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Probability-based spider monkey optimization-driven deep learning for intelligent fake news detection

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Abstract

Fake news has more effects on spreading misinformation by reducing the scale and power of online social media, which degrades people's trust in traditional journalism and the press and also changes the sentiments and opinions of the public. Therefore, this fake news detection is a crucial activity as it contains subtle differences between fake and real news. The major concept of this task is to promote a well-organized and reliable fake news detection method with intelligent technology. The pre-processing was initially performed and then it was subjected to the feature extraction phase. Here, the enhanced optimization algorithm termed as "Probability-based Spider Monkey Optimization (P-SMO)" is used for performing the selection of primary features. The detection of fake or real news is sophisticated by the Optimized Activation Function-based Deep Neural Network (OAF-DNN), in which the P-SMO helps to optimize the activation function to facilitate attaining better detection accuracy and high precision. From the overall evaluation of the results, the accuracy and precision of the offered model attain 98.3% and 98.65%. Experimental analysis of the offered approach is conducted by testing it with the baseline methods based on diverse evaluation metrics. Thus, the developed method outperformed the conventional methods to illustrate its superior performance. The developed fake news detection method can help to ultimately identify and debunk misinformation for generating optimal information, leading to enhanced public trust and decision-making. It has the ability to optimally detect unnecessary details in financial, online misinformation, healthcare, military, and election-related applications.

Keywords: Enhanced fake news detection, optimal feature selection, optimized activation function-based deep neural network, probability-based spider monkey optimization, term frequency-inverse document frequency.

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1. Introduction

In recent years, the dissemination of fake news has become one of the most severe issues, which can be described as "made-up stories written to deceive" by the New York Times. The formats of fake news are published by the New York Times and are utilized by traditional news agencies [1]. This fake news is recently used to increase partisan conflict and political polarization. Some examples of fake news include controversies identified in the "Trump falsely accuses Obama of wiretapping him [2], Japan cancels microwaves, the Indian airstrike in Balakot in 2019, alcohol kills coronavirus, and the Supreme Court has not ruled that vaccinated people are products." It can be utilized to increase attention among journalists, the general public, politicians, and researchers. This fake news is published or written to damage the image of a corresponding person. In general, fake news is defined as a text classification problem that consists of straightforward propositions [3]. Fake news has the potential to destroy, accept, and disseminate, which makes it one of the most popular threats to the concept of logical truth [4, 5]. There exists a growing population dedicated to spreading fake news, and thus, most researchers are focused on researching and developing methods for determining and identifying misleading content [2, 6].

Earlier scientific analysis has confirmed that human lacks a certain capacity to differentiate the real and false facts. While differentiating the fake news from the actual facts, humans have reduced the correctness up to 54% of the total probability of finding the fake news. Still, the effort to find fake news leads to several problems in social networks and data consumption [7-9]. The spread of malicious content in the network will affect the performance of the network and also degrade the processing resources and service credibility [10, 11]. Moreover, fake news reduces the Quality of Trust (QoT) in news distribution, which shows the reduction of user trust concerning the specific news source [12-17].

More technologies based on cues and features are being developed for detecting fake news [18-20] that differentiate between true news and fake news content. This can be achieved by implementing linguistic analysis-based methods with the collection of linguistic cues, which contain information about the content veracity [21, 22]. This linguistic method differentiates fake news by utilizing the uniqueness of language, writing style, and sentiment. This method does not depend on the hand-engineered and task-specific cue sets but it requires an automatic way of extracting the linguistic features from the text [23]. The performance of linguistic analysis techniques is superior to the cue-based methods, yet it does not fully utilize the entire syntactic and semantic information present in the content. In addition, machine learning methods are utilized for capturing the irregular mapping of the data, mostly in deep structured architectures. This neural network method is involved in automatically performing fake news detection [24-26] and provides enhanced performance in real-time applications. On the other hand, deep learning models [27] with dense feature extraction suffer from detecting fake news, because the fake news content is more similar to the truth content to deceive the readers. Further, it is difficult to evaluate the veracity with the help of text analysis independent of using additional information and fact-checking [28]. On observing the issues of fake news in social networks, it is important to implement improved fake news detection with a high accuracy rate to overcome the challenges that are faced by the baseline detection of fake news methods.

The core innovations of this task are depicted below:

- To design a fake news detection approach using the suggested DNN method along with the optimal feature selection by an enhanced optimization algorithm for achieving accurate fake news detection from the given data.
- To design the latest selection of optimal feature approaches by the offered P-SMO that could enhance the classifier to train faster and minimize the complexity.
- To implement the new optimized deep structured architectures named OAF-DNN by using the developed P-SMO for assisting the categorization of real news with fake news effectively, with diverse architectural improvements.
- To promote a novel optimization algorithm termed as P-SMO for elevating the detection performance of fake news, thus influencing the selection of the best solution to attain the best detection outcome.

The leftovers of this work are provided as follows. Module II depicts the superiorities and the downsides of the offered approach. In module III, the developed model using OAF-DNN and the offered P-SMO algorithm is depicted. In module IV, the optimal feature selection and feature extraction are carried out. In module V, the OAF-DNN for fake news detection is studied. Module VI shows the yield results of the offered approach. In module VIII, the given enhanced fake news detection is completed.

2. Desk Review

2.1. Hybrid Deep Structured Technique

In 2021, Asghar et al. [29] implemented a detection method for identifying fake news based on hybrid deep learning techniques with CNN and RNN. The presented framework has attained elevated detection outcomes when tested with other conventional non-hybrid methods. But it was required to build a large database for further improvements. In 2021, Hanshal et al. [30] investigated a DNN-based method for detecting tumors in the given data. The hybrid method was developed by correlating the features of "Bidirectional Long Short-Term Memory (B-LSTM) with Convolutional Neural Network (CNN)" for categorizing the rumors and non-rumors in the data. This method has minimized the overfitting problem and also has enhanced the accuracy value. Yet, it was affected by its performance while using a larger number of samples for training. In 2022, Kaliyar et al. [31] recommended automatic fake news detection through a hybrid-improved deep learning model. They have adopted an automated data augmentation approach using a Generative Adversarial Network-based Auxiliary Classifier.

Finally, through the evaluation of the designed model with standard datasets, it has shown better outcomes than traditional approaches.

2.2. Transformers (BERT)-Based Deep Learning Framework

In 2021, Palani et al. [32] developed a "Bidirectional Encoder Representations from Transformers (BERT)-based deep learning approach (FakeBERT)" for utilizing the detection performance of the fake news by concatenating the various blocks of the CNN layer with different kernel sizes. The designed approach was utilized for acquiring the more trivial features from every layer and was less prone to overfitting problems. Conversely, the suggested model has not encoded the position of the object and its orientation. Also, it was considered to be "spatially invariant to the given input data". In 2022, Kaliyar et al. [33] recommended a novel approach for creating multi-modal high information content with a feature vector. The textual features were extracted using the BERT approach for preserving the semantic correlations among words. They have used a capsule neural network (CapsNet) for capturing the prominent visual attributes from the images. Those gathered features were integrated to obtain a richer data illustration for helping the determination of the news. The experimental analysis on various standard datasets has shown maximum efficiency when compared with traditional models.

2.3. Deep Learning-Based Approaches

In 2021, Li et al. [34] proposed an "EchoFakeD" framework, which was used for obtaining enhanced performance by utilizing an effective DNN approach. The proposed model was employed for modeling the concatenated representation while detecting fake news. Yet, it has the problem of cost inefficiency due to its complex data models. In 2020, Zervopoulos et al. [35] implemented a new framework based on the "multi-level word features" for identifying fake news. These features were obtained from the CNN method for achieving improved detection performance in cultural communication. This developed method was used for generating the "local Convolutional features and global semantic features" for getting effective semantic data capturing. On the other hand, this suggested model has to be further improved for applying it to a wide range of applications. In 2022, Ozbay and Alatas [36] evaluated various sets of input features for predicting fake news using deep learning approaches. It has depicted its superiority on various performance metrics.

2.4. Artificial Intelligence Method

In 2020, Kaliyar et al. [37] investigated a new detection framework for estimating fake news from a given set of online social media data by utilizing "several artificial intelligence methods". The proposed model has performed pre-processing and formatted the given text into a structured format. The developed model has obtained the output with fewer errors from the given data. On the other hand, the involved methods have to be enhanced to achieve better performance and also suffer from handling highly complicated tasks.

2.5. Tensor Decomposition-Based DNN Method

In 2020, Reddy et al. [38] presented an enhanced detection framework for identifying fake news based on the "tensor decomposition-based DNN method". The tensor shows the social context that was generated by using the community and user information. The data were decomposed and classified using the ensemble learning algorithm. It has achieved the best classification performance. Conversely, it has a requirement for a huge amount of data to achieve optimal performance.

2.6. Ensemble Learning Approach

In 2020, Kadhim [39] investigated a text-mining approach for determining fake news by employing the ensemble learning approach. The offered approach has considered only the text features of the data and has not included any other metadata for detection. The suggested model has the ability to precisely identify fake news. However, the offered approach was not able to interpret the model and also required more time for designing and computation.

2.7. Problem Statement

Fake news denotes a category of daily mail that actively spreads lies or falsifications that propagate across both conventional print news outlets and online social media. As the "Great Moon Hoax" was published in the year 1835, fake news has been present for a longer time. In the online environment, fake news for discrete political and commercial reasons is found to be more in the earlier years. There are some advantages and disadvantages of the baseline fake news detection models as given in Table 1. Among them, CNN and RNN [18] achieve a good identification rate and improve classification accuracy. Conversely, it is essential to generate a larger database. Deep CNN [19] is employed for extracting many features in each layer and is less vulnerable to overfitting problems. It doesn't encode the object's position and orientation and also requires being spatially invariant to the input data. B-LSTM and CNN [29] reduce the overfitting problem and improve the overall accuracy rate. A deep Neural Network [32] is utilized for modeling the combined representation of fake news detection. It is quite expensive because of complex data models. A supervised artificial intelligence algorithm [30] is used to apply the fake news dataset and is employed for estimating the output with a minimum error rate from the input data. However, there are some disadvantages, such as ensemble approaches and various feature extraction models that need to be integrated for best performance, and it can't handle some of the cross-domain and complex classification tasks. Deep Neural Network [38] has attained the best classification results. But, it needs more amount of data to attain the best performance. MCNN [35] is employed for developing the local Convolutional features and global semantic features for efficient semantic data capturing, and it is utilized for extracting the article representation. But, it requires being implemented in a broad variety of applications and is very slow because of the max pooling operation. Ensemble Methods [39] have the ability to predict fake news with more accuracy, and in order to attain voting results, ensemble models are applied to the accumulation of skip-gram, write prints and stylometric features. Yet, it doesn't have the ability to interpret the model, and it requires more computation and design time. Hence, it is concluded that the aforementioned critical issues are useful for implementing a novel method for superior detection of fake news.

Table 1.
Upper hands and critical issues of baseline fake news detection model

Author [citation]	Infrastructure	Upper Hands	Critical issues
Asghar et al. [29]	CNN and RNN	• It is utilized to attain a better recognition rate. • It improves the categorization accuracy.	• It is essential to generate a larger database.
Palani et al. [32]	Deep CNN	• It is employed for extracting many features in each layer. • It is less vulnerable to overfitting problems.	• It doesn't encode the object's position and orientation. • It requires being spatially invariant to the input data.
Hanshal et al. [30]	B-LSTM and CNN	• The major innovation of this approach is to ignore the local optima issue and also to improve the accuracy rate.	• When the count of training samples increases, the efficacy rate can be affected.
Li et al. [34]	Deep Neural Network	• It is useful for creating the combined representation detection framework.	• It is quite expensive because of complex data models.
Kaliyar et al. [2]	Supervised artificial intelligence algorithm	• It is used to apply to the fake news dataset. • It is employed for estimating the output with a minimum error rate from the input data.	• Ensemble approaches and various feature extraction models need to be integrated for the best performance. • It doesn't have the ability to handle some of the complicated tasks.
Reddy et al. [38]	Deep Neural Network	• It has attained the best classification results.	• It needs more amount of data to attain the best performance.
Zervopoulos et al. [35]	MCNN	• It is employed for developing the local Convolutional attributes and global semantic features for efficient semantic data capturing. • It is utilized for extracting the article representation.	• Needs to be developed in a wide range of applications. • It is very slow because of the max pooling operation.
Kadhim [39]	Ensemble Methods	• It has the capacity to discover fake news with more accuracy. • In order to attain voting results, ensemble models are given the accumulation of "skip-gram, writeprints, and stylometric features".	• It doesn't have the ability to interpret the model. • It requires more computation and design time.

