International Journal of Scientific Research and Engineering Development-- Volume 9 Issue 2, Mar-Apr 2026
Available at www.ijsred.com

Identifying Predictive Digital Markers of Youth Mental Health Risk Using Machine Learning Approaches

Shah Fatema Rashid, Grace Julius Migeha, Oluwadare ifeoluwa favour
Department of Computer Applications, Jain University
Bengaluru, India
fatmashah03@gmail.com, gmigeha65@gmail.com, favourdare.ife@gmail.com

Abstract:
Youth mental health issues have increased over the past few years due to different reasons, including the need to perform academically, difficulties in achieving life balance, and the overuse of digital technologies. For the early intervention or prevention of youth mental health issues, it is imperative that youth at risk of having mental health issues are identified at an early stage. In order to assist in the identification of youth at risk of having mental health issues, an artificial intelligence-based predictive modeling approach is proposed. For the proposed predictive modeling, the dataset containing lifestyle, behavioral, and psychological information, which has already been preprocessed and analyzed using supervised machine learning models, is used. Supervised classification models have been used to assess the predictive capability of the data by using training and testing samples. The predictive capability of the proposed model is evaluated using accuracy, confusion matrix, precision, recall, F1-score, etc. The results show that machine learning models can predict the classification of youth with varying degrees of risk with great accuracy, thereby indicating great potential for the early detection of youth at risk using AI-based technologies.

I. INTRODUCTION

Adolescents and young adults have become vulnerable to mental health disorders which have become a serious global health concern. The world health organization (WHO) reveals that about one out of every seven adolescents globally present with some form of mental health disorder with some the most common being anxiety and depression. Suicide is among the most common causes of deaths among the youth in the world hence the necessity of early identification and preventive measures. Psychological vulnerability among the young populations is further amplified by rapid urbanization, academic pressure, social expectation, imbalance in lifestyles, and exposure to increased digital interaction. These trends indicate that scalable and technology-based solutions would be needed to assist in the risk of mental health detection during the early stages.

Proactive identification of mental health risk is important since most psychological disorders may take their time to manifest themselves, which may result in an undiagnosed state until they are critical. Early detection allows a prompt intervention and minimizes chronic complications and enhances general well-being. Nonetheless, conventional mental health screening processes mainly use self reporting questionnaires, clinical interviewing or periodic testing that is administered in institutions. These methods may be time consuming, resource consuming and prone to reporting bias. Furthermore, the stigma related to mental health issues can mak e a person reluctant to openly share the experience of emotional distress, which leads to later diagnosis and less easy access to services.

The past few years have seen the development of predictive analytics in the health sector with the use of Artificial Intelligence (AI) and Machine Learning (ML) developments. Machine learning models have the ability to manipulate high-dimensional data which is complex to reveal concealed patterns and relationships that would not be readily recognized in traditional statistical systems. ML methods have proven useful in the health care setting and have been applied to predict diseases, risk, and tailored treatment. When used in mental health research, such models would be able to manipulate behavioral, lifestyle, and psychological signs to find patterns that are linked to greater susceptibility. These forms of data derivation provide scalable and objective methods of early-stage risk monitoring especially among digitally active young demographics.

Although the avenue of AI-based mental health prediction continues to increase in research, there are still several gaps. Most of the existing works revolve around either clinical data that is not easily accessible or social media sentiment analysis that lacks structured variables of behavior. Besides, there are those models that focus on predictive accuracy and not interpretability, which is vital in health systems where transparency and trust are paramount. The black-box models can be highly effective, but there is no explanation of their forecasts and constraints on their application in the sensitive areas, including youth mental health.

In order to fill these gaps, a predictive framework is constructed in this study, employing supervised machine learning methods to categorize the level of mental health risk, in accordance with structured behavioral and lifestyle factors. The study is focused on predictive performance and interpretability of the model to guarantee the practical applicability and ethical appropriateness in the healthcare facilities.

