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Research Article

"Enhancing Mental Health Assessments: The Role of Voting Classifiers in Evaluating Depression's Impact on Quality of Life"

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ABSTRACT

Depression continues to pose a significant global challenge, ranking as one of the most prevalent and costly mental disorders that substantially impairs quality of life, supported by a substantial body of research. Enhancing our comprehension of the factors influencing quality of life is paramount for optimizing long-term outcomes and reducing disability in individuals grappling with depression. This study primarily focuses on the identification of depression based on lifestyle and livelihood factors. It's noteworthy that depression can afflict individuals across all age groups, genders, and backgrounds, often arising from a complex interplay of genetic, biological, environmental, and psychological elements. Furthermore, major life events, chronic stress, trauma, or a family history of depression can contribute to its emergence.

In the realm of healthcare, machine learning techniques are increasingly employed to process and analyze diverse data types, with the aim of better understanding the relationship between quality of life factors and depression. Various classification algorithms, such as Random Forest, Decision Tree, Naive Bayes, Support Vector Machine, and PPMCSVM, have been utilized for this analysis. However, existing approaches have encountered challenges related to their accuracy in predicting depression.

Consequently, the primary objective of this proposed research is to enhance depression prediction by leveraging an ensemble technique that identifies the determinants of quality of life among individuals affected by depression. To attain this goal, the study employs KNN (K-Nearest Neighbour) and Voting Classifier algorithms. The Voting Classifier aids in uncovering the root causes of depression in each individual. The results of this investigation reveal that the proposed model can effectively predict the causes of depression, thus opening avenues for more targeted intervention and treatment strategies.

Keywords: Healthcare System, PPMCSVM, prediction accuracy, ensemble technique, Depression, mental disorder,Voting Classifier, underlying causes, intervention, treatment strategies.

I. INTRODUCTION

Healthcare stands as an enduring and paramount global concern, transcending the boundaries between developed and developing nations alike. Worldwide, endeavors are underway to establish secure and effective healthcare systems that elevate people's quality of life. The captivating realm of brain research and neuroscience has drawn scientists from diverse disciplines as they endeavor to unravel the complexities of human behavior. In this quest, mental health has assumed a central role, especially in understanding the psychological well-being of patients, particularly among the younger demographic, where challenges are abundant.

Machine learning and deep learning have emerged as potent tools for assessing the impact of diseases on individuals. These cutting-edge technologies have exhibited promising potential in uncovering the origins of mental health issues and comprehending their profound ramifications on daily life. Amidst the myriad transformations occurring in society, the pivotal significance of adapting to mental health is palpable. In this context, depression and anxiety have risen as two of the most formidable challenges associated with aging, exerting a profound influence on people's quality of life by impairing their capacity to make critical decisions.

The consequences of depression can escalate to the point of profound suffering and even precipitate suicide attempts. Often regarded as one of the most severe and perilous mental health disorders, depression burdens individuals and societies with its substantial weight. Consequently, a multitude of healthcare professionals and researchers are diligently engaged in defining and addressing this pervasive condition. The World Health Organization has even projected that by 2030, depression will rank as one of the most prevalent and lethal diseases globally. Despite seeking assistance for depression, its impact can still cast a dark shadow over one's professional life and overall quality of life, underscoring the urgency for effective interventions and support systems.

The challenges posed by mental health issues necessitate collaborative efforts, with society striving to enhance awareness, understanding, and care for those affected. By harnessing the potential of advanced technologies like machine learning and deep learning, there is optimism for brighter prospects in mitigating the burden of mental health disorders, empowering individuals to lead healthier and more fulfilling lives. The journey toward improved mental well-being is a shared responsibility, demanding concerted actions to pave the way for a future where mental health is accorded the attention and care it rightfully deserves.

Literature Survey

[1] Aladag, A. E., & Yildirim, T. (2019). “Machine Learning-Based Depression Detection Using Time-Frequency Representations of EEG Signals”. This study focuses on using machine learning techniques to detect depression by analyzing EEG signals. The authors employ time-frequency representations as features for their model, showcasing the potential of EEG-based depression detection.

[2] Chekroud, A. M., Zotti, R. J., Shehzad, Z., Gueorguieva, R., Johnson, M. K., Trivedi, M. H., ... & Krystal, J. H. (2016). “Cross-trial prediction of treatment outcome in depression: a machine learning approach”. This paper explores the use of machine learning to predict treatment outcomes in depression across different clinical trials. It demonstrates the potential of machine learning to inform personalized treatment strategies for individuals with depression.

