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ORIGINAL ARTICLE

Utilizing social media and machine learning for personality and emotion recognition using PERS

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Abstract
Personality reflects how people can behave in different situations and affects their decisions. Analyzing personality is useful in many fields, for example in the prediction of performance in a job. Emotion recognition is another important research topic due to the wide spread of social media. People express their feeling in form of Facebook posts, tweeter real reactions, and shares. Understanding both personality and emotions from the written text is much easier when it comes to humans. However, this task is impossible with the huge amount of data spread all other social media. The use of machine learning algorithms for personality and emotion recognition from text data is a new research field. In this paper, we propose an enhanced recognition system for personality recognition and emotion recognition. The proposed enhanced recognition system is composed of four main modules, namely data acquisition module, data preprocessing module, personality recognition module, and emotion recognition module. Several machine learning algorithms are used for the multiclass classification process. Gray wolf optimization (GWO) algorithm is used for hyperparameter optimization, while group GWO (GGWO) algorithm is used for feature selection. The proposed model could achieve an accuracy of 99.99% using the random forest algorithm for personality detection and 88.06% using a decision tree for emotion recognition, which outperforms other state-of-the-art studies. We can profit from social media despite some of its drawbacks by understanding people's emotions through their tweets, posts, etc. For instance, before someone commits suicide, we can tell what their intentions are. Most suicide committers, according to recent studies, leave suicide notes on their social media accounts, and these letters need to be taken seriously.

Keywords Emotion recognition · Personality prediction · Suicide detection · Machine learning · Social media

1 Introduction

Personality, which comprises distinctive features of what people believe, how they feel, and how they act, has been acknowledged as a factor in decisions and behavior [1]. Considering that personality is a combination of qualities and the way in which individuals respond to the occurrence of events, understanding personality offers a method to understand how a person's many different characteristics come together to form a whole [2]. Selections and decisions are influenced by personality (for example, in music, books, and movies) [3]. Relationships, interpersonal interactions,

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and the environment in which they occur are all influenced by personality [4]. Any type of interaction has been found to be associated to personality. Additionally, it has been demonstrated to be beneficial in predicting professional happiness, performance in interpersonal interactions, and even preference for particular user interfaces. [5].

User receptivity and confidence have been observed to increase when personality is taken into account when designing user interfaces, according to earlier study on the subject. Applications can use personality predictions from user social media profiles to tailor presentations and messaging [5]. Every person has a personality that often holds true throughout time, according to researchers. In light of this, personality testing can be a crucial tool. The Myers-Briggs type assessment [6, 7], the five-factor model [6, 7], the psychoticism, extraversion, and neuroticism (PEN) model [7, 8], and the dominance, influence, stability, and compliance (DISC) model [6] are some examples of the psychological models of personality that have been presented.

Typically, these models advocate using straightforward techniques to identify personality, such as questionnaires. On the other hand, personality can be discovered by linguistic analysis [5, 9]. The results of linguistic analysis can be used to discover correlations between writing style and personality. Machine learning has been one of the most researched techniques for the examination of linguistic data to identify personality that has been proposed by researchers in natural language processing [10].

Techniques for automating processes that are based on a collection of instances, such as learning machines, are helpful in the identification of people's personalities. The literature has a number of machine learning-based proposals for personality recognition [11, 12]. The algorithms that are used in machine learning are designed to learn directly from data through the use of computational methods [13]. These algorithms do not use an existing equation as a model. As there are more learning cases available, the algorithms adaptively improve their performance [14].

Emotion recognition is the process of identifying human feelings and expressions of emotion. There is a wide range of accuracy with which individuals are able to read the feelings of other people [15]. A relatively new area of research focuses on the application of technology to the process of assisting people in identifying their feelings. In most cases, the optimal performance of the technology can be achieved when it combines a number of different modalities with the environment [16]. The greatest amount of focus up to this point has been placed on developing automated methods for recognizing facial expressions, verbal expressions, written expressions, and physiology as recorded by wearables [17].

Since there are so many texts, it is impossible to classify emotions manually, necessitating the use of precise automatic methods. While it is often easy for individuals to tell whether a writer of a piece was furious or happy, computers often struggle with this task because they lack the implicit background knowledge that humans take into account [18]. When given a piece of writing, emotion detection algorithms can determine the feelings the author intended to convey.

Using ideas from deep learning, identification of feelings within written documents is a problem of material identification [19]. Human emotions are significant in everyday life [20]. Generally speaking, intuition that differs from intellect or understanding is what is meant by emotion. Emotion affects a person's capacity to weigh many factors and regulate how they react to incentives [21]. Many professions, including medical, law, advertising, and e-learning, use emotional acceptance [22].

The emotional description is additionally regarded as a crucial component of advanced human communication [23]. In addition to human interaction, emotion detection algorithms help uncover criminal motivations and benefit from psychosocial therapies [24]. Psychological messages can be sent by a person's speech, gesture, and writing when they are identifiable by voice, appearance, and text expression [25].

There is enough effort put into speech and facial emotion recognition, but a framework for text-based emotion identification still has to be developed [26]. From a data analysis standpoint, language modelling makes it extremely beneficial to identify human emotions in the document [27]. There are examples of the emotions like happiness, grief, rage, pleasure, hatred, fear, etc. Although the word “feelings” has no standard structure, emotional research is prioritized in cognitive science [28].

Emotion recognition from text data is useful in many applications such as identifying users’ opinions about products, analyzing user response to different situations, and human–computer interaction such as e-mails [29]. Emotion recognition in text is the procedure of automatically matching a presented text with an emotion from a list of predetermined emotions [30]. Explicit emotion recognition from keywords can be effective. However, these keywords may be negated in the expression using—for example—“not” and therefore, it does not represent the actual emotion [31]. Implicit emotion recognition in text is a more complex task. To correctly label the text to the correct emotion, an intelligent model must be built and trained on a wide dataset [32]. However, it is still very difficult to improve the accuracy of emotion recognition from real-world data [33].

