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Predictive Insights into Depression and Suicide Through Machine Learning Models

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***Abstract*—This study explores the relationship between depression and suicide using machine learning models, including SVM, Random Forest, XGBoost, and Naïve Bayes. By analyzing psychological, social, and behavioral data, we identify key patterns linking depression severity with suicidal tendencies. Among the tested models, Naïve Bayes and XGBoost demonstrated the highest predictive performance, achieving strong accuracy and cross-validation metrics. These findings highlight the potential of machine learning in mental health research, offering scalable, data-driven frameworks for early risk detection and intervention.**

Keywords—Machine learning, depression, suicide, predictive modeling, behavioral analysis, data-driven interventions, cross-validation, accuracy metrics, Naïve Bayes, XGBoost.

I. Introduction

A. Background

Depression and suicide constitute significant global health challenges. Depression often acts as a precursor to suicidal ideation, making early detection crucial. According to WHO, over 280 million people worldwide have depression [1]. Researchers estimate that about 60% of people who lose their lives to suicide had a mood disorder such as depression [2], many of which could have been prevented with timely interventions. Understanding the link between these two phenomena through data-driven methodologies is vital for effective prevention strategies. With the increasing availability of healthcare data, machine learning (ML) provides opportunities to identify hidden patterns in patient information [3]. ML's flexibility allows researchers to go beyond traditional statistical analyses, identifying nuanced, nonlinear relationships [4]. Mental health practitioners can benefit from predictive frameworks powered by these technologies. AI and ML in healthcare have catalyzed diagnostic tools that detect risks and suggest actionable interventions [5]. In mental health, such frameworks can save lives by offering predictive insights based on large-scale datasets. Moreover, integrating ML-driven models with existing mental health services can enhance early diagnosis and intervention strategies, improving patient outcomes. As wearable devices and mobile applications collect vast behavioral data, real-time ML-driven insights could provide instant alerts, enabling proactive mental health care.

Advancing predictive frameworks for mental health also holds promise for remote care [6][7]. With wearable devices and mobile applications generating real-time behavioral data, integrated systems can alert practitioners and patients about sudden mental health risks, shifting the focus toward preventive care.

B. Research Gap

While many studies have explored traditional statistical methods to investigate the depression-suicide nexus, limited work incorporates ML to enhance predictive precision and scalability. Existing approaches often rely on small datasets or fail to address the complexities introduced by multifaceted factors influencing mental health [8]. This highlights the need for robust, model-driven approaches capable of processing diverse datasets efficiently.

C. Objective and Scope

This study aims to utilize machine learning (ML) algorithms to assess the association between depression and suicide while providing insights into significant predictive variables. By employing a diverse set of ML models, the research seeks to develop a comprehensive comparative framework that evaluates performance and robustness. The study focuses on supervised learning methods applied to demographic, behavioral, and clinical datasets. Model evaluation includes metrics such as accuracy, precision, and recall, ensuring reliable predictive insights for mental health diagnostics. Additionally, the findings aim to establish a benchmark for implementing scalable and data-driven systems in healthcare applications, enhancing early detection and intervention strategies.

II. Materials and Methods

A. Materials

The study utilized a structured dataset comprising 4,13,769 samples with 16 key features [9]. The features include demographic attributes such as age, marital status, and income, alongside behavioral and clinical attributes such as sleep patterns, history of mental illness, and family history of depression. The data was preprocessed to eliminate redundancies and inconsistencies. The dataset represented diverse populations, ensuring broader generalizability of the findings. Advanced preprocessing steps, including outlier removal and imputation for missing values, were employed to enhance data quality and reliability. Key tools and frameworks used include:

- Programming Languages & Libraries: Python with Pandas, NumPy, and Scikit-learn for preprocessing and model building.

- Specialized ML Frameworks: XGBoost for advanced boosting techniques and TQDM for progress visualization.

- Hardware Configuration: Standard desktop environment.

B. Methods

Figure 1 below summarizes the workflow of the methodology used in this study, highlighting key steps from data preparation to result interpretation. This process ensures a systematic approach to analyzing the relationship between depression and suicide. By emphasizing key techniques such as feature selection, model training, and evaluation, the methodology aims to provide actionable insights for mental health diagnostics [10][11].

