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An improved conversation emotion detection using hybrid f-nn classifier

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ABSTRACT

Emotion recognition from text is a crucial task in natural language processing (NLP) with applications in sentiment analysis, human-computer interaction, and psychological research. In this study, we present a novel approach for text-based emotion recognition using a modified firefly algorithm (MFA). The firefly algorithm is a swarm intelligence method inspired by the bioluminescent communication of fireflies, and it is known for its simplicity and efficiency in optimization tasks. In this paper MFA-based model is evaluated on the international survey on emotion antecedents and reactions (ISEAR) dataset, which includes text entries categorized by various emotions. Experimental results indicate that our approach achieved promising outcomes. Specifically, the proposed method, which combines the firefly algorithm with a multilayer perceptron (MLP), attained an accuracy of 92.07%, surpassing most other approaches reported in the literature.

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1. INTRODUCTION

Emotion recognition from text is important research domain in natural language processing (NLP) due to its wide range of applications [1]-[3]. Understanding human emotions embedded in textual data can enhance the performance of various systems such as chatbots, social media analyzing tools, and mental health applications. Understanding emotion is considered as challenging task [1], [2]. Emotion recognition is important because emotions can appear in different ways, like stress. Health psychologists study how to identify emotions to help patients by understanding the connection between physical well-being, stress, and emotional state [3]. Among the numerous datasets available for emotion recognition, the International Survey on Emotion Antecedents and Reactions (ISEAR) dataset stands out due to its comprehensive collection of emotional responses across diverse scenarios [4]-[6].

Traditional ML and DL approaches have been extensively used for emotion recognition tasks. However, these approaches often require large amounts of labelled data and important computational resources, which may not always be feasible. Traditional algorithms have not provided good results on ISEAR dataset. As an alternative, swarm intelligence algorithms, influenced by the collective behaviour of social organisms, offer a promising solution [7], [8]. These algorithms are identified for their simplicity, flexibility, and ability to find feasible solutions in challenging search spaces with relatively low computational cost [9]. Our study aims to involve the Firefly Algorithm to improve how features are selected and classified for emotion recognition using the ISEAR dataset. The ISEAR dataset consists emotional responses categorized into seven emotions (joy, fear, anger, sadness, disgust, shame, and guilt), provides a robust foundation for evaluating the proposed approach.

In this study, we investigate how well the firefly algorithm (FA), a type of swarm intelligence method, works for identifying emotions in text. The FA is inspired by how fireflies use light to communicate and attract each other. It has been effectively used in many optimization tasks, showing fast and accurate results. We begin by pre-processing the text data to extract meaningful features that can accurately represent the emotional content. Next, we employ the firefly algorithm to optimize the selection of these features, aiming to increase the classification performance. Finally, we assess the results of our proposed method with traditional techniques to demonstrate its effectiveness. In this work, we give a thorough investigation of emotion recognition in conversation text using feature selection and the firefly algorithm. Through this interdisciplinary research, we aim to provide ground for future studies at the intersection of computer science and biology, encouraging new ideas and discoveries in emotion recognition and other areas.

While sentiment analysis and emotion recognition are both concerned with understanding the feelings expressed in text, they serve different purposes and require different approaches [10]. Sentiment analysis gives a summary of the overall sentiment, whereas emotion recognition digs into identifying specific emotional states. Both are valuable in various applications, from market research and customer service to psychological studies and human-computer interaction [11]. Emotion recognition, also known as emotion detection, is the method of identifying the emotions conveyed in data. Emotion recognition is promising new field [12]. It goes beyond the general sentiment to pinpoint particular emotions such as happiness, sadness, anger, fear, surprise, or disgust.

The contributions of this research are threefold: i) introducing the firefly algorithm as a novel approach for emotion recognition from text, ii) optimizing feature extraction using the firefly algorithm to increase classification accuracy, and iii) offering a thorough assessment of the suggested approach on the ISEAR dataset. In the following sections, we present a detailed overview of related work, describe the methodology, and discuss the experimental results.

