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Optimizing LSTM Networks with Genetic and Q-Learning Algorithms for Persian COVID-19 Fake News Detection

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Abstract—**Currently, the development of the coronavirus as a pandemic and its global spread are a significant concern for our society and the international community. In recent years, however, a growing number of people have transferred their primary source of news and information to social networks. Therefore, the widespread dissemination of inaccurate and misleading information on social media is a significant concern for most politicians. Not only are we fighting against COVID-19, but also an "infodemic." To address this, we have collected and released a labeled dataset of 7,000 Persian social media postings, including both true and fake news. Several languages, including Arabic, English, Chinese, and Hindi, have recognized COVID-19 fake news. This study employs a deep neural network approach to simplify feature extraction, develop a strong ability to learn, and automatically discover features, compared to typical machine learning approaches. Additionally, it presents a novel approach to improving outcomes using a deep neural network. The genetic algorithm and reinforcement learning are utilized to set and optimize the hyperparameters of the deep learning algorithm, resulting in better outcomes than previous research and achieving an accuracy rate of 0.92%.**

Keywords—COVID-19 pandemic, detecting false news, deep learning, reinforcement learning, genetic algorithm.

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I. INTRODUCTION

The coronavirus disease (COVID-19) is a disease or illness caused by the severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2), formerly known as 2019-nCoV. It was initially discovered in Wuhan, Hubei, China. The first confirmed case of COVID-19 was announced by the World Health Organization (WHO) on December 31, 2019. On January 30, 2020, the COVID-19 pandemic was declared a global health emergency. Since 2009, the WHO has classified H1N1 as a pandemic disease; COVID-19 was the second pandemic disease to be proclaimed [72]. Although researchers continue to investigate the disease's potential means of infection spread, the disease is primarily transmitted through close contact with infected individuals. The most prominent symptoms of COVID-19 infection are fever, dry cough, and shortness of breath [72]. Up to 10% of patients may develop GI-related symptoms, such as diarrhoea [73]. Some patients may experience muscle aches, lethargy, and loss of taste or smell (anosmia). Direct contact, as previously believed, is one of the possible means by which the virus can travel between humans. Hence, social distancing can minimize the risk of infection. Disease transmission can take place at a distance of up to 6 feet. As a result, the breathing droplets produced by an infected person while speaking or sneezing can be considered a primary cause of disease transmission [72]. However, in other instances, COVID-19 signs are not noticeable. Figure 1 depicts how COVID-19 is transmitted from one person to another in the absence of social distancing [74]. The proliferation of media platforms, such as Facebook, Twitter, and Instagram, has enabled the rapid dissemination of information. Without concern for the authenticity or veracity of the content they publish, social network users are free to share anything they want. This creates difficulties in ensuring data accuracy. Twitter is one of the most renowned social media networks. With the advent of the COVID-19 epidemic, numerous tweets are made daily, resulting in harmful effects for individuals and society. For instance, erroneous information on the symptoms of COVID-19 can cause harm [1]. False news and disinformation are often used interchangeably, as they are closely related. The aforementioned methods aid in assessing the authenticity of a piece of information by comparing it to corpora containing both fake and true information [2].

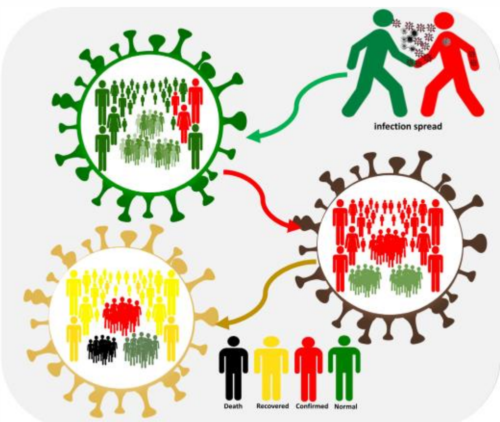

Figure 1. COVID-19 Person-to-person spread [74].

Human annotations, machine/deep learning, and natural language processing may all be utilized to perform the task [3]. Another definition supplied in [4] is as follows: "unverified and instrumentally relevant information assertions that circulate in situations of uncertainty, danger, or potential harm to aid individuals in making sense of and managing risk." According to the authors of [5], it is "a theory created in the absence of verifiable facts about uncertain conditions that is crucial to people who are later concerned about their lack of control due to this uncertainty." Many studies and datasets [6] have been published on the topic of identifying false news in English tweets. Hence, the results of false news detection algorithms may be significantly influenced by the availability of relevant datasets. This paper focuses on detecting fake news about the COVID-19 outbreak by using Persian data. We built a manually annotated dataset using 1) popular social networks, including Twitter, Facebook, WhatsApp, and Instagram, and 2) news agencies, including Irna, Mehrnews, and Fars news. It is considered that news agencies help reduce the spread of incorrect information.

In addition to the preceding techniques, methods based on adaptive genetic algorithms, as described in [7], [8], and [9], are widely used to develop prediction techniques due to their capacity to adapt to the environment, albeit at a slower speed compared to artificial intelligence techniques. As described in [10], artificial intelligence clustering approaches are employed for fraud detection, medical work, and data science prediction. In addition, the efficiency and deployment of these systems in all environments, regardless of the operating system or other system conditions, including self-automating environments as described in work [12], or the use of these methods to improve numerous tasks, such as task [13], are facilitated by the container methods described in [11]. Using deep learning, we have addressed the challenge of rumor detection in Persian data. Additionally, in the deep learning model, we analyzed the input data using an LSTM network [33].

To achieve better results and enhance the performance of the LSTM network using genetic algorithms and reinforcement learning, we modified the network's parameters, resulting in a high level of detection accuracy in this field. The evaluation results demonstrate that the proposed method is more effective than six other machine learning algorithms (Logistic Regression (LR), Support Vector Machine (SVM), Decision Tree (DT), Naive Bayes (NB), K-Nearest Neighbors (KNN), and Random Forest (RF)) and RNN, GRU, standard LSTM, and MLP. Using feature extraction techniques such as TF-IDF, the dataset's essential characteristics have been extracted. The findings demonstrate a very high level of precision in recognizing both fraudulent and authentic (real) postings, including those related to COVID-19 information.

II. Related Work

In this section, a range of machine learning and deep learning algorithms for identifying fake news are presented. Since it is the most current topic, the first section addresses the identification of fake news related to COVID-19.

When the first case of COVID-19 was discovered on December 31, the World Health Organization declared a global health emergency. Social media articles and tweets often provide either accurate or incorrect information about COVID-19. Regular people are more inclined to acquire self-defense knowledge through reading. The [14] authors investigated the sources of COVID-19 misinformation. Their analysis revealed that the majority of disinformation around COVID-19 is based on facts rather than lies. Attention was drawn to the detection of false news regarding COVID-19 by data scientists. The researchers [15] used ten machine learning approaches and seven feature extraction techniques to determine the veracity of a news collection. They evaluated their proposed classifier on 3,075,255 tweets with the hashtag #COVID-19. The classifiers with the highest performance metrics are NN, DT, and LR. The researchers [16] retrieved linguistic information from COVID-19 tweets in addition to user and media characteristics. Since then, they've developed a neural network approach known as mBERT (Multilingual Bidirectional Encoder Representations from Transformers). Traditional machine learning methods, such as SVM, RF, and a multilayer perceptron, were outperformed by mBERT. The researchers [17] employed BERT and ALBERT, two pipelined, pre-trained deep learning models for natural language processing. Over 5000 COVID-19 canards were found in a publicly accessible COVID-19 dataset. Their proposed approach was the most successful in terms of performance.