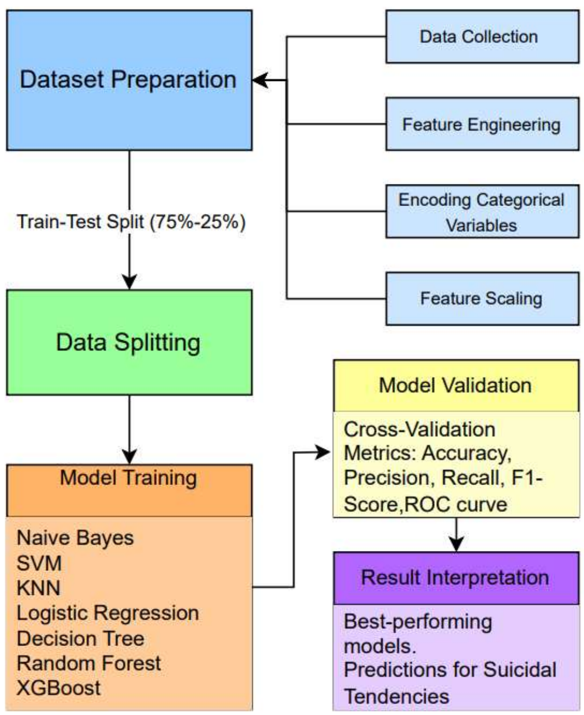

Fig 1. Methodology workflow.

- DataPreprocessing: The dataset underwent preprocessing steps, including encoding categorical variables into numerical representations using LabelEncoder and normalizing numerical variables with MinMaxScaler to ensure uniform feature scaling. These steps minimized biases and prepared the dataset for effective modeling.

- Feature Selection and Splitting: Key independent variables were selected based on their clinical relevance and feature distribution analysis. The data was then split into training (75%) and testing (25%) subsets, maintaining class stratification for balanced representation in both datasets.

- Model Training: Multiple machine learning models were evaluated, including Naive Bayes, Logistic Regression, SVM, KNN, Decision Trees, Random Forests, and XGBoost. To ensure consistency and reduce overfitting, three-fold cross-validation was applied during training.

- Evaluation Metrics: Performance was assessed using confusion matrices, accuracy, precision, recall, F1-scores, ROC curves, and probability distributions of suicidal tendencies. These metrics provided critical insights into the models' ability to identify high-risk cases while minimizing errors, highlighting the strengths of the best-performing models [12].

III. Results and Discussion

A. Results

The machine learning models effectively predicted individuals at higher risk for suicide based on depression-related features. Evaluated across various metrics, the models demonstrated strong potential in identifying high-risk cases. Real-world features, such as sleep patterns and family history of depression, further enhanced prediction robustness. Performance metrics are summarized in Table 1.

TABLE I. Comparative Performance Metrics

Model Name	**Results**			
	Accuracy	***Precision***	***Recall***	***F1-Score***
Naïve Bayes	0.7322	0.5036	0.2923	0.3699
SVM	0.7311	1.0000	0.0000	0.0000
KNN	0.6959	0.3816	0.2113	0.2720
Logistic Regression	0.7316	0.5049	0.0909	0.1541
Decision Tree	0.7313	0.5009	0.1382	0.2166
Random Forest	0.7150	0.4296	0.1824	0.2561
XGBoost	0.7320	0.5051	0.1531	0.2350

To visualize the classification performance of the best-performing models, confusion matrix heatmaps for Naïve Bayes and XGBoost are presented below. These matrices provide a detailed breakdown of true positives, false positives, true negatives, and false negatives, offering insight into each model's ability to identify high-risk individuals correctly. Figure 2 illustrates the confusion matrix for the Naïve Bayes.

