,1]; m refers to chaotic mapping vector; and $Chaotic\ value$ stands for chaos factor value.

(3) To allow the attacker to hunt in a broad spectrum that improves the capability of the model to overcome the local best, the dynamic feature selected by the preceding study to get the cosine dynamical aspect with an extensive searching range. Especially the mathematic representation of the dynamic feature is presented in Equation (18), and the mathematic modelling of the cosine dynamic feature is presented in Equation (19):

$$\omega = 1 - \sin\left(\frac{\pi}{2} \cdot \frac{t}{t_{\max}} + 2\pi\right) \quad (18)$$

$$\varepsilon = \cos\left(\frac{10\pi}{9} \cdot \frac{t}{t_{\max}} - \frac{\pi}{9}\right) \quad (19)$$

Whereas t characterizes the recent iteration count, $t_{\max}$ denotes the greatest iteration, ε refers to the cosine dynamics feature, ω symbolizes the dynamics feature correspondingly.

The maximal iteration counts $t_{\max} = 10$ is assigned, and the present iteration counts t ranging from (1-10). Once the searching range lies within [0,1], the dynamic feature is dispersed with 3, and the searching variety of the cosine dynamical feature is widespread and additionally uniform within the interval; after the searching variety lies within

$[-1,0]$, whereas the cosine dynamical feature distribution is uniform, and the searching variety is further comprehensive. In short, it was estimated that the cosine dynamical element allows the attacker to pursue the large field more uniformly, which is additionally efficient.

$$\begin{cases} X_1 = \varepsilon X_{Attacker} - a_1 \cdot d_{Attacker} \\ X_2 = X_{Barrier} - a_2 \cdot d_{Barrier} \\ X_3 = X_{Chaser} - a_3 \cdot d_{Chaser} \\ X_4 = X_{Driver} - a_4 \cdot d_{Driver} \end{cases} \tag{20}$$

$$\begin{cases} d_{Attacker} = |c_1 \cdot X_{Attacker} - m_1 \cdot x| \\ d_{Barrier} = |c_2 \cdot X_{Barrier} - m_2 \cdot x| \\ d_{Chaser} = |c_3 \cdot X_{Chaser} - m_3 \cdot x| \\ d_{Driver} = |c_4 \cdot X_{Driver} - m_4 \cdot x| \end{cases} \tag{21}$$

$$X(t+1) = \frac{X_1 + X_2 + X_3 + X_4}{4} \tag{22}$$

Here, $X_{Attacker}$, $X_{Barrier}$, X_{Chaser}, and X_{Driver} Signify the location vectors of the Attacker, Barrier, Chaser, and Driver individually and X_1, X_2, X_3, and X_4 represent the corresponding upgrade coordinated vectors, and $X(t+1)$ represents the upgrade localization vectors of the single chimpanzee afterwards iteration. Compared to the original CHOA, the ICHOA confirms uniform population initialization, averts local optima and efficiently optimizes hyperparameters by utilizing the optimal values to achieve the model's outcome. Fitness selection is a crucial feature that impacts ICOA performance. The procedure of hyperparameter range comprises the solution encrypted method for assessing the ability of the candidate outcome. The ICOA indicates precision as the primary measure to compute the fitness function. Its mathematical formulation is shown below:

$$Fitness = \max(P) \tag{23}$$

$$P = \frac{TP}{TP + FP} \tag{24}$$

Meanwhile, FP and TP correspondingly signify the false and true positive values.

4. Experimental Analysis

The validation of the ADFND-ICOYC method is inspected under the Fake News Detection dataset [30]. This dataset contains 4000 samples of dual news, such as real and fake, as shown in Table 1. Table 2 describes the sample texts.

Table 1. Dataset description

News	Samples Numbers
Real (0)	2000
Fake (1)	2000
Total Samples	**4000**

Table 2. Sample texts

S.no	Class Labels	Sample Text
1	Real (0)	"Need help contact cq hotline 800 6788511 hotlinecqrollcallcom"
2	Real (0)	"so dope â•¤drake flew memphis take cousin ðŸ‘‘ hyfrjalaah prom fairleyhighschool prom2k17 family unconditionallove drake ovo globalambassador aubrih welcomeovo ovosound post shared rhenna dhrek papixriri May 13, 02 pm pdt"
3	Fake (1)	"evan ross enjoyed a family trip wife ashlee simpson daughter weekend"
4	Fake (1)	"kourtney kardashian sources told us in december bieber hooking up and keeping up with kardashians star kourtney kardashian split from longtime boyfriend scott disick the two were seen hanging together at various clubs throughout december"

Figure 3 presents the confusion matrix of the ADFND-ICOYC method below 80:20 and 70:30 of TRAPH/TSPH. The ADFND-ICOYC technique illustrates efficacious identification and detection of overall classes.