Scientists in natural language processing (NLP) have been developing methods for detecting online COVID-19-related misinformation. A corpus is necessary to construct any algorithm. As a result, the NLP community has developed numerous fake news datasets, including FakeCovid [18], ReCOVery [19], CoAID [20], and CMU-MisCOV19 [21]. The MM-COVID corpora created by Yichuan Li et al. [22] encompass six languages and are multidimensional and multilingual. Disinformation concerning COVID-19 was uncovered by Mabrook et al. [23] in a large dataset from Twitter. Six machine learning techniques were employed to construct an ensemble-stacking method for identifying disinformation within the collection. By merging seven feature extraction methodologies and ten machine learning algorithms, Elhadad et al. [24] built a voting ensemble machine learning detector to identify false content. Tamanna et al. [25] detected disinformation using the COVIDLIES dataset by obtaining the misunderstandings associated with Twitter messages. Rutvik et al. [26] developed a two-step model for identifying and fact-finding COVID-19 false media transformers. Model one employs an innovative fact-finding method to obtain the most crucial information about COVID-19, while Model two utilizes textual entailment to verify the accuracy of the information. Additionally, false news may be discovered in the form of fabricated treatments, as shown in [27] and [28], demonstrating its impact on medicine's decision-making process.

Chen [29] used TextCNN and TextRNN models to incorporate the pre-trained BERT model. The suggested model was developed using data consisting of 3737 rumors gathered from several Chinese sites. The suggested BERT model outperformed the other techniques, as shown by the findings. Additionally, all three models demonstrated exemplary performance and may be used to refute COVID-19-related claims.

Alsudias and Rayson [30] collected almost one million Arabic tweets about COVID-19. They were not only searching for canards, but also attempting to determine what was being discussed at the time and where the canards originated. The researchers manually categorized slightly more than 2000 tweets for canard identification. Subsequently, SVM, LR, and NB classifiers were used to distinguish canards from truthful tweets. LR with count vector and SVM with TF–IDF achieved the highest accuracy of 84.03 percent.

For data representation, WH Bangyal et al. utilized a semantic model with word frequency and inverse document frequency weighting. During the measurement and evaluation phase, eight machine-learning algorithms, including Naive Bayes, AdaBoost, K-Nearest Neighbors, Random Forest, Logistic Regression, Decision Trees, Neural Networks, and Support Vector Machines, as well as four deep learning algorithms—CNN, LSTM, RNN, and GRU—were applied. Then, based on the results, they boiled a highly efficient prediction model with Python, trained and evaluated the classification model based on the performance measures (confusion matrix, classification rate, true positives rate), and tested the model on a set of unclassified fake news on COVID-19, to predict the sentiment class of each fake news on COVID-19. In comparison to previous models, the research results showed better accuracy [61].

Alouffi et al. proposed a hybrid deep learning method for detecting COVID-19 fake news that combines a convolutional neural network (CNN) and a long short-term memory (LSTM) network. The proposed model includes the following layers: embedding layer, convolutional layer, pooling layer, LSTM layer, flatten layer, dense layer, and output layer. Three COVID-19 fake news datasets are utilized to test six machine learning models, two deep learning models, and our proposed model for experimental outcomes. DT, KNN, LR, RF, SVM, and NB are the machine learning models, whereas CNN and LSTM are the deep learning models. Additionally, the results are validated using four key metrics: accuracy, precision, recall, and F1-measure. Experiments demonstrate that the proposed approach outperforms six machine learning models and two deep learning methods [62].

In [34], an LSTM model is used to forecast new COVID-19 confirmed cases in Canada. They used information between January 22 and March 31, 2020. Similarly, in [35], an enhanced LSTM model is used to forecast the epidemic patterns of COVID-19 in Russia, Peru, and Iran. In [36], support vector regression, LSTM, bidirectional LSTM (BiLSTM), and GRU are utilized to predict COVID-19 time-series data in the ten countries most impacted by the virus. Using COVID-19 data accessible through June 27, 2020, the results demonstrate the better performance of the BiLSTM.

Malla et al. evaluated COVID-19 misinformation on social media platforms, including Twitter, Facebook, and Instagram. The purpose of this paper is to classify tweets as either fake or true news. The authors have evaluated numerous deep learning models using a simulated dataset of COVID-19. Ultimately, CT-BERT and RoBERTa outperformed other deep learning models, including BERT, BERTweet, AlBERT, and DistilBERT. Using multiplicative fusion, the proposed ensemble deep learning architecture beat CT-BERT and RoBERTa on the COVID-19 fake news dataset. The performance of the proposed model in this technique was determined by multiplying the final predicted values of CT-BERT and RoBERTa. This method addresses the inaccuracy of the predictive nature of the CT-BERT and RoBERTa models. The proposed architecture outperforms both well-known ML and DL models, achieving an F1-score of 98.93% and an accuracy of 98.88% [63].

Al-Sarem proposed utilizing a hybrid deep learning approach (LSTM–PCNN) to identify COVID-19-related misinformation on social networks. Long Short-Term Memory (LSTM) and Parallel Convolutional Neural Networks are utilized to create the proposed model (PCNN). The studies utilized an ArCOV-19 sample of 3,157 tweets, of which 1,480 (46.87%) were misinformation and 1,677 were not (53.12%). The proposed model outperformed earlier solutions [31] in terms of accuracy, recall, precision, and F-score.

Kaliyar proposes a hybrid model that combines multiple branches of a convolutional neural network (CNN) with Long Short-Term Memory (LSTM) layers, featuring varying kernel sizes and filters. To create a model with three dense layers to extract more effective features automatically. In this study, a dataset (FN-COV) of 69,976 fake and true news stories published during the COVID-19 pandemic was compiled, tagged with terms such as "social distance," "COVID-19," and "quarantine." PHEME has been used to validate the performance of our proposed model. The capabilities of our C-LSTM network's combined kernels and layers are advantageous for both datasets. Using PHEME, they achieved an accuracy of 91.88%, which is better than existing models, and 98.6% with the FN-COV dataset [64].

Abdelminaam [32] proposed a stronger neural network to detect fake news. The modified-LSTM (with one to three layers) and the modified GRU (with one to three layers) are two examples of deep learning algorithms. The outcomes of applying the proposed framework demonstrate a high degree of accuracy in identifying between fake and real tweets, as well as tweets including COVID-19 data. These results demonstrate that the effectiveness of a breakthrough baseline machine learning method has been greatly improved. Their highest accuracy rate was 98.57 percent.