The number of people using various forms of social media is steadily rising all around the world by Internet

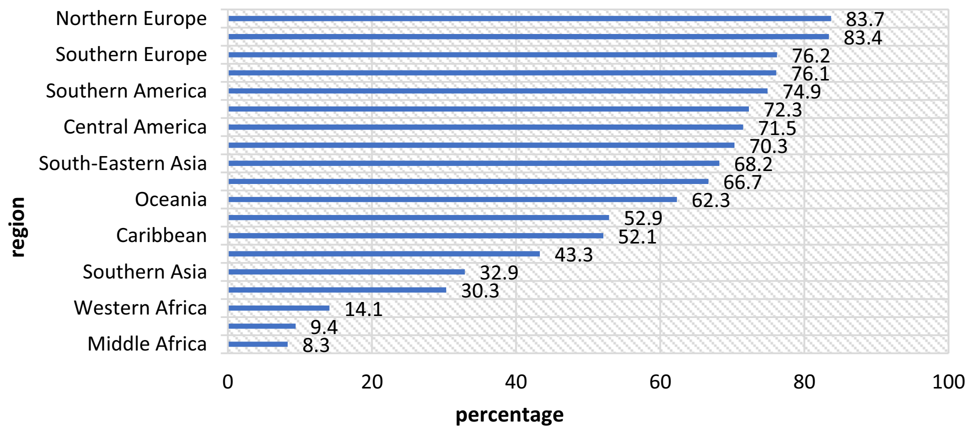


Fig. 1 Social media users per region in October 2022

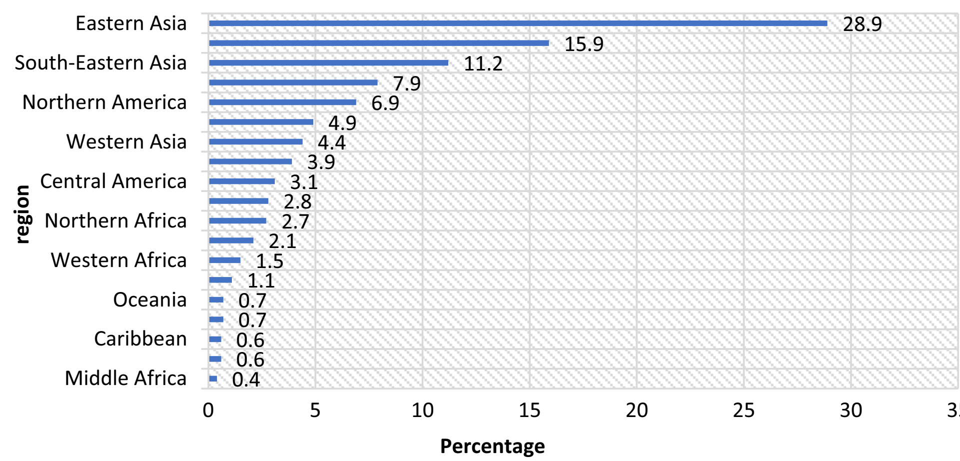


Fig. 2 Distribution of Social media users per region Worldwide in October 2022

users [5]. As seen from Fig. 1, the percentage of social media users to overall population in every region worldwide is relatively high [34]. The global distribution of social media users per region is given in Fig. 2 [34]. People use social media to interact with each other, share their personal lives, and give their opinions regarding different topics. Therefore, the behavior of the users on the social media, i.e., likes, posts, comments, and shares, can be used to study their personality and preferences [35]. The variations in language from user to user are another indicator of personality because language reflects what people think in vocal or written text [36]. The idea of building a model for personality prediction from online posts is more efficient than standard personality tests, in which the person answers to questions written by experts due to the cost required to spread these tests on a large scale [37].

Nowadays, social media has turned into a digital life-saver for communicating information and locating people in emergency circumstances [38]. Since the information spread across these sites is mainly textual, data can be extracted from the text to help managing crises such as hurricane events, earthquakes, and train crash [39]. However, it is time-consuming and exhausting process to manually analyze the huge amount of data over the social media [40]. Therefore, automatic classification of textual data has been currently adopted in research [41].

Because people share their personal life, thoughts, interests, locations, and so many data on social media platforms, analyzing the personality and recognizing the emotion of the person is very important. For example, suicide is one of the leading causes of death worldwide according to World Health Organization (WHO) [42]. The distribution of suicide rates according to WHO regions from 2000 to 2019 is given in Fig. 3. People suffering from depression and psychiatric stress may commit suicide, i.e., attempt to end their own lives [43]. Therefore, early identification of at-risk patients can help save their lives [44]. Although not every person with suicidal thoughts actually commit suicide, it is important to consider the overall circumstances and factors leading to suicide [45]. Some recent studies discussed the negative effect of social media on suicidal thoughts in users [46, 47]. However, according to recent studies, most suicide committers leave suicide note on their social media account, and these notes must be treated seriously [48]. Hence, we can profit from social media despite some of its drawbacks by understanding

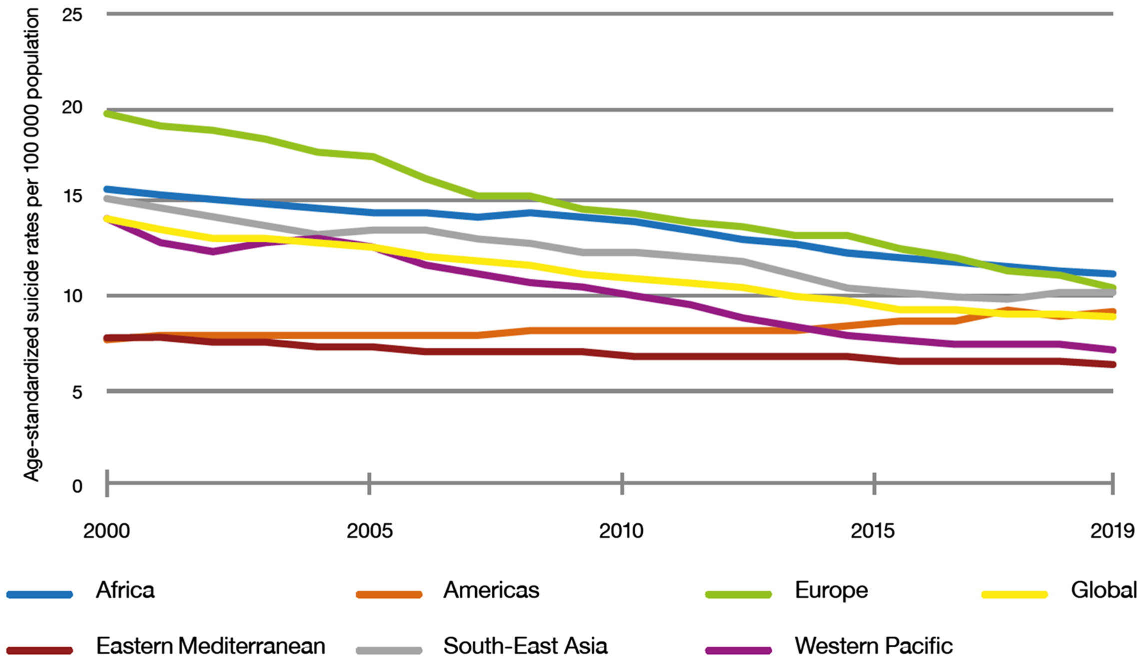


Fig. 3 Distribution of suicide rates according to WHO regions from 2000 to 2019 [42]

people's emotions through their tweets, posts, etc. For instance, before someone commits suicide, we can tell what their intentions are.

