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Article

Natural Language Processing with Optimal Deep Learning Based Fake News Classification

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Abstract: The recent advancements made in World Wide Web and social networking have eased the spread of fake news among people at a faster rate. At most of the times, the intention of fake news is to misinform the people and make manipulated societal insights. The spread of low-quality news in social networking sites has a negative influence upon people as well as the society. In order to overcome the ever-increasing dissemination of fake news, automated detection models are developed using Artificial Intelligence (AI) and Machine Learning (ML) methods. The latest advancements in Deep Learning (DL) models and complex Natural Language Processing (NLP) tasks make the former, a significant solution to achieve Fake News Detection (FND). In this background, the current study focuses on design and development of Natural Language Processing with Sea Turtle Foraging Optimization-based Deep Learning Technique for Fake News Detection and Classification (STODL-FNDC) model. The aim of the proposed STODL-FNDC model is to discriminate fake news from legitimate news in an effectual manner. In the proposed STODL-FNDC model, the input data primarily undergoes pre-processing and Glove-based word embedding. Besides, STODL-FNDC model employs Deep Belief Network (DBN) approach for detection as well as classification of fake news. Finally, STO algorithm is utilized after adjusting the hyperparameters involved in DBN model, in an optimal manner. The novelty of the study lies in the design of STO algorithm with DBN model for FND. In order to improve the detection performance of STODL-FNDC technique, a series of simulations was carried out on benchmark datasets. The experimental outcomes established the better performance of STODL-FNDC approach over other methods with a maximum accuracy of 95.50%.

Keywords: Natural language processing; text mining; fake news detection; deep belief network; machine learning; evolutionary algorithm

1 Introduction

In recent decades, Natural Language Processing (NLP), a field in which Machine Learning (ML) method, has been widely employed in different applications. However, NLP stopped its representation as an area of interest completely, a long time ago. At present, a significant number of global companies is interested in examining the sentiment from movie or product reviews and attain the themes or opinions of a discussion from a user automatically, based on their content in social networking sites [1]. In this background, it is vital to identify fake news. Numerous brokers exist in stock markets who are interested in forecasting the stock market trends by extracting the sentiment from financial news articles. These scenarios show how NLP should be widely deployed in different domains [2].

Fake news is a part of pervasive marketing in which the false information is spread online especially through social networking sites such as Snapchat, Facebook, and Twitter to manipulate public perception. Social networking sites have two sides for news' usage; the first is employed to update the community regarding the latest news while the second one is used as a source of spreading false news [3]. But social network-based spread of fake news is quick to achieve, easy to disseminate the false information, and incurs low cost. Moreover, due to its simplicity and lack of control on internet, the spreading of 'fake news' is unprecedented in the recent years [4]. This pattern of spreading articles online that do not conform to fact has affected almost all the public domains such as science, health, sports, politics etc., [5]. Financial market is one of the major domains targeted by fake news peddlers [6]. Here, a rumor may bring the market to a halt which can bring disastrous consequences. The capability to take a decision mostly depends on the kind of data that a user receives; the world view is shaped according to the data that consumed by the user. This situation gets worsens once the people are manipulated by online fake content. It is challenging to recognize and differentiate the legitimate news from fake news [7].

World Wide Web comprises of information in different formats like audio, video, and documents. Computation methods like NLP are utilized in the detection of anomalies, whereas other methods including propagation analysis, are used to check the spread of fake news. Several researches have focused primarily on classification and detection of fake news on social networking sites like Twitter, Facebook, LinkedIn etc. [8]. From theoretical viewpoint, fake news can be categorized into distinct kinds whereas the knowledge is extended to generalize ML models for various fields [9]. DL methods are highly capable of detecting fake news. A few research studies has already been conducted to understand the significance of NNs in this domain. In literature [10], a hybrid method was presented by integrating RNN and CNN [10]. This method is essential to categorize a news as either legitimate or fake and is cast as a binary classification issue.

In this background, the current study focuses on the design of Natural Language Processing with Sea Turtle Foraging Optimization-based Deep Learning model for Fake News Detection and Classification (STODL-FNDC). The proposed STODL-FNDC model has two primary stages such as pre-processing and Glove-based word embedding. In addition, STODL-FNDC model employs Deep Belief Network (DBN) technique for FND and classification. Furthermore, STO algorithm is utilized to optimally adjust the hyperparameters involved in DBN model. In order to improve the detection performance of STODL-FNDC approach, a series of simulations was carried out on benchmark datasets.

Rest of the paper is organized as follows. Section 2 offers a brief literature review. Section 3 discusses the proposed model whereas Section 4 validates the proposed model. Lastly, Section 5 draws the conclusion for the study.

2 Related Works

Sahoo et al. [11] presented an automatic FND method in chrome to detect the spread of fake news on Facebook. In detail, the method can be utilized with several features that are connected with Facebook account. With numerous news content features, the method is used to analyze the performance of the account using DL technique. Nasir et al. [12] presented a new hybrid DL technique by integrating CNN and RNN to create a fake news classifier. This technique was effectively validated on two fake news data sets (ISO and FA-KES) and it attained excellent recognition outcomes which were significantly superior to other non-hybrid baseline approaches. Kaliyar et al. [13] presented a BERT-based DL technique (FakeBERT) by integrating distinct parallel blocks of a single-layer DCNN that contains distinct kernel size and filter with BERT.

