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Application of Hybrid Deep Learning Algorithm for Sentimental Analysis & Emotional Behavior for Recognition and Classification on Twitter Data Set

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Abstract:
The rapidity with which technology is developing is changing the way people talk to one another. Face book, Twitter, and Instagram are just a few of the many online communities where people may connect with others who share their interests and express themselves through the written word, visual media, and sound. This opens up the possibility of examining users' emotions and sentiments in their online communications by analyzing data from social networks. In order to glean useful information from user reviews, psychologists utilize a text-processing technique called psychological analysis. Depression is an emotion that can have a significant impact on a person's ability to function normally. Worldwide, the percentage of people dealing with recurrent emotions keeps rising. Self-harming activities are common among depressed people and can sometimes lead to suicide. Those who study the mind rely on social media to spot signs of depression-related behavior and activities. Many indicators of depression's beginnings can be gleaned from a person's social network, including a lack of interest in others, a preoccupation with one's own needs, and increased day- and nighttime activity. High social media use has been linked to more feelings of depression, according to recent research. Recognizing persons with mental health issues and getting them help as soon as feasible is a very difficult endeavor. Patient interviews & PHQ scores were traditionally used to diagnose depression, but these procedures are highly inaccurate. Machine learning, deep learning, & artificial intelligence are examples of cutting-edge technologies that have contributed significantly to these breakthroughs. This study also intends to employ machine learning methods to identify a depressed Twitter user by analyzing their online activity and tweets. To this end, we gathered variables from a user's network activity and tweets and used them to train and evaluate classifiers that can determine whether a user is depressed. The results of this work were tested on datasets taken directly from the scientific literature. For highly accurate depression detection, the suggested Hybrid method outperforms the current gold standard.

Keywords: Psychiatry, Social Media Analysis, Machine Learning, Treatment response and Detecting Depression

1.Introduction:

Many people suffer from depression in today's modern culture. Depression, as defined by Parekh, is a medical illness that can have unfavorable effects on a person's thoughts, feelings, and actions.

According to data published by the World Health Organization, there were surrounding 322 million cases in 2015, with approximately 788.000 ending in suicide[1]. Despite how grave the problem appears to be, there is still a widespread belief that mental illness is a sign of weakness and can result in social isolation. People see worry as a significant issue, but they believe it to be less treatable than other mental health issues, according to a study[2]. As a result, fewer persons with mental health issues will seek professional help, increasing the treatment gap. Seventy percent to eighty percent of people with despair do not get the treatment they need[3].

A person's physical health can be negatively impacted by depression in addition to the patient's mental health. Predicting a patient's mental health status allows us to assess the severity of their Depression. Anxiety disorders, restlessness, sleeping problems, eating disorders, addiction disorders, Depression, traumatic stress, and stress-related diseases account for the majority of reported cases of psychological disorders [4]. To put it simply, depression is a mental disorder characterized by persistent feelings of hopelessness, de-motivation, poor mood swings, and a lack of interest in one's usual routine of physical, mental, and social activities. It has a devastating effect on one's ability to learn, as well as their emotional stability and productivity at work. Depending on how severe depression is, a patient may have a wide range of symptoms [5]. When its severity is high, brain activity slows down and the body releases the hormone cortex, which has an effect on neuronal growth. It messes with people's heads and might even cause others to consider suicide. Clinical depression, bipolar depression, dysphoria, seasonal adjustment disorder, and others are all distinct forms of depression [6]. Available services and treatments range from counseling to other types of therapy. There is also the option of brain simulation therapy [7].Figure 1 depicts a variety of the most fundamental emotions experienced by humans.

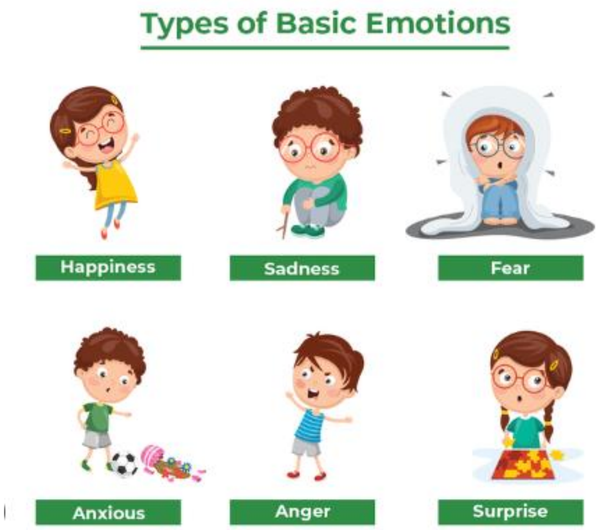

Figure 1.Various Basic Human Emotions [source: internet]

