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Unveiling the Emotional and Psychological States of Instagram Users: A Deep Learning Approach to Mental **Health Analysis**

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Abstract: People can now communicate with others who have common tastes to them and engage in conversation together while furthermore exchanging ideas, photos, and clips that convey their emotional states due to social media's technology. As a consequence, there is an opportunity to investigate person sentiments and thoughts in social networking sites data in order to understand their viewpoints and sentiments when utilizing these digital platforms for interaction. Utilizing social network data to diagnose depression has gained extensive acceptance, there is still a number of unidentified characteristics. Due to its potential to shed light on the forecasting model, model complexity is crucial for facilitating communication. For example, the majority of algorithms for machine learning produce results in the automatic depression forecasting test that are challenging for people to understand. In this research the mental health condition is analyzed using deep learning approach by considering the data from Instagram data. In this investigation, researchers created the Hybrid deep learning approach, which divided the sentiment ratings into different categories: Neutral, Positive, Negative. Researchers also contrasted the performance of the recommended approach with other machine learning algorithm on a number of criteria, including accuracy, sensitivity, F1 score, and precision.

Keywords: Mental health; social media; depression; hybrid deep learning.

1 Introduction

The Internet is crucial in adapting and frequently reshaping communication to match our evolving social and economic demands. Researchers can find satisfying outlets in many aspects of life by chasing knowledge, expanding their horizons, buying, socializing, and more thanks to the practical qualities of the Internet. The realm of human connectedness is defined by social connections that are established and sustained in virtual worlds, and its boundaries are expanded. They support the capacity to completely take part in community life and improve overall wellbeing by enabling us to meet and interact with many people, strengthen the feeling of "belonging" to a bigger social group, and bring to light problems that might had before neglected or had just a passing interest throughout [1]. Communicating with former acquaintances, family members, coworkers, and individuals with like interests is becoming a common activity all around the world. Social media improves communication among nonprofit final users and providers as well as public awareness of social problems. Members of particular special interests are also given access to pertinent information and updates about upcoming shows, and involvement in local communities is increased. Researchers pay particular attention to differences social media platforms that enable individuals to communicate with one another based on shared interests, particularly when face-to-face connection is difficult or impossible. Engaging in social media is simple, and it eliminates the difficulties of physical engagement for people who have mobility issues due to age or economical limits due to parenthood, long workdays, or lesser money [2].

Youngsters utilize social media in a way that is distinctive nowadays. Youth now have a platform thanks to digital platforms to create social networking sites or other types of relationships. Young people are today's biggest consumers of digital merchandise and services, which step in conducting them to become hooked to them. Financially rewarding

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technological devices are drawing their interest. The wide-ranging and potentially harmful effects of using social media on one's mental health and well-being have indeed been determined to be especially susceptible in young people who are not yet smart sufficiently discriminate between fiction and reality. Additionally, frequent use of social media cuts down on the amount of time available for activities that are beneficial for users' psychological and physical well-being in addition to spending time with their family [3]. A broad category of participatory Internet-based apps that enable the production and distribution of user-generated material is referred to as social networking. For the majority of adolescents worldwide, online sites such as Facebook and YouTube are indeed a daily part of their lives. According to a global poll, those under 30 were much more inclined to utilize social media as people older than 50. Additionally, over than 60 of mobile phone users reported that they frequently browse social networking sites while using their devices. Social media is being used more and more by professionals in social services. Online Youth Advocacy in the UK, for example, began providing social media services in the UK and Flanders in 2010. Throughout 2011, the Hong Kong Special Administrative Region's Social Welfare Department (SWD) has provided funding to Non-Governmental Organizations (NGOs) to test out digital youth awareness campaigns. Additionally, social work professional organizations have created guidelines for moral social networking use, including the Australian Association of Social Workers (AASW) and the British Association of Social Workers (BASW) [4]. One of the most significant catastrophes of the contemporary era is the ongoing COVID-

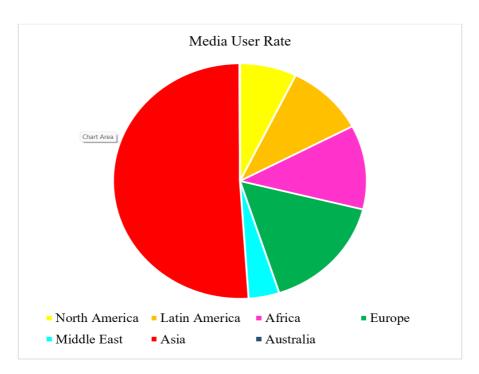


Fig. 1: Social Media User rate.