In [65], we investigate the ability of deep neural networks, namely Long Short-Term Memory (LSTM), Bi-directional LSTM, Convolutional Neural Network (CNN), and a hybrid of CNN and LSTM networks, to automatically classify and identify fake news content related to the COVID-19 pandemic that has been posted on social media platforms. These deep neural networks were trained and evaluated using the "COVID-19 Fake News" dataset, which comprises 21,379 instances of true and fake news related to the COVID-19 pandemic and its associated vaccines. True news data were collected from independent and internationally reputable institutions on the Internet, including the World Health Organization (WHO), the International Committee of the Red Cross (ICRC), the United Nations (UN), and the United Nations Children's Fund (UNICEF), as well as their official Twitter accounts. The data on fake news was obtained from various fact-checking websites (such as Snopes, PolitiFact, and FactCheck). With an accuracy of 94.2%, the CNN model outperformed the other deep neural networks, according to the evaluation results.

Kumar et al. [66] investigated a variety of deep learning models (CNN, LSTM, and hybrid models) to address the problem of fake news on social media platforms. The results demonstrated that the hybrid model, consisting of a CNN and a Bi-LSTM with an attention mechanism, achieved the highest accuracy level, 88.78%.

Abdelminaam et al. [67] proposed a modified LSTM (from one to three layers) and a modified GRU (from one to three layers) for detecting coronavirus-related fake news. In addition, they evaluated the performance of the proposed model in comparison to conventional machine learning models, including Decision Trees, Random Forests, Logistic Regression, K-nearest neighbors, Naive Bayes, and Support Vector Machines. Two feature extraction approaches were utilized: N-gram and TF-ID, along with a traditional machine learning model and word embedding with deep neural networks. The outcomes demonstrated a considerable improvement over the results of traditional machine learning models, as well as the capacity to recognize fake news related to the coronavirus pandemic. Ajao et al. [68] studied and compared three deep learning algorithms for detecting fake news tweets on Twitter: LSTM, LSTM-drop, and the hybrid model of LSTM and CNN. The results demonstrated that LSTM achieved the highest level of prediction accuracy (82 percent). Another CNN and RNN (Recurrent Neural Network) hybrid model was assessed in [69]. While CNN and RNN models performed well on datasets of fake news, the hybrid model performed better in predicting fake news. Utilizing a deep neural network and word embedding representation, the model in [70] achieved an accuracy of 93.92% on a dataset of 10,700 records. Deep learning outperformed other traditional machine learning techniques for detecting fake news, as demonstrated by the comparison in this study.

In [71], a machine learning approach for analyzing Arabic tweets from Twitter was proposed. In this model, Word2Vec is utilized for word embedding, which serves as the primary source of features. Two pre-trained continuous bag-of-words (CBOW) models are examined, and the Naive Bayes classifier serves as a baseline. With and without SMOTE, numerous single-based and ensemble-based machine learning classifiers have been utilized (synthetic minority oversampling technique). Comparing the baseline classifier and other classifiers (single-based and ensemble-based) without SMOTE to the baseline classifier and other classifiers (single-based and ensemble-based) with SMOTE, the experimental results demonstrate that applying word embedding with an ensemble and SMOTE resulted in a significant improvement in the average F1 score.

In [75], a deep learning strategy for sentiment analysis of Twitter details relating to COVID-19 reviews is presented. The proposed technique is based on an LSTM-RNN network and an attention layer-enhanced feature weighting approach. This technique utilizes an improved framework for feature transformation via the attention mechanism. In this study, a total of four class labels (sadness, joy, fear, and anger) were extracted from publicly accessible Twitter data stored in the Kaggle database. Based on the use of attention layers with the existing LSTM-RNN approach, the proposed deep learning approach significantly improves the performance metrics, with a 20% increase in accuracy, 10% to 12% improvement in precision, and 12–13% improvement in recall compared to current approaches. There were 45.5% good, 30.0% neutral, and 25.0% negative tweets out of a total of 179.108 tweets on COVID-19. This demonstrates that the proposed deep learning approach is efficient and feasible, and can be deployed for sentiment categorization of COVID-19 reviews.

In [76], a method was given for analyzing sentiment utilizing both syntactical and semantic information on the COVID-19-related Nepali Twitter dataset. To accomplish this, they first apply two widely used text representation approaches, TF-IDF and FastText, and then combine them to generate hybrid features that capture highly discriminatory features. Second, they implement nine well-known machine learning classifiers (Logistic Regression, Support Vector Machine, Naive Bayes, K-Nearest Neighbor, Decision Trees, Random Forest, Extreme Tree Classifier, AdaBoost, and Multilayer Perceptron) based on three feature representation methods: TF-IDF, FastText, and Hybrid. NepCov19Tweets, a publicly accessible dataset of Nepali COVID-19 tweets, is used to evaluate our approaches. This dataset is comprised of Nepali tweets divided into three types (Positive, Negative, and Neutral). The evaluation results on the NepCOV19Tweets demonstrate that the hybrid feature extraction method not only outperforms the other two individual feature extraction methods while applying nine distinct machine learning algorithms, but also provides superior performance when compared to the most advanced methods.

Text Classification has been extensively investigated in information retrieval and data mining problems. Many objectives, including medical diagnosis, the health and care department, targeted marketing, the entertainment business, and group filtering, can benefit from its use. Recent advancements in both data mining and natural language processing have drawn the attention of scientists worldwide to the development of automated systems for text classification. NLP enables the categorization of documents comprising diverse texts. Social media users generate an enormous amount of data on social media platforms. For experimental purposes, three datasets were utilized: the COVID-19 false news dataset, the COVID-19 English tweet dataset, and the extremist-nonextremist dataset, which contains news blogs, articles, and tweets related to the coronavirus and hate speech. Transfer learning strategies do not involve conducting experiments with COVID-19 fake news and datasets that are either extremist or non-extremist. Hence, the proposed work evaluated the effectiveness of transfer learning classification models by applying them to both of these datasets. Models are trained and evaluated based on their precision, accuracy, recall, and F1-score. Furthermore, heat maps are generated for each model. In conclusion, further directions are suggested [77].

III. Deep Learning Techniques

In this study, forecasting confirmed and recovered COVID-19 time-series data involves the use of deep learning techniques, which can automatically learn relevant patterns from the time-series data. LSTM [37], CNN [38], [39], RBM [40], Generative adversarial networks based on deep fully connected neural networks (GAN-DNN) [41], GAN-GRU [41], [42], and LSTM-CNN are briefly described in this section.

Recurrent Neural Network (RNN): RNN is used to process and recognize patterns in sequential data. RNN was designed to process temporal data. Similar to artificial neural networks (ANN), RNN comprises three unique layers of neurons (input, hidden, and output). The hidden layers distinguish an ANN from a traditional ANN. This layer's temporal loop enables the RNN to not only generate output, but also feed this output back into itself. In this way, they build a form of short-term memory. Due to their ability to recall sequences, they have significant applications in various fields. They are useful for natural language processing (NLP), machine translation, speech recognition, and text summarization.

Long Short-Term Memory (LSTM) is an artificial neural network used in deep learning techniques. Feedforward neural networks do not contain feedback connections, whereas LSTM neural networks do. It can handle both single data points, such as a single image or word, and entire sequences, including entire videos or texts. It consists of an input gate, a forget gate, an output gate, and a cell. The cell stores the value for each interval, while the remaining gates control the flow of data into and out of the cell. When weights are updated by gradient descent during backpropagation, RNNs suffer from the vanishing gradient problem. As previously stated, LSTM addresses this problem by incorporating gates within its structure that regulate the flow of information both within and outside the cell. It is utilized extensively in speech analysis, text generation, and speech recognition [43].