The process of assigning predetermined classes or categories to a specific document is called text classification [49]. This process includes six major steps, namely (1) data collection, (2) data preprocessing, (3) feature extraction, (4) feature selection, (5) classification, and (6) evaluation [50]. Data collection means combining the required data for training the model. Preprocessing phase is required so that all the unnecessary characters and spaces are removed. For feature extraction phase, useful information represents the extracted features. If the algorithm extracts too many features, the accuracy of the algorithm will be poor due to increased unnecessary data. Therefore, a feature selection phase is required to choose only the most essential characteristics for classification [51].

In classification phase, text documents are mapped to a specific class among set of available classes. A number of different machine learning approaches have been effectively employed in text categorization challenges. For example, Naïve Bayes classifier has been applied in text classification of Wikipedia pages [52], the captions on Instagram have been subjected to text categorization using support vector machine. [53], KNN, Naïve Bayes, and the use of support vector machines for text classification of the news has been implemented. [54]. The inclusion of deep learning in text classification have gained interest in the recent research [55–57].

The final step in text classification process is the evaluation of the outcomes determined by utilizing the various performance metrics including accuracy, precision, and recall [58]. Classification of text has found usage in a variety of applications in the real world, including the filtering of spam. [59], displaying web pages according to search terms [60], sentiment mining [61], and other natural language processing applications [62].

In the current study, we propose an enhanced recognition system for personality recognition and emotion recognition. The proposed enhanced recognition system (PERS) is composed of four main modules, namely data acquisition module (DAM), data preprocessing module (DPM), personality recognition module (PRM), and emotion recognition module (ERM). DAM is the first phase concerning gathering the required data for analysis. This data is presented to DPM, where the required preprocessing of data is done by collecting necessary Information only and removing Noise. PRM and ERM are done via feature extraction and classification (FECM). In FECM, feature selection is done using GGWO, and the multiclass (MC) classification process makes use of a number of different machine learning techniques. For the purpose of hyperparameter optimization, the gray wolf optimization (GWO) algorithm is utilized.

The main contributions of the current work are as follows:

1. Proposing an enhanced recognition system for personality recognition and emotion recognition.

2. The paper highlights the potential benefits of utilizing social media data for understanding people's emotions, such as detecting suicidal intentions based on suicide notes posted on social media accounts.
3. Comparing the results with state-of-the-art studies.

The remaining work are structured as follows: In Sect. 2, some recent developments in emotion recognition algorithms are discussed. Section 3 describes the suggested structure. Evaluation of experiments is presented in Sect. 4. Furthermore, we finish this work in Sect. 5.

2 Literature review

Numerous studies have been carried out in an attempt to achieve an understanding of the emotional context of English literature and obtain emotional insight. In this section, we will talk about studies that are generic to emotion detection as well as studies that are closely related to them. The authors of the article [30] carried out an in-depth investigation on the most recent advancements made in the field of emotion detection (ED) in written text. This investigation covered not only the English language but also a variety of other languages. They discussed the difficulties involved in dealing with ED tasks as well as the tools (corpora and lexicons) that are available to help with this work, such as the following: (1) the difficulty of identifying implicit emotions that are contained in a text; (2) the reaction proceeds with the size and quality of existing datasets; and (3) the limitation of resources available in certain languages, such as Arabic, for example. One more survey study [63], which focus at the ED problem in text content, discussed all of the available emotion-related datasets, such as EMOBANK, SemEval, ISEAR, EmoInt, daily dialog, Cecilia Ovesdotter Alm's directly effect data, grounded emotion data, emotion-stimulus data, AMAN's emotion, crowdsourcing, emotion, smile, and MELD dataset), among others. This study examined that in addition to this, they have talked about the many techniques that are used to analyze that data in order to identify emotional insights (the rule construction approach, the ML approach, and the hybrid approach). In addition to this, they have carried out a comparative examination of a number of works that are related to one another (in terms of approaches, datasets, and limitations).

In the same way, they gave a systematic literature review (SLR) and focused on research that was closely related to other research and was used to identify depression based on text [64]. In addition to this, they aimed to find further text-based ways for the early detection of depression in social media posts and do research on such strategies. When they applied both the BiLSTM and the attention model to the problem, their findings indicated that the textual data linked to depression performed quite well. In addition to this, they carried out an experiment with the use of a BERT-based model and produced findings that were superior to the studies that were referenced in the SLR. In addition, they suggested a novel strategy for dealing with lengthy sequences, it involved analyzing the text and producing a summary of it before putting it into the model. This was done in order to save time. In order for the model to work, the dataset must be crawled from Reddit. The authors of [65] contributed to the SemEval-2018 competition by sharing a task titled “affect in Tweets”. This effort is broken down into a number of smaller activities that, when combined, will determine, on the basis of text-based tweets, the emotional states of tweeters. They did this by streaming and labeling a selection of tweets published in Arabic on Twitter, and then generating Twitter-based labeled datasets in English, Arabic, and Spanish. Roughly two hundred individuals signed up to take part in the activity in question, which was a competition. We employed many machine learning and deep learning strategies, such as BiLSTM, gradient boosting, CNN, linear regression, RNN, logistic regression, LSTM, random forest, and support vector machines (SVM).

During the work that was done by the authors on [66], they achieved the best evaluation metrics for (Arabic EC subtask) by using an SVC L1 classifier that achieved 48.9% accuracy, 61.8% micro F1, and 46.1% macro F1 scores, respectively. This allowed them to improve the performance of the emotion classification task. Aravec is a pre-trained word embedding model. As part of the SemEval-2018 competition, participants were asked to classify the feelings expressed in Arabic tweets that were shared. The authors of [67] presented a Bi-LSTM deep learning model as a solution. In preparation for the process of cross-validation, the individual files comprising the dataset have been combined into a single document. During the phase of word embedding, Aravec has been deployed in conjunction with CBOW has been deployed. According to what they discovered, the Jaccard accuracy was 0.498% and it was micro precise.

