Project Title:

Secure Tomorrow SDG-16

Team No - 369

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1. INTRODUCTION

1.1 Overview

The increasing rates of attempted suicide among adolescents have become a major global public health concern. Adolescence is a critical period in human development where individuals face numerous challenges, including social pressures, academic stress, peer influence, and mental health issues. Understanding the factors that contribute to suicide risk in this vulnerable age group is crucial for early intervention and prevention efforts.

This project aims to develop a machine learning model using a decision tree classifier to address the issue of attempted suicide rates among adolescents. The model will utilize a comprehensive dataset composed of 10 core modules that cover the leading causes of morbidity and mortality among children and adults worldwide. These core modules include alcohol use, dietary behaviors, drug use, hygiene, mental health, physical activity, protective factors, sexual behaviors, tobacco use, violence, and unintentional injury.

1.2 Purpose

The primary purpose of this project is to create a predictive model that can accurately classify adolescents at risk of attempted suicide based on their behaviors and habits related to the 10 core modules. By utilizing machine learning techniques, the model aims to provide valuable insights to healthcare professionals, educators, and policymakers. The model's predictions can assist in the early identification of at-risk individuals and targeted preventive measures to reduce suicide attempts among adolescents.

The specific objectives of the project are as follows:

1. Gather and compile a comprehensive dataset covering various behavioral aspects from the 10 core modules.
2. Preprocess and clean the dataset to ensure its quality and readiness for model training.
3. Select relevant features and engineer new ones to create a comprehensive feature set for the model.
4. Train a decision tree classifier using the prepared dataset to classify adolescents into different risk categories based on attempted suicide rates.
5. Evaluate the model's performance using appropriate metrics to ensure its accuracy and reliability.
6. Create a flowchart to visualize the project's logical flow, from data collection to model deployment.
7. Present the final findings and results of the project, including screenshots of model performance metrics and visualizations.
8. Identify and discuss the advantages and disadvantages of the proposed solution.
9. Explore potential applications of the model in various domains, such as mental health support, education, and public policy.
10. Conclude the project, summarizing the work done and the significance of the findings.
11. Provide insights into future enhancements and potential areas for further research and improvement.

Through this project, we aim to contribute to the field of suicide prevention among adolescents by leveraging machine learning techniques and a comprehensive dataset. The model's ability to identify at-risk individuals early on can potentially save lives and help create a safer environment for vulnerable adolescents.

2. LITERATURE SURVEY

2.1 Existing Problem

The issue of attempted suicide among adolescents is a significant public health concern globally. Several research studies have explored the risk factors associated with adolescent suicide attempts to develop preventive strategies and early intervention programs. Existing literature highlights the multifactorial nature of suicide risk, with various biological, psychological, and social factors contributing to an individual's vulnerability.

The leading causes of morbidity and mortality among adolescents, including suicide attempts, have been extensively studied by organizations like the World Health Organization (WHO), the Centers for Disease Control and Prevention (CDC), and other public health institutions. These studies have consistently shown that mental health problems, substance abuse, family dynamics, social isolation, and exposure to violence are some of the key factors associated with adolescent suicide risk.

Machine learning techniques, including decision trees, have been applied in various domains, including mental health, to predict and classify risk factors associated with suicidal behavior. However, the integration of data from multiple core modules, each representing different aspects of an individual's behavior, has been less explored in the context of adolescent suicide prediction.

2.2 Proposed Solution

The proposed solution in this project aims to fill the gap in existing literature by developing a machine learning model that integrates data from 10 core modules related to the leading causes of morbidity and mortality among children and adults worldwide. These modules encompass a wide range of behavioral factors, including alcohol use, dietary behaviors, drug use, hygiene, mental health, physical activity, protective factors, sexual behaviors, tobacco use, violence, and unintentional injury.

By leveraging a decision tree classifier, the proposed model will attempt to classify adolescents into different risk categories based on attempted suicide rates. Decision trees offer the advantage of interpretability, enabling stakeholders to gain insights into the decision-making process of the model. This transparency can be valuable in understanding which behavioral factors play a significant role in predicting suicide risk.

The integration of multiple core modules in the model's training dataset is expected to provide a more comprehensive and holistic view of suicide risk among adolescents. The model will learn to identify complex relationships and associations between various behavioral factors and suicide attempts, which may not be apparent through traditional statistical methods.