2. LITERATURE REVIEW

Swarm intelligence algorithms are commonly applied for handling complex problems by mimicking how social creatures like ants, birds, and bees work together [13], [14]. These algorithms are different from traditional methods because they can quickly explore possible solutions and find very good answers. This review looks at important research and uses of swarm intelligence algorithms, focusing on how they're used in different areas and how well they solve real problems. By studying these algorithms, a understanding to see how the firefly algorithm can be useful for recognizing emotions from text in the ISEAR dataset is proposed.

Arun *et al.* [15] introduced approach to facial micro expression emotion recognition using swarm based modified CNN. This approach achieved 99.4% accuracy in identifying facial emotions. Olmez *et al.* [16] proposed modified swarm intelligence based PSO algorithm to improve effectiveness for EEG-based human emotion recognition. Hamdi *et al.* [17] presented an affirmative ant colony optimization (ACO) approach combined with a SVM to identify the sentiments and emotions hidden in the textual words. SVM was used as the classifier and the ACO algorithm was used for feature selection. Significant gains in categorization accuracy were noted by the study.

Hadni *et al.* [18] suggested a new method for Arabic feature selection using the firefly algorithm (CFA) and the chaotic approach. The results from the chaotic application is used to replace the firefly algorithm's attraction coefficient. The improvement also brought a new search method. Utilising classifiers like Naive Bayes (NB), SVM, and K-nearest neighbours (KNN), performance evaluation is carried out. The experiments demonstrated that combining CFA with SVM classifiers outperformed other combinations, particularly excelling in precision. The paper highlighted the challenge of dimensionality reduction in classification processes, particularly when dealing with datasets containing numerous features, some of which may be unreliable. However, in the Arabic language, the application of meta-heuristic algorithms for feature extraction is limited due to the language's rules and rich morphology.

Ismail *et al.* [19] presented the Grey Wolf Optimizer, a ground-breaking bio-inspired optimisation algorithm that mimics wolves' natural hunting techniques, along with the KNN classifier, to create an intelligent feature selection approach. Using three different databases the Arabic Emirati-accented speech database, RAVDESS and the surrey audio-visual expressed emotion dataset (SAVEE) emotion classification tasks are used to demonstrate the effectiveness of this method. Both combined and single feature extraction methodologies are used across these datasets. In speech emotion recognition systems, the new GWO-KNN technique outperformed more established approaches including the bat algorithm (BAT), cuckoo search (CS), white shark optimizer (WSH), and arithmetic optimisation algorithm (AOA).

Elangovan *et al*. [20] proposed feature selection (FS) and categorization methods to develop an efficient SA approach for internet reviews. In particular, feature extraction from web-based evaluations is done using the FireFly (FF) and levy flights (FFL) algorithms, while emotion categorization is done using the Multilayer Perceptron (MLP) framework. The study of the FF-MLP model on a common DVD database showed its effectiveness. With accuracy of 97.97%, F-score of 98.75 the findings showed remarkable performance gains. This paper focused on sentiment analysis (SA) applied to web-based customer reviews.

The performance of different AI algorithms in text-based emotion identification for conversational agents was investigated by Kusal *et al*. [21] in their study. They tested BERT and other models in identifying emotions from textual input. The researchers used methods including adjusting BERT on datasets labelled with emotions and assessing its classification precision across various emotional categories. The outcomes showed that BERT performed competitively in emotion identification tasks when compared to conventional machine learning techniques by utilizing its contextual understanding of language. However, in order to achieve the best fine-tuning, significant computational resources and a huge volume of annotated data are required.

The research reviewed shows that many different methods have been used to choose the best features and classify data in various datasets. Some new methods like the Return-cost-based binary FFA, modified firefly algorithm, chaotic firefly algorithm, and grey wolf optimizer have been used. Review studies have also looked at how these methods can improve text classification using swarm intelligence. Swarm intelligence algorithm provide good results in tasks like sentiment analysis, feature selection in Arabic language, recognizing and classifying emotions from text. This shows that using optimization techniques can really help in many different situations.

3. METHOD

Figure 1 outlines a systematic process for emotion recognition from text using a modified firefly algorithm (MFA). The process begins by loading the text emotion data, which contains labelled emotions. This data is then arranged and prepared for processing, involving steps such as text cleaning, normalization, and formatting.