3. Diagrammatic View of Fake News Detection System with The Depiction of Dataset Description and Process of Pre-Processing

3.1. Developed Methodology

In recent days, the usage of the World Wide Web (WWW) and social media like "Twitter, Facebook, etc.," has increased, which has initiated a problem known as information dissemination. On these social media platforms, most people have started creating and sharing more information, in which some people are misled by sharing wrong information without any relevance to the real news. Social media with useful information is very powerful for users to share their ideas regarding health, education, and democracy. At the same time, these platforms are utilized for illegal purposes for monetary gains or spreading absurdity or satire, and also for manipulating people's mindsets to create biased opinions. This is generally known as fake news. There exist various repositories of researchers, which have certain lists of identified websites as fake and ambiguous. However, it requires human expertise to determine whether the websites or any resources are fake. The essential part is present in fact-checking websites, which have exact domains like politics and are not practical for finding fake news in multiple domains like sports, entertainment, and technology. So, it is crucial to set the real and fake news in an automated way with more accuracy. The automatic way of detecting fake news was established through RNN, but it needs more cost when huge text datasets are used in it. Several other studies have been researched; yet, they require more exploration and attention for accurately detecting fake news. Moreover, intelligent tools like Natural Language Processing (NLP) tools and Artificial Intelligence (AI) have performed better in recognizing types of news, and it is easy to implement the system. Conversely, fake news detection is a complex activity owing to its requirement of models for summarizing the text and for comparing it with the original news to classify the fake news. Therefore, the new detection of fake news approach is promoted using the classifier that is given in Figure 1.

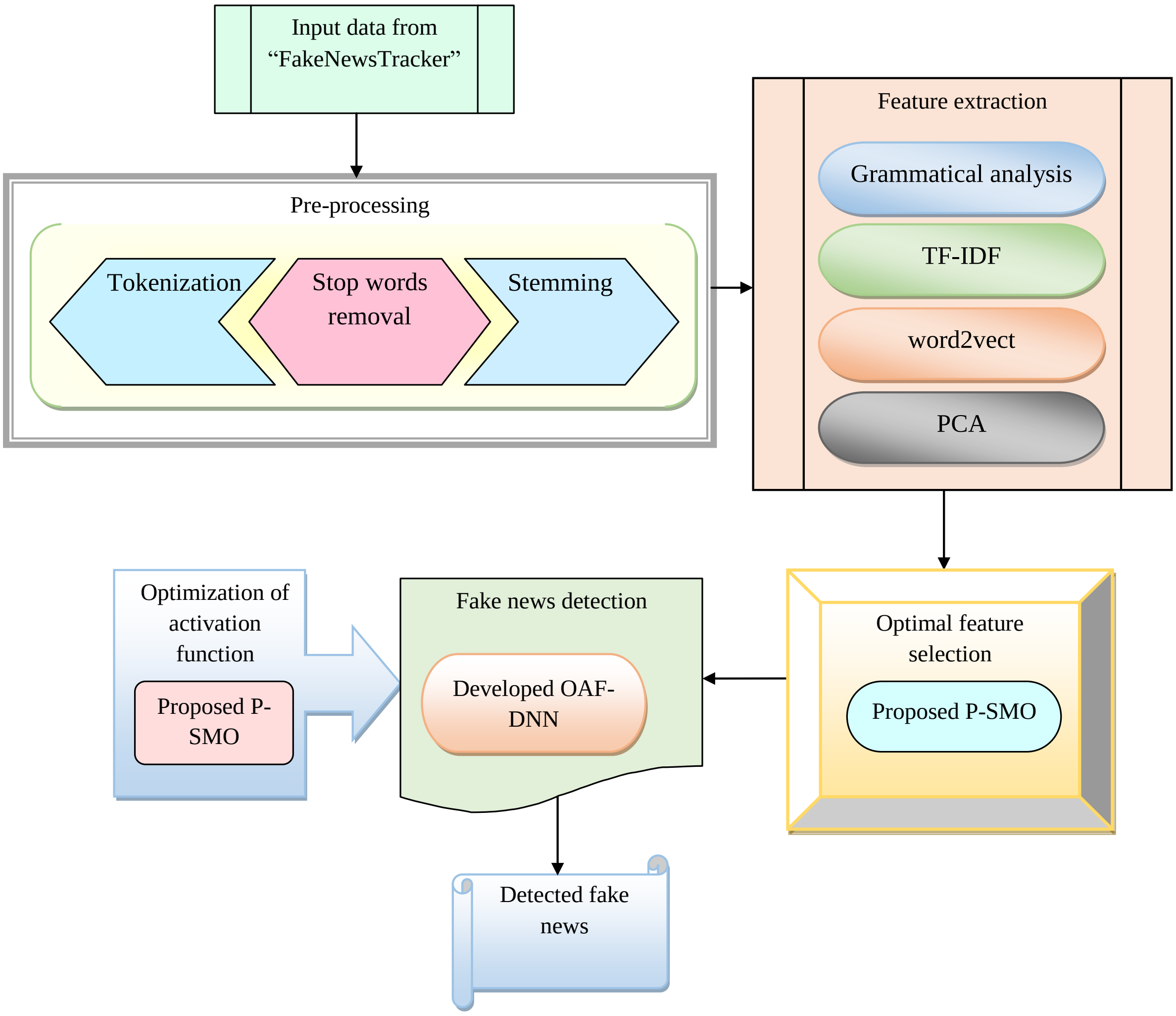


Figure 1.
Proposed detection of fake news model by deep structured architectures

The novel detection of fake news methods are promoted for optimally detecting fake news by utilizing deep structured architecture models with the enhanced meta-heuristic algorithm. Initially, the required datasets for evaluating the developed fake news detection model are collected and subjected to pre-processing. In this stage, tokenization, removal of stop words, and stemming methods are performed. These methods are used for removing words that do not carry much information, and eliminating these words can help focus on key features of the data. Additionally, this data is put forward towards the extraction of features via word embedding using word2vec, PCA, VSM using TF-IDF, and grammatical analysis using "mean, Q25, Q50, Q75, Max, Min, and standard deviation." The significant features are acquired for improving accuracy, reducing the risk of overfitting problems, and achieving faster training speed. The size of the acquired features is large; therefore, it is required to reduce the length by choosing the accurate features using the developed P-SMO. This enables the enriched performance of the classification algorithm by providing faster training and also decreases complexity. Finally, the optimally preferred features are considered for the categorization and detection of fake news by the suggested OAF-DNN technique, in which the performance is then improved by tuning the activation function of the DNN using the designed P-SMO. The DNN technique contains a more flexible nature as it can adapt to any problem. It can also be useful for many real-time applications and data types. The core innovations of the implemented detection of fake news model are to enrich the precision and accuracy of the detected fake news.

3.2. Dataset Description

The offered fake news detection collects the corresponding datasets from the "https://dataverse.harvard.edu/dataset.xhtml?persistentId=doi:10.7910/DVN/UEMMHS: access date: 2021-09-07". It is a "multi-dimensional data repository", which has two datasets with spatiotemporal information, news content, and social context. These datasets are generated based on the end-to-end system named "Fake News Tracker" [3]. These datasets have the capability to enrich the research and also, this database is divided into datasets 1 and 2. The collected data from datasets 1 and 2 are presented as DA_m^{input}, where $m = 1,2,\ldots,M$ and M shows the average of the data.

3.3. Data Pre-Processing

The input data gathered in the offered detection of fake news approach is pre-processed utilizing stemming, stop-word elimination, and tokenization techniques.

Tokenization [40]: The sentences with a greater number of words in the input data DA_m^{input} are classified into small tokens. The “higher chunks of text” are divided into a number of sentences that are tokenized into a number of words. Here, entire sentences in the data are modified into tokens as separate words, which are used for further “text analytics process”. These tokens are referred to as the tiny sequence. The pre-processed data by tokenization are denoted as DA_m^{token}.

Stop words removal [40]*:* Some of the commonly repeated words present in the tokenized data DA_m^{token} are removed through the stop words removal process. The repetitive words like conjunctions, pronouns, etc., are neglected due to their less effectiveness and also pose no value in the data. Also, certain information as special typesets and numbers, are also minimized with the help of their frequency. Repeated terms are generally carried with high frequency as they appear many times, and therefore, these types of words are differentiated. Therefore, the data without any stop words are presented as DA_m^{stop}.

Stemming [40]*:* It is the removal process of affixes like prefixes and suffixes from the input data DA_m^{stop} to reduce the “derived words of the stem”. The source terms are removed and it is utilized for determining the resulting words that are similar to the actual root words. This procedure is utilized for decreasing the number of features to enhance the efficacy of the classifier. Finally, the pre-processed data using stemming are obtained and represented as DA_m^{pre}.

4. Selection of Accurate Features and Extraction of Features for an Automated Fake News Detection

4.1. Extraction of Features

The pre-processed data DA_m^{pre} are utilized in the fake news detection framework for acquiring the features by the Word to Vector, Grammatical analysis, PCA, and TF-IDF techniques.

Word to Vector [41]: This technique is ensured with several models for progressing the word embedding using the input pre-processed data DA_m^{pre}. This model is said to be a “shallow two-layer neural network” with an outcome, hidden, and input layer. The word-to-vector is performed using two structures such as “Continuous Bag of Words (CBOW) and Skip-Gram”.

CBOW: This technique is used for determining the “current word from the given context words” inside the concerned window. The respective context words are given into the input layer, and the number of suitable hidden neurons with a number of dimensions is obtained for presenting the current words. At last, the output region is achieved with the current word.

Skip Gram: The pre-processed words from CBOW are considered for the skip-gram technique for assuming the “neighboring context words” within the window. The dimensions count in the hidden regions shows the present word that belongs to the income region. Both the input and the outcome layer carry their respective present words and context words. Thus, the output extracted features are obtained using the word-to-vector technique and are represented as FE_a^{vtw}.

Grammatical analysis [5]*:* This analysis uses the valuable information that is present in the sentence pattern of the input pre-processed data DA_m^{pre}. The depth features are acquired in the sentence since it visualizes“ the difference between the fake and real news”.

Mean: It is defined as “the average sentence depth of each data” that is shown in Equation 1.

$$Mean = \frac{\sum_{j=1}^{g} DT_j}{g} \qquad (1)$$

The variable g refers to the count of sentences and depth is shown as DT in the given data.

Q25: It is described as “the 25th percentile sentence depth of each data” that is given in Equation 2.

$$q25 = 25^{th}\ percentileof\ ST_{ad}(DT) \qquad (2)$$

Here, the ascending sort function present in the sentence depth is denoted as ST_{ad}.

Q50: It is defined as “the 50th percentile sentence depth of each data” that is depicted in Equation 3.

$$q50 = 50^{th}\ percentileof\ ST_{ad}(DT) \qquad (3)$$

Q75: It is defined as “the 75th percentile sentence depth of each data” that is represented in Equation 4.

$$q75 = 75^{th}\ percentileof\ ST_{ad}(DT) \qquad (4)$$

Max: It is expressed to be “the deepest sentence depth of each data” that is given in Equation 5.

$$MAX = \max(DT) \qquad (5)$$

Min: It is expressed to be “the shallowest sentence depth of each data” that is shown in Equation 6.

$$MIN = \min(DT) \qquad (6)$$

Standard deviation: It is referred to as "the standard deviation of the sentence depths in each data" that is presented in Equation 7.

$$SD = \sqrt{\frac{1}{g} \sum_{j=1}^{g} \left(DT_j - D\overline{T} \right)^2} \quad (7)$$

Here, the variable $D\overline{T}$ is noted as the average mean of the sentence depths in every data. The total number of acquired features using grammar analysis is counted as 7 for all sentence depth distributions. The number of features taken in grammar analysis is denoted as FE_b^{grm} .