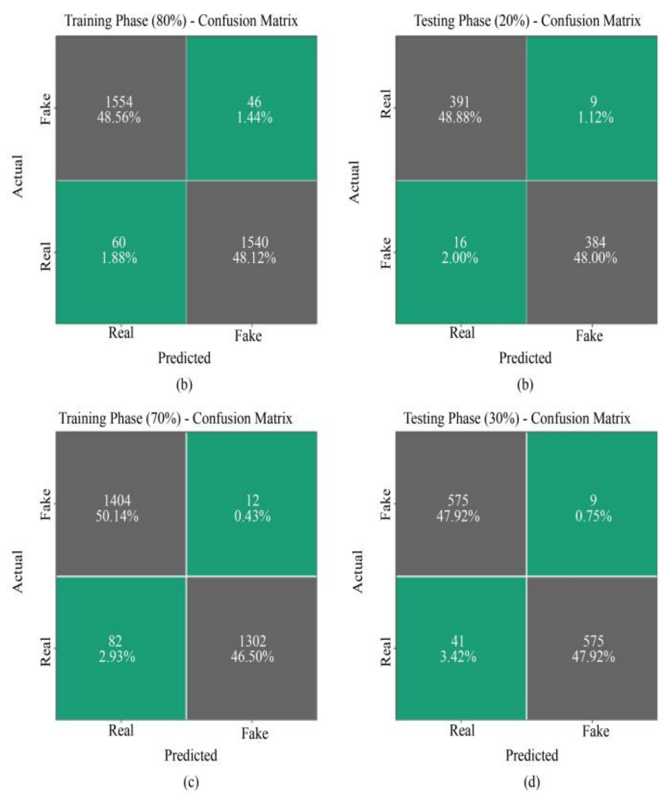

Fig. 3 Confusion matrix of ADFND-ICOYC technique (a-b) 80:20 and (c-d) 70:30 of TRAPH/TESPH

Table 3 and Figure 4 illustrate the fake news detection of the ADFND-ICOYC approach on 80:20 of TRAPH/TESPH. The ADFND-ICOYC approach has appropriately classified all class labels.

Based on 80% TRAPH, the proposed ADFND-ICOYC model obtains an average $accu_y$ of 96.69%, $prec_n$ of 96.69%, $reca_l$ of 96.69%, $F1_{score}$ of 96.69%, and AUC_{score} of 96.69%.

Moreover, according to 20% TESPH, the proposed ADFND-ICOYC model reaches an average $accu_y$ of 96.88%, $prec_n$ of 96.89%, $reca_l$ of 96.88%, $F1_{score}$ of 96.87%, and AUC_{score} of 96.88%.

Table 3. Fake news detection of ADFND-ICOYC approach under 80:20 of TRAPH/TESPH

Class Labels	$Accu_y$	$Prec_n$	$Reca_l$	$F1_{score}$	AUC_{score}
TRAPH (80%)					
Real	97.12	96.28	97.12	96.70	96.69
Fake	96.25	97.10	96.25	96.67	96.69
Average	**96.69**	**96.69**	**96.69**	**96.69**	**96.69**
TESPH (20%)					
Real	97.75	96.07	97.75	96.90	96.88
Fake	96.00	97.71	96.00	96.85	96.88
Average	**96.88**	**96.89**	**96.88**	**96.87**	**96.88**

