An LSTM-based Plagiarism Detection via Attention Mechanism and a Population-based Approach for Pre-Training Parameters with imbalanced Classes

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Abstract. Plagiarism is one of the leading problems in academic and industrial environments, which its goal is to find the similar items in a typical document or source code. This paper proposes an architecture based on a Long Short-Term Memory (LSTM) and attention mechanism called LSTM-AM-ABC boosted by a population-based approach for parameter initialization. Gradientbased optimization algorithms such as back-propagation (BP) are widely used in the literature for learning process in LSTM, attention mechanism, and feedforward neural network, while they suffer from some problems such as getting stuck in local optima. To tackle this problem, population-based metaheuristic (PBMH) algorithms can be used. To this end, this paper employs a PBMH algorithm, artificial bee colony (ABC), to moderate the problem. Our proposed algorithm can find the initial values for model learning in all LSTM, attention mechanism, and feed-forward neural network, simultaneously. In other words, ABC algorithm finds a promising point for starting BP algorithm. For evaluation, we compare our proposed algorithm with both conventional and population-based methods. The results clearly show that the proposed method can provide competitive performance.

Keywords: Plagiarism, back-propagation, LSTM, attention mechanism, artificial bee colony.

1 Introduction

Plagiarism is one of the most important problems in educational institutions such as universities and scientific centers. The purpose of an automated plagiarism detection system is to find similar items at the level of a word, sentence, or document. There are different goals for plagiarism detection. For example, some of these studies only identify duplicate documents [1]. However, low accuracy is a main problem because they do not recognize copied sentences. Several other detectors are designed to find similar source codes in programming environments. It is worthwhile to mention that most research takes into account plagiarism detection at the sentence level [2].

Generally speaking, the methods presented for plagiarism detection are based on statistical methods or in-depth learning. Statistical methods usually utilize Euclidean distance or cosine similarity to calculate the similarity between two items [3-5]. Convolutional Neural Network (CNN) and Recurrent Neural Network (RNN), as two leading deep learning models, have attracted much attention of researchers for plagiarism detection. [6] uses a Siamese CNN to analyze the content of words and selects a representation of a word relevance with its neighbors. In [7], the representation of each word is made using Glove (a word embedding method) [8], and then the representation of the sentences is obtained using a recursive neural network. Finally, similar sentences are identified using cosine similarity. [9] employed two attention-based LSTM networks to extract the representation of two sentences. In [10], the similarity between the sentences is considered for the answer selection task. Two approaches are proposed for this purpose. The first method uses two methods of embedding Language Models (ELMo) [11] and the Bidirectional Encoder Representations from transformers (BERT) and combines them with

a transformer encoder. In the second approach, the model is tuned using two pre-trained transformer encoder models. In [12], the authors presented a method based on the context-aligned RNN called CARNN. This paper suggests embedding context information of the aligned words in hidden state generation. They showed that this technique could play an effective role in measuring similarity. In addition, from the literature, there are some few papers focused on the attention mechanism for plagiarism detection [13, 14].

One of the most important reasons for the convergence of neural networks is the initial value of the parameters. The gradient-based algorithms such as back-propagation are extensively used for deep learning models. However, these algorithms have some problems such as sensitivity to initial parameters and getting stuck in local optima [15, 16]. Population-based metaheuristic (PBMH) algorithms can be considered as an alternative to these problems. Artificial Bee Colony (ABC) is an efficient PBMH which has achieved many successes in optimizing a diverse range of applications [17].

In this study, a new architecture, LSTM-AM-ABC, based on the attention mechanism for plagiarism detection at the sentence level is proposed. The proposed algorithm benefits from three main steps including pre-processing, word embedding, and model construction. LSTM-AM-ABC employs LSTM and feed-forward networks as the core model, attention-based mechanism for changing the importance of all inputs, and an ABC algorithm for parameter initialization. Here, the main responsibility of the ABC algorithm is to find a promising point to commence the BP algorithm in LSTM, attention mechanism, and feed-forward network. The proposed model learns two pairs of positive and negative inputs. Negative pairs are dissimilar sentences, while positive pairs are similar sentences. In addition, we use several methods to overcome the data imbalance problem. We evaluate our results on three benchmark datasets based on different criteria. The evaluation results show that the proposed model can be superior to the compared models that use the random value for the parameters.

The remainder of this paper is organized as follows. Section 2 explains briefly the background knowledge. Section 3 illustrates the proposed model, while Section 4 evaluates the proposed model. Finally, Section 5 concludes the paper.

2 Background

2.1 Long Short-Term Memory (LSTM)

Recurrent neural networks (RNNs) are a type of neural network based on sequential datasets. These networks are utilized in many applications, including natural language processing [18-20], due to their recurrent nature. The network uses a hidden layer to transfer information from t-1 to t. In addition, an output is generated each time t. The hidden layer and the output each time t in the RNN network are calculated as

$$h_t = \theta(W_h h_{t-1} + U_h x_t + b_h) \tag{1}$$

$$y_t = \tau(W_v h_t + b_v) \tag{2}$$

where x_t , h_t , y_t are the input vector, the hidden layer, and the output at time t, respectively. W_h , U_h , W_v are the weight matrices, and b_h , b_v are the bias values. θ , τ represent the activation functions.