PCA [42]*:* The PCA-based feature extraction technique uses pre-processed data DA_m^{pre} for extracting the significant features of fake news detection. This technique extracts the relevant attributes of the fake news, for which the pre-processed data are provided as the income in the vector configuration that is shown as MTX . The mean terms are mn further present in the input vector MTX that is calculated by Equation 8.

$$\overline{b}_w = \frac{1}{R} \sum_{v=1}^{R} B_{vw} \quad (8)$$

Here, the count of terms in the columns Q and rows R are denoted as v and w , and variables are indicated as b . Then, the covariance matrix $CM = \{cm_{vw}\}$ is computed, in which the variance cm_{ww}^2 and the term cm_{sw} are formulated as in Equations 9 and 10.

$$cm_{ww}^2 = \frac{1}{R} \sum_{v=1}^{R} \left(b_{vw} - \overline{b}_w \right)^2 \quad (9)$$

$$cm_{sw} = \frac{1}{R} \sum_{v=1}^{R} \left(b_{vs} - \overline{b}_s \right)\left(b_{vw} - \overline{b}_w \right) \quad (10)$$

Then, the term CM can be achieved by the eigenvalue λ and eigenvector ev , where $CMev = \lambda ev$. Also, it is recognized by Equation 11.

$$\left(CM - \lambda_s S \right) EV_S = 0 \quad (11)$$

Then, the matrix CM is formulated in Equation 12.

$$t^i CMT = F_d \quad (12)$$

The variable F_d presents the principal modules of the matrix. Therefore, the important attributes are acquired from the decomposed signals by the PCA approach. Hence, the acquired attributes from the PCA are noted as FE_c^{pca} , where $b = 1, \ldots, B$.

TF-IDF [43]: This method performs feature extraction for minimizing the weights of the query that appears many times in the documents to convert the documents as "good discriminator". The TF-IDF technique computes the weights by Equation 13.

$$WT_{x,y} = FQ_{x,y} \times \log\left(\frac{q}{fFQ_x} \right) \quad (13)$$

Here, the weight of the document y is denoted as $WT_{x,y}$ and the variable fFQ_x shows the document frequency and $FQ_{x,y}$ indicates the frequency of the variable x in the documents y . This model determines the relevant words to the corresponding file. TF-IDF approach measures the impact of the variable in the specified input sources. At last, the bug attributes are acquired from the pre-processed data, which is noted as FE_o^{ext} , where $o = 1, 2, \ldots, O$ and O expressed as the average of extracted features. The extracted features count is counted as 1.

The average of acquired from all the feature extraction approaches is concatenated and denoted as $FE_p^{etf} = \{FE_a^{vtw}, FE_b^{grm}, FE_c^{pca}, FE_o^{ext}\}$, where $p = 1, 2, \ldots, P$ and P express the average of extracted features.

4.2. Selection of Accurate feature

In the fake news detection framework, the acquired features FE_p^{etf} are subjected by the developed P-SMO. Here, the optimal features are selected by ignoring the length of the features, which provides in ensuring significant data. The selection of optimal features contains great effects in the data-structured architecture approaches for improving the performance of the categorization. It is also utilized to reduce the "computational resources of the offered fake news detection model". In the proposed framework, the extracted primary features are denoted as FE_{p*}^{opt} , where $p* = 1, 2, \ldots, P*$ and $P*$ shows the average of optimal features. The average count of attributes taken from "dataset 1 and dataset 2" is counted as 108; among them only 5 optimal features are chosen by the offered P-SMO. The visual presentation of the selection of better features is given in Figure 2.

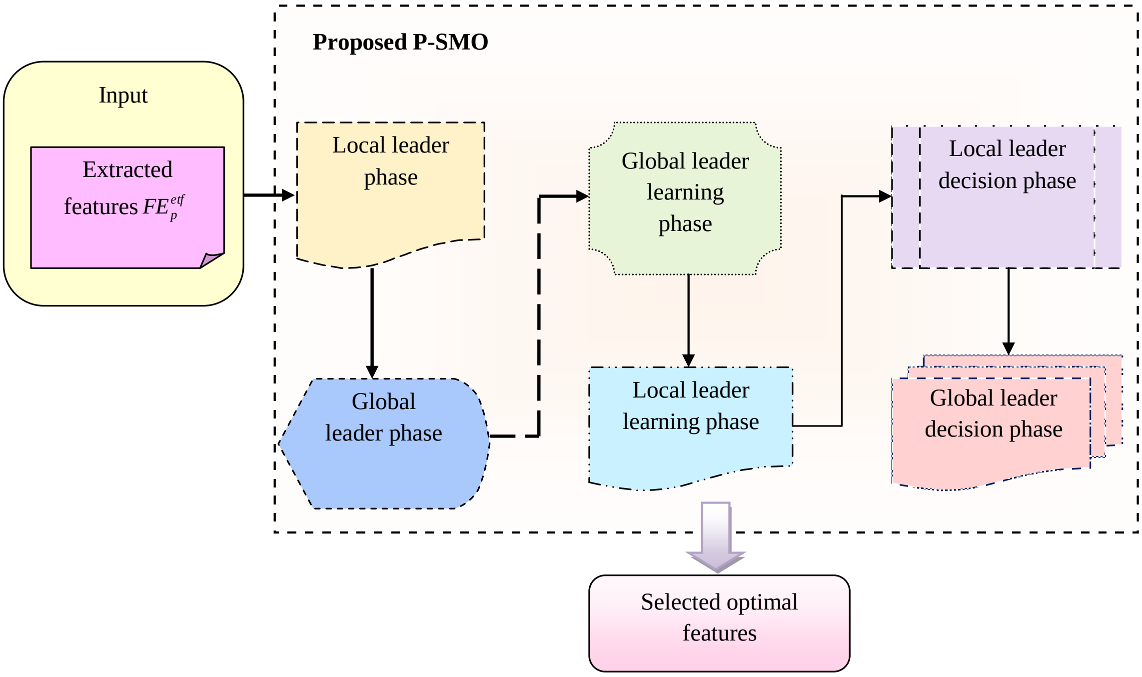


Figure 2.
Selection of Optimal features of the detection of fake news approach.

5. Designed Automated Fake News Detection by Developing an Optimization Algorithm and OAF-DNN-Based Detection

5.1. Fake News Detection of by OAF-DNN

The fake news detection approach utilizes the OAF-DNN classifier for categorizing the selected optimal features $FE_{p^*}^{opt}$. This DNN [30, 34] classifier is an efficient and consistent classifier for accurately detecting fake news with less number of samples in the training phase. The detection efficacy of the DNN classifier is then enhanced by the designed P-SMO by tuning the activation function of the DNN. The "nodes in the hidden layers" are validated in Equation 14.

$$nds_{hid} = \sqrt{p+q+V} \quad (14)$$

Here, the key entity node and the outcome node are given as p and q, and the constant value is represented as V. The non-linear capability of the activation function F_{act} is depicted in Equation 15.

$$F_{act} = \frac{1}{1+e^{-FE_{p^*}^{opt}}} \quad (15)$$

Here, the input features of the DNN are given as optimal features $FE_{p^*}^{opt}$. The mapping function is shown in Equation 16.

$$mp_f = sig(\omega_{p^*} FE_{p^*}^{opt} + \beta_{p^*}) \quad (16)$$

Here, the bias β and weight vector ω are linked with the hidden layers and output layer. The DNN utilizes the mean square error (MSE) loss, which is predicted among the predicted output and ground truth output.

The output is executed as fake news detected or non-fake news detected features in the output region. The developed OAF-DNN-based detection of fake news approach is provided in Figure 3.

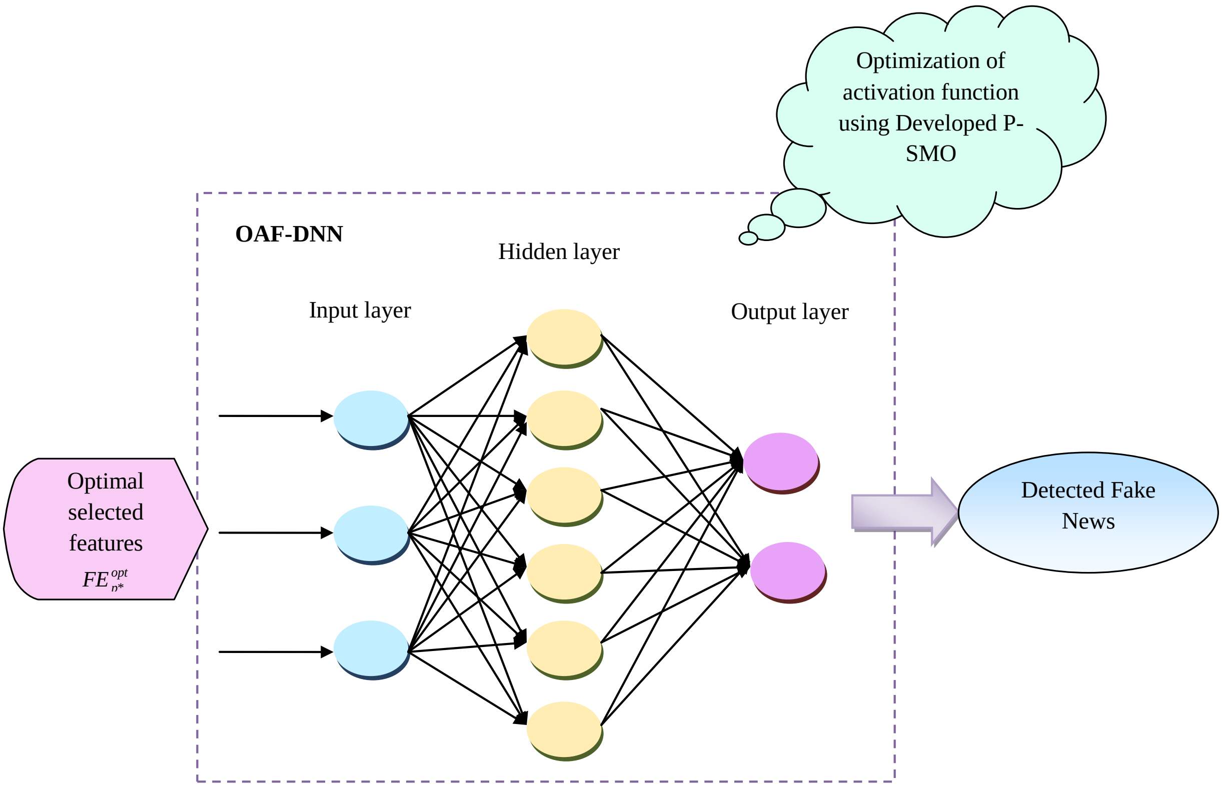


Figure 3.
OAF-DNN-based detection for fake news detection framework.

5.2. Fitness For Detection of Fake News Approach

The detection of the fake news approach by the OAF-DNN classifier enhances the efficacy of the overall performance by choosing the better features and by tuning the activation function of DNN classifiers using the proposed P-SMO. The offered method concentrates on resolving the fitness function by increasing the accuracy and precision of the system. The cost function of the offered approach is given in Equation 17.

$$O_{fn} = \underset{\{F_{act}, FE_{p*}^{opt}\}}{\arg\min}\left(\frac{1}{acr + prc}\right) \quad (17)$$

Here, the term F_{act} and FE_{p*}^{opt} is denotes the activation function of the DNN and selects accurate features. The average of optimal features is chosen as 5 by the offered P-SMO. Likewise, the proposed P-SMO optimizes the activation function's interval $[1,5]$. Accuracy AC is denoted as the "closeness of the measurements to a specific value" as equated in Equation 18.

$$AC = \frac{(T_p + T_n)}{(T_p + T_n + F_p + F_n)} \quad (18)$$

Precision prc is denoted as "the fraction of relevant instances among the retrieved instances" as shown in Equation 19

$$PC = \frac{T_p}{T_p + F_p} \quad (19)$$

The variables T_p and T_n notes the "true positive value and the true negative values" likewise F_n and F_p represent the "false negative and false positive value". The proposed detection of the fake news framework is provided in Figure 4.