A. *Hyperparameters Optimization*

Learning a deep network differs greatly from learning a deep network that can be implemented. To properly train a deep learning model, numerous procedures must be taken. Configuring hyperparameters is among them. The process of setting the model's parameters, which must be done before training the network, is known as optimizing the hyperparameters, and it aims to maximize the system's performance. Modify or optimize hyperparameters to identify the optimal values for each, enabling the model to deliver the most accurate and precise predictions. While setting hyperparameters, alternative values are always tested against a criterion. The following is a collection of common deep network hyperparameters:

- Number of Hidden Layers and Units
- Activation function
- Dropout
- Learning Rate
- Number of epochs
- Batch size
- optimizer

B. *Hyperparameter optimization approaches*

1- Manual adjustment:

The easiest way to set hyperparameters is to experiment with different values and observe the results. By manually adjusting each step, the current parameter selection and the difference between the previous result can be checked and compared. It may seem like a simple idea, but it will bring good results. A deep learning practitioner should gain experience in networking, a method that transmits valuable experiences by testing different results, which can be very helpful. In this method, it is beneficial to act regularly and record all results, controlling the process of improvement and performance to analyze and examine which parameters have the greatest impact on the model's performance. Disadvantages:

•Requires manual labor.

•You may be satisfied with the same score obtained without much testing.

2- Grid Search

Manually trying and combining multiple hyperparameter values is a challenging, time-consuming process that requires a considerable amount of model understanding. Network Search merely attempts to configure the hyperparameters within a specified value range. This method automatically evaluates the various values of each hyperparameter using multiple variable values. Disadvantages:

• Because the entire execution time of the hyperparameters is long, the number of parameters will be limited.

3- Random search

Randomly sampling the hyperparameter space is a simple alternative to network search. In other words, it is preferable to choose and test random values from the full sample space compared to conducting routine studies on the entire set of values in the issue space. Bergestra and Benjio experimentally demonstrated and conceptually in their 2012 study titled "Random Search for Optimization" that random search is more successful than network search for optimizing superparameters. [44]. Disadvantages:

•Depending on the number of searches and the size of the parameter space, some parameters may not be explored.

To circumvent these obstacles, evolutionary algorithms are an excellent option for handling hybrid optimization issues, such as hyperparameter optimization. In this paper, Genetic Algorithm and reinforcement learning are utilized to choose hyperparameters optimally. GA has achieved tremendous success. In numerous disciplines, such as software testing [45], human resource allocation [46], feature selection [47], image processing [48] [49], clustering [50], and path planning [51], genetic algorithms have achieved remarkable success. The genetic algorithm has been utilized to tune the hyperparameters of deep learning models on a variety of datasets [52] [53] [54] [55] [56] [57] [58] [59] [60].

Classic evolutionary algorithms are effective in optimizing hyperparameters, but they are time-intensive. This can be enhanced in part by applying current problem-solving expertise or by incorporating a local search phase into the evolutionary cycle. A significant issue with the genetic algorithm is that chromosomes do not attempt to improve themselves; instead, they quietly await a mutation or recombination to enhance their performance. Additionally, the genetic algorithm does not distinguish between the various sub-sections of a chromosome, and its evaluation function evaluates the chromosome as a whole. The genetic search resembles a blind search in this regard. In this research, reinforcement learning is employed as a memetic search technique to enhance the genetic algorithm, thereby addressing these issues. This portion of the augmented search focuses on the best chromosomes ever obtained and enhances them through gene manipulation. These alterations have been regulated by Q-learning.

IV. COVID-19 Fake Persian News Dataset [33]

Identifying false news is a classification problem. The objective is to determine whether or not a particular Persian post exists. To accomplish this purpose, we must first collect a high-quality dataset. We aimed to compile a dataset from Persian sources manually for this purpose. The dataset consists of 7,000 Persian postings, 3,500 actual news items, and 3,500 fake news articles. They are gathered from various social media platforms, including Twitter, Facebook, WhatsApp, and Instagram, as well as news organizations such as IRNA, Mehr News, and Fars News. Each label was carefully produced. At these organizations, every piece of news is labeled as true or fake, and this is how we determine their labels. Table 1 displays examples of true and fake news from the dataset. To date, no Persian text dataset has been published, and no equivalent text dataset is available. The dataset is divided into training and testing parts. Table 2 displays the proportion of all data splits by class.

TABLE I. DATASET EXAMPLES OF REAL AND FAKE MEDIA.

class	post
false	5G mobile networks are the cause of the coronavirus outbreak
actual	The use of a mask may help to protect you from the infection.

TABLE II. DATA DISTRIBUTION OVER PARTS AND SPLITS.

partition	false	actual	total
Training	3000	3000	6000
Test	500	500	1000
Total	3500	3500	7000

V. PROPOSED APPROACH

A. Input text preprocessing

Data preprocessing is a crucial initial phase of text content analysis, as it normalizes non-standard text into a standard form. In this study, the Hazm library is used to perform preprocessing processes on texts. Using the NLTK library, Digestion is a Python-based, open-source library for digesting the Persian language. Texts are preprocessed by normalizing the input text, tokenizing sentences and words, removing stop words, and applying stemmatization and Lemmatization.

B. Encoding Scheme and Population Creation in a Genetic Algorithm.

In GA, each individual's hyperparameter data, or LSTM model, is recorded onto what is known as a chromosome. The chromosome may have various representations, such as a string of ones and zeros. To optimize hyperparameters, the chromosomes in our studies contain numerous fields with distinct values. It specifies the hyperparameters of an LSTM architecture, including the number of neurons and the type of activation function. After a chromosome is identified, an LSTM model can be constructed accordingly.

The classical genetic algorithm requires the chromosome length to be fixed. Because the number of layers varies between LSTM models and more hyperparameters are included as the model becomes more complex, a variable-length genetic algorithm is more appropriate for our goal. To maximize the hyperparameters of deep learning models, the network layers should not be limited in their complexity. Reducing the number of layers may cause the network to be insufficiently sized for the given problem, resulting in underfitting. A fixed-length GA indicates that the number of layers in the LSTM model has been determined. Before doing tests, it is impossible to determine how many layers are sufficient for a given situation.

On the other hand, having a too large network can result in overfitting. Therefore, it makes sense to start with a modest network and expand it as needed. In the variable-length genetic method, chromosomes include parameters that specify a solution, in this case, a hyperparameter configuration for a network model. The permitted range of the search area is known as the search space, and it contains a collection of potential solutions to the problem. The technique may identify a suitable LSTM model in less time if the search space is relatively small; however, the limited number of possible models in that space may be restrictive. On the contrary, larger models are more time-consuming and require more computing power. The search area for these experiments is depicted in Table 3.

C. Fitness of individuals

An individual's fitness is measured by its accuracy on the validation dataset.

TABLE III. SEARCH SPACE.