Lastly, the model that is proposed in reference [68] is derived from three innovative deep learning models. Two of these models are specialized forms of recurrent neural networks known as Bi-LSTM and Bi-GRU. The third model, known as the MARBERT transformer, is a pre-trained language model (PLM) that is based on BERT. The experiments were judged using the dataset known as SemEval-2018-Task1-Ar-EC, which was made public during the emotion classification (EC) multilabel classification task that was a part of the SemEval-2018 competition. In terms of Arabic language support, MARBERT PLM is likened to one of the most well-known PLMs available today (AraBERT). The results of the experiments showed

Table 1 Related work in emotion detection

Reference	Year	Dataset	Used methodology	Results
[66] Badaro et al.	2018	Affect in tweets dataset	Deep neural network	Reliability scores>0.8
[67] Enas et al.	2021	SemEval2018 Task1 dataset	Recurrent neural networks	Accuracy=49.8%
[68] Mansy et al.	2022	SemEval-2018-Task1-Ar-EC dataset	Recurrent neural networks	Accuracy=51.2%
[69] Anam et al.	2020	Sentiment analysis on Twitter data	Machine learning	Accuracy=79%

that MARBERT delivered improved outcomes, with improvements in the Jaccard accuracy, recall, and F1 macro and micro scores of 4%, 2.7%, 4.2%, and 3.5%, respectively. In addition to this, the individual models were less successful than the proposed ensemble model, which was more successful (Bi-LSTM, Bi-GRU, and MARBERT). In addition to this, it accomplishes an improvement in accuracy ranging from 0.2 percent to 4.2 percent, as well as an improvement in the macro F1 score ranging from 5.3 percent to 23.5 percent [69] presented a novel mix of LR and SGD to be utilized as a voting classifier for emotion recognition. Specifically, they did this by classifying tweets as either happy or unhappy. The results of the tests showed that the performance of models can be improved by

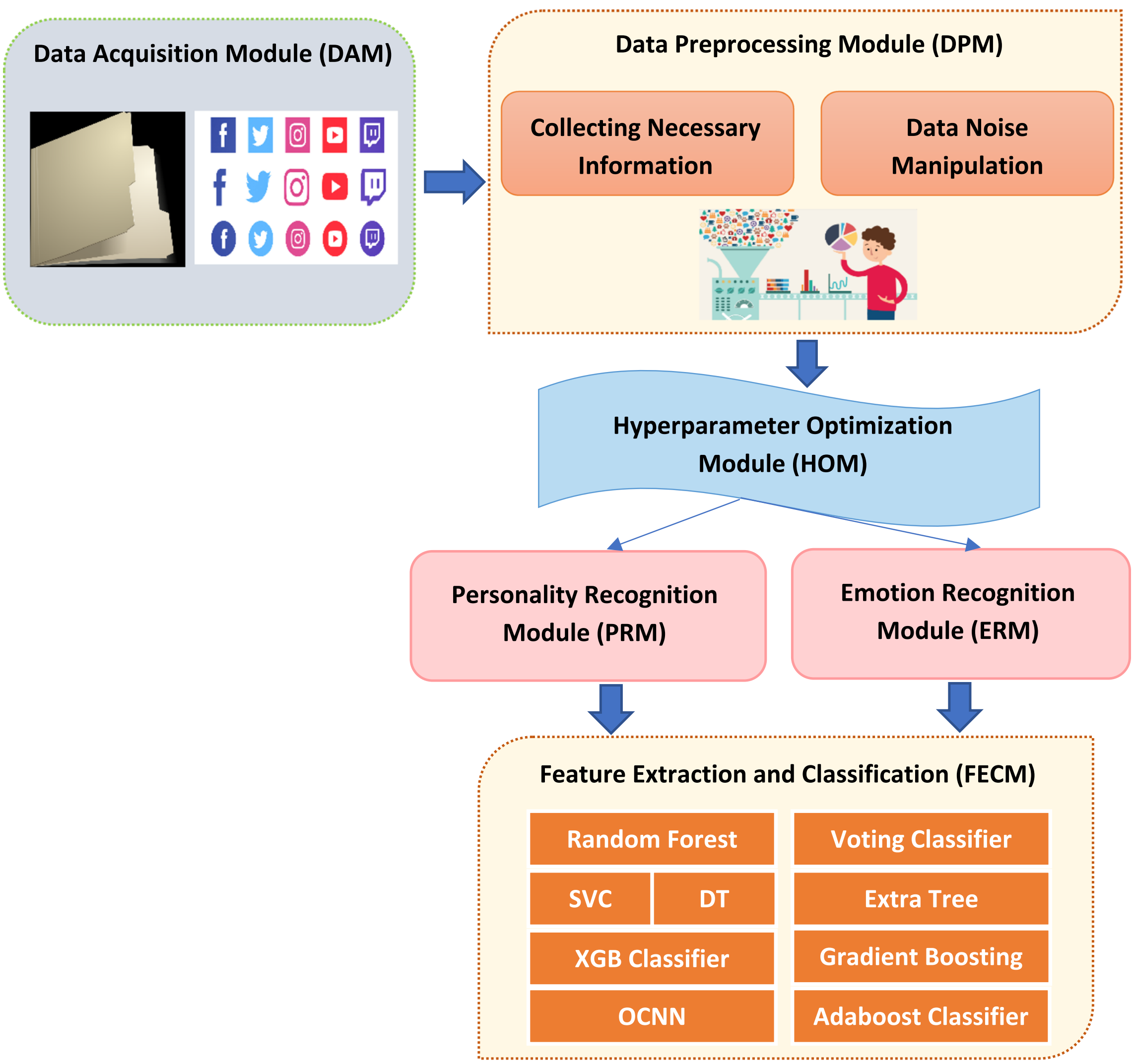


Fig. 4 The proposed enhanced recognition system (PERS)

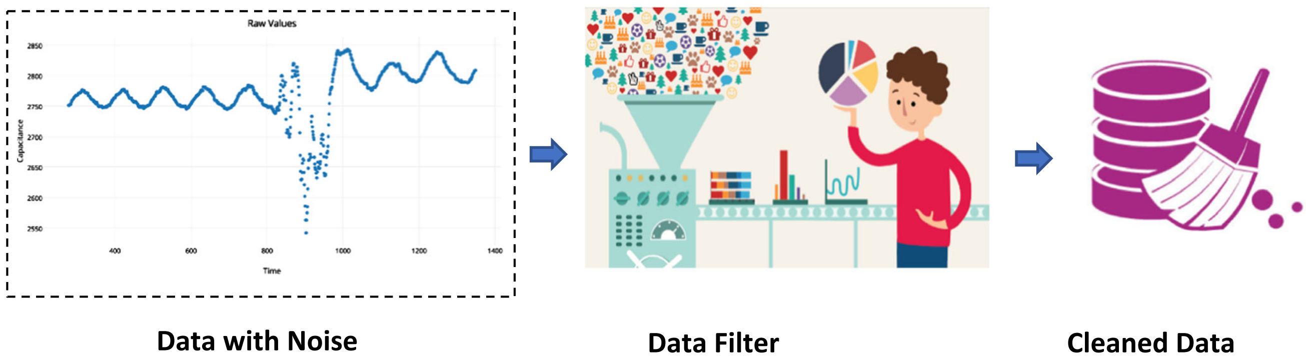


Fig. 5 Data noise manipulation using filters

merging numerous models in such a way that the performance of all the models is averaged out. Experiments are used to evaluate seven different machine learning models: (1) SVM, (2) RF, (3) GBM, (4) LR, (5) DT, (6) NB, and (7) VC. The SVM model is ranked number one (LR-SGD). In addition to that, the techniques of TF and TF-IDF for representing features were utilized in this work. According to the results, all of the models that were run on the Twitter dataset performed well; however, the suggested voting classifier, VC (LR-SGD), outscored them all by utilizing both TF and TF-IDF. The application of TF-IDF produced results of 79% accuracy, 84% recall, and an 81% F1-score. Table 1 provides a synopsis of the associated work segment.