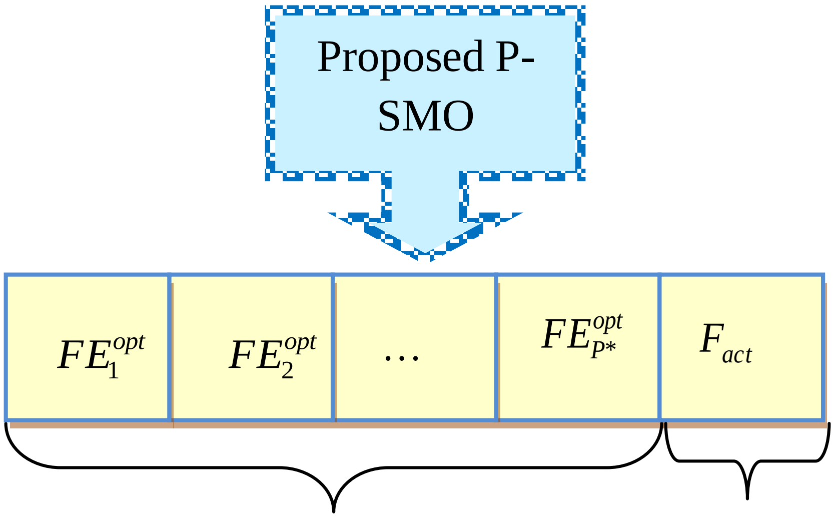


Figure 4.
Solution encoding of the offered approach

5.3. Modified P-SMO Model

The P-SMO algorithm is suggested to enhance the detection efficacy of the developed fake news detection method, particularly through optimizing the "activation function of the DNN" and also by "selecting the optimal features" for the offered approach. The SMO algorithm is chosen in this proposed method owing to its high efficacy. On the other hand, it is dependent on more user parameters for resolving the optimization problem, which leads to more complexity in solving. To resolve this complexity, the latest P-SMO algorithm is implemented. In the developed algorithm, the probability of the solution is utilized for upgrading the candidate solution location, whereas in the baseline SMO, an arbitrary number is used for upgrading the position. The probability-based location upgrade takes place in the implemented P-SMO for maximizing the convergence rate, which reduces the complexities of solving the optimization problem.

SMO Bharti and Pandey [44] are encouraged by the "social activities of the spider monkeys", which is determined based on the "intelligent foraging behavior of the spider monkey". This is performed according to the "Fusion-Fusion Social Structure (FFSS)". Based on the FFSS, the solutions in the population form a small group. The solutions split themselves from larger communities into smaller communities by using their ability and the scarcity of food sources. There are six phases in the SMO model and they are "Local Leader Phase (LLP), Global Leader Phase (GLP), Local Leader Learning Phase (LLLP), Global Leader Learning Phase (GLLP), Local Leader Decision Phase (LLDP) and Global Leader Decision Phase (GLLP)" that are described as follows.

Population generation: Initially, the SMO produces the uniformly distributed monkey as M , in which each monkey at the k^{th} iteration is denoted as $MK_k(k = 1,2,\ldots,M)$ and its dimension of MK_k is indicated as l . Then, the spider monkey of k^{th} iteration at l^{th} dimension is computed in Equation 20.

$$MK_{kl} = MK_{\min l} + RN[0,1](MK_{\max l} - MK_{\min l}) \quad (20)$$

Here, the term $MK_{\max l}$ and $MK_{\min l}$ are denoted as upper and lower limits of MK_k in l^{th} dimension and $RN[0,1]$ is given as a "uniformly distributed random number" that lies in the interval of $[0,1]$.

LLP: In this stage, the current location of the solution is modified related to the information gathered from the "experiences of the local leader and its group members". Here, the new position can be identified based on its fitness value. The new location of the k^{th} spider monkey at the n^{th} local group is depicted in Equation 21.

$$\begin{aligned} MK_{NEWkl} &= MK_{kl} + RN[0,1](LD_{nl} - MK_{kl}) \\ &+ RN[-1,1](MK_{sl} - MK_{kl}) \end{aligned} \quad (21)$$

Here, the term MK_{sl} shows the l^{th} dimension of the s^{th} solution that is chosen arbitrarily from n^{th} , a uniformly distributed random is denoted as $RN[-1,1]$, MK_{kl} is denoted as k^{th} spider monkey at l^{th} dimension; leader position of n^{th} a local group at l^{th} dimension is presented as LD_{nl} .

GLP: It is performed followed by the LLP, where entire spider monkeys are re-evaluated with their location. This phase is determined using Equation 22.

$$\begin{aligned} MK_{NEWkl} &= MK_{kl} + RN[0,1](GD_l - MK_{kl}) \\ &+ RN[-1,1](MK_{sl} - MK_{kl}) \end{aligned} \quad (22)$$

Here, the term GD_l is indicated as the l^{th} dimension of the location and $l \in \{1,2,\ldots,d\}$ is an "arbitrarily selected index".

Then, the locations of the spider monkey are upgraded PRB_k by utilizing its fitness value. According to the fitness value, the candidate with a high possibility is selected and moved to the next stage. The probability PRB_k is determined by using Equation 23.

$$PRB_k = 0.9 \times \frac{O_{fk}}{\max O_f} + 0.1 \tag{23}$$

Here, the variable O_{fk} notes the cost function value of the k^{th} spider monkey and $\max O_f$ presents the higher cost function in the entire solution.

GLLP: In this phase, the position of the solution with the greatest fitness among the population is chosen for updating according to the greedy selection. Then, the "global leader position" is verified for upgrading its location and if it is not upgraded then, the "Global Limit Count (GLC)" is added with 1.

LLLP: In this stage, the chosen of greedy is utilized for upgrading the location of the local leader, then the "Local Limit Count (LLC)" is added by 1.

LLDP: Here, any local leader location is not upgraded using a "predetermined threshold", which is referred to as the local leader limit, then the position of entire members is updated by randomly or through the information obtained from the global and local leaders that is given in Equation 24.

$$\begin{aligned} MK_{NEWkl} &= MK_{kl} + PRB_k\left(GD_l - MK_{kl}\right) \\ &+ PRB_k\left(MK_{sl} - LD_{nl}\right) \end{aligned} \tag{24}$$

Here, the random number is used for upgrading the location in the baseline SMO algorithm, whereas in the proposed P-SMO, the probability-based solution updating is utilized.

GLDP: Here, the position of the solution is evaluated as it reaches the estimated count of iterations, which is the global leader limit. This continues to form the groups till it attains the maximum groups. Then, the local leaders are selected inside the small groups. The pseudo-code of the offered model is shown in Algorithm 1.

Algorithm 1: Implemented P-SMO model

1. Load the spider monkey population
2. Set the probability PRB_k of the solution using Equation 23
3. Chosen the local and global leaders by employing the greedy selection method
4. While (until the stopping condition) do
5. The location was upgraded according to Equation 21
6. The location was upgraded according to Equation 22
7. The learning phase takes place for a global leader
8. The learning stage takes place for a local leader
9. Update the position based on Equation 24.
10. The decision of fusion or fission is based on the global leader
11. Obtain the global leadership position as the best optimal solution
12. End while

The developed P-SMO contains the advantages of using a few parameters for the position update, which reduces the complexity of solving the meta-heuristic issue. Then, it also increases the efficiency of detection results in fake news. The flow diagram of the proposed P-SMO is given in Figure 5.

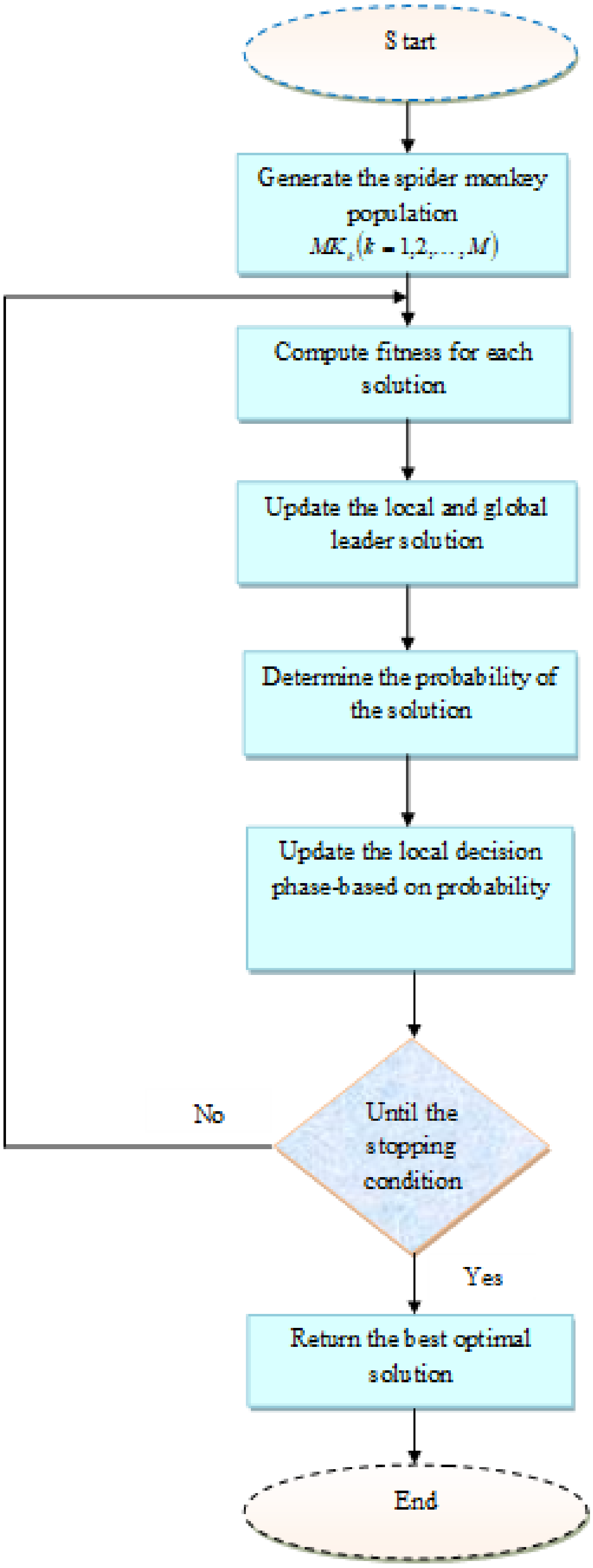


Figure 5.
The presentation of the flow diagram of the designed P-SMO algorithm

6. Calculations of Results

6.1. Experimental setup

The detection of fake news approach was examined in Python, and a tentative evaluation was conducted. The execution configuration of the designed model was considered by taking the following constraints, like RAM as 8GB, processor as a Core i3 processor, system type as 64-bit, edition as Windows 11, implemented by Pycharm in Anaconda 3. The efficacy of this approach was estimated by testing with the baseline methods: Positive measures or Type I include Negative Predictive Value (NPV), Specificity, Accuracy, MCC, Precision, Sensitivity, and F1Score. Negative measures were taken as Type II measures such as False Discovery Rate (FDR), False Negative Rate (FNR), and False Positive Rate (FPR). The estimation takes place under the population number of 10 and the iteration number of 25 in the implemented epileptic fake news detection approach. The proposed P-SMO was compared with other meta-heuristic algorithms like "Particle Swarm Optimization (PSO) [45], Whale Optimization Algorithm (WOA) [46], Tunicate Swarm Optimization(TSA) [43], SMO [44], and machine learning algorithms like Neural Network (NN) [47], LSTM [7], CNN [2], Recurrent Neural Network (RNN) [29], DNN [34]".The process of selecting the given algorithms and methods is the key aspect of the developed model. It is utilized for showing the effectiveness of the designed model, and it can also help to give better accuracy and lower error rates for the developed model. It helps to explore more details of the designed model, which helps to enhance its capacity.

6.2. Performance Measures

The performance of the proposed fake news detection model with the developed OAF-DNN method using the suggested P-SMO is evaluated using various quantitative measures that are described as follows.

(a) MCC MC is "a measure of the quality of binary classifications of testing" as provided in Equation 25

$$MC = \frac{T_p \times T_n - F_p \times F_n}{\sqrt{(T_p + F_p)(T_p + F_n)(T_n + F_p)(T_n + F_n)}} \tag{25}$$

(b) Specificity SY is "the proportion of negatives that are correctly identified" as presented in Equation 26

$$SY = \frac{T_n}{T_n + F_p} \tag{26}$$

(c) NPV NV is denoted as "the sum of all persons without disease in testing" as mentioned in Equation 27

$$NV = \frac{T_n}{T_n + F_n} \tag{27}$$

(d) F1-score FE is described as "the measurement of the accuracy in the conducted test" as shown in Equation 28

$$FE = 2 \times \frac{2T_p}{2T_p + F_p + F_n} \tag{28}$$

(e) FDR FR is "a method of conceptualizing the rate of errors in testing when conducting multiple comparisons" as noted in Equation 29

$$FR = \frac{F_p}{F_p + T_p} \tag{29}$$

(g) Sensitivity SN is "the proportion of positives that are correctly identified" as noted in Equation 30

$$SN = \frac{T_p}{T_p + F_n} \tag{30}$$

(h) FPR F^{PR} is described as "the ratio between the numbers of negative events wrongly categorized as positive (false positives) and the total number of actual negative events" as shown in Equation 31.

