Depression Detection using Machine Learning

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Abstract: Depression is a mental state in which people develop aversion to living. Depression can produce serious effects on the health of an individual, both physically and emotionally. It features sadness in extreme measures, and can often lead to suicides. Depression is a disorder of major public health importance that affects women more than men. According to a report by WHO, dated June 2019, India is the most depressed country in the world, with 6.5% of its total population being victim to depression. And to treat such an illness, the first step is identifying it. The identification process is often tedious, with no accurate result. Psychologists usually use a 'PATIENT HEALTH QUESTIONNARIE' to detect depression. But this method can be deceived easily if a patient wishes to answer differently. Hence, we come forward to provide an effective method to detect depression using Machine Learning. We obtain data in the form of text, from the patients/users on a regular basis. This textual data is interpreted by classification-based algorithm to detect signs of depression. The algorithm takes readings of emotion from the input text given by the user, before it finally announces if there is any depression found in the text. Classification algorithms such as K-Nearest Neighbors, Naïve Bayes, Decision Tree and Random Forest have been used for the detection model. This aids us in choosing the algorithm that provides best accuracy. Also, we continuously analyze previous readings of the user, to detect changes in the depression level. This is often represented as graphical representation that helps the user to easily identify their mood swings. Such accurate diagnosis reduces the psychologist's work to half. The user is immediately warned of their depression level, and they are urged to get professional help. The proposed scheme not only achieves high accuracy due to its Machine Learning Approach, but also inherits scalability regarding the input size.

Keywords: Depression detection, Machine Learning, Text classification, Supervised Learning

I. INTRODUCTION

Machine learning is a subset of Artificial Intelligence that enables the computers to automatically learn and improve from actions without being pre-programmed. Machine learning actually focuses on the development of programs that can access data from the real world,and learn from its experiences with data. The process of learning begins with observations of data. The primary aim is to allow the computers learn automatically without human intervention or assistance and adjust actions according to the results. Supervised machine learning algorithms use a set of labeled datasets to train themselves, and hence named supervised algorithm. The labeled dataset helps the supervised machine learning algorithm to predict future from data of past. The analysis of training dataset with known categories enables the learning algorithm to produce a function that makes predictions about the output values that are needed. The system that has been trained with supervised algorithm can provide acceptable output for any new input after sufficient training. The machine learning algorithm can also compare its output with the intended correct output and modify its model accordingly. This is one of the most assuring features of machine learning algorithms. Unsupervised machine learning algorithms are used when the data that has to be used for training has not been classified. Unsupervised learning helps the computers to describe a function that can identify the hidden pattern of any unlabeled dataset. Though the system doesn't figure out the right output, it explores the data and draws inference from datasets to describe hidden structures among unlabeled data. Semi-supervised machine learning algorithms falls in between supervised and unsupervised machine learning algorithms. This is because this uses both labeled and unlabeled data for training the model. Typically, the dataset contains a small amount of labeled data and remaining large amount of data being unlabeled. The computers that use this method are able to considerably improve learning accuracy due to this double approach. Usually, semi-supervised learning is chosen when the acquired labeled data is not fully classified, and yet requires skilled resources in order to train it. Otherwise, acquiring labeled data generally does not require additional resources. Reinforcement machine learning algorithms depends on a learning method that interacts with its system environment by producing actions that are later assessed for error/reward. This trial and error search and delayed rewards are the most compelling characteristics of reinforcement learning algorithm. This algorithm allows machines and system agents to automatically determine the ideal behavior that can maximize its performance, even within a specific context. The simple reward feedback system is required for the algorithm to learn which action best delivers output; this is known as the reinforcement signal for a system. Machine learning algorithm enables analysis of massive quantities of data, with less to no human interference. While it generally delivers faster and more accurate results than human programs, the results most often are probabilistic in nature. Hence, in order to identify opportunities or to avoid potential risks, the machine learning model requires additional time and adequate resources to train it properly. Combining machine learning with AI and cognitive techniques can make a model even more effective while processing large volumes of data. Classification algorithms and regression algorithms are types of supervised machine learning algorithm. The Classification algorithms are used when the output is restricted to a fixed set of values. For example, for a classification algorithm that filters spam emails, the input would be an incoming email of the respective user, and the output would be the name of the folder in which to email has to be stored, namely inbox or spam folder. This algorithm that identifies spam emails, can even have a output of either spam or not, represented by the Boolean values true and false. Such as in our case, where the classification algorithm predicts the output as very depressed, mildly depressed or not depressed. Regression algorithms are identified for their continuous outputs, which means that the output generated can be any value within a given range. Examples of these continuous values are temperature, length, or price of an object with specific fixed units. Active learning algorithms access the desired outputs (using training labels) for a limited set of given inputs based on the budget, and optimize the range of inputs for which it will acquire sample labels. When used interactively, these are presented to a human user for labeling and classification purpose.

