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A Hybrid Multitask Learning Framework with a Fire Hawk Optimizer for Arabic Fake News Detection

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Abstract: The exponential spread of news and posts related to the COVID-19 pandemic on social media platforms led to the emergence of the disinformation phenomenon. The phenomenon of spreading fake information and news creates significant concern for the public health and safety of the population. In this paper, we propose a disinformation detection framework based on multi-task learning (MTL) and meta-heuristic algorithms in the context of the COVID-19 pandemic. The developed framework uses an MTL and a pre-trained transformer-based model to learn and extract contextual feature representations from Arabic social media posts. The extracted contextual representations are fed to an alternative feature selection technique which depends on modified version of the Fire Hawk Optimizer. The proposed framework, which aims to improve the disinformation detection rate, was evaluated on several datasets of Arabic social media posts. The experimental results show that the proposed framework can achieve accuracy of 59%. It obtained, at best, precision, recall, and F-measure of 53%, 71%, and 53%, respectively, on all datasets; and it outperformed the other algorithms in all measures.

Keywords: social media platforms; fake information; multi-task learning (MTL); feature selection; Fire Hawk Optimizer (FHO)

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1. Introduction

The presence of digital technology has led to changing of habits among people who previously used conventional media. Now, they are turning to use digital media to meet their needs, especially the need to access information. Clear evidence of this change can be seen from the rapid annual increase in the consumption of digital media [1]. In emergencies and urgent situations, such as the COVID-19 pandemic, many are disseminating information through social media channels; this has an impact on billions of persons worldwide. One of the most relevant characteristics of social media platforms in this pandemic has been the rapid dissemination of protocols at regional, national, and international levels. Sharing protocols about treatment, personal protective equipment, or the vaccine have now become the new normal [2]. A number of official organizations and governments used social media as a platform to disseminate information to the public [1]. Meanwhile the results of research about news consumption on social media in 2021 showed that more than half of Twitter user get news on the site regularly [3].

In the meantime, with the growth of using social media platforms as an information source, the significance of fact-checking journalism is increasing, especially with the diffusion of fake news [4]. Fake news is a dangerous and widespread issue in the news industry [5]. There has been a rise in public concern since the Brexit referendum in the United Kingdom—most especially after the 2016 US elections—that social media spreads misinformation [5]. Fake news is as old as one can remember. However, its growth has increased in recent times because of the broad usage of the Internet and cheap access to social media platforms [6]. With the characteristics of social media—low cost, easy access, and prompt dissemination of information—it has become the primary platform for interaction and exchanging information [7]. Due to the attractiveness of social media platforms, they became the ideal grounds for spreading fake news, so they gained the attention of researchers and academics. In recent years, to help online users identify correct and factual information, there have emerged automatic frameworks and online fact-checking resources to peform online fake news detection [8]. There is a growing body of research that focuses on fake news. The authors of [9] analyzed stories that were labeled as fake news, and they found out that these stories used moderate levels of sensationalism and misinformation, whereas complete fabrications were uncommon and did not go well with audiences. The authors of [10] investigated the spread of all the verified true and false news stories on Twitter from 2006 to 2017. The results show that false news is more novel than trustworthy news, and that it spreads more because humans are more likely to spread it.

After the global outbreak of COVID-19, the WHO characterized it as a pandemic in March 2020 (https://www.who.int/europe/emergencies/situations/COVID-19, accessed on 9 November 2022). This outbreak was accompanied by increased use of social media and the explosion of misinformation about the disease. In conclusion, the WHO stated that they are fighting an infodemic, not just a pandemic, due to the levels of rumors and misinformation and the wide spread of fake news (https://www.who.int/director-general/speeches/detail/munich-security-conference, accessed on 9 November 2022). Reference [11] concludes that fake news is pervasive on social media platforms and is characterized by false claims and conspiracy theories regarding the treatment, prevention, origin, and spread of the virus. Reference [6] analyzed a dataset of 10,700 social media posts on COVID-19. The top results show that nearly 50% of the sample was fake news, and real news was more prolonged than fake news in terms of the average number of words per post. In a comparison between Arabic and English tweets originating from Qatar, the authors of [12] stated that Arabic tweets contain much false information, but English tweets are more propagandistic. Furthermore, Arabic tweets adopted a health and safety perspective, whereas English ones focused on the economic consequences of COVID-19. As for engagement and interaction of posts related to COVID-19, reference [13] found that the highest numbers of posts and comments were on mainstream platforms, such as YouTube and Twitter. As for the main topics, debates included comparisons to other viruses, requests for God's blessing, and racism; the most attention was given to the shutting down of flights. The authors of [14] studied the main channel Spanish people depend on to get information about COVID-19. Results indicated that the most credible sources of information were the online press and television, followed by institutional websites. WhatsApp and Facebook were considered more likely to present false news. To understand the motives behind sharing fake news, reference [15] concluded that the main reasons include low awareness, a lack of knowledge, and low trust in government news media.

Moreover, several feature selection (FS) methods based on metaheuristic (MH) techniques have been proposed to enhance the disinformation detection methods [16]. For example, the authors of [17] proposed a benchmarking studying fake news. In addition, FS has been used to enhance the detection of fake news within online social media based on artificial intelligence methods [18]. Ksieniewicz et al. [19] presented an alternative FS method to detect the fake news from data streams. However, these methods still need improvements to avoid limitations such as attraction to local points that affect the convergence towards to optimal solution. This motivated us to proposed an alternative FS method that depends on a modified version of the Fire Hawk Optimizer (FHO) [20]. According to the behavior of the FHO, it has been applied to various applications, including engineering problems and the BIM-Based Resource Tradeoff in Project Scheduling [21]. This indicates the strong ability of FHO to balance between exploration and exploitation during the search for the optimal subset of features.