The main problem with a RNN network is the vanishing gradient, meaning that the gradient has a tendency toward zero, which drastically prevents the parameters from being updated. In 1997 [21], LSTM networks were first proposed to solve this problem. An LSTM unit includes an input gate, a memory gate, and an output gate that make it easy to learn long dependencies [13]. The update relations of an LSTM unit in step *t* are as follows [22]

$$i_t = \sigma(W_i x_t + U_i h_{t-1} + b_i) \tag{3}$$

$$f_t = \sigma(W_f x_t + U_f h_{t-1} + b_f) \tag{4}$$

$$c_t = f_t c_{t-1} + i_t \tanh(W_i x_t + U_i h_{t-1} + b_i)$$
(5)

$$o_t = \sigma(W_0 x_t + U_0 h_{t-1} + b_0) \tag{6}$$

$$h_t = o_t tanh(c_t) (7)$$

where i, f, o, and c are the input gate, forget gate, output gate and, cell input, respectively. $W \in \mathbb{R}^{h \times d}$. $U \in \mathbb{R}^{h \times h}$, $b \in \mathbb{R}^h$ are network parameters that should be learned during the learning process. Note that the input size x and hidden size h are d and h, respectively.

LSTM networks process input from start to finish or vice versa. It has been proven that it can be more effective if the processing is done from both sides simultaneously [23]. Bidirectional Long Short-Term Memory (BLSTM) networks are a type of LSTM networks that process input from both sides and produce two hidden vectors \vec{h}_t and \vec{h}_t . In BLSTM, the combination of two hidden vectors, $h_t = [\vec{h}_t, \vec{h}_t]$, is considered as the final hidden vector.

Although LSTM networks consider long sequences, they give the same importance to all inputs. It can confuse the network in making decisions. Consider the following sentence: "Despite being from Uttar Pradesh, as she was brought up in Bengal, she is convenient in Bengali". Some words such as "Bengali", "brought up" and "Bengal" should have more weight because it has more related to the word "Bengali". The attention mechanism for this problem was later introduced [24]. In the attention mechanism, for each hidden vector, a coefficient is considered that the final hidden vector is calculated as

$$h = \sum_{t=1}^{T} \alpha_t h_t \tag{8}$$

where α_t , h_t is the coefficient of significance and the hidden vector extracted in step t. T is the number of inputs.

2.2 Artificial bee colony algorithm (ABC)

The artificial bee colony algorithm (ABC) is an effective PBMH algorithm based on collective intelligence of the bee colonies [25]. This algorithm has four main steps, which are described below:

Initial Population The initial population of food sources is created with size N, and filled randomly. Each D-dimensional solution is generated as

$$x_i^j = x_{min}^j + rand(0.1)(x_{max}^j - x_{min}^j)$$
 (9)

where i = 1, 2, ..., N, j = 1, 2, ..., D. x_{min}^{j} min and x_{max}^{j} are the lower and upper bounds for the dimension j, respectively. After initialization, the population is searched for employed bees, spectator bees, and scout bees.

The Search of the employed bees In this step, the new solution v is calculated based on the previous solution x as

$$v_i^j = x_i^j + \varphi_i^j (x_i^j - x_k^j)$$
 (10)

where $j \in \{1.2....D\}$ and $k \in \{1.2....N\}$ and $k \neq i$ are random indexes. $\varphi_i^j \in [-1.1]$ is a random number. Eq. 10 shows that the new solution v_i is generated by changing a vector element x_i . After calculating v_i , fitness v_i is calculated. A greedy selection is applied so that if the fitness value of v_i is better, v_i replaces x_i . Otherwise, x_i is retained.

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Selection of the onlooker Bees In this phase, each onlooker bee selects a food source according to the fitness value. The probability of choosing any candidate solution depending on the fitness value is computed as

$$p_i = \frac{fit(x_i)}{\sum_{n=1}^{N} fit(x_n)}$$
 (11)

where $fit(x_i)$ is the fitness value of solution x_i . It is clear that by increasing the value of $fit(x_i)$, the onlooker bee has more probability to choose this food source. After selecting the food source, the onlooker bee will move towards it and produce a new food source in its neighborhood by using Eq. 10.

Scout bee step If the position of a food source cannot be further improved than the number of predetermined cycles (*limit*), a new solution will replace it. Scout bees can discover richer solutions as

$$x_i = x_{min} + rand(0.1)(x_{max} - x_{min})$$
(12)

where x_{min} and x_{max} are the lower and upper bounds of solation x_i .