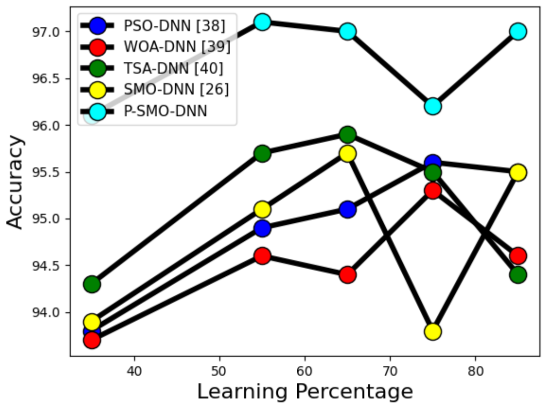
$$FR = \frac{F_p}{F_p + T_n} \tag{31}$$

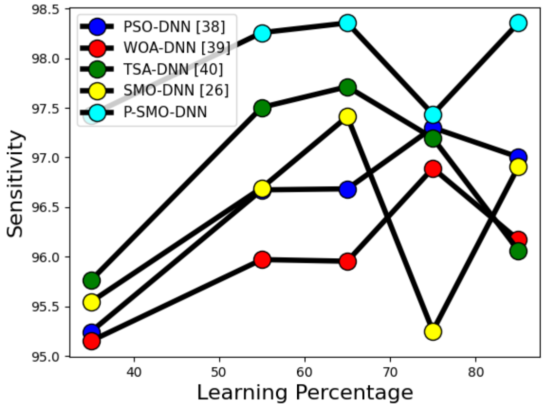
(i) FNR FP is "the proportion of positives which yield negative test outcomes with the test" as shown in Equation 32

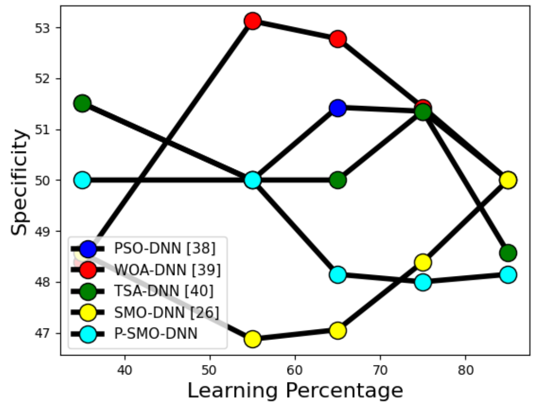
$$Fp = \frac{F_n}{F_n + T_p} \tag{32}$$

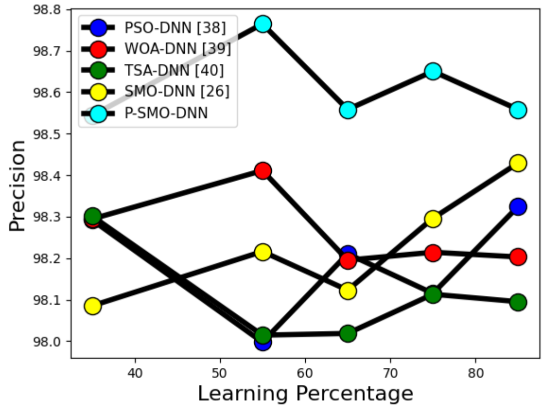
6.3. Evaluation of Dataset 1 Based on Optimization Models

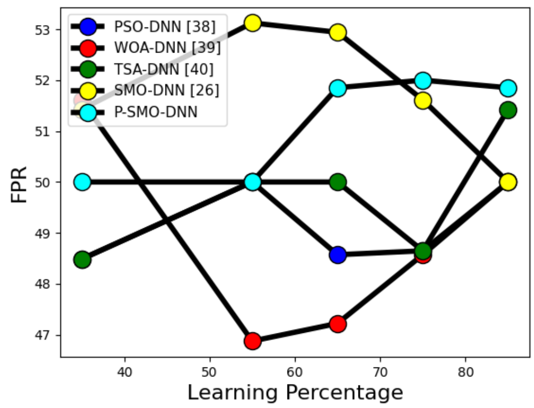
Evaluation of the developed approach for dataset 1 is given in Figure 6. The designed P-SMO-DNN attains 2.6%, 0.76%, 1.75%, and 1.02% improvement over the PSO, WOA, TSA, and SMO at 85th learning rate in terms of F1-score measure. While noticing the sensitivity of the designed P-SMO-DNN rapidly enriched at the learning rate of 50, which keeps the value of 98.4. Similarly, the proposed P-SMO-DNN of the designed detection of fake news framework outperforms regarding dataset 1 more than the baseline techniques.

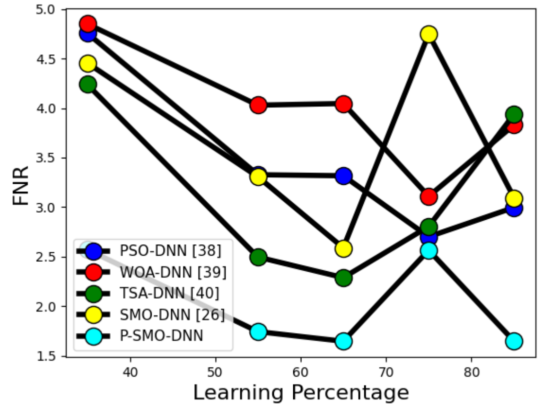

PSO-DNN [38]
WOA-DNN [39]
TSA-DNN [40]
SMO-DNN [26]
P-SMO-DNN
Accuracy
Learning Percentage
(a)

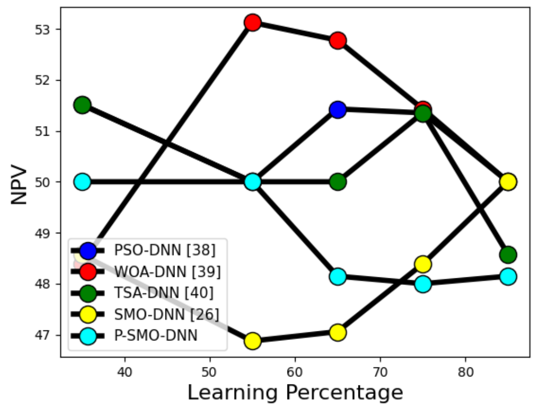

PSO-DNN [38]
WOA-DNN [39]
TSA-DNN [40]
SMO-DNN [26]
P-SMO-DNN
Sensitivity
Learning Percentage
(b)

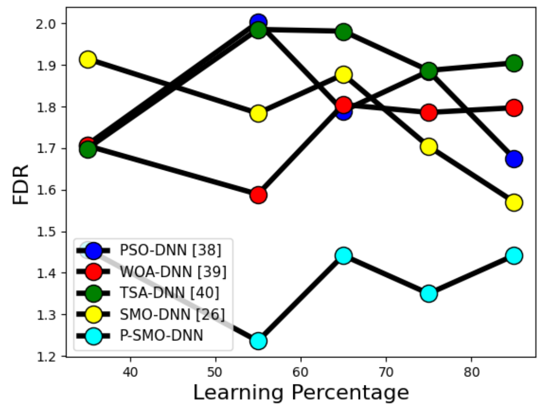

PSO-DNN [38]
WOA-DNN [39]
TSA-DNN [40]
SMO-DNN [26]
P-SMO-DNN
Specificity
Learning Percentage
(c)


PSO-DNN [38]
WOA-DNN [39]
TSA-DNN [40]
SMO-DNN [26]
P-SMO-DNN
Precision
Learning Percentage
(d)

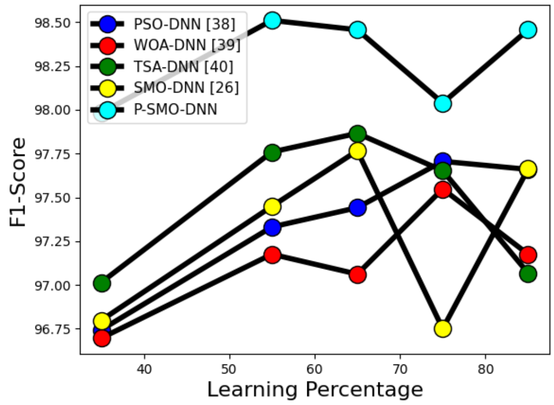

PSO-DNN [38]
WOA-DNN [39]
TSA-DNN [40]
SMO-DNN [26]
P-SMO-DNN
FPR
Learning Percentage
(e)


PSO-DNN [38]
WOA-DNN [39]
TSA-DNN [40]
SMO-DNN [26]
P-SMO-DNN
FNR
Learning Percentage
(f)

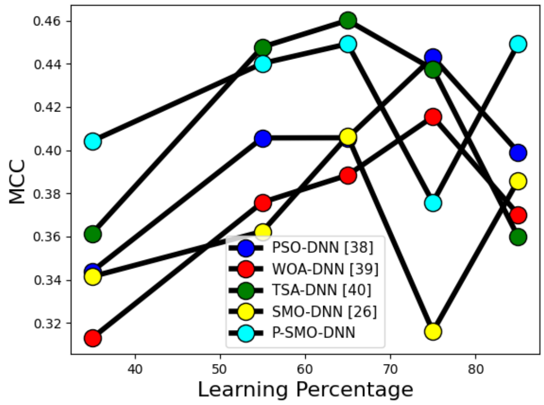

PSO-DNN [38]
WOA-DNN [39]
TSA-DNN [40]
SMO-DNN [26]
P-SMO-DNN
NPV
Learning Percentage


PSO-DNN [38]
WOA-DNN [39]
TSA-DNN [40]
SMO-DNN [26]
P-SMO-DNN
FDR
Learning Percentage

(g) (h)



(i)

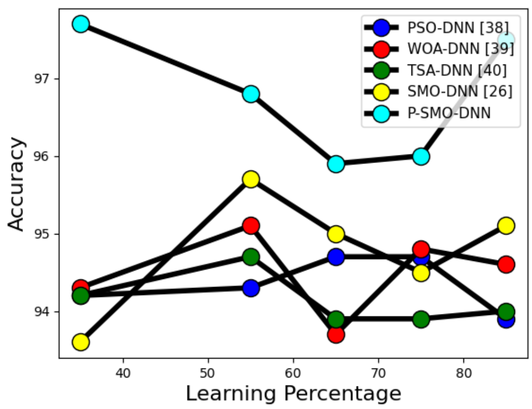


(j)

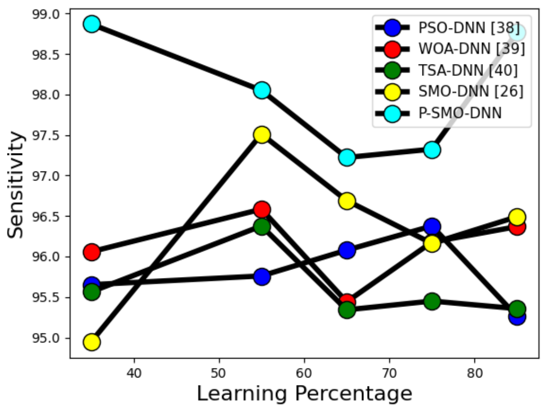
Figure 6.
Validation for the detection of fake news model according to dataset 1 concerning“(a) accuracy, (b)sensitivity, (c)specificity, (d)precision, (e)FPR, (f)FNR, (g)NPV, (h)FDR, (i) F1-Score and (j) MCC”

6.4. Estimation of Dataset 2 Along with Heuristic Algorithms

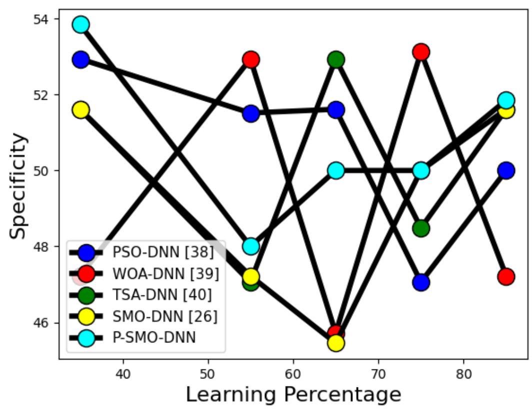
Estimation of the designed detection of fake news approach according to dataset 2 is validated with a diverse optimization algorithm that is presented in Figure 7. The efficacy of the offered P-SMO-DNN is 1.5%, 3.22%, 2.12%, and 1.05% enriched than the PSO, WOA, TSA, and SMO. The developed P-SMO-DNN approach’s F1-score value has a higher performance, in which it shows slight variation at the learning rate of 40, is further reaches a higher value at the learning rate of 80. Therefore, the detection of fake news approach with dataset 2 provides enriched effectiveness than the baseline approaches.