Multi-task learning (MTL) has been used in different applications to simultaneously leverage and learn shared information from related tasks. In addition, MTL has been widely used to tackle natural language processing tasks and improve performance on multiple shared tasks, including sentiment analysis, event detection, and hate-speech detection [22,23]. The learning processes of MTL models can differ based on the model's architecture, the data, and the task. In addition, MTL models can benefit from the recently introduced pre-trained language models that rely on transformer-based architectures, such as AraBERT for Arabic [24], which has been used for various NLP applications [25,26]. Meanwhile, the training data can be shared for multiple different tasks. In addition, MTL models can benefit from multimodality and be trained for different tasks and data types [27]. Moreover, the combination of evolutionary algorithms and multi-task learning has established its performance in several works, such as [28–30].

The proposed method depends on integration of deep learning and evolutionary methods to improve the prediction performance on the misinformation detection task. We implemented a transformer-based multi-task learning (MTL) model to tackle the misinformation detection task. The MTL model consists of two types of layers, shared and task-specific layers, to learn and extract contextual text representations. The MTL model can be trained on several datasets corresponding to different related tasks simultaneously, and share learned knowledge from each dataset across the shared layers. Meanwhile, the task-specific layers are used to perform feature extraction and classification in different datasets and tasks used to train the model. The extracted features corresponding to each task/dataset are fed to the feature selection algorithms to boost the performance and reduce the feature-representation space. Then, we use a modified version of the FHO to select the optimal features. Then, the selected subset of features which correspond to the ones in the best solution are used to reduce the features in the testing set. We evaluated the quality of the reduced testing set using different performance measures.

To summarize, the contributions of this study can be given as:

1. Developing a misinformation detection method for the social media data by integrating deep learning and meta-heuristic techniques.
2. Proposing a transformer-based MTL architecture for learning and extracting contextual text representations.
3. Proposing an alternative FS approach based on a modified version of FHO.
4. Evaluating the performance of the developed method using a set of real-world collected datasets with comparison with other well-known methods.

The rest of this paper is organized as follows: Section 2 presents the background of the Fire Hawk Optimizer. Section 3 introduces the steps of the proposed misinformation detection framework. In Section 4, the experimental results and discussion are given. Finally, the conclusion and future works are illustrated in Section 5.

2. Background

In this section, we introduce the basic steps of the Fire Hawk Optimizer (FHO). In general, the FHO, similarly to other MH techniques, starts by assigning an initial value for a set of N agents using the following formula.

$$X_{ij} = rand \times (U_j - L_j) + L_j,\ j = 1, 2, \ldots, D \tag{1}$$

where X_{ij} refers to the ith agent at dimension j. U_j and L_j are the boundaries of the parameters at the jth dimension. $rand \in [0, 1]$ is a random value, and D is the dimension of each X_i.

After that, the objective function is used to assess the performance of each X_i. Then, we determine the fire hawks ($FH_l, l = 1, 2, \ldots, n$), which represent the best solutions; the other solutions are referred to as prey ($PR_k, k = 1, 2, \ldots, m$). We compute the distance between FH and PR using the following equation.

$$D_{lk} = \sqrt{(x_2 - x_1)^2 + (y_2 - y_1)^2}, \; l = 1, 2, \ldots, n, \; k = 1, 2, \ldots, m \tag{2}$$

where m and n are the numbers of FH and PR, respectively. Then, the next task is to compute identify the territory of FH by dispersing PR. Then, we update each FH according to the following formula.

$$FH_l(t+1) = FH_l(t) + (r_1 \times X_b - r_2 \times FH_n(t)), l = 1, 2, \ldots, n \tag{3}$$

where X_b refers to the best solution and $FH_n(t)$ is one fire hawk. r_1 and r_2 are random values generated from [0, 1].

The next step is to determine the safe area in which the prey meet together to remain safe and sound during a hazard. This can be formulated by computing SP_l and SP as follows:

$$SP_l = \frac{\sum_{q=1}^{r} PR_q}{r}, \; q = 1, 2, \ldots, r, \; l = 1, 2, \ldots, n \tag{4}$$

Thereafter, the movement of PK inside the area of FH is used to simulate the animal behavior. According to this behavior, the prey can update its position using the following formula.

$$PR_q(t+1) = PR_q(t) + (r_3 \times FH_l - r_4 \times SP_l(t)), l = 1, 2, \ldots, n, \; q = 1, 2, \ldots, r \tag{5}$$

SP_l denotes the safe position under the area of the lth fire hawk.

The next step is to update the safe location outside the lth FH, and this is formulated as:

$$SP = \frac{\sum_{k=1}^{m} PR_k}{r}, \; k = 1, 2, \ldots, m \tag{6}$$

Then, update the position of prey using the following formula.

$$PR_q(t+1) = PR_q(t) + (r_5 \times FH_a - r_6 \times SP(t)), l = 1, 2, \ldots, n, \; q = 1, 2, \ldots, r \tag{7}$$

The process of updating the solutions is repeated until reaching the stop conditions, and the best solution X_b is returned to.

3. Proposed Misinformation Detection Framework

In this section, we present the steps of the developed method, which depends on the integration between the DL and modified FHO for feature selection. In general, the developed method consists of two stages. The first one is to extract the features from the text dataset. The second stage is to select the relevant features.

3.1. Feature Extraction Model

This section presents the implemented model based on multi-task learning (MTL) and a BERT pre-trained model to tackle the disinformation classification task on Arabic text data. In our study, we exploited the usage of an MTL model with a pre-trained AraBERT model on COVID-19 data. In addition, we relied on additional datasets to boost the model's performance and generalization via adding datasets from similar domains, including the COVID-19 disinformation dataset, COVID-19 rumors dataset, fake news detection dataset, and offensive and hate speech datasets. We focused in our study on the task of disinformation classification using Twitter data related to COVID-19 covering multiple Arabic dialects. Thus, we relied on an AraBERT version 2 [24] model trained on 1.5 million COVID-19 multi-dialect Arabic tweets (https://huggingface.co/moha/arabert_ arabic_covid19, accessed on 9 November 2022) as a shared representation for the proposed MTL model and to learn multiple related tasks jointly. In the upcoming paragraphs, we will detail the architecture and training process of the proposed MTL model for COVID-19 disinformation classification.