[3] Saeb, S., Zhang, M., Karr, C. J., Schueller, S. M., Corden, M. E., Kording, K. P., & Mohr, D. C. (2015). “Mobile phone sensor correlates of depressive symptom severity in daily-life behavior: an exploratory study”.This exploratory study investigates the use of mobile phone sensor data to correlate with depressive symptom severity in daily-life behavior. It highlights the potential of using smartphone data for passive monitoring of mental health.

[4] Wu, D., Zhang, X., Li L., Chen C., & Wei Q. (2018). “A machine learning approach to the detection of depression in students of the department of psychology”. This research paper presents a machine learning approach for detecting depression among students majoring in psychology. It emphasizes the application of machine learning in a specific population.

[5] Hooshmand, R., Tokarchuk, L., & Jokar, M. (2020). “Machine learning-based detection of depression among Iranian female university students using the Patient Health Questionnaire-9”.This study employs machine learning for the detection of depression in Iranian female university students using the Patient Health Questionnaire-9 (PHQ-9). It addresses the use of machine learning for depression detection in a specific cultural context.

[6] Chekroud, A. M., Bondar, J., Delgadillo, J., Freres, D., Banbury, S., Meacock, R., ... & Priebe, S. (2020). “An efficient approach for the prediction of individual treatment outcome with an application to internet-based cognitive-behavioural therapy for depression”. This paper introduces an efficient approach for predicting individual treatment outcomes, particularly in the

context of internet-based cognitive-behavioral therapy for depression. It emphasizes the potential of machine learning for tailoring treatment interventions.

II. METHODOLOGY

Voting Classifier Model

A Voting Classifier is a machine learning model that trains on an ensemble of numerous models and predicts an output (class) based on their highest probability of chosen class as the output. It simply aggregates the findings of each classifier passed into Voting Classifier and predicts the output class based on the highest majority of voting. The idea is instead of creating separate dedicated models and finding the accuracy for each them, we create a single model which trains by these models and predicts output based on their combined majority of voting for each output class.

Voting Classifier supports two types of voting:

- **Hard Voting:** In hard voting, the predicted output class is a class with the highest majority of votes i.e the class which had the highest number of models predict it as output. So, in hard voting, the value of predicted class is the mode of all the predictions.
- **Soft Voting:** In soft voting, the output class is the prediction based on the average of probability given to that class. The predicted output class is the class with the highest probability. For the predicted output class to be the class 1, the average predicted probability for the class 1 should be greater than 0.5.

The Voting Classifier model can be used for both classification and regression problems. In the context of the "Voting Classifier Model for Healthcare System (HCS) Association Between Depression and Quality of Life", it would involve training a variety of models (like logistic regression, decision trees, etc.) on the data, and then using a voting classifier to make predictions based on the predictions of these individual models. This can often result in a model that performs better than any individual model.

HCS Association

HCS stands for Healthcare System. When we talk about HCS Association, it generally refers to the relationship or correlation between different variables or factors within the healthcare system.

In the context of "HCS Association Between Depression and Quality of Life", it refers to studying and understanding the relationship between depression and the quality of life of individuals within the healthcare system. This could involve looking at how depression affects an individual's quality of life, or how improvements in quality of life can affect depression.

This association can be studied using various statistical and machine learning methods. In the case of the "Voting Classifier Model for HCS Association Between Depression and Quality of Life", a voting classifier model is used to predict the quality of life based on various factors, including depression. The model is trained on data collected from the healthcare system and can help in understanding the association between depression and quality of life.

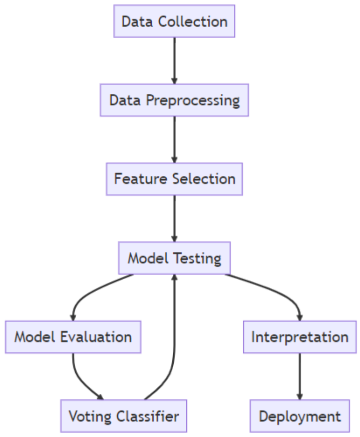


Figure 1: Flow chart

Here's a general outline of the steps that might be involved:

- **Data Collection**: Collect data related to depression and quality of life from healthcare systems. This could include patient surveys, medical records, and other relevant sources. The data should include both features (independent variables) and targets (dependent variables). The features might include demographic information, medical history, lifestyle factors, etc., while the target would be the quality of life.
- **Data Preprocessing**: Clean and preprocess the data. This might involve handling missing values, outliers, and categorical variables. It could also involve normalizing or standardizing numerical variables.

