AIPSYCH: A MOBILE APPLICATION-BASED ARTIFICIAL PSYCHIATRIST FOR PREDICTING MENTAL ILLNESS AND RECOVERY SUGGESTIONS AMONG STUDENTS

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ABSTRACT

COVID-19's outbreak affected and compelled people from all walks of life to self-quarantine in their houses in order to prevent the virus from spreading. As a result of adhering to the exceedingly strict guideline, many people developed mental illnesses. Because the educational institution was closed at the time, students remained at home and practiced self-quarantine. As a result, it is necessary to identify the students who developed mental illnesses at that time. To develop AiPsych, a mobile application-based artificial psychiatrist, we train supervised and deep learning algorithms to predict the mental illness of students during the COVID-19 situation. Our experiment reveals that supervised learning outperforms deep learning, with a 97% accuracy of the Support Vector Machine (SVM) for mental illness prediction. Random Forest (RF) achieves the best accuracy of 91% for the recovery suggestion prediction. Our android application can be used by parents, educational institutes, or the government to get the predicted result of a student's mental illness status and take proper measures to overcome the situation.

1. INTRODUCTION

A mental illness is a condition that affects a person's feelings, thoughts, behavior, and social relationships resulting in depression, anxiety, loneliness, and despair. COVID-19 is a crucial cause that activates the components that cause mental disease. The spread of COVID-19 has resulted in a global public health problem. It has begun to have an influence on individuals in a variety of ways. People all over the world have shut themselves up at home. Some people have lost their employment or suffered a significant loss in business, resulting in financial ruin. After being healed with COVID-19, some people had long-term bodily issues. All of these elements have an influence on the mental health of a person who may be suffering from a mental disease. During a pandemic, students in particular face a variety of difficulties. With the closing of educational institutions came the necessity for a quick shift from physical learning to digital learning. Online learning has been identified as a potential replacement for traditional learning. Students are required to remain at home and finish their studies. It interferes with their typical daily routines. They are isolated from social activities. They are unable to engage with their peers or participate in extracurricular activities outside of the classroom. As a result, kids find it challenging to deal with the issue at such a young age. They lose hope in their life, become lonely, and irritated, which in turn makes them psychologically unwell. As a result, some students are unable to take it, and their mental health deteriorates. According to Wang et al. [1], the death rate of COVID-19 patients with mental illnesses is 48 percent greater than that of other COVID patients. So, for the time being, it is a subject of worry to find a way to save their lives as quickly and smoothly as possible.

Although identifying someone as a mentally sick person is not an easy process, a systematic approach can be used to diagnose it. The sufferer is oblivious to the fact that he or she is growing mentally sick. They are unable to handle the scenario since they are of such a young age. Some of them may be involved in anti-social behavior, such as drug addiction. In severe circumstances, people may try suicide in order to escape such an unbearably unpleasant condition. As a result, it is critical for a student's parent, educational establishment, or any government of a country to address those pupils in order to rescue their lives from major devastation. We have created a system that will predict whether or not a pupil is mentally ill based on behavioral indicators obtained from students or students' parents. The algorithm can also recommend strategies to rehabilitate using a different set of behavioral characteristics for kids who have previously been diagnosed as mentally ill. Combining two modules of the system, an android application is also integrated with the system so that users of the system may acquire mental disease status and recovery ideas by entering input parameters into the system using a Graphical User Interface (GUI). Figure 1 depicts the system diagram, which is made up of three modules.

The remaining sections detail all of the system's modules. The following topics are covered: data preparation, data preprocessing, methods and techniques employed, results analysis, the major contribution of this study, system deployment, mobile application development, work limitations, and future scope to develop the system.

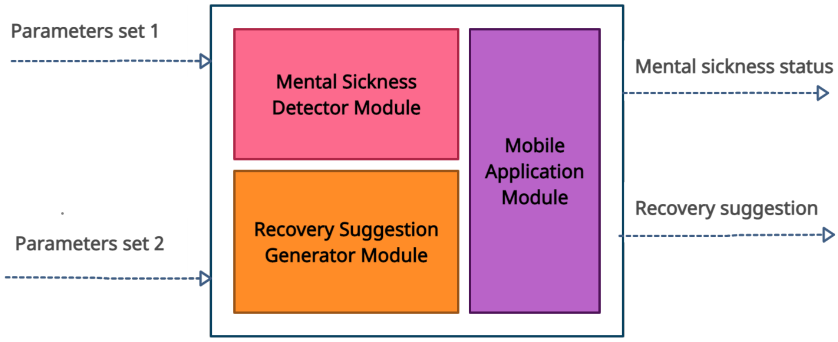


Figure 1. System diagram shows modules, inputs to the system and outputs from the system.