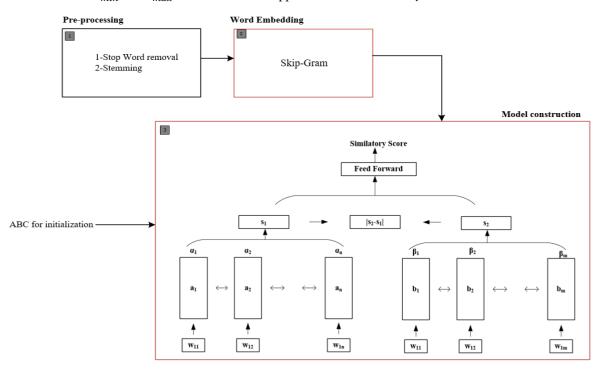


Fig. 1. Steps of the proposed model.

3 LSTM-AM-ABC approach

The proposed method, LSTM-AM-ABC, consists of three main steps, including pre-processing, word embedding, and model construction (According to Fig. 1). The details of each step are described below.

3.1 Pre-processing

Pre-processing means removing unnecessary and unimportant words, which reduces the computational load and increases the speed. Two techniques are used for this purpose.

Stop-word removal Words such as 'or' and 'with' lack semantic information due to their repetition and presence in most documents. Eliminating these words plays a crucial role in the performance of plagiarism detection.

Stemming The process of returning words to their root form is called the stemming operation (for example, the root form of *looking* is the word of *look*).

3.2 Word Embedding

One of the most important steps in natural language processing is word embedding because it is used as input and the embedding of sentences is made based on it. For this purpose, we use the well-known algorithm Skip-Gram [26]. It applies a simple neural network model to learn word vectors. Vectors are carefully generated so that the similarity of the two words can be estimated using a similarity function.

3.3 Model construction

This paper proposes a plagiarism detection method, LSTM-AM-ABC, based on LSTM and feed-forward neural network, as the core models, the attention mechanism for altering the importance of the inputs, and ABC for parameter initialization. An LSTM is provided for each sentence S. In this research, two pairs of data have been used to learn the model. In positive pair (S_1, S_2) , S_1 and S_2 are two copy sentences. The degree of similarity of the sentences depends on the dataset. In Negative pairs (S_1, \hat{S}_2) , S_1 and \hat{S}_2 are not similar. For a positive pair, class label is one, while for a negative pair, the class label is zero. Let $S_1 = \{w_{11}, w_{12}, \dots, w_{1n}\}$ and $S_2 = \{w_{21}, w_{22}, \dots, w_{2m}\}$ be two sentences, where w_{ij} is the j-th word in i-th sentence. The two sentences S_1 and S_2 are limited to n and m words, respectively. The embedding of sentences S_1 and S_2 is formulated based on the attention mechanism as

$$s_1 = \sum_{i=1}^n \alpha_i h_{a_i} \tag{13}$$

$$s_2 = \sum_{i=1}^m \beta_i \, h_{b_i} \tag{14}$$

where $h_{a_i} = [\vec{h}_{a_i} \cdot \overleftarrow{h}_{a_i}] \in \mathbb{R}^{2d_1}$, $h_{b_i} = [\vec{h}_{b_i} \cdot \overleftarrow{h}_{b_i}] \in \mathbb{R}^{2d_2}$ are the i-th output in BLSTM. Each BLSTM output plays a role in the output with a coefficient in the range [0,1]. These coefficients are calculated for both networks as

$$\alpha_i = \frac{e^{u_i}}{\sum_{i=1}^n e^{u_i}} \tag{15}$$

$$\beta_i = \frac{e^{\nu_i}}{\sum_{i=1}^m e^{\nu_i}} \tag{16}$$

$$u_i = tanh(W_u h_{a_i} + b_u) (17)$$

$$v_i = tanh(W_v h_{b_i} + b_u) (18)$$

where $W_u \in \mathbb{R}^{2d_1}$. $b_v \in \mathbb{R}$, $W_v \in \mathbb{R}^{2d_2}$. and $b_v \in \mathbb{R}$ are the parameters of the attention mechanism for two sentences. After calculating the embedding of sentences, they, along with their differences $|s_2 - s_1|$, enter a feed-forward network, and their similarity is calculated.

3.3.1 Parameter optimization

There is a plethora of parameters in the proposed model including parameters in LSTM, feed-forward networks, and attention mechanism. This paper proposes a novel approach for parameter initialization using ABC algorithm. To this end, two main issues should be considered including encoding strategy and fitness function. Encoding strategy represents the structure of each candidate solution, while fitness function is responsible to calculate the quality of each candidate solution.

3.3.1.1 Encoding strategy

The proposed model consists of three main parts including two LSTM networks, two attention mechanism systems, and one feed-forward network. Fig.2 shows a typical encoding strategy for a two-layer feed-forward network, two single-layer LSTM networks and two attention mechanisms.

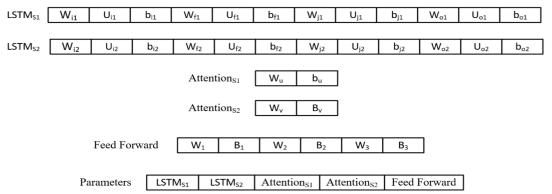


Fig. 2. Illustration of encoding strategy.