Hyper-parameter	Range
LSTM layers	2 - 6
Number of Neurons in each Recurrent Layer	50 - 200
Embedding Dropout, Recurrent Dropout, Output Dropout	.1 - .5
Activation functions	Linear, Sigmoid, TanH, ReLU
fully connected layers	1 - 3
Number of Neurons	32 - 256
Dropout	.1 - .5
Activation functions	Linear, Sigmoid, TanH, ReLU
Batch Normalization	Yes, No
Optimizer	Adam, SGD, RMSprop, Adadelta, Adagrad
epochs	10 - 50
batch size	32 - 128

D. Selection operator

Whenever a chromosome is selected in one generation, it means that the chromosome will be eligible for reproduction or direct presence in the next stage. The first stage of selection involves determining the suitability of chromosomes based on their score, which determines the probability of their participation in the reproductive stage. The second stage is the possible selection of individuals, which is based on relative fitness. Selection employs a variety of methods and techniques, depending on the type of problem and prevailing conditions; each of these techniques and methods is used accordingly. In this dissertation, the rank selection operator is used. In this method, the rank of each chromosome is determined based on its suitability, and the top chromosomes are selected accordingly.

E. Crossover

Based on the evolutionary algorithm selection procedure, the most suitable chromosomes should always be selected. Yet, it is feasible that these chromosomes will be represented several times in future generations, resulting in a population made completely of multiple copies of the same candidate solution. If the initial population is too small, there is no assurance that it contains a global optimal solution or even a solution deemed sufficient for the problem being solved. In this instance, the evolutionary process will converge on a population consisting of duplicates of the optimal solution that was initially discovered in the initial population. To overcome this limitation, crossover operators were developed as reproduction techniques and are now regarded as essential components of any algorithm that effectively evolves populations toward optimal points. In this study, Multipoint Crossover has been utilized.

F. Mutation

The mutation operator attempts to introduce new traits or gene values into the population that are not already present. The addition of new features to the population pool may be beneficial, in which case the mutant person will have a high fitness value and be selected several times, or it may be detrimental, resulting in the individual's extinction from the population pool. Hence, by constantly modifying gene values, humans are compelled to seek out the optimal.

G. Local Search with Q-Learning

At this stage, the best chromosome in the population is chosen, and the improvement cycle is initiated. To minimize significant complexity and slowness, a portion of the hyperparameters is optimized in the initial stages of the algorithm, while another portion is optimized in the latter stages. First, it is preferable to search for the ideal number of layers in both the LSTM part and the fully connected portion, since the arrangement and number of layers are more crucial than any hyperparameter. So, we currently have two states (layer state in LSTM and layer state in fully connected). In LSTM and fully connected networks, two actions consist of decreasing and increasing the number of layers. Figure 2 depicts the details. The reward associated with each status and activity is computed according to the following formula:

$$R = fitness\ value\ new - fitness\ value\ old$$

After the 10th step of the genetic algorithm (the maximum number of executions in this article is 20), we enter a new phase of Q learning in which we optimize additional hyperparameters, including the number of neurons in each layer, activation function in each layer, batch size, optimizer, regularization, batch normalization, and number of epochs. Each of these hyperparameters generates a state in which specific actions are defined. Figure 3 depicts the characteristics and activities of each state. In Figure 3, each state has a 1/7 chance of going to itself and other states. Due to congestion, only the edges of the S1 state are seen in this diagram. The steps of the proposed hyperparameter tuning method are illustrated in Fig. 2.

VI. EXPERIMENTS IN MACHINE LEARNING METHODS

As shown in Figure 3, we utilized the provided dataset to examine it within a system for detecting fake news. Using the hazm library, text normalizers, tokenizers, stop-word removers, stemmers, and lemmatizers are utilized in the preprocessing phase of this system. For feature extraction, the TF-IDF with unigrams is assessed. A key component of the system is the machine learning component, which utilizes six distinct machine learning algorithms to identify fake news. Logistic Regression (LR), Support Vector Machine (SVM), Decision Tree (DT), Naive Bayes (NB), K-Nearest Neighbors (KNN), and Random Forest (RF) are the techniques used. The scikit-learn package is used to implement all the algorithms. Lastly, we evaluate performance based on accuracy, precision, recall, and F-measure criteria. These conditions are expressed in equations (1) through (4). TP, TN, FP, and FN represent true positives, true negatives, false positives, and false negatives, respectively, in these equations.

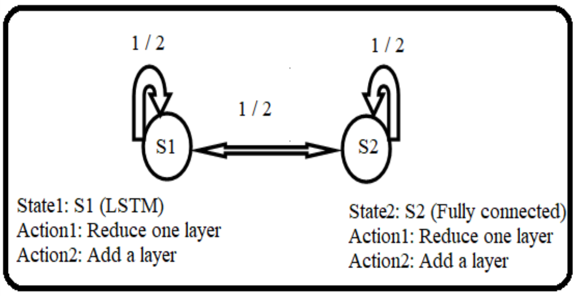

Figure 2. State and action in the early stages.

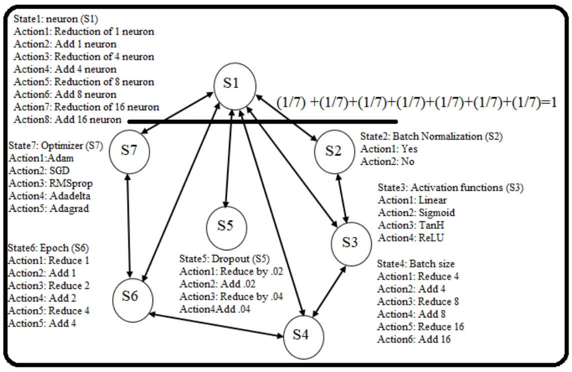

Figure 3. State and action in later stages.

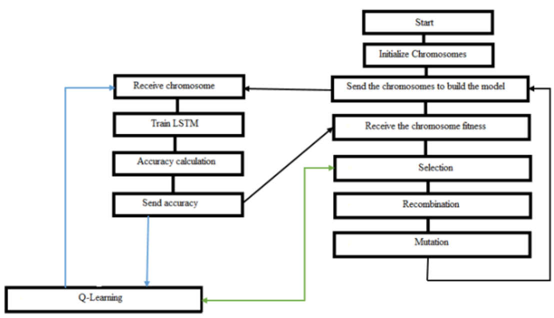

Figure 4. Proposed hyperparameter tuning method.

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} * 100 \qquad (1)$$

$$Precision = \frac{TP}{TP+FP} \qquad (2)$$

$$Recall = \frac{TP}{TP+FN} \qquad (3)$$

$$F - Measure = \frac{2*precision*recall}{precision+recall} \quad (4)$$

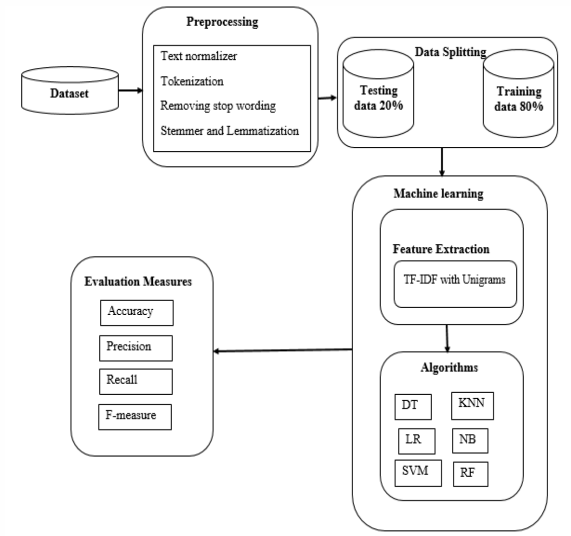

Figure 5. Proposed framework in machine learning methods.