3.1. Workflow diagram

As shown in Figure 1, an objective function is defined, typically aimed at minimizing the mean absolute error (MAE). Each feature of the text data is considered as one firefly, and initial positions and properties of the fireflies are set up. The algorithm iterates over a predefined number of generations or until a convergence criterion is met, updating the positions of the fireflies based on their attractiveness and the distance to other fireflies using a specific formula. The data is divided into training and testing sets to measure the effectiveness of the method. The selection probability of more successful fireflies increases, ensuring that the algorithm focuses on promising solutions.

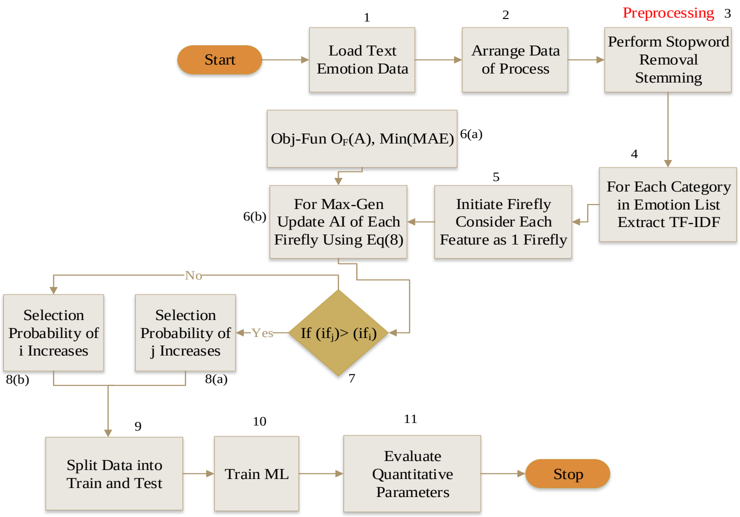

Figure 1. Workflow diagram for emotion recognition

Subsequently, a machine learning model, such as an MLP is trained using the optimized features. This method is then evaluated on the basis of quantitative parameters like accuracy, precision, recall, F-measure, and computational efficiency to assess its effectiveness. This comprehensive workflow demonstrates the use of MFA to increase the results and effectivenss of emotion detection in NLP tasks.

3.2. Dataset used in research

The ISEAR dataset, known as the International Survey on Emotion Antecedents and Reactions dataset, is widely recognized in research for its comprehensive collection of human emotional responses across various scenarios. It contains a structured compilation of emotional experiences categorized into seven primary emotions: joy, fear, anger, sadness, disgust, shame, and guilt. Each emotional response is associated with a detailed description of the triggering event, providing researchers with valuable insights into the context and factors influencing emotional reactions. Due to its richness and diversity, the ISEAR dataset serves as a robust benchmark for evaluating emotion recognition systems and has been utilized in numerous studies to explore the efficiency of different computational approaches in analyzing and understanding human emotions from textual data [22], [23].

3.3. Text preprocessing

The architecture can be illustrated using Algorithm 1 for pre-processing and stemming and the overall work architecture can be illustrated using work flow diagram shown in Figure 1.

Algorithm 1. Text pre-processing with stopword removal and stemming
```
Function\ PreprocessText\left(input_{text}\right):
tokenized_{text}\longleftarrowTokenize(input_{text})
stop_{words}\getsLoadStopwords()
filtered_{words}\getsRemoveStopwords(tokenizd_{text},\ stop_{words})
stemmed_{words}\getsApplyStemming(filtered_{words})
clean_{text}\getsJoinWords(stemmed_{words})
return\ clean_{text}\
Function\ Tokenize\left(txt\right):
return\ List\ of\ words\ obtained\ by\ splitting\ text
Function\ LoadStopwords():
return\ List\ of\ common\ stopwords
Function\ RemoveStopwords\left(text,\ Stop_{words}\right)
filtered_{text}\gets[]
for\ word\ in\ text\ do
\ if\ word\ not\ in\ stop_{words}\ then
filtered_{text}.append(word)
end\ if
end\ for
return\ filtered_{text}
Function\ ApplyStemming\left(text\right):
stemmed_{text}\longleftarrow[]
for\ word\ in\ text\ do
Stemmed_{word}\ \getsApply\ stemming\ algorithm\ to\ word
stemmed_{text}.appwnd\left(stemmed_{word}\right)
end\ for
return\ Stemmed_{text}
Function\ JoinWords\left(words\right):
return\ Concatenate\ words\ into\ single\ string
```

Term frequency (TF): A term's (word's) TF value indicates how frequently it appears in a given document. It measures a term's relative weight inside a given document. The TF formula is:

$$TF(t,d) = \frac{O_t}{C} \tag{1}$$

Where t is the current term, Ot is the occurrence of the terms in a total count of words C.

