Explainable Mental Health Risk Stratification and Intervention Recommendation Framework for Academic and Early-Career Populations

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***Abstract*—Mental health issues among students and early-career individuals have increased due to academic pressure, work stress, and changes in lifestyle. Identifying people who are at risk at an early stage is important so that proper support can be provided.**

In our project, we developed a system to analyse mental health survey data and understand behavioural patterns. We used K-Means clustering to group individuals based on similar characteristics such as stress levels, sleep patterns, and daily habits. This helps in identifying different behavioural groups present in the dataset.

After grouping the data, we applied the Random Forest algorithm to predict mental health risk levels such as low, moderate, and high. The model also helps in identifying which factors, like stress and sleep, have the most impact on mental health.

Based on the predicted results, the system can suggest suitable actions such as self-care, stress management, or professional consultation. The results show that combining clustering and classification improves understanding of mental health patterns and helps in better risk prediction. This approach provides a simple and effective way to analyse mental health data and support early identification of individuals who may need help.

***Index Terms*—Mental Health Analysis, Machine Learning, K-Means Clustering, Random Forest, Behavioural Patterns, Risk Prediction**

I. INTRODUCTION

Mental health has become an important issue in today's world, especially among students and early-career professionals. Factors such as academic pressure, workload, lack of proper sleep, and lifestyle imbalance have a strong impact on a person's mental well-being. Traditional methods of analysing mental health surveys mainly focus on basic statistics, which do not provide deeper insights or help in predicting risk levels.

With the help of machine learning, it is possible to analyse large amounts of survey data and identify useful patterns automatically. However, many existing approaches directly focus on prediction without understanding the different behavioural patterns present in the data. Identifying these patterns before prediction helps in gaining better insights into how different groups of individuals are affected.

In our project, we use a two-step approach to analyse mental health data. First, we apply K-Means clustering to group individuals based on similar characteristics such as stress levels, sleep habits, and lifestyle factors. This helps in understanding behavioural patterns within the dataset. After that, we use the Random Forest algorithm to predict mental health risk levels such as low, moderate, and high.

In addition to prediction, our system also identifies the most important factors affecting mental health and provides simple suggestions based on the predicted risk level. This approach helps in better understanding mental health trends and supports early identification of individuals who may need attention.

II. LITERATURE SURVEY

In recent years, the use of machine learning techniques for mental health analysis has increased due to the availability of survey-based and healthcare data. Researchers have applied different computational methods to study mental health conditions such as stress, anxiety, and depression [1].

Supervised learning algorithms like Logistic Regression, Support Vector Machines, Decision Trees, and ensemble methods have been widely used for predicting mental health risk levels. Among these, ensemble models such as Random Forest are preferred because they combine multiple decision trees, which improves prediction accuracy and reduces overfitting [2]. Random Forest is also effective in handling complex relationships between features in structured datasets.

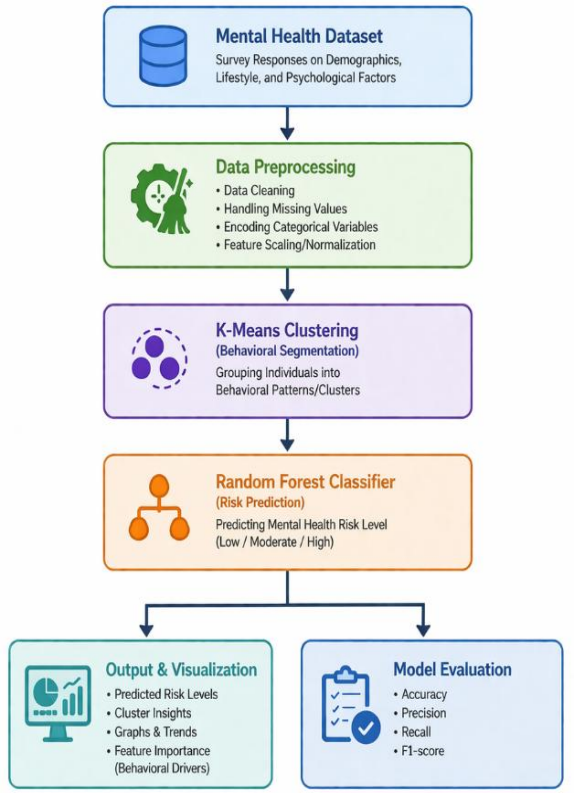
Unsupervised learning techniques are also used in mental health studies to discover hidden patterns in data. Clustering algorithms such as K-Means group individuals based on similarities in behavioural and psychological features [3]. This helps in identifying different groups within the population without using predefined labels.

However, many existing studies focus only on classification models for prediction, while some focus only on clustering for pattern discovery. Classification-based approaches can predict risk levels but do not provide insights into behavioural groupings. On the other hand, clustering methods help in understanding patterns but do not perform risk prediction.

