International Journal of Computer Science Trends and Technology (IJCST) – Volume 10 Issue 3, May-Jun 2022

RESEARCH ARTICLE OPEN ACCESS

Mental Health Monitoring Using Machine Learning: A Survey

Maria Ashigha [1], Rasha Shajahan [2], Shifana Abdul Azeez [3], Kashish S Shah [4], Veena K Viswam [5]

[1], [2], [3], [4], [5] Department of Computer Science and Engineering, A P J Abdul Kalam Technological University, KMEA Engineering College - Edathala

ABSTRACT
In the fast-paced modern world, psychological health issues like anxiety, depression, Borderline Personality disorder (BPD), Bipolar disorder, stress, Obsessive compulsive disorder (OCD), Post Traumatic disorder (PTSD) etc have become very common among the masses.Our study aims to conduct a various mental health disorder assessment of the effects of mental health among today's generation.We conducted surveys with users to understand the effects of the psychological health issue on their mental health and well-being. The data were analysed through quantitative and qualitative methods.
Keywords – Mental Health Disorder, Support Vector Machine, Random Forest Tree, Naive Bayes.

I. INTRODUCTION

According to the World Health Organization, fear, anxiety, intense insecurity and increased stress are normal reactions to various types of "threats", as well as in cases where we are faced with the "unknown". In this case, we were faced with an emerging disease, which experts have not yet fully understood, but also with a home confinement, which seems to be endless, without currently knowing exactly when it will occur its coveted ending. Mental health problems are common worldwide including changes in mood, personality, inability to cope with daily problems or stress, withdrawal from friends and activities, and so on. In 2010 mental health problems were the leading causes of years lived with disability (YLDs) worldwide with depressive and anxiety disorders among the most frequent disorders. Mental disorders can have a serious impact for the patients but also for their families, friends and society, since it is difficult to cope with the implications of someone close having a mental illness.

Dealing with a mental disorder can be physically, economically and emotionally demanding. Work impairment is one of the adverse consequences of mental illness and is also the leading cause for hospital admissions. According to the World Mental Health Survey Consortium, the proportion of respondents who received treatment for emotional or substance use problems is much larger in developed countries than in less-developed countries. Nonetheless, the unmet need for treatment of mental disorders is a major problem in both, developed and less-developed countries but being larger in the latter.

The chronic and relapsing nature of many mental health disorders are the rule and not the exception, thus, the need for long-term follow up and assessment methods become essential for patients' symptoms reduction and recovery. Traditional monitoring methods rely on retrospective reports which are subject to recall bias. This approach limits the ability to accurately characterize, understand, and change behaviour in real world settings as pointed out by Shiffmon et al. An alternative to retrospective reports, is the so called Ecological Momentary Assessment (EMA) which allows repeated sampling of thoughts, feelings and behaviours as close in time to the experience as possible in real-life situations.. EMA measurements have been shown to outperform paper and pencil reports in the assessment of some mental states in terms of sensitivity to detect changes. The increasing capabilities of smartphones and wearable devices make them potential platforms for EMA measurements, monitoring mental illness, treatment, self-management and interventions, thus, reducing costs and expanding the coverage of mental health services to larger populations.

Smartphones and similar devices have been demonstrated to have potential in providing mental health interventions. Wearable devices like smartphones, smartwatches and fitness bands , have a vast variety of embedded sensors. These can include communication devices (Wi-Fi, Bluetooth, etc.), inertial sensors (accelerometer, gyroscope, etc.), physiological sensors (heart rate, dermal activity, etc.) and ambient sensors (ambient pressure, temperature, etc.) to name a few. This opens the possibility of multimodal sensing applications in the healthcare domain. By combining the data from subsets of those sensors, it is possible to infer contextual information such as physical activity, location, mood and social relationships; among others. Multimodal sensing settings have shown to produce better results in some applications, compared to single sensor modalities. Knowing the contextual information about a user, can help in providing more fine grained personalized just-in-time services. On the other hand, general solutions do not take into account the individual characteristics of each person. Analysing large amounts of sensor data is a complicated task (if not impossible) to do by hand and this is where machine learning becomes important. By using machine learning methods, it is possible to extract meaningful information from sensor data and use it to continuously monitor the current users' state. It has been shown that mental states can manifest through physiological and behavioral changes. For example, a systematic review states that hypoactive electro dermal response is an established feature of patients affected by depression. In this review the authors also found evidence that monitoring electro dermal activity may be useful to differentiate phases of mood disorders. Based on the evidence that there are associations between physiological/behavioral and mood states, wearable sensors have the potential to monitor mental conditions continuously and in an unobtrusive manner.

