



AN EFFICIENT MEDICAL FRAMEWORK FOR DEPRESSION RISK PREDICTION USING ENSEMBLED LEARNING

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Abstract:

In contemporary world, a man or women is engaged with different worldly duties in their profession, work, commitments, family maintenance etc. Smart medicine has emerged to contribute the evolution of healthcare and medical services by applying machine learning together with advanced computing techniques like cloud computing to computer-aided diagnosis and treatments. Depression is another name for mental illness. It can lead to severe health complications and increase the risk of stroke, and sometimes death. Machine learning is mainly focusing on Mind and then Matter. Mainmotive of this project is to give the analysis and prediction of depression because 21% people are affected in this psychological disease across the nation. In this paper, we collected the datasets which contains patient records and histories with medication process. We analyzed the hypothesis from the records, to point out which are all the major factors to affect the man or women. Besides we are highlighting the factors with grades in different geographical structures like Family problem, Physical illness, Lust or desire not obtained so far. We are introducing ensemble learning method for predicting the disease level for the particular node. Ensemble learning is the process by which multiple models, such as classifiers or experts, are strategically generated and combined to solve a particular computational intelligence problem. We compute a unified medicine framework based on the depression identification parameters using

I INTRODUCTION

Depression is one of the most common mental disorders in the entire world. It causes severe symptoms that negatively affect how people feel, think, and handle daily activities. Depression symptoms may include feelings of sadness, tearfulness, emptiness or hopelessness and many other signs. Although depression is so common, it is often over-detected or under-detected by doctors. Currently, less than 25% of people with depression receive treatment. A study about clinical diagnosis of depression found out that general practitioners only correctly identified depression only 47.3%. Behavioral psychopathology relates anxiety and depression closely and anxious depression is defined as a mental state of individuals who are diagnosed with depression present in a manner that is more consistent with feeling anxious instead of sad. It is a major depressive disorder (MDD) with a co-morbid anxiety disorder. Symptoms of both anxiety and depression are of equal intensity and none of them clearly predominates, characterizing a mixed anxiety-depressive disorder. Pertinent studies have linked anxious depression to greater depression severity, reduced treatment response, elevated risk for suicide, and higher risk for cardiovascular disease. These findings highlight the importance of expounding issues pertaining to anxious depression as a distinct psychological disorder. Social media is omnipresent and allows people to self-express, stay connected and in touch with friends and acquaintances across the globe. Social media and mental health of users can be related in three different ways as follows:

- **Social media anxiety disorder:** An active social media user with an addictive pattern, who is distressed by negative interactions and social comparisons on social networking sites affecting self-esteem and mental wellness
- **Anxious Depression social media verbalization:** An active social media user who uses social media postings as an outlet to share feelings in a non-threatening atmosphere
- **Social Anxiety:** A passive social media user with no engagement and is comfortable with virtual connections rather than real interaction

Though feelings are hard to articulate but online self-expression provides a means to convey a mental condition into a physical form. Social Media can facilitate pre-diagnosis of a clinical mental health condition related to anxiety, depression or anxious depression in active extroverts who verbalize and share their internal restlessness

1.1 Motivation

Major depression is a highly prevalent and often recurrent disorder. Since most depressed patients are treated by general practitioners, it is clear that more effective treatments in this primary care setting are needed. The main motivation of the research presented in this project was to evaluate the effects of enhanced care for depression with a continuation-phase compared with usual care on the course with machine learning approach. A diagnosis of depression is made after certain criteria are met for a specific period of time and if a level of distress or functional impairment has occurred. Measuring depression when it co-occurs with a comorbid medical condition is a challenge. We tend to achieve the major utilization features of Ensemble learning and its boosting techniques to analyze the depression level and precautions also.

1.2 SCOPE

This project has a focus on selective prevention and to a larger extent an even more narrow focus on indicated prevention.