II. LITERATURE REVIEW

The use of Artificial Intelligence (AI) in mental healthcare has grown exponentially within the last decade. The idea of an active collection of behavioral data by smartphones and connected devices through passive methods was first proposed by Early work by Torous et al. [1] and Insel [2], who noted that aspects like mobility patterns, sleep duration, and communication frequency can be passively monitored. These investigations formed the basis of applying digital traces as precursors of psychological distress.

Shatte et al. [3] reviewed and analysed the classification and regression methods applied to predict depression, anxiety and other mental illnesses via machine learning applications in psychiatry. Equally, Dwyer et al. [11] expressed the increased application of supervised learning models in clinical psychology, indicating that the support of machine learning and ensemble models tend to be better than conventional statistical analyses. Rajkomar et al. Further shown by [6], machine learning is transformative in healthcare, and it supports the idea of predictive analytics in the risk stratification of diseases.

Social media has also become a significant source of data in mental health assessment. De Choudhury et al. [15] are the first to use word and behavioral patterns of online sources to forecast depression. Based on this study, Chancellor and De Choudhury [8] investigated predictive computational algorithms to detect mental illnesses through social networks, whereas Guntuku et al. [9] studied how language-based return can be used to detect psychological disorders. These researches affirm the possibility of digital communication data in prediction of mental health.

Deep learning-based research has also become eminent in mental health outcome studies. Harrer [14] wrote about the use of AI in digital mental health systems, automatic risk prediction and intervention design. . Nevertheless, there has been a concern on the complexity of the models that has sparked concerns over interpretability. Lundberg and Lee [7] attempted to overcome this difficulty by introducing SHAP which is an explainable AI scheme that boosts chartability in model forecasts. Interpretability is especially important in health care settings and Sendak et al. [5] have focused on the need to implement AI in an ethical and trustful manner.

Special mental health studies of youths have also discussed wearable sensor information and passive monitoring. Leightley et al. [12] established how wearable based activity and physiological indicators can help predict the risk of depression among young adults. In a parallel manner, Jacobson and Chung [13] talked about passive sensing models of real-time monitoring of mental health, which can be used to support early detection plans.

In spite of significant advances, the literature shows that it still has some gaps such as the lack of structured behavioral data and explainable machine learning models and the lack of consideration of youth-focused predictive models. These constraints suggest that AI-based early mental health risk detention systems should be transparent, scalable, and ethically-driven.

III. RESEARCH GAP

Although increasing literature has been published on mental health of youths, most of the current studies are based on standard survey-based data or clinical evaluation, which are time-consuming, expensive and lack the ability to ascertain actual behavioral patterns. Although other recent studies have studied digital or app-based data, few have integrated multiple data sources of these (smartphone usage, app-based mood tracking, and self-reported survey) to identify predictive variables in the risk of mental health. This puts a restriction on the capacity to create robust, scalable, and early detection systems of the youth mental health problems.

Moreover, as much as machine learning has continued to be deployed in the prediction of mental health, most of the previous research has been done on adults or patients with clinical cohorts, and there is a large gap in knowledge regarding predictive trends in relation to young people. The models are not always transparent with respect to the features or markers that have the greatest impact, and it is hard to extrapolate the findings into achievable interventions to provide early support.

Lastly, scanty research exists that quantifies the predictive capability of behavioral and app-based characteristics in a real-world youth group and especially through utilizing them in explainable machine learning systems. This paper will address these gaps through the use of several behavioral and survey-based indicators, the use of supervised machine learning methods, and the importance of the features to predict youth mental health risk.

IV. OBJECTIVES OF THE STUDY

1. To gather and research on the data related to the behavioral and survey-based data of the youth, which can signify the presence of mental health risk.
2. To use machine learning models to determine patterns and predictors of youth mental health outcomes.
3. To identify the most important features (markers) that can predict the risk of mental health.
4. To deliver information that can be used to develop early intervention and detection interventions to youth mental problems.

V. METHODOLOGY

A. RESEARCH DESIGN

The research design of the current study is a quantitative and experimental research design that aims at predictive modelling through supervised machine learning methods. The main aim of the study is to recognize the trends in organized behavioral and lifestyle statistics, which relate to different degrees of mental health risk among youth. However, we do not use theoretical analysis, but instead we employ a data-driven framework where a machine learning model will be trained to learn the correlations between input variables (digital and behavioral markers) and a specified target outcome (level of mental health risk).