TABLE IV. RESULTS OF THE EVALUATION USING THE PROPOSED DATASET.

	LR	SVM	DT	NB	KNN	RF
Accuracy	0.85	**0.87**	0.71	0.85	0.81	0.86
Precision	0.81	**0.87**	0.82	0.85	0.78	0.83
Recall	0.90	**0.87**	0.55	0.85	0.87	0.89
F1-Score	0.85	**0.87**	0.66	0.85	0.82	0.86

A. Results

The findings of the system for detecting fake news, as reported in the provided dataset, are presented in Table 3. This table demonstrates that SVM has the highest test accuracy at 0.87. DT, in contrast, had a significantly lower accuracy of.71. Further specifications are detailed in Table 3.

VII. EXPERIMENTS IN LSTM

Recursive neural networks, particularly LSTM, are one of the most important topics we have covered in this study. It is a common and effective tool for working with sequential data, such as text or time series. Fig. 4 depicts the general structure of the proposed system for detecting bogus news.

TABLE V. RESULTS OF THE PROPOSED METHOD

	Proposed method	LSTM	RNN	MLP
Accuracy	0.92	.88	.86	.85
Precision	0.92	.88	.86	.85
Recall	0.91	.88	.86	.84
F1 measure	0.91	.88	.86	.84

To classify COVID-19 news as Fake/Real, several experiments were undertaken to develop an accurate false news detector. The COVID-19 Fake News dataset was used to train LSTM models capable of recognizing COVID-19 fake news using word embeddings. Table 5 displays the performance of LSTM models trained on the COVID-19 Fake News dataset. Throughout the training phase for deep learning models, we employed the early stopping strategy and the dropout layer to prevent overfitting and underfitting. The overfitting problem occurs when the model is trained with too many epochs, preventing it from accurately predicting when differences arise. The underfitting problem occurs when the model is trained with too few epochs, preventing it from learning enough from the data's features. Figure 5 depicts the training and test loss values at the end of ach model's training procedure.

Figure 6 illustrates the degree of fit of the best chromosome for 20 replicates (population size is 20) as well as the results of the algorithm's overall evaluation.

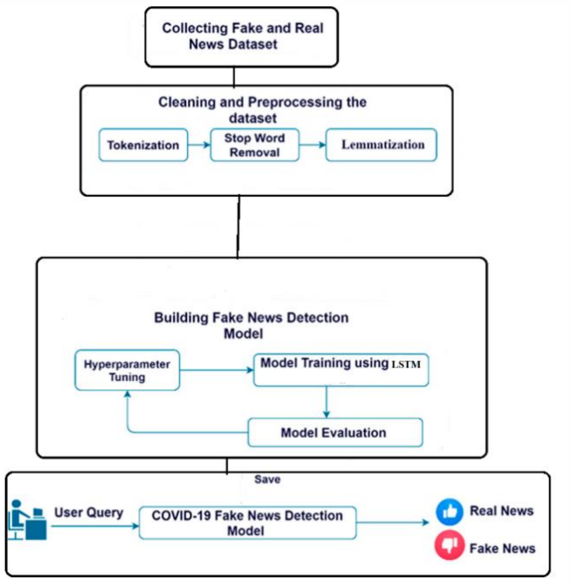

Figure 6. Framework for fake news detection.

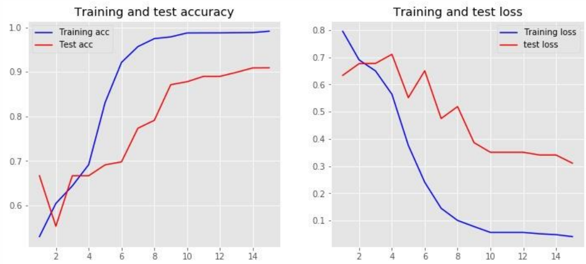

Figure 7. Result obtained from the best chromosomes on training and test data based on accuracy and function criteria.

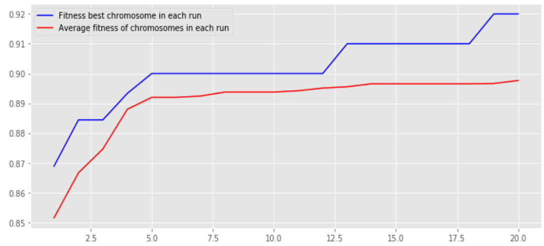

Figure 8. Results in life progress for the best and average chromosomes in 20 replicates.

VIII. Conclusion and Future Work

To acquire a good result and enhance the performance of the LSTM network, it is preferable to obtain the ideal hyperparameter values. We utilized the LSTM model to optimize and determine the optimal hyperparameter values. The evaluation findings demonstrate that our proposed method outperforms previous approaches in this field. Future research ideas for this study may include implementing the proposed system using the powerful BERT network, which is highly effective in text analysis, and utilizing more effective algorithms and methods, such as other search algorithms and reinforcement learning, to adjust all network hyperparameters. Collecting a significantly larger amount of input data for enhanced learning and designing a dynamic and robust system for rumor identification on Persian data.

References

[1] J. AlHumaid, S. Ali, and I. Farooq, "The psychological effects of the covid-19 pandemic and coping with them in saudi arabia." Psychological Trauma: Theory, Research, Practice, and Policy, vol. 12, no. 5, p. 505, 2020.

[2] M. K. Elhadad, K. F. Li, and F. Gebali, "Fake news detection on social media: a systematic survey," in 2019 IEEE Pacific Rim Conference on Communications, Computers and Signal Processing (PACRIM). IEEE, 2019, pp. 1–8.

[3] R. Oshikawa, J. Qian, and W. Y. Wang, "A survey on natural language processing for fake news detection," arXiv preprint arXiv:1811.00770, 2018.

[4] DiFonzo, N., & Bordia, P. (2007). Rumor, gossip and urban legends. Diogenes, 54(1), 19-35.

[5] H. B. Dunn and C. A. Allen, "Rumors, urban legends and internet hoaxes," in Proceedings of the Annual Meeting of the Association of Collegiate Marketing Educators, 2005, p. 85.

[6] M. K. Elhadad, K. F. Li, and F. Gebali, "Covid-19-fakes: a twitter (arabic/english) dataset for detecting misleading information on covid- 19," in International Conference on Intelligent Networking and Collaborative Systems. Springer, 2020, pp. 256–268.

[7] Damia, A. H., Esnaashari, M., & Parvizimosaed, M. R. (2021). Software Testing using an Adaptive Genetic Algorithm. Journal of AI and Data Mining, 9(4), 465-474.

[8] Damia, A., Esnaashari, M., & Parvizimosaed, M. (2021, May). Automatic Web-Based Software Structural Testing Using an Adaptive Particle Swarm Optimization Algorithm for Test Data Generation. In 2021 7th International Conference on Web Research (ICWR) (pp. 282-286). IEEE.

[9] Damia, A., Esnaashari, M., & Parvizimosaed, M. (2021, May). Adaptive Genetic Algorithm Based on Mutation and Crossover and Selection Probabilities. In 2021 7th International Conference on Web Research (ICWR) (pp. 86-90). IEEE.

