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Article

Hunter Prey Optimization with Hybrid Deep Learning for Fake News Detection on Arabic Corpus

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Abstract: Nowadays, the usage of social media platforms is rapidly increasing, and rumours or false information are also rising, especially among Arab nations. This false information is harmful to society and individuals. Blocking and detecting the spread of fake news in Arabic becomes critical. Several artificial intelligence (AI) methods, including contemporary transformer techniques, BERT, were used to detect fake news. Thus, fake news in Arabic is identified by utilizing AI approaches. This article develops a new hunter-prey optimization with hybrid deep learning-based fake news detection (HPOHDL-FND) model on the Arabic corpus. The HPOHDL-FND technique undergoes extensive data pre-processing steps to transform the input data into a useful format. Besides, the HPOHDL-FND technique utilizes long-term memory with a recurrent neural network (LSTM-RNN) model for fake news detection and classification. Finally, hunter prey optimization (HPO) algorithm is exploited for optimal modification of the hyperparameters related to the LSTM-RNN model. The performance validation of the HPOHDL-FND technique is tested using two Arabic datasets. The outcomes exemplified better performance over the other existing techniques with maximum accuracy of 96.57% and 93.53% on Covid19Fakes and satirical datasets, respectively.

Keywords: Arabic corpus; fake news detection; deep learning; hunter prey optimizer; classification model

1 Introduction

Fake news, otherwise called rumors, is described as "data or claim confirmed as untrue". False data posted over social networking sites become an important issue because it could spread quickly and reaches hundreds or thousands of people very quickly [1]. Therefore, manual techniques to detect fake news are impossible about cost and time. Thus, to restrict the spreading of questionable content and alert people that the news that one was reading is unreal, techniques which could automatically detect fake news were needed [2]. Further, during the COVID-19 pandemic, false or misleading coronavirus information became a serious issue that hugely impacted people's health [3,4]. Fake news detection (FND) can be described as "the forecasting the probabilities of a specific news article (expose, news reports, editorials, and so on) being intentionally deceptive". Other terminologies regard tasks closely based on FND, adding credibility assessment, rumour detection, misleading data detection, stance classification of news articles, rumor veracity classification, checking "the valuation of news authenticity", and claiming confirmation [5,6]. Recently, FND tasks have grasped substantial attention from the natural language processing (NLP) research community. And the usage of machine learning (ML), predominantly Deep Learning (DL)-related techniques, for identifying these phenomena has allured the interest of the research community [7,8].

In the Arab world, fake news has affected events occurring all over Arabic-speaking nations [9]. Uncertain times are even tougher; the public cannot decide what events happened and what was being reported incorrectly [10,11]. Many earlier studies have been carried out on identifying fake news utilizing DL pre-trained methods from transformers [12,13]. The reason behind this is that Arabic NLP has become one such challenging domain in NLP. Initially, the format and the word spelling also varies, which could change the word meanings [14]. It is identified just by the pronunciation and the sentence. Moreover, the Arabic language comprises several dialects, and certain dialects differ from others [15].

This article develops a new hunter-prey optimization with hybrid deep learning-based fake news detection (HPOHDL-FND) model on the Arabic corpus. The presented HPOHDL-FND technique majorly intends to recognize and classify the fake news effectually in the Arabic corpus. To attain this, the HPOHDL-FND technique undergoes extensive data pre-processing steps to transform the input data into a useful format. Besides, the HPOHDL-FND technique utilizes long-term memory with recurrent neural network (LSTM-RNN) methodology for detecting fake news and classification. Finally, hunter prey optimization (HPO) algorithm is exploited for optimal modification of the hyperparameters related to the LSTM-RNN approach. The performance validation of the HPOHDL-FND technique is tested using two Arabic datasets.

2 Related Works

Hindi et al. [16] examine the problem of fake news identification in the Arabic language through treated textual analysis. The Author presents a supervised ML approach to address the difficulties of authenticating news; this technique categorises Arabic news articles based on their credibility of context. The author further presents the initial dataset of Arabic fake news articles has crowdsourcing. Then, for extracting text features from the articles, the author frames a novel technique of constituting Arabic lexical wordlists and devises an Arabic NLP tool for performing text feature extractions. Aljwari et al. [17] intend to sort out how it forecasts the features which act as a reason for the spreading of Arabic online fake news. It utilizes Random Forest (RF), Naive Bayes (NB), and Logistic Regression (LR) to accomplish this. And discovered by utilizing the Term Frequency-Inverse Document Frequency (TF-IDF). The optimal partition for validating and testing the estimation has been selected randomly and employed in the analysis. Hence, all 3 ML classifications to forecast fake news in Arabic online are formulated.

Najadat et al. [18] offer an Arabic fake news identification technique utilizing various DL techniques, including LSTM and convolutional neural network (CNN) related to article-headline pairs, for distinguishing if a news headline was relevant or irrelevant to similar news articles. This presents a dataset on the conflict in Syria and the Middle East's political problems. Alzanin et al. [19] encounter the issue of identifying fake news in Arabic tweets. The author utilized a feature set derived from the user and the content. Such features are examined to decide their importance. Semi-supervised expectation–maximization (E–M) has been employed for training the devised mechanism with matters of newsworthy tweets. A semi-supervised mechanism utilizing a minor base of labelled data outpaces Gaussian NB achievement through a comparison between supervised Gaussian NB and a semi-supervised system. Jehad et al. [20] modelled 2 different ML techniques (RF and decision tree (DT)) for detecting fake news. The pre-processing steps commence with cleaning data by removing inessential white spaces, special characters, English letters, and numbers and eliminating stop words. Then, the famous feature extraction method TF-IDF was utilized before applying the 2 suggested classifier methods.

Khalil et al. [21] authors were advancing ML techniques for identifying warn readers and fake content. But there exist a restricted number of Arabic fake news dataset relating to news sources and articles. This study focuses on presenting the initial large Arabic fake news corpus comprising 6,06,912 articles gathered from 134 Arabic online news sources. An Arabic fact-check platform annotated news sources as undecided, credible, and not-credible. Further, various ML techniques were employed for identification. Alzanin et al. [22] devise a method for classifying the textual tweets in Arabic related to their linguistic features and content into 5 diverse categories. The author explores 2 textual representations they are stanched text with tf-IDF and word embedding utilizing Word2vec. The hyperparameters of all the classifiers had been tuned.