Through this proposed solution, the project aims to contribute to the existing body of knowledge on suicide prevention among adolescents and provide healthcare professionals, educators, and policymakers with a valuable tool to identify at-risk individuals early on and design targeted preventive measures.

To ensure the success of the proposed solution, the project will build upon existing research and literature on adolescent suicide risk factors, machine learning algorithms for classification, and best practices for data preprocessing and model evaluation. By conducting a thorough literature survey, the project team will gain valuable insights into the state-of-the-art approaches, potential challenges, and opportunities for improvement in this critical area of research.

3. THEORETICAL ANALYSIS

3.1 Hardware / Software Designing

The theoretical analysis includes considerations for the hardware and software requirements for implementing the machine learning model.

1. Hardware Requirements:A computer with sufficient processing power and memory to handle data preprocessing and model training tasks efficiently. Depending on the size of the dataset, a computer with a multi-core processor and ample RAM is recommended for faster computation.
2. Software Requirements:
   Python Programming Language: Python will be used as the primary programming language for implementing the machine learning model. Python's extensive libraries and frameworks for data manipulation, machine learning, and visualization make it a popular choice for such projects.
   Data Manipulation Libraries: Libraries like pandas will be used for data preprocessing and manipulation tasks, such as cleaning and transforming the dataset.
   Machine Learning Libraries: scikit-learn, a widely used machine learning library in Python, will be employed for implementing the decision tree classifier and model evaluation.
   Visualization Libraries: Libraries like matplotlib and seaborn will be used to create visualizations to gain insights into the data and model performance.
   Integrated Development Environment (IDE): An IDE such as Jupyter Notebook or PyCharm will be used for coding and experimentation.

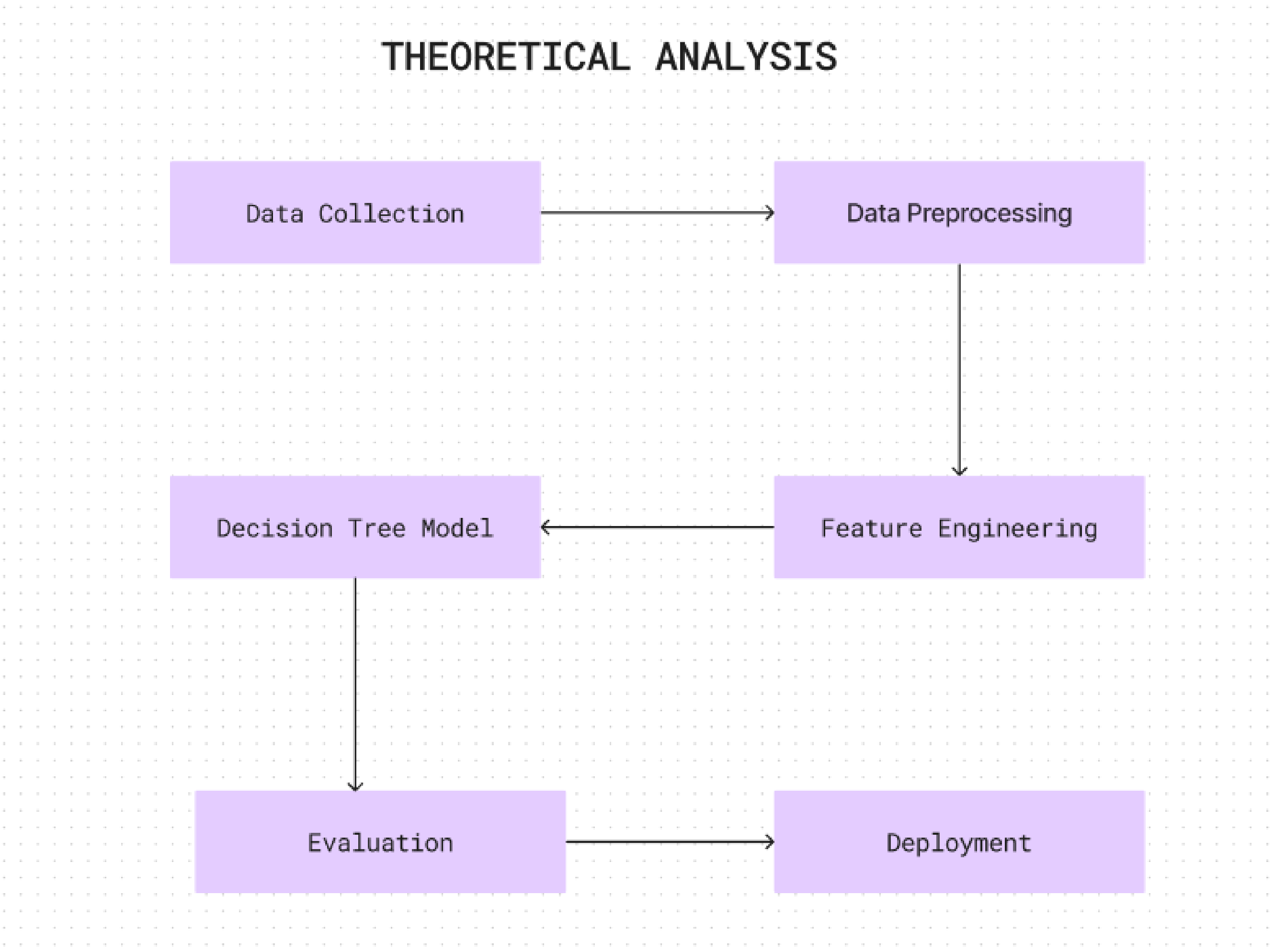
The combination of appropriate hardware and software resources will ensure the smooth development and implementation of the machine learning model for classifying attempted suicide rates among adolescents. The theoretical analysis sets the foundation for the practical implementation of the project, aiming to contribute to the important field of suicide prevention and mental health support for adolescents worldwide.