Inverse Document Frequency (IDF): IDF analyses a term's global significance by assessing its rarity throughout the whole corpus of documents. It gives less weight to common terms and more weight to rare terms. The formula for IDF is:

$$IDF(t) = \log(\frac{d_A}{d_{O_t}}) \tag{2}$$

Where d_{O_t} denotes the total number of documents containing t and d_A denotes the total number of documents in the list.The overall TF-IDF can be victoried as follows:

$$TF - IDF(t,d) = TF(t,d) * IDF(t) \quad (3)$$

In feature selection, it helps identify the most relevant terms (features) for emotion analysis. Firefly algorithms consider the TF-IDF values as the attractiveness of features and iteratively refine the feature set to maximize the classification of emotions. These techniques have evolved to handle large and high-dimensional text datasets efficiently, ensuring that the most informative features are retained for accurate emotion recognition. By simulating the swarm intelligence of fireflies, the Firefly algorithm and other SI techniques have become crucial tool in the area of text-based emotion analysis, enabling improved model performance and more detailed emotion understanding.

3.4. MLP classifier

Table 1 presents hyper parameters used in experimentation for MLP algorithm. Total 10 neurons are used in hidden layer. Learning rate applied for model is 0.01.

Table 1. Hyper parameters of MLP

Hyper parameter	Description	Values
Hidden Layer Size	Total neurons in the hidden layer.	10
Activation Function	Activation function in the hidden layer.	Sigmoid
Learning Rate	The rate at which the model learns.	0.01
Number of Epochs	The number of training epochs.	100

4. RESUSLTS AND DISCUSSION

Initially, a comparative analysis is performed using ISEAR dataset for performance evaluation factors namely, precision, recall, f-measure and accuracy using number of samples ranging from 1,500 to 7,500. The study assessed how performance trends change as the number of samples increases. Results also gives insights into how dataset size influences classification effectiveness.

4.1. Precision, recall, f measure and accuracy

4.1.1. Precision

The precision analysis summarized in Table 2 shows that "Proposed Firefly + MLP" model exhibits an exceptional precision score of 0.9647, indicating its ability to make highly accurate positive predictions. Other models such as "MLP Only," "PSO+ MLP," and "ACO+MLP" also demonstrate high precision values around 0.945, suggesting their capacity to make accurate positive predictions. "PSO+ KNN" maintains a competitive precision value of 0.9455, implying that it also excels in reducing false positive predictions.

Table 2. Performance analysis of emotion recognition using precision over ISEAR

Total number of Samples	Precision proposed firefly+MLP	Precision MLP Only	Precision PSO+MLP	Precision PSO+KNN	Precision ACO+MLP
1500	0.96558256	0.94176373	0.94024276	0.93837535	0.94625284
2500	0.96505334	0.94933712	0.93816156	0.95086321	0.94457948
3500	0.96248461	0.94582393	0.94967532	0.94935022	0.94088099
4500	0.95958759	0.94725335	0.94962093	0.94818927	0.94763471
5500	0.96036966	0.94791209	0.94963876	0.93654638	0.94437086
6500	0.96499099	0.94107673	0.94832995	0.94595061	0.93607492
7500	0.96470851	0.94248766	0.94125998	0.9491576	0.93706165

4.1.2. Recall

The "Proposed Firefly + MLP" model score a recall value of 0.9895, which demonstrates its excellent ability to properly identify almost all positive cases in the dataset. Models like "MLP Only," "PSO+ MLP," and "ACO+MLP" also display high recall values, indicating their proficiency in capturing positive instances. Table 3 shows that "PSO+ KNN," while slightly lower in recall at 0.8359, still maintains a respectable performance, correctly identifying a significant portion of positive instances.