3 The proposed enhanced recognition system (PERS)

The development of the predictive model for recognizing emotions and personalities is discussed in this work. The proposed enhanced recognition system (PERS) is composed of four main modules as shown in Fig. 4 which are as follows: (i) data acquisition module (DAM), (ii) data preprocessing module (DPM), (iii) personality recognition module (PRM), and (iv) emotion recognition module (ERM). Both targeted modules, i.e., PRM and ERM, are done via feature extraction and classification (FECM).

3.1 Data preprocessing module (DPM)

Models require data to function. It is the model's capability cap. There cannot be a good model without good data. The data preprocessing module is composed of two submodules which are as follows: (i) collecting necessary information and (ii) data noise manipulation.

3.1.1 Collecting necessary information

The personality recognition may not require all of the information contained in the collected data, which lengthens the processing and training of the data, the computational process, and reduces the effectiveness of our classification model's training [70]. The solution for this challenge is removing the unnecessary information via different techniques according to the type of the data.

3.1.2 Data noise manipulation

Neuroimages may contain adversarial noise, which lowers the classification process' efficiency. The training of the classification model is improved with the use of filters like the Gaussian, median, and several others that eliminate noise from images as shown in Fig. 5.

3.2 Hyperparameter optimization module (HOM)

The optimization of the hyperparameters is based on using the gray wolf optimization (GWO). The GWO algorithm is shown in Algorithm 1.

GWO Algorithm

```
1: N particles Xi (i=1, 2, …, n)
2: Calculate the fitness value (FV)
        //sort
        α = wolf with least FV
        β = wolf with second least FV
        λ = wolf with third least FV
3: For u in range(max_iter):
            a = 2*(1 - u/max_iter)
        For i in range(N):
            A1 = a*(2*r1 -1), A2 = a*(2*r2 -1), A3 = a*(2*r3 -1)
            C1 = 2*r1, C2 = 2*r2, C3 = 2*r3

            X1 = α.position -
                A1*abs(C1* α _position - ith_wolf.position)
            X2 = beta_wolf.position -
                A2*abs(C2* β _position - ith_wolf.position)
            X3 = gamma_wolf.position -
                A3*abs(C3* λ _position - ith_wolf.position)

          Compute new solution and it's fitness
            Xnew = (X1 + X2 + X3) / 3
            fnew = fitness( Xnew)
          Update the ith_wolf greedily
            if( fnew < ith_wolf.fitness)
              ith_wolf.position = Xnew
              ith_wolf.fitness = fnew
        End-for
        # compute new α, β and λ
          α = wolf with least FV
          β = wolf with second least FV
          λ = wolf with third least FV
      End -for
4: Return best wolf in the population
```

Algorithm 1: GWO Algorithm

3.3 Feature extraction and classification (FECM)

The feature extraction and classification (FECM) combines two submodules which are as follows: (i) feature selection using GGWO and (ii) multiclass (MC) classification.

3.3.1 Feature selection using GGWO

In this submodule, the most effective features are chosen to be tested using the classification module. The Feature selection is done via using the group gray wolf optimization (GGWO) algorithm through four steps as shown in Fig. 6: (i) feature set initialization, (ii) grouping model, (iii) objective function evaluation, and (iv) updating feature selection.

(i) Feature set initialization.

The GGWO algorithm populates the arrangement subjectively in order to improve the features. A crucial improvement to the algorithm that quickly recognizes this perfect solution is solution creation. The chosen feature set is shown in the following manner as shown in Eq. (1).

$$F_s = \{F_1, F_2, F_3, \ldots, F_n\} \tag{1}$$

where F_s is the subset of the chosen features and there are n features.

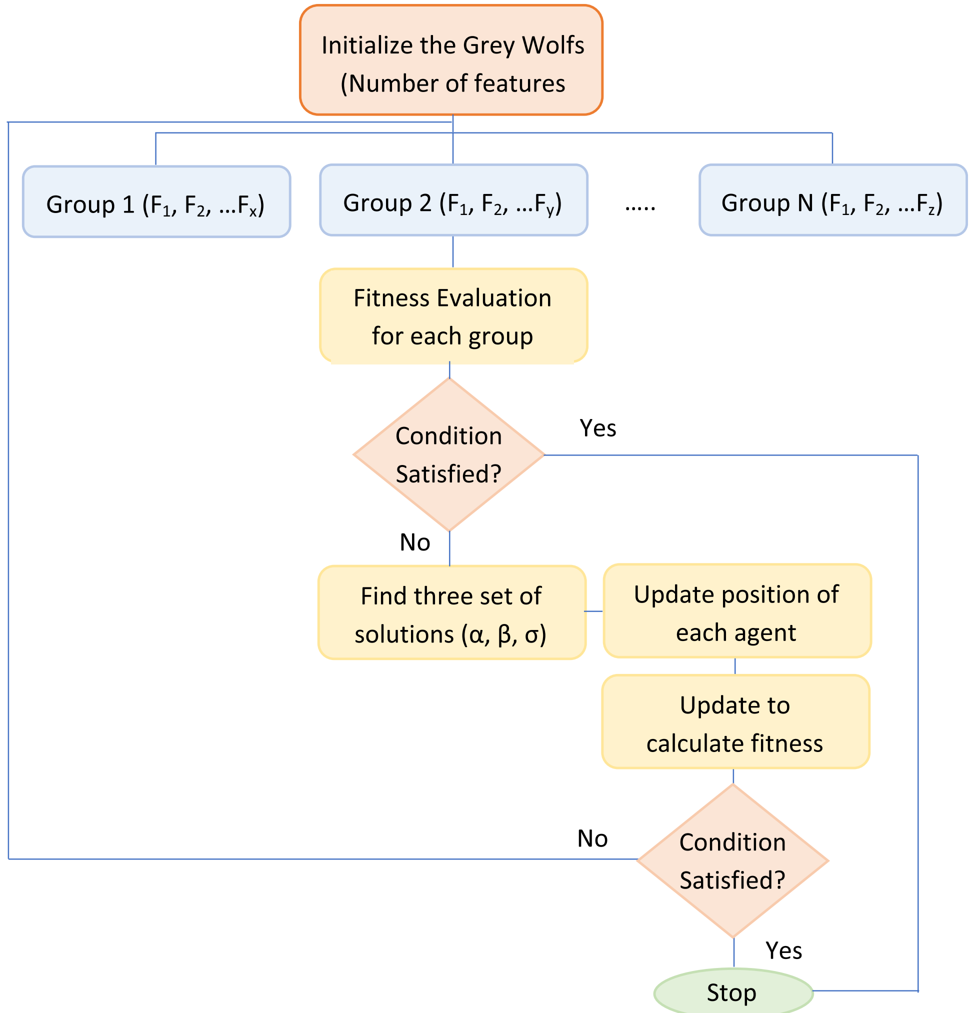
(ii) Grouping paradigm

Gray wolves (features) were first arranged in groups for group formation based on how they were used in the diving request. The ordered wolves' primary characteristics are the most effective. Shade is used to differentiate each particle group from the next.