- This project aims to detect whether the user is depressed, from his / her psychological background. It can be further used to identify other mental illnesses and might even form an underlying infrastructure for new mechanisms that would help detect and limit depression diffusion in social networks.
- This project exploits data collected from medical profiles and data repository. Many classifier techniques are employed to identify the depression level, of which support vector machine (SVM)-linear shows the best results, with the accuracy reaching 82.5 and F-measure reaching 0.79. Even though, classifiers are giving some theoretical result comparisons; we analyzed the practical based result data with efficient accuracy
- We implemented the proper utilization of Ensemble Learning features for getting the linear output
- Test cases and Black box and white box testing techniques are applied in this project for getting betterment of result

1.3 Objectives:

- In contemporary world, a man or women is engaged with different worldly duties in their profession, work, commitments, family maintenance etc.
- Machine learning is mainly focusing on Mind and then Matter. Main motive of this project is to give the analysis and prediction of depression because 21% people are affected with this psychological disease across the nation.
- Firstly, we purpose to collect the datasets which contains patient records and histories with medication process
- The purpose model extract the hypothesis from the records, to point out which are all the major factors to affect the man or women. Highlight the factors with grades in different geographical structures like Family problem, Physical illness, Lust or desire not obtained so far.
- To introduce ensemble learning method for predicting the disease level for the particular node. **Ensemble learning** is the process by which multiple models, such as classifiers or experts, are strategically generated and combined to solve a particular computational intelligence problem. Ensemble learning is primarily used

to improve the (classification, prediction, function approximation, etc.) performance of a model, or reduce the likelihood of an unfortunate selection of a poor one

1.4 Problem Statement:

1. To achieve better personalized treatment for the symptoms of depression
2. There is a need of smart systems to analyze the symptoms and work on the data sets for accurate and timely prediction of emotions of a person. Also, a test based on AI algorithms under different scenarios for detection of emotional imbalance.
3. Predictive analytics includes a broad set of statistical tools that identify trends, relationships, and patterns within data that can be used to predict a future event or behavior

1.4.1 Proposed System:

a number of variables predict symptom improvement following an internet intervention, but each of these variables makes relatively small contributions. Machine learning ensembles may be a promising statistical approach for identifying the cumulative contribution of many weak predictors to psychosocial depression treatment response. Ensemble learning is the process by which multiple models, such as classifiers or experts, are strategically generated and combined to solve a particular computational intelligence problem

Advantages:

1. More number of parameters are incorporating to predict the depression level
2. Hypothesis are lead to produce more than 95 % accuracy
3. No data redundancy
4. Medical Expert and AI techniques are combined together.

II LITERATURE SURVEY

N. Srivastava and R. R. Salakhutdinov [1] had discussed about multiple diverse modalities. For example, images are tagged with textural information and videos are accompanied by audio. Each modality is characterized by having distinct statistical properties. They proposed a Deep Boltzmann Machine for learning a generative model of such multimodal data. They show that the model can be used to create fused representations by combining features across modalities. These learned representations are useful for classification and information retrieval. We further demonstrate that this multimodal model helps classification and retrieval even when only uni-model data is available at test time.

Meenal J, Patel Alexander Khalaf Howard J. Aizenstein [2] had narrated the depression and it is a complex clinical entity that can pose challenges for clinicians regarding both accurate diagnosis and effective timely treatment. These challenges have prompted the development of multiple machine learning methods to help improve the management of this disease. These methods utilize anatomical and physiological data acquired

from neuroimaging to create models that can identify depressed patients vs. non-depressed patients and predict treatment outcomes.