19 pandemic. COVID-19 is a straightforward infectious disease that can be contracted by touching, coughing, sneezing, or communicating to an infected person. Owing to the conflicting information that has been broadcast on social networks, it is now thought to be a new cause of tension, despair, and worry for folks. The spread of misleading information about COVID-19 through social media has a direct impact on an individual's mental health [5]. People who received a positive diagnosis perished as a result of the panic brought on by inaccurate stories spread on social media. The government enacted new laws (stay at home and social isolation) and placed limits on people's movement freedom in an effort to stop the disease from spreading. The main way to communicate with the world at large in this circumstance is through the internet. Fig. 1 illustrates the rise in internet usage during the coronavirus. Everyone utilizes the internet to their greatest advantage, including those who work from home and they all read the coronavirus-related content that is shared through social media [6].

According to Chakraborty et al [7] estimation, 11% to 27% of the burden of handicap in Europe is attributable to psychological disorders, and mentally and drug use problems constitute the primary source of years spent living with a handicap globally. Our understanding of these issues of mental health remains more restricted than it is for many physical



disorders, as patients may return even after receiving effective therapies or show resistance to several therapies. The majority of mental illnesses manifest in childhood, interfere with learning, and can last a lifetime, resulting in handicap when some of those afflicted would otherwise be when they are most productive. According to statistics from the UK, 17% of adults get a low current prevalent mental problem, and up to 30% of folks with nonpsychotic prevalent psychiatric abnormalities also exhibit switching frequency psychotic symptoms, indicating that a substantial chunk of mental disorder goes undiagnosed despite having a significant negative influence on their lives. Patients with problems that fulfil diagnostic standards are either managed in primary care settings or by mental health professionals [8].

Recent times have seen a substantial rise in the utilization of social networking monitoring to investigate a wide range of health-related issues, from identifying flu epidemics and cardiac arrests to investigating emotion and disorders of the mind. The study of mental illnesses like depression has completely embraced the prevalence of social networking sites, wherein users can freely and openly express their thoughts, views, sentiments, and daily struggles with mental wellbeing. The present survey-based methodologies that could help both government and non-governmental groups in policy formation can be supplemented with information from social networking sites, like Twitter, YouTube, Instagram, Facebook [9]. The textual and visual content shared on social media sites like Twitter offers new opportunities to understand those who exhibit despair both in private and in public. For instance, the news article "Twitter Fail: Teen Sent 160 Tweets Before Going to commit Death & No One Helped" highlights the need for improved machinery for trying to extract informative information from consumer subject material published to socioeconomic online services that could aid policy developers in providing advantages for individuals with depressive symptoms. In addition to the traditional social science procedure of evaluating hypotheses, latest studies have produced data-driven breakthroughs. They claim that the usage of language, emotion, user behaviour, and interaction in social media messages can help predict the chance of melancholy [3].

This rise has raised questions about a possible connection as it has occurred at the same time that social media has becoming widely used. Additionally, as a child gets older, their utilization technologies usually increase, with teenagers utilizing social networking sites in particularly and new media in general more frequently and at greater percentages than youngsters. One of most popular social media networks right now are YouTube (80%), Instagram (75%), Snapchat (70%), and Facebook (55%), with well almost all teenagers between the ages of 13 and 17 using them [10]. Even so, developer kits are often initiated, and some—like TikTok—quickly garner attention between many teenagers. The impact of social media on people is graphically represented in Fig. 2 below. From 2012 and 2015, the rates of depression in men and women increased by 21% and 50%, respectively. By 2015, 92% of teenagers and young adults owned cellphones. However, depressed symptoms increased along with the use of feature phones. A 2017 poll of students in the eighth through twelfth grades found that there was a 33% increase in the number of high symptoms of depression during 2010 and 2015. Girls' suicide rates in this age group increased by 65% [11]. learning (ML) approaches such the decision tree, k-

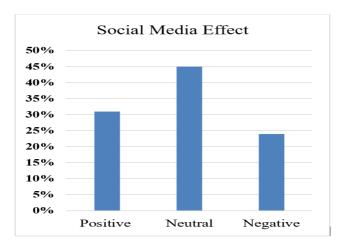


Fig. 2: Social Media Effect.

nearest neighbors (KNN), multi-layer perceptron (MLP) fuzzy logic, and support vector machine (SVM). Constant patient tracking, meanwhile, produces a lot of medical data, including sensed data, patient characteristics, hospital information, lab results, and doctor's notes. Big data refers to the enormous growth in social networks and patient records in recent years (both unstructured and structured). Conventional means and Machine learning algorithms might not be able to



manage these data sufficiently to extract useful information or detect abnormalities. Additionally, till this analysis was conducted smartly in real time, they might not be of much use to the health industry. This calls for a massive data cloud infrastructure and a sophisticated deep learning methodology, like long short-term memory [12]. The key contribution of proposed research is mentioned as follows:

- -To develop a structural approach that can identify sadness from user data gathered through social media networks.
- -To divide the sentiment rating into specified categories.
- -To define the mental health performance using optimized deep learning model.