A person's socio-economic standing could be negatively affected by depression. Depressed people are more likely to withdraw from their social circles. Depression treatment options include talking therapy and counseling. With the help of data and extensive training, machine learning (ML) algorithms can learn to recognize previously unseen patterns. This skill is useful for solving new challenges by drawing on past experience. Most ML algorithms are designed to produce predictable results [8]. Algorithms for machine learning can be broken down into several broad categories, including learning under supervision, unsupervised learning, semi-supervised learning and reinforcement learning. Unsupervised ML techniques [10] reveal hidden patterns and clusters in the provided data, while unsupervised ML algorithms [9] use primary inputs to forecast known values. Located between unsupervised and supervised learning, semi-supervised learning [11] explores system behavior by integrating both labeled and unlabeled information. Learning through trial and error, with the goal of improving performance with each attempt, is at the heart of reinforcement learning [12]. As they are able to analyze vast amounts of diverse data and yield effective therapeutic insights, ML applications in healthcare have been shown to be pragmatic. Effective knowledge of mental illnesses and support for predictive decision making by mental health professionals is provided by ML-based techniques [13]. By producing insights from otherwise unstructured medical data, ML approaches improve healthcare prediction and diagnosis. The results of the predictions aid in the early diagnosis of patients at risk for serious medical complications. To better aid healthcare professionals in anticipating the vicissitudes of mental diseases and offering appropriate treatment outcomes, ML approaches help arbitrate the prospective behavioral biomarkers [14]. The methods improve the presentation and comprehension of intricate healthcare data. The visualization is useful for creating a working hypothesis for identifying mental problems. The intricacy of depression is not properly identified by the standard clinical diagnostic technique. Using ML techniques, we can readily recognize and anticipate the composition of symptoms connected to mental diseases like depression. Therefore, it would appear that the ML-based diagnostic technique is the best option for predictive analysis. Sensors, text, organized information, and multifunctional technology interactions are the most common types of data sources used in the healthcare industry for ML-based observation extraction of mental diseases. The information gathered by the sensors can be evaluated by employing sound waves and cell phones. Text can be mined from various places, including social media, SMS, and medical records. Standardized screening instruments, questionnaires, and patient medical records all contribute to what we call "structured data." Information gathered through people's interactions with common pieces of technology, robots, and digital representations of people are all part of this multimodal data set. The ML methods can be utilized to aid in the diagnosis of psychological disorders. Most of these research look at Twitter [15] or mobile device sensor [16] data to diagnose mental health issues. The patient's psychiatric history can be mined for useful diagnostic information through the use of textual analysis [17].

Many models and methods have been created to detect the indications and symptoms of mental diseases using social media data because of its significant value in identifying persons at risk for depression or with additional mental illnesses. For instance, Renara et al. [18] found that analyzing sentiment on social media could help monitor a person's mood. This is especially useful because people with symptoms of depression experience identical emotions and have comparable conduct, which frequently comes out through what they post on social media. The n-gram model, which is a sequence of n successive words, is frequently used for sentiment analysis. In reality, the n-gram model—also known as the unigram—is used by a number of authors when n=1. De Choudhury and Gamon [19] found that the following unigrams that are associated with depression: retraction, mental illness, harsh, delusions, ADHD, inequalities, sleeplessness, self-harming, vertigo, retching, assaults, sleep, epileptic fits, addictive, weaned, fluctuations, dysfunction, hunger, fuzzy, irritability, seasons, headache, fatigue, edging, nervousness, burden, heaviness, and somnolence. However, studies by these writers [20] have shown the success of this approach. From this vantage point, it makes sense for researchers to conduct a systematic review of the literature to learn more about the social media platforms and dataset characteristics, linguistic feature extraction techniques, machine learning algorithms, computing resources, and statistical analyses currently used to identify signs of depression online.