The implemented MTL model relies on a multi-task multi-corpora learning objective where the main objective is to improve the model's performance on disinformation classification tasks with the help of additional tasks and corpora. In addition, the selected transformer-based model trained using AraBERT v2 on COVID-19 multi-dialect Arabic tweets can help to learn contextual representations related to the tackled task instead of training the MTL model from scratch using random initialization. The MTL model architecture is shown in Figure 1. The core component of the MTL model is the shared layers, initialized using a pre-trained version of AraBERT v2 on COVID-19 data. The shared layers benefit from the training on different tasks to learn general contextual representations simultaneously. In addition, the shared-layers-learned representations could help the task-specific layers to learn specific representations related to the tackled task and improve the model's overall performance. Thus, the MTL model can overcome several single-task model training problems, including data shortage, context variation, class imbalance, and the lack of generalization on unseen data or tasks.

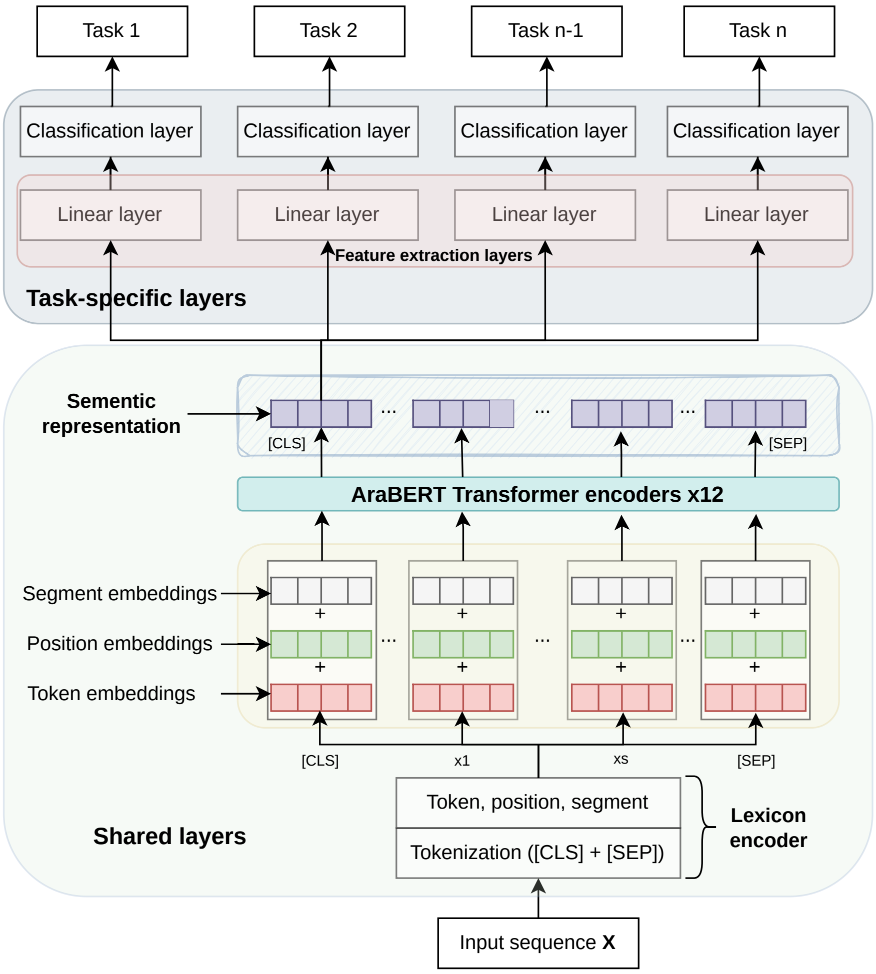

Figure 1. The feature extraction model architecture based on MTL and AraBERT.

3.1.1. The MTL Shared Layers

The input data for the MTL model were processed similarly to the pre-trained multi-layer bidirectional transformer encoder (BERT) model input using the SentencePiece [31] algorithm to perform input segmentation and relying on a lexicon encoder (pre-trained neural-based tokenization vocabulary). The SentencePiece is a multi-layered RNN (recurrent neural network) with the objective of mapping each token x from the input sentence $X = x_1, \ldots, x_s$ of length s to three embedding vectors representing the word, the segment, and the positional (ID). At this stage, the lexicon encoder pads special tokens at the beginning and the end of the tokenized input sentence, which are [CLS] and [SEP], respectively. Finally, the word, segment, and positional embeddings are summed up for each token x to form the embedding vectors for X. The shared layer consists of 12 transformer encoders similar to the canonical BERT encoders used to fine-tune the weights of the pre-trained AraBERT v2 used in this study to learn shared global contextual representations in different tasks. For instance, each transformer encoder consists of a self-attention mechanism to gather contextual information for each input token x. Rather than learning a single objective function, as in single-task training, the MTL model shares representations learned by the transformer encoders with a multi-task objective. At the last transformer encoder, all the learned contextual embeddings for the sentence X are concatenated to generate a single semantic embedding vector stored in the [CLS] token and fed to the task-specific layer.

3.1.2. The MTL Task-Specific Layers

The task-specific layers are fully-connected layers randomly initialized and placed on top of the shared task layer corresponding to each learned task. The task-specific layers were used as single-sentence classifiers to perform sentence classification tasks followed by a softmax output layer and trained using the categorical cross-entropy loss. We perform feature extraction by placing a fully-connect layer before each task-specific layer to extract a representation vector of size 128 for each input sample. Later, the extracted representation vectors are fed to a feature selection algorithm to enhance the performance on specific tasks by removing nonrelevant features and reduce the feature space.

The Algorithm 1 demonstrates the training process of the proposed MTL model using a mini-batch Adamax optimizer with a 5×10^{-5} learning rate to update the model's weights. All datasets are merged in mini-batches as dataset D, and in each epoch, a random mini-batch $batch_T$ corresponding to task T is selected for fine-tuning the model's weights using the task-specific objective, similarly to [32].