2. Objective

The public is experiencing fear and mental health stress as a result of COVID-19. Munk et al. computed statistically that prevalence of suffering from any of the measured mental disorders was 50.6% whereas 35.3% have clinically depressive symptoms [2]. Chirikov et al. computed that 35% undergraduates, 32% graduates, 36% doctoral, and 31% masters students have suffered from depression [3]. They also computed that 39% undergraduates, 39% graduates, 43% doctoral, and 36% masters have anxiety disorder during pandemic [3]. A mental disorder is a serious problem that can ruin a student's life. Mental illness is a difficult condition to diagnose since it is based on a person's behavioral activities. As a result, a system that can detect mental disease based on certain factors is necessary. Our goal is to create a system that first recognizes mental illness and then proposes strategies to recover from illness through therapy or counseling. If a student is primarily identified, the government or educational institute can arrange a counseling program or treatment for the victim student. A student is also able to identify himself from an android application integrated with our system and personally take steps to be cured.

3. AiPsych System (APS)

A mental disorder is a sickness that must be treated as soon as possible. Early detection allows a sufferer to be quickly healed, however late diagnosis might deteriorate the victim's situation. This is why, we designed AiPsych, a system that not only identifies mental illnesses but also suggests strategies to recover from them. Our system is divided into three subsystems: Detection of Mental Illness Subsystem, Recovery Suggestion Subsystem, and Mobile Application Subsystem. The detection subsystem determines whether a student has a mental illness by reporting the Yes or No classification. For mentally ill students, the recovery suggestion subsystem recommends therapy or counseling as a method to recover from mental illness. The mobile application subsystem offers a user interface for accessing the system and providing attributes for mental disease status (yes or no) and recovery options (treatment or counseling). The general technique of the APS system is depicted in Figure 2. All subsystems have been explored in detail below:

Detection of Mental Illness Subsystem (DMIS). The first and most critical step is to determine a victim's mental disorder. The major aim of this subsystem, as envisaged, is to create a module to recognize students with mental illnesses. To do so, we employed a dataset that contains characteristics that contribute to an individual's mental condition. Then we cleaned up the data, dealt with missing values, and looked at characteristics to see which ones had the least influence on the output. Then we used a combination of supervised and deep learning algorithms to forecast a student's illness status. We are now ready to test the system with real parameters once we have trained our algorithms. As a result, the subsystem uses behavioral factors to forecast whether a person's mental health status is YES (mental disorder) or NO (no mental disorder).

Recovery Suggestion Subsystem (RSS). Once a student has been diagnosed as mentally disturbed, the Recovery Suggestion Subsystem (RSS) determines how the victim may be treated. A psychiatrist's job is to detect mental patients and recommend treatment options for them. AiPsych System (APS) uses machine learning approaches to accomplish the same goal. For this, a dataset with a collection of characteristics that influence the generation of recovery proposals is required. To generate recovery suggestions, we initially trained multiple machine learning techniques on different values of the dataset's feature to provide recovery suggestions. The subsystem generates therapy or counseling recommendations based on behavioral data provided by students, parents, or educational institutions.

Mobile Application Subsystem. We need a solution to create a user interface that allows users to submit data and receive results. We designed a mobile application that interfaces with other subsystems to interact with them. The smartphone application contains two graphical user interfaces, one for detecting mental problems and the other for recovery advice. In the first step, the user completes the forms with behavioral parameters and receives a diagnosis of mental disorder after completing the form. Second, if the person is identified as having a mental condition, another GUI is displayed. After submitting the form, the user enters the second set of parameters and receives a recovery recommendation. This subsystem outlines how the user interacts with the app and gives inputs, while the app displays outputs and communicates with other subsystems.

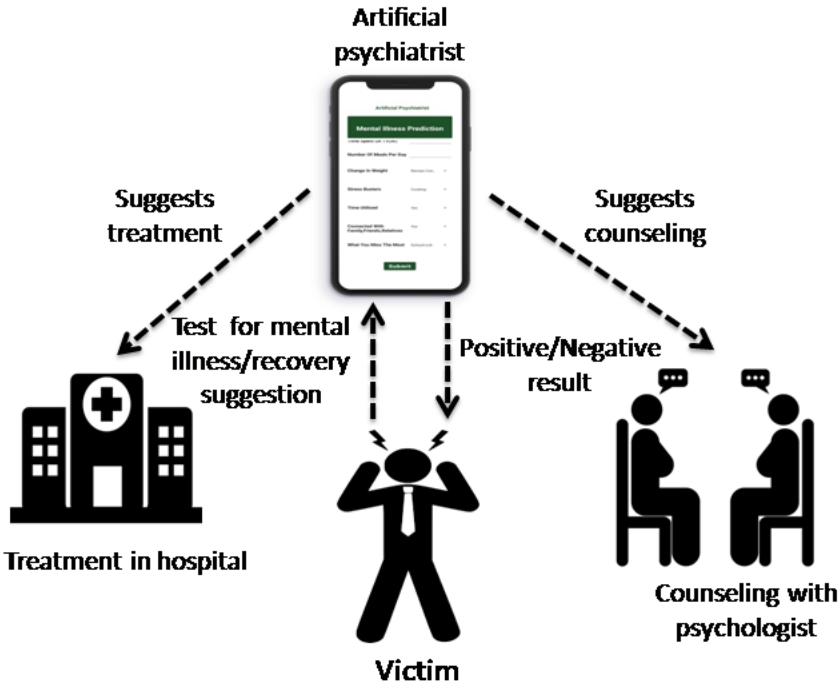


Figure 2. The victim enters parameters for mental illness testing and receives a positive or negative result. If the result is affirmative, the victim is given suggestions for recovery and is given therapy or counseling.