The rest of the paper can be written down as follows: Emotion detection techniques developed using machine learning are discussed in Section 2. Our suggested ACO-PSO-SVM hybrid classification technique and method for emotion classification are discussed in Section 3. Section 4 evaluates our work considering all of the relevant literature, and Section 5 concludes the work.

2. Literature Survey:

The textual collection allows for numerous approaches to psychological study. In this section, we review the literature on the subject of depression detection and the various methods that have been used thus far. The use of linguistics in depression identification is promising since it reveals that depressed and non-depressed individuals may use language differently. People who are depressed tend to think only of themselves. Nguyen analyzed two online "control" and "clinical" groups in 2014. People who shared comparable interests and were generally up for a good time made up the "control" group, while those with mental health issues such bipolar disorder, severe depression, seasonal affective disorder, or panic attacks made up the "clinical" group. Members of the clinical group were able to open up about their struggles and accept recommendations for treatment without fear of repercussions. The author notices a distinction between these two types of online communities. People in the "clinical" group are more likely to use first person pronouns ("I," "me," and "my") and talk about themselves, whereas those in the "control" group are less likely to do so and talk about things like singing, dancing, and running. This study shows that the way a person uses language is significant in determining whether or not they are depressed.

According to the research of Choudhury et al. [21], the experience of depression is a true test of one's personal and societal health. A sizable population suffers from depression, yet only a fraction of those people receive effective therapy each year. They also looked into the potential of using social media to spot and analyze the early warning signs of major depression in people. Social networking posts were analyzed for quantifiable behavioral credits related to emotional expression, communication patterns, language use, self-awareness, and the use of antidepressants.

Choudhury et al. [22] viewed social media as a useful tool for public health, namely the opportunity Twitter provides for developing predictive models of the long-term effects of childbirth on mothers' attitudes and behaviors. Three hundred and seventy-six mothers' Twitter postings were analyzed for changes in social engagement, emotion, informal network, and phonological style after giving birth. O'Dea et al. [23] looked into how Twitter is increasingly being studied as a way to detect mental health issues like depression and suicidality. Through a combination of human coders and a pre-programmed machine classifier, they discovered that it is possible to identify the amount of concern among tweets mentioning suicide. Zhang et al. [24] demonstrated that it is possible to implement a dynamic intervention mechanism to save the lives of people at risk of suicide by identifying them through online networking, such as microblog [47].

Several studies have shown that UGC may be used to assess people's mental health if it is used correctly. For instance, Aldarwish & Ahmad [25] looked at how the use of SNS is growing, especially among younger generations. Customers are able to share their passions, opinions, and services on a daily basis [26], all thanks to the convenience of social networking sites.Nguyen et al. [27] used machine learning including statistical methods to categorize online conversations about depression and controls by excluding topics related to mood, language use, and substance use[45][46][48].

Depression, imaging, & ML methods are all discussed in [28], which provides a historical perspective. Research using imaging & ML to investigate depression is also reviewed. SVM (linear kernels), SVM (nonlinear kernels), and significance vector regression are the algorithms being analyzed. In this poll, we only look at one aspect of mental health. Depression screening scales were not discussed in this study, and an algorithm comparison was not performed. Garcianert et al. [29] conducted a literature review of ML with sensor data in psychological surveillance systems (MHMS). Anxiety, depression, bipolar disorder (BD), migraine, and stress were only some of the mental health conditions that were examined with supervised, unsupervised, semi-supervised, the transfer, and reinforcement learning. However, the study only provides a superficial summary of the relevant instances and applications involving MHMS. Research papers on diagnosis using brain imaging categorization and prediction were compared by Gao et al. [30]. The MRI data was used in conjunction with the study of major depressive disorder (MDD) and BD. In this research, we examine SVM, LDA, the GPC, DT, which is RVM, NN, & LR algorithms. However, little information is provided about the depression screening instruments utilized in the various trials. Only research on MDD & BD is discussed. In their study of ML algorithms for the diagnosis of mental diseases, Gyeongcheol et al. [31] focused on SVM, Gradient Boosting Machines (GBM), RF, Nave Bayes, and KNN. Research on BD, ASD, schizophrenia, depression, and PTSD were all included. Only a small subset of ML algorithms were covered, and the benefits of any one ML technique were not highlighted.In [28], the researchers examined Facebook data in search of indicators of depression. LIWC was used to evaluate information from Facebook users. Data was processed using DT, KNN, SVM, or an ensemble model, all of which are supervised learning machine learning (ML) techniques. The classification accuracy improved experimentally with DT. As an example of how AI might be used to investigate potential biomarkers for mental illness, Liuert et al. [32] provided a brief overview of generic applications that use AI for mental illnesses. The research [33] examined five AI methods, including the Bayesian model, LR, DT, SVM, and DL, in addition to the three major ways for brain imaging for psychiatric disorders: MR imaging (MRI), electroencephalography, or EEG, & kinesics diagnosis. A representation of depressive cues in audio and video has been extracted using DL approach by the authors of [34][41][42].