AnuPriya, ShrutiGarg, Neha PrernaTigga [3] in this paper, predictions of anxiety, depression and stress were made using machine learning algorithms. In order to apply these algorithms, data were collected from employed and unemployed individuals across different cultures and communities through the Depression, Anxiety and Stress Scale questionnaire (DASS 21). Anxiety, depression and stress were predicted as occurring on five levels of severity by five different machine learning algorithms – because these are highly accurate, they are particularly suited to predicting psychological problems. After applying the different methods, it was found that classes were imbalanced in the confusion matrix. The machine learning algorithms were applied in R programming language using Rstudio version 3.5. This predicts the percentage of people suffering from symptoms of stress, anxiety and depression, according to the level of severity. The dataset was divided into the ratio 70:30, representing the training and test sets, respectively. Data were collected using a standard questionnaire measuring the common symptoms of anxiety, depression and stress (DASS-21)

Ashley Ann Fuss et. al [5] have demonstrated the behavioral health disorders, specifically depression, are a serious health concern in the United States and worldwide. The consequences of unaddressed behavioral health conditions are multifaceted and have impact at the individual, relational, communal, and societal level. Despite the number of individuals who could benefit from treatment for behavioral health concerns, their difficulties are often unidentified and unaddressed through treatment. This dissertation addresses the role of health disparities, specifically gender and race, related to depression and mental health treatment. In sum, this dissertation highlights how a machine learning forecasting tool could be used to inform prevention strategies and understanding of factors associated with receiving a depression diagnosis

III IMPLEMENTATION

3.1 System Architecture

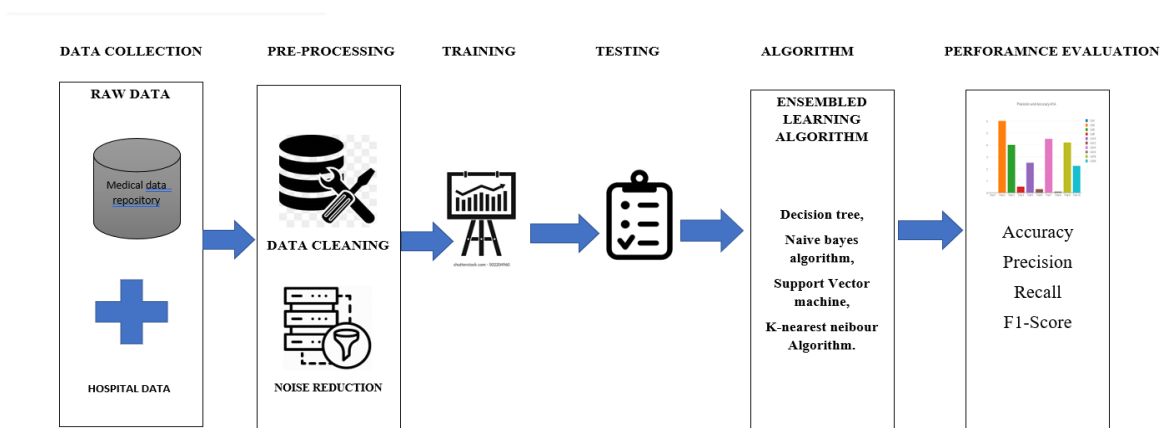


Figure 3.1 System Architecture

3.1.1 DATA COLLECTION:

Data collection is defined as the procedure of collecting, measuring and analyzing accurate insights for research using standard validated techniques. A researcher can evaluate their hypothesis on the basis of collected data. In most cases, data collection is the primary and most important step for research, irrespective of the field of research. The approach of data collection is different for different fields of study, depending on the required information.

This project focuses on Image distortions and errors present in MRI scans, and CT scan images, included with the personal information of the patients. There are three different data sets present for this experiment module.

- MRI scan video/ MRI scan image
- CT scan video/ CT scan images
- Personal medical record of patient