The "Recall Proposed Firefly+MLP" algorithm has the highest average recall, around 0.98943, indicating its competence in properly detecting positive events. These data indicate changes in the algorithms' capacities to accurately detect positive cases across varying sample sizes, with the "Recall Proposed Firefly + MLP" method consistently displaying greater performance.

Table 3. Performance analysis of emotion recognition using recall over ISEAR

Total number of Samples	Recall Proposed Firefly + MLP	Recall MLP Only	Recall PSO+ MLP	Recall PSO+ KNN	Recall ACO+MLP
1500	0.98925501	0.98606272	0.98435973	0.80143541	0.76499388
2500	0.99011603	0.98719842	0.98594848	0.87352582	0.75691469
3500	0.99047912	0.98854061	0.98850963	0.90761389	0.88868613
4500	0.98949128	0.98662112	0.98753815	0.83691087	0.93160905
5500	0.98944488	0.98718242	0.98784262	0.83430421	0.87395301
6500	0.98974529	0.98513424	0.98713023	0.77592068	0.83966399
7500	0.98953555	0.98558719	0.98550725	0.82173745	0.75697033

4.1.3. F-measure

F-measure analysis using ISEAR dataset given in Table 4 shows that the "Proposed Firefly+MLP" model attains the highest F-measure of 0.9769, reflecting its exceptional balance between precision and recall. "MLP Only," "PSO+MLP," and "ACO+MLP" models also demonstrate competitive F-measure values, indicating their effectiveness in sentiment analysis. "PSO+KNN" achieves a respectable F-measure of 0.8869.

The "F-measure Proposed Firefly+MLP" algorithm exhibits the highest average F-measure at approximately 0.97647, indicating its effectiveness in achieving a balance between precision and recall. Following closely is the "F-measure MLP Only" algorithm with an average F-measure of approximately 0.96558, showcasing its competitive performance.

Table 4. Performance analysis of emotion recognition using F-measure over ISEAR

Total number of Samples	F measure Proposed Firefly + MLP	F measure MLP Only	F measure PSO+ MLP	F measure PSO+ KNN	F measure ACO+MLP
1500	0.97727545	0.96340426	0.96179561	0.86451613	0.84602369
2500	0.97742405	0.96789766	0.9614616	0.91055532	0.84039792
3500	0.97628122	0.96671061	0.96870343	0.92801303	0.91403904
4500	0.97431004	0.96653653	0.96820845	0.88908167	0.93955355
5500	0.97469049	0.96714878	0.96836403	0.88247376	0.90779841
6500	0.9772114	0.96260163	0.96734118	0.85254066	0.88525221
7500	0.97696432	0.96355571	0.96287556	0.88086343	0.8374433

4.1.4. Accuracy

Analyzing the accuracy trend across the various algorithms used on the ISEAR dataset reveals some notable patterns. The "Accuracy Proposed Firefly + MLP" algorithm consistently achieves the best levels of accuracy, with a steady performance trend across various sample sizes as shown in Table 5. In contrast, the "Accuracy PSO+ KNN" and "Accuracy ACO+MLP" algorithms show a decreasing trend in accuracy as the sample size increases, indicating potential constraints or inefficiencies in handling larger datasets. When we analyze the average value using the ISEAR dataset, we see that the "Accuracy Proposed Firefly + MLP" technique has the highest average accuracy, around 92.07%. The "Accuracy MLP Only" method follows closely behind, with an average accuracy of approximately 89.95%. These findings indicate that the "Accuracy Proposed Firefly + MLP" technique surpasses others on average in terms of accuracy when applied to the ISEAR dataset, demonstrating its usefulness in obtaining high accuracy levels.

