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Computational Linguistics and Intelligent Learning for Automated Article Credibility Classification

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Abstract

In social media, non-credible article is a complicated issue because of the rapid expansion and amount of data, as well as the comfort of making and sharing content namelessly. Non-credible article concerns are difficult not only for the reliability of digital journalism, but also owing to their deleterious real-world outcomes. Research workers are attempting for analyzing the reliability of information and limit false information on these platforms. Reliability is the trustworthiness of the piece of information at hand. Examining the credibility of fake news is difficult because of the purpose of its making and the polychromatic nature of the news. Social network platforms are conflicted to lessen the consequences of Non-credible article, depends heavily on standard techniques relay on human knowledge and expertise. Therefore, deep learning (DL) and machine learning (ML) models now perform an important part in differentiating fake news, requiring their widespread deployment for addressing extensive range of false information across all languages. This manuscript presents a Next-Generation Deep Linguistics Framework for Intelligent Article Credibility Identification (NGDLF-IACI) methodology. The aim of this study is to design an intellectual approach for fake news detection by utilizing advanced deep learning approaches, which improves the reliability of information and decreases the spread of fake news. Towards that aim, the proposed NGDLF-IACI model begins with a text preprocessing stage that comprises tokenization, noise removal, removing stop word removal, and lemmatization, which ensures the reliability of textual data. Moreover, the GloVe based word embedding is used to convert text into a vector representation model that improves the model's capability and recognize sematic patterns. For classification, a soft voting-based ensemble model is employed that integrates a stacked sparse autoencoder and graph convolutional network for precisely categorizing fake new. To boost the performance of the classification model, rectified adam is conducted for parameter tuning. A comprehensive set of experimental outcomes is carried out to verify the significance of the NGDLF-IACI approach. A brief comparative analysis reported the greater solution of the NGDLF-IACI approach over other existing methodologies.

Keywords: Article credibility; Parameter Tuning; Deep Learning; Social Media; Ensemble Classification; False Information

1 Introduction

The information is important for human dynamics and influence every-day practices. In the past, the daily news or details have been offered by newspapers, printed and electronic media like radio and television [1]. The information from these publishing technologies is more reliable because it is either self-censored or constrained by experts. In the early days, individuals are provided with a high-volume of information from multiple sources, especially with the significance of online and web-based media platforms [2]. The simplicity of internet admittance has provided the potential for harmful development of a broad range of false information, such as fabrications, harmful discourse, double-dealing, spam assessment, non-credible article, which spreads broadly

and rapidly in human culture [3]. The falsehoods of social media platforms have developed as a world-wide concern in public reliable and society, as it becomes an important mode of networking and communication in recent days [4]. Non-credible article is a one of widespread advertising in which the falsehoods is diffuses digitally by online platforms like Facebook, Snapchat, and Twitter to influence public opinion [5]. Social networking platforms include two different sides for news' applications; the first is applied to enhance society considering the recent news, and the second is usages of the source of diffusing false information. But social media enables the rapid diffusion of fake news, making it simple to spread the falsehoods, and it results in lower cost [6]. However, because of the ease and more control on the internet, the diffusion of 'wrong information is without precedent in the past years. This structure of diffusing articles on the internet that don't conform to the fact has caused nearly all the public fields like health, science, politics, sports etc., The capital market is one of the main fields aimed at disseminators of non-credible articles [7]. Now, a rumor might disrupt market activity that could bring devastating outcomes. The ability to take a choice most of the time based on the particular information that the user gets; the global perspective is influenced based on the data viewed by the user. It is complex to identify and classify the legal news from false content [8]. To address this contest, examiners have moved to machine learning (ML) and deep learning (DL) techniques have dependable possibilities for automated article credibility identification. These methods influence multiple news articles and their spreading, comprising legal patterns, optical symptoms, user attraction, and propagation features [9]. Conventional ML methods like support vector machines (SVM), random forests (RF), and gradient boosting were broadly utilized. Moreover, DL frameworks have obtained important adoption due to their higher performance in acquiring difficult patterns. Latest article displays a developing change to futuristic DL technique, comprising convolutional neural networks (CNNs) and recurrent neural networks (RNNs), like Gated Recurrent Units (GRU), Long Short-Term Memory (LSTM), and Bidirectional Encoder Representations from Transformers (BERT), which have validated higher efficiency over non-credible article identification functions [10]. Therefore, news resource credibility identification is earlier than AI in this analysis, as expected to help the audience, by technology, in improving the news sources literacy and minimizing the adverse effects of misinformation [11]. This study presents a Next-Generation Deep Linguistics Framework for Intelligent Article Credibility Identification (NGDLF-IACI) model for identifying and classifying fake news and improving the reliability of information. For accomplishing that, the proposed NGDLF-IACI technique follows text preprocessing, word embedding, deep learning-based ensemble classification and parameter tuning for boosting the performance of the model. The performance of the NGDLF-IACI approach is calculated through a wide range of simulations with several measures. The major contributions of this paper are summarized below:

- Design a GloVe-based word embedding model to transform words into a vector representation that captures semantic representations.
- Employ soft voting-based ensemble classification (SVEC) incorporated with stacked sparse autoencoder (SSAE) and graph convolutional network (GCN) techniques for categorizing fake news as credible, not credible, or undecided.