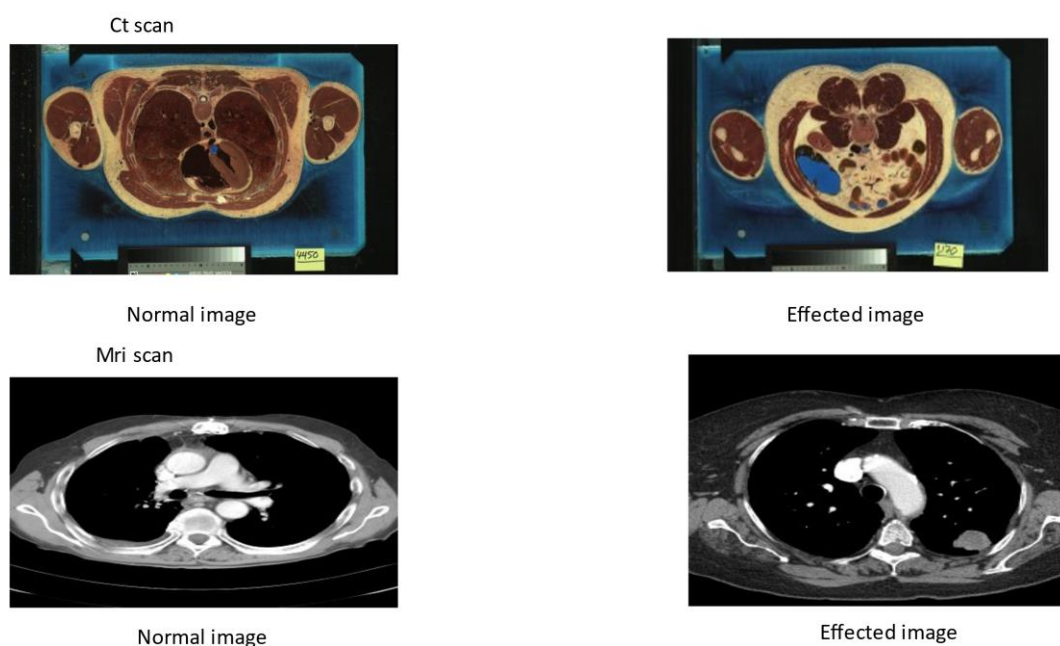


Figure 3.2 CT and MRI scan images

3.1.2 DATA PRE-PROCESSING:

- In any Machine Learning process, Data Preprocessing is that step in which the data gets transformed, or *Encoded*, to bring it to such a state that now the machine can easily parse it. In other words, the *features* of the data can now be easily interpreted by the algorithm.
- In this project we are processing MRI scan video and/or CT scan videos to export individual distinct frames of MRI scan and/or CT scan for particular patients and using them as data set for data processing.
- We also use a segmenting algorithm to remove duplicate copies of the scans and images produced by the previous algorithm.
- Finally we include a noise reduction algorithm to remove any unwanted noises, grains present in the image dataset.

3.1.3 Segmentation

- Data Segmentation is the process of taking the data you hold and dividing it up and grouping similar data together based on the chosen parameters so that you can use it more efficiently within marketing and operations.
- The above frame conversion only extracts separate individual frames from the video and collect them in the provided location
- To extract distinct images from the group we use a separate segmentation

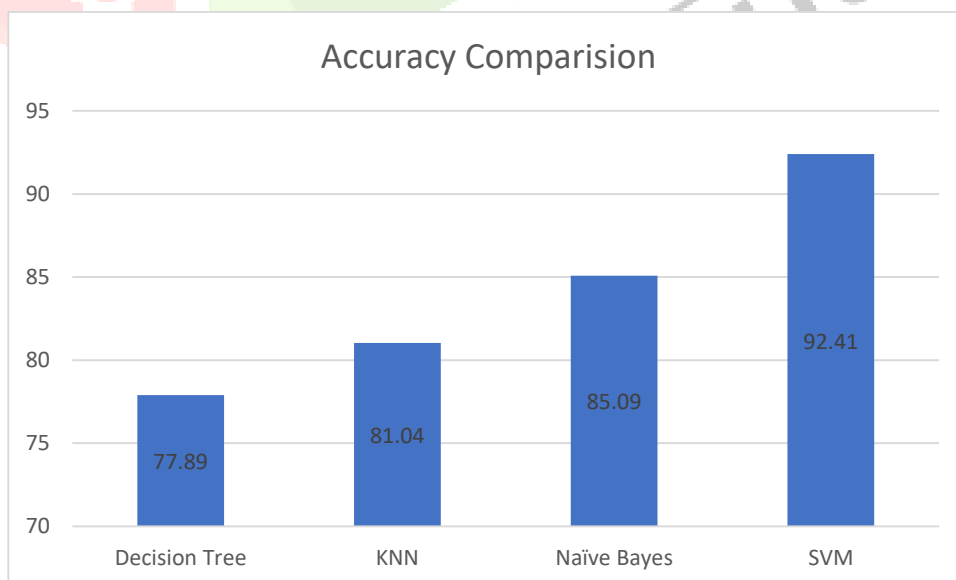
3.1.4 Algorithms:

Ensemble learning is the process by which multiple models, such as classifiers or experts, are strategically generated and combined to solve a particular computational intelligence problem. Ensemble learning is primarily used to improve the (classification, prediction, function approximation, etc.) performance of a model, or reduce the likelihood of an unfortunate selection of a poor one. Other applications of ensemble learning include assigning a confidence to the decision made by the model, selecting optimal (or near optimal) features, data fusion, incremental learning, non-stationary learning and error-correcting.

There are four different modelling algorithms used in this project, which includes:

- KNN algorithm
- Decision Tree algorithm
- Naïve Bayes algorithm
- SVM algorithm

Results Accuracy measures are used to evaluate the performance of the ensemble vote classifier. The accuracy of the ensemble predictive model is compared to the three individual classifiers.



- This algorithm is used to solve the classification model problems. K-nearest neighbor or K-NN algorithm

basically creates an imaginary boundary to classify the data. When new data points come in, the algorithm will try to predict that to the nearest of the boundary line.

- Therefore, larger k value means smother curves of separation resulting in less complex models. Whereas, smaller k value tends to overfit the data and resulting in complex models.

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3.1.4.2 Decision tree implementation

Decision Tree is one of the most powerful and popular algorithm. Decision-tree algorithm falls under the category of supervised learning algorithms.

sklearn :

- In python, sklearn is a machine learning package which include a lot of ML algorithms.
- Here, we are using some of its modules like train_test_split, DecisionTreeClassifier and accuracy_score.

NumPy :

- It is a numeric python module which provides fast maths functions for calculations.
- It is used to read data in numpy arrays and for manipulation purpose.

Pandas :

- Used to read and write different files.
- Data manipulation can be done easily with dataframes

3.1.4.3 Naive Bayes Implementation:

Naive Bayes is among one of the very simple and powerful algorithms for classification based on Bayes Theorem with an assumption of independence among the predictors. The Naive Bayes classifier assumes that the presence of a feature in a class is not related to any other feature. Naive Bayes is a classification algorithm for binary and multi-class classification problems.

Bayes Theorem

- Based on prior knowledge of conditions that may be related to an event, Bayes theorem describes the probability of the event
- conditional probability can be found this way

Assume we have a Hypothesis(H) and evidence(E),

According to Bayes theorem, the relationship between the probability of Hypothesis before getting the evidence represented as $P(H)$ and the probability of the hypothesis after getting the evidence represented as $P(H|E)$ is:

$$P(H|E) = P(E|H)*P(H)/P(E)$$

3.1.4.4 Support Vector Machine:

Support Vector Machine (SVM) is a relatively simple Supervised Machine Learning Algorithm used for classification and/or regression. It is more preferred for classification but is sometimes very useful for regression as well. Basically, SVM finds a hyper-plane that creates a boundary between the types of data. In 2-dimensional space, this hyper-plane is nothing but a line.

To perform SVM on multi-class problems, we can create a binary classifier for each class of the data. The two results of each classifier will be :

- The data point belongs to that class OR
- The data point does not belong to that class.

Algorithm Steps:

Step 1: Initialize MRI Scan images and videos ,CT scan images and videos and personal media records of patients are initialized

Step 2: Data pre-processing is used

Step 3: Training the video will be extracted into separate frames and identify the affected area

Step 4: Now we will apply the four algorithms

Step 5: The highest accuracy results for the proposed algorithm is given as the outcomes

Step 6: Performance evaluation is done by accuracy and precision

3.1.5 Performance Evaluation

Performance Evaluation Criteria Four different metrics i.e., accuracy, precision, recall, and F1- measures are used to evaluate the performance of the proposed system.