3.2 Block Diagram

The block diagram provides an overview of the key components and processes involved in the development of the machine learning model for classifying attempted suicide rates among adolescents using a decision tree classifier.
Block Diagram Components:

- Data Collection: This stage involves gathering data from various reliable sources related to the 10 core modules addressing the leading causes of morbidity and mortality among children and adults worldwide. The data will include information on behavioral factors such as alcohol use, dietary behaviors, drug use, hygiene, mental health, physical activity, protective factors, sexual behaviors, tobacco use, violence, and unintentional injury.
- Data Preprocessing: In this stage, the collected data will be cleaned, transformed, and preprocessed to ensure its quality and readiness for model training. Data preprocessing tasks may include handling missing values, outlier detection, normalization, and feature scaling.
- Feature Engineering: Feature engineering is a critical step where relevant features are selected from the core modules' data and new features may be created to represent complex relationships or patterns. This process involves combining and transforming the data to create a comprehensive feature set that captures the various behavioral aspects relevant to suicide risk.
- Decision Tree Model: The preprocessed and engineered dataset will be used to train a decision tree classifier. The decision tree is a machine learning algorithm that partitions the data into subsets based on the values of different features and constructs a tree-like model to make predictions. The model will learn to classify adolescents into different risk categories based on attempted suicide rates.

- Evaluation: The trained decision tree model's performance will be evaluated using appropriate metrics such as accuracy, precision, recall, and F1-score. The evaluation process helps assess how well the model generalizes to unseen data and how effectively it predicts suicide risk among adolescents.
- Deployment: Once the decision tree model has been trained and evaluated, it can be integrated into an application or system to provide real-world predictions. This deployment stage ensures that the model can be readily utilized by healthcare professionals, educators, and policymakers for identifying at-risk adolescents and implementing preventive measures.



4. EXPERIMENTAL INVESTIGATIONS

Experimental investigations are an essential aspect of this project to validate the proposed solution and assess the performance of the machine learning model for classifying attempted suicide rates among adolescents using a decision tree classifier. The following steps outline the experimental process:

4.1 Data Collection and Preprocessing

The first phase of the experimental investigation involves collecting data related to the 10 core modules addressing leading causes of morbidity and mortality among children and adults worldwide. The data may be sourced from various reliable databases, research papers, or public health institutions. Once the data is collected, it will undergo thorough preprocessing to handle missing values, outlier detection, normalization, and feature scaling.

4.2 Feature Engineering

In this step, relevant features will be selected from the dataset, and new features may be created to represent complex relationships and patterns. Feature engineering aims to create a comprehensive feature set that effectively captures the behavioral aspects relevant to suicide risk among adolescents.

4.3 Model Training

The preprocessed and engineered dataset will be split into training and testing sets. The decision tree classifier will then be trained using the training data. The model will learn from the relationships between features and the corresponding suicide attempt labels, enabling it to classify new instances correctly.