3 The Proposed Model

This study has developed a new HPOHDL-FND model to recognize and classify fake news effectually in the Arabic corpus. To attain this, the HPOHDL-FND technique undergoes extensive data pre-processing steps to transform the input data into a useful format. Besides, the HPOHDL-FND technique utilized the HPO with the LSTM-RNN model for fake news detection and classification.

3.1 Arab Data Pre-Processing

The major component of the attainment of training a DL algorithm is data preparation. Most of the effort and time are typically placed into this phase as it crucially impacts the subsequent phases of learning. Feeding a DL algorithm clean and normalized dataset grants appropriate learning. This subsection defines the procedure to be followed for preparing the training dataset. Data pre-processing in ML represents the method of preparing (organizing and cleaning) the raw dataset making them fit to build an improved prediction ML model. Normally, the real-time dataset is inaccurate, incomplete, inconsistent (has outliers or errors), and frequently lacks definite attribute trends or values. There exist distinct methods for pre-processing text datasets, which are dependent mainly on language [23]. In Arabic, the pre-processing task includes tokenization, stop-word removal, morphological analysis, normalization, and removing foreign symbols and punctuation marks from the text. We have implemented some pre-processing tasks to combine the dataset's structure from different sources. Initially, English letters, numbers, and special characters are eliminated from the text. Also, Noisy data are eliminated, namely, incomplete words and missing letters in the text. Additional spaces were eliminated from all the sentences. In all the text files, the paragraph is divided into a sentence which has a single sentence for all the lines. The paragraph is separated into one or more sentences at the next ending punctuation mark:: '.', ':', ',', '«', '»', '?', ';', '[', ']', '{', '}'. Then, the lines with lengths higher than ten words are separated into lines of lengths no higher than 10. This method could limit the usage of memory, and we preserve the semantic structure of the text. The position of the diacritics was combined, where every diacritic was directly inserted into the respective letter afterwards. Once Shaddah and other diacritics were utilized, the series was united, from which Shaddah approached first. Normalization of Arabic letter is a general pre-processing stage while handling Arabic text, and it aims at normalizing specific letter that has various forms in similar word to a single form. In this phase, letters ' @', '@ ' and ' @' are substituted with '@' whereas the letter 'ø' is substituted with 'ø ' and the letter ' è' is substituted with ' è'. Furthermore, we removed additional Tatweel symbols and white spaces. In this work, many pre-processing tasks were conducted by the regular expression in Python. A Regular Expression (RegEx) is a programming language embedded within Python. RegEx uses a character sequentially that determines a search pattern to check whether a specific string matches a provided RegEx. Regexes are widely applied for searching text files and parsing text for a specific pattern. Similarly, RegEx is written to eliminate noisy data and special characters and normalize specified letters into one form.

3.2 Fake News Detection Module

The HPOHDL-FND technique utilized the LSTM-RNN model for fake news detection and classification in this study. Compared to classical NN, RNN uses feedback loops in which the output from every step (step n − 1) is reinserted into the RNN to affect the result of the recent step (i.e., step n); this procedure can be repeated for every subsequent phase. RNNs prove to reach optimal outcomes on text classifications. RNN has been elected as an effective method utilized to process sequential data. RNNs mathematical approach contains an input tex_t, a hidden state h, updated during step t, and an output layer 0_t in the following way:

$$h_t = tanh\ (W * h_{t-1} + I * x_t) \tag{1}$$

Whereas $tanh$ indicates the hyperbolic tangent function, W denotes the recurrent weight matrix, and I represents a projection matrix. The hidden state h can be employed for predicting the output layer 0_t, whereas W refers to a weight matrix, and softmax offers a normalized probability distribution on the likely classes.

$$0_t = soft\ max\ (W * h_{t-1}) \tag{2}$$

The RNN can be trained by leveraging the semantic, word embedding, syntactic, and morphological features discussed earlier, which helps enhance the outcomes for the baseline technique. By integrating neurons with self-feedback connection, RNN accomplishes the exclusive ability of modelling time-sequence datasets, in contrast to other kinds of DL algorithms like stacked autoencoder (SAE), CNN, and deep belief network (DBN). Fig. 1 illustrates the infrastructure of the LSTM technique.

LSTM-RNN was intended to address the vanishing gradient problems while discovering long-term temporal correlation in time sequence. The LSTM-RNN is built from an LSTM unit for replacing the classical hidden neuron [24]. Every LSTM component is made up of memory cells (c_t), input gate (i_t), forget gate (f_t), and output gate (0_t). The operation in LSTM-RNN is formulated as follows

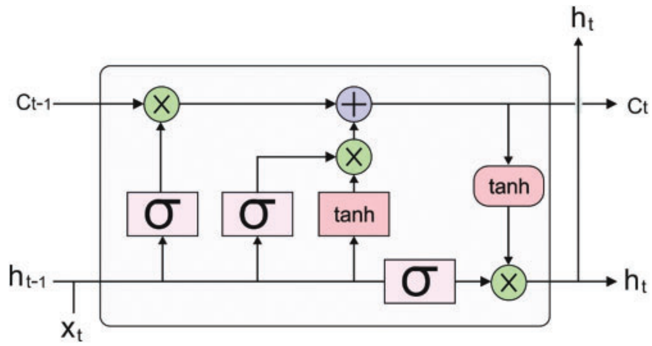


Figure 1: Structure of LSTM

$$g_t = \varphi\left(W_{ih} \cdot x_t + W_{hh} \cdot h_{t-1} + b_h\right) \tag{3}$$

$$i_t = \sigma\left(W_{ii} \cdot x_t + W_{hi} \cdot h_{t-1} + p_i \odot c_{t-1} + b_i\right) \tag{4}$$

$$f_t = \sigma\left(W_{if} \cdot x_t + W_{hf} \cdot h_{t-1} + p_f \odot c_{t-1} + b_f\right). \tag{5}$$

$$0_t = \sigma\left(W_{io} \cdot x_t + W_{ho} \cdot h_{t-1} + p_0 \odot c_t + b_o\right) \tag{6}$$