Jiang et al. [14] estimated the performance of five ML techniques and three DL techniques on two fake and real news data sets of distinct size with cross-validation. The study also utilized Term Frequency (TF), TF-IDF, and embedded approaches to obtain text representation for ML and DL techniques correspondingly. Mouratidis et al. [15] projected a new approach for automatic recognition of fake news on Twitter. This model contains pairwise text input, a new DNN learning structure that allows flexible input fusion at several network layers, and different input modes such as word embedded and combined linguistic and network account features. In the study conducted earlier [16], the content from news articles and the presence of echo chambers (social media community-based user opinion distribution) from social networks were obtained to perform FND.

In literature [17], an FND system was presented utilizing DL technique. Primarily, the news article is pre-processed and analyzed based on various training methods. Afterward, an ensemble learning method relating four distinct methods was presented to FND. In addition, in order to achieve superior accuracy results from FND, the optimizing weight of ensemble learning methods was defined utilizing Self-Adaptive Harmony Search (SAHS) technique. Islam et al. [18] presented a new solution in which the authenticity of news is ensured using NLP approaches. In detail, this work presented a new method with three stages such as stance recognition, author credibility confirmation, and ML-based classifier to verify the authenticity of the news.

3 The Proposed Model

In current study, a novel STODL-FNDC technique has been developed to effectually discriminate the fake news from legitimate news. The proposed STODL-FNDC model encompasses a series of processes namely, pre-processing, word embedding, DBN-based fake news detection, and STO-based hyperparameter optimization. STO algorithm is used to fine tune the hyperparameters of DBN model which in turn considerably improves the detection performance. Fig. 1 depicts the overall process of the proposed STODL-FNDC technique.

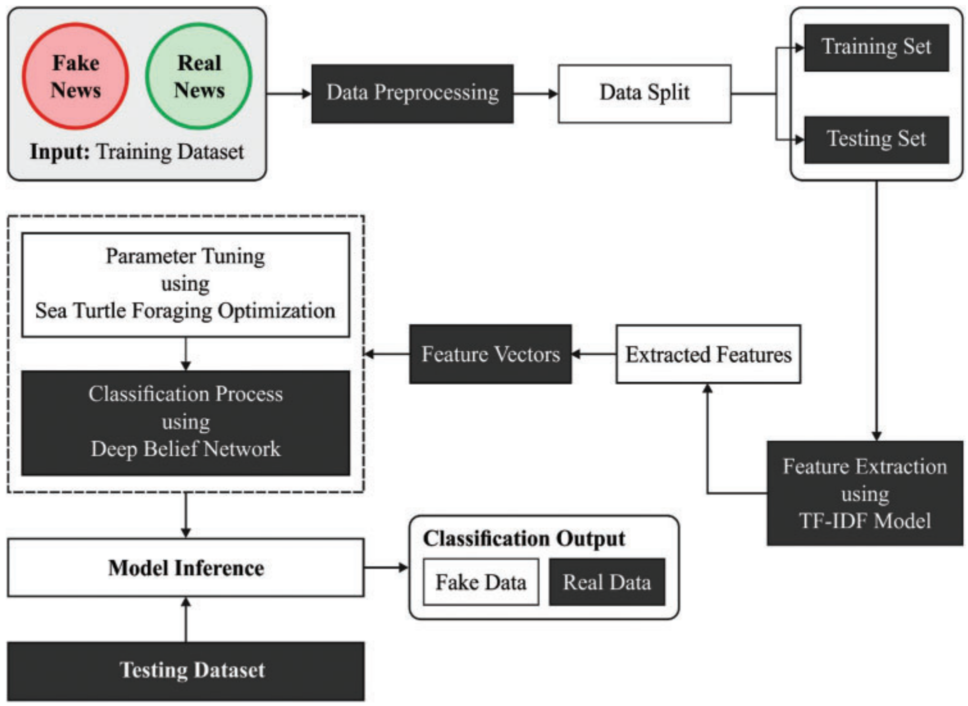

Figure 1: Overall process of STODL-FNDC technique

3.1 Preprocessing

The new text format has different unstructured features and is relatively free to analyze. It is impossible to utilize the existing algorithms to classify the emotions expressed in web comments. So, it becomes essential to convert the text data into real number vector for processing and analysis. This technique depends on the statistical data of global vocabulary co-occurrence for learning word vectors, thereby integrating the statistical data with local context window technique. To save further co-occurrence data from text vocabulary, GloVe method constructed an accurate matrix of vocabulary *co* occurrence matrix as given herewith.

$$X_i = \sum_{k=1}^{V} X_{i,k} \tag{1}$$

$$P_{ik} = \frac{X_{i,k}}{X_i} \tag{2}$$

$$R_{i,j,k} = \frac{P_{i,k}}{P_{j,k}} \tag{3}$$

Here, X_i indicates the number of words that emerge in a row of matrix, i; V denotes the overall number of words from the dictionary; $X_{i,j}$ characterizes the number of times, the words j and i appear together in a fixed window from training corpus; P_{ik} characterizes the possibilities that the word k arises from a set window out of the word i; and $R_{i,j,k}$ shows the relationships among the three words, i, j, and k. When the value of $R_{i,j,k}$ is higher, it implies that i and k words are correlated, however, J and K are not; when the value of $R_{i,j,k}$ is smaller, it implies that j and k words are correlated whereas T and

K are not. When the value of $R_{i,j,k}$ approach is 1, it implies that j and k words are correlated, while i and k are interrelated or j and k words are not interrelated, and i and k words are not correlated. In comparison with original probability P_{ik}, $R_{i,j,k}$ can differentiate the relationships among the words in a better way.