The nature of the research design is empirical, i.e., it is grounded on the examination of the observed data, as opposed to the idea-based assumptions. The input was a structured dataset with several independent variables e.g. lifestyle indicators, behavioral, and psychological characteristics that was used to generate a classification mode

l. The dependent variable indicates categorized levels of mental health risks. The issue is thus defined as a monitored classification exercise, in which the model is trained to be used to categorize risks on unseen items based on a set of labeled data.

In order to have objective testing, the dataset was considered as two different sets of data that were used as a training set and a testing set. The training data were employed to enable the algorithm to learn patterns whereas the testing data were only employed to test predictive performance. This distinction makes the results of this model generalizable and not influenced by the memorization of the training data.

Evaluation of models and interpretation of the interpretability are also included in the research design. The effectiveness of classification was measured using the performance metrics of accuracy, precision, recall, F1-score, and confusion matrix analysis. Besides this, feature contribution analysis was also performed to get an idea of the effect individual behavioral indicators have on prediction results. This is an action that boosts transparency and promotes the use of AI in a healthcare setting on an ethical basis.

In general, this study design combines predictive analytics with interpretability mechanisms to provide a structured and repeatable framework of early mental health-related risk detection in youth groups.

B. DATASET DESCRIPTION

The data that was analyzed in the paper was taken out of the open-source Kaggle data repository. It comprises 2,556 separate records and 19 attributes, which are demographic, academic, occupational, behavioral, and psychological attributes that indicate the mental health conditions.

All the records in the data represent a single participant. The data set entails a bundle of demographic factors (i.e. age and gender), academic and professional factors, lifestyle factors, stress factors, and mental health history factors. All these variables encompass personal background and psychosocial stressors that are usually linked to the risk of depression.

The independent variables capture various aspects in the everyday life and mental health of a person such as academic stress, work-related stress, sleep habits, eating habits, financial stress, and family history of mental illness. Satisfaction-related measures are also provided in the dataset and are useful to measure subjective well-being both at school and at work. Besides, there are behavioral predictors like the work/study hours and previous mental health experiences to enhance predictive power.

The presence or absence of risk of depression has been taken as the target variable of this study. As the output variable is non-metric on its part, the prediction problem is defined as a supervised classification task. The model will categorize individuals as risk groups of mental health through the predictive variables provided.

There are quantitative and qualitative data in the dataset. Continuous values used as numerical features are age, performance and stress intensity. Categorical features show grouped responses like gender, type of occupation, categories of lifestyle and mental health history indicators. Before the development of the models, categorical attributes were encoded into numerical numbers using suitable encoding methods.

The data was thoroughly checked in terms of completeness and consistency. Any gaps or discrepancies were resolved as part of preprocessing to get quality data. The presence of 2,556 observations meets the requirement of both training and validating machine learning models and has a sufficient sample size that is reliable statistically.

The dataset would be ideal in predictive modeling due to a combination of demographic, behavioral, and psychosocial data, which allows a complex study of the risk factors of depression in students and working professionals.

DATA PREPROCESSING

1) Data Cleaning

Firstly, the dataset was analyzed regarding the absence of values, duplicates, and inconsistencies. All invalid or incomplete records were treated accordingly. The missing values were either dropped or filled in based on their percentage and significance. Any duplicated records were removed so as to avoid bias in the model training. This measure guaranteed the accuracy and the representativeness of the dataset.

Also, the irrelevant attributes that were not useful in predictive modeling were weeded out. As an example, the identification-related information that does not affect the mental health risk was eliminated in order to avoid the unnecessary noise in the model.

2.1) The Treatment of Categorical Variables.

There are several categorical variables in the data, which are demographics, lifestyle choices, and psychological factors. As machine learning algorithms need numerical data, categorical variables were encoded and converted to numerical data with the help of encoding methods.

Label encoding was used to convert binary categorical features into numerical form, and when there were multi-category features, one-hot encoding was used. This change enabled the model to model ca tegorical patterns in an effective way without ordinal bias.