$$c_t = i_t \odot g_t + \odot c_{t-1} \tag{7}$$

$$h_t = 0_t \odot \varphi\left(c_t\right) \tag{8}$$

$$\sigma\left(t\right) = 1/(1 + e^{-t}) \tag{9}$$

$$\varphi\left(t\right) = (e^t - e^{-t})/(e^t + e^{-t}) \tag{10}$$

Here, i_t refers to the input instance at time t; h_t denotes the hidden outcome at t time; h_{t-1} indicates the hidden outcome at the preceding instant; σ shows the activation operation of the 3 gates; φ signifies the activation operation of output and input units; $\odot$ symbolizes the dot product function; W_{ih}, W_{ii}, W_{if}, W_{if}, W_{io} indicate the weight connecting the input and LSTM units; W_{hich}, W_{hi}, W_{hf}, W_{ho} represent the self-connection weights among the current time t and the preceding time t − l; b_h shows the bias of input unit, b_i, b_f, b_o indicates the bias of 3 gates in the LSTM; and p_i, p_f, p_0 demonstrates the weight that connects the peephole and 3 gates. The weight and bias are augmented through the stochastic gradient descent (SGD) process to minimalizehe mean square error (MSE) among the predicted and actual outputs.

3.3 Hyperparameter Tuning Module

At last, the HPO algorithm is exploited for optimal modification of the hyperparameters related to the LSTM-RNN technique. The overall architecture of HPO algorithm is elaborated in the following [25]. Firstly, the early population is set at random as $\left(\vec{x}\right) = \left\{\vec{x}_1, \vec{x}_2, \ldots \vec{x}_n\right\}$, and later the objective function was evaluated by $\left(\vec{O}\right) = \{O_1, O_2, \ldots O_n\}$ for each member of the population. The population is directed and controlled in the searching domain with a sequence of strategies and rules based on the projected model. This step is continued until the process is completed. In all the iterations, the location of all the population members is upgraded based on the rules of the projected method, and the novel location is computed using the objective function. This algorithm causes the solution to increase with all the iterations. The location of every member of the population is generated randomly in the search space as follows.

$$x_i = rand\,(1,\ d)\,.*\,(ub - lb) + lb \tag{11}$$

In Eq. (11), the hunter position or prey can be represented as X_i, lb, and ub denote the minimal and maximal value for the problem variable (lower and upper boundaries), *and d* shows the amount of parameters (dimensions) of the problem. Eq. (12) describes the lower and upper bounds of the search space. Note that a problem might have different or the same lower and upper boundaries for each variable.

$$lb = [lb_1,\ lb_2,\ \ldots lb_d\,], ub = [\,ub_1,\ ub_2,\ ub_d] \tag{12}$$

Afterwards, the generation and determination of early population and every agent location, the solution fitness, is evaluated by $O_i = f\left(\vec{x}\right)$, the objective function. Usually, the search method includes two stages: exploitation and exploration. Exploration represents the algorithm's tendency to extremely random behaviour such that the solution changes significantly and solution causes additional exploration of the search space and discovering the potential region. Then, random behaviour should be decreased so that the process could search around the promising region, representing exploitation.

$$x_{ij}\,(t+1) = x_{ij}\,(t) + O.5\left[\left(2CZP_{pos(j)} - x_{i,j}\,(t)\right) + \left(2\,(1-C)\,Z\mu_{(j)} - x_{i,j}\,(t)\right)\right]. \tag{13}$$

where the above equation upgrades the position of the hunter, whereby $x\,(t)$ denotes the present hunter location, $x\,(t+1)$ indicates the hunter's next location, PPOs show the prey location, μ denotes the mean of each position, and Z denotes an adaptive variable evaluated as follows

$$P = \vec{R}_1 < C;\ IDX = (P == 0)\,; \tag{14}$$

$$Z = R_2 \otimes IDX + \vec{R}_3 \otimes (\sim IDX)$$

In Eq. (14), $\vec{R}_1$ and $\vec{R}_3$ denote random number ranges within [0, 1], P indicates an arbitrary vector within [0, 1] equivalent to the amount of parameters in the problem, R_2 represents a random vector lies between 0 and 1, and IDX refers to the index number of the vector $\vec{R}$ that conditions are satisfied $(P == 0)$. The parameter structure Z and its correlation with *the* C parameter. Note that this is an instance for the reader to understand. Numbers are random, and their order and value change in all the iterations.

Parameter C indicates the balance between exploitation and exploration, whose value reduces from 1 to 0.02 in each iteration, and it is evaluated by using Eq. (15):

$$C = 1 - it\left(\frac{0.98}{MaxIt}\right) \tag{15}$$

Eq. (15) is the present iteration number, and $MaxIt$ indicates the maximal amount of iterations. The location of the prey (PPOs) is evaluated such that initially compute the average of each position (μ) according to the following equation and later the distance of every searching agent as follows

$$\mu = \frac{1}{n}\sum_{i=1}^{n}\vec{x}_i \tag{16}$$

We calculate the distance based on Euclidean distance according to Eq. (17)

$$D_{euc(i)} = \left(\sum_{j=1}^{d}\left(x_{i,j} - \mu_j\right)^2\right)^{\frac{1}{2}} \tag{17}$$

The searching agent with maximal distance from the mean of position is deliberated as prey (P_{POs}) based on the following equation

$$\vec{P}_{pos} = \vec{x}_i | i\ represent\ an\ index\ of\ \ Max\ \ (end)\ sort\ (D_{ec})\ . \tag{18}$$

Considering the search agent with the maximal distance from the average location (μ) in all the iterations, the process has late convergence. Based on the hunting strategy, once the hunter takes the prey, the prey dies, and the next time, the hunter moves toward the new prey. To resolve these problems, we assume a decreasing model as follows:

$$kbest = round\,(C \times N) \tag{19}$$

In Eq. (19), N indicates the searching agent count.