II. RELATED WORK

Michael Riegler et al.[1] A survey on the state-of-the-art research works on mental state monitoring with a primary focus on those which use sensors to gather behavioral data and machine learning to analyse these data. Identified key characteristics among the reviewed literature and proposed a classification taxonomy that will be believed that it will help new researchers in this field to understand the overall structure of such systems. Also identified the key phases of mental state monitoring systems starting with the experiment design to deployment. These include key aspects and considerations for the data collection process, data analysis, and machine learning model training and evaluation. And presented some of the research challenges of MHMS and future opportunities to advance the field. Based on the surveyed literature, the application of multimodal sensing technologies along with machine learning methods represents a great opportunity in the advancement of providing mental health care technology tools for treatment.

Katerina Karaivazoglou et al.[2] Experimental results have displayed that the MLP algorithm significantly outperforms the rest of the algorithm's classification performance. Moreover, table 1 and 2 reveals that the MLP classifier is the most suitable for stress and depression prediction according to our dataset. In our point of view, Machine Learning algorithms can be used by physicians to anticipate mental disorders and support patient care. Furthermore, early detection and treatment can help any patient in the early stages of any disease. The application of Machine Learning to mental health has demonstrated a range of benefits across the areas of diagnosis, treatment and support, research and clinical administration. With the majority of studies identified focusing on the detection and diagnosis of mental health conditions, it is evident that there is significant space for the application of Machine Learning to improve other areas of psychological functioning .

Hatoon AISagri et al.[3] Identifying whether a person is sad based on his tweets and Twitter profile activity is defined as a binary classification problem. Although social media certainly has several remarkable features, the demerits are undeniable as well. Because of its widespread use, social media presents a valuable opportunity to improve the data available to mental health clinicians and academics, resulting in a better-informed and equipped mental health field. Furthermore, infectious negative emotions spread through social media have a harmful impact on people, leading to depression and other mental illnesses. So, the tweets posted by the individuals , as well as their social media activity, can be utilized to classify and predict if they are suffering from depression or likely to suffer in the future. Different machine learning techniques are used, and various feature datasets. Data preparation and alignment, data labelling, and feature extraction and selection are just a few of the pre-processing procedures. The SVM (Support Vector Machine) model reduces an enormously non-linear classification problem into a linearly separable problem by achieving optimal accuracy metric combinations. The accuracy of SVM reaches up to 82.5 and F-measure reaches 0.79. Despite the fact that the DT model is thorough and follows logical processes, it can fail when faced with brand-new data. This research might be seen as a first step in developing a comprehensive social media-based platform for analysing and predicting mental and psychological difficulties in users and recommending treatments. The most important contribution of this research is exploiting a rich , diverse and discriminating feature set that contains both tweets text and behavioral trends of different users.

Camellia Sakaria et al.[4] StressMon, a system to detect severe stress and depressive episodes in individuals. StressMon is designed to be a scalable solution that does not require installing specific applications or owning specific devices. Using coarse-grained location data collected directly from the Wi-Fi infrastructure, we extracted features of individuals' routine behaviours and features that sufficiently describe an individual's physical interaction patterns. These features were used in two different models to detect stress and depression, respectively. We demonstrated, via three different semester long user studies involving 108 students at a university campus, that StressMon has an Area Under the Curve (AUC) score of 0.97 (96.01% TPR and 80.76% TNR) at detecting stress using 6-days interval, and an AUC of 0.88 (91.21% TPR and 66.71% TNR) at detecting depression using 15-day intervals.

Nor Safika Mohd Shafie et al.[5] shares about the mental health problems among higher education students. Review on mental health problems among higher education students and the contributing factors give the illustration on what is happening to the student with mental health problems. Moreover, it gives more information on the factors of mental health problems among the students. The most common factors have been identified which are lack of social support, financial problems and a learning environment. Lastly, the supervised learning technique most popular is Support Vector Machine (SVM). SVM has high accuracy between 70% to 96%.