- Present rectified adam (RAdam) optimizer for tuning parameters and accomplishes improved performance of model.
- Validate the performance of the proposed approach on the benchmark dataset and calculate the outcomes under several aspects.

2 Existing research on fake news classification

This section briefly reviews previous research works on the classification of fake news. Sneha et al. [12] introduce BiLSTM-LIME, a hybrid architecture incorporating BiLSTM models with LIME for explainable and effective fake news identification. This method used a pre-trained GloVe embeddings to acquire syntactic and semantic dependences, when LIME offer token level interpretability, improving transparency in the model's predictions. A normalized English dictionary with an enhanced pre-processing pipeline has been created to confirm strong and renewable assessment. Choudhary and Chouhan [13] proposed a MmCAF to recognize whether the provided user-generated content with least errors. It focusses sentence-level embeddings for denoting complete sentences and their semantical data represents vector. Abdullah et al. [14] presented an ensemble-driven architecture that incorporates textual and optical data utilizing ViLBERT's two-stream framework, integrates VADER based SA to identify affective language, and applies Image–Text content-based Similarity to detect disparities among textual and visual elements. In [15], how estimating users' sharing behaviors could enhance FND. The regression-driven method to predict a user's TSFN through utilizing language-based features extracted by their online posts. Then, it uses the trained TSFN predictive method for the identification of fake news, offering a two-step FND application. Patel [16] develops a detailed survey of ML approaches are implemented for fake review and FND. To deploy sophisticated NLP approaches and hybrid ML models, the analyzes assesses different types of algorithms comprising SVM, RF, LSTM models, and ensemble methods regarding their performance in deception detection. Gul et al. [17] introduce a developed technique that uses GNN along with modern DL methodologies for enhancing the detection false information. Conversely to the conventional technique that majorly depends on examining text and evaluating the Authenticity of resources, this method implements the structural data of the news diffusion system. This enable for a comprehensive understanding of the patterns and interrelationships that are highlighting of false information. Through complex analyzes, graph-driven relation among news content, this method not only results the limitations of traditional fake news identifications techniques but also validates important developments in identification precise. Huang and Zheng [18] developed an innovative technique for multi-modal fake news identification, called CPEHGN. Particularly, three hierarchical graphs to clearly implement both cross-modal correlations and intra-modal relations in the news nodes. The multiple methods are subsequently upgraded with specific modality GCN, which improve the balancing relations from both textual and optical insights. Embarak [19] introudces the efficiency of DL methods in identifying fake news in Facebook's false information applications. A detailed dataset of original and fake news articles has been studied utilizing an ANN method, which has been trained and assessed against conventional ML models, comprising

Logistic Regression (LR) and SVM. Table 1 signifies the comparison related works on fake news classification.

Table 1 Overview of related works

References	Methodologies	Datasets	Findings	Research aim
Sneha et al. [12]	BiLSTM and LIME models	True news and fake news datasets.	Accuracy of 97.21%.	To design an interpretable and efficient fake news detection model using DL techniques.
Choudhary and Chouhan [13]	Deep learning approaches	Twitter datasets.	Accuracy of 0.95%.	Develop a multiple approach for accurately assessing the trustworthiness of user-generated content using text and image features
Abdullah et al. [14]	Bi-GRU and DistilBERT techniques	Fakeddit and Weibo datasets.	Accuracy of 96% and 94%.	Design a robust ensemble-based multimodal approach for accurate fake news identification by combining text and visual aspects.
Hashemi et al. [15]	Regression model	FakeNewsNet dataset.	Attains better outcomes.	To improve fake news classification by predicting users' tendency to spread misinformation using linguistic and behavioural features.
Patel [16]	Machine Learning models	Fake news dataset.	Accuracy of 91.2%.	To analyse and compare ML techniques for effective detection of fake reviews and fake news.

Gul et al. [17]	Graph Neural Network approach	Fake news dataset.	Accuracy of 97%.	To improve fake news detection by leveraging graph neural networks to analyze propagation patterns and relationships in news data.
Huang and Zheng [18]	Graph Convolution Network model	Fake news dataset.	Accuracy of 94.9% and 89.6%.	To enhance multimodal fake news detection using graph-based approach gives better performance.
Embarak [19]	DL methodologies	Real and fake article datasets.	Accuracy of 89.2%.	To detect fake news on media platforms utilizing DL methodologies for improved accuracy and reliability.

3 Research Design

The proposed NGDLF-IACI approach follows a systematic approach to precisely categorize non-credible articles and increase the reliability of information, thereby boosting the performance of the DL model. Fig. 1 denotes the overall process of proposed model. The proposed model involves five steps: text preprocessing, GloVe-based word embedding, soft voting-based ensemble classification, optimization and performance analysis are described below.