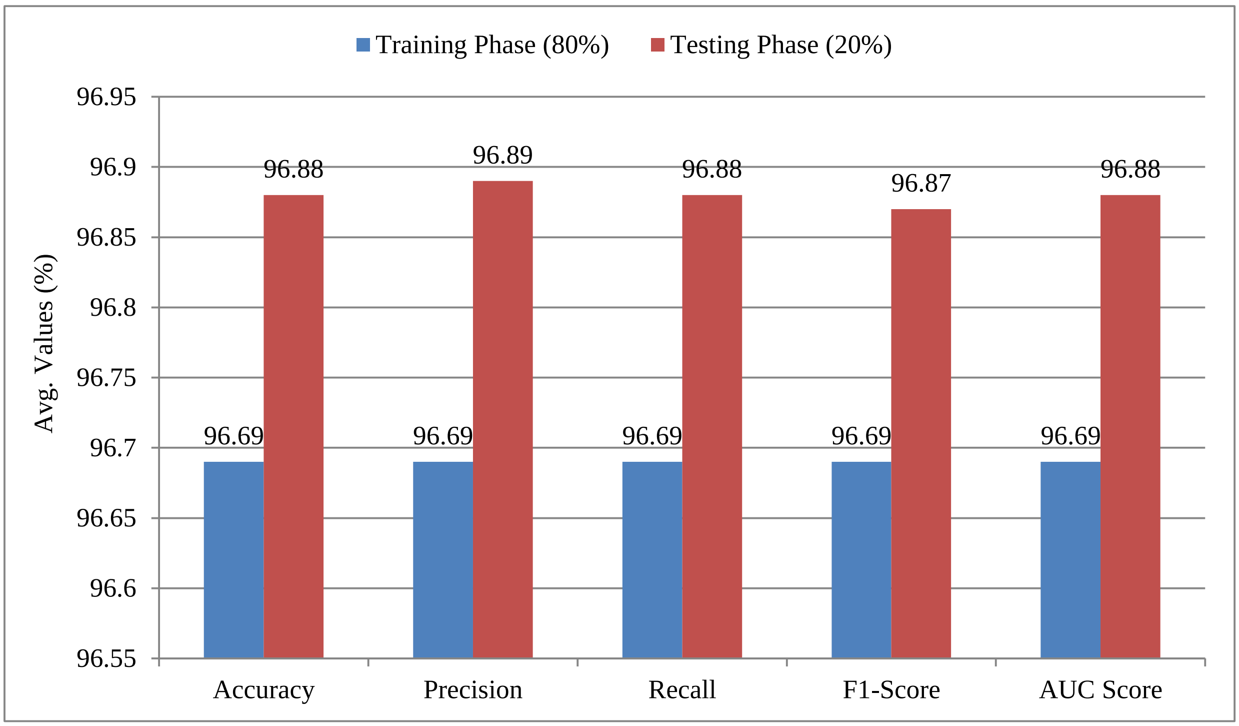

Fig. 4 Average of ADFND-ICOYC approach under 80:20 of TRAPH/TESPH

Table 4 and Figure 5 show the fake news detection of the ADFND-ICOYC approach on 70:30 of TRAPH/TESPH. The ADFND-ICOYC approach correctly classified all the distinct class labels.

Based on 70% TRAPH, the proposed ADFND-ICOYC method attains an average $accu_y$ of 96.61%, $prec_n$ of 96.78%, $reca_l$ of 96.61%, $F1_{score}$ of 96.64%, and AUC_{score} of 96.61%.

Moreover, belonging to 30% TESPH, the proposed ADFND-ICOYC method reaches an average $accu_y$ of 95.90%, $prec_n$ of 95.90%, $reca_l$ of 95.90%, $F1_{score}$ of 95.83%, and AUC_{score} of 95.90%.

Table 4. Fake news detection of ADFND-ICOYC model under 70:30 of TRAPH/TESPH

Class Labels	$Accu_y$	$Prec_n$	$Reca_l$	$F1_{score}$	AUC_{score}
TRAPH (70%)					
Real	99.15	94.48	99.15	96.76	96.61
Fake	94.08	99.09	94.08	96.52	96.61
Average	**96.61**	**96.78**	**96.61**	**96.64**	**96.61**
TESPH (30%)					
Real	98.46	93.34	98.46	95.83	95.90
Fake	93.34	98.46	93.34	95.83	95.90
Average	**95.90**	**95.90**	**95.90**	**95.83**	**95.90**