Anu Priya et al.[6] has predicted mental disorders using machine learning algorithms, for determining five different severity levels of anxiety, depression and stress. This study was conducted on a total of 348 participants aged between 20 and 60 years, both males and females, employed and unemployed and with a wide range of responsibilities from household chores to professional duties who were asked to complete a questionnaire. Data were collected using a standard questionnaire measuring the common symptoms of anxiety, depression and stress DASS-21 (Depression, Anxiety, and Stress Scale questionnaire). Following the data collection, the participants' responses were encoded using numeric values of 0 to 3, and the scores were then calculated by adding the values associated with each question. Once the final scores had been calculated, these were labelled according to severity. All machine learning algorithms were applied in the R programming language using R studio version 3.5. The dataset was divided into the ratio 70:30, representing the training and test sets, respectively. Subsequently, five different classification techniques were applied, such as Decision Tree (DT), Random Forest Tree (RFT), Naïve Bayes, Support Vector Machine (SVM) and K- Nearest Neighbour (KNN). And they obtained confusion matrices to all three classes of Stress, Anxiety, and Depression. After that, they calculated accuracy, error rate, precision, recall, specificity. The accuracy of naïve Bayes was found to be the highest. Nevertheless, the results show that the classes were imbalanced. In such cases, accuracy alone is not a sufficient measure, and the f1 score becomes an important measure for determining the best model. The f1 score is a harmonic mean of precision and recall, whose value is higher when both precision and recall are higher. The f1 score of Random Forest was the highest. Random Forest was identified as the best model when F1 score is calculated for all the five algorithms. Due to the fact that this problem produced imbalanced classes, the best-model selection was made on the basis of the f1 score, which is used for cases of imbalanced partitioning.

Nur Hayati et al.[7] Designed system for tracking and monitoring patients with mental disorders by using the IoT LoRa based technological platform. The system consists of a LoRa end device (client side) as the wearable devices attached to the individual patient, the LoRa gateway with a star topology, the local or cloud server and the mobile applications for the relevant medical officers (physiatrist and caregiver). The data communications transmission between LoRa client and gateway sides is operated over the ISM frequency band. On the other hand, the WiFi and mobile cellular network can be utilized for data transmission among LoRa gateway side, server and mobile applications. Discussions have been presented concerning the feasibility of LoRa network performance, power battery and scalability. Those advantages of LoRa are argued to make the proposed design feasible .

Srividya et al.[8] It provides an intuitive understanding of the mental health analysis amongst different target groups. We have developed a framework for determining the state of mental health of an individual. This framework was used to build prediction models. Prior to building models, clustering algorithms were used to identify the number of clusters. The class labels obtained were validated using MOS, which were given as inputs to train the classifier. The experiments have demonstrated that SVM, KNN, Random Forest have performed almost equivalently. Also the use of ensemble classifiers was found to significantly improve the performance of the mental health prediction with 90% accuracy. This work can be extended to include different sections of the society and also categorizing different mental illnesses like anxiety, depression, etc. From the results obtained we feel that the workflow suggested here can be used as a mechanism to perform behavioral modeling of a target population. The use of physiological parameters like electrocardiogram (ECG), respiratory rate could also be included as featured in order to predict the mental state of an individual more appropriately. The inclusion of physiological parameters also adds to the increase in the number of features in the dataset. The interpretation of physiological values and arriving at features could itself be a challenging task. An estimate of the contribution of features can be used to determine the optimal number of features to be used for building the model. Feature subset selection strategies could then be used to select the appropriate features. This would reduce the time taken to build prediction models. The decision of choosing between different models can be done and validated using the LIME package. The framework suggested here could also cater to a wide range of mental illness by including the concept of fuzziness in building models. When there are more categories of mental illness in the target population, naturally it will result in more class labels. In such cases there tends to be more overlap between some class labels. This problem can be addressed by writing fuzzy rules in cases where the overlap is expected. The concept of Deep Learning can be used for very large datasets. The classification accuracy can also be improved using deep learning methods such as recursive neural networks. It also enables us to cater to a much wider community which will result in more data samples.