II. LITERATURE REVIEW

A. Existing System

Authors of [3] had used convolutional neural networks (CNN), Gated Recurrent Units (GRUs), and Multilayer Perceptions (MLPs) for training their predictive model. The results had shown the differences in extracted patterns between the two user groups, with around 72% of accuracy in classification. Authors of [4] had conducted pooled analysis and critical appraisal of around 8917 individuals. The experimental results show that the physicians of the Italy and Netherlands are the most successful in screening depressed individuals with 83.5% and 81.9% accuracy. Authors of [6] had generated confusion matrix for the predictive analysis for using the HADS classification. This matrix is used for further prediction. The results delivered through the Random Forest (RF) classifier have the highest accuracy rate of 89%. Authors of [16] ensemble a convolutional neural network based on different word embeddings and classification based on user-level language-based metadata. On the basis of these analysis, a new word embedding was trained on a large word corpus for early depression detection.

Authors of [11] used LIWC (Linguistic Inquiry and Word Count Tool) for the classification tool. Between the four variants of the LIWC used in the experiment, LIWC with ŋgram model is the best with 81.8% performance accuracy. Authors of [12] talk about the various advances in the natural language processing techniques and their characteristics. Many techniques such as Named Entity Recognition and Machine Reading have been analysed. Authors of [14] use an NLP system named MTERMS as their classification model to classify free-text classification. The results of the MTERM's knowledge-based decision tree generates a F-measure of 89.6%. Authors of [22] analyse and compare the various sources of data in internet from which data can be collected for natural language processing tools. The result delivers that the online support groups and blogs are the best source of reliable data for NLP researches. Authors of [15] perform a comparison between natural language processing versus the administrative data base codes to identify depression. The experimental results prove that using NLP tool in place of administrative methods has actually increased diagnosis rate by one-third.

Authors of [17] focus on different dimensions of social media data to detect depression signs. Their results show that the decision tree algorithm has the highest accuracy in emotional process and linguistic style. Authors of [19] discuss various signs of depression that can be read through social media to identify the persons with depression. The data collected through these signs on social media were used to build an SVM classifier. The result was a 70% classification accuracy. Inaccuracy of input data is the major disadvantage among other disadvantages. The system requires access to social media content that can be private to the user. The social stigma surrounding depression affects the quality of input data.

B. Proposed System

The proposed system detects depression in the user through machine learning technique. The system analyses the text dataset collected from people who were clinically diagnosed with depression. This helps the machine learning model to detect the traces of depression in the user's submitted input text. For the input, the user submits a random piece of text written by them to the application. This means that the proposed system does not access to the sensitive social media content of the user. Furthermore, this input is voluntarily bestowed by the user, which means that there is no privacy breach. The user can access the system in the comfort of his privacy, that protects him from surrounding social stigma, As the fear of social stigma is eradicated from user, the accuracy of the input data that is fed into the proposed system also increases. The machine learning model trained in text classification algorithms analyze the input text and produces its current depression diagnostics. As depression is not a spontaneous occurrence, and needs at least a week to set in, we consider pieces of text from previous times and combine their results to pass a verdict. The conclusion can be very depressed, mildly depressed, or not depressed. The final output consists of a brief description of the conclusion, assisted with the graphical representation of depression levels from various times. The purpose of the graphical representation is to represent the depression patterns of the user. The detected pattern can be helpful for the user, to understand their emotional swings. This depression pattern from the graphical representation consists both the past depression readings, along with the present one.

III. METHODOLOGY

A. Architecture of Proposed System

The Depression Detection system under proposal has been given below. The Machine Learning model takes preprocessed training data acquired from various test subjects and generates a pickle file using various text classification algorithms. These algorithms are namely, Decision Tree algorithm, Naïve Bayes algorithm, KNN Algorithm and Random Forest Algorithm.

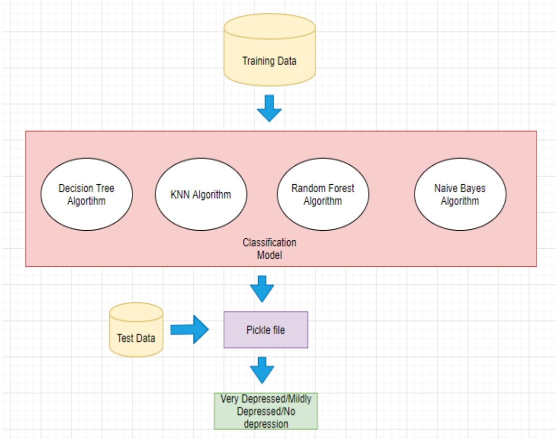

Fig. 1

The generated pickle file takes the input data fetched from the user through web application and gives out depression reading to be stored in json file. This json file is exclusive for each user and helps in generating graphical representation. The graphical representation along with conclusion is displayed to the user in end. This delivery of result is done through python web framework flask.