GloVe method constructs a function $F\left(w_i,\ w_j,\ w_k^{'}\right)$ to increase the ratio closer to P_{ik}/P_{jk} as the convergence target. Thus, the word vector comprises of data in co-occurrence matrix, whereas $w, w' \in R^d$ denotes the word vector. Thus, a weight equation $f\left(X_{i,j}\right)$ is presented, while creating the loss function which is shown below.

$$J = \sum_{i,j=1}^{V} f\left(X_{i,j}\right)\left(\left(w_i^T w_j^{'} + b_i + b_j^{'}\right) - \log\left(X_{ij}\right)\right)^2 \tag{4}$$

Whereas $X_{i,j}$ denotes the number of times w_i and w_j words appear together in the window; W_i^T illustrates the transposition of word vector from the context of word i, once the word w_i is utilized as context; wj' denotes the word vector of j, once wj denotes the center word of the context; bi and bj' denote the biases; and V shows the overall number of words in the dictionary.

3.2 DBN-Based Fake News Detection Module

The next stage of data preprocessing is Fake News Detection module using DBN model to categorize the news as either fake or legitimate. DL technique extracts the optimum features in primary processing of map features. It utilizes RBM technique in the learned procedure [19]. The system implements the learning procedure to perform emotion classifiers in user comments on social networks. The two important steps are followed in the next stage. All the nodes of x in the group of nodes, X are utilized as input v_i for RBM learning processing. The hidden unit h_j is expressed as follows.

$$p(h_j = 1|v) = \sigma\left(\sum_i w_{ij} v_i + b_j\right) \tag{5}$$

where $\sigma(\cdot)$ implies the sigmoid function and b_j stands for bias to hidden state. It can recreate all the visible vectors as v with a subsequent formula that is same as Eq. (6):

$$p(v_i^{'}|h) = \sigma\left(\sum_j w_{ij} + a_i\right) \tag{6}$$

where $\sigma(\cdot)$ defines the sigmoid function and a_i demonstrates the bias to recreate the novel vector state. a_i refers to bias which takes place, if the input state is recreated as a novel input vector state from RBM learning. RBM is a powerful NN to extract the features from data. This strength can be utilized to extract the essential features from 50-D input vector. RBM infrastructure contains 1 input state, 3 hidden states, and 1 output state. The output state contains 50 nodes which are later utilized as input towards DBN input state. It is appealed to the output state as feature map (X). The secondary part of the presented DL technique is DBN [19]. Eq. (6) shows the computation of NN between input state (X) and hidden state (H) to all the input nodes (Xi), whereas h defines the index of hidden states. The sigmoid function is utilized to calculate the resultant nodes of hidden states.

$$H_h = f\left(net_h\right) = \frac{1}{1 + e^{-net_k}} \tag{7}$$

$$net_h = \sum_i W_{ih} X_i - \theta_h \tag{8}$$

Eq. (8) depicts the computation of weighted sum to all the nodes from all the hidden states. Theta (θ) is biased to all the nodes, while W_{ih} refers to the weight of all the nodes in input to hidden states. The computation is repeated until a sufficient target output is attained. In next stage, it can compute the resultant value $\left(Y_j\right)$ between the hidden (H) and output states (Y) and is utilized in Eq. (9). The sigmoid function $f\ (net_h)$ is utilized to compute the resultant node of the output state.

$$Y_j = f\ (net_h) = \frac{1}{1 + e^{-netj}} \tag{9}$$

$$net_j = \sum_i W_{hj} H_h - \theta_j \tag{10}$$

Eq. (10) defines the computation of weighted sum to all the nodes from all output states. Theta (θ) is biased to all the nodes. W_{hj} demonstrates the weight to all the nodes in hidden-to-output states. The computation is repeated until the fulfilled target output is achieved.

3.3 STO Based Hyperparameter Tuning Module

In order to adjust the hyperparameter values of DBN model in an optimal manner, STO algorithm is employed. In general, sea turtles do not swarm the animals, whereas they forage independently for food. Their foraging behavior is effective and interesting. They are skilled ocean navigators, long-lived and migrate continuously during their lifetime. Their foraging and migration behaviors are unique and motivate the research community to develop a technique that imitates their behavior. Naturally, sea phytoplankton, grasses, and algae produce a substance that disintegrates into stronger smelly dimethyl sulfide (DMS) to regulate the climate through ocean and help them in their survival. The sea turtles detect DMS and find those areas with high concentrations of the prey [20,21]. It moves towards the food source that releases this chemical with stronger odor. The pseudo-code of STO approach is given herewith.

Step 1: Arbitrarily initialize the position of N sea turtles in D-dimension searching space

$$T_i\,(0) = \left[t_i^1,\ t_i^2, \ldots,\ t_i^D\right] \tag{11}$$

When $i = 1$ to N.