III. METHOD

A range of steps are involved in developing automatic mental health monitoring systems. In contrast to conventional sensing and monitoring pipelines, mental health apps necessitate a few extra processes due to their nature, including ethical approvals and user authorization for data gathering. Another distinction is that data can be collected both on-site (in a hospital or clinic) and off-site (in a naturalistic setting). Clinical evaluation is essential for mental health applications, as opposed to standard machine learning work flows that may just require review in terms of computer models.

A. Prerequisites

The prerequisites are a crucial part of the procedure. The following are the most significant steps/goals to achieve at this phase:

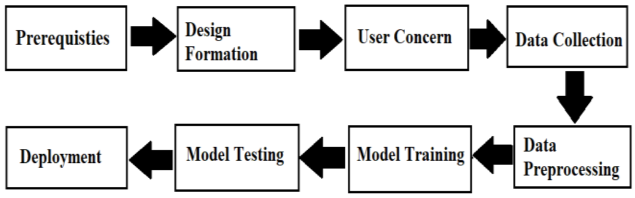

Fig 3.1: Workflow for the mental health monitoring system.

(i) Common understanding of the task/research: It should be clear what is the goal of the research and what are the hypotheses to address.

(ii) Common terms and way to communicate: It often occurs that the same terms are used to describe different things within the fields.

(iii) Legal requirements: Legal requirements such as ethical approval of patient data and dissemination of

results should be discussed and sorted out at this stage.

(iv) Common understanding of experimental designs and publication cultures within the fields: Experiments have to be designed in ways that they fulfill both fields' standards. This includes power calculations and standards in clinical testing but also algorithmic evaluation

(v) Infrastructure, software and hardware requirements: At this phase also requirements such as IT infrastructure, software, hardware, etc., should be decided.

B. Design Formation

Design Formation is a foundation phase of the entire process leading to the realisation of the monitoring system, and decisions taken here will have an impact on all later phases. Several components of the target audience, setting (on-site or off-site), data gathering procedure, and so on must be specified during this phase. Because of their pervasive and portable nature, wearable sensors are becoming increasingly popular for out-of-lab applications. Battery consumption, obtrusiveness, relevance, and privacy should all be considered when choosing the type and number of sensors. Sensor sampling rates are also defined during the experiment design.

Battery life and storage capacity needs are affected by sampling rates. High sampling rates will necessitate more processing resources, but they will allow for more fine-grained pattern features to be captured. However, because this may diminish the battery life of their smartphone, this may cause participants to drop out. In long-term research, it's also critical to put in place methods to maintain participant compliance and limit dropout rates. This can be accomplished via various incentives such as gift cards, discount vouchers, allowing the participant to keep the equipment after the study, and so on. Other considerations during this phase include the study's design: longitudinal, cohort, cross-sectional, qualitative, quantitative, and so on. The type of study that is commonly undertaken in a mental health monitoring system is as follows:longitudinal and quantitative.

C. User Concern

The agreement of users and ethical clearances are critical for MHMS. The primary concept for doing medical research on human subjects is that all methods must adhere to the World Medical Association Decleration's ethical norms. Before data collection can begin, patients' health and best interests must be considered, and every proposed medical research on people must have a research protocol authorised by an ethical committee. Before signing the consent, all included participants must be sufficiently informed about the study's goals, methods, source of funding, possibly negative effects, and other important elements, as well as their right to withdraw consent at any time. It is seen that mental health data is frequently seen as more sensitive than other health data.

D. Data Collection

This phase corresponds to the participants' actual data gathering. The data collecting and thier labelling phase of MHMS is frequently divided into two types: on-site and off-site. In the on-site setting, the patient is required to be at the hospital or clinic while the data collection and/or labeling (clinical assessment) takes place. In the off-site setting, the data collection and labeling occurs while the participants perform their daily routines at home/work/etc.

The following is a list of some things to think about when collecting data:

(i) To ensure the participants' privacy, sensitive data about them must be kept and secured. The sort of data being gathered, the intended purpose, and the implications must all be explained to participants.

(ii) During and after the data gathering process, the data will be managed and kept. When using a smartphone, data is normally saved in the device's internal memory. The data can be transferred periodically to a smartphone through Bluetooth for smaller devices with limited non-volatile memory, such as smart watches or wrist bands. The data is normally encrypted if it contains sensitive information about the participant. The final storage location for research analysis is frequently a server. These servers should be able to deliver extremely safe settings.