4. DATASET

We have two datasets in the AiPsych system (APS), one for the diagnosis of mental disease and the other for the prediction of recovery recommendations. Both datasets were obtained from kaggle.com. DMIS dataset contains 1182 instances with sixteen features and two target classes: YES (mental illness) or NO (no mental illness). Six of the sixteen features are categorical, while the others are numerical. The dataset has some missing values and we handled them during the data preprocessing phase. The dataset is imbalanced with 161 positive instances and 1021 negative instances. In RSS, a standard dataset is also collected from the same source that has 335 instances. Among 335 instances, 290 are positive (treatment) instances and 45 are negative (counseling) instances. We removed the irrelevant features from the dataset and ended up with twenty-one features as well as two target classes: YES for treatment and NO for counseling. Three of the twenty-one attributes are categorical, while the rest are numerical. This dataset also includes missing values and imbalance, and we have handled them accordingly. In the later sections, we will proceed with our work on these datasets.

4.1. Handling Missing Data

Missing data or absent values refer to when no data value for a variable in an observation is missing. If missing data isn't handled, performance suffers. Link empty, NA (Not Available), None, NaN (Not a Number), and so on are examples of missing data in our dataset. Both datasets have missing data and have six features that have missing data. Missing data can be handled in a variety of ways, including zeroing it out, filling forward, falling backward, and replacing it with mean values, among others. In our example, we replaced missing data in both datasets with maximum occurring values in corresponding features.

4.2. Handling Imbalanced Dataset

Imbalanced datasets are those datasets in which the target class has an unequal distribution of data. Alternately, we can say that one class label has a large number of records than another class that has a low number of records. The problem with an imbalanced dataset is that it impacts the prediction of minority class and performance reduces. Both datasets used in our system are imbalanced. We handled our imbalanced dataset using Synthetic Minority Oversampling Technique (SMOTE). SMOTE is an oversampling technique that generates the logistic samples for that class that has a low number of records.

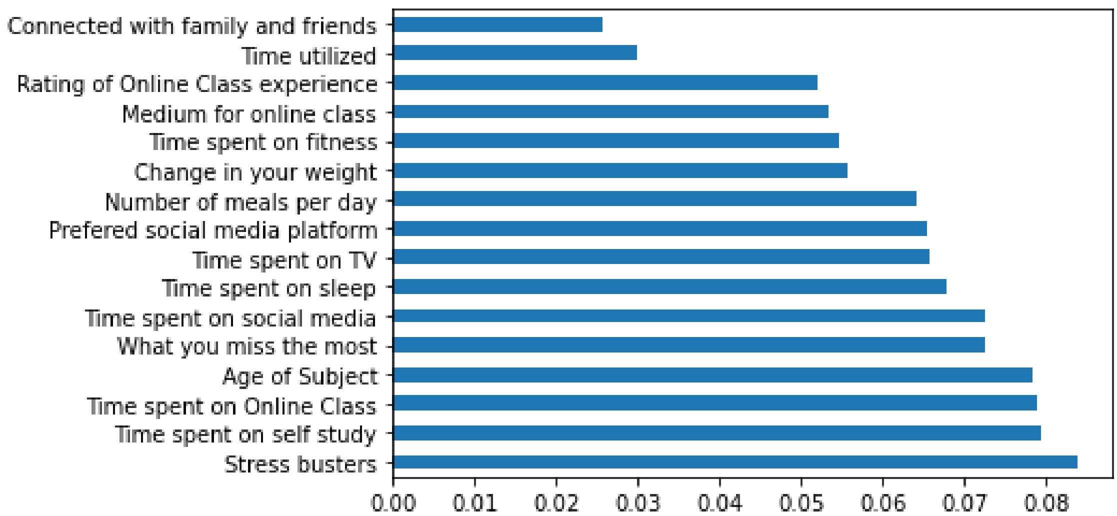


Figure 3. Feature importance calculation is crucial step in data preprocessing. This figure shows importance of features for detection of mental illness where "Connected with family and friends" is the lowest ranked feature.