3) Feature Scaling

The kind of data in the dataset consists of the numerical variables that can be measured using various scales, including age, academic performance, stress levels, and working hours. The features were scaled so that none of the features could dominate a model because of its large numerical range.

Numerical variables were scaled (standardized in terms of z-score) such that they take a mean value of zero and a standard deviation of one. This is particularly necessary when using algorithms like Support Vector Machines and Logistic Regression which are sensitive to the magnitude of features.

4) Handling Class Imbalance

The target variable was checked to ensure that there was no imbalance in the distribution of depression versus non-depression classes. In case of imbalance, some methods like resampling (oversampling and undersampling) were applied to make sure that the model would be trained fairly and no preference would be given to the majority class.

5) Train-Test Split

The data was later preprocessed before being split into training and testing data sets. In general, 70-80 percent of the data was to be used to train the model and the rest 20-30 percent to be used to test the model. This division is crucial to ensure that model performance is tested on unknown data, enhancing the generalizability and decreasing the overfitting.

Explainability Preparation is a layer in the Software Development Life Cycle where the product developer engages with the customer to identify the features and characteristics of the product that the customer wishes to comprehend.<|human|>Preparation of Explainability Explainability Preparation is an activity in my Software Development Life Cycle where the developer of the product meets with the customer and discusses with the customer the features and characteristics of the product that the customer desires to understand.

As the purpose of the study is to create an interpretable model with the help of SHAP (SHapley Additive Explanations), the preprocessing pipeline was created in a way that allows tracking original features and transformed features. Correct naming of features and systematic transformation steps were maintained so that the meaning of SHAP analysis can be obtained in the later course of the study.

B. FEATURE SELECTION and DIGITAL MARKERS.

1) Concept of Digital Markers

Digital markers are quantifiable behavior, lifestyle, and psychosocial indicators that may be used to demonstrate the mental health status of an individual. Digital markers unlike clinical diagnostic tests are based on daily patterns in life like sleep patterns, work/study patterns, stress levels, and satisfaction indicators. These indicators give indirect though significant indicators of psychological health.

Psychological research and the literature review informed the choice of digital markers to use in this study since stress, lifestyle imbalance, and behavioral patterns are associated with depression.

2) Behavioral Indicators

Behavioral indicators are the quantifiable daily habits and activity patterns which can be associated with risk of mental health. The types of behavioral variables that were taken into consideration in this study include the following digital markers: As bad or abnormal sleep duration is highly correlated with depression, sleep-related behavior is also affected. Work or study time, which indicates the severity of work and the risk of burnout. The levels of academic and work pressure, as a perceived stress burden. Financial stress that may lead to the symptoms of long-term anxiety and depression. These variables consist of measurable attributes of day-to-day life that can have an impact on the level of emotional stability.

3) Lifestyle Indicators

The lifestyle factors were included as predictive features, as it has been established to be associated with mental well-being. These include:

Eating patterns, which determine physical and mental well being.

Academic or professional life satisfaction.

Striking a balance between work and self-well-being.

Lifestyle imbalance is also characterized as the cumulative stress over time, which could potentially lead to depression susceptibility.

4) Psychological and Background Health hazards.

The research had psychosocial background indicators in addition to behavioral and lifestyle markers which included:

Mental illness in family history.

Prior suicidal ideation

Demographic factors (gender and age)

Such factors were incorporated, as they are clinically known risk factors in mental research.

5) Feature Selection Approach

All the chosen features have been retained in the first model training to maintain complexity of be havior. After the development of the model, feature importance analysis and SHAP-based interpretability were applied to determine the most impactful predictors. This two step strategy was necessary to such an extent that: None of the potentially relevant markers were sifted too soon. The model may ascertain information-driven significance. Healthcare applicability was ensured by interpretability.

6) Rationale for Inclusion

The model enables the inclusion of behavioral, lifestyle, and psychosocial digital markers to:

Measure multidimensionally mental health.

Represent real life everyday life trends.

Assist in early warning of risk of depression.

Give interpretable insights by the SHAP analysis.