Algorithm 1 MTL learning process.

Require: D
  for $epoch$ in 1,2,…,$epoch_{max}$ **do**
    for $batch_T$ in D **do**
      Compute loss for task T
      Compute gradient
      Update model's weights
    end for
  end for

3.2. Feature Selection

Within this stage, the steps of presented FS method based on the modified version of FHO are introduced. The developed FS approach named BFHO starts by dividing the dataset into training and testing sets. Then, it uses the training set to find the relevant features, and this process begins by building the population of N solutions to compute the fitness value of each one. After that. it allocates the best solutions and uses it with the operators of FHO to update the population X. The next step is to select the relevant features from the testing set based on the binary version of the best solution. The details of these steps are given in the following subsections.

3.2.1. First Stage: Generating Population

The first step in this stage is to split the social data into training and testing samples, which represent 80% and 20%, respectively. After that, the population X with N solutions is generated, and each solution $X_i, i = 1, 2, ..., N$ has D dimensions, and the value of each X_i is given as:

$$X_{ij} = L_j + r_1 \times (U_j - L_j),\ i = 1, 2, \ldots, N,\ j = 1, 2, \ldots, D \tag{8}$$

In Equation (8), U_j and L_j denote the maximum and minimum values in the search space at dimension j.

3.2.2. Second Stage: Updating Solutions

In this section, the population X is updated through using the operators of modified FHO. This stage begins by converting each X_i into Boolean form using the following formula.

$$BX_{ij} = \begin{cases} 1 & if\ X_{ij} > 0.5 \\ 0 & otherwise \end{cases} \tag{9}$$

Thereafter, the features of training set that corresponding to ones in BX_{ij} are selected and evaluated using the following fitness value (Fit_i).

$$Fit_i = \rho \times \gamma + (1 - \rho) \times \left(\frac{|BX_{ij}|}{D} \right) \tag{10}$$

where $\rho \in [0, 1]$ is a weight parameter used to balance between the two parts of Equation (10). γ denotes the classification error obtained using the KNN classifier with the training set. $|BX_{i,j}|$ and D refer to the number of selected features and the total number features in the dataset, respectively.

The next process is to determine the best solution X_b which has best Fit_b. After that, the solutions X are updated using the operators of the FHO defined in Equations (2)–(7). The updating steps are conduced until stop conditions are reached.

3.2.3. Third Stage: Evaluation of Selected Features (X_b)

In this stage, the features of the testing set which correspond to ones in the best solution X_b are selected to evaluate their quality. This is achieved using the same fitness value defined in Equation (10). Then, the quality of predicted output using different performance measures is computing. Algorithm 2 provides the steps of the developed FS approach based on the BFHO.

3.3. Implementation of Disinformation Detection Framework

As described in the above-mentioned section, the proposed disinformation detection framework for Arabic language consists of two main phases, which are feature extraction (text representation learning) and feature selection. In this section, a summary of the proposed implementation is given. We started by learning and extracting contextual text representations using an MTL model which benefits from training on several data sources at the same time. In addition, the MTL model learned to generate contextual representations from different tasks while relying on the training mechanism introduced in the shared layers. The shared layers were initialized using a pre-trained language model trained on a large amount of Arabic text. Later, the learned contextual representations were fine-tuned based on their associated tasks using the MT task-specific layers; a feature extraction layer was added to extract the fine-tuned representations and feed them to the BFHO. Then, the steps of BFHO method that are defined in Algorithm 2 were used to determine the relevant features and evaluate their quality using various performance measure.

Algorithm 2 The FS based on the BFHO method.

Input: number of solutions (N), social data contains D features, number of iterations ($tmax$), and parameters of FHO.
First Stage
Split the data into two sets training and testing sets.
Generate population X based on Equation (8).
Second Stage
Assign $t = 1$.
while ($t < tmax$) **do**
  Generate Boolean form of X_i based on Equation (9).
  Calculate fitness value of X_i based on training samples as in Equation (10).
  Find the best solution X_b which has the smallest fitness value.
  update X using Equations (2)–(7).
  $t = t + 1$.
end while
Third Stage
Select the features of testing set which corresponding to ones in X_b.
Compute the quality of predicted output using performance metrics.

4. Experimental Results

4.1. Description of Datasets

In our experiments, we used a multilingual dataset from [33] having 16K annotated tweets related to COVID-19 used for disinformation analysis collected from January 2020 to March 2021. Moreover, the dataset can be used for other tasks, such as fact checking. The dataset contains seven class labels, including questions Q1–Q7. Table 1 lists the questions and their corresponding tweets. We used this dataset in our primary task to optimize focusing on Arabic tweets while only tackling binary and multi-class classification tasks. For instance, each class question (e.g., Q1) contains a question such as "Does the tweet contain a verifiable factual claim?" and the corresponding tweets are annotated as "Yes" or "No" to indicate whether the tweet contains a harmful factual claim related to COVID-19 or not. The question classes can be used for binary and multi-class classification based on the question type and the answers provided by the annotators. Meanwhile, OSACT, ArCOV19, and FKD datasets were used in our experiments to improve the contextual representations learned by the proposed MTL model and refine the learned embeddings based on data from a similar domain as the main task (Q1–Q7). The OSACT [34] dataset was created in a shared task called Open-Source Arabic Corpora and Corpora Processing Tools, which contains two sub-tasks, offensive detection (OSACT-OFF) and hate-speech detection (OSACT-HS), for the Arabic language. The OSACT-OFF is a binary classification of Arabic tweets as containing or not containing offensive speech (OFF or NOT OFF), and with OSACT-HS, the task is to detect hate speech in a tweet (HS or NOT HS). The ArCOV19 [35] dataset was used for the Arabic COVID-19 rumors tweet verification task; the dataset was collected for misinformation detection from 27th January till the end of April 2020. The FKD [36] dataset was used for the Arabic COVID-19 fake news detection task. Tables 2 and 3 list the statistics of each dataset used in our experiments.