Here, we modify Eq. (18) and evaluate the prey location as follows:

$$\vec{P}_{pos} = \vec{x}_i | i\ is\ sorted\ D_{euc}\ \ (kbest)\ . \tag{20}$$

Consider that the optimal safe location is the optimum global location since it provides the prey with a good opportunity for survival, and the hunter might select another prey; it is shown as follows

$$x_{i,j}\,(t+1) = T_{pos(j)} + CZcos\,(2\pi R_4) \times \left(T_{ops(j)} - x_{i,j}\,(t)\right)\ . \tag{21}$$

In Eq. (21), $x\,(t)$ indicates the existing location of the prey, $x\,(t+l)$ shows the following location of the prey, Tops denotes the optimal global location, Z denotes an adaptive variable evaluated using Eq. (14), and $R4$ represents an arbitrary value within $[-1,\ 1]$. Parameter C indicates the balance between exploitation and exploration; that value is reduced in every iteration. The COS function and their input variable allow the following prey location to be situated at global optimal distinct angles and radials and increase the exploitation phase's performance.

$$\begin{aligned} x_i\,(t+1) = \{x_i\,(t) + O.5\left[\left(2CZP_{pos} - x_i\,(t)\right) + (2\,(1-c)\,Z\mu - x_i\,(t))\right]\ if\ \ R_5 < \beta\ T_{pos} \\ + CZcos\,(2\pi R_4) \times \left(T_{pos} - x_i\,(t)\right)\ \ else \end{aligned} \tag{22}$$

In Eq. (22), $R5$ denotes a random value within$[0, 1]$, and β indicates a regulatory variable that value is fixed to 0.1. Once the $R5$ value is small when compared to β, the search agent is assumed as a hunter, and the following location of the searching agent is upgraded; once the $R5$ value is large when compared to β, the search agent regards prey, and the following location of the searching agent is upgraded. Fig. 2 depicts the flowchart of the HPO technique.

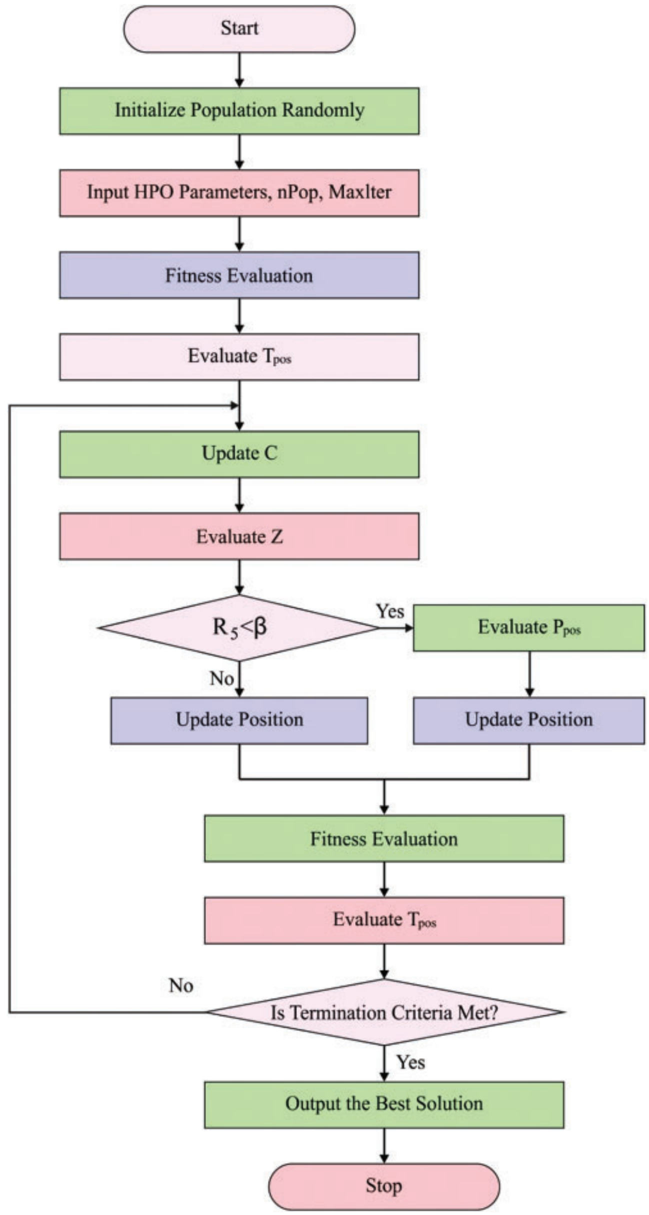


Figure 2: Flowchart of HPO technique

4 Performance Validation

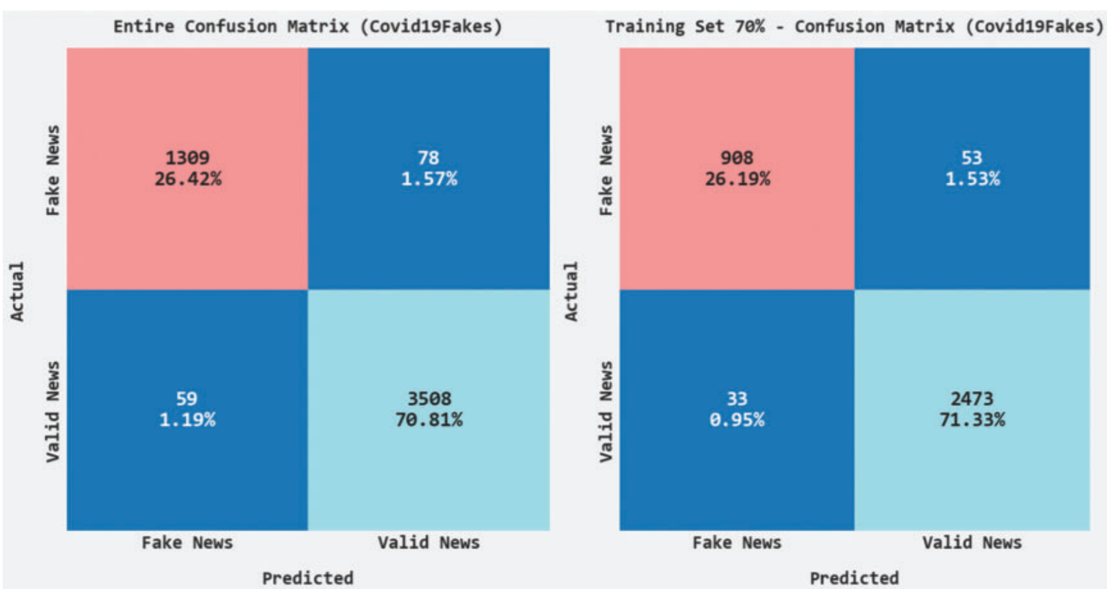
In this study, the Arabic fake newidentification outcomes of the HPOHDL-FND model are tested using the Covid19Fakes dataset [26] and Satirical dataset [27], as depicted in Table 1.