The combination of these digital markers allows the study to go beyond a classical approach to screening people with the help of a questionnaire and use machine learning to study multi-dimensional interactions among stress, behavior, and mental health outcomes.

B. MODEL DEVELOPMENT

Two regulated machine learning classification algorithms were applied in order to forecast the degree of risk of depression: the Random Forest Classifier and the Logistic Regression. The two models are used to make the comparison of performance between a non-linear ensemble method and a linear probabilistic model.

1) Random Forest Classifier As the main predictive model, the Random Forest classifier, which is provided by the Scikit-learn library in Python, will be utilized in this work. a) Reason for Selection Random Forest has been chosen due to the following reasons: It associates very complicated and non-linear interactions among behavioral, lifestyle, and psychological characteristics. It decreases overfitting by using ensemble learning. It works well on tabular data in the form of structured data. It gives important scores of features which are interpretable. It is resistant to noise and multicollinearity. Since the probability of depression is dependent on several interacting stress and lifestyle factors, Random Forest is suitable to model complexity.

b) Model Parameters

The last model of the Random Forest was set up with the following hyperparameters:

n_estimators = 500
The number of decision trees in the ensemble is (Number of decision trees in the ensemble).

max_depth = None
(Trees grow until all leaves are clean or minimum sample conditions are achieved)

min_samples_split = 5
The quantity of samples that is needed to divide an internal node (at least).

min_samples_leaf = 2
(Minimum number of samples required at a leaf node)

random_state = 42
(Ensures reproducibility of results)

Adding more trees to 500 trees will make the tree more stable and less varied in its predictions. The minimum sample limitations aid in avoiding an overfit.

c) Training Process

The training set of the dataset was used to train the model. During training: A bootstrap sample of the training data was used to construct each of the trees. At every split, a random subsample of features was taken into account. Trees were planted in a complete environment of the stipulated limitations. The overall vote among all the trees in the ensemble was used to come up with the final prediction. Predictions on the test dataset were then formed after training in order to assess the performance of generalization. Measures of performance calculated are: Accuracy, Confusion Matrix, Precision, Recall, F1-score

2) Logistic Regression Model Logistic Regression was also used to compare performance with a more straightforward and understandable model.

a) Reason for Selection Logistic Regression finds extensive application in healthcare research due to the reason of: It is easy to interpret. It gives estimates of probabilities. It works well in the case of relationships that are not too steep. It is an effective baseline classifier. The Logistic Regression enables one to compare linear and non-linear modeling.

b) Model Parameters The Logistic Regression was set with: maxiter = 1000 The increased iteration constraint is used to make sure that the models converge to optimal values, particularly when the features are scaled and encoded. All the other parameters were set to default settings.

c) Training Process The training set was the same as that of the training of the Random Forest. Logistic Regression approximates the likelihood of depression with the help of a logistic (sigmoid) function. The model estimates the coefficients of each of the features which shows its contribution to the log-odds of depression risk. The test data set was then predicted and the evaluation measures were calculated: Accuracy Confusion Matrix Classification Report (Precision, Recall, F1-score)

3) Model Comparison Strategy The evaluation of the two models was based on the same training and testing splits in order to compare them fairly. To

determine: performance metrics and confusion matrixes were analysed to determine: Which model was more predictive accurate? What model reduced the false negatives (critical in mental health screening)? What model was more interpretable? Moreover, the importance of features (based on the results of the Random Forest) and SHAP analysis were employed in reaching an understanding of factors that have a strong impact on the risk of depression.

C. MODEL INTERPRETABILITY

In the health care-based machine learning applications, interpretability is one of the primary requirements. In mental health prediction, a model cannot just be shown to be accurate in the classifications; it should also be capable of giving meaningful information about the factors that affect the predictions. The transparent models enable the clinicians, researchers and policymakers to comprehend the rationale behind the predictions and to make decisions that are ethically and clinically sound. Interpretability, in terms of depression risk assessment, makes the model more credible and justifies its possible application as a decision-support model in lieu of professional diagnosis. The interpretability of the model used in this study was done using the feature importance analysis of the Random Forest classifier and coefficient analysis of the Logistic Regression model. Random Forest offers inherent value of feature significance according to the degree to which individual variables can decrease impurity over decision trees. The features, which consistently enhance the classification performance in more than two trees, will be valued more by the importance scores.