Section 2 define the related works based on mental health problem due to social networking sites and impact of social media in day today life. Methodology section is presented in Section 3. Section 4 presents the result and discussion. Finally the main finding of the paper is concluded in section 5.

2 Related Works

The determination of the project is to progress a technique for analyzing platforms on social media for melancholy and poor mental wellbeing. However, for the study and treatment of depression. Psychologists are chosen over computers since they can manipulate people 's feelings and are more sensitive to them. Machine learning does have an extra benefit. It doesn't feel anything; it doesn't study faces or beauty or even other things; it analyses trends. It analyses a wide range of data, trains, and then accurately predicts. Both it and physicians are not entirely dependable. Additionally, implanting ML depression recognition processes in social media along with suggestion processes to cure a human psyche optimistically while still being undetectable is a tremendous boost to human civilization, especially in countries like India in which folks do not really cure depressive episodes as a serious disease or even recognize it to be an ailment of any kind. Documents retrieved from individuals who have given their approval and who have had their data preprocessed are helpful to the research. For the finest data gathering, a variety of machine learning techniques are applied. A VAPID Technique is created that outperforms a traditional feed-forward neural network significantly. In order to spot a recurring trend, this research aims to establish a correlation with depressive characteristics and individuals. Additionally, the goal is to draw the conclusion that digital networks might be a brand-new, superior approach for studying melancholy and understanding oblique patterns, benefiting many people's lives. The primary constraint on the outcomes is the absence of a database as a consequence of Instagram's Application programming interface being discontinued by Facebook after it had acquired it. It was quite difficult to obtain datasets and carry out studies because each single entity had to give permission for this study to use its Instagram profile details. A method on investigating the Social media websites contribute to sadness and mental health issues utilizing predictive technique was proposed [13].

The research is based on the post that the user shares in the social media to express their feelings such as anger, happiness, sadness etc. In this research, a deep learning algorithm was created to determine a user's psychological condition using the information they posted. Researchers gathered articles for this purpose from Reddit forums dedicated to psychological health. Our suggested model may correctly determine whether such a user's post is associated with a certain mental illness, such as melancholy, anxiousness, bipolar disorder, borderline character dysfunction, mental illness, or autism, by evaluating and understanding posted content published by account holders. Depending on their posts, researchers think the algorithm could help us pinpoint those who could be suffering from mental health. The implications of the approach, that could be utilized as a complement to evaluate the conditions of mental health of those who regularly use social networks, are also discussed in this paper. Numerous variables that could have an impact on the classification techniques were not considered in the proposed investigation, including social economic and geographical differences. Upcoming research that could enhance the deep learning networks' precision or efficiency could take these elements into account. From the user content on social media an approach on identifying the mental illness using deep learning model is suggested [14].

One of the main causes of disabilities in the society, schizophrenia is a serious psychological condition. Yet, due to misdiagnosis, self-denial, and social stigma, numerous schizophrenia episodes go undiagnosed. Social media has made it easier for people with illness to communicate their struggles with mental illness and look for assistance and therapeutic choices. By examining social network members' social platform messages, this research aims to see if machine learning could be employed to accurately identify symptoms of schizophrenia in them. In order to achieve this, researchers gathered post from the social networking site Reddit that discussed schizophrenia as well as postings for the comparison group that didn't have anything to do with psychological health (such as those about parenthood, partnerships, comedy, wellness, and education). From the comments, researchers gleaned language characteristics and subject matter. In order to find linguistic indicators of schizophrenia, researchers categorized posts as pertaining to schizophrenia utilizing supervised machine learning and analyzed key aspects. To identify a consistent semantic word representation in schizophrenia, researchers used unsupervised classification on the characteristics. Ultimately, researchers discovered that the best way to identify schizophrenia was through cohesive semantic clusters of words. Our research suggests that utilizing machine learning



methodology, we may be able to recognize people with schizophrenia or even other risk factors in social media writings and understand better the language traits of this disorder. The research's main limitation is that it raises the possibility that utilizing NLP and ML techniques, it may be possible to identify people who have psychosis or who are others at risk of developing it using social networking writings. Thus, the research Schizophrenia detection on social media content using machine learning approach is proposed [15].