Table 5. Performance analysis of emotion recognition using accuracy over ISEAR

Total number of Samples	Accuracy Proposed Firefly + MLP	Accuracy MLP Only	Accuracy PSO+ MLP	Accuracy PSO+ KNN	Accuracy ACO+MLP
1500	92.0666667	89.3449092	88.9575972	73.3576642	71.2250712
2500	92.1600001	90.5191874	88.6315789	81.0260279	70.4751542
3500	92.1428571	90.4130703	90.5853205	83.7202468	81.031614
4500	92.0666667	90.0727651	90.8516612	77.6238909	85.5641846
5500	92.0363636	90.0793651	90.5022276	76.2872361	80.3833145
6500	92.0615385	89.0672016	90.3322201	72.2024516	76.8253968
7500	92.0700001	89.9487097	89.1728312	76.3767247	69.6720187

4.2. Comparison proposed method result with ISEAR dataset

Table 6 presents comparison of result with ISEAR Dataset. The combination of the Firefly Algorithm, a swarm intelligence optimization technique, with MLP, a type of feedforward neural network, achieved a significantly higher accuracy of 92.07% compared to results mentioned in existing literature. This indicates a substantial improvement over traditional deep learning methods. The firefly algorithm likely optimized the feature selection process effectively, enabling the MLP to focus on the most relevant features for emotion classification. This superior performance highlights the potential of integrating swarm intelligence with neural networks to enhance emotion recognition accuracy.

Table 6. Comparative performance analysis over ISEAR dataset

Reference	Dataset	Method	Result
[2]	Combined dataset (ISEAR, WASSA, and Emotion-stimulus)	SVM	78.97 Accuracy
		Random Forest	76.25 Accuracy
		NB	68.94 Accuracy
		Bi-GRU	79.46 Accuracy
		Hybrid (CNN+ Bi-GRU+SVM) Model	80.11 Accuracy
[24]	ISEAR	LSTM	57.65 Accuracy
		BiLSTM	59.30 Accuracy
		GRU	60.26 Accuracy
[25]	ISEAR	Unigram Mixture Model (UMM)	39.48 F score
[26]	ISEAR	A two-stage text feature extraction method	72.43 Accuracy
[27]	ISEAR	SVM	80 Precision, 78 F Measure, 79 Recall
		KNN	75 Precision, 78 F Measure, 76 Recall
		XG-Boost	67 Precision, 69 F Measure, 68 Recall
		Logistic Regression	86 Precision, 84 F Measure, 85 Recall
[28]	ISEAR	Random Forest	47.0 Accuracy
		SVM	54.3 Accuracy
[29]	ISEAR	Rule Based	65 Accuracy
[30]	ISEAR + OANC dataset	MLP	92.16 Accuracy
		DT	91.82 Accuracy
		KNN	78.16 Accuracy
		RF	89.41 Accuracy
		Adaboost	63.82 Accuracy
		GB	90.32 Accuracy
		CNN	99.14 Accuracy
[31]	ISEAR	Naïve Bayes	43.24 Accuracy
		Random Forest	37.26 Accuracy
		SVM	14.48 Accuracy
[32]	ISEAR	BiGRU	54 Accuracy
		BiLSTM + Word2Vec	57 Accuracy
		CNN + Word2Vec	36 Accuracy
		BiGRU + GloVe	53 Accuracy
Proposed Method	ISEAR	Firefly with MLP	92.07 Accuracy

5. CONCLUSION

The "Improved Firefly + MLP" provide accuracy of 92.07% over ISEAR dataset. This indicates a significant enhancement compared to conventional approaches. Results achieved in this work validate the model's consistency and success in emotion recognition. The Improved Firefly Algorithm, as proposed in this work, represents a powerful tool for feature selection, enhancing emotion recognition in real-world applications. By combining swarm intelligence with MLP's learning ability, this approach offers substantial improvements in emotion recognition accuracy. These discoveries bring up opportunities for enhanced emotion recognition analysis to the natural language processing and other domains.

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Abhishek A. Vichare	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓		✓	
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C : **C**onceptualization	I : **I**nvestigation	Vi : **Vi**sualization
M : **M**ethodology	R : **R**esources	Su : **Su**pervision
So : **So**ftware	D : **D**ata Curation	P : **P**roject administration
Va : **Va**lidation	O : Writing - **O**riginal Draft	Fu : **Fu**nding acquisition
Fo : **Fo**rmal analysis	E : Writing - Review & **E**diting	

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

The data that support the findings of this study are available from the corresponding author, upon reasonable request.

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