Table 1. The main datasets' descriptions and their corresponding samples.

Question	Classes	Binary Instances	Multi-Class Instances	Task
Q1: Does the tweet contain a verifiable factual claim?	2	4966	-	Binary (Yes or No)
Q2: To what extent does the tweet appear to contain false information?	4	3417	3439	Binary/Multi-class
Q3: Will the tweet's claim have an impact on or be of interest to the general public?	4	3425	3439	Binary/Multi-class
Q4: To what extent does the tweet appear to be harmful to the society, a person(s), a company(s) or a product(s)?	4	2870	3439	Binary/Multi-class
Q5: Do you think that a professional fact-checker should verify the claim in the tweet?	4	3439	3439	Binary/Multi-class
Q6: Is the tweet harmful to the society and why?	9	4954	4966	Binary/Multi-class
Q7: Do you think that this tweet should get the attention of a government entity?	10	4954	4966	Binary/Multi-class

Table 2. Descriptions and statistics for OSACT, ArCOV19, and FKD datasets.

Dataset	Language	Total Samples	Label	Training Set	Development Set	Test Set
OSACT-HS	Arabic MSA Arabic DA	10K	HS NOT HS	361 6639	44 956	101 1899
OSACT-OFF	Arabic MSA Arabic DA	10K	OFF NOT OFF	1410 5590	179 821	402 1598
ArCOV19	Arabic MSA Arabic DA	3584	False True	1220 1288	261 277	272 266
FKD	Arabic MSA Arabic DA	1537	Fake NOT Fake	593 482	113 118	129 102

Table 3. Descriptions and statistics for the tested dataset.

Dataset	Language	Labels	Total Samples	Training Set	Development Set	Test Set
Q1	Arabic MSA Arabic DA	2	1809	1172	320	317
Q2	Arabic MSA Arabic DA	5	1355	891	220	244
Q3	Arabic MSA Arabic DA	5	1360	893	223	244
Q4	Arabic MSA Arabic DA	5	1444	892	219	243
Q5	Arabic MSA Arabic DA	4	1365	896	223	246
Q6	Arabic MSA Arabic DA	9	1803	1171	317	315
Q7	Arabic MSA Arabic DA	10	1805	1169	319	317

4.2. Results and Discussion

This section evaluates the proposed FHO method in classifying a set of datasets. The FHO method received the datasets in a text form; then, it extracted the features from these data as described in Section 3. Therefore, the output of this stage produced a numerical dataset. After that, the FHO method started a new stage to select the most important features within the dataset. The produced features were evaluated using binary and multi-class classification, as described in this section.

The experimental results of the FHO are compared to those of nine methods: HBA, bGWO, QChamRSA, RunEFO, RSA, LSHADE_cnEpSin, SaDE, LSHADE_SPACMA, and CHCLPSO. Four performance measures were used: accuracy, precision, recall, and F-measure. The experiments were divided into two parts. The first used binary-class datasets, whereas the second used multi-class datasets. The results are presented in Tables 4–10.

For the binary-class experiment, Table 4 shows the classification accuracy results for FHO and other methods. In this measure, the FHO achieved the best accuracy results and was ranked first for 6 out of 11 datasets (i.e., HS, OFF, Q2, Q4, Q6, and Q7); FHO, HBA, and bGWO obtained the best accuracy on the FKD dataset. The HBA came in second; it obtained the best accuracy on both ArCR and Q3 datasets. LSHADE_SPACMA and RSA obtained the third and fourth ranks, respectively, followed by SaDE, bGWO, LSHADE_cnEpSin, CHCLPSO, and EFO; QChamRSA shows the worst results. Figure 2 illustrates the average accuracy. The results of the precision measure are listed in Table 5. In this table, we can see that the FHO outperformed the other methods in 5 out of 11 datasets: ArCR, FKD, Q3, Q4, and Q6. It shows promising results on the other datasets. The HBA obtained the second rank, achieving the best precision results on three datasets HS, Q1, and Q2. The RSA had the best results for two datasets (OFF and Q7); therefore, it was ranked third, followed by LSHADE_SPACMA, SaDE, bGWO, CHCLPSO, and EFO, respectively. Figure 3 illustrates the average precision.

Table 4. Accuracy results obtained by FHO and other methods in the binary case.

Acc	FHO	HBA	bGWO	QChamRSA	EFO	RSA	LSES	SaDE	LSSC	CHCLPSO
ArCR	0.9554	**0.9628**	0.9554	0.9554	0.9554	0.9517	0.9535	0.9591	0.9554	0.9554
FKD	**0.9483**	**0.9483**	**0.9483**	0.8966	0.9138	0.9138	0.9310	0.9138	0.9138	0.9138
HS	**0.9820**	0.9760	0.9740	0.9740	0.9740	0.9800	0.9740	0.9760	0.9760	0.9760
OFF	**0.9480**	0.9460	0.9400	0.9300	0.9440	0.9420	0.9420	0.9420	0.9420	0.9440
Q1	0.8801	0.8801	0.8770	0.8486	0.8738	**0.8833**	0.8738	0.8770	0.8738	0.8644
Q2	**0.8730**	0.8689	0.8484	0.8115	0.8484	0.8443	0.8607	0.8525	0.8566	0.8484
Q3	0.9713	**0.9754**	0.9631	0.9631	0.9672	0.9713	0.9713	0.9672	0.9672	0.9672
Q4	**0.9593**	0.9342	0.9136	0.9053	0.9136	0.9136	0.9136	0.9177	0.9177	0.9136
Q5	0.7236	0.6951	0.7236	0.6463	0.6992	0.6789	0.7073	0.7033	**0.7276**	0.6992
Q6	**0.9698**	0.9333	0.9143	0.8825	0.8984	0.9079	0.9048	0.9048	0.9048	0.9048
Q7	**0.8107**	0.8076	0.7760	0.7603	0.7886	0.7792	0.7855	0.7918	0.7950	0.7886

Table 5. Precision results obtained by FHO and other methods in the binary case.