3.3.1.2 Fitness function

Fitness function calculates the quality of each candidate solution. In this paper, we propose an objective function based on similarity as

$$Fitness = \frac{1}{1 + \sum_{i=0}^{N} (y_i - \tilde{y}_i)^2}$$
 (19)

where N is training data, y_i is the i-th target, and \tilde{y}_i is the predicted similarity value for the i-th data. The goal of optimization here is to find the optimal initial seeds for the BP algorithm.

3.3.2 Imbalance Classification

One of the most important challenges of machine learning is the problem of data imbalance. Data imbalance means that the number of data in the classes is not the same and, one of the classes (or even more) has more data. It reduces system performance because it causes the classifier to bias the output to one side. In our case, the problem of imbalance is due to a large number of negative pairs. This paper proposes a combination of imbalance methods to tackle the problem.

Augmentation The goal is to increase the positive pair. For this purpose, we combine the embedding of each word in the sentence with Gaussian noise and produce new sentences that are similar to positive sentences.

Penalty In this technique, the minority and majority class error values are applied with different coefficients in the Loss function. Eq. 20 illustrates the concept of this technique

$$Loss = \alpha Loss_{C_1} + \beta Loss_{C_2}$$
 (20)

where C_1 and C_2 are the minority and majority classes, respectively, and the coefficients α and β are the importance of the Loss function. If α and β are equal, we have a common classification problem.

4 Experiments and Analysis

In this section, we evaluate LSTM-AM-ABC algorithm compared to other competitors and different criteria.

4.1 Corpus

Plagiarism detection is a classification problem

$$sim(S_1.S_2) = \begin{cases} \geq \varepsilon & S_1 \text{ is a copy of } S_2 \\ < \varepsilon & S_1 \text{ is not a copy of } S_2 \end{cases}$$
 (21)

According to Eq. 21, when the proposed model detects the degree of similarity of S_1 and S_2 above 0.5, a copy is detected. In this research, three common plagiarism datasets are utilized for this purpose.

SemEval2014 This dataset is taken from the Sentences Involving Com-positional Knowledge (SICK) dataset [27] for semantic evaluation of English sentences. It has 5000 pairs of sentences for training, and 5,000 sentences for testing. Each pair of sentences has a similarity label $\in \{1.2.3.4.5\}$, which 1 means that the sentences are irrelevant and 5 meaning the most similar sentences. We consider the label = 0 as class 0 and the label $\in \{2.3.4.5\}$ as class 1.

STS Semantic Text Similarity (STS) [9] is based on image captions, news headlines, and user forums. This database has 6928 sentences for training, and 1500 sentences for testing. To make unrelated pairs, we put unrelated sentences together.

MSRP Microsoft Research Paraphrase corpus (MSRP) [13] is a paraphrasing corpus containing 4076 pairs of sentences for training and 1725 pairs of sentences for testing. The sentences in this dataset are tagged by humans.

4.2 Metrics

Recall For plagiarism systems, it is vital not to recognize sentences that are copies so that copies can easily pass through the filter without being detected. The recall criterion is one of the valuable criteria for this problem because this criterion considers the number of copied sentences is not recognized. The recall metric is defined as

$$Recall = \frac{TP}{TP + FN} \tag{22}$$

where TP is the number of states that the system has correctly detected the copy, and FN is the number of states that the system has not detected the actual copy.

Pearson's correlation This criterion distinguishes negative correlation and negative correlation numerically in the interval [-1,1] as

$$r = \frac{Cov(sim_{y'}.sim_{y})}{\sqrt{var(sim_{y'})var(sim_{y})}}$$
 (23)

According to this relation, the value of r in the range [0,0.2], [0.2,0.4] and [0.4,0.6] means zero correlation, weak correlation and moderated correlation, respectively [13].

Mean Square Error(**MSE**) The MSE criterion indicates the difference between the degree of actual and predicted similarity defined as

$$MSE = sum((sim_{v'} - sim_{v})^2)$$
 (24)

4.3 Results

We compare the proposed method with a series of previous researches. To this end, we use k-fold cross-validation (k=10 or 10CV) in all experiments, in which the dataset is divided into k subsets. One of the subsets is used for test data, while the remaining is employed for training. This procedure is repeated k times, and all data is used exactly once for testing. We report statistical results including mean, standard deviation, and median for each criterion and each dataset. Table 1 shows the parameter settings of the proposed model. In addition, ϵ was set to 0.515, 0.525, and 0.52 for SemEval2014, STS dataset, and MSRP datasets, respectively.

We compare our method with seven methods, including Siamese CNN+LSTM [6], Recurrent NN, 100D, dropout 20 [7], CETE [10], CA-RNN [12], STS-AM [9], AttSiaBiLSTM [13], and LSTM + FNN + attention [14]. Also, we compare our algorithm with the LSTM-AM that employ random number as the initial point of parameters to show that our proposed ABC approach can effectively improve the results. The results of the evaluation are shown in Tables 2, 3, and 4. For the SemEval2014 dataset, LSTM-AM-ABC has been able to overcome other methods in the recall and r criteria. Comparing LSTM-AM-ABC with LSTM-AM clearly indicates the effectiveness of our proposed initialization approach. For the STS dataset, LSTM-AM-ABC again presented the best results compared to other algorithms. By comparing LSTM-AM-ABC, we can observe that LSTM-AM-ABC could decrease the error more than 40%, indicating the effectiveness of initialization approach. The results of Table 4 are consistent with other tables. For MSRP dataset, our proposed algorithm obtained the highest mean recall followed by CETE algorithm.