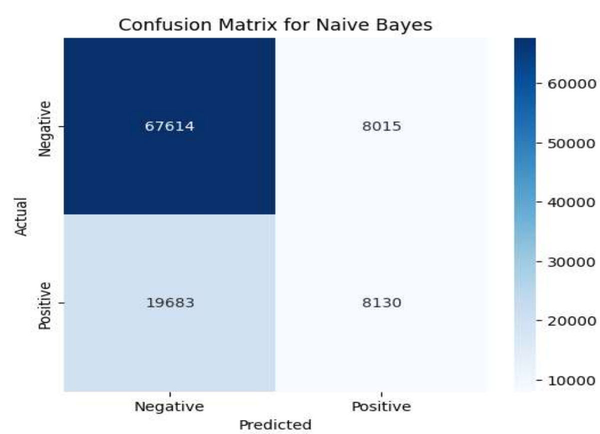

Fig 2. Confusion Matrix Heatmap for Naïve Bayes.

The heatmap highlights Naïve Bayes' ability to classify high-risk and low-risk individuals. It shows a strong performance in identifying true negatives but struggles with false negatives, which is critical for mental health diagnostics. Despite its simplicity, the model provides a good baseline for comparison. Figure 3 illustrates the confusion matrix for the XGBoost.

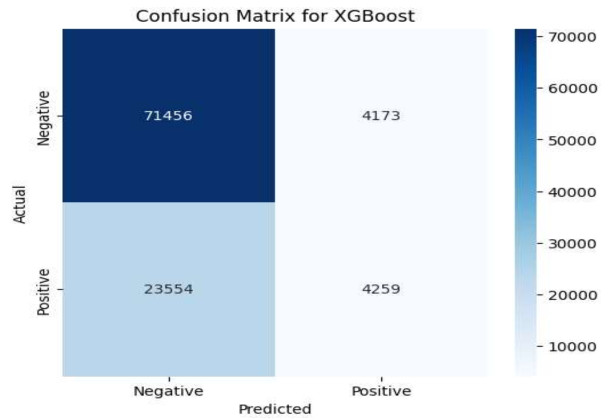

Fig 3. Confusion Matrix Heatmap for XGBoost.

The XGBoost's heatmap demonstrates superior classification, with high true negatives and reduced false negatives. This makes it a reliable model for detecting high-risk individuals, crucial for early intervention. Its robustness in minimizing errors sets it apart.

The Receiver Operating Characteristic (ROC) curves for Naïve Bayes and XGBoost are shown below to evaluate the models' trade-offs between sensitivity (true positive rate) and specificity (false positive rate) across thresholds. The Area Under the Curve (AUC) serves as a quantitative measure of the models' discriminative power. These curves illustrate the effectiveness of each model in distinguishing high-risk individuals and demonstrate their potential for mental health diagnostics. Improvements in minimizing false negatives could further enhance their application in clinical settings. Figure 4 shows the ROC curve for Naïve Bayes.

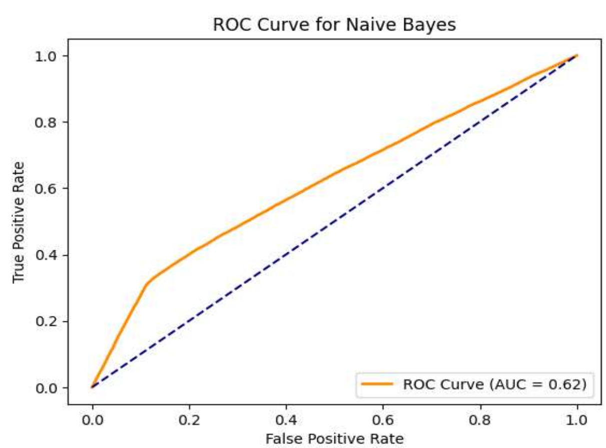

Fig 4. ROC Curve for Naïve Bayes.

The ROC curve for Naïve Bayes shows moderate performance, with a balanced trade-off between sensitivity and specificity. While the AUC score reflects its effectiveness, improvements in reducing false negatives are needed for critical applications.

Naive Bayes, despite its simplicity and assumptions of feature independence, demonstrated reasonable accuracy with good precision and recall. These results underscore its utility as a baseline model for binary classification tasks. However, its reliance on the assumption of feature independence limits its applicability for datasets with complex interdependencies. Figure 5 shows the ROC curve for XGBoost.