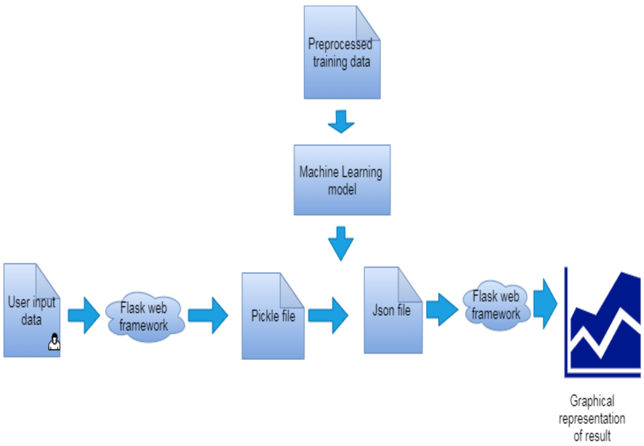

Fig. 2

IV. MODULES

The front page lets the user upload their text input. This text input can be of any size; this means there is no upper limit on input size. This page is user interactive, and lets the user upload their self-assessing text easily to the application. The machine learning algorithm model that detects the depression needs to be trained by a training dataset that imprints the depression pattern into the model. The collected and cleaned dataset is uploaded to the training model, to train the model. The trained model is converted to pickle file for future use in detecting depression levels. The input text uploaded by the user is cleaned and taken to the model module. The input is processed using the generated pickle file, to predict depression levels. The training data set helps in detecting the depression levels, with high accuracy. The detected depression levels need to be saved for future reference. This is an efficient move that saves processing time and memory. The depression levels are recorded in a local file for this purpose. The number of rows equals to the number of user entries.

The depression levels from the current entry and the previous entries are read together, to plot a graph that represents the depression levels of a selected timeline. This graphical representation helps the user understand his emotional fluctuation and depression levels. The depression levels that have been plotted in the graph are considered to generate depression conclusion. The conclusion shall be very depressed, mildly depressed, or not depressed depending on the consolidated depression readings of the user. The final diagnostic report consists of the graphical representation and the derived conclusion. This diagnostic report is displayed to the user, through a webpage.

V. PERFORMANCE ANALYSIS

Though the result is generated from only a single algorithm, we test four different algorithms in the model to compare their accuracies. These classification algorithms are Naïve Bayes Algorithm, Decision Tree Algorithm, KNN Algorithm and Random Forest Algorithm. In the proposed system, the Decision Tree Algorithm is the most efficient algorithm with an accuracy of 98.24%, with Random Forest Algorithm being the least efficient with an accuracy of 50%.

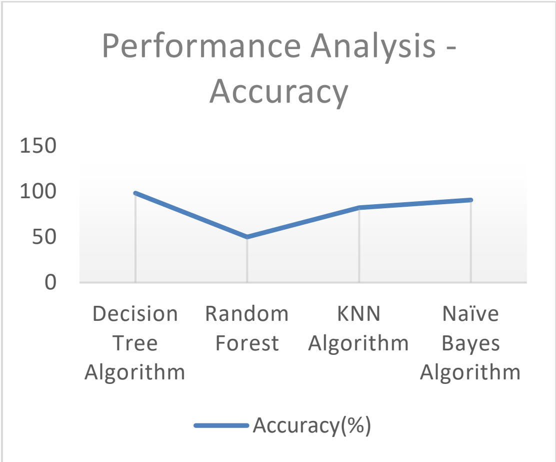

Figure 3

Among the Algorithms, Naïve Bayes Algorithm is the fastest algorithm with 7.6seconds tie taken, while KNN Algorithm was the slowest with time taken as 514.8seconds.

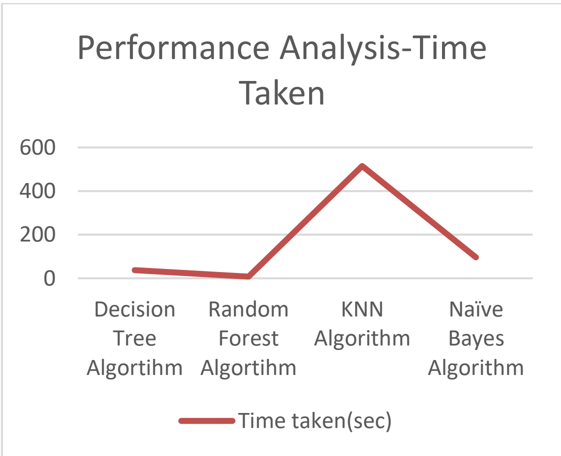

Figure 4

VI. CONCLUSION AND FUTURE WORK

Proposed system aims upon reducing physical intervention of the human beings in the process of detecting depression in an individual. Previously, one had to look up to human doctors to identify depression through standardized methods. On the other hand, our application automates this procedure, and quickly provides us with a diagnostic report in private. The provided diagnostic comes with high accuracy, owing to the large dataset on which model has been trained upon.

The future developments on the proposed system shall be focused on making the application more reachable to the people. This could be achieved by adding different languages for diagnosis, mainly the native languages spoken in India.

Further improvements shall be made by moving out of the text classification model, and adapting to voice recognition model that can detect depression in various languages with varied accents.

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