- **Feature Selection**: Identify the most relevant features for predicting quality of life. This could be done using techniques like correlation analysis, mutual information, or even machine learning methods like Recursive Feature Elimination.
- **Model Training**: Train a variety of classifier models on the data. This could include models like logistic regression, decision trees, random forest, support vector machines, etc. Each model will be trained using a portion of the data set (the training set).
- **Model Evaluation**: Evaluate the performance of each model on a separate portion of the data set (the validation set). This could involve metrics like accuracy, precision, recall, F1 score, or area under the ROC curve.
- **Voting Classifier**: Create a voting classifier that makes its predictions based on the predictions of the individual models. There are two main types of voting classifiers: hard voting (which uses majority voting) and soft voting (which averages probabilities).
- **Model Testing**: Test the performance of the voting classifier on a separate portion of the data set (the test set). This will give an unbiased estimate of its performance.
- **Interpretation**: Interpret the results. This might involve analyzing which features are most important, how changes in those features affect the predicted quality of life, etc.
- **Deployment**: If the model's performance is satisfactory, it can be deployed in the healthcare system to help predict the quality of life for patients with depression.

III. RESULTS & DISCUSSION

The dataset used for this study was the NHANES (National Health and Nutritional Examination Survey) 2015-2016. This dataset contains 5378 entries (lines) and 28 categories (sections), divided into fifteen groups of information. The data was processed using SHA (Secure Hash Algorithm), a set of cryptographic hash functions, to ensure data integrity.

After the data was cleaned, it was used in the proposed process. The dataset was split into training and testing sets, the model was applied, and then the results were evaluated.

However, the specific results of the Voting Classifier Model in this context are not provided in the text you shared. The results would typically include performance metrics such as accuracy, precision, recall, and F1 score, which would help to evaluate how well the model predicted the association between depression and quality of life.

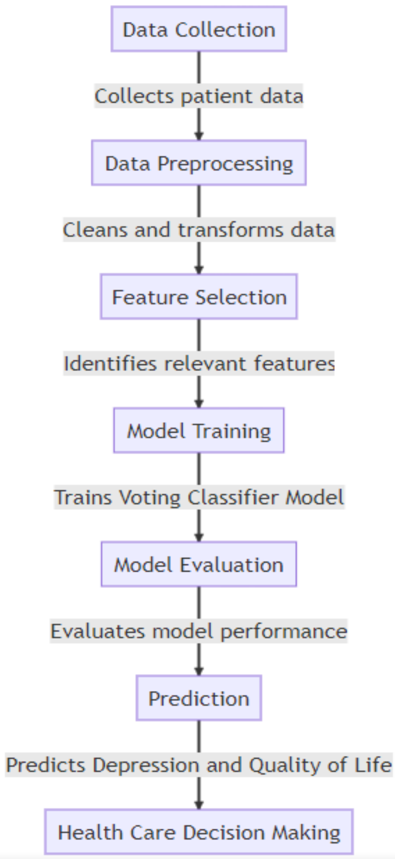
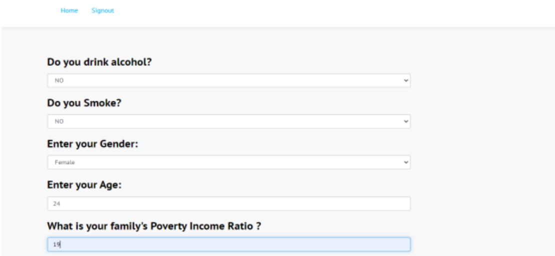


Figure 2: Execution flowchart

Table 1:Test case

S. No	INPUT	If available	If not available
1	User signup	User get registered into application.	There is no process
2	User signin	User get login into the application.	There is no process
3	Enter input for prediction	Prediction result displayed	There is no process