Table 1. Parameter setting for the	he proposed model.
Parameter	Value

Parameter	Value
max sentence length	100
embedding dim	80
penalty rate for positive pairs (α)	1
penalty rate for negative pairs (β)	0.5
blstm hidden dim	50
dense hidden layer	3
dense hidden dim	256,128,64

Table 2. 10CV classification results on SemEval2014 dataset.

	Recall			MSE			r		
Method	mean	std.dev.	median	mean	std.dev.	median	mean	std.dev.	median
Siamese CNN+LSTM [6]	82.136	5.360	86.403	0.286	0.096	0.292	0.506	0.314	0.741
Recurrent NN, 100D, dropout 20 [7]	82.563	2.068	83.128	0.164	0.092	0.183	0.721	0.217	0.863
CETE [10]	91.153	1.143	92.119	0.055	0.063	0.057	0.709	0.206	0.817
CA-RNN [12]	85.436	1.890	85.763	0.034	0.067	0.062	0.754	0.145	0.786
STS-AM [9]	88.477	1.683	89.809	0.059	0.041	0.060	0.791	0.262	0.826
AttSiaBiLSTM [13]	84.016	0.935	84.639	0.036	0.053	0.039	0.759	0.249	0.790
LSTM + FNN + attention [14]	86.103	2.360	88.509	0.062	0.092	0.099	0.776	0.174	0.820
LSTM-AM	93.129	3.390	94.208	0.076	0.068	0.089	0.812	0.170	0.912
LSTM-AM-ABC	95.268	1.791	97.018	0.053	0.047	0.062	0.804	0.183	0.963

Table 3. 10CV classification results on STS dataset.

	Recall				MSE		r		
Method	mean	std.dev.	median	mean	std.dev.	median	mean	std.dev.	median
Siamese CNN+LSTM [6]	85.153	4.712	88.106	0.125	0.088	0.147	0.549	0.229	0.570
Recurrent NN, 100D, dropout 20 [7]	86.100	3.190	88.247	0.099	0.081	0.121	0.769	0.187	0.775
CETE [10]	95.014	1.371	96.053	0.043	0.082	0.056	0.784	0.225	0.809
CA-RNN [12]	89.056	0.441	89.610	0.029	0.054	0.035	0.771	0.215	0.797
STS-AM [9]	92.101	3.943	94.105	0.048	0.072	0.059	0.820	0.042	0.826
AttSiaBiLSTM [13]	86.283	1.800	87.120	0.031	0.062	0.039	0.782	0.162	0.798
LSTM + FNN + attention [14]	89.156	1.089	89.664	0.049	0.070	0.054	0.801	0.140	0.819
LSTM-AM	96.206	3.610	97.421	0.061	0.052	0.072	0.832	0.129	0.840
LSTM-AM-ABC	97.410	3.811	98.163	0.041	0.051	0.054	0.840	0.091	0.849

The proposed algorithm employs ABC in conjunction with BP algorithm for training. In the following, we indicate the proposed training algorithm is effective compared to others. To have a fair comparison, we fix all remaining parts of our proposed algorithm including LSTM, feedforward network, attention-based mechanism and only the trainer is changed. To this end, we compare our proposed trainer with five conventional algorithms, including Gradient Descent with simple Momentum (GDM) [28], Gradient Descent with Adaptive learning rate backpropagation (GDA) [29], Gradient Descent with Momentum and Adaptive learning rate backpropagation (GDMA) [30], One-Step Secant backpropagation (OSS) [31], and Bayesian Regularization backpropagation (BR) [32], And four metaheuristic algorithms, including Grey Wolf Optimization (GWO) [33], Bat Algorithm (BA) [34], Cuckoo Optimization Algorithm (COA) [35], and Whale Optimization Algorithm (WOA) [36]. For all metaheuristic algorithms, the population size and number of function evaluations are set to 50 and 20,000, respectively. Other parameter settings can be seen in Table. 5.

Table 4. 10CV classification results on MSRP dataset.