	FHO	HBA	bGWO	QChamRSA	EFO	RSA	LSES	SaDE	LSSC	CHCLPSO
ArCR	**0.9628**	0.9555	0.9554	0.9554	0.9519	0.961	0.9536	0.9591	0.9554	0.9554
FKD	**0.9531**	**0.9531**	**0.9531**	0.9143	0.9265	0.9394	0.9394	0.9183	0.9183	0.9265
HS	0.8667	**0.8895**	0.8743	0.8574	0.8698	0.8836	0.8574	0.8836	0.8836	0.8836
OFF	0.9122	0.917	0.9124	0.8905	0.9083	**0.9232**	0.9143	0.9083	0.9112	0.9195
Q1	0.8357	**0.8447**	0.832	0.7816	0.8393	0.8295	0.831	0.8347	0.8282	0.81
Q2	0.8141	**0.8235**	0.7814	0.7115	0.7821	0.8173	0.8116	0.7876	0.797	0.7787
Q3	**0.9877**	0.7376	0.4855	0.4855	0.7376	0.7376	0.7376	0.6542	0.4856	0.4856
Q4	**0.9338**	0.9202	0.8967	0.8782	0.903	0.9101	0.8967	0.9005	0.9066	0.8967
Q5	0.6653	0.6977	0.6977	0.6233	0.6493	0.6935	0.6815	0.681	**0.7024**	0.6738
Q6	**0.8976**	0.8876	0.8675	0.8294	0.8635	0.871	0.8599	0.8635	0.8599	0.8675
Q7	0.7646	0.7501	0.7204	0.6979	0.724	**0.7648**	0.7344	0.7457	0.7512	0.7386

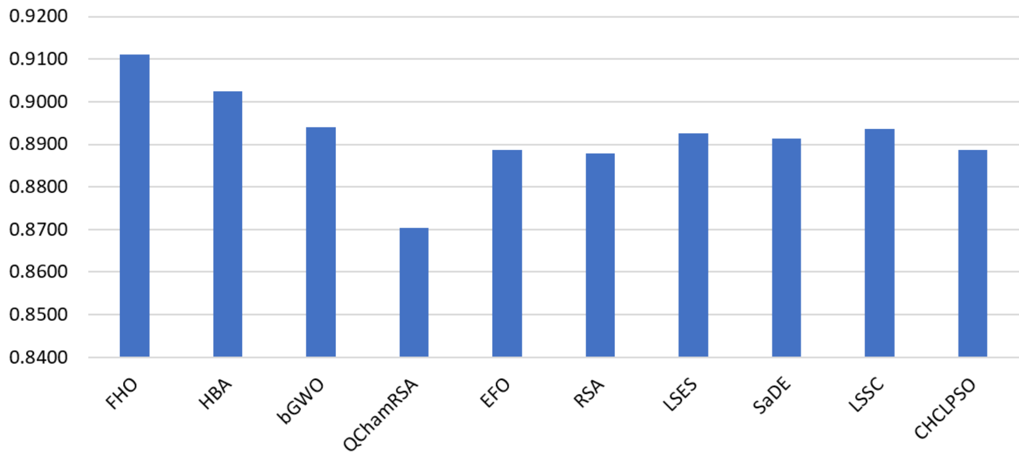

Figure 2. Average of the accuracy measure in the binary case.

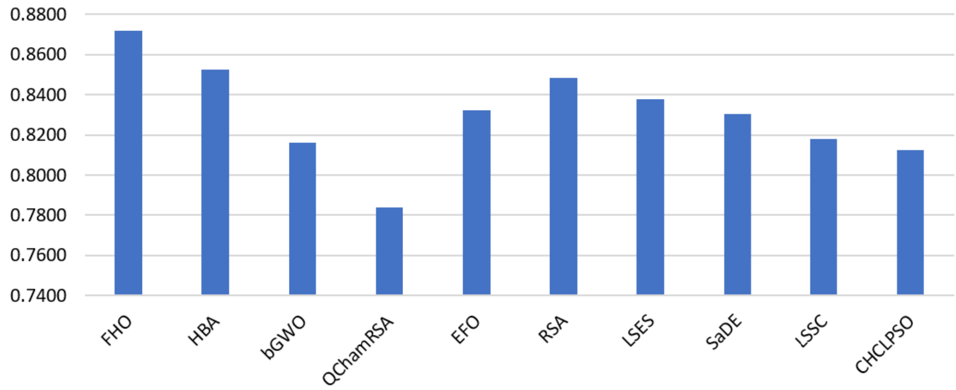

Figure 3. Average of the precision measure in the binary case.

The results of the recall measure are listed in Table 6. In this table, the FHO shows the best recall results for 72% of all datasets, whereas for FKD datasets, the FHO, HBA, and bGWO obtained the same recall values equal 0.948. The HBA and RSA are ranked second and third, respectively, followed by EFO, bGWO, SaDE, LSHADE_SPACMA, LSHADE_cnEpSin, and CHCLPSO. Figure 4 illustrates the average of recall measures. In addition, the results of the F-measure are also considered and recorded in Table 7. This measure is used as the weighted mean of both precision and recall. In this measure, the FHO is ranked first; it obtained the best F-measure in 4 out of 11 datasets and showed the best results, equal with those of the HBA and bGWO, for the FKD dataset. The second and third-best algorithms were the HBA and RSA, followed by LSHADE_SPACMA, SaDE, EFO, bGWO, and LSHADE_cnEpSin. The QChamRSA had the worst F-measure results.