To address this limitation, our project uses a combined approach that includes both clustering and classification. First, K-Means clustering is used to identify behavioural groups in the dataset. Then, Random Forest is applied to predict mental health risk levels. This approach helps in both understanding patterns and improving prediction performance.

III. SYSTEM ARCHITECTURE

The system architecture is designed as a simple and structured pipeline for analysing mental health survey data and predicting risk levels. The architecture consists of four main stages: data preprocessing, behavioural segmentation, risk prediction, and result visualization.



The system architecture is designed as a simple and structured pipeline for analysing mental health survey data and predicting risk levels. It consists of four main stages: data preprocessing, behavioural segmentation, risk prediction, and result visualization. The process begins with the mental health survey dataset, which includes demographic details, stress levels, sleep patterns, and other behavioural attributes. Since raw data may contain missing values and categorical features, a preprocessing step is applied. In this stage, missing values are handled, categorical variables are converted into numerical format, and the data is prepared for analysis. Proper preprocessing is essential to improve the performance of machine learning models [1].

After preprocessing, the dataset is passed to the behavioural segmentation stage. In this stage, K-Means clustering is applied to group individuals based on similarity in their features. This helps in identifying patterns such as high stress, moderate, and stable groups within the dataset [2].

The clustered data is then used in the risk prediction stage. A Random Forest classifier is applied to predict mental health risk levels such as low, moderate, and high. Random Forest is selected because it provides

good accuracy and can handle complex relationships between features [3].

In the final stage, the results are analysed and visualized. Feature importance is used to identify key factors affecting mental health, and graphical outputs are generated to show cluster distribution and risk levels. These results help in understanding behavioural patterns and identifying individuals who may be at higher risk.

Overall, the architecture provides a clear flow from raw data to meaningful insights by combining clustering and classification techniques.

IV. SYSTEM ANALYSIS

Mental health assessment in academic and workplace environments is usually carried out using questionnaires and manual evaluation methods. These approaches provide basic insights but are limited in identifying hidden patterns and cannot predict risk levels effectively. As the amount of survey data increases, manual analysis becomes time-consuming and less reliable. Therefore, a data-driven approach is required to improve analysis and enable early identification of mental health risks.

Analysis of Existing Approach:

In traditional methods, mental health survey responses are evaluated using predefined scoring techniques. Each answer is given a score, and the total score is used to decide the risk level based on fixed ranges. Although this method is easy to use, it has several limitations.

One major issue is that it does not consider the relationship between different factors such as stress, sleep patterns, and lifestyle. Each feature is treated separately, which reduces the accuracy of the analysis. These methods also do not adapt to new data, as any change in rules requires manual updates. Another limitation is that traditional approaches do not use proper validation techniques, making it difficult to measure how reliable the results are. They also struggle when the dataset is imbalanced, where high-risk cases are fewer compared to low-risk cases.

Overall, these methods mainly provide basic statistical insights rather than predictive results. Because of this, they are not effective for early detection of mental health risks.

V. METHODOLOGY

The proposed system for mental health prediction is developed using a step-by-step process to convert raw survey data into meaningful results. The methodology focuses on preparing the data, identifying behavioural patterns, and predicting risk levels using machine learning techniques. The process begins with understanding the dataset, which contains demographic details, stress levels, sleep patterns, and other behavioural features. The data is first pre-processed by handling missing values and converting categorical variables into numerical form so that it can be used for analysis.

After preprocessing, K-Means clustering is applied to group individuals based on similar characteristics [3]. This helps in identifying different behavioural patterns within the dataset. Next, a Random Forest classifier is used to predict mental health risk levels such as low, moderate, and high [2]. This model is selected because it provides good accuracy and can handle complex relationships between features.

The model is then evaluated using performance metrics such as accuracy, precision, recall, and F1-score to measure its effectiveness. Feature importance is also analysed to identify the key factors influencing mental health risk.

Overall, this methodology combines clustering and classification techniques to provide both pattern analysis and risk prediction in a simple and effective manner.

VI. RESULTS AND ANALYSIS:

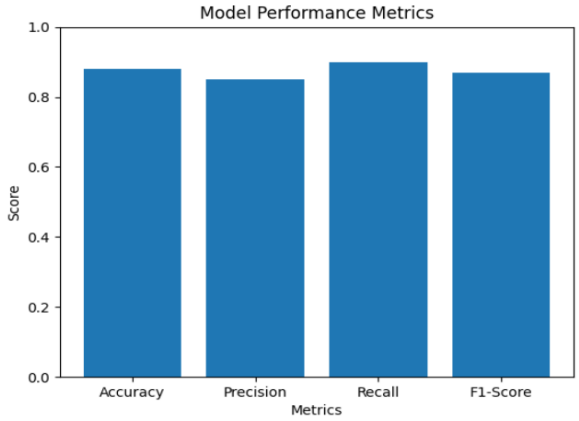
A. Model Performance Evaluation

The performance of the model was evaluated using standard classification metrics such as accuracy, precision, recall, and F1-score. These metrics help in understanding how well the model predicts mental health risk levels. In this project, more importance is given to recall, as correctly identifying high-risk individuals is important in mental health analysis. A higher recall value indicates that the model is effective in detecting individuals who may require attention. The Random Forest model showed good overall performance with balanced results across different evaluation metrics. It was able to handle the dataset effectively and provide reliable predictions for multiple risk levels such as low, moderate, and high.