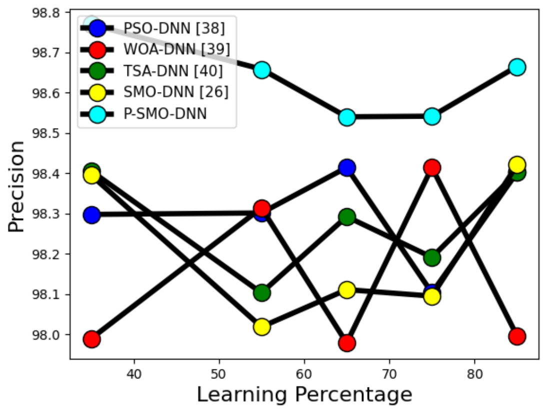
(a)



(b)



(c)



(d)

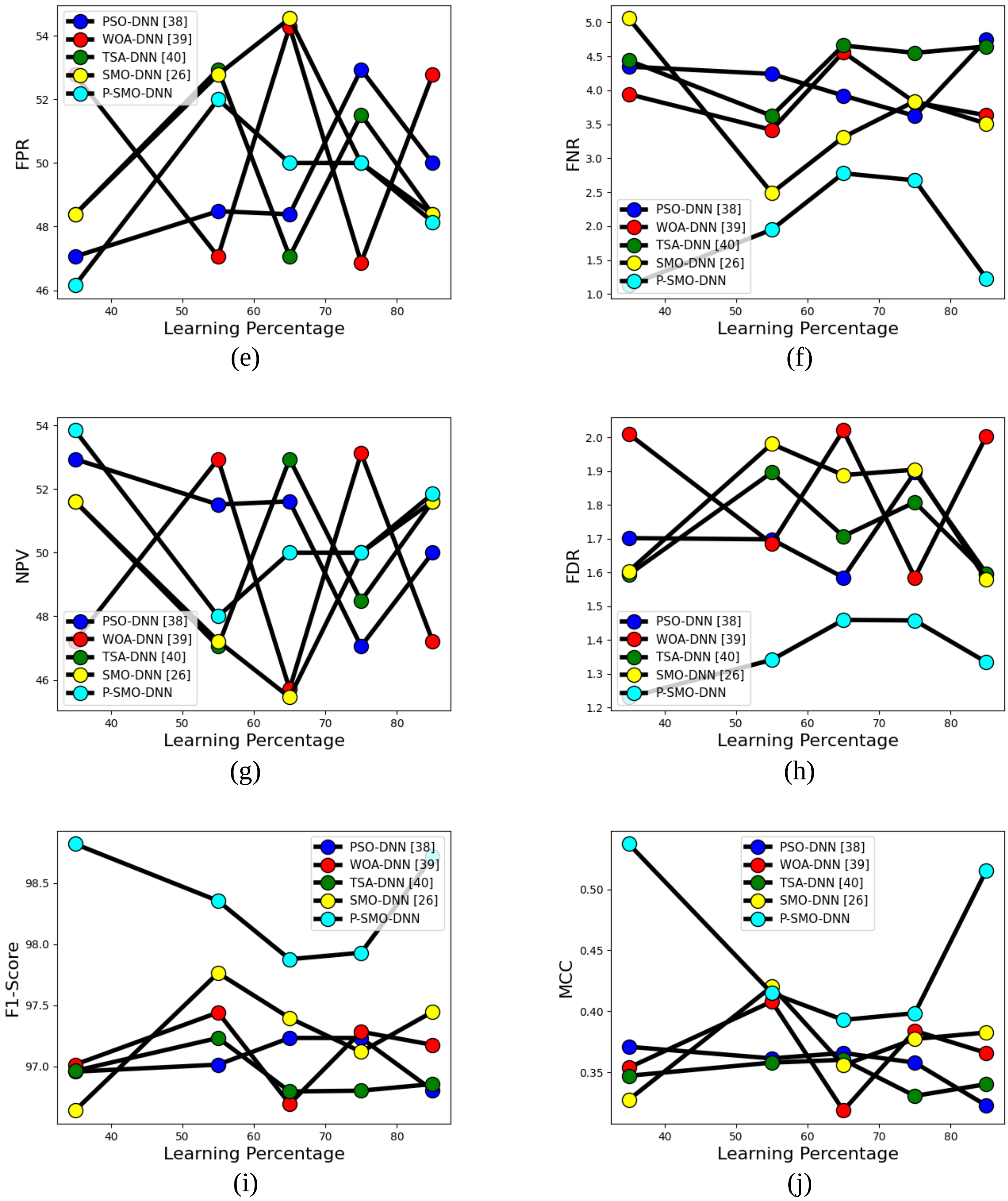
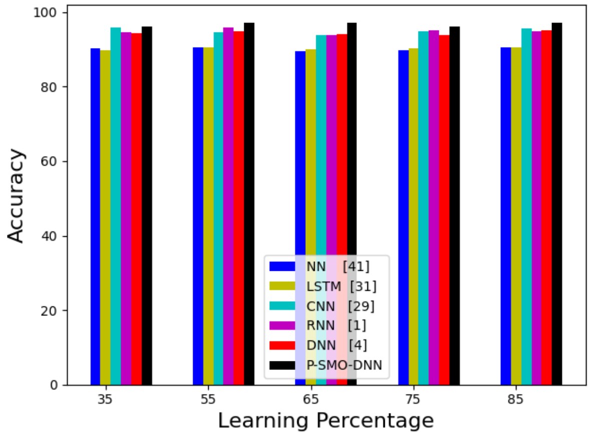
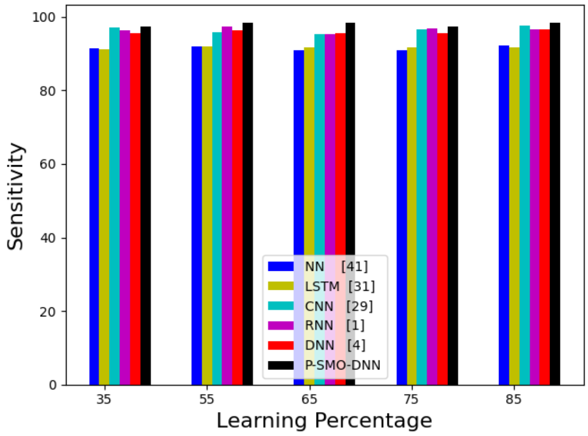


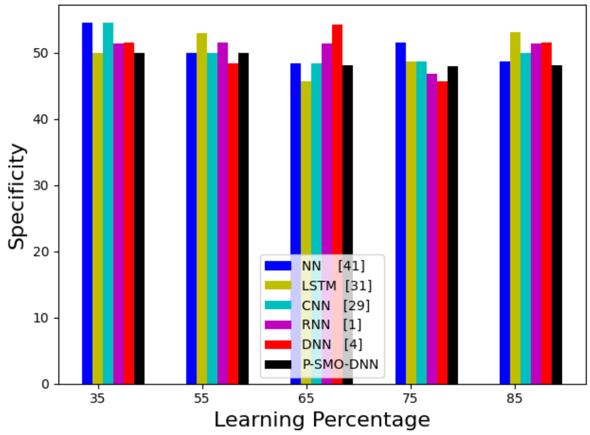
Figure 7.
Estimation for detection of fake news approach along with dataset 2 regarding “(a) accuracy, (b)sensitivity, (c)specificity, (d)precision, (e)FPR, (f)FNR, (g)NPV, (h)FDR, (i) F1-Score and (j) MCC”


Accuracy
Learning Percentage
NN [41]
LSTM [31]
CNN [29]
RNN [1]
DNN [4]
P-SMO-DNN

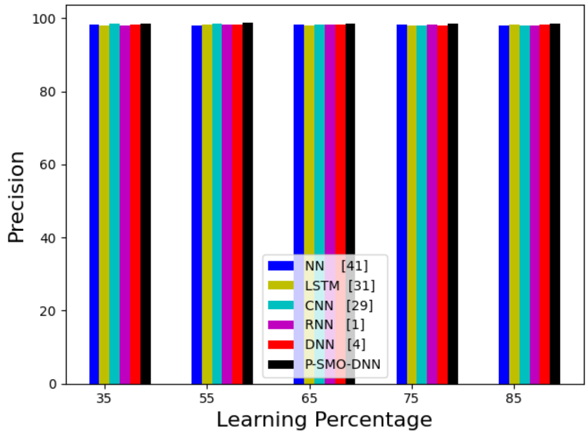
(a)


Sensitivity
Learning Percentage
NN [41]
LSTM [31]
CNN [29]
RNN [1]
DNN [4]
P-SMO-DNN

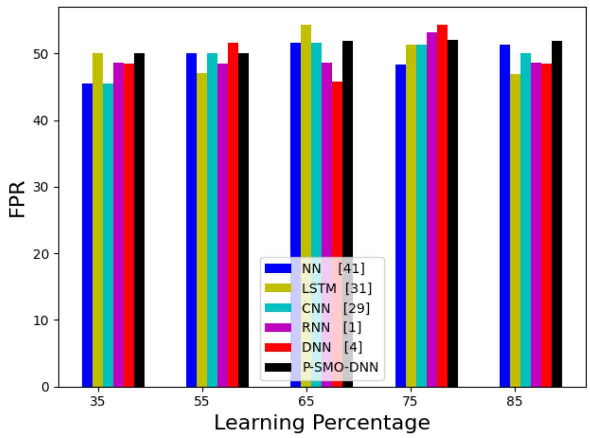
(b)


Specificity
Learning Percentage
NN [41]
LSTM [31]
CNN [29]
RNN [1]
DNN [4]
P-SMO-DNN

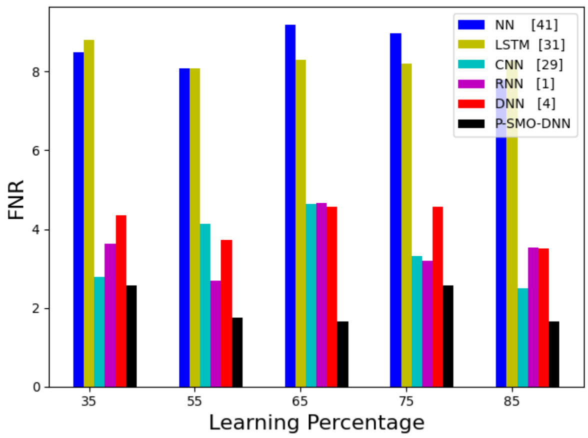
(c)


Precision
Learning Percentage
NN [41]
LSTM [31]
CNN [29]
RNN [1]
DNN [4]
P-SMO-DNN

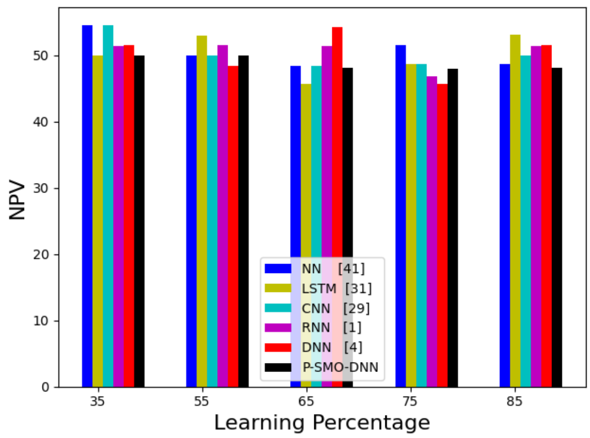
(d)