The communication habits of people are changing as a result of rapid technology improvements. Social media sites like Twitter, Facebook, Telegram, and Instagram have grown in popularity as attractive destinations for individuals to express their thoughts, emotions, and mental behaviour. Language is analyzed psychologically such that facts, characteristics, and important data can be gleaned from it. Users' perspectives social media networks are a valuable resource for psychiatric analysts who use them to spot depressive-related behaviour and activities. Social networks offer a wealth of information on a person's mental states prior to the development of melancholy, including low sociability, hospital attention, a focus on oneself, and a higher incidence of activities. Social media provide a wealth of information on a person's pre-depression mentality, including low sociability, a focus on itself, and high levels of physical activity both throughout the daytime and at nighttime. In this study, we investigated how to identify melancholy in twitter using different machine learning classification algorithms decision trees, support vector machines, logistic regression, K-nearest neighbor, and long short term memory. Technical research on sampling approaches is done using the database, which is obtained in two ways: even and uneven. According to the findings, the Long short - term memory categorization model performs better than the other base algorithms in the depression diagnosis healthcare strategy for both even and uneven data. In the upcoming years, researchers could be able to measure depressive episode and everyday activities, which will enable more precise analysis of depression. Researchers can develop a hybrid algorithm that will more precisely detect melancholy by combining LSTM and Support vector machine which will help individuals all around the community. This is considered as the major limitation of the research on depression analysis from social media networking sites [16].

With the development of various social networking platforms, anyone may now quickly generate, communicate, and communicate their thoughts, emotions, opinions, and thoughts with thousands of other individuals around the world. Mini processors and smartphone have entered human pocket as a result of technological advancements, and it has become quite simple to share your thoughts on any topic on social networking sites like Google+, Twitter, Facebook, Wikipedia, Instagram, LinkedIn, etc. The usage of social media platforms is increasing, and they are utilized for a variety of reasons as a result of the rapid development in population and telecommunication technologies over the past ten years. Nevertheless, one product whose utilization might be examined is a post-diagnostic evaluation of individuals who have been given a depression diagnosis. In this study, we show how to watch and extract sentiments from text on several social media platforms to assess a person's level of depression using emotion theories, machine learning techniques, and natural language processing techniques. This approach uses different algorithm to gain better result but the outcome predict that the accuracy of each algorithm is less than 80% which is one of the drawback of the research [17].

2.1 Problem Statement

Based on the literature analysis several problems were identified on predicting the mental health problem due to social media network which are mentioned as follows. Some studies fall short in their attempt to evaluate user tweets while concurrently taking subjects and attitudes into account in order to assist each Depression [18]. To recover phrases and words from more categories of emotional traits, researchers intend to employ a different technique [19]. Additionally, researchers intend to employ more information to confirm the effectiveness and productivity of the strategies. Researcher concur with the corpus of research already in existence that implies that further targeted research in depression analysis are required [11]. A certain architecture does not take into account the multimodal data, such as videos, emoticon, photographs, etc., which may be incorporated with the aforementioned model to enhance the system's overall functionality [20]. By considering all this drawback researcher proposed a deep learning model integrated CNN with Spider monkey-firefly optimization to analysis the mental health on using Instagram data.

3 Materials and Method

In order to identify and analyses depressed received information as Instagram posts, researchers first concentrated on four sorts of characteristics, including emotional experience, temporal processes, language style, and all aspects combined. Then, using deep learning, researchers examine each type of element separately. In this essay, sentiment classification has been studied using Instagram-generated data. Researchers categorized the sentiment scores as positive, negative, and neutral using Hybrid deep learning model. The following Fig. 3 shows the proposed model on analyzing the mental health.



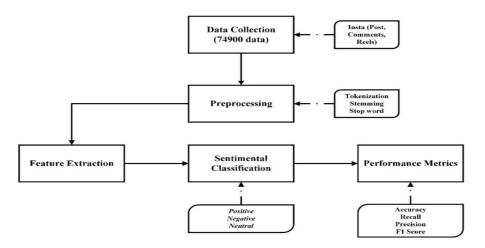


Fig. 3: Proposed Model.

3.1 Data Collection

The Click worker crowdsourcing platform, which rewards involvement with financial compensation, was predominantly used to find individuals for this study. The survey, which could be accessed online, was open to anybody who was 18 years or older, while some respondents were found through other channels, such term and social media marketing. Since traditional marketing techniques weren't as effective and took too long to draw people, researchers opted for Click worker. Because of their unique rules regarding the posting of social media messages on these platforms, other crowdsourced apps like MTurk were not utilized in this research. Around 74900 dataset is collected from Instagram in which 10000 is used as testing data and 64900 data set is used as training set as shown in table 1.