3.1 Preprocessing

Text preprocessing is the is employed to prepare and clean text data to make it suitable for analysis or computational processing. Tokenization: The tokenization process is to separate the text into tokens or distinct words. The above method allows the text segmentation to semantically significant units [20]. This technique supports in structuring and simplifying the text for more examination. This is an important phase in the NLP procedure. Breaking down the text into lesser units, it enables functions like classification and feature extraction. This technique follows the established tokenization practices in the text pre-processing study. Noise Removal: It is a text pre-processing stage which removes the extraneous or unrelated components from text data. It contains special characters, numbers, HTML tags, punctuation, and more whitespace. Eliminating noise supports in standardizing and cleaning the text for examination. That can enhance the quality of the extracted text features. This method is important for improving the execution of NLP challenges. Removing Stop Words: Words, which

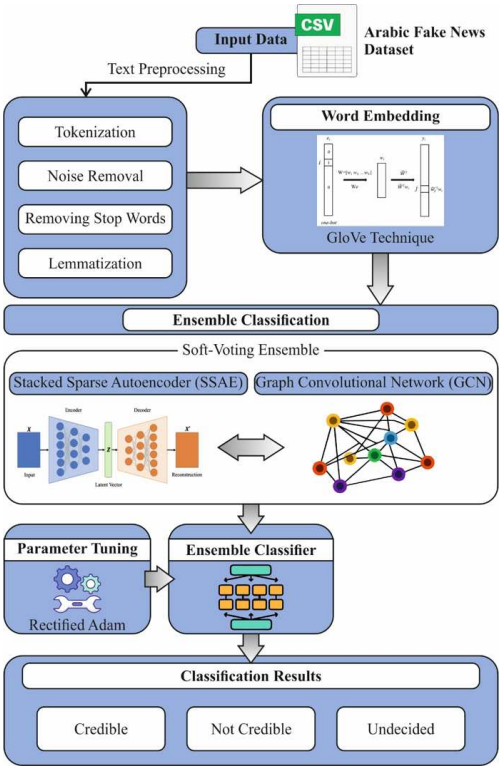


Fig. 1 Overall process of proposed model

are often employed in a language but usually never considerably modify the meaning of sentence are called stopwords. While preparing the text data for NLP functions, stopwords are frequently ignored. In several tasks, like removing stopwords, text classification supports for reducing the dataset dimensionality and enhancing the statistical effectiveness. Removing such common words enables the model to concentrate on more significant features. So, the process eliminates stopwords to decrease the dimension and improve the efficiency and effectiveness of the following examines. Lemmatization: It is a text pre-processing approach, which eliminates words to their dictionary or base form (lemma). This method employs linguistic context and rules, like part-of-speech, for ensuring the word remains significantly. Different stemming, it gives valid words rather than simply chopping off conclusions. It supports in normalizing text for NLP tasks and analysis.

3.2 Word Representation using GloVe Embeddings

GloVe is a word embedding method, which learn the vectorized representation of a word depending upon global word frequency data [21]. It acquires relations among words to recognize patterns that emerge big texts. This approach formed by the instinct, which the proportion of co-occurrence possibilities between words capably encodes any of a relationship between words. This methods execution is greater than

another word embedding since it employs to non-zero components and a subsection of a corpus, not an entire corpus or a distinct window of the important corpus. The key factor of GloVe reliant on the co-occurrence of word in a specific framework acquires some semantic denotation. This technique is intended for decomposing the co-occurrence matrix with 2-d layer matrices, which acquires the word relations. Enable the co-occurrence matrix provided by X. Every component X(i,j) represents how frequently word i occurs in the word j setting. The intention of this technique was to discover 2 matrices W and C with W*C gets nearest to the depiction of X that highlights co-occurrence matrix.

$$J = \sum_{i,j,=1}^{V} f(X(i,j)) \left(w_i c_j + b_i + b_j - \log(X(i,j))\right)^2 \tag{1}$$

Whereas, $X(i,j)$ denotes co-occurrence sum of word i through word j; c_j and w_i represent context word vectors and word, correspondingly; b_j and b_i signifies biased term related with the context word vectors and word; $f(X(ij))$ implies weighted function used for the count of co-occurrence, usually in the method $f(x) = \left(\frac{X}{x_{\max}}\right)^{\alpha}$, whereas $x_{\max}$ and α are constants that regulate the impact of occasional co-occurrence pairs. Fig. 2 denotes the structure of word embeddings.

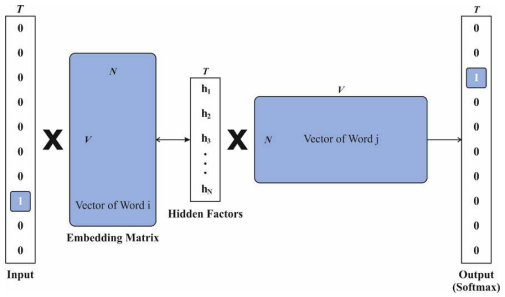


Fig. 2 Structure of word embeddings

3.3 Soft Voting based Ensemble Approach

SVEC is employed to incorporate two techniques for categorizing fake information, better to better handle complex linguistic patterns and boost the performance of the model. SVEC is a meta-classifier, which uses an Expert-based system with training and integrates forecasts from many models [22]. It combines such predictions to produce the last decision, usually depends on the major results. A voting classifier may utilize soft or hard voting: in hard-voting, the class with the maximum counts of vote has been designated, but in soft voting, the class with the maximum combined possibility over models is selected. Every algorithm donates the group decision-making method, and soft voting was frequently selected for the last categorization. This approach uses the capacities of several techniques for reducing the random faults and enhance whole