(iii) Machine learning algorithms require training data in order to learn and detect patterns. To produce good prediction models, they rely on the quantity and quality of data. The sensor data is tagged with their associated ground truth state during the data labelling process. Periodic clinical exams are conducted in person (at the hospital, clinic, etc.) or over the phone for mental health applications. Some studies have employed a combination of in-person and phone assessments to acquire more trustworthy data. In addition to deciding a method to employ for labelling the data, the periodicity must be established. Longer durations of time between self-reports, for example, will result in less labelled training data.

(iv) Energy expenditure has an effect on usability, data quality, and data quantity, collecting data from additional sensors at faster sample rates may provide more information for the studies, but it may reduce device battery life, thereby preventing users from participating. Some or all preprocessing can be done locally on the devices during the prediction phase, or the data can be sent to a central server.

E. Data Preprocessing

After collecting the data, EDA (Exploratory Data Analysis) and preprocessing take place. EDA is a method for gaining a better understanding of data. Histograms, scatter plots, heat maps, box plots, and other visualisation approaches can be used for this purpose. An EDA can also be used to identify anomalies and missing results caused by sensor failure. Preprocessing is the process of applying filters and adjustments to raw data in order to prepare it for future analysis. To minimise noise and eliminate outliers, filtering methods might be used. Scaling, quantization, binarization, and other transformations are examples. The two typical dimensionality reduction techniques are Principal Component Analysis (PCA) and Multidimensional Scaling (MDS).

Instead of sensor raw signals, many machine learning methods require concise representations of the data. Feature vectors, which are numerical n-dimensional vectors that represent an object, are frequently used in these representations. Feature extraction is the process of extracting feature vectors from raw data, and it is one of the most crucial phases in mental state prediction.

Arithmetic mean, standard deviation, min, max, skewness, kurtosis, root mean square, power spectrum density, energy, correlation coefficient, and so on are some of the most commonly retrieved features for mental state identification. It's possible that not all of the features in the feature vector are useful or offer a significant amount of value to the forecast. In order to determine the importance of each feature, some feature selection algorithms can be applied for reducing the dimensionality of the data..

F. Model Training

The amount of data generated every day is rapidly increasing as a result of the advancement of information technology and communications. It is now possible to leverage that computing capacity to analyse and extract knowledge from massive amounts of data. Machine learning can be conceived of (but is not limited to) as a set of computing algorithms that uncover interesting patterns and relationships in massive amounts of data automatically. Learning produces information that the system can apply to new issues. The properties of a specific collection of data are inferred by an algorithm, and this information helps it to make predictions about other data it may encounter in the future. Because practically all nonrandom data has patterns, this is conceivable.

A prediction model $f(x, \varphi) : y$ is a function that maps a set of input variables x into a response variable y with a set of parameters φ. Training a machine learning model means finding the parameters' values that optimize some criteria such as: maximizing the prediction accuracy, minimizing model size, minimizing time complexity of prediction, maximizing final model comprehensibility, etc. The data must be in predetermined numerical formats to train a machine learning model, which is performed during the preprocessing step.

Several machine learning classification algorithms used are Decision Tree, Random Forest, Support Vector Machine, Naive Bayes, MLP and K-Nearest Neighbour.

(i) Random Forest: Random forests, also known as random choice forests, are an ensemble learning method for classification, regression, and other tasks that work by building a large number of decision trees during training. For classification tasks, the random forest's output is the class chosen by the majority of trees. The mean or average prediction of the individual trees is returned for regression tasks.

(ii) Decision Tree: It is a decision-making aid that employs a tree-like model of decisions and their potential results, such as chance event outcomes, resource costs, and utility. It's one approach to show an algorithm made up entirely of conditional control statements. A decision tree is a flowchart-like structure in which each internal node represents a "test" on an attribute, each branch represents the outcome of the test, and each leaf node represents a class label. The paths from root to leaf represent classification rules.

(iii) MLP: A feedforward artificial neural network called a multilayer perceptron (MLP) is a type of feedforward artificial neural network (ANN). MLP is a phrase that is sometimes used ambiguously to refer to any feedforward ANN. Multilayer perceptrons, especially those with a single hidden layer, are commonly referred to as "vanilla" neural networks. There are at least three levels of nodes: an input layer, a hidden layer, and an output layer. Each node, with the exception of the input nodes, is a neuron with a nonlinear activation function. Backpropagation is a supervised learning technique used by MLP during training. MLP is distinguished from a linear perceptron by its numerous layers and non-linear activation. It can tell the difference between data that isn't linearly separable.