Table 1: Data Collection.

Training set	Testing set	Total
10000	64900	74900

3.2 Preprocessing

Objective research and sentiment classification utilizing this method simultaneously demand for pretreatment in order to remove attributes from raw user input and making it employed by deep learning algorithm. Each item in the dataset is subjected to tokenization, function word deletion, and lemmatization by the algorithm. In this stage, the paragraphs are first divided into phrases, and the phrases are then tokenized into keywords. The word vector is then cleared of the stop words. Stop words are terms that are frequently unnecessary and lack considerable significance, such as "the", "much", "under", "over", "in", "from", "on", and "so" forth in the English language. Researchers apply stemming, or locate the roots of the terms, to the unused phrases [20].

3.3 Feature Extraction

The ability of a term or cord of words to constitute a feature is relevant to the question of how to identify characteristics in textual content. Adjectives, adjectival terms, pronouns, and adverbs are the primary methods to the issue of features extraction, along with a collection of words, a bag of ideas, lexicon-based data, and dictionary-based information. Here are a few examples of techniques for feature extraction [21].



1.N-grams Feature

N-grams are essentially words, graphemes, groups of words (agreed and strongly agreed, character segmentation, and more), or phenomes that occur together in a text document or language sequences.

2.Part of Speech

A word or phrase Software known as a "tagger" reads material in a language and classifies each word's components of speech, such as adjectives, verbs, adjectives, etc.

3. Negation

Negative words, such as not awful and not decent, could transform a word's sentimental meaning from negativity too optimistic as well as from optimistic to affirmative.

4. Sentiment Analyzer

Negative and positive word sentiment in a particular document is analyzed by a sentiment analysis tool. Wonderful, for instance, conveys a sentimental orientation toward the good.

3.4 Hybrid Firefly-Spider Monkey Optimization

Given that each optimization model has a unique set of advantages and disadvantages, a hybrid that incorporates them would offer greater dependability and adaptability in handling challenging problems. A hybrid algorithm (HFFSMO) that uses the Firefly and Spider Monkey optimization methods is described in this part. The following list of SMO and Firefly algorithm fundamentals: Explanation of the hybrid technique that may be employed to integrate these two techniques [21].

A new stochastic optimization strategy called the Spider Monkey Optimization (SMO) approach was introduced. It takes inspiration from nature. SMO has been deemed to be the most advanced in the field of particle swarm approaches. According to the group of animals with a fusion and fission social structure, the word "spider money" relates to a type of monkey. Frequently spotted in groups, these spider monkeys engage in deft hunting techniques to locate food. By sharing pertinent information to other team members, they facilitate food gathering in a variety of ways. Inspired by the advanced food-seeking strategy used by spider monkeys, this optimization technique is implemented [23]. The evacuation zone (the whole hosts, set of data centers, and virtual machines (VMs)) of the optimal solution is represented by the region where the spider monkeys go in quest of prey (source preparation problem). Each answer depicts the position of the spider monkeys in the food-finding area (the subcategory of hosts or VMs that may be allocated to errands). The swarm is a collection of tools (a subdivision of hosts or VMs) that can aid in efficiency improvement. The health of a system is related to how nearby the spider monkey is the cause of food (the fitness value reflects the accessible of host or VMs at a given time depending on the number of activities entering the Hadoop optimization technique) as shown in Fig. 4.

1- Initialization

During the initiation phase, SMO creates a starting colony of M spider monkeys that are arbitrarily distributed, where SM_u represents the spider monkey that is uth in the colony. Each SM_u is configured in following eqn. (1):

$$SM_{u,v} = SM_{min(v)} + P(0,1) \times (SM_{max(v)} - SM_{min(v)})$$
 (1)

 $SM_{min}(v)$ and $SM_{max}(v)$, accordingly, serve as the low and high limits of the penetrating region in the jth axis, while P(0,1) is a random variable evenly distributed throughout the range (0,1).