dependability and accuracy. SSAE: The topological network to the standard auto-encoder (AE) algorithms contains of the three-layer neural networks (NNs). Also, both the output and input layers include an equal count of neuron [23]. The conversion of vectorized input to the latent state outcome is the encoded procedure of the AE method, when the decoded technique is the change of the latent state feature outcome to outputting layer. AE method concentrates to diminish the loss function with the aim of rebuilding the input data from outputting information. Hidden state attributes could be employed as inputting data rebuilding and deeper representations. The presence of the sparseness term in the loss function used within AE algorithm causes the making of the SAE method, consequently, which the output of hidden state. The SAE algorithms may know factors and design of inputting data further efficiently with the numerical formulation of the training method declared in the equation:

$$H = XW + b \tag{2}$$

$$\Upsilon = HW' + b' \tag{3}$$

$$KL\left(\rho \| \hat{\rho}_i\right) = \rho \log \frac{\rho}{\hat{\rho}_i} + (1-\rho) \log \frac{(1-\rho)}{(1-\hat{\rho}_i)} \tag{4}$$

$$L_{\text{loss}} = \frac{\sum_{i=1}^{N} (X_i - Y_i)}{N} + \beta \sum_{i=1}^{n} KL\left(\rho \| \hat{\rho}_i\right) + \frac{\lambda}{2} \sum_{i=1}^{m} \sum_{j=1}^{n} W_{ij}^2 \tag{5}$$

Whereas n and m denote the amount of neuron in given inputs and latent state, with N signifying amount of instances in the SAE algorithms. H, Y, and X implies the given output and input, and the feature vector outcomes of the latent state, correspondingly. b, W', B' and W denotes connection weighted parameter and biased matrices distributed forward by the latent, output, and input states. L_{loss} designates the loss function in the training operation that contains of weighted regularization term, a sparse penalty term, and rebuilding error. λ and β are weighted regular term and sparse term factors. $KL\left(\rho \| \hat{\rho}_i\right)$ in loss function has Kullback-Leibler (KL) difference as a more penalty for confining the sparseness of activation outcomes of the neurons in latent state. ρ and $\hat{\rho}_i$ are the average value of the i_{th} latent state neuron and the sparse constants. GCN: The GCN denotes a CNN particularly intended for graph-structured information. When conventional-CNNs excel at eliminating spatial aspects in the various non-Euclidean structures, Euclidean structures present with robust systems [24]. GCN gives an innovative technique process these data and has found widespread applications. Assume a graph G, output Y, and input X, the GCN approach could be illustrated in below equation:

$$f(X, A) = Y \tag{6}$$

Whereas A signifies adjacency matrix, with components in matrix A denotes association relations among nodes in graph G.

The propagation calculation for graph convolutional has been demonstrated in the equation below equation:

$$H^{(l+1)} = \sigma\left(\tilde{D}^{-1/2}\tilde{A}\tilde{D}^{-\frac{1}{2}}H^{l}W^{l}\right) \tag{7}$$

Whereas $\tilde{A} = A + I$ symbolizes adjacency matrix with more self-connection (l represents identity matrix); $\tilde{D}$ denotes diagonal degree matrix; W^l and H^l designate parameter and output values of l layer; and $\sigma(\cdot)$ implies an activation function. The given layer of input obtains graph data as signal X, with many layers of GCN, the attributes of avery nodes in the graph were converted from X to Z, when the network relations A among nodes. The decayed by diverse stages, using GNN for predicting and modeling, may efficiently acquire various ramp features, so improving precision.

The above research presented an advanced GCN framework integrating 3 specialized GCN algorithms. Every module is built with separate node configuration for classifying the dynamic coupling relations. The edge weights are calculated by reflecting the linear connection strength among nodes, Pearson correlation coefficients, and the structure of regular graph edge signifies an inter-node relationship.

$$G_{up} = \sigma\left(\sum_{x=1}^{L}\left(\sum_{y=1}^{V}\hat{D}^{-\frac{1}{2}}(i,i)\hat{A}(i,y)D^{-\frac{1}{2}}(y,y)P_{t-x+1}(y)\right)W(j,x)\right) \tag{8}$$

$$G_{down} = \sigma\left(\sum_{x=1}^{L}\left(\sum_{y=1}^{v}\hat{D}^{-\frac{1}{2}}(i,i)\hat{A}(i,y)\hat{D}^{-\frac{1}{2}}(y,y)WS_{t+x}(y)\right)W(j,x)\right) \tag{9}$$

$$G_{\text{none}} = \sigma\left(\sum_{x=1}^{L}\left(\sum_{y=1}^{v}\hat{D}^{-\frac{1}{2}}(i,i)\hat{A}(i,y)\hat{D}^{-\frac{1}{2}}(y,y)WS_{t+x}(y)\right)W(j,x)\right) \tag{10}$$

$$w_{ij} = \frac{\operatorname{cov}\left(v_{i'}v_j\right)}{\sigma_{v_l}\sigma_{v_i}} \tag{11}$$

whereas G_{down} , G_{none} , and G_{up} denotes GCN methods for ramp-down, ramp-up and non-ramp stage features, correspondingly. L represents eliminated length of time sequence, v signifies meteorological series, A declares used to alter fluctuation correlations and ramp features, and W has been used to extract the temporal attributes. The threshold w_{ij} recollects edges with $|w_{ij}| > 0.5$, removing lower networks to lessen noise. Also, edge design and refined node, the physical modules were encoded clear relations in the layer of graph, allowing the precise GNN approach. Fig. 3 signifies the architecture of GCN technique.