(iv) Support Vector Machine: Supervised learning models with associated learning algorithams that analyze data for classification and regression analysis. SVMs, which are based on statistical learning frameworks or the VC theory introduced by Vapnik and Chervonenkis, are one of the most reliable prediction approaches.Because of its remarkable classifying power and presentation quality, this classifier has recently been used in a variety of applications. It divides data linearly into two independent classes (also known as hyperplanes), with the maximum distance between the two classes.

(v) Naive Bayes: Naive Bayes is a simple technique for constructing classifiers: models that assign class labels to problem instances, represented as vectors of feature values, where the class labels are drawn from some finite set. Naive Bayes classifiers are a collection of classification algorithms based on Bayes' Theorem. It is not a single algorithm but a family of algorithms where all of them share a common principle,The number of parameters required for Naive Bayes classifiers is linear in the number of variables (features/predictors) in a learning task, making them extremely scalable. Instead of using expensive iterative approximation, maximum -likelihood training can be done by evaluating a closed-form equation, which requires linear time.

(vi) K-Nearest Neighbour: For classification and regression tasks, K-NN is one of the most easy methods used in machine learning. KNN collects and categorises recent data points based on the closest measures. The data is subsequently distributed to the class with the most immediate neighbour. Because of its simplicity and adequacy, KNN is frequently used to classify future data.

G. Model Testing

The purpose of model evaluation is to assess how well the trained model will be able to generalize. One method to estimate the generalization capability of a model is to divide the dataset into two subsets: a training and a testing set. With this scheme, the model is first trained with the training set and its performance is assessed using the testing set and this is called holdout validation. The samples are often assigned randomly to one of the training and testing subsets. Machine learning models tend to memorize patterns (overfitting) from the data they were trained with, thus, they will usually perform very well when evaluated with the same data but they may not be able to generalize well to new data. By using holdout validation, we make sure that the trained model does not contain information about the testing set samples and in consequence, this allows us to have better generalization estimates. To avoid the risk of overfitting, the entire data set can be divided into three subsets: training, validation, and testing sets. The training set is used to build the model and the validation set is used to tune its parameters. Then, the testing set is used to assess the generalization performance. When the amount of data is limited, k-fold cross validation is preferred. This method consists of dividing randomly the data into k subsets of approximately equal size. Then k iterations are performed. The advantage of this method is that the estimated variance is reduced as k increases but the computational demands also increase. When k is equal to the total number of samples in the data set it is called Leave-one-out cross validation (LOOCV).

In machine learning, bootstrapping is another process for computing performance measures using several randomly selected training and test datasets which are selected through a process of sampling with replacement, that is, through bootstrapping. Sample datasets are selected multiple times. The bootstrap procedure will create one or more new training datasets some of which are repeated. The corresponding test datasets are then constructed from the set of examples that were not selected for the respective training datasets.

A confusion matrix is used to describe the performance of a classification model (or “classifier”) on a set of test data for which the true values are known. A confusion matrix is a table that categorizes predictions according to whether they match the actual value. For a two-class dataset, a confusion matrix is a table with two rows and two columns that reports the number of false positives, false negatives, true positives, and true negatives. Confusion matrices can be constructed for multiclass datasets also. For classification problems common performance metrics are:

Let a binary classifier classify a collection of test data.

TP = Number of true positives

TN = Number of true negatives

FP = Number of false positives

FN = Number of false negatives

• Accuracy: Proportion of correctly classified instances.

Accuracy = (TP + TN) / (TP + TN + FP + FN)

• Sensitivity: Also called recall and is the true positive rate, i.e., the proportion of positives that are correctly classified as such.

Recall = TP / (TP + FN)

• Specificity: This is the true negative rate, i.e., the proportion of negatives that are correctly classified as such.

Specificity = TN / (TN + FP)

• Precision: Also called the positive predictive value and represents the fraction of true positives among those classified as positives.

Precision = TP / (TP + FP)

• F1 score: This measure is a weighted average of the precision and recall.