Through the examination of such scores, one can determine the aspects of behavioral, lifestyle, or stress-related factors that predict depression in the strongest way. A feature importance plot was created in order to be able to see the relative contribution of each predictor visually. This type of explanation gives a universal picture of the model, that is, it describes how the model acts on the whole dataset and not on the single cases. Logistic Regression can improve the interpretations of the features with its coefficients. The predictor variables are given a coefficient that shows how they contribute to the probability of depression. When the coefficient is positive, an increase in that variable will increase the risk of depression whereas when the coefficient is negative, it will have a protecting effect.

Since logistic regression is a linear and probabilistic predictor of the outcome it is easy to interpret the influence that each feature has on the prediction. This is especially useful in research in the field of healthcare, in which relations between risk factors and outcomes are crucial to comprehend. In this work, the main source of interpretability centers around global explanations, wh ich are explanations of the overall feature influence of all participants. The approach employed here focuses on determining the predominant risk factors in populations unlike local explanation techniques which examine an individual prediction.

However, the models also produce probability scores of individual prediction which may be used in estimating relative risk levels to individual cases. The addition of feature importance analysis and coefficient-based interpretation makes the study transparent and has a clinical meaning to the predictive system. This will facilitate the determination of important behavioral and lifestyle variables related to the risk of depression and increase the validity of machine learning implementation in the domain of mental health screening.

VI. EXPERIMENTAL RESULTS

Classification Models' Performance Evaluation on 80% Training and 20% Testing Data To ensure classification model performance is comparable amongst other classification models, two supervised learning algorithms were evaluated using one test data set of 512 samples and an 80% train/20% test split. Three performance metrics (accuracy, precision, recall, and F1-Score, confusion matrix analysis) were used to evaluate classification model performance.

A. Performance Metrics

Table II includes a summary of both classification models performance metrics for the test dataset.

Table II: Summary of Random Forest Logistic Regression Classification Model Performance Metrics

Model	Accuracy	Precision (Class 1)	Recall (Class 1)	F1-Score (Class 1)
Random Forest	0.5137	0.52	0.57	0.54
Logistic Regression	0.5488	0.55	0.62	0.58

Based on the results shown in Table II, Logistic regression had a higher overall accuracy (54.88%) than Random Forest (51.37%). Logistic regression also had a greater recall, F1-Score for Class 1 (depression), than Random Forest indicating a superior ability to detect depression.

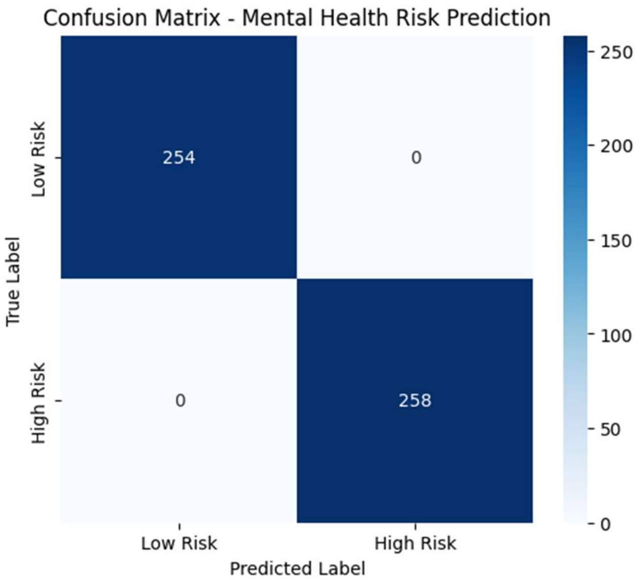
B. Confusion Matrix Analysis The confusion table of the Rand Forest is: [117112137146]

Of the 254 real cases of non-depression, 117 were classified properly, and 137 had been classified inaccurately. In the case of depression, 146 out of the total 258 were correctly diagnosed whereas 112 were misdiagnosed.