3.4 Hyperparameter Tuning

This method enhances the unbiased function at an accurate time depend upon the probable variance divergence by employing the RAdam optimizer [25]. It presents further efficient learning technique, especially in the initial training stages that increases the whole model's performance. This method integrates a rectified term, which allows the adaptive momentum to be steadily and progressively specified as a capable

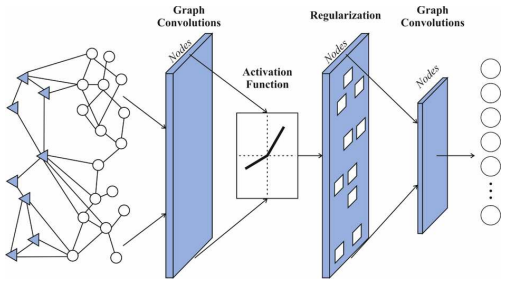


Fig. 3 Architecture of GCN technique

square divergence function. It supports for improving the training model stability and attain greater simplification and rapid integration, particularly while performing with compound data the unbiased function is denoted in Eq. (12):

$$o(T,\hat{T}) = \frac{1}{n}\sum_{i=1}^{n}\left(T^i - \hat{T}^i\right)^2 \tag{12}$$

Whereas $O(T,T)$ represents objective function, which enumerates errors among the real T and predicted $\hat{T}$ value, n signifies instance series, T designates a certain value for i_{th} instance, and $\hat{T}$ defines predicted value for i_{th} sample.

Table 2 shows the parameter settings employed in the presented approach. The SSAE module uses three autoencoder layers with 512 hidden neurons, along with dropout and sparsity mechanisms to improve feature learning. The GCN component utilizes two layers with Rebut activation and dropout for enhancing the graph-based representation. Model training is improved employing the RAdam optimizer with carefully tuned learning parameters. The size of batches 32 and 25 training epochs are chosen for ensuring the efficient and stable convergence.

Table 2 Parameter table

Modules	**Parameters**	**Symbols**	**Selected Value**
SSAE	Number of Autoencoder Layers	L_{ae}	3
	Hidden Neurons per Layer	H_{ae}	512
	Sparsity Parameter	ρ	0.05
	Dropout Rate	d_{ae}	0.3
GCN	Number of GCN Layers	L_g	2
	Hidden Units per Layer	H_g	128
	Activation Function	φ	ReLU
	Dropout Rate	dg	0.4
Optimizer (RAdam)	Learning Rate	η	0.001
	Beta_1	β_1	0.9
	Beta_2	β_2	0.999
	Weight Decay	λ	0.001
Training	Batch Size	B	32
	Epochs	E	25

3.5 Evaluation Metrics

Performance measures are metrics utilized for evaluating the system or model performance. They support enumerate the reliability, accuracy, and efficiency of the model. Accuracy: It is the counts of sample properly categorized by the classifier with the overall counts of sample.

$$\text{Accuracy } = \frac{T_rP_s + T_rN_g}{T_rP_s + T_rN_g + F_aP_s + F_aN_g} \tag{13}$$

Precision: it signifies the amount of positive instances amid those foretold as positive by the algorithms.

$$\text{Precision } = \frac{T_rP_s}{T_rP_s + F_aP_s} \tag{14}$$

Recall: It symbolizes the number of positive samples, which were properly recognized by the algorithms.

$$\text{Recall } = \frac{T_rP_s}{T_rP_s + F_aN_g} \tag{15}$$

F1-Score: The F1-score is an important parameter for assessing the execution of methods. The harmonic despicable of recall and precision, utilized for evaluating the balance among the model's capability to properly predict positive instances and its capability for covering the allreal positive samples.

$$F1 - \text{ Score } = \frac{2^* \text{ Recall } \text{ Precision}}{\text{Recall } + \text{ Precision}} \tag{16}$$

MCC: A quantity, which displays how well a classification method forecasts both negative and positive classes and all kinds of results TN, TP, FN and FP.

$$MCC = \frac{(T_rP_s + F_aP_s)\,(T_rP_s + F_aN_g)}{\sqrt{(T_rN_g + F_aP_s)\,(T_rN_g + F_aN_g)\,(T_rP_s \times T_rN_g) - (F_aP_s \times F_aN_g)}} \tag{17}$$

4 Result and Discussion

This article studies the performance of the NGDLF-IACI technique on the Arabic Non-credible articles Dataset from Mendeley [26, 27]. It consists of 606912 news articles composed from 134 various public news websites. Mishar, is a public Arabic news fact checking platform, is employed for classifying the articles into not credible, credible, and unsure are defined in Table 3.

In Table 4 and Fig. 4, articles classification outcomes of the NGDLF-IACI method is represented for 80:20 of training-testing splits. The tabulated values inferred that the NGDLF-IACI model capably identifies the article samples. With 80% training split, the NGDLF-IACI technique reaches average of accur_y of 98.28%, preci_n of 97.40%, recal_l of 97.21%, F1_score of 97.29%, and MCC of 96.03%. Also, with 20% testing split, the NGDLF-IACI model achieves average of accur_y of 98.33%, preci_n of 97.43%, recal_l of 97.25%, F1_score of 97.33%, and MCC of 96.11%.