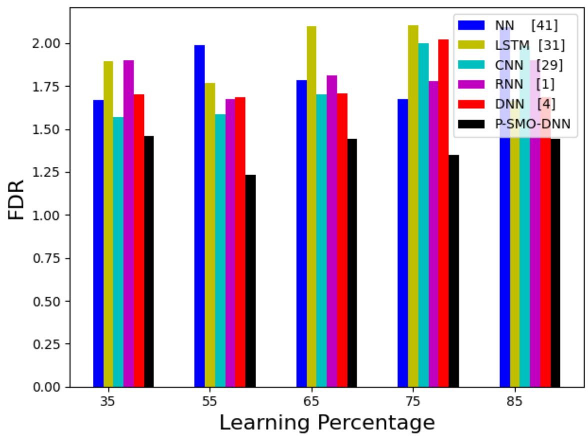

FPR
Learning Percentage
NN [41]
LSTM [31]
CNN [29]
RNN [1]
DNN [4]
P-SMO-DNN

(e)

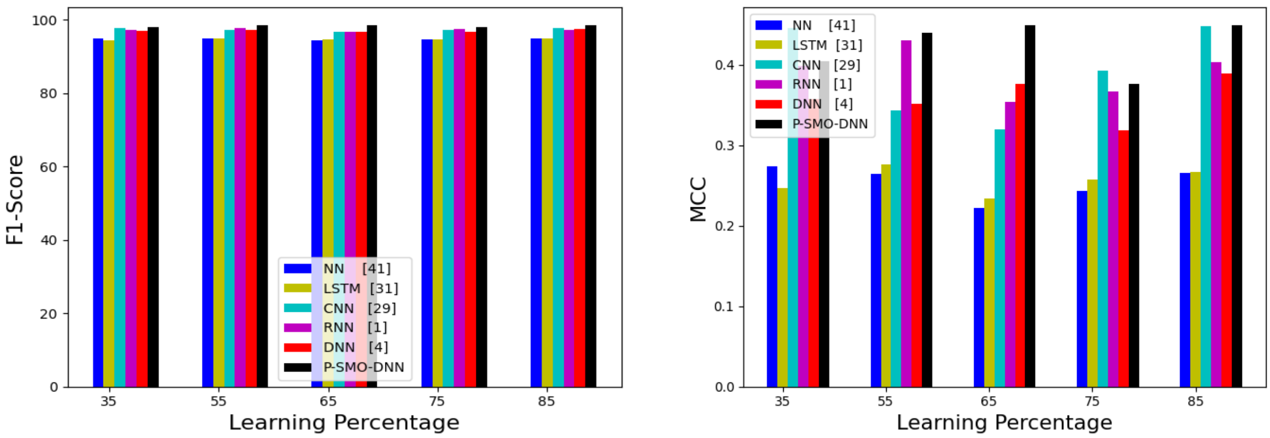

FNR
Learning Percentage
NN [41]
LSTM [31]
CNN [29]
RNN [1]
DNN [4]
P-SMO-DNN

(f)


NPV
Learning Percentage
NN [41]
LSTM [31]
CNN [29]
RNN [1]
DNN [4]
P-SMO-DNN


FDR
Learning Percentage
NN [41]
LSTM [31]
CNN [29]
RNN [1]
DNN [4]
P-SMO-DNN

(g) (h)



(i) (j)

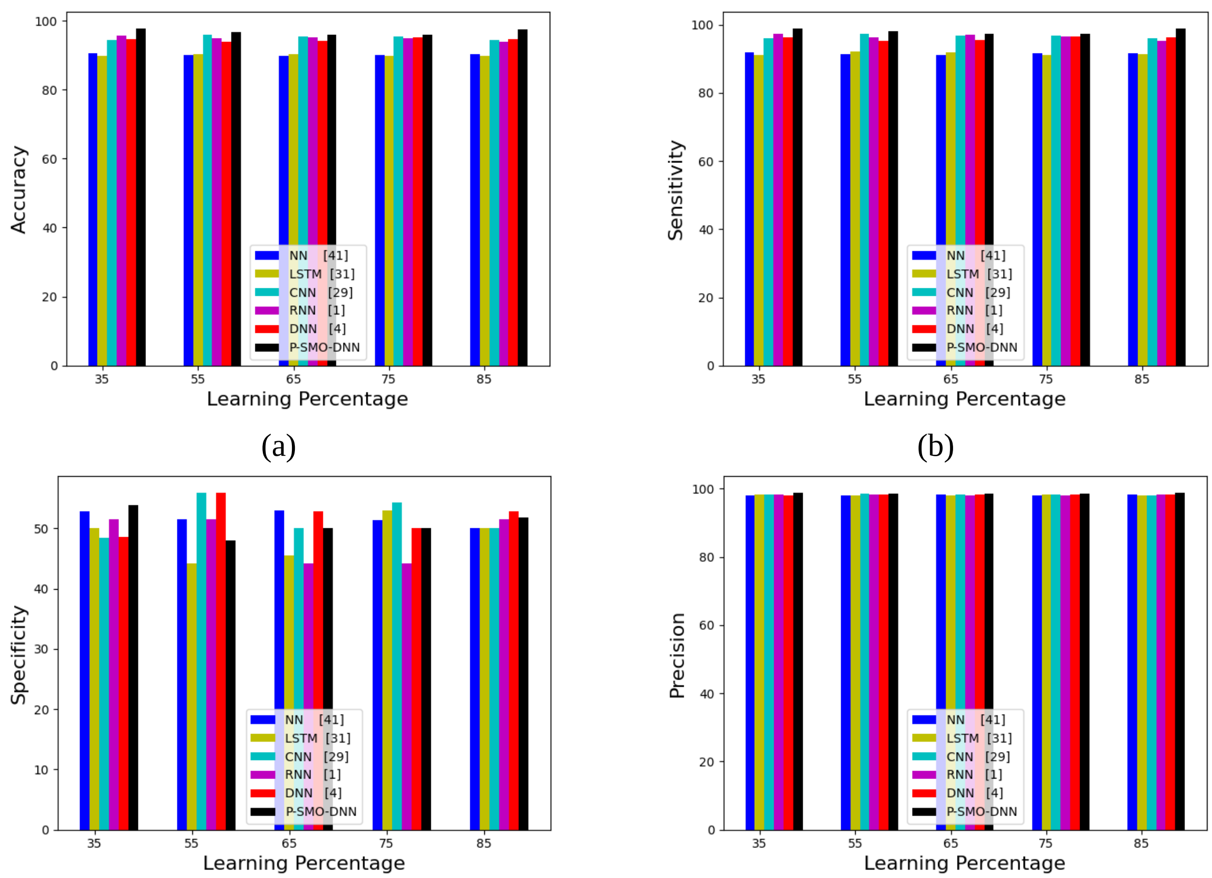
Figure 8.
Examination of the developed approach according to dataset 1 concerning“(a) accuracy, (b)sensitivity, (c)specificity, (d)precision, (e)FPR, (f)FNR, (g)NPV, (h)FDR, (i) F1-Score and (j) MCC”

6.5. Validation of Dataset 1 According To Diverse Techniques

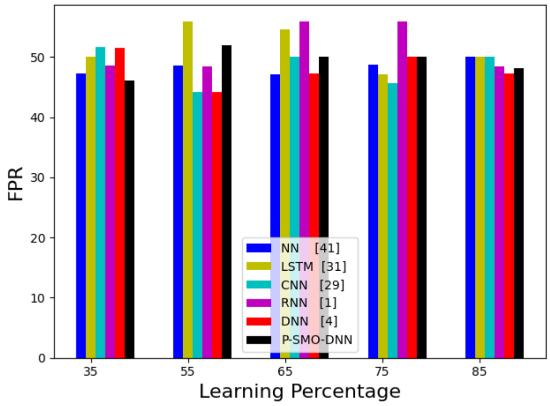
The estimation of the developed approach is estimated with the help of dataset 1 is provided in Figure 8. The accuracy of the offered P-SMO-DNN is tested with diverse classifiers, which provide 8.88%, 7.69%, 2.08%, 2.08%, and 2.08% enhanced effectiveness than the NN, LSTM, CNN, RNN, and DNN in terms of accuracy measure. While considering the FNR performance, the offered P-SMO-DNN maintains a constantly lower value for all the learning percentages up to 85, which indicates the errors in the fake news detection are mostly decreased than other algorithms.

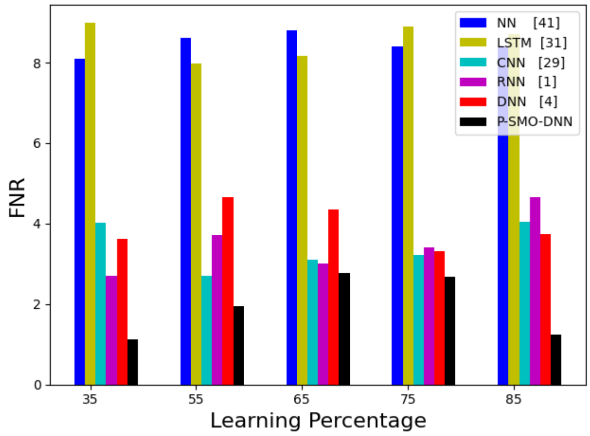
6.6. Estimation of Dataset 2

Estimation of the implemented approach along with dataset 2 is tested with diverse classifiers that are shown in Figure 9. The precision of the offered P-SMO-DNN shows 2.06%, 2.06%, 2.06%, 2.06%, and 2.06% enriched than the NN, LSTM, CNN, RNN, and DNN, at the learning rate of 55. Here, the offered P-SMO-DNN has significantly reduced all the errors regarding negative metrics when tested to the baseline classifier approaches at every learning rate.

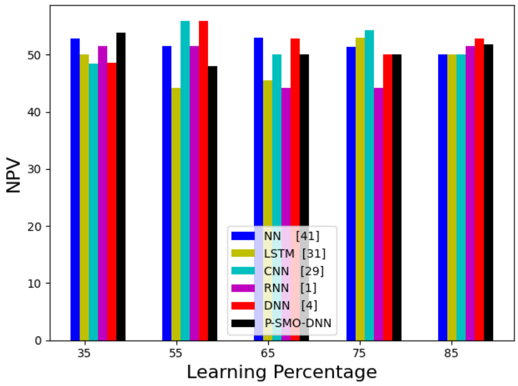


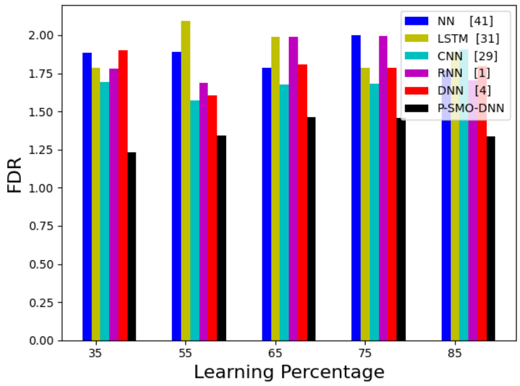
(c) (d)



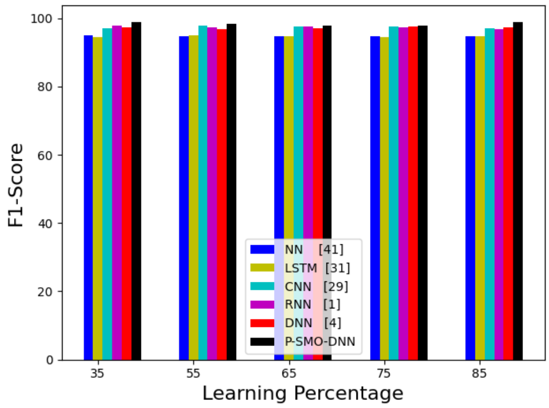


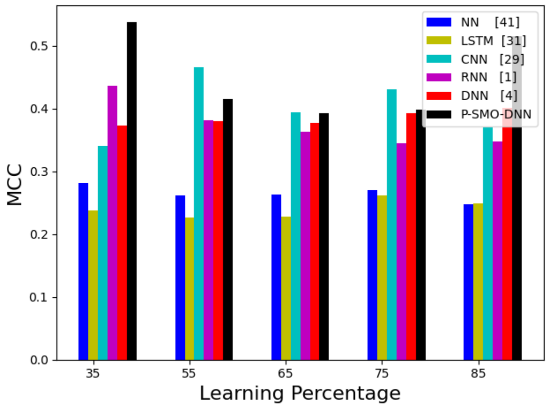
(e) (f)





(g) (h)





(i) (j)

Figure 9.
Examination of the proposed approach according to dataset concerning"(a) accuracy, (b)sensitivity, (c)specificity, (d)precision, (e)FPR, (f)FNR, (g)NPV, (h)FDR, (i) F1-Score and (j) MCC"

6.7. Comparative Validation of the Developed Algorithm

The estimation of the developed method is tested with diverse optimization models for datasets 1 and 2which are shown in Table 2. The efficacy of the offered P-SMO-DNN is 1.97%, 1.58%, 1.92%, and 1.3% enhanced in MCC value than the PSO, WOA, TSA, and SMO regarding dataset 2. Thus, the offered fake news detection method with offered P-SMO-DNN has improved its performance on dataset 1.