4.3. Feature Analysis

We have performed Feature Importance Ranking (FIR) that computes benefactions of individual input features to the performance of a machine learning model. The inclusion of lower important features degrades the performance of the system. The purpose of feature rank is to filter out higher importance features and drop out lower important features, thus increasing the performance of a system. In the DMIS dataset “Connected with family and friends” feature has the lowest rank and is dropped out. Figure 3 shows the feature rank of the DMIS dataset. In the RSS dataset, “device apart from phone” is the lowest-ranked feature. Feature rank for RSS dataset is shown in figure 4. In both DMIS and RSS, We have computed correlation through correlation matrix and have not found any strongly correlated features in the datasets.

4.4. Train and Test Data Preparation

In the Machine Learning approach, one of the most important data preprocessing steps is the split of the dataset into training and testing that should be precisely taken up. Separate samples for training and testing is an important step to evaluate model performance. SKlearn is a machine learning package that has train_test_split method which is used to create training and testing samples. We have taken 80% of the data from the data set for training purposes and 20% of the data for testing purposes in the mental illness prediction dataset. In the recovery suggestion subsystem, the training part contains 70% data and the testing part contains 30% data.

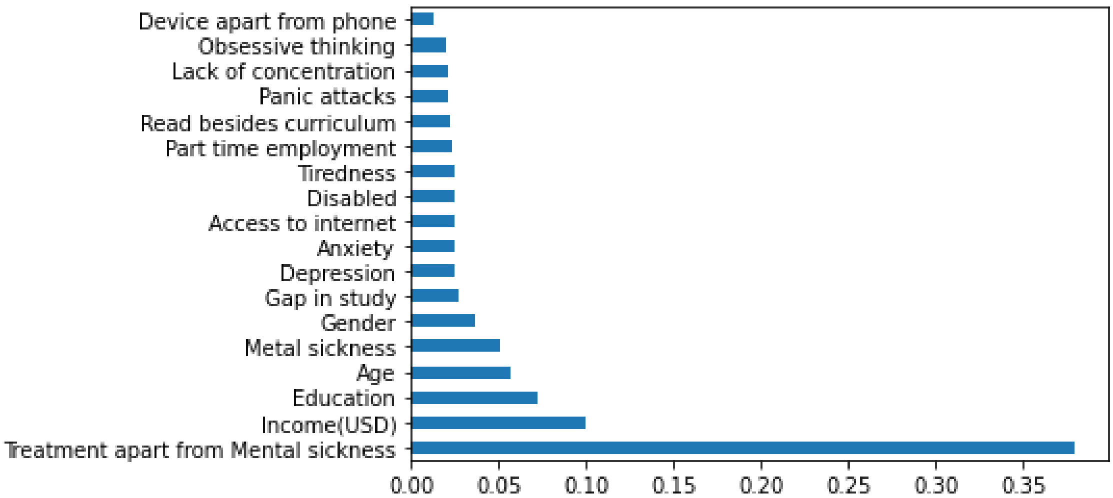


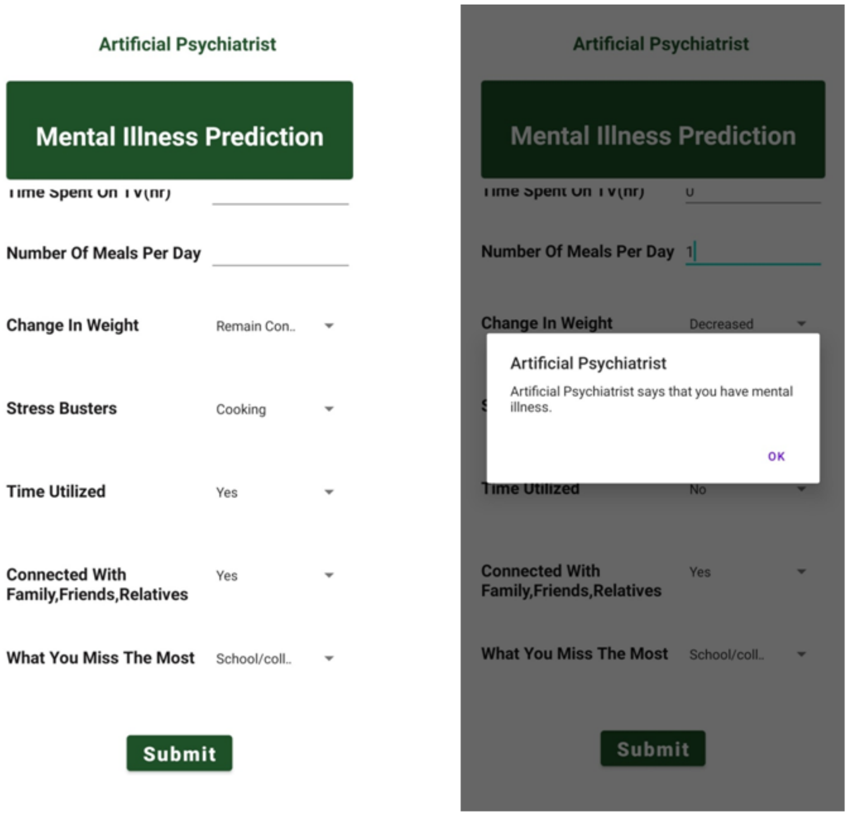
Figure 4. Feature importance calculation is one of the most important steps of data preprocessing. This figure shows importance of features for recovery suggestion subsystem where "Device apart phone" is lowest ranked feature.