This article provides a summary of the research on automatic depression estimating (ADE) by introducing the databases and describing objective markers for ADE. To further extract the depiction of sadness from audio and video, they further reviewed the DL techniques (DCNN, RNN, & LTMS) to perform automatic depression detection. They have concluded their discussion by pointing out certain problems and prospective future developments in the field of automatic depression diagnosis using DL methods[40][44].

3. Proposed Methodology:

The initial step of the proposed method is data collection. Known Twitter datasets are used in this work to develop a text-based depression detector. This consists of the tweets collected from the Kaggle-available work [36]. Depressive data was obtained from Twitter posts, and its recognition and processing were the primary focuses of this work. These characteristics included emotional procedure, temporal process, language style, and all (emotional, temporary, linguistic style) features together. We then use supervised machine learning techniques to investigate each type of component separately. The notations Depression (DPR) and Non-Depression (N-DPR) are used to distinguish between depressive and non-depressive states. The data in the Kaggle repository [37] is skewed and contains a lot of dirty tweets. There is an unbalanced number of records in the dataset between the Depression vs non-depression groups. There is no perfect data sampling strategy that works for every classification model. In order to keep the data evenly distributed, only 7352 data are collected rather than using a sampling technique to get the precise balance in each category. There is no change in the number of records (3676) between the Depression and non-depression categories, out of a total of 7352.Some of the comments and phrases from the social media datasets are displayed in tables 1 below.

Table 1: A Sample of DPR & N-DPR Tweets from a Dataset

S.No	Social Media Post from Dataset	Category
1	I'm depressed and can't concentrate on my academics	DPR
2	I find flaws in everyone around me; I'm lonely and alone;	DPR
3	I really over think everything, which causes me to stress out.	DPR
4	I shall be eternally grateful to my friends for making me happy.	N-DPR
5	Merry Christmas to everyone!	N-DPR
6	My life story. I battle with these issues on a regular basis.	N-DPR

3.1 Data Collection:

Accuracy of data is of the utmost importance, and this holds true across a wide range of research approaches. The goal of every data collection endeavor should be to amass high-quality data, the kind that can be utilized to evaluate rich data sets and provide credible and definitive answers to the questions such sets are designed to answer. So, there it is: Tweet collection refers to the process of gathering tweets that are pertinent to a given topic. To compile the tweets, an API is employed. Input data can be gathered using these APIs. This program provides a safe and encrypted connection between the user and the server that keeps and retrieves tweet information. Due to the time-consuming nature of the method, data for this study was acquired from a wide range of websites instead of directly from Twitter.Getting them ready to be used Similarly, data pre-processing can be a pivotal stage since it affects the success of later stages. Making the necessary grammatical adjustments to the tweets is part of the process.

Table 2 Twitter dataset statistics.

Data Quantity Estimated	569783
Positive Reviews	256123
Negative Reviews	223395
Neutral Reviews	90265
Amount of Features Remaining After Extracting	72458

The dataset consists of the three types of reviews shown in Table 2: positive, negative, and neutral. Extraction and statistical analysis of the dataset show characteristics like favorable, negative, and neutral reviews.

3.2 Data Pre-Processing:

The two main components of this process are stop word deletion and stemming. Removed stop words and applied stemming to get at the views' actual verbs and adverbs. Any extraneous digits, punctuation, or words (such as an, the, a, and, or, etc.) are removed during the stop word removal process. In most cases, stemming will return a derived word to its basic form (in this case, "smoother" would be "smooth"). We employ the N-Gram method for processing the information and cleaning it of extraneous material.