(iii) Objective function evaluation

Finding the fitness in each block of data is more crucial. Here, the primary criterion for outlining a fitness function is classification accuracy. This fitness function can be determined for each cycle that has been registered as shown in Eq. (2).

Fig. 6 Feature extraction using GGWO



$$Acc = \frac{GC + GN}{GC + GN + WC + WN} \tag{2}$$

where Acc is the classification accuracy which is equal to the number of correctly classified features (GC, GN) to all classified (GC, GN, WC, WN).

iv Updating feature selection.

After calculating fitness, the answer is updated depending on gray wolf updates.

3.3.2 Multiclass (MC) classification

In this section, the multiclass classification process is discussed. It uses a variety of classifiers as shown in Fig. 7, including support vector classifier (SVC), Random Forest, XGB classifier, decision tree (DT), optimized convolutional neural network (OCNN), voting classifier, extra tree classifier, gradient boosting, AdaBoost classifier.

4 Implementation and evaluation

The utilized dataset and the suggested algorithm's outcomes are introduced in this section.

4.1 Characteristics of personality dataset

The dataset that is used to determine personality [71] categorizes individuals into 16 different personality types and presents their 50 most recent tweets, split by "|||." The 16 various personality types are categorized along four axes by the Myers-Briggs Type Indicator, or MBTI for short. The MBTI, often known as the Myers-Briggs Type Indicator, divides people into 16 different personality types along four axes as shown in Table 2. A sample of data is shown in Fig. 8.

Remember that the opposite personalities are aligned above to help one understand how the meanings of the personalities differ when comparing them. So, for instance, a person who values introversion, intuition, thinking, and

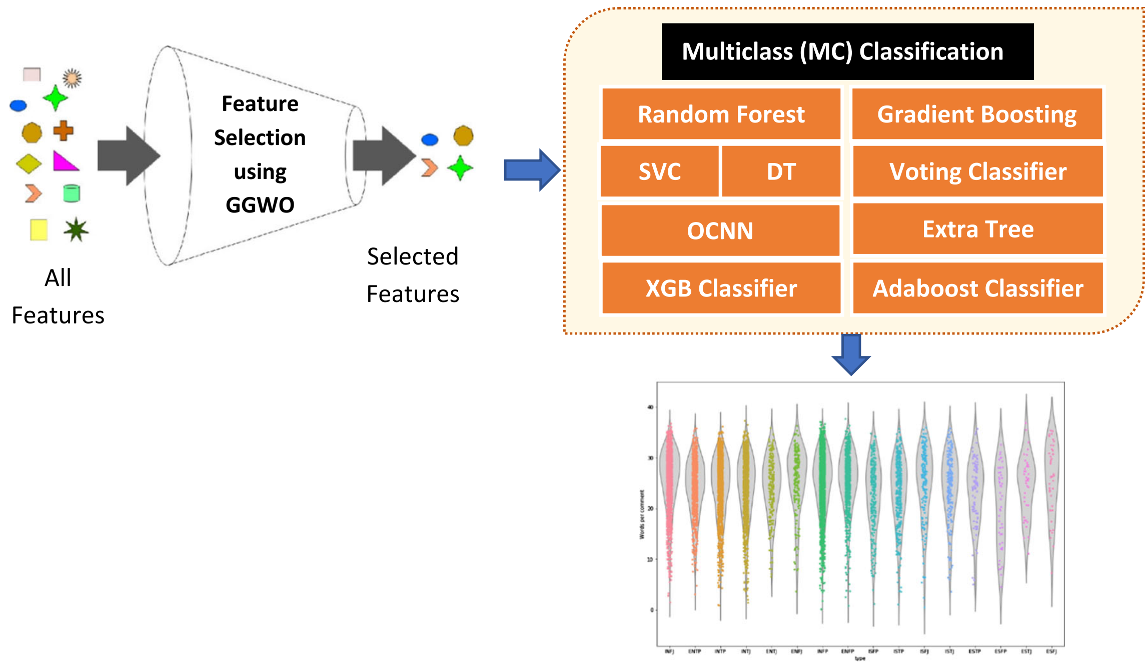


Fig. 7 Multiclass (MC) classification

Table 2 Data description

Axis *i*	Axis *j*
Introversion (*I*)	Extroversion (*E*)
Intuition (*N*)	Sensing (*S*)
Thinking (*T*)	Feeling (*F*)
Judging (*J*)	Perceiving (*P*)

```
   type                                              posts
0  INFJ  'http://www.youtube.com/watch?v=qsXHcwe3krw|||...
1  ENTP  'I'm finding the lack of me in these posts ver...
2  INTP  'Good one  _____  https://www.youtube.com/wat...
3  INTJ  'Dear INTP,   I enjoyed our conversation the o...
4  ENTJ  'You're fired.|||That's another silly misconce...
5  INTJ  '18/37 @.@|||Science  is not perfect. No scien...
6  INFJ  'No, I can't draw on my own nails (haha). Thos...
7  INTJ  'I tend to build up a collection of things on ...
8  INFJ  I'm not sure, that's a good question. The dist...
9  INTP  'https://www.youtube.com/watch?v=w8-egj0y8Qs|||...
*****************************************
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 8675 entries, 0 to 8674
Data columns (total 2 columns):
type     8675 non-null object
posts    8675 non-null object
dtypes: object(2)
memory usage: 135.6+ KB
None
```

Fig. 8 A sample of data classification

perceiving classified as an INTP in the MBTI. Based on this classification, a number of personality-based components would serve to either explain or mimic this person's tastes or actions.

It is the most well-liked personality test in the entire globe, if not the most. It is used for many purposes, including study, for amusement, in enterprises, and online. The test has been used in numerous ways over the years, as may be seen by conducting a quick internet search. It is safe to state that this test's application is still very much in the globe today.

It is founded, from a scientific or psychological standpoint, on Carl Jung's research on cognitive functions, known as Jungian Typology. This was a model that indicated the mind has 8 different functions, thought processes, or ways of thinking. This work was then transformed into numerous unique personality systems to improve accessibility.

Recently, its utility and validity have been questioned due to, among other things, the inaccuracy of the experiments that surround it. The goal of this dataset is to examine if any patterns can be found in particular types and their writing style, which ultimately explores the usefulness of the test in analyzing, forecasting, or categorizing behavior. However, it is still adhered to as being a very valuable tool in a lot of areas.