4.5. Label Encoding and Scaling

For categorical variables, label encoding is a popular encoding approach. Each label is given a unique integer based on alphabetical order in this technique. After applying the label encoding technique, machine learning algorithms can work properly. It is an inseparable part of preprocessing techniques. In our system, six features of the DMIS dataset and two features in the RSS dataset are labeled values. We have used the label encoding technique to convert those to numeric values. Feature Scaling is a method that presents the data in a fixed range. This method is applied to handle highly varying units of data. In our case, we have applied the scaling technique to convert data to a uniformed unit of data so that machine learning models can be properly trained to perform better.

5. PREDICTION MODULE OF APS

The key aspect of the prediction module is the selection of perfect models from various machine learning and deep learning techniques used in the experimentation. In our case, We used various predictive machine learning models such as Decision Tree (DT), Logistic Regression (LR) and Support Vector Machine (SVM), Random Forest (RF), Naive Bayes (NB), K-Nearest Neighbor (KNN). Our goal is to pick the best classifier for our system. Each classifier must therefore be trained on the feature set and the classifier with the best classification results is used for prediction. The classification algorithms taken into consideration are all the models mentioned above. Naive Bayes and Logistic mostly work better when the target variable is categorical. Decision Tree, SVM works well both for classification and regression fields. Random Forest (RF) is an ensemble learning algorithm for classification and regression. The k-Nearest Neighbors (KNN) algorithm can be used to solve both classification and regression problems. SVM commonly furnishes maximum performance in classification problems than regression. We have utilized Artificial Neural Network (ANN) which is a deep learning algorithm. It is mainly designed as a way that it performs much better in classification than regression. In ANN algorithms we have an input layer, hidden layer, and output layer. In the hidden layer, we have used 16, 32, 64, 128 neurons to train up the ANN algorithm. We have trained up all the algorithms DMIS dataset and RSS dataset. Then we have analyzed all the algorithms to choose the best one for both subsystems. In DMIS, we have chosen SVM for prediction as it performed best. In RSS, Random Forest (RF) have worked best and is chosen for prediction purpose.



(a) (b)

Figure 5. (a) includes mental illness prediction interface, user has to fill up the fields and submit for getting prediction. (b) After submission, user will get predicted value either positive or negative. Positive case is shown here. For negative output will be similar.

6. RESULTS

AiPsych System (APS) is a machine learning-based system. The goal of APS is to develop a system that is generally applicable, reliable, and robust. APS system uses different machine learning models and proper models can be chosen for deployment through result analysis. Result analysis is a process or method that evaluates a system and is the most significant part of the development of any system. The system can be evaluated in different ways like error analysis, performance analysis, and so on. Error analysis is the method that computes erroneous predictions of machine learning algorithms and helps to choose the proper algorithm that encounters the least error. Performance analysis is a process or method that computes the accuracy of machine learning algorithms and suggests choosing the algorithm that has the best performance.

Algorithm	Module	Precision	Recall	F1
NB	DMIS	76%	76%	76%
	RSS	92%	66%	77%
SVM	**DMIS**	**97%**	**97%**	**97%**
	RSS	95%	70%	80%
RF	DMIS	91%	90%	90%
	RSS	**98%**	**93%**	**96%**
LR	DMIS	73%	73%	73%
	RSS	93%	73%	82%
DT	DMIS	71%	71%	71%
	RSS	88%	74%	80%
KNN	DMIS	80%	76%	75%
	RSS	85%	73%	79%
ANN	DMIS	75%	87%	81%
	RSS	76%	79%	77%