Table 2.
Overall efficacy of the designed P-SMO algorithm for the offered fake news detection approach.

Dataset 1					
Terms	**PSO -DNN [45]**	**WOA -DNN [46]**	**TSA -DNN [43]**	**SMO -DNN [44]**	**P-SMO-DNN**
“Accuracy”	95.50	94.60	94.40	95.50	97.00
“Sensitivity”	97.00	96.17	96.06	96.91	98.36
“Specificity”	50.00	50.00	48.57	50.00	48.15
“Precision”	98.32	98.20	98.10	98.43	98.56
“FPR”	50.00	50.00	51.43	50.00	51.85
“FNR”	3.00	3.83	3.94	3.09	1.64
“NPV”	50.00	50.00	48.57	50.00	48.15
“FDR”	1.99	2.80	3.90	1.57	1.44
“F1-Score”	96.66	98.18	98.07	96.66	99.46
“MCC”	39.91	37.02%	35.98	38.60	44.92
Dataset 2					
“Accuracy”	93.90	94.60	94.00	95.10	97.50
“Sensitivity”	95.26	96.37	95.36	96.49	98.77
“Specificity”	49.00	47.22	45.61	51.61	51.85
“Precision”	96.40	97.00	93.38	98.42	99.67
“FPR”	60.75	52.78	58.36	48.39	45.32
“FNR”	5.74	3.63	3.64	4.51	1.23
“NPV”	44.95	47.22	49.58	50.61	51.85
“FDR”	1.60	2.00	1.60	1.58	1.33
“F1-Score”	95.80	96.18	97.86	96.45	99.72
“MCC”	32.26	36.58	34.01	38.25	51.56

6.8. Comparative Validation of the Implemented Framework Based on Diverse Classifiers

The offered model is in Table 3 for testing its overall performance according to datasets 1 and 2. The developed P-SMO-DNN algorithm shows elevated performance concerning accuracy rate, in which it provides7.06%, 7.18%, 1.35%, 2.32%, and 2.10% elevated values while testing with the NN, LSTM, CNN, RNN, and DNN, on dataset 1. Thus, the designed fake news detection method with offered P-SMO-DNN is elevated with its performance on both datasets 1 and 2.

Table 3.
Overall efficacy of suggested P-SMO algorithm for the offered fake news detection approach using existing classifiers.

Dataset 1						
Terms	NN [47]	LSTM [7]	CNN [2]	RNN [29]	DNN [34]	P-SMO-DNN
“Accuracy”	90.60	90.50	95.70	94.80	95.00	97.00
“Sensitivity”	92.21	91.74	97.51	96.47	96.48	98.36
“Specificity”	48.65	53.13	50.00	51.35	51.52	48.15
“Precision”	97.91	98.34	98.01	98.10	98.31	98.56
“FPR”	51.35	46.88	50.00	48.65	48.48	51.85
“FNR”	7.79	8.26	2.49	3.53	3.52	1.64
“NPV”	48.65	53.13	50.00	51.35	51.52	48.15
“FDR”	2.09	1.66	1.99	1.90	1.69	1.44
“F1-Score”	94.97	94.92	97.76	97.28	97.39	98.46
“MCC”	26.56	26.68	44.77	40.29	38.97	44.92
Dataset 2						
Terms	NN [47]	LSTM [7]	CNN [2]	RNN [29]	DNN [34]	P-SMO-DNN
“Accuracy”	90.30	89.90	94.30	93.90	94.70	97.50
“Sensitivity”	91.63	91.30	95.95	95.35	96.27	98.77
“Specificity”	50.00	50.00	50.00	51.52	52.78	51.85
“Precision”	98.23	98.11	98.09	98.29	98.20	98.67
“FPR”	50.00	50.00	50.00	48.48	47.22	48.15
“FNR”	8.37	8.70	4.05	4.65	3.73	1.23
“NPV”	50.00	50.00	50.00	51.52	52.78	51.85
“FDR”	1.77	1.89	1.91	1.71	1.80	1.33
“F1-Score”	94.82	94.58	97.01	96.80	97.22	98.72
“MCC”	24.76	24.84	36.93	34.71	40.07	51.56

6.9. Computational Complexity of the Designed Method

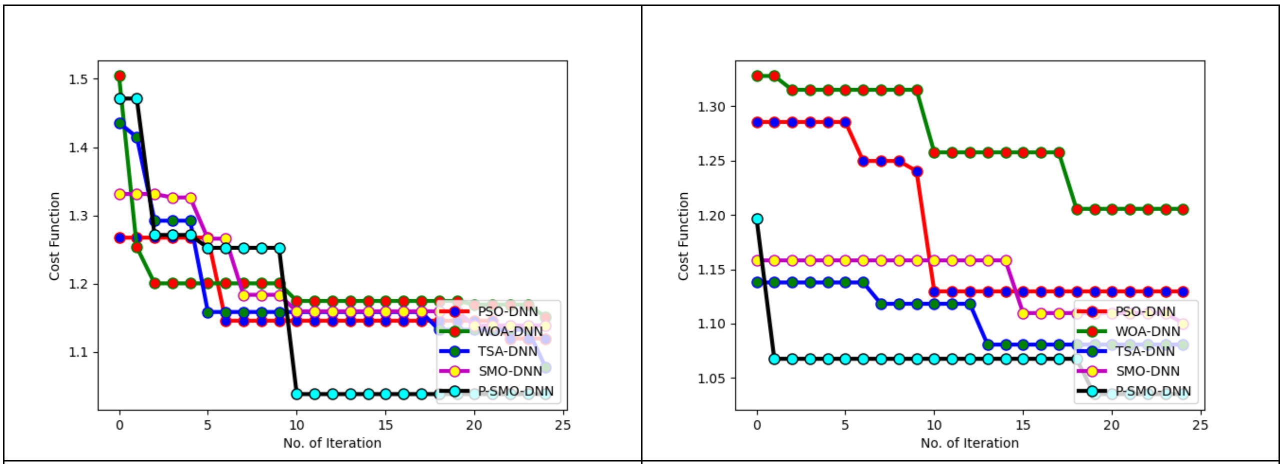
The computational complexity of the detection of the fake news approach is given in Table 4. Here, the variable N_{pop} is denoted as the number of populations, and the variable $MaxIter$ is defined as the maximum iterations. Moreover, the variable $chlen$ is described as the chromosome length.

Table 4.
Computational complexity of the detection of fake news approach

Proposed approach	The complexity of the proposed approach
P-SMO-DNN	$O[N_{pop}+N_{pop}+(3*N_{pop})+N_{pop}+[(MaxIter*(N_{pop}*chlen)+(2*N_{pop})+N_{pop}+N_{pop}+(3*N_{pop})+(N_{pop}*chlen))]$

6.10. Convergence Validation of the Designed Approach

The convergence validation of the detection approach is provided in Figure 10.



(a) (b)

Figure 10.
Convergence evaluation of the developed fake news detection model for (a) dataset 1 and (b) dataset 2

6.11. Validation of the Implemented Framework Utilizing Recent Approaches

The evaluation of the proposed framework over the recent approaches for datasets 1 and 2 is given in Table 5. The developed P-SMO-DNN method has a better accuracy value than the conventional 4.24% MS-EL, 4.80% HERO, and 20.5% MVCAN methods in dataset 1. Consequently, the F1-score of the designed P-SMO-DNN is attained as 30.3%, 29.6%, and 18.4% superior to MS-EL, HERO, and MVCAN for dataset 2. Thus, the developed fake news detection model is confirmed to be enriched.

Table 5.
Evaluation of the proposed method using recent approaches.

Methods	MS-EL [48]	HERO [49]	MVCAN [50]	P-SMO-DNN
Dataset 1				
Accuracy	93.05	92.55	95.05	97.00
Sensitivity	94.61	93.95	96.78	98.36
Specificity	49.32	51.56	49.29	48.15
Precision	98.11	98.27	98.05	98.56
FPR	50.68	48.44	50.71	51.85
FNR	5.39	6.05	3.22	1.64
NPV	49.32	51.56	49.29	48.15
FDR	1.89	1.73	1.95	1.44
F1-Score	96.32	96.05	97.41	98.46
MCC	33.23	31.85	40.38	44.92
Dataset 2				
Accuracy	92.10	92.25	94.15	97.50
Sensitivity	93.44	93.84	95.66	98.77
Specificity	50.00	48.61	50.81	51.85
Precision	98.32	98.05	98.25	98.67
FPR	50.00	51.39	49.19	48.15
FNR	6.56	6.16	4.34	1.23
NPV	50.00	48.61	50.81	51.85
FDR	1.68	1.95	1.75	1.33
F1-Score	95.81	95.88	96.93	98.72
MCC	28.51	30.71	35.47	51.56

6.12. Statistical Validation of the Presented Framework

Table 6 shows the developed method's statistical validation with various conventional methods in terms of datasets 1 and 2. The best measure rate of the implemented P-SMO-DNN approach is attained as 7.27%, 9.80%, 3.63%, and 8.83%, progressed than PSO, WOA, TSA, and SMO for dataset 1. The median value of the designed P-SMO-DNN model is attained as 5.48%, 15.09%, 4.52%, and 7.81% superior to PSO, WOA, TSA, and SMO for dataset 2.

Table 6.
Statistical analysis of the presented method for all datasets.

Algorithms	PSO -DNN [45]	WOA -DNN [46]	TSA -DNN [43]	SMO -DNN [44]	P-SMO-DNN
Dataset 1					
Worst	1.267312	1.504264	1.435563	1.331249	1.471149
Mean	1.171626	1.197311	1.18623	1.200557	1.143505
Standard Deviation	0.054407	0.065714	0.086603	0.071675	0.139986
Best	1.119446	1.150833	1.077151	1.138527	1.037988
Median	1.145527	1.17451	1.158348	1.159308	1.037988
Dataset 2					
Worst	1.28533	1.327639	1.137817	1.158121	1.196934
Mean	1.185805	1.266901	1.105705	1.138372	1.065028
Standard Deviation	0.069828	0.046013	0.025016	0.024254	0.030239
Median	1.129629	1.257447	1.118205	1.158121	1.067642
Best	1.129629	1.205489	1.080722	1.100239	1.035202

7. Conclusions

This task has developed a new model by suggesting P-SMO with the developed OAF-DNN for accurately detecting fake news from the given data. Initially, the garnered data were fed to the preprocessing stage with stemming, removing stop words, and tokenization. Then, the extraction of features was done using word to vector, TF-IDF, PCA, and grammatical examination utilizing "mean, Q25, Q50, Q75, Max, Min, and standard deviation" for acquiring the significant features of fake news. The detection of real or fake news was achieved by the OAF-DNN detector, in which the P-SMO has optimized the activation function of DNN for attaining high detection accuracy and high precision. Throughout the overall analysis, the proposed P-SMO is 7.06% enhanced compared to NN, 7.18% enriched compared to LSTM, 1.35% improved compared to RNN, 2.32% enhanced compared to CNN, and 2.10% better compared to DNN. Therefore, the offered fake news detection technique with OAF-DNN using the proposed P-SMO has achieved elevated performance compared to other existing fake news detection methods. The utilization of a single classifier in classifying fake news, however, faces complications regarding lack of performance and the computationally expensive nature of DNN. Hence, the upcoming work will be the design of detecting fake news with ensemble approaches by using large-scale datasets. We will combine our designed method with style-based approaches, and we will discuss more details about the other applications of fake news detection.

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