[10] M. Noei, M. Parvizimosaed, A. Saleh Bigdeli and M. Yalpanian, "A Secure Hybrid Permissioned Blockchain and Deep Learning Platform for CT Image Classification," 2022 International Conference on Machine Vision and Image Processing (MVIP), 2022, pp. 1-5, doi: 10.1109/MVIP53647.2022.9738736.

[11] Khoobbakht, M., Noei, M., & Parvizimosaed, M. (2021, October). Hybrid Flow-Rule Placement Method of Proactive and Reactive in SDNs. In 2021 11th International Conference on Computer Engineering and Knowledge (ICCKE) (pp. 121-127). IEEE.

[12] Noei, S.; Parvizimosaed, M.; Noei, M. Longitudinal Control for Connected and Automated Vehicles in Contested Environments. Electronics 2021, 10,1994.https://doi.org/10.3390/electronics10161994

[13] M. Khoobbakht, M. Noei and M. Parvizimosaed, "Hybrid Flow-Rule Placement Method of Proactive and Reactive in SDNs," 2021 11th International Conference on Computer Engineering and Knowledge (ICCKE), 2021, pp. 121-127, doi: 10.1109/ICCKE54056.2021.9721507.

[14] J. S. Brennen, F. Simon, P. N. Howard, and R. K. Nielsen, ``Types, sources, and claims of COVID-19 misinformation," Reuters Inst., vol. 7, pp. 1-3, Apr. 2020.

[15] M. K. Elhadad, K. F. Li, and F. Gebali, ``Detecting misleading information on COVID-19," IEEE Access, vol. 8, pp. 165201-165215, 2020.

[16] D. Kar, M. Bhardwaj, S. Samanta, and A. P. Azad, ``No rumours please! A multi-indic-lingual approach for COVID fake-tweet detection," 2020, arXiv:2010.06906. [Online]. Available: http://arxiv.org/abs/2010.06906

[17] R. Vijjali, P. Potluri, S. Kumar, and S. Teki, ``Two stage transformer model for COVID-19 fake news detection and fact checking," 2020, arXiv:2011.13253. [Online]. Available: http://arxiv.org/abs/2011.13253

[18] L. Cui and D. Lee, ``CoAID: COVID-19 healthcare misinformation dataset," 2020, arXiv:2006.00885. [Online]. Available: http://arxiv.org/abs/2006.00885

[19] S. A. Memon and K. M. Carley, ``Characterizing COVID-19 misinformation communities using a novel Twitter dataset," 2020, arXiv:2008.00791. [Online]. Available: http://arxiv.org/abs/2008.00791

[20] Y. Li, B. Jiang, K. Shu, and H. Liu, ``MM-COVID: A multilingual and multimodal data repository for combating COVID-19 disinformation," 2020, arXiv:2011.04088. [Online]. Available: http://arxiv.org/abs/2011.04088

[21] G. K. Shahi and D. Nandini, ``FakeCovidA multilingual cross-domain fact check news dataset for COVID-19," arXiv e-Prints, 2020.

[22] X. Zhou, A. Mulay, E. Ferrara, and R. Zafarani, ``ReCOVery: A multimodal repository for COVID-19 news credibility research," 2020, arXiv:2006.05557. [Online]. Available: http://arxiv.org/abs/2006.05557

[23] M. S. Al-Rakhami and A. M. Al-Amri, ``Lies kill, facts save: Detecting COVID-19 misinformation in Twitter," IEEE Access, vol. 8, pp. 155961-155970, 2020.

[24] T. Hossain, R. L. Logan, IV, A. Ugarte, Y. Matsubara, S. Young, and S. Singh, ``COVIDLies: Detecting COVID-19 misinformation on social media," in Proc. 1st Workshop NLP COVID-19 (Part) EMNLP, 2020.

[25] L. Rundo, R. Pirrone, S. Vitabile, E. Sala, and O. Gambino, ``Recent advances of HCI in decision-making tasks for optimized clinical work- flows and precision medicine," J. Biomed. Informat., vol. 108, Aug. 2020, Art. no. 103479.

[26] A. Ghenai and Y. Mejova, ``Fake cures: User-centric modeling of health misinformation in social media," Proc. ACM Hum.-Comput. Interact., vol. 2, pp. 1-20, Sep. 2018.

[27] Chen, S. Research on Fine-Grained Classification of Rumors in Public Crisis—Take the COVID-19 incident as an example. In E3S Web of Conferences; EDP Sciences: Les Ulis, France, 2020; Volume 179, p. 02027.

[28] Alsudias, L.; Rayson, P. COVID-19 and Arabic Twitter: How can Arab World Governments and Public Health Organizations Learn from Social Media? In Proceedings of the 1st Workshop on NLP for COVID-19 at ACL 2020, Seattle, WA, USA, 9–10 July 2020.

[29] Al-Sarem, Mohammed, et al. "A Novel Hybrid Deep Learning Model for Detecting COVID-19-Related Rumors on Social Media Based on LSTM and Concatenated Parallel CNNs." Applied Sciences 11.17 (2021): 7940.

[30] Abdelminaam, Diaa Salama, et al. "Coaid-deep: An optimized intelligent framework for automated detecting covid-19 misleading information on twitter." IEEE Access 9 (2021): 27840-27867.

[31] Syarif, Iwan, Adam Prugel-Bennett, and Gary Wills. "SVM parameter optimization using grid search and genetic algorithm to improve classification performance." Telkomnika 14.4 (2016): 1502.

[32] https://github.com/jigsaw373/covid-rumors

[33] LeCun, Yann, Yoshua Bengio, and Geoffrey Hinton. "Deep learning." nature 521.7553 (2015): 436-444.

[34] Chimmula, Vinay Kumar Reddy, and Lei Zhang. "Time series forecasting of COVID-19 transmission in Canada using LSTM networks." Chaos, Solitons & Fractals 135 (2020): 109864.

[35] Wang, Peipei, et al. "Time series prediction for the epidemic trends of COVID-19 using the improved LSTM deep learning method: Case studies in Russia, Peru and Iran." Chaos, Solitons & Fractals 140 (2020): 110214.

[36] Shahid, Farah, Aneela Zameer, and Muhammad Muneeb. "Predictions for COVID-19 with deep learning models of LSTM, GRU and Bi-LSTM." Chaos, Solitons & Fractals 140 (2020): 110212.

[37] Hochreiter, Sepp, and Jürgen Schmidhuber. "Long short-term memory." Neural computation 9.8 (1997): 1735-1780.

[38] LeCun, Yann, et al. "Gradient-based learning applied to document recognition." Proceedings of the IEEE 86.11 (1998): 2278-2324.

[39] LeCun, Yann, Yoshua Bengio, and Geoffrey Hinton. "Deep learning." nature 521.7553 (2015): 436-444.

[40] Smolensky, Paul. Information processing in dynamical systems: Foundations of harmony theory. Colorado Univ at Boulder Dept of Computer Science, 1986.

[41] Goodfellow, Ian, et al. "Generative adversarial nets." Advances in neural information processing systems 27 (2014).

[42] Cho, Kyunghyun, et al. "Learning phrase representations using RNN encoder-decoder for statistical machine translation." arXiv preprint arXiv:1406.1078 (2014).