This dataset has over 8600 rows of data with a person's information. A portion of each of the 50 most recent things they posted, with "|||" (three pipe characters) separating each entry. The exploratory data analysis is shown in Fig. 9.

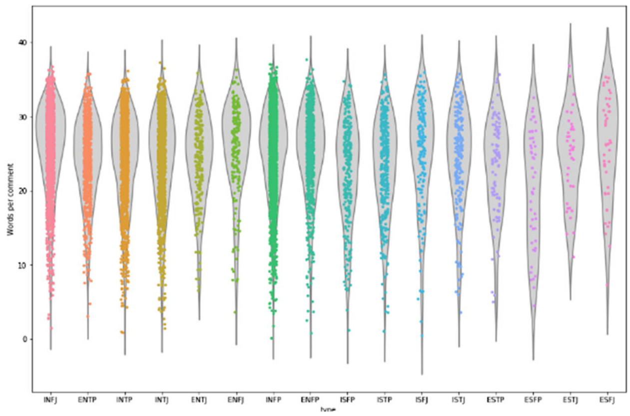


Fig. 9 Exploratory data

4.2 Emotion dataset description [72]

Robert Plutchik created an eight-emotion wheel in 1980, drawing inspiration from his Ten Postulates. The eight emotions are as follows: joy, trust, fear, surprise, sadness, disgust, anger, and anticipation. Table 3 displays an illustration of the emotion dataset. Table 4 and Fig. 10 both display the data description.

4.3 Results of each classifier

The results for each classifier for personality detection in normal without optimization and after using the optimal features and optimal hyperparameters for each classifier are shown in Table 5 and in Fig. 11. As shown from the results without optimization, the Random Forest classifier gives the best accuracy followed by the KNN classifier. SGD and Logistic Regression Classifiers give least accuracy. When optimization is introduced, the accuracies of all classifiers have improved. However, Random Forest classifier still gives the best accuracy, 99.99%, over all the used classifiers.

The results for emotion recognition are shown in Table 6. From Table 6, it is shown that the average precision is equal to 89%, the average recall is 87.5%, the average f1-score is 88.16%, and the average accuracy is 88.06%. Table 7 contrasts the suggested algorithm with the most recent algorithms.

Table 4 Emotion dataset description

Feeling	Sl no	Length
Angry	4932.246085	165.794183
Disgust	4262.874411	170.572998
Fear	4122.549247	152.156431
Happy	4560.091141	160.319501
Sad	5739.734995	161.599158
Surprise	7632.000000	136.441103

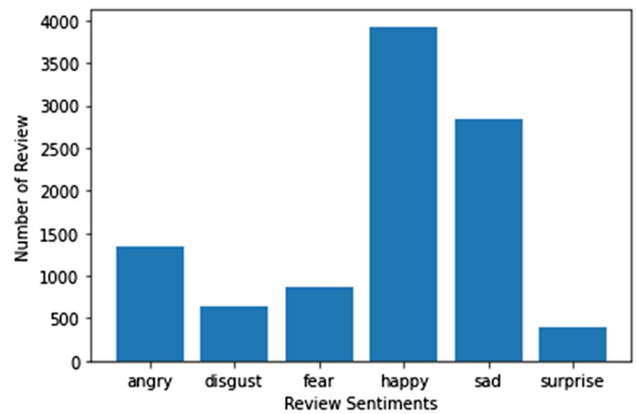


Fig. 10 Emotion dataset

It can be seen from Table 7 and Fig. 12 that the recommended approach outperforms other cutting-edge studies.

4.4 Results discussion

Personality detection The outcomes of the personality detection task show how optimization affects how well certain classifiers perform. The random forest classifier, which has an accuracy of 97.51%, and the KNN classifier, which has an accuracy of 80.30%, are the two that perform the best without optimization. SGD classifier and logistic regression, on the other hand, exhibit poorer accuracy.

Table 3 A sample of emotion dataset

	Sl no	Tweets	Search key	Feeling
0	1	#1: @fe ed “RT @MirayaDizon1: Time is ticking…	Happy moments	Happy
1	2	#2: @蓮花 &はすか ed ”RT @ninjaryugo: #コナモンの日 だそうで…	Happy moments	Happy
2	3	#3: @Ris ♡ ed “Happy birthday to one smokin h…	Happy moments	Happy
3	4	#4: @□□ [□□□□□□□] jwinnie is the best, cheer u…	Happy moments	Happy
4	5	#5: @Madhurima wth u vc♥ ed ”Good morning dea…	Happy moments	Happy

Table 5 Classification results on multiclass

Classifier	Accuracy without optimization (%)	Accuracy with optimization (%)
Random forest	97.51	99.99
SGD classifier	76.70	77.11
Logistic regression	74.94	77.10
KNN	80.30	83.66

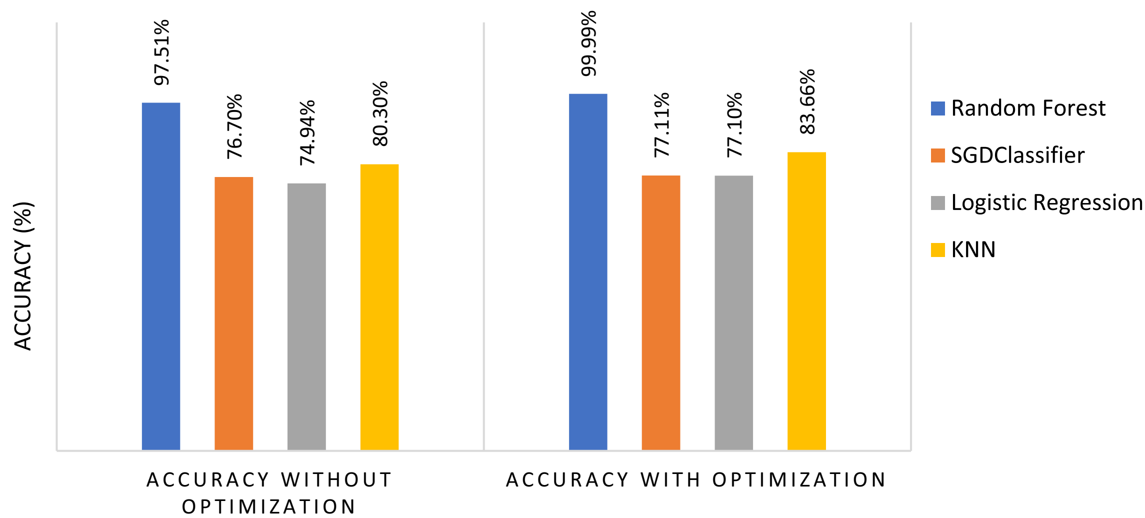


Fig. 11 The performance for each classifier without optimization vs. with optimization

Table 6 The results for emotion recognition

Classification report				
	Precision	Recall	f1-Score	Support
Angry	0.90	0.89	0.90	395
Disgust	0.90	0.90	0.90	198
Fear	0.88	0.84	0.86	250
Happy	0.85	0.90	0.87	1222
Sad	0.90	0.87	0.88	830
Surprise	0.92	0.85	0.88	111

However, all classifiers exhibit increases in accuracy when optimization is included. The random forest classifier maintains its superiority despite this advancement, outperforming the other classifiers with a stunning accuracy of 99.99%.