3.3 Feature Extraction and Optimization

In this research, ACO and PSO are used to modify the procedure. The term "combinatory optimization" is used to describe this situation. It's probable that multi-objective functions need certain techniques of looking for preliminary values in order to lessen the end outputs of our function. Here, it's all about picking the most important characteristics out of a large pool. This is done with the help of optimization techniques. Both optimization of ant colonies and particle swarm optimization draw inspiration from the natural behavior of real-world organisms. It used this technique to discover the shortest routes taken by the ants. The optimization procedure clearly decreased the total number of ACO paths, but it also located the quickest path to a longer path. These algorithms provide the most useful characteristics because they are based on the same ideas as ants. Then, the hybrid ACO-PSO method is applied to this dataset for optimization.

3.4 Classification

The classification method is used as a final stage while processing Twitter data. Here, we'll use ACO, PSO, and SVM to create a hybrid classifier. The sentiment analysis performed with the hybrid classifier will be quite precise.

3.5 Optimization Algorithms:

3.5.1 Particle Swarm optimization (PSO)

As a result, PSO acts similarly to a school of birds or fish. Most social behavior (in terms of intellect) in flocks of birds or schools of fish is the result of the individual actions and impacts of other members of the population or group. The acts of other herd members can have an effect on the behavior of an individual animal. The PSO algorithm is then modified to account for the collective's actions.

3.5.2 Ant Colony Optimization (ACO)

The ants in a colony must figure out the quickest route from one location to another. When they decide that the path they're on isn't the best one, they leave a certain quantity of pheromones behind to let others know. As more pheromone is added, the ant trail with the greatest amount will be encouraged by more ants. One of the most effective computing methodologies inspired by ant behavior is ant colony optimization. In order to construct the artificial ant, we will employ network nodes to denote origin and end locations. This is according to a recent study.The robotic ants forage their way from the colony to the food source, leaving scent trails in the wake. They leave and return to the colony immediately after (see source).Seeing that ants were easily noticed on the most direct paths, it is not uncommon for other insects to follow in the same footsteps, and for future ants to take the shortest and most pheromone-rich route. The strength of the pheromone trail decreases with increasing distance.

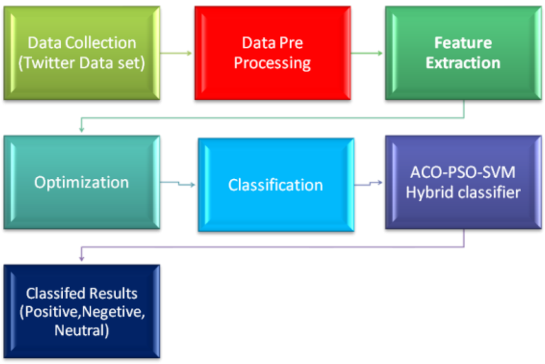

Figure 2.Block diagram of the proposed system

3.5.3 HYBRID ACO-PSO ALGORITHM for Emotion Detection Based on Social Media Data:

The hybrid ACO/PSO approach combines particle swarm optimization & ant colony optimization to boost efficiency and precision. Swarming intelligence is a novel and well-known approach to solving difficult issues. ACO and PSO are the two top swarm intelligence algorithms. We offer a combination of algorithms called ACO-PSO.Dr. James Kennedy and Dr. Eberhart, who developed the PSO idea in 1995, developed a new optimization strategy that outperforms the traditional ACO-PSO method. The PSO method is a swarming strategy, like that used by animals such as birds and fish. Problems with optimization can be overcome with the use of a flexible and adaptable algorithm. An initial population is generated by PSO through a search in which every living thing or particle moves to a new location at regular intervals. In the PSO system, particles can move about. Particles make decisions on where to settle depending on their own past experiences and those of their neighbors. Particle has, in the opinion of both itself and its neighbor, located the optimal location. Therefore, PSO is a global as well as a local search method.

In the first step, we use a GA (Genetic Algorithm) to generate a population of particles.

1. Start : create a new population and execute
2. Compute the fitness value using the e particle's function.
3. Apply to the particles the three phases of selection, crossovers, and mutation.
4. In the end, an estimated population can be created..
5. If the criterion is met, end; otherwise, proceed to Step 2.
6. The final population data will be sent to ACO-PSO.