Table 1: Dataset details

Class	No. of instances in each dataset	
	Covid19Fakes	Satirical
Fake news	1387	1604
Valid news	3567	1638
Total no. of instances	**4954**	**3242**

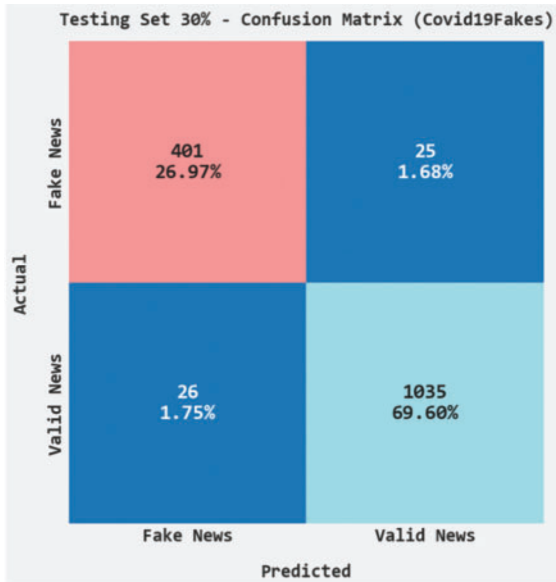
Fig. 3 highpoints the confusion matrices offered by the HPOHDL-FND approach on the Covid19Fakes dataset. On the entire dataset, the HPOHDL-FND algorithm has identified 1309 samples under the fake news class and 3508 samples under valid news class. Additionally, on 70% of training (TR) data, the HPOHDL-FND technique has detected 908 samples under the fake news class and 2473 samples under valid news class. In addition, on 30% of testing (TS) data, the HPOHDL-FND approach has detected 401 samples under the fake news class and 1035 samples under valid news class.

Table 2 and Fig. 4 report detailed fake news classifier results of the HPOHDL-FND model on the Covid19Fakes dataset. The results indicated that the HPOHDL-FND model had shown improved outcomes in all classes. On the entire dataset, the HPOHDL-FND model has attained average $accu_y$, $prec_n$, $reca_l$, F_{-score}, and MCC of 97.23%, 96.76%, 96.36%, 96.56%, and 93.12%, respectively. At the same time, on 70% of TR data, the HPOHDL-FND approach has achieved average $accu_y$, $prec_n$, $reca_l$, F_{-score}, and MCC of 97.52%, 97.20%, 96.58%, 96.88%, and 93.78% correspondingly. In parallel, on 30% of TS data, the HPOHDL-FND technique has gained average $accu_y$, $prec_n$, $reca_l$, F_{-score}, and MCC of 96.57%, 95.78%, 95.84%, 95.81%, and 91.62% correspondingly.



(a) (b)

Figure 3: (Continued)



(c)

Figure 3: Confusion matrices HPOHDL-FND approach under Covid19Fakes dataset (a) Entire dataset, (b) 70% of TR data, and (c) 30% of TS data

Table 2: Result analysis of HPOHDL-FND approach with distinct measures under the Covid19Fakes dataset

Covid19Fakes-dataset					
Labels	$Accu_y$	$Prec_n$	$Reca_l$	F_{score}	MCC
Entire dataset					
Fake news	97.23	95.69	94.38	95.03	93.12
Valid news	97.23	97.82	98.35	98.08	93.12
Average	**97.23**	**96.76**	**96.36**	**96.56**	**93.12**
Training set (70%)					
Fake news	97.52	96.49	94.48	95.48	93.78
Valid news	97.52	97.90	98.68	98.29	93.78
Average	**97.52**	**97.20**	**96.58**	**96.88**	**93.78**
Testing set (30%)					
Fake news	96.57	93.91	94.13	94.02	91.62
Valid news	96.57	97.64	97.55	97.60	91.62
Average	**96.57**	**95.78**	**95.84**	**95.81**	**91.62**

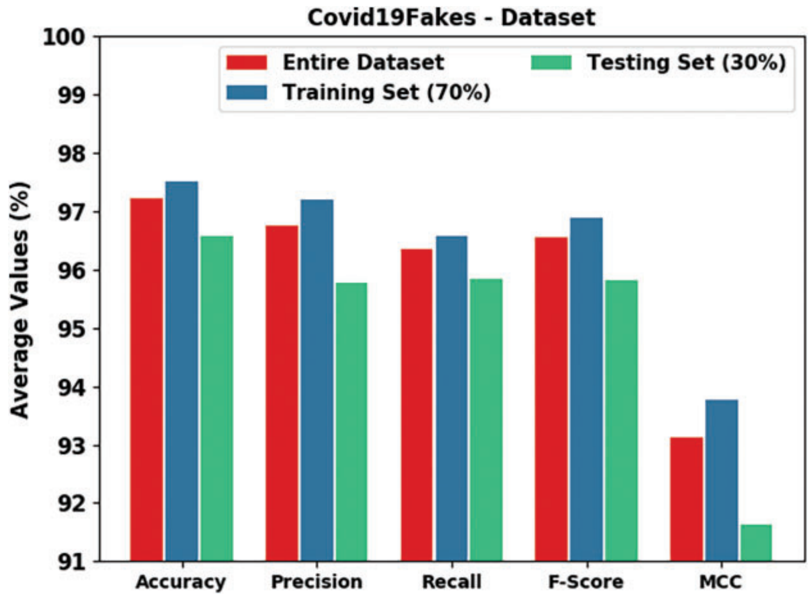


Figure 4: Result analysis of HPOHDL-FND approach under the Covid19Fakes dataset

The training accuracy (TRA) and validation accuracy (VLA) acquired by the HPOHDL-FND methodology on the Covid19Fakes dataset is displayed in Fig. 5. The experimental outcome implicit in the HPOHDL-FND approach has attained maximum values of TRA and VLA. Seemingly the VLA is greater than TRA.