Emotion recognition The performance on the emotion recognition challenge is encouraging, as demonstrated in Table 6. For various emotion categories, the average precision, recall, and f1-score varied from 0.85 to 0.92, with an average accuracy of 88.06%. These outcomes demonstrate how well the suggested algorithm performs when it comes to correctly identifying and categorizing emotions from textual input. In addition, Table 7 contrasts the suggested algorithm with other cutting-edge strategies. The suggested method performs better than the previous state-of-the-art investigations, demonstrating its superiority in attaining precise emotion recognition.

Table 7 Evaluating the suggested algorithm against the most advanced algorithms

References	Year	Dataset	Used methodology	Accuracy (%)
Proposed	2022	Twitter-emotion-analysis/data	Multiclass classification process	88.06
Bi-LSTM and Bi-GRU [68]	2022	SemEval-2018-Task1-Ar-EC dataset	Recurrent Neural Networks	51.2
Bi-LSTM DL [67]	2021	SemEval2018 Task1 dataset	Recurrent neural networks	49.8
LR and SGD [69]	2020	Sentiment Analysis on Twitter data	Machine Learning	79
LR and SGD [66]	2018	Affect in Tweets dataset	deep neural network	80

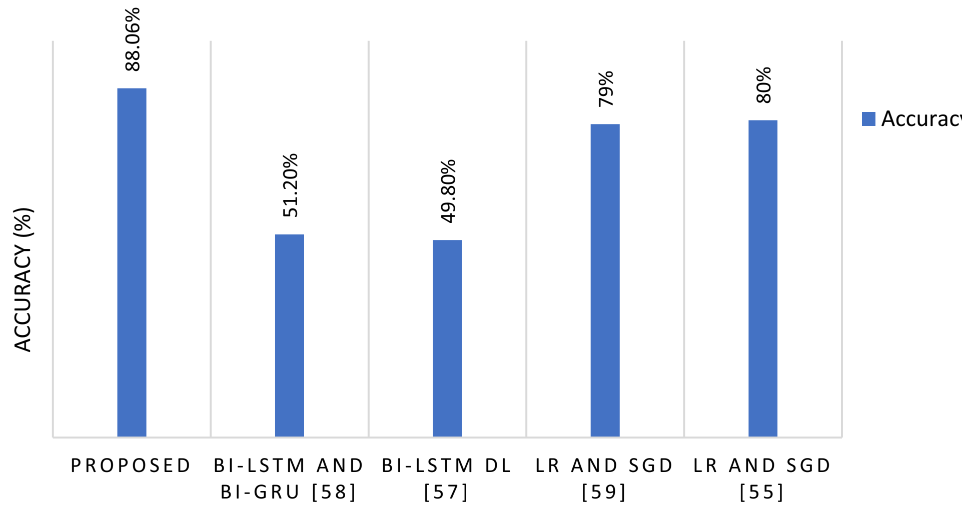


Fig. 12 Comparing the suggested algorithm's accuracy to that of modern algorithms

Overall, the findings show that both personality detection and emotion recognition tasks may be successfully completed using the suggested enhanced recognition system (PERS). In comparison to other cutting-edge techniques, the suggested algorithm obtains greater accuracy in emotion recognition while the optimized random forest classifier displays excellent performance in personality classification. These results demonstrate the practical usability and efficacy of the suggested approach in deciphering personality and emotions from textual data, making a contribution to the study of social media.

Mysteries, difficulties, and worries with the suggested: Managing the enormous volume of data: The research concedes that because of the vast amount of data present on social media sites, analyzing personality and emotions from written text is difficult. For researchers, managing and digesting such a massive amount of data is a significant difficulty.

Extracting significant features Accurately capturing personality traits and emotions from text data requires the extraction of pertinent elements. A problem that needs to be solved is choosing the most illuminating traits that support efficient recognition and categorization.

Ensuring generalizability It is impressive to use machine learning algorithms to recognize personalities and emotions with great accuracy. The research community is still working to make sure that the suggested model generalizes well to various datasets and environments. For the model to be useful, it must be able to be applied to many social media sites and text sources.

Privacy issues and ethical considerations The use of social media data to decipher people's emotions poses ethical issues with regard to data security and privacy. When conducting research in this area, it is crucial to protect user privacy and make sure that data is handled responsibly and with permission.

Addressing the shortcomings of previous research By contrasting the suggested Enhanced assessment System (PERS) with other cutting-edge studies, the report emphasizes the need for enhanced techniques in personality and emotion assessment. A constant struggle is getting over the drawbacks of earlier methods and performing better.

The paper discusses the significance of detecting suicidal intentions by analyzing suicide notes posted on social media accounts, which introduces the difficulty of precisely detecting such crucial signals and taking appropriate precautions to avoid harm.

5 Conclusion

Understanding personality and recognizing emotions from written texts are relatively new fields of study in research. People express how they feel using facial expressions, or spoken speech, or written text. There is few researches in recognizing personality and emotions from written text despite the wide spread of social media platforms. This research presented an enhanced recognition system for personality recognition and emotion recognition. The proposed enhanced recognition system (PERS) is composed of four main modules, namely data acquisition module (DAM), data preprocessing module (DPM), personality recognition module (PRM), and emotion recognition module (ERM). After acquiring the data, DPM is responsible for collecting necessary information and noise removal. Several machine learning algorithms, namely random forest, decision tree, and XGBoost, are used for the multiclass classification process. Gray wolf optimization (GWO) algorithm is used for hyperparameter optimization, while group gray wolf optimization (GGWO) algorithm is used for feature selection. The proposed model could achieve an accuracy of 99.99% using the random forest algorithm for personality detection and 88.06% for emotion recognition using decision tree, which outperforms other state-of-the-art studies.

As future work, we aim to use our proposed system on data written in other languages, for example Arabic. We also aim to apply deep learning techniques rather than machine learning techniques.

Data availability https://www.kaggle.com/code/kehlinswain/predict-personality-types-using-ml-social-media/data.https://www.kaggle.com/code/shainy/twitter-emotion-analysis/data.

Declarations

Conflict of interest The authors declare that they have no conflicts of interest to report regarding the present study.

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