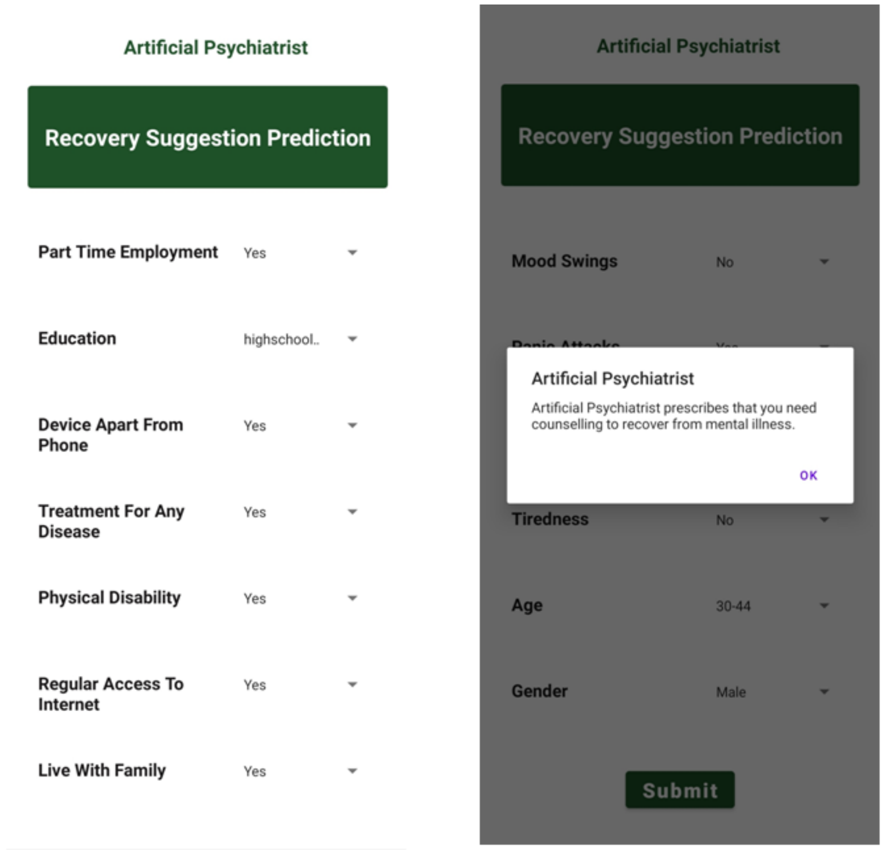
Table 1. Precision, Recall, and F1-score for different machine learning models for both Detection of Mental Illness Subsystem (DMIS) and Recovery Suggestion Subsystem (RSS). In DMIS, Support Vector Machine (SVM) achieved best performance of all algorithms having F1 of 97%, precision of 97% and a recall of 97%. In RSS Random Forest (RF) achieves the best performance having 98% of precision, 93% of recall and 96% of F1

6.1. Performance Analysis

To evaluate the algorithms, we have used precision, recall, and f1 score metrics. Table 1 shows the performance of the mental illness predictor module. The random forest has a precision of 91%, recall of 90%, and f-score of 90% which is a better performance. SVM performed better than Random forest (RF) having a precision of 97%, recall of 97%, and f1-score of 97%. The table also shows the performance of the recovery suggestion module where the performance parameter of each model is enlisted. In this module, Random Forest (RF) has the maximum accuracy with the precision of 98%, recall of 93%, and f1-score of 96%. Random forest has a precision of 91%, recall of 90%, and f-score of 90%. Logistic Regression (LR) has a precision of 93%, recall of 73%, and f-score of 82%.

6.2. Error Analysis

Error analysis is the process of comparing error rates among the ML algorithms. The major goal of error analysis is to sort out the algorithm that has the least error rate. Error analysis can be done



(a) (b)

Figure 6. (a) shows recovery suggestion interface, user has to fill up the fields and submit for getting prediction. (b) After submission, predicted value will be generated either counseling or treatment. One case is shown here.

through a different method of error analysis. Error analysis methods are False Positive Rate (FPR), False Negative Rate (FNR), Mean Squared Error (MSE), Mean Absolute Error (MAE), and so on. We have covered FPR, FNR, MSE error analysis methods to evaluate DMIS and RSS.

FPR and FNR. False Positive Rate (FPR) and False Negative Rate (FNR) are the most important part of the measurement of error. FPR means the rate of erroneous prediction of true value instead of false. FNR is the rate of incorrectly predicting a negative scenario that is true in fact. In our case, FPR is the rate of predicting a student as a mental patient who is actually not and FPR is the rate of predicting a student as mentally well incorrectly instead of mentally ill. Performance of the system degrades with an increase of FPR and FNR. Figure 7(a) shows the FPR and FNR of the mental illness module and figure 7(b) shows the FPR and FNR of recovery suggested on the module.

Mean Squared Error (MSE). Mean Squared Error (MSE) is the straightforward and common loss function. It is an important aspect of evaluating a machine learning system. Mean Squared