Step 2: Arbitrarily initialize the velocity, $V_i\,(0) = \left[v_i^1, v_i^2, \ldots,\ v_i^D\right]$. The velocity in all the dimensions of turtle, v_i^d, is a constraint in $\left[v\_\min^d,\ v\_\max^d\right]$:

$$v\_\max^d = \lambda \left[XUB^d - XLB^d\right] \tag{12}$$

$$v\_\min^d = -v\_\max^d \tag{13}$$

Whereas XUB^d and XLB^d denote the upper and lower limits of d^{th} dimension of searching space and λ shows a real value within $[0, 1]$.

Step 3: Arbitrarily create the position of M food sources

$$K_j = \left[k_j^1,\ k_j^2, \ldots,\ k_j^D\right] \tag{14}$$

When $j = 1$ to M. the fitness value of each food source is defined.

Step 4: Estimate the fitness of each turtle. The stronger turtle is defined as follows.

$$I = \arg\max_i [f(T_i(t))] \tag{15}$$

Here $f(T_i(t))$ denotes the fitness of turtle i at time t.

Step 5: Estimate the ocean current velocity at turtle location, $VC_i = \left[vc_i^1, vc_i^2, \ldots, vc_i^D\right]$:

$$VC_i(t) = \gamma [T_I(t) - T(t)] \tag{16}$$

Step 6: Upgrade the velocity using Eq. (17):

$$V_i(t+1) = V_i(t) + VC(t) + \left[\frac{f(T_i(t)) - f(T_i(t-1))}{f(T_i(t-1))}\right][T_i(t) - T_i(t-1)] \tag{17}$$

Whereas $T_i(t)$ denotes the location of turtle i in time t and $f(T_i(t))$ indicates the fitness of turtle i in time t.

Step 7: Estimate the strength of DMS odor in food resource j viz. identified by the turtle, $C_{ij}(t)$, and compare the fitness of turtles with the fitness of food sources.

When the turtle fitness is high than the food resource, the odor strength from food source is considered as zero.

$$C_{ij}(t) = \frac{f\left(K_j\right)}{\sum_{q=1}^{M} f(K)} e^{-\left[\frac{d_{ij}^2}{2\sigma^2(t)}\right]} \tag{18}$$

Whereas $f\left(K_j\right)$ denotes the fitness of food source j. d_{ij} indicates the distance between turtle i and food source j. $\sigma(t)$ controls how farther, the DMS odor can spread, while it gets exponentially reduced with time:

$$\sigma(t) = \sigma_0 e^{-[\frac{t}{T}]} \tag{19}$$

Step 8: Find the optimal food source for turtle i. The optimal food source has the maximum value of $C_{ij}(t)$ amongst each food source.

$$J = \arg\ \max \left[C_{ij}\right] \tag{20}$$

Step 9: Upgrade the location.

$$T_i(t+1) = T_i(t) + \eta V_i(t+1) + C_{iJ}(t)[K_J - T(t)] \tag{21}$$

Step 10: Check the end condition. When the condition is satisfied, the process world is ended. Otherwise, two criteria are checked: i) when t/T value is an integer, return to step 3; ii) When t/T value is not an integer, return to step 4. Fig. 2 demonstrates the steps involved in STO technique [22].

4 Result and Discussion

The proposed STODL-FNDC model was experimentally validated using three benchmark datasets. Among these, the first ISOT Fake news dataset [23] includes 44,898 articles with 21,417 true articles and 23,481 fake articles. The total corpora comprise of articles from diverse fields particularly, political news. Kaggle fake news dataset [24] is constructed using various internet sources. In this work, 1,000 fake and 1,000 real articles were used from the datasets. Finally, Kaggle, Fake News Detection USA dataset [25] includes a total of 3352 articles.

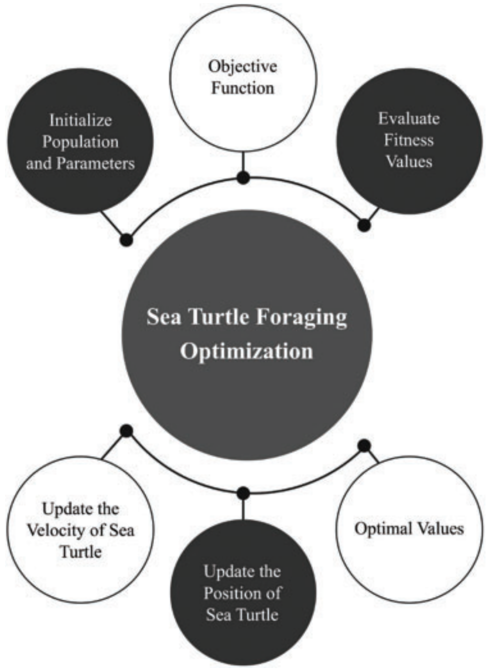

Figure 2: Steps involved in STO

Fig. 3 demonstrates the confusion matrices generated by the proposed STODL-FNDC model under three distinct runs on ISOT Fake News Dataset. The figures report that STODL-FNDC technique identified 21,288 original news and 23,392 fake news appropriately under run-1. In addition, STODL-FNDC technique categorized 21,315 original news and 23,400 fake news under run-2. Lastly, in run-3, the proposed STODL-FNDC technique organized a total of 21,316 original news and 23,339 fake news.