		Recall			MSE			r	
Method	mean	std.dev.	median	mean	std.dev.	median	mean	std.dev.	median
Siamese CNN+LSTM [6]	87.089	2.790	88.119	0.096	0.093	0.106	0.713	0.181	0.723
Recurrent NN, 100D, dropout 20 [7]	89.207	1.341	89.690	0.043	0.080	0.051	0.787	0.210	0.817
CETE [10]	97.296	0.910	97.429	0.016	0.073	0.024	0.819	0.189	0.820
CA-RNN [12]	90.179	1.207	91.092	0.018	0.091	0.043	0.787	0.163	0.799
STS-AM [9]	91.396	1.179	91.647	0.057	0.087	0.069	0.809	0.187	0.816
AttSiaBiLSTM [13]	87.493	3.410	89.190	0.025	0.067	0.049	0.801	0.018	0.809
LSTM + FNN + attention [14]	89.269	2.107	91.018	0.029	0.058	0.057	0.818	0.196	0.839
LSTM-AM + random weight	95.208	1.874	96.410	0.069	0.059	0.072	0.829	0.100	0.841
LSTM-AM-ABC	97.379	1.270	97.941	0.035	0.064	0.057	0.857	0.073	0.869

 Table 5. Parameter setting for metaheuristic algorithms.

algorithm	parameter	value
ABC [37]	maximum number of failures	population size × dimensions of each
		solution
BAT [34]	constant for loudness update	0.5
	constant for an emission rate update	0.5
	initial pulse emission rate	0.001
COA [35]	Discovery rate of alien solutions	0.25
GWO [33]	no parameters	
WOA [36]	b	1

 Table 6. Results of 10CV classification of metaheuristic algorithms on SemEval2014 dataset.

		Recall			MSE			r	
Algorithm	mean	std.dev.	median	mean	std.dev.	median	mean	std.dev.	median
LSTM-AM-GDM	89.126	1.142	90.250	0.072	0.096	0.084	0.774	0.125	0.850
LSTM-AM-GDA	88.473	1.480	88.892	0.076	0.024	0.081	0.759	0.107	0.800
LSTM-AM-GDMA	88.421	3.189	90.547	0.082	0.035	0.086	0.752	0.114	0.792
LSTM-AM-OSS	87.634	5.103	89.420	0.085	0.042	0.089	0.743	0.120	0.810
LSTM-AM-BR	92.169	1.300	92.962	0.070	0.029	0.075	0.788	0.103	0.824
LSTM-AM-GWO	90.145	1.250	91.123	0.072	0.025	0.077	0.775	0.102	0.836
LSTM-AM-BAT	91.160	0.146	91.532	0.068	0.012	0.072	0.780	0.094	0.792
LSTM-AM-COA	92.790	1.365	93.475	0.057	0.062	0.061	0.792	0.106	0.821
LSTM-AM-WOA	91.756	1.250	92.750	0.061	0.020	0.065	0.782	0.112	0.835
LSTM-AM-ABC	95.268	1.791	97.018	0.053	0.047	0.062	0.804	0.183	0.963

 Table 7. Results of 10CV classification of metaheuristic algorithms on STS dataset.

		Recall			MSE			r	
Algorithm	mean	std.dev.	median	mean	std.dev.	median	mean	std.dev.	median
LSTM-AM-GDM	90.100	1.967	91.250	1.020	0.047	1.046	0.775	0.092	0.781
LSTM-AM-GDA	92.580	1.500	93.473	0.075	0.042	0.082	0.791	0.096	0.802
LSTM-AM-GDMA	91.140	2.450	93.485	0.062	0.051	0.067	0.782	0.112	0.791
LSTM-AM-OSS	89.263	3.593	91.530	0.066	0.068	0.071	0.760	0.132	0.773
LSTM-AM-BR	96.256	2.850	97.253	0.064	0.062	0.070	0.836	0.115	0.842
LSTM-AM-GWO	93.020	1.740	93.863	0.025	0.052	0.034	0.818	0.082	0.826
LSTM-AM-BAT	95.418	1.425	95.920	0.072	0.059	0.079	0.831	0.079	0.838
LSTM-AM-COA	96.520	3.475	97.835	0.053	0.072	0.062	0.838	0.121	0.846
LSTM-AM-WOA	93.120	2.148	95.128	0.061	0.068	0.069	0.824	0.118	0.836
LSTM-AM-ABC	97.410	3.811	98.163	0.051	0.047	0.054	0.840	0.091	0.849

 Table 8. Results of 10CV classification of metaheuristic algorithms on MSRP dataset.

		Recall			MSE			r	
Algorithm	mean	std.dev.	median	mean	std.dev.	median	mean	std.dev.	median
LSTM-AM-GDM	89.180	2.893	90.658	0.082	0.090	0.089	0.782	0.126	0.819
LSTM-AM-GDA	93.185	2.459	94.150	0.072	0.089	0.081	0.810	0.093	0.827
LSTM-AM-GDMA	90.163	3.485	92.635	0.079	0.093	0.086	0.786	0.150	0.824
LSTM-AM-OSS	91.280	2.963	92.895	0.064	0.082	0.072	0.792	0.092	0.080
LSTM-AM-BR	96.000	1.285	96.142	0.042	0.060	0.050	0.819	0.035	0.082
LSTM-AM-GWO	95.183	1.590	95.740	0.053	0.072	0.062	0.804	0.020	0.816
LSTM-AM-BAT	96.180	2.010	97.005	0.038	0.094	0.049	0.832	0.081	0.843
LSTM-AM-COA	96.138	2.583	96.935	0.045	0.085	0.052	0.826	0.070	0.831
LSTM-AM-WOA	92.052	1.390	93.128	0.068	0.072	0.076	0.796	0.068	0.802
LSTM-AM-ABC	97.379	1.270	97.941	0.035	0.064	0.057	0.857	0.073	0.869