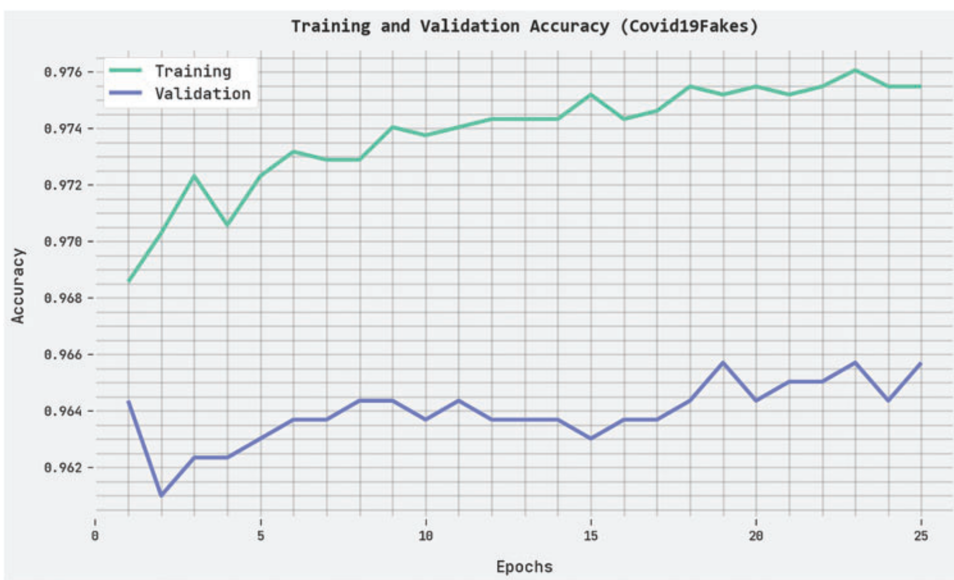


Figure 5: TRA and VLA analysis of HPOHDL-FND approach under the Covid19Fakes dataset

The training loss (TRL) and validation loss (VLL) obtained by the HPOHDL-FND methodology on the Covid19Fakes dataset are presented in Fig. 6. The experimental outcome denoted the

HPOHDL-FND technique has exhibited minimal values of TRL and VLL. Particularly, the VLL is lesser than TRL.

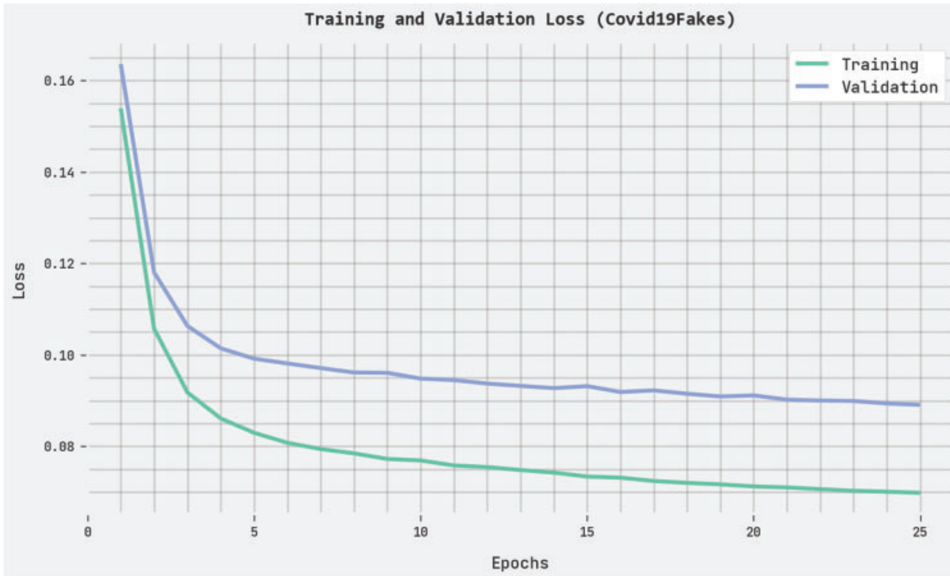


Figure 6: TRL and VLL analysis of HPOHDL-FND approach under the Covid19Fakes dataset

A clear precision-recall analysis of the HPOHDL-FND method on the Covid19Fakes dataset is displayed in Fig. 7. The figure represents the HPOHDL-FND algorithm has resulted in enhanced values of precision-recall values in all classes.

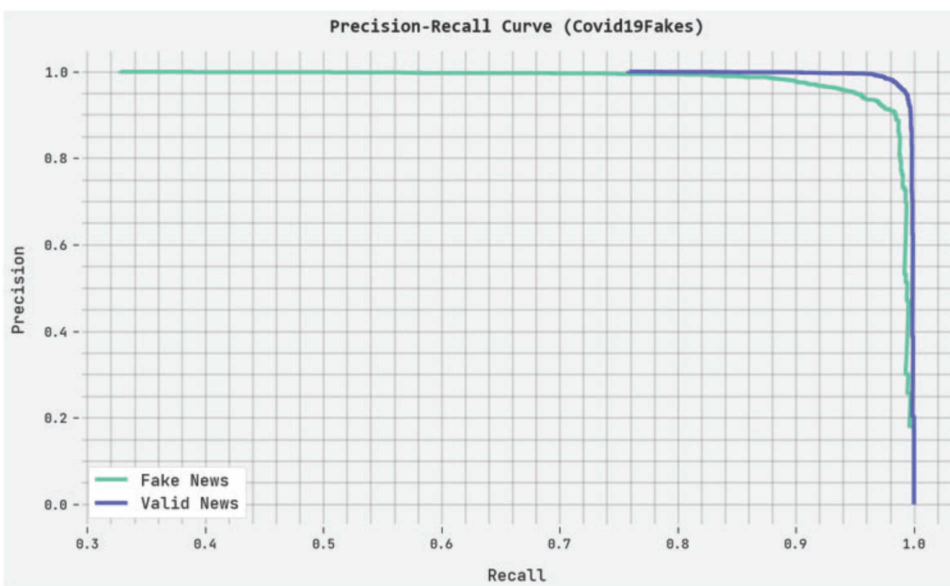


Figure 7: Precision-recall analysis of HPOHDL-FND approach under the Covid19Fakes dataset

Fig. 8 exemplifies the confusion matrices rendered by the HPOHDL-FND approach on the satirical dataset. On the entire dataset, the HPOHDL-FND algorithm has recognized 1530 samples under the fake news class and 1485 samples under valid news class. In addition, on 70% of TR data, the HPOHDL-FND technique has identified 1059 samples under the fake news class and 1046 samples under the valid news class. Additionally, on 30% of TS data, the HPOHDL-FND method has recognized 471 samples under the fake news class and 439 samples under the valid news class.