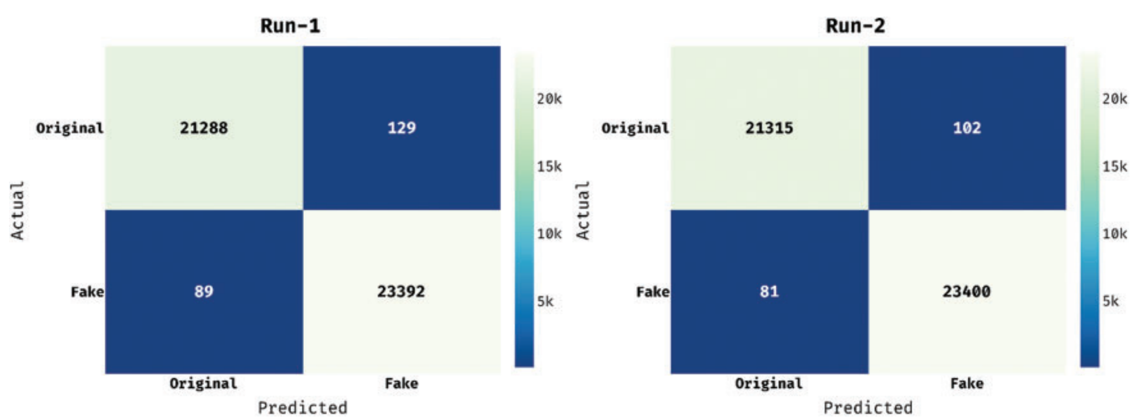

Figure 3: (Continued)

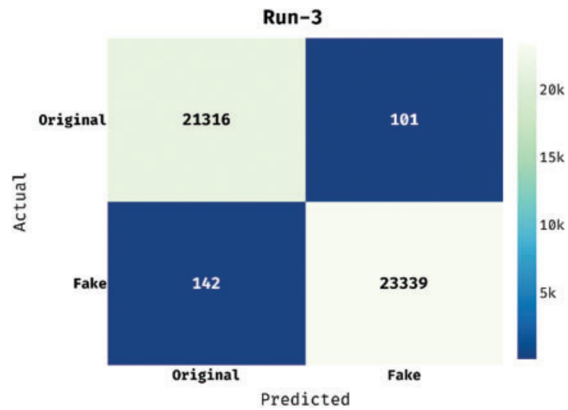

Figure 3: Confusion matrix of STODL-FNDC technique on ISOT fake news dataset-1

Tab. 1 and Fig. 4 illustrate the overall classification results obtained by the proposed STODL-FNDC model on ISOT Fake News Dataset. The experimental values indicate that the proposed STODL-FNDC model accomplished the maximum fake news' classification outcomes. For instance, with run-1, STODL-FNDC model obtained a $prec_n$ of 99.58%, $reca_l$ of 99.40%, $accu_y$ of 99.51%, and an F_{score} of 99.49%. At the same time, with run-2, the proposed STODL-FNDC model obtained a $prec_n$ of 99.62%, $reca_l$ of 99.52%, $accu_y$ of 99.59%, and an F_{score} of 99.57%. Along with that, with run-3, the proposed STODL-FNDC model obtained a $prec_n$ of 99.34%, $reca_l$ of 99.53%, $accu_y$ of 99.46%, and an F_{score} of 99.43%.

Table 1: Results of the analysis of STODL-FNDC technique on ISOT fake news dataset-1

No. of runs	$Prec_n$	Rec_l	Acc_y	F_{Score}
Run-1	99.58	99.40	99.51	99.49
Run-2	99.62	99.52	99.59	99.57
Run-3	99.34	99.53	99.46	99.43
Average	99.51	99.48	99.52	99.50

Tab. 2 and Fig. 5 provides the results accomplished from detailed comparative analysis by STODL-FNDC model against existing techniques on ISOT Fake News Dataset [26]. The results indicate that KNN, CNN, and BiLSTM models achieved low classification performance over other methods. Followed by, LOR and XGBoost models produced slightly improved classification outcomes.

Along with that, ADB technique accomplished a reasonable classification performance. However, the proposed STODL-FNDC model produced superior results with a $prec_n$ of 99.62%, $reca_l$ of 99.52%, $accu_y$ of 99.59%, and an F_{score} of 99.57%.

The accuracy outcome analysis was conducted for STODL-FNDC technique on ISOT Fake News dataset-1 and the results are portrayed in Fig. 6. The outcome infer that STODL-FNDC technique accomplished a high validation accuracy compared to training accuracy. Further, it can also be inferred that the accuracy values got saturated with the count of epochs.

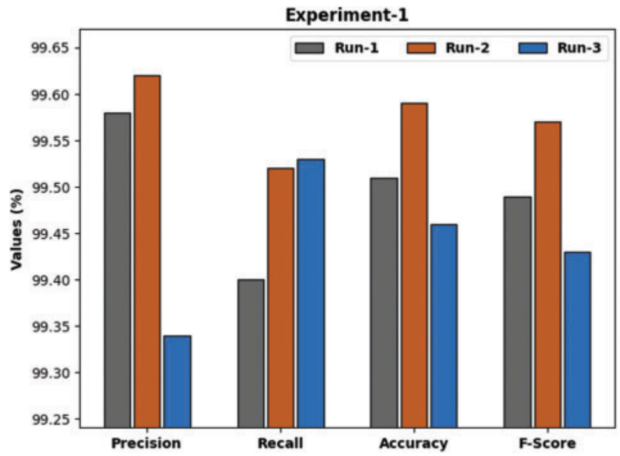

Figure 4: Results of the analysis of STODL-FNDC technique on ISOT fake news dataset-1