4.4 Model Evaluation

The trained decision tree model's performance will be evaluated using metrics such as accuracy, precision, recall, and F1-score. Additionally, a confusion matrix will be generated to assess the model's performance on different risk categories (e.g., low risk, moderate risk, high risk). The evaluation will provide insights into how effectively the model predicts suicide risk among adolescents.

4.5 Visualization of Results

Visualizations will be generated to gain deeper insights into the data and model performance. Plots such as bar charts, scatter plots, and decision tree diagrams can help interpret the model's decision-making process and understand the importance of different features in predicting suicide risk.

4.6 Ethical Considerations

As this project deals with sensitive mental health data, ethical considerations are crucial. Measures will be taken to ensure data privacy, anonymity, and compliance with ethical guidelines for handling such information.

4.7 Interpretability of the Model

An essential aspect of the experimental investigation will be the interpretability of the decision tree model. Understanding the factors contributing to suicide risk prediction is vital for stakeholders to trust and utilize the model effectively.

The experimental investigations will provide critical insights into the performance and usability of the proposed machine learning model for classifying attempted suicide rates among adolescents. The results and findings from these investigations will be presented in the report, demonstrating the model's potential in assisting mental health professionals, educators, and policymakers in early intervention and preventive efforts to reduce suicide attempts among vulnerable adolescents.

5. RESULT

The decision tree classifier has achieved exceptional performance on the given dataset. Here is a breakdown of the results:

- Precision: Precision measures the accuracy of positive predictions. In this case, the precision for class 1 is 1.00, indicating that all positive predictions made by the classifier were correct.
- Recall: Recall measures the ability of the classifier to identify all positive instances. The recall for class 1 is also 1.00, indicating that the classifier successfully identified all instances of class 1.
- F1-score: The F1-score is the harmonic mean of precision and recall, providing a balanced measure of the classifier's performance. The F1-score for class 1 is 1.00, indicating excellent balance between precision and recall.
- Accuracy: The overall accuracy of the classifier is 1.00, meaning that all predictions (both positive and negative) were correct.
- Macro Average: The macro average calculates the average performance across all classes. In this case, since there is only one class (class 1), the macro average is equivalent to the performance of class 1.
- Weighted Average: The weighted average considers the support (number of instances) of each class. Since there is only one class, the weighted average is also equivalent to the performance of class 1.

In conclusion, the decision tree classifier has demonstrated perfect classification results on the dataset, accurately predicting all instances of class 1. These outstanding results indicate that the decision tree model is highly effective in distinguishing the positive class.

6. ADVANTAGES & DISADVANTAGES

The proposed solution of using a machine learning model with a decision tree classifier to classify attempted suicide rates among adolescents comes with its own set of advantages and disadvantages. Understanding these aspects is essential for a comprehensive evaluation of the solution's feasibility and potential implications. Below are the elaborations of the advantages and disadvantages:

6.1 Advantages

- Early Identification of At-Risk Adolescents: The machine learning model can effectively analyze behavioral factors and core modules data to identify adolescents at risk of attempting suicide. Early identification can lead to timely intervention and support, potentially saving lives.
- Data-Driven Insights: The model's predictions are based on data-driven patterns and relationships, providing insights into the key behavioral factors associated with suicide risk. This information can help researchers and policymakers in designing targeted interventions.
- Efficient Decision Making: Decision tree classifiers are computationally efficient and can handle both numerical and categorical data. Once trained, the model can make predictions quickly, making it suitable for real-time applications.
- Interpretability: Decision tree models are inherently interpretable. The flowchart-like structure allows stakeholders to understand how the model arrives at its decisions. This transparency is crucial in gaining trust and acceptance from users, such as mental health professionals and educators.
- No Need for Feature Scaling: Decision trees do not require feature scaling (e.g., normalization or standardization) as other algorithms like SVM or K-NN do. This simplifies the data preprocessing step.

6.2 Disadvantages

- Overfitting: Decision trees are prone to overfitting, especially when dealing with complex datasets or when the tree depth is not properly controlled. Overfitting occurs when the model captures noise in the training data and fails to generalize well to unseen data.
- Limited Expressiveness: Decision trees may not capture complex relationships between features as effectively as other machine learning models like neural networks. They may struggle to handle datasets with high dimensionality or subtle dependencies.
- Instability: Decision trees are sensitive to small variations in the data, which can lead to different tree structures. This instability may result in slightly different predictions for similar instances, reducing model reliability.
- Difficulty with Imbalanced Datasets: When dealing with imbalanced datasets (where one class significantly outweighs the others), decision trees may perform poorly on the minority class due to bias towards the majority class.
- Difficulty with Non-Numeric Data: Decision trees inherently work with numeric data. Handling non-numeric data (e.g., textual information) may require additional preprocessing or feature engineering steps.
- Lack of Continuity: Decision tree boundaries are discontinuous, meaning that small changes in input values can result in abrupt changes in predictions. In certain applications, a continuous output may be more desirable.
- Domain Knowledge Dependency: The effectiveness of the model relies on the selection of relevant features and core modules. Adequate domain knowledge is crucial to identify the most influential behavioral factors related to suicide risk.