[43] Dairi, Abdelkader, et al. "Comparative study of machine learning methods for COVID-19 transmission forecasting." Journal of Biomedical Informatics 118 (2021): 103791.

[44] Bergstra, James, and Yoshua Bengio. "Random search for hyper-parameter optimization." Journal of machine learning research 13.2 (2012).

[45] Esnaashari, Mehdi, and Amir Hossein Damia. "Automation of Software Test Data Generation Using Genetic Algorithm and Reinforcement Learning." Expert Systems with Applications (2021): 115446.

[46] Lin, Chi-Ming, and Mitsuo Gen. "Multi-criteria human resource allocation for solving multistage combinatorial optimization problems using multiobjective hybrid genetic algorithm." Expert Systems with Applications 34.4 (2008): 2480-2490.

[47] Sayed, S., Nassef, M., Badr, A., & Farag, I. (2019). A nested genetic algorithm for feature selection in high-dimensional cancer microarray datasets. Expert Systems with Applications, 121, 233-243.

[48] Mirjalili, Seyedali, et al. "Genetic algorithm: Theory, literature review, and application in image reconstruction." Nature-inspired optimizers (2020): 69-85.

[49] Nematzadeh, H., Enayatifar, R., Motameni, H., Guimarães, F. G., & Coelho, V. N. (2018). Medical image encryption using a hybrid model of modified genetic algorithm and coupled map lattices. Optics and Lasers in Engineering, 110, 24-32.

[50] Islam, M. Z., Estivill-Castro, V., Rahman, M. A., & Bossomaier, T. (2018). Combining K-Means and a genetic algorithm through a novel arrangement of genetic operators for high quality clustering. Expert Systems with Applications, 91, 402-417.

[51] Nazarahari, M., Khanmirza, E., & Doostie, S. (2019). Multi-objective multi-robot path planning in continuous environment using an enhanced genetic algorithm. Expert Systems with Applications, 115, 106-120.

[52] Xiao, Xueli, et al. "Efficient hyperparameter optimization in deep learning using a variable length genetic algorithm." arXiv preprint arXiv:2006.12703 (2020).

[53] Han, J. H., Choi, D. J., Park, S. U., & Hong, S. K. (2020). Hyperparameter optimization using a genetic algorithm considering verification time in a convolutional neural network. Journal of Electrical Engineering & Technology, 15(2), 721-726.

[54] Nikbakht, Saeid, Cosmin Anitescu, and Timon Rabczuk. "Optimizing the neural network hyperparameters utilizing genetic algorithm." Journal of Zhejiang University-Science A 22.6 (2021): 407-426.

[55] Aszemi, Nurshazlyn Mohd, and P. D. D. Dominic. "Hyperparameter optimization in convolutional neural network using genetic algorithms." Int. J. Adv. Comput. Sci. Appl 10.6 (2019): 269-278.

[56] Mattioli, Fernando, et al. "An experiment on the use of genetic algorithms for topology selection in deep learning." Journal of Electrical and Computer Engineering 2019 (2019).

[57] Lee, Sanghyeop, et al. "Genetic algorithm based deep learning neural network structure and hyperparameter optimization." Applied Sciences 11.2 (2021): 744.

[58] Kumar, Puneet, Shalini Batra, and Balasubramanian Raman. "Deep neural network hyper-parameter tuning through twofold genetic approach." Soft Computing 25.13 (2021): 8747-8771.

[59] Han, Junjie, et al. "Heuristic hyperparameter optimization of deep learning models for genomic prediction." G3 11.7 (2021): jkab032.

[60] Li, Chen, et al. "Genetic Algorithm based hyper-parameters optimization for transfer Convolutional Neural Network." arXiv preprint arXiv:2103.03875 (2021).

[61] Bangyal, Waqas Haider, et al. "Detection of Fake News Text Classification on COVID-19 Using Deep Learning Approaches." Computational and Mathematical Methods in Medicine 2021 (2021).

[62] Alouffi, Bader, et al. "An Optimized Hybrid Deep Learning Model to Detect COVID-19 Misleading Information." Computational Intelligence and Neuroscience 2021 (2021).

[63] Malla, SreeJagadeesh, and P. J. A. Alphonse. "Fake or real news about COVID-19? Pretrained transformer model to detect potential misleading news." The European Physical Journal Special Topics (2022): 1-10.

[64] Kaliyar, Rohit Kumar, Anurag Goswami, and Pratik Narang. "A Hybrid Model for Effective Fake News Detection with a Novel COVID-19 Dataset." ICAART (2). 2021.

[65] Tashtoush, Yahya, et al. "A Deep Learning Framework for Detection of COVID-19 Fake News on Social Media Platforms." Data 7.5 (2022): 65.

[66] Kumar, Sachin, et al. "Fake news detection using deep learning models: A novel approach." Transactions on Emerging Telecommunications Technologies 31.2 (2020): e3767.

[67] Abdelminaam, Diaa Salama, et al. "CoAID-DEEP: an optimized intelligent framework for automated detecting COVID-19 misleading information on Twitter." Ieee Access 9 (2021): 27840-27867.

[68] Ajao, Oluwaseun, Deepayan Bhowmik, and Shahrzad Zargari. "Fake news identification on twitter with hybrid cnn and rnn models." Proceedings of the 9th international conference on social media and society. 2018.

[69] Nasir, Jamal Abdul, Osama Subhani Khan, and Iraklis Varlamis. "Fake news detection: A hybrid CNN-RNN based deep learning approach." International Journal of Information Management Data Insights 1.1 (2021): 100007.

[70] Pathwar, Prathmesh, and Simran Gill. "Tackling COVID-19 infodemic using deep learning." Proceedings of International Conference on Computational Intelligence and Data Engineering. Springer, Singapore, 2022.

[71] Al-Hashedi, Abdullah, et al. "Ensemble Classifiers for Arabic Sentiment Analysis of Social Network (Twitter Data) towards COVID-19-Related Conspiracy Theories." Applied Computational Intelligence and Soft Computing 2022 (2022).

[72] Alyasseri, Zaid Abdi Alkareem, et al. "Review on COVID‐19 diagnosis models based on machine learning and deep learning approaches." Expert systems 39.3 (2022): e12759.

[73] Tsatsakis, Aristides, et al. "SARS-CoV-2 pathophysiology and its clinical implications: An integrative overview of the pharmacotherapeutic management of COVID-19." Food and Chemical Toxicology 146 (2020): 111769.

[74] Al-Betar, Mohammed Azmi, et al. "Coronavirus herd immunity optimizer (CHIO)." Neural Computing and Applications 33.10 (2021): 5011-5042.

[75] Singh, Chetanpal, et al. "A Deep Learning Approach for Sentiment Analysis of COVID-19 Reviews." Applied Sciences 12.8 (2022): 3709.

[76] Shahi, T. B., C. Sitaula, and N. Paudel. "A Hybrid Feature Extraction Method for Nepali COVID-19-Related Tweets Classification." Computational Intelligence and Neuroscience 2022 (2022).

[77] Qasim, Rukhma, et al. "A Fine-Tuned BERT-Based Transfer Learning Approach for Text Classification." Journal of healthcare engineering 2022 (2022).

[78] Sutton, Richard S., and Andrew G. Barto. Reinforcement learning: An introduction. MIT press, 2018.

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