- First, we denote TP, FP, TN, and FN as True positive (the number of instances correctly predicted as required)
- False positive (the number of instances incorrectly predicted as required)
- True negative (the number of instances correctly predicted as not required) and
- False negative (the number of instances incorrectly predicted as not required) respectively.
- Then, we can obtain four metrics: accuracy, precision, recall, and F1- measure as follows:
- $Accuracy = \frac{TP + TN}{TP + FP + TN + FN}$
- $Precision = \frac{TP}{TP + FP}$
- $Recall = \frac{TP}{TP + FN}$
- $F1 - Measure = \frac{2 \times Precision \times Recall}{Precision + Recall}$
- Using only accuracy can be sometimes misleading. Sometimes selecting the model which has lower accuracy is desirable, because it provides more robust predictor for the problem. All predictions can be predicted as the value of majority class by model when the problem domain has a large class imbalance. Therefore, we prefer the four different factors to get more accurate results.

IV RESULT AND DISCUSSION

F1 score is a weighted harmonic mean of precision and recall, such that the best score is 1.0 and the worst is 0.0. F1 measure equally considers both precision and recall in the performance measurement. We use F1 measure for the main indicator of model's performance. According to Eqs. (1) and (2), we can calculate the weight for each base model (see Table 2) and further generate the complete form of ensemble classifier:

$$F_e = 0.228 \cdot f_{svm} + 0.283 \cdot f_{nb} + 0.266 \cdot f_{knn} + 0.223 \cdot f_{dt}$$

Table 2 Performance and weights for sub-models

Models	Accuracy	F1 score	1 - F1	Weight
SVM	0.921	0.958	0.042	0.228
Naïve Bayes	0.905	0.948	0.052	0.283
KNN	0.908	0.951	0.049	0.266
DT	0.925	0.959	0.041	0.223

Table 3
Features
and
performance
s of the
ensemble
classifier

Dataset	F1 score	Accuracy	Precision	Recall
DoDo	0.976	0.954	0.956	1.000
DphDph	0.964	0.931	0.934	1.000
DrDr	0.963	0.929	0.929	1.000
DsDs	0.964	0.931	0.931	1.000
DmDm	0.975	0.953	0.960	0.999
DpaDpa	0.961	0.925	0.925	1.000
DgDg	0.964	0.931	0.930	1.000

Table 4 Performances in F1 score

Models	DoDo	DphDph	DrDr	DsDs	DmDm	DpaDpa	DgDg
SVM	0.958	0.950	0.950	0.950	0.957	0.950	0.951
Naïve Bayes	0.948	0.944	0.935	0.942	0.961	0.950	0.930
KNN	0.951	0.947	0.945	0.944	0.958	0.938	0.949
DT	0.959	0.950	0.949	0.950	0.960	0.950	0.950
Ensemble	0.976	0.964	0.963	0.964	0.975	0.961	0.964

Table 5 Performances in accuracy

Models	DoDo	DphDph	DrDr	DsDs	DmDm	DpaDpa	DgDg
SVM	0.921	0.904	0.904	0.904	0.919	0.904	0.907
Naïve Bayes	0.905	0.895	0.879	0.892	0.928	0.904	0.873
KNN	0.908	0.900	0.896	0.895	0.923	0.886	0.904
DT	0.924	0.905	0.904	0.905	0.926	0.904	0.906
Ensemble	0.954	0.931	0.929	0.931	0.953	0.925	0.931

The ensemble classifier performed better compared to the baseline models, including an F1 score of 0.976 vs 0.959 achieved by DT, and an accuracy of 0.954 vs 0.924, which was the again achieved by DT. Performances in functionality sub-sets is compromised in this experiment, but is still comparable to other machine learning methodologies [18,19,20,21].