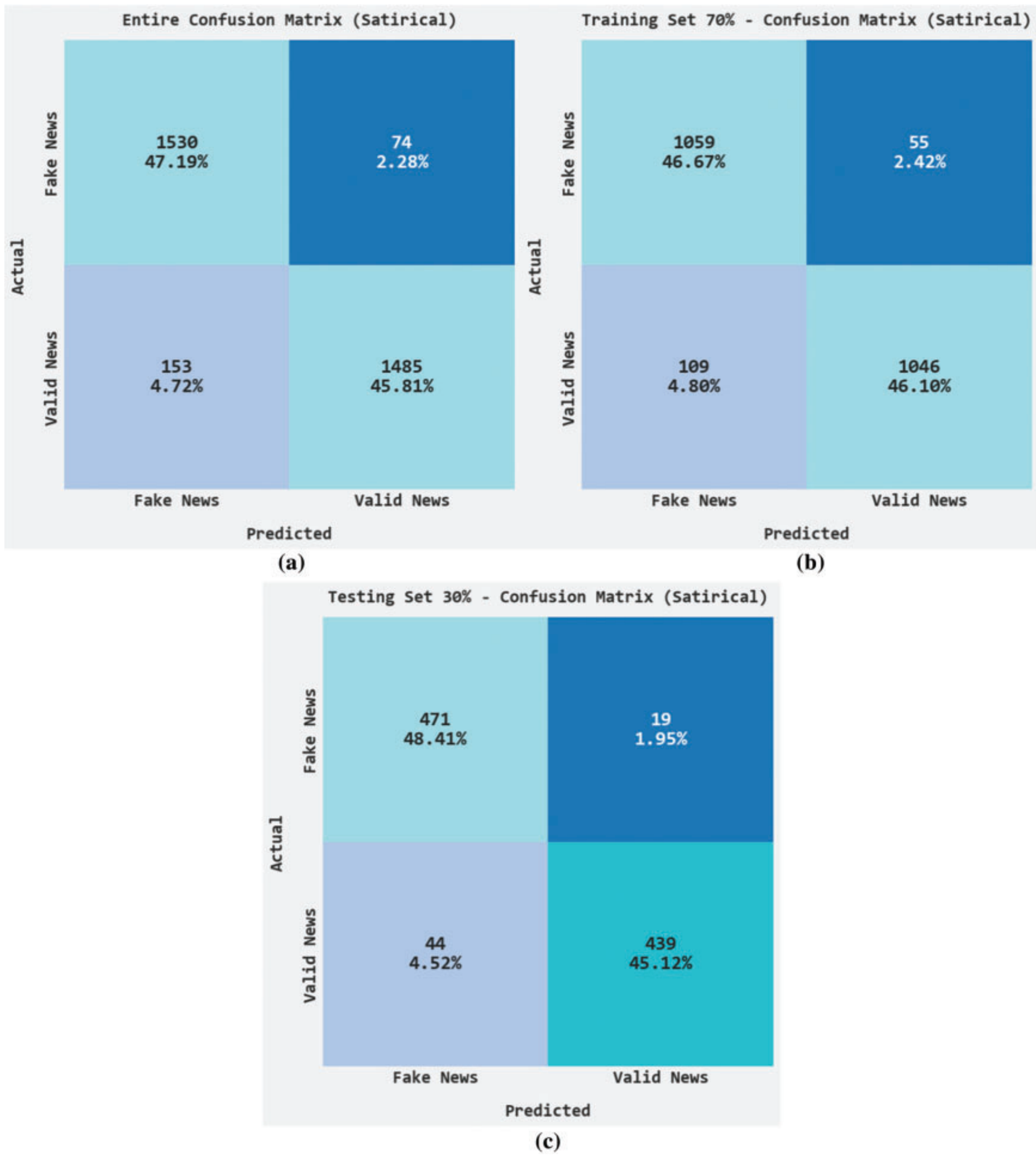


Figure 8: Confusion matrices HPOHDL-FND approach under satirical dataset (a) Entire dataset, (b) 70% of TR data, and (c) 30% of TS data

Table 3 and Fig. 9 demonstrate brief fake news classifier outcomes of the HPOHDL-FND approach on the Satirical dataset. The results showed that the HPOHDL-FND method had exhibited improved outcomes in all classes. On the entire dataset, the HPOHDL-FND technique has gained average $accu_y$, $prec_n$, $reca_l$, F_{-score}, and MCC of 93%, 93.08%, 93.02%, 93%, and 86.10%, correspondingly. Concurrently, on 70% of TR data, the HPOHDL-FND approach has reached average $accu_y$, $prec_n$, $reca_l$, F_{-score}, and MCC of 92.77%, 92.84%, 92.81%, 92.77%, and 85.65% correspondingly. In Parallel, on 30% of TS data, the HPOHDL-FND method has acquired average $accu_y$, $prec_n$, $reca_l$, F_{-score}, and MCC of 93.53%, 93.65%, 93.51%, 93.52%, and 87.16% correspondingly.