Table 3 Details on dataset

Statistical	**number of articles**
Credible	20731
Not Credible	16723
Undecided	23237
Total Samples	**60691**

Table 4 Article classification of NGDLF-IACI approach under 80:20 splits

Classes	$Accur_y$	$Preci_n$	$Recall_l$	$F1_{Score}$	**MCC**
Training Phase (80%)					
Credible	98.11	96.13	98.46	97.28	95.85
Not Credible	97.86	97.49	94.70	96.07	94.62
Undecided	98.88	98.58	98.47	98.53	97.62
Average	**98.28**	**97.40**	**97.21**	**97.29**	**96.03**
Testing Phase (20%)					
Credible	98.12	96.27	98.24	97.24	95.83
Not Credible	97.87	97.32	94.75	96.02	94.58
Undecided	99.00	98.69	98.76	98.73	97.91
Average	**98.33**	**97.43**	**97.25**	**97.33**	**96.11**

In Fig. 5, the ROC investigation of the NGDLF-IACI system from 80:20 splits is researched. The solutions recommend that the NGDLF-IACI algorithm accomplishes superior ROC analysis through each class, depicting substantial ability of discriminating the classes. This reliable tendencies of enhanced ROC analysis by several classes indicate the execution of NGDLF-IACI model on predicting classes, underscoring the robust nature under categorization approaches.

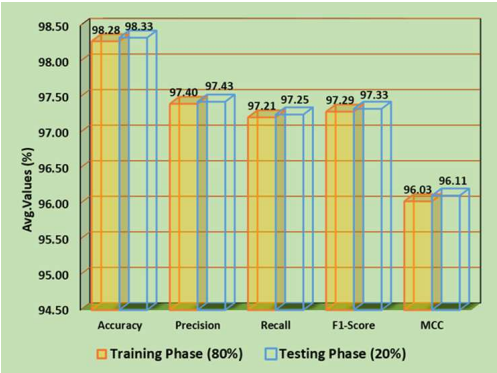


Fig. 4 Average of NGDLF-IACI approach under 80:20 splits

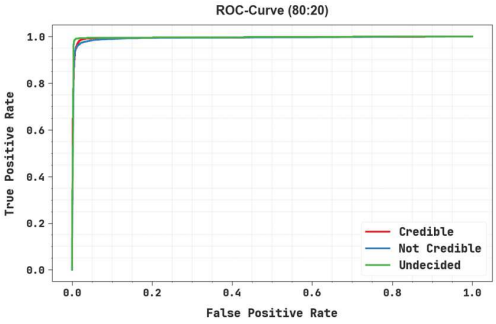


Fig. 5 ROC curve of NGDLF-IACI approach under 80:20 splits

In Table 5 and Fig. 6, articles classification outcomes of the NGDLF-IACI approach is showed for 70:30 of training-testing splits. The tabulated values inferred that the NGDLF-IACI method capably identifies the article samples. With 70% training split, the NGDLF-IACI technique reaches average of accur_y of 97.18%, preci_n of 95.78%, recal_l of 95.74%, F1_score of 95.76%, and MCC of 93.62%. Also, with 30% testing split, the NGDLF-IACI methodology reaches average of accur_y of 97.14%, preci_n of 95.74%, recal_l of 95.71%, F1_score of 95.72%, and MCC of 93.55%. In Fig. 7, the ROC

Table 5 Articles classification of NGDLF-IACI approach under 70:30 splits

Classes	$Accur_y$	$Preci_n$	$Recall_l$	$F1_{Score}$	**MCC**
Training Phase (70%)					
Credible	96.50	94.11	95.75	94.92	92.26
Not Credible	97.78	96.41	95.50	95.95	94.42
Undecided	97.26	96.83	95.98	96.40	94.19
Average	**97.18**	**95.78**	**95.74**	**95.76**	**93.62**
Testing Phase (30%)					
Credible	96.38	93.71	95.84	94.76	92.01
Not Credible	97.90	96.62	95.67	96.14	94.70
Undecided	97.13	96.88	95.61	96.24	93.93
Average	**97.14**	**95.74**	**95.71**	**95.72**	**93.55**

investigation of the NGDLF-IACI system with 70:30 splits has been inspected. The outcome signifies that the NGDLF-IACI method achieves upgraded ROC outcomes through every class, depicting important competence of discerning the class labels. This dependable trend of better ROC investigation across several classes indicates the proficient execution of the NGDLF-IACI technique on predicting classes, underscoring the strong nature from model.