Table 2: Comparative analysis results of STODL-FNDC technique against existing techniques on ISOT fake news dataset-1

Methods	$Prec_n$	Rec_l	Acc_y	F_{Score}
STODL-FNDC	99.62	99.52	99.59	99.57
LOR algorithm	98.97	97.53	97.77	98.52
KNN algorithm	91.75	86.74	87.67	90.10
ADB algorithm	98.79	99.01	98.05	98.11
XGBoost algorithm	99.60	98.92	97.83	99.51
CNN algorithm	83.59	89.59	87.72	88.09
Bi-LSTM algorithm	91.88	77.49	85.99	84.62

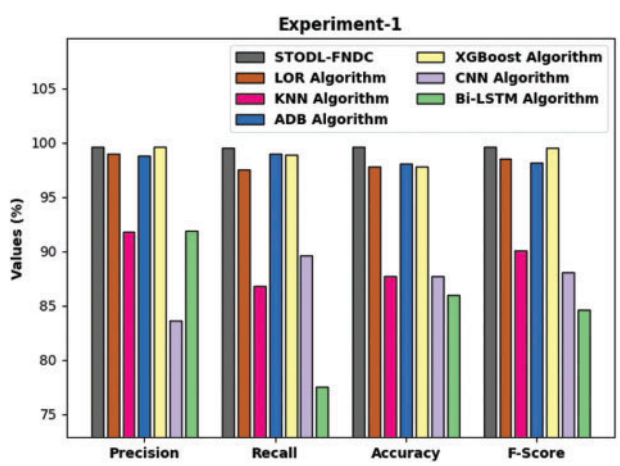

Figure 5: Results of the analysis of STODL-FNDC technique on ISOT fake news dataset-1

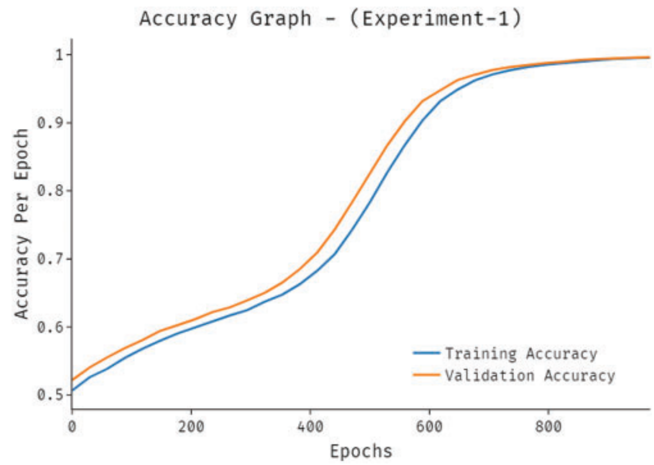

Figure 6: Accuracy analysis results of STODL-FNDC technique on ISOT fake news dataset-1

Loss outcome analysis was conducted for STODL-FNDC technique on ISOT Fake News dataset-1 and the results are shown in Fig. 7. The figure reveals that the proposed STODL-FNDC technique reduced the validation loss over training loss. Further, it can be observed that the loss values got saturated with the count of epochs.

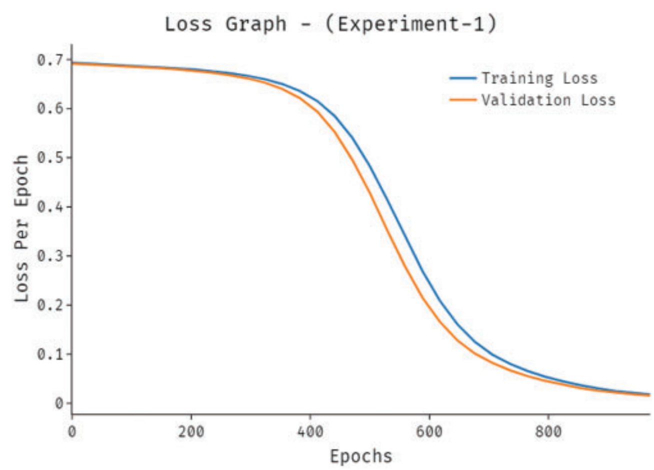

Figure 7: Loss analysis results of STODL-FNDC technique on ISOT fake news dataset-1

Fig. 8 demonstrates the confusion matrices generated by STODL-FNDC model under three distinct runs on ISOT Fake News Dataset. The figures report that the proposed STODL-FNDC technique categorized 941 original news and 960 fake news properly under run-1. In addition, the proposed STODL-FNDC approach categorized 950 original news and 960 fake news under run-2. Lastly, in run-3, STODL-FNDC technique organized 947 original news and 957 fake news appropriately.