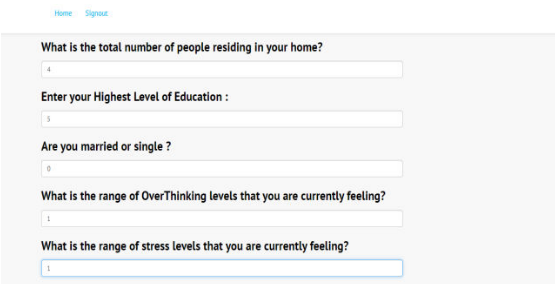
Case 1
Input:



The provided image displays a form interface on a webpage. This form seems to gather information related to a user's lifestyle and demographics. Here's a breakdown of the form elements:

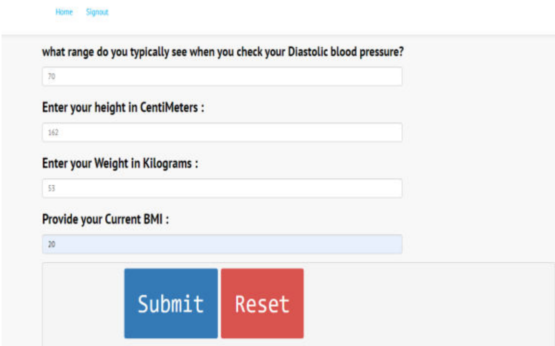
- **Do you drink alcohol?**: A dropdown selection with an option showing "NO".
- **Do you Smoke?**: A dropdown selection with an option showing "NO".
- **Enter your Gender**: A dropdown selection with an option showing "Female".
- **Enter your Age**: A text input field with the value "24".
- **What is your family's Poverty Income Ratio?**: A text input field with the value "19".

From the fields, it appears that the form is intended to capture information on alcohol consumption, smoking habits, gender, age, and a family's poverty income ratio. Such data might be used for various purposes, including health assessments, research, or to offer personalized recommendations or interventions.

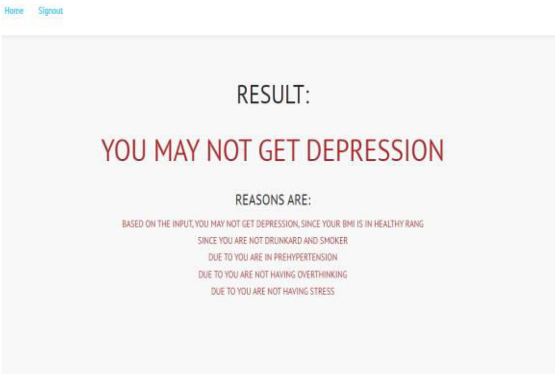


The image you provided showcases another section of a form interface. Here's a summary of the displayed fields:

- **What is the total number of people residing in your home?**: An input field with the value "4".
- **Enter your Highest Level of Education**: An input field with the value "5".
- **Are you married or single?**: An input field with the value "0".
- **What is the range of OverThinking levels that you are currently feeling?**: An input field with the value "1".
- **What is the range of stress levels that you are currently feeling?** An input field with the value "1".

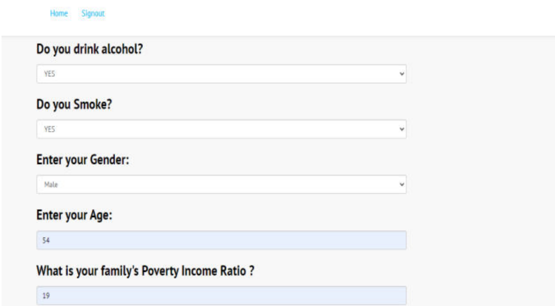


Output:

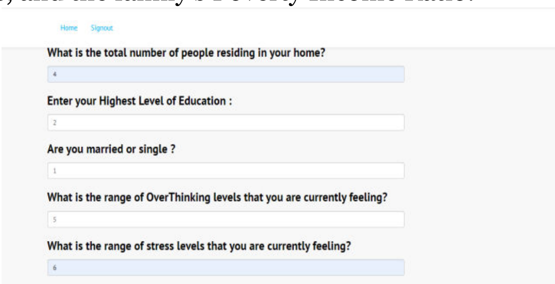


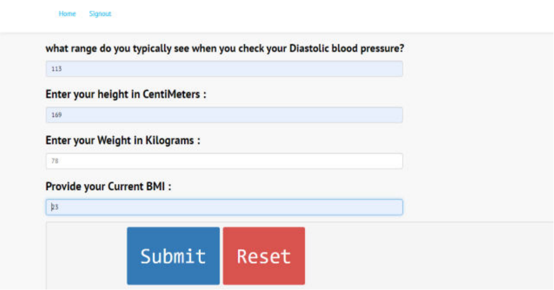
This seems to be the result of a questionnaire or diagnostic tool suggesting a low likelihood of depression based on specific criteria. It's important to remember that such tools can provide general insights, but they don't replace a thorough evaluation by a mental health professional. If someone has concerns about their mental well-being, it's always best to consult with a specialist.