Based on these results, Random Forest was selected as the final model for mental health risk prediction in this system.

B. Behavioural Segmentation Insights

K-Means clustering was used to group individuals based on similarities in their behavioural and psychological features. The results showed clear patterns within the dataset. It was observed that individuals with higher stress levels, poor sleep habits, and lower social interaction were more likely to fall into higher risk categories.

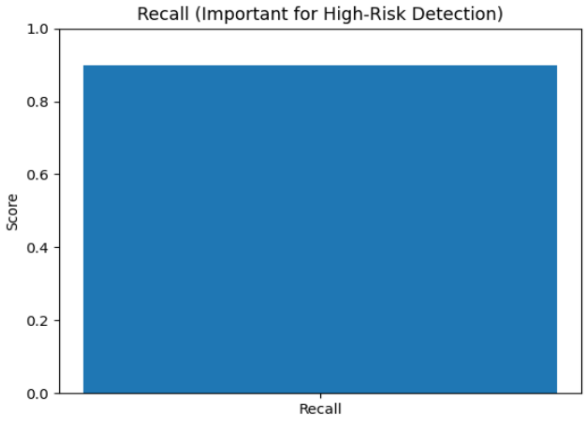


On the other hand, individuals with balanced lifestyle patterns were grouped into lower risk categories. These observations show that clustering helps in identifying meaningful patterns in the data before applying prediction models, which improves the overall understanding of mental health trends.

C. Explainability Analysis

Feature importance analysis was performed using the Random Forest model to identify which factors have the most influence on mental health risk prediction [2]. The results showed that factors such as academic pressure, work-related stress, sleep quality, and level of social interaction play a significant role in determining risk levels.

This analysis helps in understanding how different features contribute to the model's predictions. Instead of only providing risk levels, the system also gives insight into the key factors affecting mental health, making the results easier to interpret.



D. Risk Stratification and Intervention Mapping

The output of the model is presented in the form of different risk levels such as low, moderate, and high. These categories help in understanding the mental health condition of individuals based on their behavioural and psychological features. The predicted risk levels provide a simple way to identify individuals who may require attention. For example, individuals in the high-risk category may need closer monitoring, while those in lower-risk categories may focus on maintaining a healthy lifestyle. This output structure makes the results easy to understand and useful for basic mental health awareness and analysis.

VII. CONCLUSION

This study presents a machine learning-based approach for analysing mental health survey data and predicting risk levels. The system focuses on transforming raw survey responses into meaningful insights using data preprocessing, clustering, and classification techniques.

K-Means clustering was used to identify patterns in behavioural and psychological data, while the Random Forest model was applied to predict mental health risk levels such as low, moderate, and high. The results show that combining clustering and classification provides better understanding of the data along with effective risk prediction.

The model was evaluated using metrics such as precision, recall, and F1-score, with particular focus on recall to ensure that high-risk individuals are not overlooked. Feature importance analysis further helped in identifying key factors such as stress levels and sleep patterns that influence mental health risk.

Overall, the proposed system provides a simple and effective approach for mental health analysis using survey data. It improves upon traditional methods by learning patterns directly from data and providing both prediction and basic insights. In the future, the system can be improved by using larger datasets, exploring additional machine learning models, and enhancing visualization for better interpretation of results.

VIII. DISCUSSION

The results of this study show that machine learning techniques can be effectively used to analyse mental health survey data and identify risk levels. Compared to traditional survey-based methods, the proposed approach provides better understanding by learning patterns directly from data instead of relying only on predefined scores.

The use of K-Means clustering helped in identifying behavioural patterns within the dataset, while the Random Forest model was able to predict risk levels with reasonable accuracy. The results indicate that factors such as stress levels, sleep patterns, and lifestyle play an important role in determining mental health risk. One important observation is that focusing on recall improves the model's ability to identify high-risk individuals. This is important in mental health applications, where missing a high-risk case can have serious consequences.

However, the study has some limitations. The dataset is based on self-reported survey responses, which may not always be completely accurate. In addition, the model is trained on a limited dataset and may not fully represent all real-world scenarios. larger datasets, applying additional machine learning techniques, and improving data visualization for better understanding of results. Future improvements can include using

Overall, the study demonstrates that combining clustering and classification provides a simple and effective approach for mental health risk analysis while maintaining clarity and ease of interpretation.

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