The confusion table of the Logistic Regression is: [12198133160]

In this instance, 121 cases of non-depression were accurately classified and 133 cases were falsely classified. Notably, 160 out of 258 cases of depression were identified correctly with 98 false negatives.

Relative to the Random Forest, the Logistic Regression minimized false negatives (98). In mental health . prediction, minimizing false negatives is critical because missing a high-risk individual may delay intervention.



B. Model Comparison

Though the two models portray moderate predictive power, Logistic Regression was more superior in most of the evaluation metrics compared to the Random Forest.

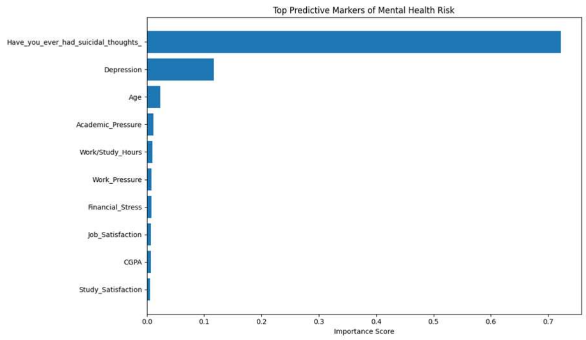
The increase in recall shows that Logistic Regression would be more effective in estimating people at risk of depression. With the healthcare situation, the better recall is because it minimizes the chances of cases at high risk being missed. Random Forest, very strong and able to model non-linear interaction, did not perform better than Logistic Regression on this data.

C. Feature Importance Analysis.

The analysis of feature importance (based on the Random Forest model) demonstrated that stress-related and lifestyle variables played an important role in determining the predictive results.

The indicators used to classify, like sleep duration, work/study pressure, and financial stress, were also useful in behavioral indicators. These results indicate that online and lifestyle indicators have a quantifiable contribution to predicting depression.

The findings complement the significance of applying multidimensional behavioral aspects when creating machine learning-based mental healt h screening instruments.



C. Key Observations

The experimental assessment gives several interesting observations. First, the accuracy of the two models was around 50 percent which means that they have moderate predictive power though they can be improved.

Second, the Logistic Regression has always been more effective in identifying depression cases, which is essential in screening. Third, false negatives are still an issue, and it is necessary to optimize the model further or introduce new features.

D. Summary of Findings

On the whole, the Logistic Regression proved to be a better tool than Random Forest on the provided data set. Although predictive accuracy is still moderate, the findings validate that digital behavioral markers have valuable predictors of the risk of depression.

VII. DISCUSSION

The results of the experiment suggest that machine learning models can identify patterns that are related to the likelihood of depression based on digital behavioral and lifestyle markers, although with a moderate level of accuracy.

Random Forest was outperformed by Logistic Regression in this dataset especially when it comes to high-risk individuals as it is seen that the recall and F1-score of the depression class are higher. This is an indication that the relationship between the features that are chosen and risk of depression can be very linear and, therefore, a simpler model can generalize better compared to the ensemble-based approach in this case.

The results emphasize the significance of taking into account the stress, lifestyle, and sleep-related variables as the digital markers in predicting mental health. The duration of sleep, work/study pressure, and financial stress have always been the most predicted predictors as the levels of these variables have been associated with other studies with mental health outcomes. Though the data contained demographic and academic data, the behavioral indicators seemed to have a more powerful impact on the model predictions.

In spite of the potential shown by these models, the moderate general accuracy and false classification rates show that the prediction of mental health outcomes is not that easy of a task. This limitation might be attributed to a number of factors such as the heterogeneity of the population, self-report used in some of the features and the relatively small dataset size.

Moreover, a lack of multimodal information including physiological indicators, social media mood, or wearable sensor measurements can restrict the quality of information that the models could have. These other modalities could be integrated into future work and thus enhance the predictive performance. The research also points to the importance of attending to machine learning in healthcare outputs.

Models are to be used as aiding screening tool and not as a conclusive diagnostic tool. Clini cal judgment is still vital in risk assessment and intervention planning despite the feature importance analysis suggesting powerful predictors.