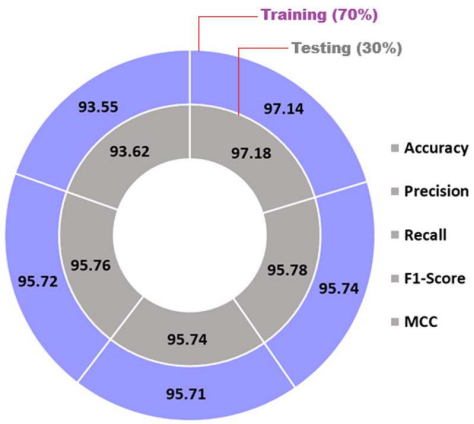


Fig. 6 Average of NGDLF-IACI approach under 70:30 splits

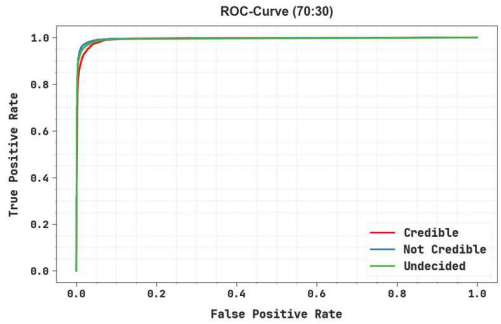


Fig. 7 ROC curve of NGDLF-IACI methodology with 70:30 splits

In Table 6 and Fig. 8, the experimental outcomes of the NGDLF-IACI method with present techniques are given [28–30]. The outcome show that the AraBERTv2 system has presented worse performance with accur $_y$, preci $_n$, recal $_l$, and $F1_{\text{score}}$ of $85.00\%, 94.38\%, 94.02\%$, and 92.95%, correspondingly. Simultaneously, the AraGPT2 approach has attained slightly better results with accur $_y$, preci $_n$, recal $_l$ and $F1_{\text{score}}$ of $90.00\%, 86.33\%, 91.26\%$, and 88.97%, correspondingly. Also, the Xception, SVM, EfficientNetB4, and AraELECTRA methods have reaches moderately nearer performance. Besides, the ConvLSTM technique has outcomes in significant results with accury $_y$, preci $_n$, recal $_1$, and $F1_{\text{score}}$ of $95.84\%, 96.98\%, 96.71\%$, and 96.82%, correspondingly. But the NGDLF-IACI system outperforms the other approaches with maximum accur $_y$, preci $_n$, recal $_l$, and $F1_{\text{score}}$ of 98.33%, 97.43%, 97.25%, and 97.33%, correspondingly.

Table 6 Comparative outcome of NGDLF-IACI system with recent approaches

Techniques	Overall Performance (%)
EfficientNetB4	Accuracy : 93.42, Precision : 94.30, Recall : 96.29, F1score : 95.48
Xception	Accuracy : 92.52, Precision : 94.74, Recall : 94.74, F1 score : 94.74
ConvLSTM	Accuracy : 95.84, Precision : 96.98, Recall : 96.71, F1 score : 96.82
SVM	Accuracy : 90.00, Precision : 90.00, Recall : 90.00, F1 score : 90.00
AraGPT2	Accuracy : 90.00, Precision : 86.33, Recall : 91.26, F1 score : 88.97
AraBERTv2	Accuracy : 85.00, Precision : 94.38, Recall : 94.02, F1 score : 92.95
AraELECTRA	Accuracy : 93.00, Precision : 88.68, Recall : 95.16, F1 score : 88.12
NGDLF-IACI	Accuracy : 98.33, Precision : 97.43, Recall : 97.25, F1 score : 97.33

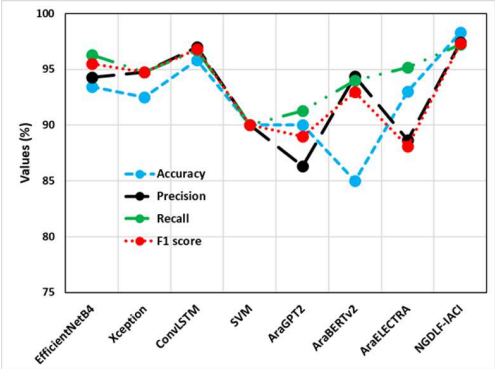


Fig. 8 Comparative outcome of NGDLF-IACI model with other techniques

The computation time (CT) and Error rate outcomes of the NGDLF-IACI approach is related with other methods in Table 7 and Fig. 9. Depend on CT, the NGDLF-IACI system reaches minimal CT of 1.08s while the Xception, ConvLSTM, SVM, EfficientNetB4, AraBERTv2, AraELECTRA, and AraGPT2 techniques attains higher CT values of 5.58s, 7.07s, 6.04s, 2.30s, 4.98s, 8.87s, and 3.08s, respectively. Concurrently, relay on error rate, the NGDLF-IACI model reaches minimal error rate of 1.67% while the Xception, EfficientNetB4, SVM, AraGPT2, AraBERTv2, AraELECTRA, and ConvLSTM approaches reaches improved error rate values of 6.58%, 7.48%, 4.16%, 10.00%, 10.00%, 15.00%, and 7.00%, respectively.