2- Local Leader Phase (LLP)

The Spider Monkey Optimization method utilizes this as a crucial phase. Here, every spider monkey gets the chance to develop their abilities. According to the findings of a spider monkey's local teammates and commander, the spider monkey's posture has already been modified. Each SM workout value is computed at its different extreme, if it is greater than the preceding one, the spider monkey is promoted; if not, the spider monkey is not updated. The renewal formula is the level after that and the newly formed eqn. (2) is presented below:

$$SM_{new(u,v)} = SM_{u,v} + P(0,1) \times (ff_{q,v} - SM_{u,v}) + P(-1,1) \times (SM_{wv} - SM_{u,v})$$
 (2)

where SM_{wv} is the jth size of an arbitrarily chosen Spider Monkey from the kth category with r not identical to $ff_{q,v}$ is the jth aspect of the local leader of the kth group, $SM_{u,v}$ is the ith SM's vth aspect, P(-1, 1) is an uniformly allocated arbitrary integer in the region (-1, 1), and so forth.

3- Global Leader Phase (GLP)

The alternatives are modified in line with how the activity affects the probability of picking once the technique has passed the local leader stage and entered the global leader stage. It is possible to assess fitness using the optimization technique a_u and the eqn. (3) that ensues.

'fitness function
$$(Au) = \begin{cases} \frac{1}{1+a_u} & \text{if } a_u \ge 0\\ 1+ab(a_u), & \text{if } a_u < 0 \end{cases}$$
 (3)



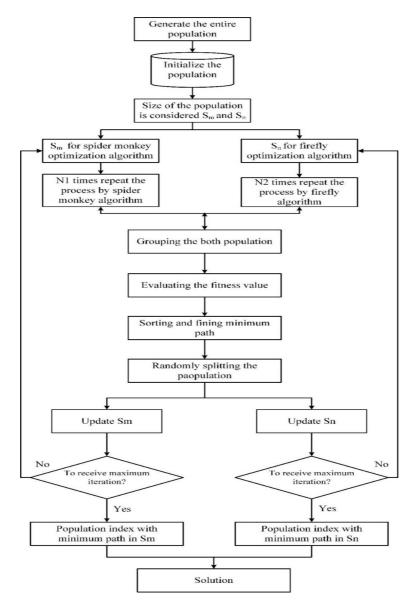


Fig. 4: Spider Monkey-Firefly Optimization.

The firefly technique is one of the most recent heuristic solutions for optimization problems. The system takes its cues from the flashing patterns of fireflies. The technique treats randomly generated solutions as fireflies, and intensity is distributed according to how successfully they solve the optimization issue.

The phosphorescence activities are what cause fireflies to glow. Different theories exist concerning the significance of flashing light during the firefly's courtship period and the reasons why it occurs. The primary goal of lights flashing is to reach prospective mates. Depending on the rhythmic of the sparkles, the pace of lighting, and the length of time about which flashing are recorded, each of these repetitive flashes has a specific pattern [18].

For particular jobs, it has been demonstrated that the SMO system integrates more quickly than alternative methods. As a result, it can decelerate quickly as it enters the globe performance in comparison. The probability of becoming trapped in the region of global optimization rises as the method continuously integrates with the globally suitable location. The SMO method's dependency on search parameters is yet another flaw. Based on the options made, the substrate concentration may change. The SMO approach has undergone numerous modifications to increase its efficacy, with the main goal of balancing the innovation aspects. Among some of the suggestions are tweaks to the development technique, adjustments to the parameters, adjustments to the upgraded requirements, and the introduction of enhanced emerging methods. It has

been demonstrated that the Firefly algorithm is much more efficient and has a bigger rate of performance in multipurpose scenarios than the SMO, despite the fact that the FF's methodology somehow doesn't take acceleration into account. The hybrid firefly and spider monkey optimization algorithm (HFSMO) aim to utilize the most advantageous aspects of both approaches. The SMO techniques will help with exploration, while the FA will manage search strategy [24]. The parameter will be continuously altered in the interim. The first stage in HFSMO phase is initializing all variables. After that, random parameter is assigned to component positions and speeds. The fitness, global best (G_b) , and personal record calculations come next (P_b) . At a later time, the subatomic particle vitality and past recombine would be assessed. All firefly' and particles' maximum velocities are investigated. When the workout number reaches the desired level and the end outcome is made public, the process has been completed.

$$R = \left(\frac{R - R_u}{iteration (max)}\right) \times iteration \tag{4}$$

3.5 Hybrid FF-SMO-RNN based Sentimental analyzer

The suggested FF-SMO-RNN hybrid classifier model's description is thoroughly covered in this section in order to analyze the mental health issue using Instagram data. The suggested model is illustrated in Fig. 5.

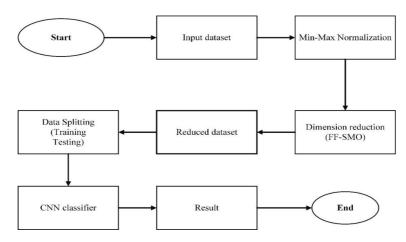


Fig. 5: Hybrid FF-SMO-RNN.