An ordinal variable having the values low, medium, and high can be used to model depression levels. Typical performance metrics treat all faults equally: mixing up low and medium has the same error weight as mixing up low and high, yet the latter error should clearly be penalised more harshly.The mean squared error, root mean squared error, mean absolute error, correlation coefficients, and other performance indicators for regression issues are common. The output class in mental state detection is frequently ordinal. This indicates that it follows a natural order.

H. Deployment

The deployment process involves getting the entire system ready to use. To have a reliable operational monitoring system, several factors must be taken into mind. When it comes to deployment, the hardware and software infrastructure are crucial. They must be scalable, dependable, secure, and robust, among other things. Machine learning models are deployed for production use after they have been validated. To make training and prediction time faster and scalable, they are sometimes translated into different computer languages and/or dispersed among numerous processing units. Some or all of the preprocessing can be done locally, or some of the work can be delegated to a server.

IV. DISCUSSION

Here we discussed 6 mental health algorithms for implementing 12 mental health disorders. While using Machine learning methods, the most common used was Random Forest. Talking about advantages of the Decision Tree algorithm , the algorithm requires little data preparation and performs well even if its assumptions are somewhat violated but the drawback is that results are not accurate. SVM algorithm works well when there is a clear margin of separation between classes but Svm cannot use data in their original form. MLP algorithm provides 100% accuracy but this indicates overfitting of data which makes the algorithm inefficient. KNN is intuitive to understand and has no explicit training step but the major drawback is it is time consuming as we need to compute distance of each query distance to all training samples. Naive Bayes classifier is highly scalable and does not require much training data but the accuracy rate is comparatively low when compared to Random Forest. Random Forest overcomes all the majority drawbacks of other algorithms and provides an accuracy of 61.67%.

V. CONCLUSION

In this paper, we discussed workflow for the mental health monitoring system and several machine learning algorithms for reducing the dimensionality of the data such as Decision Tree, Random Forest , Support Vector Machine, Naive Bayes, MLP and K-Nearest Neighbour. Among these algorithms we use Random Forest Tree for classifying the mental health disorders like depression, stress and anxiety from the data collected through DASS 21 (Depression Anxiety Stress Scaling) Questionnaire. The users can choose the doctors that are listed according to their test result. Doctors can treat the user through online video conferences. Doctors are provided with users social media ID's so that they get a complete detail of activities, mood modulation etc. For further proper treatment, users can approach the doctor directly. The severity of the issue in the mental health disorder and the fear in consulting a doctor directly due to several unwanted talks prevailed in the society led to the Mental Health Monitoring and Consultation App. The world should be of a healthy person, and a healthy person possesses a healthy brain along with physical wellness.

REFERENCES

[1] Mental health monitoring with multimodal sensing and machine learning: A survey, Enrique Garcia-Ceja, Michael Riegler, Tine Nordgreen, Petter Jakobsen , Ketil J. Oedegaard, Jim Torresen.

[2] Machine Learning Algorithm methods for the psychological distress (Or Depressive Anxiety symptoms) of the Greek general population during the COVID19 lockdown. Georgia Konstantopoulou, Theodoros Iliou, Katerina Karaivazoglou, Konstantinos Assimakopoulos, Panagiotis Alexopoulos, George Anastassopoulos.

[3] Machine Learning-based Approach is for Depression Detection in Twitter Using Content and Activity Feature, Hatoon AlSagri and Mourad Ykhle.

[4] StressMon:Scalable Detection of Perceived Stress and Depression Using Passive Sensing of Changes in Work Routines and Group Interactions, Camellia Zakaria, Rajesh Balan, Youngki Lee.

[5] Prediction of Mental Health Problems among Higher Education Student Using Machine Learning, Nor Safika Mohd Shafie and Sofianita Mutalib.

[6] Predicting Anxiety, Depression and Stress in Modern Life using Predicting Anxiety, Depression and Stress in Modern Life using Machine Learning Algorithms Machine Learning Algorithms . Anu Priya, Shruti Garg and Neha Prerna Tigga.

[7] The IoT LoRa System Design for Tracking and Monitoring Patient with Mental Disorder, Nur Hayati

[8] Behavioral Modeling for Mental Health using Machine Learning Algorithms, Srividya & S. Mohanavalli and N. Bhalla.