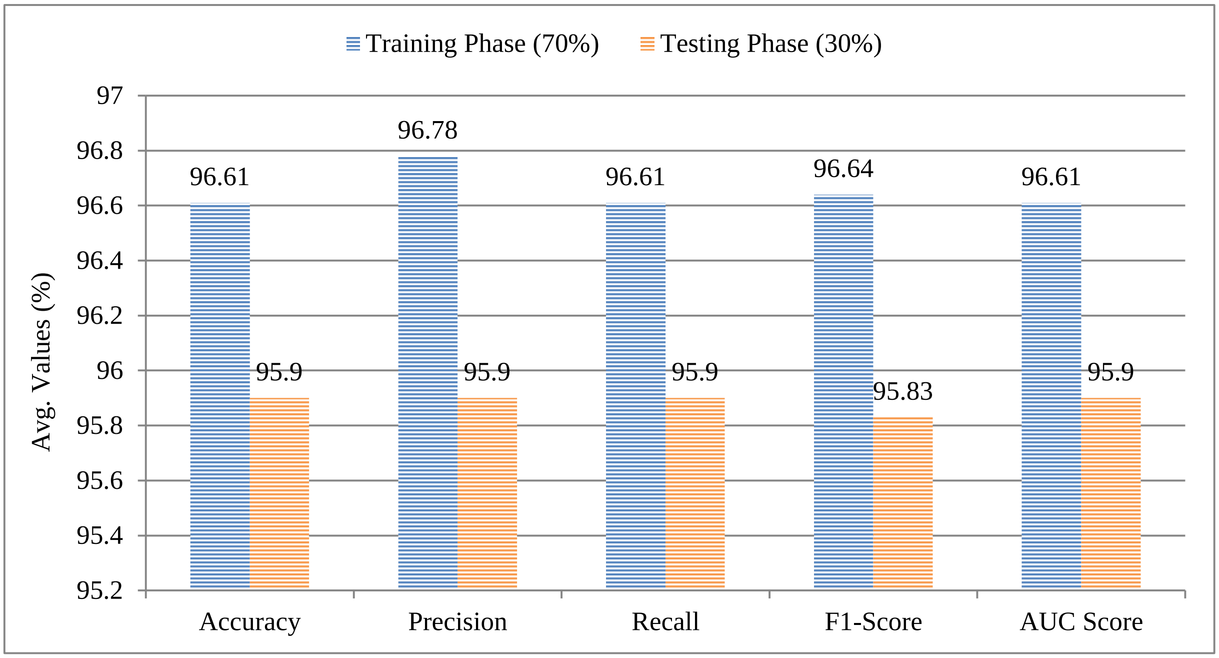

Fig. 5 Average of ADFND-ICOYC approach under 70:30 of TRAPH/TESPH

Figure 6 exemplifies the training (TRA) $accu_y$ and validation (VAL) $accu_y$ of the ADFND-ICOYC method below 80:20 of TRAPH/TESPH. The values of $accu_y$ are computed over 0-25 epochs, indicating growth in TRA/VAL $accu_y$, depicting the effectiveness of the ADFND-ICOYC technique with optimal performance across epochs. The close values of TRA/VAL $accu_y$ exhibit reduced overfitting, emphasizing the greater and consistent performance of the ADFND-ICOYC technique on undetected instances.

Figure 7 shows the TRA loss (TRALOS) and VAL loss (VALLOS) of the ADFND-ICOYC method under 80:20 TRAPH/TESPH over 0-25 epochs. The result illustrates a decreasing trend, showing the ADFND-ICOYC approach's capability to balance generality and data fitting. The subsequent reduction in loss values confirms the superior performance of the approach and refined output over time.

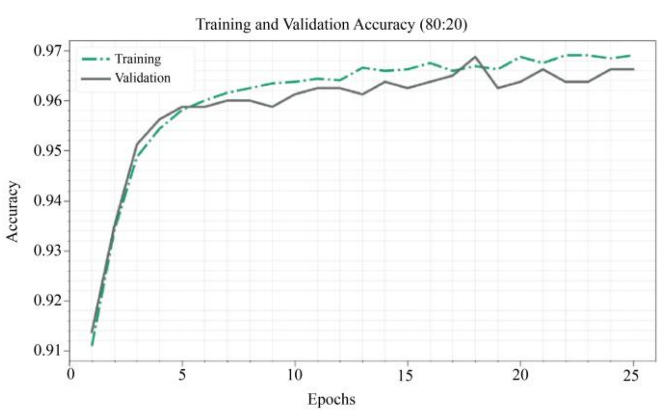

Fig. 6 Accuracy curve of ADFND-ICOYC technique below 80:20 of TRAPH/TESPH

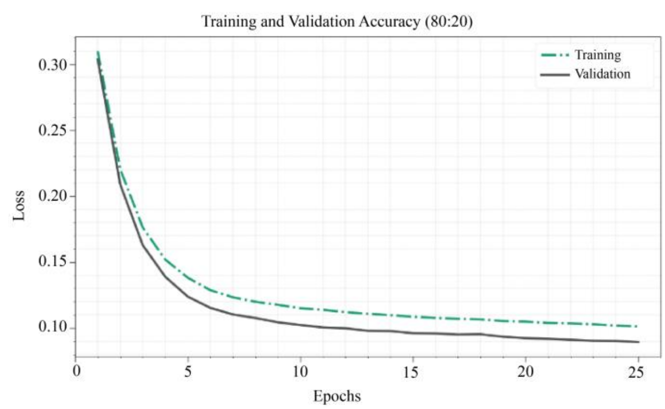

Fig. 7 Loss curve of ADFND-ICOYC model under 80:20 of TRAPH/TESPH

Table 5. Comparison evaluation of the ADFND-ICOYC model with existing methods [31-33]