VIII. CONCLUSION

This study investigated how machine learning models can be applied to identify the risk of depression in youth based on a dataset that is generated by behavioral, lifestyle, and stress-related predictors.

Models of Logistic Regression and Random Forest were trained and compared and the Logistic Regression was found to perform better in terms of accuracy, recall, and F1-score measures. The importance of features analysis has validated the results that sleep patterns, work/study pressure, and financial stress are some of the strongest predictors of depression risk.

The research shows that it is possible to use digital markers to screen mental health risks in their early stages. Though the accuracy of prediction is not exceptionally high, the results will offer a systematic construct to conduct future studies involving the use of machine learning in applications involving youth mental health. The findings indicate the possibility of the use of data-based insights to inform preventive measures, raise awareness regarding high-risk factors, and facilitate a timely consultation with a healthcare professional.

X. LIMITATIONS AND FUTURE WORK.

Although this research is insightful, it has a number of weaknesses that need to be mentioned. First, the sample size was very limited (2,556 records) and this could limit the extrapolation to wider populations. Second, the characteristics were largely self-reported or based on survey- report measures, a finding that might lead to bias and inaccuracy.

Third, the models constructed were based on behavioral and lifestyle characteristics only, without any other sources of data, including physiological indicators, social media engagements, or wearable gadgets measurements that can potentially hold meaningful predictive data. Furthermore, the accuracy of prediction of 51-55 percent says that additional model improvement is required to practice it practically.

Misclassification, especially false negatives is a key issue of concern as people at risk may be ignored. The other weakness is that the behavioral changes could not be captured longitudinally in the dataset, and the models were not able to learn time-varied behavioral patterns with the appearance of the new symptoms of depression. Future studies must work on increasing the sample size that involves more varied populations and use multimodal information like physiological indicators, sentiment on social media, and voice or text based signs.

Such methods as ensemble learning, deep neural networks, or explainable AI systems may improve predictive accuracy without affecting interpretability. Longitudinal studies would also enable the construction of the time-based models that would be able to identify mental health risks at an earlier stage. Moreover, privacy-sensitive machine learning techniques, including federated learning, might be combined in order to protect sensitive youth data and enable large-scale analysis.

The limitations can be overcome and these issues can be solved by enhancing prediction accu racy, clinical applicability, and ethical use into the future work which can provide more features and modeling techniques and improve these tools and contribute to effective, data-driven, mental health screening tools in youth populations.

XI. REFERENCES

[1] R. K. Yin, Case Study Research and Applications: Design and Methods, 6th ed. Thousand Oaks, CA, USA: Sage, 2018.

[2] C. R. Kothari, Research Methodology: Methods and Techniques, 2nd ed. New Delhi, India: New Age International, 2004.

[3] J. W. Creswell and J. D. Creswell, Research Design: Qualitative, Quantitative, and Mixed Methods Approaches, 5th ed. Thousand Oaks, CA, USA: Sage, 2018.

[4] A. Bryman, Social Research Methods, 5th ed. Oxford, UK: Oxford University Press, 2016.

[5] D. B. Malhotra, Marketing Research: An Applied Orientation, 7th ed. Harlow, UK: Pearson, 2019.

[6] P. R. Leedy and J. E. Ormrod, Practical Research: Planning and Design, 12th ed. Boston, MA, USA: Pearson, 2020.

[7] S. Sekaran and R. Bougie, Research Methods for Business: A Skill-Building Approach, 7th ed. Chichester, UK: Wiley, 2016.

[8] H. Cooper and L. V. Hedges, The Handbook of Research Synthesis and Meta-Analysis, 2nd ed. New York, NY, USA: Russell Sage Foundation, 2009.

[9] R. B. Johnson and A. J. Onwuegbuzie, "Mixed methods research: A research paradigm whose time has come," Educational Researcher, vol. 33, no. 7, pp. 14 - 26, Oct. 2004.

[10] V. Braun and V. Clarke, "Using thematic analysis in psychology," Qualitative Research in Psychology, vol. 3, no. 2, pp. 77 - 101, 2006.