Table 7 Error and CT outcomes of NGDLF-IACI approach with existing methods

Techniques	Error Rate (%)	Computational Time (sec)
EfficientNetB4	6.58	5.58
Xception	7.48	7.07
ConvLSTM	4.16	6.04
SVM	10.00	2.30
AraGPT2	10.00	4.98
AraBERTv2	15.00	8.87
AraELECTRA	7.00	3.08
NGDLF-IACI	1.67	1.08

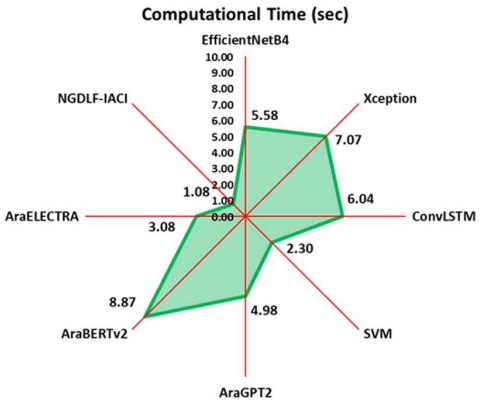


Fig. 9 CT outcome of NGDLF-IACI approach with other systems

An ablation study is showed to systematically analyze the contribution of every component in the presented method by modifying or removing them separately. This research support in understanding how various modules, like optimization strategy, learning architecture, and feature representation, effect whole performance. The outcomes establish that the presence of every component causes to reliable performance developments. Table 8 shows the ablation study of the NGDLF-IACI techniques emphasizing the influence of separate components on classification method. The SSAE+GloVe (with word embedding without parameter tuning and GCN) model has demonstrated lesser performances. Also, the SSAE+GloVe+RAdam (with word embedding and parameter tuning without GCN) approach has exhibited slightly higher results. Meanwhile, the GCN+GloVe (with word embedding without parameter tuning and GCN) and GCN+GloVe+RAdam (with word embedding and parameter tuning without GCN) approaches have outperformed closer performance. However, the proposed NGDLF-IACI (Soft voting-based ensemble model with GloVe word embedding and RAdam parameter tuning process) approach has exhibited effective result with higher accur_y of 98.33%, preci_n of 97.43%, recal_l of 97.25%, and F1_score of 97.33%, respectively. Therefore, the NGDLF-IACI technique can be effectively applied

to accurately classify and reliably assess the credibility of non-credible articles across diverse online sources.

Table 8 Ablation study of NGDLF-IACI methodology

Model	$Accur_y$	$Preci_n$	$Recall_l$	$F1_{Score}$
SSAE+GloVe (with word embedding without parameter tuning and GCN)	95.95	94.65	94.32	94.89
SSAE+GloVe+RAdam (with word embedding and parameter tuning without GCN)	96.52	95.45	95.10	95.60
GCN+GloVe (with word embedding without parameter tuning and GCN)	97.15	96.25	95.90	96.10
GCN+GloVe+RAdam (with word embedding and parameter tuning without GCN)	97.75	96.77	96.48	96.79
NGDLF-IACI (Soft voting-based ensemble model with GloVe word embedding and RAdam parameter tuning process)	98.33	97.43	97.25	97.33

5 Conclusion

This manuscript has presented a novel NGDLF-IACI technique for detecting non-credible articles that enhances the consistency of information and lessens the spread of fake information. Initially, the proposed NGDLF-IACI model preprocesses the text that contains tokenization, noise removal, removing stop word removal, and lemmatization, which assures the trustworthiness of textual data. Furthermore, the GloVe based word embedding is applied to convert text into a vectorized representation model that increase capability and identify sematic patterns. For classification, a soft voting-based ensemble model is deployed that combines SSAE and GCN to accurately classify non-credible articles. To boost the performance of the classification model, RAdam is employed for parameter tuning. An extensive set of simulation analyses is carried to verify the significance of the NGDLF-IACI model. A brief comparative analysis reported the superior outcomes of the NGDLF-IACI methodology over other existing techniques.

Declarations:

Data Availability

The data that support the findings of this study are openly available at https://data.mendeley.com/datasets/67mhx6hhzd/1 , reference number [26].

Conflicts of Interest

The authors declare that they have no known competing financial interests or personal relationships that could have influenced the work reported in this paper.

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Author Contribution

Danah Algawiaz: Conceptualization, methodology, research design, literature review,

data collection and curation, text preprocessing, tokenization, noise and stop-word removal, lemmatization, GloVe-based word embedding, model development, implementation of the stacked sparse autoencoder and graph convolutional network, soft voting ensemble design, Rectified Adam-based parameter tuning, experimental design, performance evaluation, validation, data analysis, visualization, interpretation of results, and writing—original draft. Alya Alshammari: Conceptualization, methodology, linguistic analysis, computational linguistics framework development, textual feature analysis, validation, interpretation of findings, and writing—review and editing. Jahangir Khan: Methodology, machine learning and deep learning model implementation, experimental analysis, model evaluation, validation, and writing—review and editing. Abdullah Suliman Almutlaq: Conceptualization, educational and linguistic analysis, methodology, interpretation of results, validation, and writing—review and editing. Mohammad Albshry: Data curation, preprocessing, experimental evaluation, performance analysis, visualization, and writing—review and editing. Fahad Alshamrani: Methodology, deep learning analysis, ensemble model evaluation, validation, interpretation, and writing—review and editing. Mofadal Alymani: Computational analysis, model implementation, parameter optimization, validation, and writing—review and editing. Abdullah Heleil Alenezi: Conceptualization, methodology, technical supervision, project administration, interpretation of findings, validation, and writing—review and editing. All authors contributed to the development and refinement of the manuscript, critically reviewed the final manuscript, approved the final version, and agreed to be accountable for all aspects of the work.

Ethical Approval

This article does not contain any studies involving human participants or animals performed by any of the authors.

Consent to Participate

Not applicable.

Consent to Publication

All authors have provided consent for publication of this manuscript.

Competing Interests

The authors declare no competing interests

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