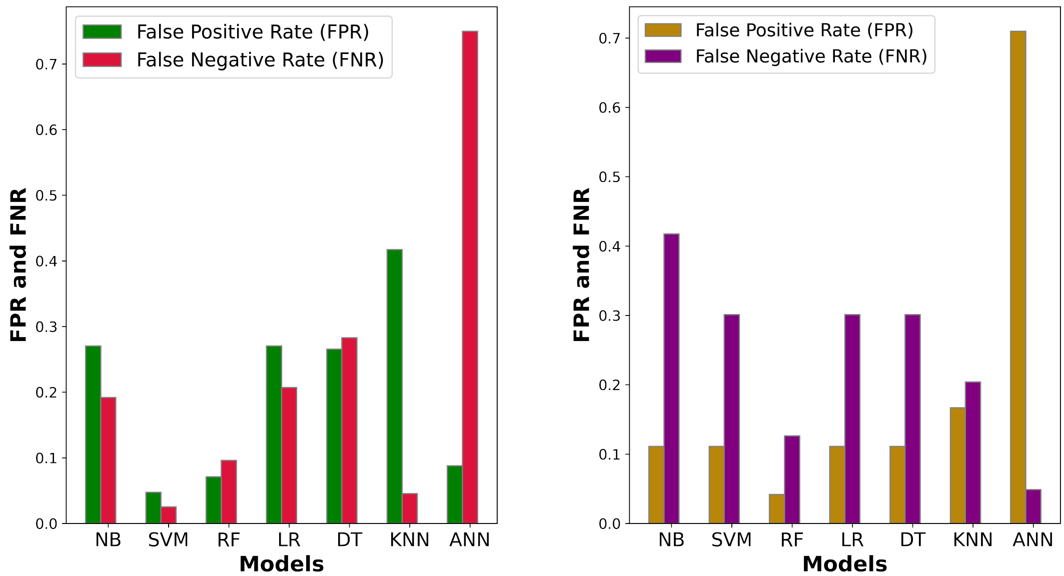


Figure 7. (a) False Positive Rate (FPR) of all models. FPR and FNR are important aspects of evaluating a system. Among all models, SVM has the lowest FPR and FNR. (b) FPR and FNR are computed to measure performance. Random Forest (RF) has the lowest FPR and FNR of the recovery suggestion module.

Error (MSE) is measured by taking the difference between the model's predictions, squaring it, and averaging it out across the whole dataset. In the mental illness module, SVM has the lowest MSE of all models shown in figure 8(a). Figure 8(b) shows the MSEs of all models in the recovery suggestion module where RF has the lowest MSE.

7. Deployment

In terms of a machine learning system, the first step is to choose the model that works best that is already done in the previous sections. Support Vector Machine (SVM) performed best out of all models implemented in the mental illness prediction module. In the recovery suggestion module, Random Forest (RF) outperformed better than all the models implemented. As a consequence, we deployed SVM for predicting mental illness and RF for predicting recovery suggestions.

Firstly, We have created a web application that includes two APIs. First API uses an SVM algorithm to predict mental illness and the second API uses an RF algorithm. We have converted our model to run in a web server using the pickle package of python. We have used the Flask

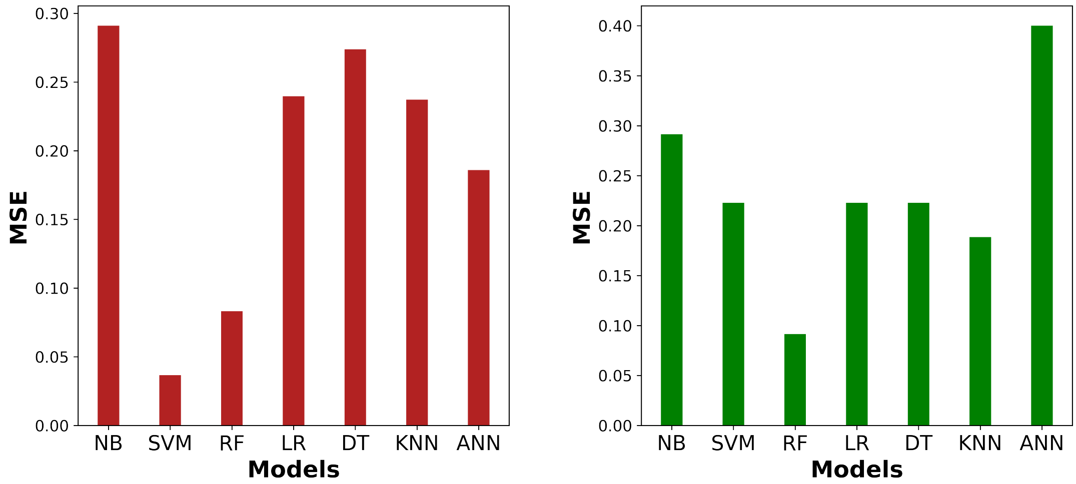


Figure 8. (a) Shows Mean Squared Error (MSE) of all models in mental where SVM has the lowest MSE. (b) RF is the best performing model in the recovery suggestion module. The figure shows the MSEs of all models in the recovery suggestion module.

package to launch the webserver. First API takes features as input and performs label encoding to covert the features to a format so that the preferred model in web server can take as input in the prediction routine. The output of the first API is mental illness status YES or NO. Similarly, the second API takes a different set of features as input and performed label encoding. The second API predicts recovery suggestion and send them back to the application that is called the API. We have deployed the webserver in https://www.heroku.com/ which is a free web hosting site.