Table 3: Result analysis of HPOHDL-FND algorithm with distinct measures under satirical dataset

Satirical–Dataset					
Labels	$Accu_y$	$Prec_n$	$Reca_l$	F_{score}	MCC
Entire dataset					
Fake news	93.00	90.91	95.39	93.09	86.10
Valid news	93.00	95.25	90.66	92.90	86.10
Average	**93.00**	**93.08**	**93.02**	**93.00**	**86.10**
Training set (70%)					
Fake news	92.77	90.67	95.06	92.81	85.65
Valid news	92.77	95.00	90.56	92.73	85.65
Average	**92.77**	**92.84**	**92.81**	**92.77**	**85.65**
Testing set (30%)					
Fake news	93.53	91.46	96.12	93.73	87.16
Valid news	93.53	95.85	90.89	93.30	87.16
Average	**93.53**	**93.65**	**93.51**	**93.52**	**87.16**

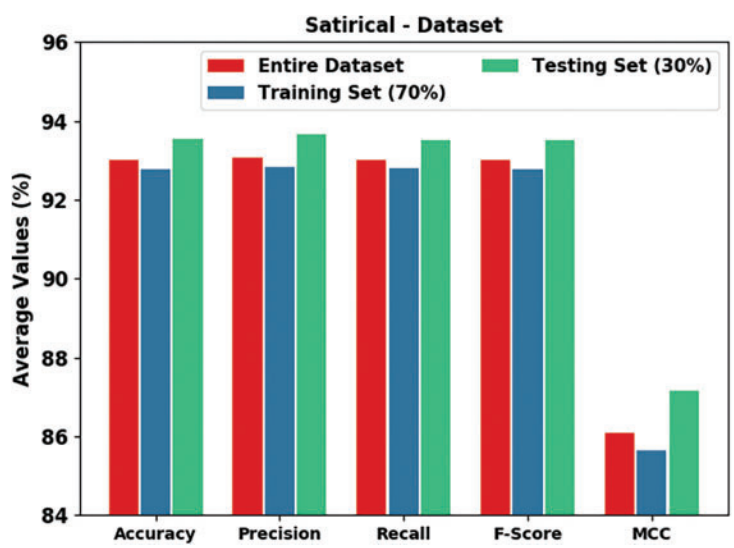


Figure 9: Result analysis of HPOHDL-FND approach under satirical dataset

Table 4 offers a brief analysis of the HPOHDL-FND model with other models on Covid19Fakes dataset. The table values pointed out that the HPOHDL-FND model achieves better results than other models. With respect to $accu_y$, the HPOHDL-FND model has offered enhanced $accu_y$ of 96.57%, whereas the QARiB, AraBERT, AraGPT2, and jointBERT models have provided reduced $accu_y$ of 53.15%, 42.89%, 45.62%, and 85.19% respectively. Likewise, with respect to *pr*ice, the HPOHDL-FND approach has granted enhanced $prec_n$ of 95.78%, whereas the QARiB, Arabic Bidirectional Encoder Representations from Transformers (AraBERT), Pre-Trained Transformer for Arabic Language Generation (AraGPT2), and jointBERT techniques have granted reduced *pr*ice of 95.71%, 95.20%, 96.10%, and 86.46% correspondingly.

Table 4: Comparative analysis of HPOHDL-FND approach with existing algorithms under Covid19Fakes dataset

Covid19Fakes–Dataset				
Methods	$Accu_y$	$Prec_n$	$Reca_l$	F_{score}
QARiB	53.15	95.71	54.60	67.76
AraBERT	42.89	95.20	44.53	57.78
AraGPT2	45.62	96.10	46.69	60.28
jointBERT	85.19	86.46	85.61	85.58
HPOHDL-FND	96.57	95.78	95.84	95.81

In addition, with respect to $reca_l$, the HPOHDL-FND methodology has presented an enhanced $reca_l$ of 95.84%, whereas the QARiB, AraBERT, AraGPT2, and jointBERT algorithms have rendered reduced $reca_l$ of 54.60%, 44.53%, 46.69%, and 85.61% correspondingly. Finally, with respect to F_{-score}, the HPOHDL-FND technique has presented an enhanced F_{score} of 95.81%, whereas the QARiB, AraBERT, AraGPT2, and jointBERT approaches have presented a reduced F_{-score} of 67.76%, 57.78%, 60.28%, and 85.58% correspondingly.

Table 5 delivered a detailed study of the HPOHDL-FND method with other techniques on satirical dataset. The table values highlighted the HPOHDL-FND technique reaches superior better results over other models. With respect to $accu_y$, the HPOHDL-FND algorithm has granted enhanced $accu_y$ of 93.53%, whereas the QARiB, AraBERT, AraGPT2, and jointBERT approaches have granted reduced $accu_y$ of 47.12%, 46.52%, 48.38%, and 55.66% correspondingly.

In addition, with respect to *pr*ice, the HPOHDL-FND technique has presented an enhanced $prec_n$ of 93.65% whereas the QARiB, AraBERT, AraGPT2, and jointBERT models have granted reduced *pr*ice of 50.25%, 50.78%, 50.12%, and 50.29% respectively. Also, with respect to $reca_l$, the HPOHDL-FND method has rendered enhanced $reca_l$ of 93.51%, whereas the QARiB, AraBERT, AraGPT2, and jointBERT models have presented reduced $reca_l$ of 45.12%, 50.66%, 50.46%, and 51.33% correspondingly. Finally, with respect to F_{-score}, the HPOHDL-FND approach has provided an enhanced F_{score} of 93.52% whereas the QARiB, AraBERT, AraGPT2, and jointBERT models have offered reduced F_{score} of 44.13%, 46.75%, 48.71%, and 54.78% correspondingly. These results demonstrated the enhanced outcomes of the HPOHDL-FND model compared to other models.

Table 5: Comparative analysis of HPOHDL-FND approach with existing algorithms under satirical dataset

Satirical-Dataset				
Methods	$Accu_y$	$Prec_n$	$Reca_l$	F_{score}
QARiB	47.12	50.25	45.12	44.13
AraBERT	46.52	50.78	50.66	46.75
AraGPT2	48.38	50.12	50.46	48.71
jointBERT	55.66	50.29	51.33	54.78
HPOHDL-FND	93.53	93.65	93.51	93.52

5 Conclusion

In this study, a new HPOHDL-FND algorithm was projected to effectively recognize and classify fake news in Arabic corpus. To attain this, the HPOHDL-FND technique undergoes extensive data pre-processing steps to transform the input data into a useful format. Besides, the HPOHDL-FND technique utilized the LSTM-RNN approach for fake news detection and classification. Finally, the HPO algorithm is exploited for optimal modification of the hyperparameters related to the LSTM-RNN model. The performance validation of the HPOHDL-FND technique is tested using two Arabic datasets, and the outcomes exemplified better performance over the other existing approaches with maximum accuracy of 96.57% and 93.53% on Covid19Fakes and satirical datasets, respectively. Thus, the HPOHDL-FND model can be exploited for the automated fake news detection process. In future, the detection efficacy of the HPOHDL-FND model can be boosted by the feature selection process.

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