The suggested FF-SMO-RNN hybrid classifier model's processing consists of the steps listed below:

1- Data Selection

The suggested FF-SMO-RNN hybrid classifier's first step is dataset selection. We looked at datasets from Instagram. The suggested FF-SMO-RNN hybrid system is used to demonstrate how to forecast mental health problems using the common classification approach.

2- Minimax Normalization

By comparing and contrasting the pieces of data for the dimension, machine learning methods are employed to uncover trends in the database. A fundamental problem when attempting to employ machine learning is that certain dimensions have vastly different sizes. In this study, the various scales of the dimensions are reduced using the min-max normalization. By applying a linear modification to the original information, normalization modifies the data in a certain limited range. Applying min-max normalization, the dimensional elements of the dataset are normalized within the interval [0, 1]. The data are transformed by the following eqn. (5) by the min-max:

$$s = \frac{x - min_a}{max_a - min_a} (tran \underline{\ max_a} - tran \underline{\ min_a}) + tran \underline{\ min_a}$$
 (5)

where s is the data point x in dimensions a's converted value, max_a is the dimensions a's original largest value and corresponds to the original threshold level.

Correspondingly, the terms $tran_min_a$ and $tran_max_a$ correspond to the converted maximum and minimal values of the dimension a, respectively.

3.6 Dimension Reduction (FF-SMO)

The FF-SMO optimization algorithm is used in this step to reduce the input dataset's dimensions. FF-SMO is a combined iterative method that draws on the fission-fusion social structure (FFSS) of animals, specifically the foraging behaviour of spider monkeys. Numerous studies have created methods that use deep neural networks instead of standard dimension decrease methods or extraction of features. The models over-fitting issue occurs when the number of variables in the CNN training stage is excessive [25]. The suggested model takes advantage of the spider monkey optimization method, an FFSS behavior-based approach used for lowering the number of parameters, in order to deal with this problem. The least number of extracted characteristics and the highest accuracy or lowest error rate make up the optimum dimension set. Segmentation technique is typically subject to objectives situations in order to minimize the dimension count and maximize the classification precision or decreased error rate. Getting the best results was challenging due to trade-offs between competing objectives. Therefore, it is impossible to explain this situation effectively under several limitations with a single goal. It is imperative to use a multi-objective optimization strategy in this case to minimize or maximize the collection of optimization methods [22].

3.7 Classification

The process of analyzing a phrase or word's emotion is known as sentiment classification. The major techniques for sentiment classification are two. Using the dictionary, where every other word is denoted by a number value as polarity, is one approach. The next technique is deep learning, which uses statistical techniques to determine a word's variable length value via language model. There were two distinct jobs for the automatic classification of Instagram data. The first step was to determine if the posts were connected to mental health or not. The second task was to classify the manually specified and mechanically analyzed concepts in order to identify which category the post falls within (multiclass category) [26]. The outputs of the Convolutional Neural Network (CNN)-based technique are the focus of the findings shown here, as it constantly produced the best forecast. Researchers employed identical, 80/20 training-test splits across the whole set of data for all classifications' development and evaluation, and researchers present the findings for the testing dataset. The Research methodology provides additional information regarding the classifications and parameters.

With the help of CNN sentiment analysis, we were able to categories the Instagram data according to its sentiment scores. The experiment considers Instagram data for a sample of 20, 50, and 250 posts. Bar charts are used to display the acquired results. It has been noted that a sample of 250 posts, divided into positive and neutral ones, is presented in Fig. 6.

4 Result and Discussion

Utilizing Instagram's datasets, the proposed method has been tested. The FFSMO-based Convolutional Neural Network is used to distinguish between healthy and unhealthy databases and identify brain cancers. Performance indicators including Precision, Accuracy, Recall, and F-measure are used to assess the demonstration of the suggested model.