The results of the proposed algorithms compared to other trainers are shown Tables 6, 7, and 8. For the SemEval2014 dataset, as expected, metaheuristic algorithms generally work better than conventional algorithms. BR algorithm has been able to overcome metaheuristic algorithms including GWO, BAT, COA, and WOA. It can be seen that LSTM-AM-ABC outperformed all metaheuristic and conventional algorithms. In SemEval2014 datasets, the proposed trainer can reduce error more than 34% compared to the second best algorithm, LSTM-AM-BR. Such a difference exists in two other datasets, so that LSTM-AM-ABC improved error more than 25% and 32% for STS and MSRP datasets, respectively.

5 Conclusions

The goal of plagiarism is to find the similar items in a typical document or source code. This paper proposes a novel model for plagiarism detection based on LSTM-based architecture, feedforward neural networks, attention mechanism incorporating a population-based approach for parameter initialization (LSTM-AM-ABC). Gradient-based optimization algorithms such as back-propagation (BP) is so popular for learning process in LSTM, attention mechanism, and feed-forward neural network, whereas have some problems such as being sensitive in the initial conditions. Therefore, this paper proposed an artificial bee colony (ABC) mechanism to find initial seed for BP algorithm. ABC algorithm is employed on LSTM, attention mechanism, and feed-forward neural network, simultaneously. For evaluation, we compared LSTM-AM-ABC with both conventional and population-based methods. The experimental results on three datasets demonstrate that LSTM-AM-ABC is superior to previous systems. As future work, we intend to provide a suitable solution for imbalanced classification. A simple solution could be to use reinforcement learning. Reinforcement learning can be effective because of the rewards and punishments involved.

References

- 1. El Moatez Billah Nagoudi, A.K., H. Cherroun, and D. Schwab, 2L-APD: A two-level plagiarism detection system for Arabic documents. Cybern. Inf. Technol, 2018. 18(1): p. 124-138.
- 2. He, H., K. Gimpel, and J. Lin. *Multi-perspective sentence similarity modeling with convolutional neural networks*. in *Proceedings of the 2015 conference on empirical methods in natural language processing*. 2015.
- 3. Joodaki, M., M.B. Dowlatshahi, and N.Z. Joodaki, *An ensemble feature selection algorithm based on PageRank centrality and fuzzy logic.* Knowledge-Based Systems, 2021: p. 107538.
- 4. Joodaki, M., N. Ghadiri, Z. Maleki, and M.L. Shahreza, A scalable random walk with restart on heterogeneous networks with Apache Spark for ranking disease-related genes through type-II fuzzy data fusion. Journal of Biomedical Informatics, 2021. 115: p. 103688.
- 5. Joodaki, M., N. Ghadiri, and A.H. Atashkar. Protein complex detection from PPI networks on Apache Spark. in 2017 9th International Conference on Information and Knowledge Technology (IKT). 2017. IEEE.
- 6. Pontes, E.L., S. Huet, A.C. Linhares, and J.-M. Torres-Moreno, *Predicting the semantic textual similarity with siamese CNN and LSTM.* arXiv preprint arXiv:1810.10641, 2018.
- 7. Sanborn, A. and J. Skryzalin, *Deep learning for semantic similarity*. CS224d: Deep Learning for Natural Language Processing Stanford, CA, USA: Stanford University, 2015.
- 8. Pennington, J., R. Socher, and C.D. Manning. Glove: Global vectors for word representation. in Proceedings of the 2014 conference on empirical methods in natural language processing (EMNLP). 2014.
- 9. Moravvej, S.V., M. Joodaki, M.J.M. Kahaki, and M.S. Sartakhti. A method Based on an Attention Mechanism to Measure the Similarity of two Sentences. in 2021 7th International Conference on Web Research (ICWR). 2021. IEEE.
- 10. Laskar, M.T.R., X. Huang, and E. Hoque. Contextualized embeddings based transformer encoder for sentence similarity modeling in answer selection task. in Proceedings of The 12th Language Resources and Evaluation Conference. 2020.
- 11. Peters, M.E., M. Neumann, M. Iyyer, M. Gardner, C. Clark, K. Lee, and L. Zettlemoyer, *Deep contextualized word representations*. arXiv preprint arXiv:1802.05365, 2018.
- 12. Chen, Q., Q. Hu, J.X. Huang, and L. He. CA-RNN: using context-aligned recurrent neural networks for modeling sentence similarity. in Proceedings of the AAAI Conference on Artificial Intelligence. 2018.
- 13. Bao, W., W. Bao, J. Du, Y. Yang, and X. Zhao. Attentive Siamese LSTM network for semantic textual similarity measure. in 2018 International Conference on Asian Language Processing (IALP). 2018. IEEE.
- 14. Chi, Z. and B. Zhang, A sentence similarity estimation method based on improved siamese network. Journal of