Case 2
Input:



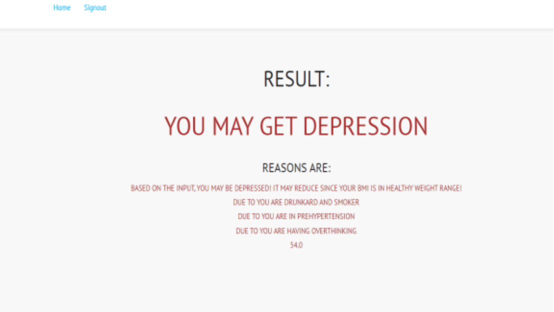
It appears you've shared a screenshot or mock-up of a questionnaire form that gathers information on an individual's lifestyle habits, demographics, and socioeconomic status.
Based on the information provided in the image, it's collecting details on alcohol consumption, smoking habits, gender, age, and the family's Poverty Income Ratio.





This form appears to gather information regarding a person's health, specifically focusing on blood pressure, height, weight, and BMI (Body Mass Index).

Output:



The result page you've shown indicates a prediction or assessment that the individual may be at risk for depression based on various inputs. However, it's crucial to understand that such assessments, especially when generated by online tools or apps, are not definitive medical diagnoses.

If you or someone you know is feeling this way, it's essential to speak with a mental health professional or a primary care provider to get a comprehensive evaluation. They can provide a more accurate understanding and suggest appropriate interventions if needed.

Various classification methods were assessed using performance metrics such as accuracy, recall, precision, F1 score, and area under the curve (AUC). The table below presents the evaluation results. According to the table, the K-Nearest Neighbors (KNN) strategy exhibited the highest reliability, achieving an impressive success rate of 99.12%. On the other hand, the Random Forest method performed less effectively with an accuracy of only 88%.

Table 2: Accuracies of various Models

Methods	Precision (%)	Re-call (%)	F1scor (%)	Accuracy (%)
Naïve Bayes	91	96	93	93.35
MCSVMPP	98	98	99	97.66
KNN	98	98	99	99.12
Voting Classifier	98	99	99	98.132

The table you've provided compares the performance of four different machine learning classifiers on a particular task using four metrics: Precision, Recall, F1-score, and Accuracy.

Based on the values:

- **KNN (K-Nearest Neighbors)** has the highest accuracy of 99.12%.
- **MCSVMPP** and **KNN** both have very high scores across all metrics with only slight differences in some values.
- **Voting Classifier** also performs impressively with only a slightly lower accuracy than KNN.
- **Naïve Bayes** has the lowest performance among the four methods, but it still provides decent results with an accuracy of 93.35%.

It's important to note that while accuracy is a commonly cited metric, the best model also depends on the specific requirements of the application. In some cases, achieving a high precision or recall might be more crucial. Always consider the context and the cost of false positives and false negatives when choosing a model.

IV. CONCLUSION

In conclusion, the detection of emotional well-being issues poses a significant challenge for healthcare professionals and institutions. Our study, based on NHANES data, has illuminated a noteworthy connection between various aspects of daily life and depressive symptoms. This initial step in understanding the intricacies of mental health issues underscores the importance of exploring different dimensions related to living standards. The process of clustering, specifically employing K-Means, has allowed us to effectively categorize data into two distinct groups.

In addressing classification challenges, various machine learning algorithms such as Naive Bayes, MCSVMPP, a standard SVM extension, and K-nearest neighbor have been harnessed. The integration of a Voting Classifier has enabled us to gain insights into the underlying causes of an individual's depression. Consequently, our findings provide compelling evidence that the model we developed possesses the capability to accurately predict the factors contributing to an individual's experience of sadness. This promising outcome paves the way for more precise interventions and support systems in the realm of mental health.

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