Model	$Accu_y$	$Prec_n$	$Reca_l$	$F1_{score}$
CART	96.07	96.06	96.07	95.20
NNET	91.80	85.70	90.00	92.30
Hybrid CNN+RNN	93.85	90.13	89.37	92.38
HyproBert	90.40	95.37	92.66	95.40
DeepCnnBilstm	90.54	89.87	89.99	92.23
CNN-Text	90.50	91.82	94.36	94.74
BC-FN	95.75	90.95	90.87	91.62
ADFND-ICOYC	96.88	96.89	96.88	96.87

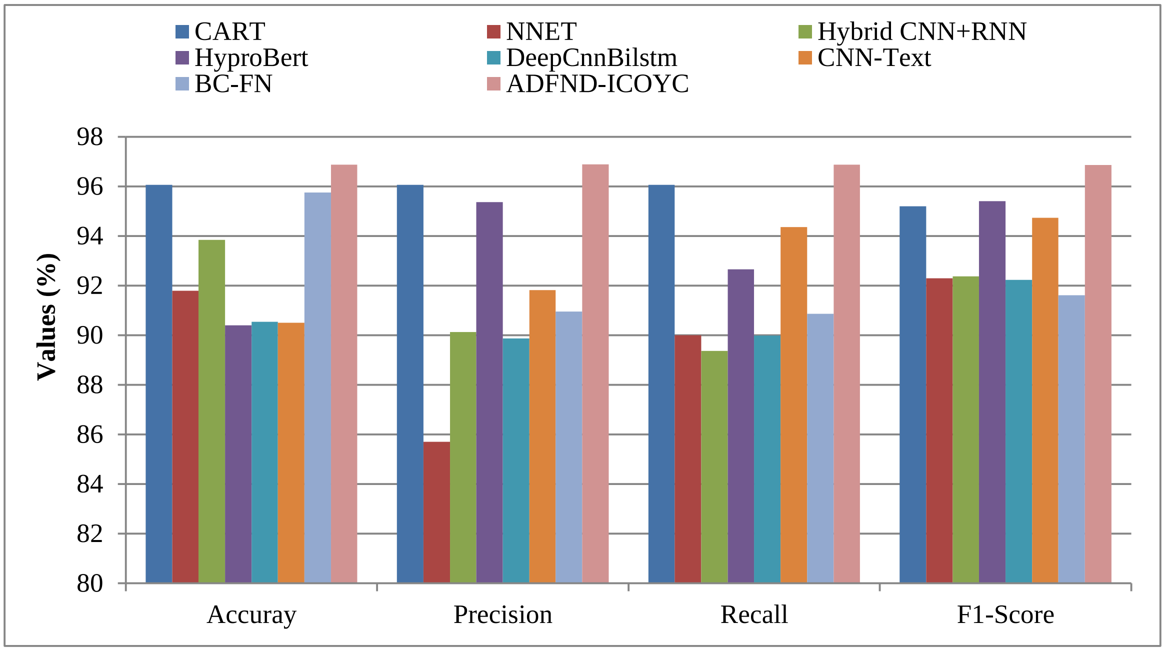

Fig. 8 Comparison evaluation of the ADFND-ICOYC model with existing methods

Table 5 and Figure 8 compare the outcomes of the ADFND-ICOYC approach with existing techniques [31-33]. The performances underscored that the NNET, Hybrid CNN+RNN, HyproBert, DeepCnnBilstm, and CNN-Text techniques exhibited poorer results. Also, CART and BC-FN methods attained closer outputs. Additionally, the ADFND-ICOYC approach indicated maximum performance with increased $accu_y$, $prec_n$, $reca_l$, and $F1_{score}$ of 96.88%, 96.89%, 96.88%, and 96.87%, subsequently.

5. Conclusion

In this study, the ADFND-ICOYC method is proposed. This model comprises distinct processes such as text pre-processing, feature extractor, BiLSTM-AM detection, and parameter selection. Initially, the text pre-processing stage cleans and transforms raw text into a structured format. The word2vec method is employed for feature extraction. Besides, the proposed ADFND-ICOYC model implements the BiLSTM-AM method for the fake news classification process. Finally, the ICOA optimally alters the BiLSTM-AM method's hyperparameter value, resulting in higher classification performance. The efficacy of the ADFND-ICOYC method is examined under the Fake News Detection dataset. The performance analysis of the ADFND-ICOYC method demonstrated a superior accuracy value of 96.88% over existing models.

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