In terms of the multi-class experiment, six datasets were used in this experiment (Q2, Q3, Q4, Q5, Q6, and Q7). The results are listed Tables 8–10. The results of the classification accuracy measure are shown in Table 8. In this table, the FHO is shown to have achieved the best accuracy results and is ranked first for 4 out of 6 datasets (i.e., Q2, Q3, Q4, and Q7). The HBA obtained the second rank and achieved the best accuracy in two datasets (Q5 and Q6). The third and fourth-best methods were LSHADE_SPACMA and CHCLPSO, respectively, followed by bGWO, LSHADE_cnEpSin, SaDE, EFO, and RSA. The QChamRSA failed to obtain the best value in any dataset. Figure 5 illustrates the average accuracy measure.

Table 6. Recall results obtained by FHO and other methods in the binary case.

	FHO	HBA	bGWO	QChamRSA	EFO	RSA	LSES	SaDE	LSSC	CHCLPSO
ArCR	**0.9629**	0.9555	0.9554	0.9554	0.9518	0.961	0.9536	0.9591	0.9555	0.9554
FKD	**0.9483**	**0.9483**	**0.9483**	0.8966	0.9138	0.931	0.931	0.9138	0.9138	0.9138
HS	**0.9483**	0.8708	**0.9483**	0.8966	0.9138	0.931	0.931	0.9138	0.9138	0.9138
OFF	**0.9088**	0.8799	0.8843	0.874	0.898	0.9017	0.8897	0.898	0.8939	0.8909
Q1	0.7958	0.7925	0.7469	0.7708	**0.8698**	0.7719	0.7708	0.7719	0.7719	0.7719
Q2	0.8075	0.7682	0.8005	0.7872	**0.8146**	0.8055	0.7884	0.7955	0.7935	0.7874
Q3	**0.7656**	0.5693	0.7238	0.6789	0.6996	0.7414	0.7316	0.7336	0.7362	0.731
Q4	**0.8738**	0.8621	0.8477	0.8424	0.8412	0.8594	0.8477	0.8568	0.8503	0.8477
Q5	0.6627	0.6977	0.6977	0.6301	0.6501	0.6945	0.6851	0.6898	**0.7034**	0.6788
Q6	**0.8929**	0.8829	0.8631	0.7837	0.8413	0.8294	0.8333	0.8274	0.8333	0.8214
Q7	**0.7339**	0.7273	0.691	0.6766	0.7142	0.7177	0.7011	0.702	0.7041	0.7068

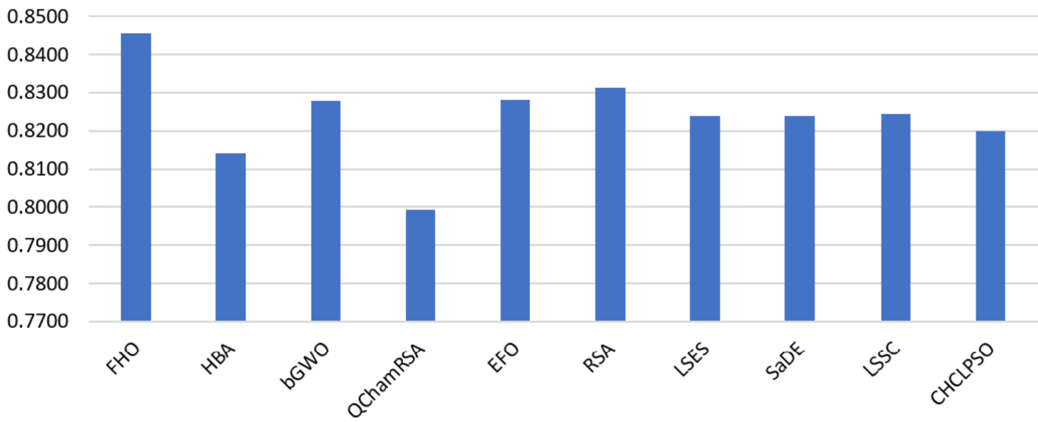

Figure 4. Average of the recall measure in the binary case.

Table 7. F-measure results obtained by FHO and other methods in the binary case.

	FHO	HBA	bGWO	QChamRSA	EFO	RSA	LSES	SaDE	LSSC	CHCLPSO
ArCR	**0.9628**	0.9554	0.9554	0.9554	0.9517	0.961	0.9535	0.9591	0.9554	0.9554
FKD	**0.9481**	**0.9481**	**0.9481**	0.8954	0.9131	0.9307	0.9307	0.9136	0.9136	0.9131
HS	0.8271	**0.9134**	0.7963	0.8075	0.8698	0.8173	0.8075	0.8173	0.8173	0.8173
OFF	0.9105	0.91	0.8975	0.8819	0.903	**0.9119**	0.9013	0.903	0.9022	0.9043
Q1	0.8202	0.814	0.8145	0.7844	**0.8259**	0.8165	0.8065	0.8124	0.8086	0.7977
Q2	0.7857	**0.7906**	0.7458	0.6919	0.7268	0.7692	0.76	0.7548	0.7595	0.7501
Q3	0.6188	0.6038	0.5217	**0.6317**	0.6038	0.6038	0.6038	0.5916	0.6138	0.5529
Q4	**0.8993**	0.8867	0.8688	0.8583	0.8668	0.8813	0.8688	0.8759	0.8741	0.8688
Q5	0.6639	0.6977	0.6977	0.6248	0.6497	0.694	0.6831	0.6838	**0.7029**	0.6759
Q6	**0.8952**	0.8852	0.8653	0.8032	0.8517	0.8478	0.8456	0.8436	0.8456	0.8415
Q7	**0.7461**	0.7368	0.702	0.6849	0.7187	0.7341	0.7134	0.717	0.72	0.7188

Table 8. Accuracy results for the multi-class experiment.