Secondly, We have developed an android application to provide a Graphical User Interface (GUI) to the client so that client can provide inputs and get predicted outputs. The android application communicates with the web server through APIs. The mobile application has two user interfaces. The first interface is for diagnosing mental illness. Users fill-up the forms like survey data and after submission gets predicted value as YES or NO, where YES indicates the user has a mental illness and NO indicates he has no mental illness. The second interface for predicting recovery suggestions. When a person is predicted as a mental patient then the application redirects to the recovery suggestion interface. Users fill up the forms, submit to get a predicated suggestion as treatment or counseling where treatment means the user has to take medical treatment for mental illness and counseling means the user has to lead his under the supervision of a psychologist. Figure 5 shows the detection of mental illness interface and figure 6 shows the recovery suggestion interface in mobile application.

8. RELATED WORKS

Machine learning has been used in solving social network problems [4–7] to cybersecurity issues [8, 9], building automated digital systems [10] to e-governance solution [11]. However, there have been very limited attempts to apply this technique to tackle the mental illness issue. The works that closely relate to our approach are summarized below:

Related Works For Machine learning. Oyebode et al. developed an app that evaluates mental health using sentiment analysis [12]. Ren et al. developed a machine learning system that measures the psychological impact of COVID-19 after school reopening like anxiety and depression among students through machine learning [13]. Flesia et al. developed a machine learning system that assessed the effect of the pandemic on stress levels in Italian adults [14]. Herbert et al. surveyed data related to physical and mental health and analyzed it with both statistical and machine learning models [15]. Rezapour et al. analyzed the impacts the COVID-19 pandemic has had on the mental health of front-line workers in the United States using machine learning techniques [16]. Shafiee et al. reviewed mental health problems among students of higher studies and applied machine learning to analyze and predict mental health problems [17]. Srividya et al. presented an analysis of applying machine learning algorithms to identify mental illness [18]. Cho et al. reviewed techniques of diagnosing mental health problems using ML algorithm and suggest how ML techniques can be employed in practice [19]. Mutalib et al. proposed a system that classifies students into different categories of mental health problems using several machine learning algorithms [20]. Ge et al. explored the prevalence rate of probable anxiety and probable insomnia to find the risk factors among a longitudinal study of undergraduate students using the approach of machine learning [21]. Wang et al. experimented with the severity of anxiety among non-graduating undergraduate students during pandemic also evaluated through machine learning as XGBoost model [22].

Related Works For Statistics. Lee et al. developed a signal processing-based mental illness detection system [23]. Wang et al. analyzed the mortality risk of mental disorders during COVID-19 using statistical method [1]. Chaturvedi et al. analyzed the impact of COVID -19 on the social life and mental health of students using statistics [24]. Dhar et al. proposed a method to find out the psychological impact of the COVID-19 pandemic on university students applying statistical methods [25]. Rahman et al. proposed a system that analyzed the impact of COVID-19 on the psychological state of people in Bangladesh [26]. Aristovnik et al. used a statistical approach to compute impacts of COVID-19 on various aspects of the lives of students of higher studies [27]. Faisal et al. developed a statistical system that analyzes anxiety, depression, and mental illness among university students in Bangladesh [28]. Mani et al. statistically analyzed mental health and the relevant social factors during the pandemic [29]. Essadek et al. evaluated the impact of COVID-19 on the mental health of French students [30]. Usher et al. analyzed the impact of COVID-19 on the mental health of people all over the world statistically [31]. Roy et al. reviewed methods for prevailing mental health issues during the COVID-19 pandemic [32]. Marsh et al. analyzed the behavior of the mental patient and came up with a solution for identifying students with mental health issues using behavioral activities [33]. Kaparounaki et al. developed a system that computes the impact of lockdown and quarantine on the mental health of university students [34]. Wyatt et al. experimented with relationships among stress, mental health, and academic classification of college students [35]. Vlachy et al. experimented with evidence of mental health and analyzed prediction of mental illness [36]. Banks et al. estimated the effects of the COVID-19 pandemic on mental health among the citizen of the UK using statistical analysis [37].

9. LIMITATIONS

One limitation of our method is that it cannot anticipate the type of mental illness that an individual may have developed. It can only tell you how likely you are to develop a mental disease. We intend to add more data in the future to anticipate particular illness types and specific recovery recommendations for the general public.

Our system also can not decide the specific treatment for a mental illness. We intend to improve the system in the future by including more robust technologies that will allow the system to predict exact treatment.

Another drawback is that the quantity of records in each of our databases is restricted. When a dataset comprises a large number of records, a machine learning system may perform precisely. In the future, we hope to gather and incorporate additional informative datasets into our system.

10. CONCLUSION

We introduced AiPsych, a prediction-based system that works as an artificial psychiatrist. The technology identifies the mental disease and then suggests ways to rehabilitate it. We used Naive Bayes, SVM, Random Forest, Logistic Regression, KNN, ANN, and CNN to train supervised learning algorithms. With an F1 of 97%, the Support Vector Machine classifier performs best in the prediction of mental illness. Random Forest classifier is modeled for recovery suggestion module that offers the best F1 score of 96%. Our method has the potential to be utilized by students, the government, and educational institutions to diagnose and help students recover from mental illness.

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