- Intelligent Learning Systems and Applications, 2018. 10(4): p. 121-134.
- 15. Ashkoofaraz, S.Y., S.N.H. Izadi, M. Tajmirriahi, M. Roshanzamir, M.A. Soureshjani, S.V. Moravvej, and M. Palhang, *AIUT3D 2018 Soccer Simulation 3D League Team Description Paper*.
- 16. Vakilian, S., S.V. Moravvej, and A. Fanian. Using the Cuckoo Algorithm to Optimizing the Response Time and Energy Consumption Cost of Fog Nodes by Considering Collaboration in the Fog Layer. in 2021 5th International Conference on Internet of Things and Applications (IoT). 2021. IEEE.
- 17. Vakilian, S., S.V. Moravvej, and A. Fanian. *Using the Artificial Bee Colony (ABC) Algorithm in Collaboration with the Fog Nodes in the Internet of Things Three-layer Architecture*. in 2021 29th Iranian Conference on Electrical Engineering (ICEE). 2021.
- 18. Zhou, Q., X. Liu, and Q. Wang, *Interpretable duplicate question detection models based on attention mechanism*. Information Sciences, 2021. **543**: p. 259-272.
- 19. Zhang, Y. and Y. Peng. Research on Answer Selection Based on LSTM. in 2018 International Conference on Asian Language Processing (IALP). 2018. IEEE.
- 20. Sartakhti, M.S., M.J.M. Kahaki, S.V. Moravvej, M. javadi Joortani, and A. Bagheri. *Persian Language Model based on BiLSTM Model on COVID-19 Corpus*. in 2021 5th International Conference on Pattern Recognition and Image Analysis (IPRIA). 2021. IEEE.
- 21. Hochreiter, S. and J. Schmidhuber, *Long short-term memory*. Neural computation, 1997. **9**(8): p. 1735-1780.
- 22. Graves, A., Generating sequences with recurrent neural networks. arXiv preprint arXiv:1308.0850, 2013.
- 23. Graves, A. and J. Schmidhuber, *Framewise phoneme classification with bidirectional LSTM and other neural network architectures*. Neural networks, 2005. **18**(5-6): p. 602-610.
- 24. Bahdanau, D., K. Cho, and Y. Bengio, *Neural machine translation by jointly learning to align and translate.* arXiv preprint arXiv:1409.0473, 2014.
- 25. Teodorovic, D. and M. Dell'Orco, *Bee colony optimization—a cooperative learning approach to complex transportation problems.* Advanced OR and AI methods in transportation, 2005. **51**: p. 60.
- 26. Moravvej, S.V., M.J.M. Kahaki, M.S. Sartakhti, and A. Mirzaei. A Method Based on Attention Mechanism using Bidirectional Long-Short Term Memory(BLSTM) for Question Answering. in 2021 29th Iranian Conference on Electrical Engineering (ICEE). 2021.
- 27. Marelli, M., S. Menini, M. Baroni, L. Bentivogli, R. Bernardi, and R. Zamparelli. A SICK cure for the evaluation of compositional distributional semantic models. in Lrec. 2014. Reykjavik.
- 28. Phansalkar, V. and P. Sastry, *Analysis of the back-propagation algorithm with momentum*. IEEE Transactions on Neural Networks, 1994. **5**(3): p. 505-506.
- 29. Hagan, M., H. Demuth, and M. Beale, *Neural Network Design (PWS, Boston, MA)*. Google Scholar Google Scholar Digital Library Digital Library, 1996.
- 30. Yu, C.-C. and B.-D. Liu. A backpropagation algorithm with adaptive learning rate and momentum coefficient. in Proceedings of the 2002 International Joint Conference on Neural Networks. IJCNN'02 (Cat. No. 02CH37290). 2002. IEEE.
- 31. Battiti, R., First-and second-order methods for learning: between steepest descent and Newton's method. Neural computation, 1992. **4**(2): p. 141-166.
- 32. Foresee, F.D. and M.T. Hagan. *Gauss-Newton approximation to Bayesian learning*. in *Proceedings of international conference on neural networks (ICNN'97)*. 1997. IEEE.
- 33. Mirjalili, S., S.M. Mirjalili, and A. Lewis, *Grey wolf optimizer*. Advances in engineering software, 2014. **69**: p. 46-61.
- 34. Yang, X.-S., A new metaheuristic bat-inspired algorithm, in Nature inspired cooperative strategies for optimization (NICSO 2010). 2010, Springer. p. 65-74.
- 35. Yang, X.-S. and S. Deb. Cuckoo search via Lévy flights. in 2009 World congress on nature & biologically inspired computing (NaBIC). 2009. Ieee.
- 36. Mirjalili, S. and A. Lewis, *The whale optimization algorithm*. Advances in engineering software, 2016. **95**: p. 51-67.
- 37. Karaboga, D. and B. Basturk, *A powerful and efficient algorithm for numerical function optimization: artificial bee colony (ABC) algorithm.* Journal of global optimization, 2007. **39**(3): p. 459-471.