4.1 Accuracy

Accuracy assesses how precisely the system model functions. The ratio of accurately anticipated measurements to all measurements is generally what determines mental health. Accuracy is uttered in eqn. (6),

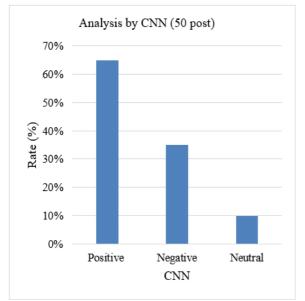
$$Accuracy = \frac{T_{Pos} + T_{Neg}}{T_{Pos} + T_{Neg} + F_{Pos} + F_{Neg}}$$

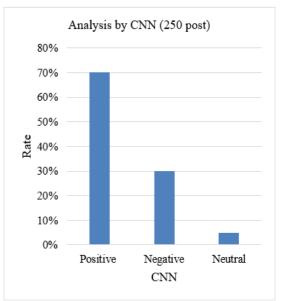
$$\tag{6}$$

4.2 Precision

The number of accurate positive estimates that are disregarded by the total positive estimations is used to estimate precision. The percentage of accurately diagnosing mental health in the afflicted area is determined using eqn. (8),

$$P = \frac{T_{Pos}}{T_{Pos} + F_{Pos}} \tag{7}$$





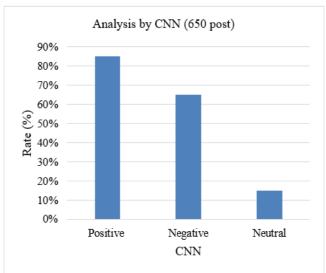


Fig. 6: Post Analysis.

4.3 Recall

The ratio of all true positives and false negatives to the accuracy of correctly predicting positive outcomes is known as the recall. It indicates what proportion of mental health diagnostic predictions made were accurate using Eqn (8)

$$R = \frac{T_{Pos}}{T_{Pos} + F_{Neg}} \tag{8}$$

4.4 F1-Score

Precision and recall are combined in the F1-score measurement. The F1-score metric, denoted by eqn. (9) is calculated using precision and recall.

$$F1 - score = \frac{2 \times precision \times recall}{precision + recall}$$

$$(9)$$



Researchers investigate model characteristics in our studies, such as the mathematical effectiveness of the hybrid model. Researchers would combine the user's timeline conceptual characteristics attribute and the multi-aspect features attribute. Researchers assess the model's effectiveness by categorizing user behaviour in social media and the evaluation of the performance is listed in table 2 and the graphical chart is presented in Fig 7.

Table 2: Performance Evaluation.

Metrics	Proposed Model
Accuracy	98%
Precision	91%
Recall	97%
F1-Score	90%

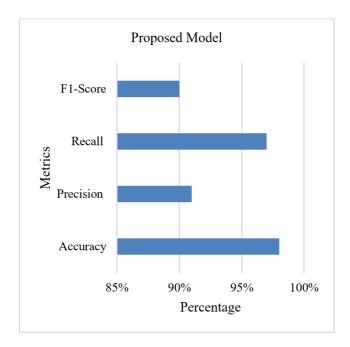


Fig. 7: Performance Evaluation.

The following table ?? shows the comparison of accuracy rate based on different method carried out in predicting the mental health problem on using different social media.

 Table 3: Comparison Evaluation.

Metrics	LSTM	PCA+DNN	CNN	SVM	Proposed
					Model
Accuracy	80%	89%	80%	64%	98%
Precision	82%	88%	81%	72%	91%
Recall	73%	89%	80%	63%	97%
F1	77%	88%	80%	60%	90%
Score					

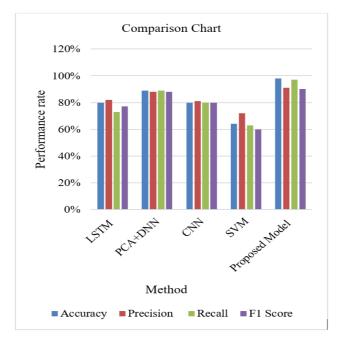


Fig. 8: Comparison Chart.

In the above Fig. 8, the comparison on different method involved in predicting the mental health performance of the people using different social media platform and it is observed that the proposed FF-SMO-CNN method has high accuracy rate when compared to other method like SVM, CNN, LSTM etc.

5 Conclusion

This conversation has highlighted the growing importance of social media in the lives of many people who struggle with mental illnesses. Several of these people utilize Instagram to share their personal stories with mental disorder, ask for help from everyone else, and look for guidance on how to obtain mental health services, find treatment options, and manage symptoms. The research utilized the hybrid deep learning model to analysis the mental health condition of the users and gained better result. An innovative, first-of-its-kind FF-SMO-CNN hybrid classifier model for mental health detection is described in this research effort. When compared to machine learning approach deep learning gained more interest in this topic and accuracy rate is high when compared to other approaches. Finally stated that the Anxiety is caused by influencers' demand on immediate and quick job performances, which is a byproduct of games and social networking sites consumption. The youthful generation of tomorrow expects immediate results from all of their work, and so when they don't get them, they get anxious and concerned.

Conflict of Interest

The authors declare that there is no conflict regarding the publication of this paper.

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