Second, the ACO-PSO hybrids algorithm:

Ant Colonyoptimization Algorithm

a. GA provides the final population.
b. Set up a starting point for the heuristics.
c. Turn on the artificial pheromones.
d. Do if halting condition is not met
e. For Output
f. Add Regional Path
g. Pheromone Revision
h. When a local optimal path is found to be more desirable than the global optimal path, we say that it is "global ideal."

Particle Swarm Optimization Algorithm

a) The global distribution of the final population is based on ACO.

b) Determine one's fitness level by utilizing an objective function.

c) If the current location of a particle is superior to the previous best location, it should be elevated to the G best location.

d) The particle's mobility and direction are recalculated.

e) If the desired number of people have been attained then the process ends.

3.5.4 svm classifier:

Here, we provide a brief explanation of what SVM is. The generalized linear SVM solves the following optimisation problem to determine the optimal separating hyper plane (x) =€ w. x +b given a trained set of instance-label pairings (x_i, y_i), i = 1, 2,..., m where x_{ic} R_n and y_{ic} +1, 1.improves a metric that was set as the goal. Two values, x_{id} and v_{id} that, uniquely identify each particle as shown in equations 1 & 2.

$$minimize\ €x.x\varepsilon + D\varepsilon N_{£} \text{-------------(1)}$$

The free variables are denoted by i, while the penalty variable is D. The least-wrong hyper plane in training is identified by support vector machines. Nonlinear SVM uses a mapping function F to map samples used for training from the input space to a higher-dimensional space of features. The Radial Basis Function (RBF) is one of the most popular kernel functions.

$k(x\ ,x) = \ \exp(Y^{-1}\|x - x^2)$ ------------(2)

Test findings and an analysis of our technique are presented and analyzed in this study.[59] First, we'll take a look at what happens when you change the methods for analyzing and looking into data from Twitter. Consequences talks of featured items are introduced in the second stage. Along these lines, we talked about the best results (obtained by the SVM, KNN, ACO, PSO, and NB approaches). The NB, NB-SVM connection yields a bar chart similar to the one shown below, whereby the x-pivot stands for correctness, review, and accuracy, and the y-hub for frequency.

4. Results:

The effectiveness of both the present study and previous research is evaluated through a series of experiments. Devices with a Core i7 processor & Python programming languages were used throughout the model's creation. The NLTK and Gensim [38] libraries are used during pre-processing and word embedding. Keras [39] & Tensor-flow [40] are used to develop models for machine learning. The created model merges the helpful tweets utilizing the gensim with Keras functional application development interface. The confusion matrix is used to calculate the necessary parameters for evaluating the efficacy of a Hybrid Machine Learning (ML) classification system. This methodology can be used to assess a procedure's efficacy. Error matrices, special tables with the format depicted in Figure 3, can be used to illustrate the efficacy of an algorithm. Total probability (TP), total probability (TN), final probability (FP), and final probability (FN) are the four parameters represented by this equation. This equation represents four different kinds of probabilities: the total likelihood (TP), the total likelihood (TN), the final likelihood (FP), and its final likelihood (FN).

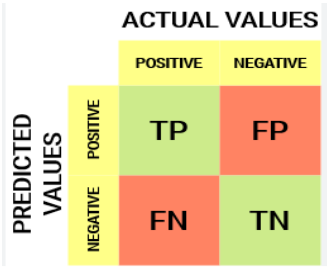

Figure 3.Confusion Matrix

4.1 Performance Metrics:

The model is tested using precision, recall, precision, accuracy, and F1-Score. Specificity, the false positive rate, and the rate of false negatives are additional measures used to evaluate performance. Accuracy measures how well the predicted research does in comparison to actual studies. The parameters of the metrics are indicated by the following notations.

P: True positive Q: False Positive R: True Negative S: False Negative

- **Precision (P):** It produces accurate predictions from all expected occurrences. It is quantifiable, as seen here.

Precision= P/P+Q ------------- (3)

- **Recall (R):** It is a choice of the most relevant events from all relevant occurrences. It is quantifiable, as seen here.

Recall=P/P+R ------------- (4)

- **F1-Score**: The F1 Score correlates recollection and accuracy as depicted below.

F1-Score= (2*P*R) / (P+R) --------------- (5)

- **Accuracy:** It provides an accurate representation of instances over a specified collection of instances.