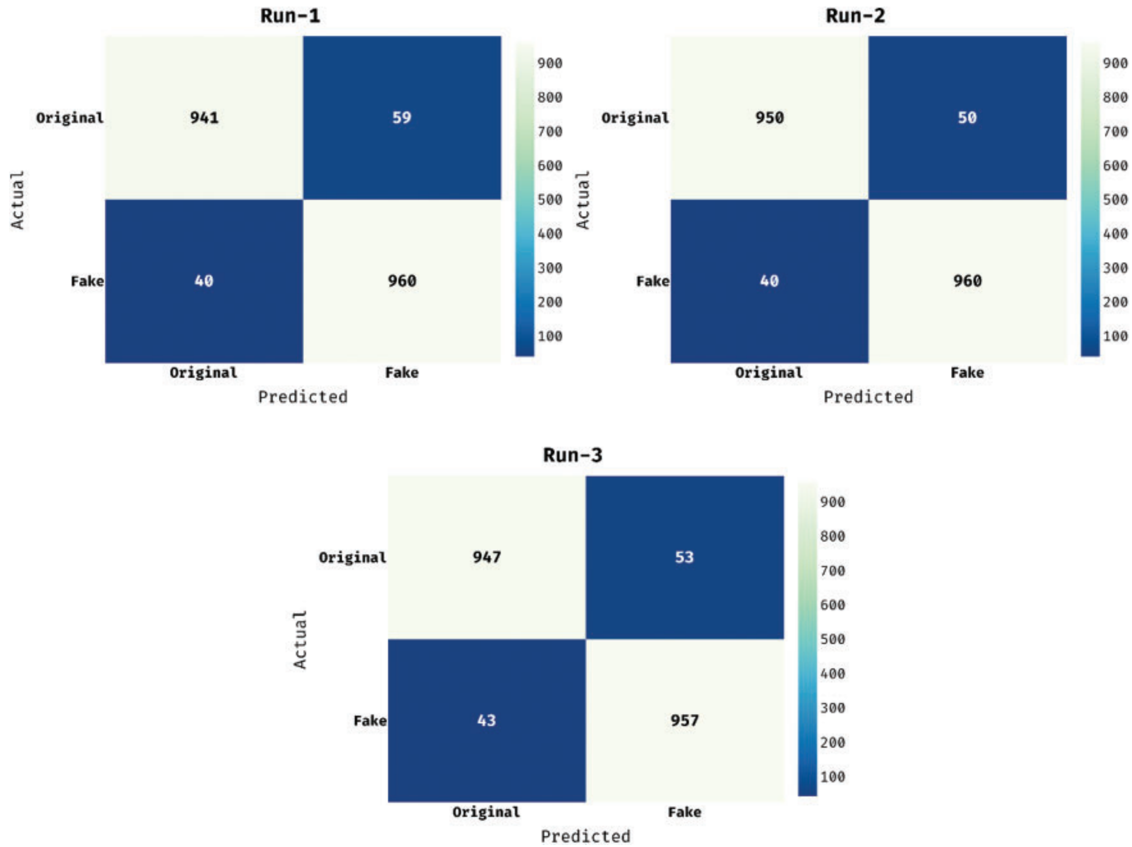

Figure 8: Loss analysis results of STODL-FNDC technique on ISOT fake news dataset-2

Tab. 3 and Fig. 9 illustrate the overall classification results obtained by the proposed STODL-FNDC model on ISOT Fake News Dataset. The experimental values indicate that the proposed STODL-FNDC model accomplished the maximum fake news' classification outcomes. For instance, with run-1, the STODL-FNDC system obtained a $prec_n$ of 95.92%, $reca_l$ of 94.10%, $accu_y$ of 95.05%, and an F_{score} of 95%. Similarly, with run-2, STODL-FNDC algorithm obtained a $prec_n$ of 95.96%, $reca_l$ of 95%, $accu_y$ of 95.50%, and an F_{score} of 95.48%. Eventually, with run-3, the proposed STODL-FNDC methodology obtained a $prec_n$ of 95.66%, $reca_l$ of 94.70%, $accu_y$ of 95.20%, and an F_{score} of 95.18%.

Table 3: Results of the analysis of STODL-FNDC technique on ISOT fake news dataset-2

No. of runs	$Prec_n$	Rec_l	Acc_y	F_{Score}
Run-1	95.92	94.10	95.05	95.00
Run-2	95.96	95.00	95.50	95.48
Run-3	95.66	94.70	95.20	95.18
Average	95.85	94.60	95.25	95.22

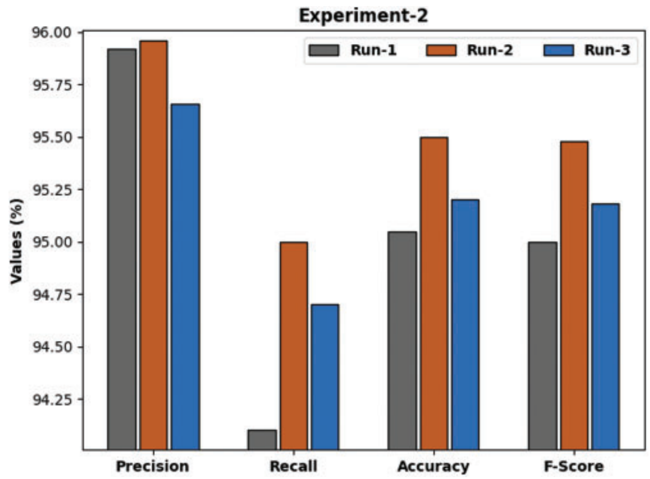

Figure 9: Results of the analysis of STODL-FNDC technique on ISOT fake news dataset-2

Tab. 4 and Fig. 10 demonstrates the results attained from detailed comparative analysis by STODL-FNDC model against existing techniques on ISOT Fake News Dataset. The results reveal that KNN, CNN, and BiLSTM systems achieved the least classification performance over other methods. Then, LOR and XGBoost algorithms produced somewhat higher classification outcomes. Moreover, ADB technique accomplished a reasonable classification performance. Finally, the proposed STODL-FNDC methodology produced superior results with a $prec_n$ of 95.96%, $reca_l$ of 95%, $accu_y$ of 95.50%, and an F_{score} of 95.48%.