	FHO	HBA	bGWO	QChamRSA	EFO	RSA	LSES	SaDE	LSSC	CHCLPSO
Q2	**0.7927**	0.7805	0.7846	0.7642	0.7642	0.7602	0.7724	0.7683	0.7764	0.7805
Q3	**0.6626**	0.6423	0.6301	0.5854	0.6179	0.6098	0.6301	0.6341	0.6382	0.6179
Q4	**0.5407**	0.5203	0.4878	0.4675	0.4919	0.4797	0.5	0.4959	0.5041	0.5041
Q5	0.6098	**0.6423**	0.6057	0.5732	0.6057	0.6138	0.6301	0.6138	0.6179	0.622
Q6	0.8454	**0.8707**	0.8549	0.8297	0.8391	0.8328	0.8454	0.836	0.8454	0.8486
Q7	**0.6058**	0.6032	0.5987	0.5556	0.5873	0.6	0.5732	0.5892	0.5974	0.5924

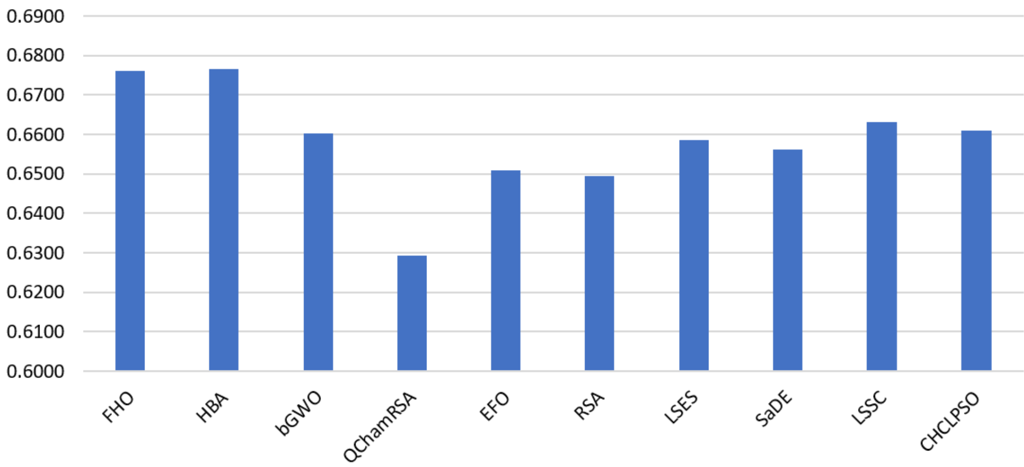

Figure 5. Average of the accuracy measure for the multi-class experiment.

Table 9. Precision results for the multi-class experiment.

	FHO	HBA	bGWO	QChamRSA	EFO	RSA	LSES	SaDE	LSSC	CHCLPSO
Q2	**0.7927**	0.7805	0.7846	0.7642	0.7642	0.7602	0.7724	0.7683	0.7764	0.7805
Q3	**0.6626**	0.6423	0.6301	0.5854	0.6179	0.6098	0.6301	0.6341	0.6382	0.6179
Q4	**0.5407**	0.5203	0.4878	0.4675	0.4919	0.4797	0.5	0.4959	0.5041	0.5041
Q5	0.6098	**0.6423**	0.6057	0.5732	0.6057	0.6138	0.6301	0.6138	0.6179	0.622
Q6	**0.8454**	0.6423	0.6057	0.5732	0.6057	0.6138	0.6301	0.6138	0.6179	0.622
Q7	0.5962	**0.8707**	0.8549	0.8297	0.8391	0.8328	0.8454	0.836	0.8454	0.8486

The same results are shown for the recall measure listed in Table 10. For this measure, the FHO had the best recall results in 66% of all datasets, whereas the HBA and LSHADE_cnEpSinwere were ranked second and third, followed by LSHADE_SPACMA, CHCLPSO, SaDE, and bGWO, respectively.

Table 10. Recall results for the multi-class experiment.

	FHO	HBA	bGWO	QChamRSA	EFO	RSA	LSES	SaDE	LSSC	CHCLPSO
Q2	**0.7927**	0.7805	0.7846	0.7642	0.7642	0.7602	0.7724	0.7683	0.7764	0.7805
Q3	**0.6626**	0.6423	0.6301	0.5854	0.6179	0.6098	0.6301	0.6341	0.6382	0.6179
Q4	**0.5407**	0.5203	0.4878	0.4675	0.4919	0.4797	0.5	0.4959	0.5041	0.5041
Q5	0.6098	**0.6423**	0.6057	0.5732	0.6057	0.6138	0.6301	0.6138	0.6179	0.622
Q6	**0.8454**	0.6423	0.6057	0.5732	0.6057	0.6138	0.6301	0.6138	0.6179	0.622
Q7	0.5962	**0.8707**	0.8549	0.8297	0.8391	0.8328	0.8454	0.836	0.8454	0.8486

These results indicate that the proposed FHO can correctly classify different types of datasets in both experiments (binary-class and multi-class classification) and can obtain better classification accuracy compared to the other methods.

5. Conclusions and Future Works

This paper presents a framework using three methods, namely, multi-task learning, a transformer-based model, and an optimization algorithm, to tackle the misinformation detection problem and help decrease the COVID-19 infodemic in the Arabic community on social media. The framework combines several tasks to learn contextual feature representations from Arabic social media posts. The proposed framework relies on two core phases: feature extraction and selection. The feature extraction is performed using a pre-trained AraBERT model via fine-tuning and a multi-task learning approach. Several tasks and datasets were incorporated to enhance this phase to extract meaningful feature representations. For the feature selection phase, we developed a metaheuristic algorithm to select the most relevant features from the contextual feature representations and boost the detection accuracy of the framework. The algorithm used in this phase was the Fire Hawk Optimizer (FHO). After applying these phases, the proposed method was evaluated in classifying the obtained features, and its results were compared to the state-of-the-art optimization algorithms. The results showed that the proposed framework outperforms the compared approaches in terms of accuracy and F1-score, and other existing optimization algorithms. In future work, we plan to extend the proposed framework with other languages and natural language processing tasks, such as hate-speech detection and sentiment analysis. We also plan to investigate the proposed framework using multimodal data. In terms of optimization algorithms, we plan to modify the performance of the FHO using chaotic maps or opposite-based optimization techniques.

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