Accuracy= ((P+S) / (P+Q+R+S)) --------------- (6)

Among the many available options, those based on machine learning are rapidly gaining popularity due to their superior accuracy in identifying spam. Support vector machines, Bayesian clustering using k-means, choice trees, and neural networks are only few of the methods used in these approaches. Many existing machine learning-based solutions rely on either SVMs (support vector machines) or NBs (naive bayes). When it comes to spam filtering, an SVM-based solution typically has significant advantages in accuracy, precision, and recall rate, but it is slow and requires a large training set. In contrast, a naive Bayes-based solution is typically faster and requires a smaller training set, but it provides less accuracy. But in terms of spam filtering, these current options are either too sluggish or too wrong. Therefore, due to inadequate accuracy, some spam messages are unnoticed, and others are caught slowly. Results are gathered by using the current NB, SVM, NB-SVM, SVM-PSO, SVM-ACO, and the proposed ACO-PSO-SVM algorithms to the Twitter data set. Table 3 displays the results of our comparisons of the current NB, SVM, NB-SVM, SVM-PSO, and SVM-ACO algorithms with regard to the aforementioned four parameters.

Table3 Results of Applying Various Algorithms on the Twitter Data set

Parameter	**NB**	**NB-SVM**	**SVM**	**SVM-ACO**	**SVM-PSO**	**ACO-PSO-SVM**
Precision	58.63	61.52	72.59	83.56	84.56	87.82
Recall	49.56	56.57	86.45	91.75	93.46	95.45
F1-Score	72.56	76.45	82.45	89.45	92.43	96.85
Accuracy	81.52	83.45	86.45	92.42	94.56	97.89

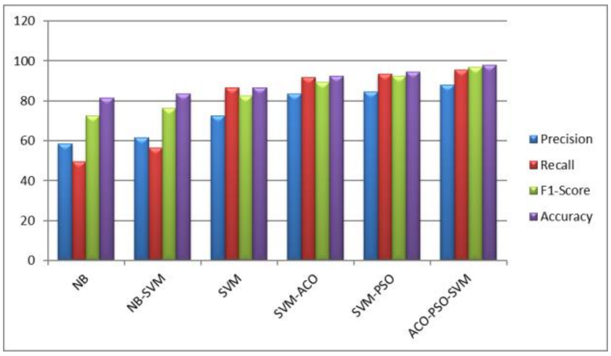

Figure 4. Evaluated Results of all the algorithms.

The results presented above show that our suggested ACO-PSO-SVM algorithm outperforms the existing conventional and Hybrid algorithms across the board, as we determined by comparing our work to five existing algorithms. Our ACO-PSO-SVM algorithm outperforms its counterparts by a factor of 4% compared to SVM-PSO, 7% compared to SVM-ACO, 10% compared to SVM, 12% compared to NB-SVM, and 15% compared to NB methods. There is now a substantial amount of potential for improvement; therefore a special kind of composite Model requires more research.

5. Conclusion:

Depression is a serious mental condition affecting people of all ages all over the world. Patients with Depression disorders are less likely to provide feedback during clinical procedures. With the rise of the internet and the prevalence of social media sites like Twitter, it is now possible to detect depressive symptoms online. Text analysis is currently revolutionizing the monitoring of the underlying patterns in the shared text, which aids in disease diagnosis. In this study, we use a hybrid machine learning method to grade stress, sadness, and anxiety on a five-point scale. People are capable of holding both optimistic and pessimistic worldviews. The Element of speech function is widely used in computational linguistics to determine the author's intent from textual input. In this study, a number of methods are used to the dataset, including the effective values of NB, SVM, NB-SVM, SVM-ACO, and a classifier that discriminates based on SVM. Both SVM-ACO and SVM-PSO perform well, but the results demonstrate that SVM-ACO-PSO is superior, with an accuracy of 97.89 percent. This occurs because SVM-ACO-PSO iteratively modifies the edge if the weight varies across boundaries. Parameter selection in an ACO is intended to be based on robust particles search instead of artificial experience, and PSO is used to improve these characteristics. ACO helped us figure out which of several possible ant routes was the quickest overall. Better performance metrics for massive datasets can be attained with the use of alternative methods. Multiple extraction methods can be combined to produce a more robust feature collection for use in classification.

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