The results in Table 3 indicate that for the mental functionalities sub-set, the F1 score (0.975) and accuracy (0.953) is closest to the scores for the overall dataset. The accuracy and F1 scores in physical, social and role functionalities in isolation are below the performance of the overall dataset. This indicates that mental functionalities are most relevant to the classifier. DmDm had 4

features, which suggests that these are the most relevant features to the psychological knowledge used to underpin the method. This is consistent with domain knowledge.

The prediction performance in the mental functionality sub-set shown in Table 5 is close to the whole dataset even though it has less features involved. This may indicate that features for mental functionality are more depression-related than features in other categories, because non-criteria items in the depression scale decreased in specificity of performance [4].

Table 6 Performances in recall

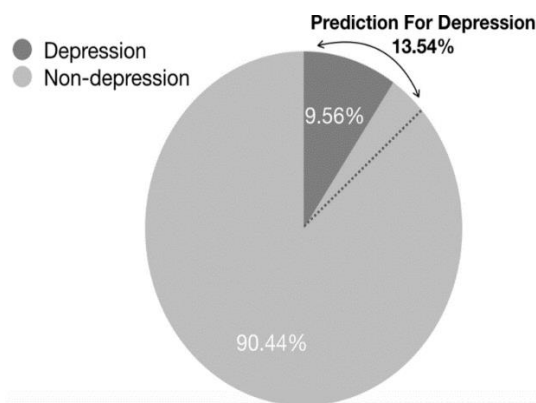
Models	DoDo	DphDph	DrDr	DsDs	DmDm	DpaDpa	DgDg
SVM	0.990	1.000	1.000	1.000	0.996	1.000	0.999
Naïve Bayes	0.955	0.970	0.961	0.969	0.985	1.000	0.937
KNN	0.993	0.981	0.986	0.977	0.980	0.968	0.994
DT	0.981	0.992	0.997	0.993	0.982	1.000	0.992
Ensemble	1.000	1.000	1.000	1.000	1.000	1.000	1.000

DISCUSSION

The ensemble classifier is superior to the baseline models in both F1 measure and Accuracy. It led the test results of both the overall dataset and all experiment results in sub-datasets as shown in Tables 4 and 5, respectively. It gathered different predictions from the baseline models and combined them into a better prediction. The ensemble proved more stable and robust than any involved baseline algorithm during the experiment. We utilized a random under-sampling technique with ensemble method to leverage the class imbalance problem where non-depression instances is about 10 times larger than depressed instances.

The proposed ensemble method significantly improved predictive performance with class imbalance. By analysis of the performance in recall measure (see Table 6), the preferred ensemble method covers all depressed cases in PHQ-9 screening measurement where no depressed instance has been mistakenly labelled as non-depression.

$$P_o = 1 - (P_p \cdot N_1) = 1 - 0.956 \cdot 90.44\% = 13.54\%$$



This algorithm ensures the majority of features consisted by mental diagnostic criteria and mixes partial health criteria to avoid the scenario that temporary mental status change occurs by sudden events like losing close relatives. It simulates the proceedings that psychologist did in the standard clinical interview.

V CONCLUSION AND FUTURE WORK

Social media has revolutionized the way we interact with the world, allowing us all to stay connected and self-express. Mixed anxiety depression and social media seem to exist in a vicious cycle with one problem often stimulates the other. A supervised learning based prediction model is proposed in this research, where first 100 followers forum are analyzed using various linguistic, semantic and activity features to detect anxious depression disorder. The presence of anxiety related words were considered as linguistic markers a model to efficiently predict anxious depression in users. Nearly 85% predictions are found to be accurate in the preliminary analysis. As a possible future work, fine grain emotion analysis can be done to detect anxiety indicators instead of using SentiWordNet which categorizes the words into three polarities. Further, the model can be tested on different user base: geographic, age, profession etc. Neuro-fuzzy and deep learning models can be explored for superlative prediction perform

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