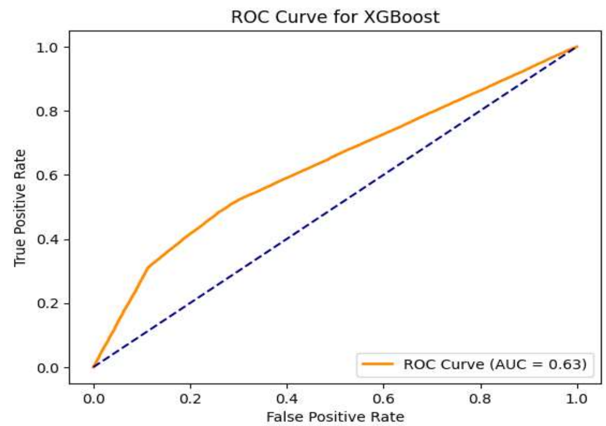

Fig 5. ROC Curve for XGBoost.

The ROC curve for XGBoost illustrates excellent discriminative power with a high AUC score. Its steep rise indicates strong sensitivity, making it ideal for prioritizing high-risk individuals in mental health care.

Additionally, Figure 6 illustrates the distribution of suicidal tendencies based on the probability prediction of the best-performing model (XGBoost).

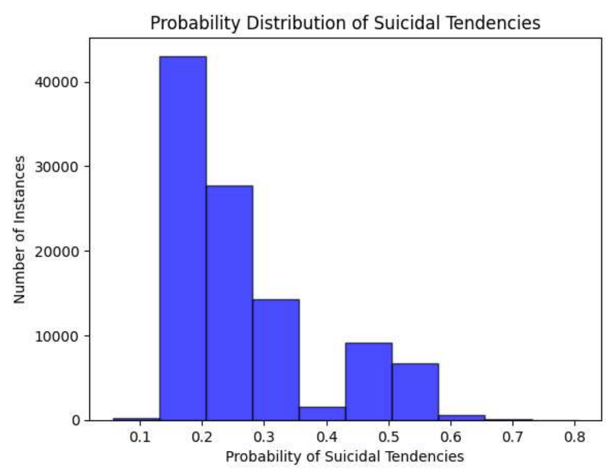

Fig 6. Probability of Suicide Tendencies (XGBoost).

Figures 6 highlight the concentration of predictions in the low-risk region, with distinct peaks for high-risk cases. This distribution reaffirms the models' reliability in prioritizing at-risk individuals and aiding mental health professionals in early intervention.

B. Discussion

The results illustrate the capability of machine learning to model complex relationships inherent in mental health data. XGBoost's superior performance aligns with its design to handle heterogeneity and capture intricate patterns. Meanwhile, ensemble models demonstrate their utility in delivering robust predictions even with feature interdependencies. As seen in this study the limitation of Naïve Bayes highlights the advantage of more advanced models like XGBoost, which can better capture intricate patterns in the data. These findings are consistent with previous research, affirming that genetic and behavioral factors, coupled with environmental triggers, significantly influence mental health outcomes. Moreover, incorporating these models into clinical settings could facilitate early risk detection, promoting timely interventions.

However, some challenges persist, such as ensuring the interpretability of black-box models like XGBoost. Future research can explore integrating SHAP or LIME frameworks to make predictive models more explainable and trustworthy for practitioners.

IV. Conclusion

This study examined the relationship between depression and suicide through machine learning-based predictive modeling. Our results show that Naïve Bayes and XGBoost outperformed other models in identifying high-risk individuals, with key predictors including sleep patterns, family history of depression, and clinical behaviors. These findings reinforce the potential of machine learning in mental health diagnostics, supporting early intervention efforts.

However, challenges remain, particularly in minimizing false negatives and improving the interpretability of complex models like XGBoost. Future research should focus on integrating real-time data sources, expanding datasets to include more diverse populations, and implementing explainability techniques such as SHAP or LIME to enhance model transparency. Addressing these issues will be crucial for deploying AI-driven mental health solutions in clinical practice.

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