Table 4: Comparative analysis results of STODL-FNDC technique against existing techniques on ISOT fake news dataset-2

Methods	$Prec_n$	Rec_l	Acc_y	F_{Score}
STODL-FNDC	95.96	95.00	95.50	95.48
LOR algorithm	91.30	90.58	92.02	92.15
KNN algorithm	21.44	24.18	27.45	23.49
ADB algorithm	91.59	92.77	91.58	92.75
XGBoost algorithm	93.30	93.81	93.29	93.52
CNN algorithm	65.60	70.79	66.16	67.83
Bi-LSTM algorithm	43.63	59.12	52.84	44.39

Accuracy analysis was conducted for STODL-FNDC technique on ISOT Fake News dataset-2 and the results are portrayed in Fig. 11. The outcomes exhibit that the proposed STODL-FNDC technique enhanced the validation accuracy compared to training accuracy. Further, it can also be observed that the accuracy values got saturated with the count of epochs.

Loss outcome analysis was conducted for STODL-FNDC technique on ISOT Fake News dataset-2 and the results are depicted in Fig. 12. The figure reveals that the proposed STODL-FNDC method reduced the validation loss over training loss. So, it can be inferred that the loss values got saturated with the count of epochs.

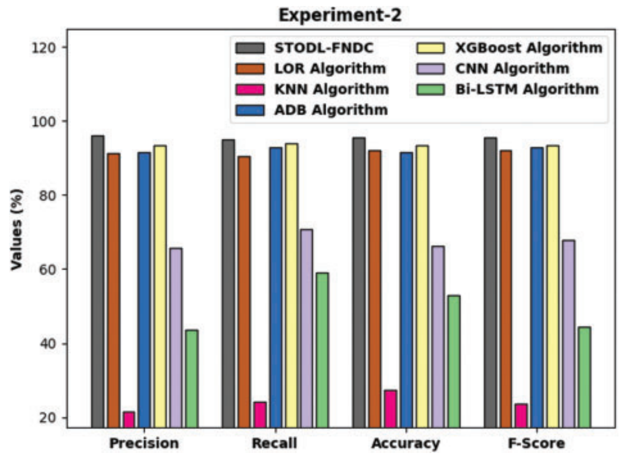

Figure 10: Comparative analysis results of STODL-FNDC technique on ISOT fake news dataset-2

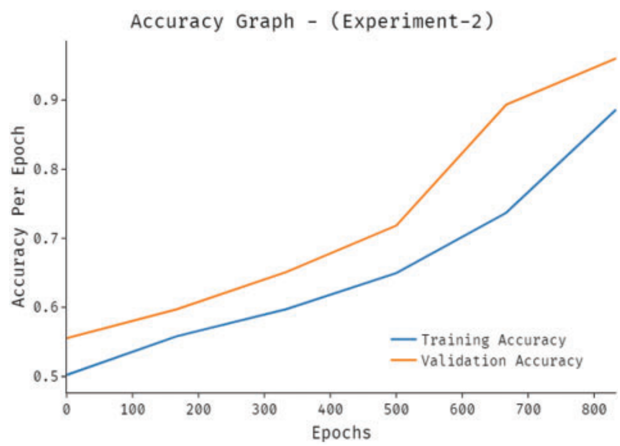

Figure 11: Accuracy analysis results of STODL-FNDC technique on ISOT fake news dataset-2

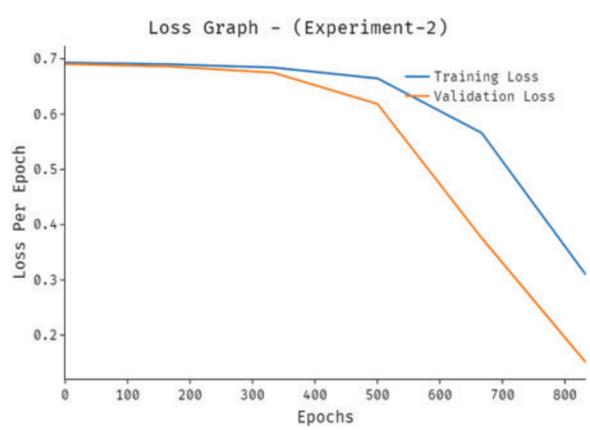

Figure 12: Loss analysis results of STODL-FNDC technique on ISOT fake news dataset-2

5 Conclusion

In this study, a novel STODL-FNDC technique has been developed to effectually discriminate the fake news from legitimate news. The proposed STODL-FNDC model encompasses a series of processes namely pre-processing, word embedding, DBN-based fake news detection, and STO-based hyperparameter optimization. STO technique is used to fine tune the hyperparameters of DBN model which considerably improves the detection performance. In order to validate the detection performance of STODL-FNDC approach, a series of simulations was carried out on benchmark datasets. The experimental results established that the proposed STODL-FNDC approach excelled in its performance over other methods under diverse evaluation metrics. Therefore, the proposed STODL-FNDC technique can be employed for effectual detection of fake news in real-time scenarios. In future, advanced hybrid DL models can also be developed to improve the detection performance.

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