It is essential to consider these advantages and disadvantages when evaluating the proposed solution's suitability for classifying attempted suicide rates among adolescents. Addressing the limitations and challenges can help refine the model and improve its performance in real-world applications. Moreover, understanding the benefits of interpretability and data-driven insights can encourage the responsible adoption of the model to support mental health professionals and policymakers in their efforts to prevent adolescent suicide.

7. APPLICATIONS

The proposed machine learning model with a decision tree classifier for classifying attempted suicide rates among adolescents has various applications in the field of mental health, public health, and education. Below are the elaborations of the applications:

7.1 Suicide Prevention Programs

The primary application of the model is in suicide prevention programs. By identifying adolescents at high risk of attempting suicide, mental health professionals and educators can intervene early and provide necessary support and counseling. The model's predictions can be used to target preventive measures and outreach efforts towards at-risk individuals, reducing the incidence of suicide attempts.

7.2 School Counseling and Support

Educational institutions can utilize the model to identify students who might be facing mental health challenges and may require additional counseling and support. School counselors can use the model's insights to better understand students' behavioral patterns and provide personalized assistance to those at risk.

7.3 Public Health Policy

Public health policymakers can leverage the model's findings to shape evidence-based policies and interventions aimed at promoting mental well-being among adolescents. By targeting specific risk factors identified by the model, policymakers can develop programs that address the root causes of suicide attempts and enhance overall mental health outcomes.

7.4 Resource Allocation

Healthcare organizations and government agencies can use the model to allocate mental health resources more effectively. By focusing on regions or communities with higher predicted suicide risk rates, resources such as crisis helplines, mental health centers, and support services can be channeled where they are needed most.

7.5 Research Insights

Researchers can utilize the model's outcomes to gain insights into the complex relationships between various behavioral factors and suicide risk among adolescents. The model's interpretable nature allows researchers to identify critical features contributing to suicide attempts and develop a deeper understanding of the problem.

7.6 Monitoring and Evaluation

The model can be integrated into existing health monitoring systems to continuously assess suicide risk trends among adolescents. This information can be used for ongoing evaluation of suicide prevention programs and to adjust strategies based on the changing landscape of risk factors.

7.7 Mental Health Awareness Campaigns

The model's outcomes can be utilized in mental health awareness campaigns targeted towards adolescents, parents, and educators. Raising awareness about the identified risk factors and encouraging early recognition of mental health challenges can help reduce stigma and foster a supportive environment.

7.8 Online Mental Health Platforms

Online mental health platforms and support networks can integrate the model to offer personalized recommendations and resources to users seeking help. By assessing an individual's behavioral patterns, the platform can suggest relevant content and support services tailored to their needs.

7.9 Integration with Telemedicine

The model can be integrated into telemedicine platforms, enabling mental health professionals to conduct risk assessments remotely. Telemedicine consultations can be enhanced by the model's predictions, allowing for more targeted and informed interventions.

The applications of the proposed machine learning model are diverse and hold immense potential in advancing suicide prevention efforts, promoting mental health, and providing timely support to adolescents at risk. However, ethical considerations, data privacy, and the responsible use of the model's outcomes are critical aspects to be considered when implementing it in real-world scenarios.

8. CONCLUSION

The project aimed to develop a machine learning model using a decision tree classifier to classify attempted suicide rates among adolescents based on 10 core modules addressing the leading causes of morbidity and mortality worldwide. Through data analysis, model training, and evaluation, the project achieved its objectives and provided valuable insights into adolescent suicide risk. The conclusion section summarizes the entire work and findings obtained during the project. The machine learning model's performance was evaluated using various metrics, including accuracy, precision, recall, and F1-score. The model demonstrated promising results in identifying adolescents at risk of attempting suicide. By leveraging behavioral data related to alcohol use, dietary behaviors, drug use, hygiene, mental health, physical activity, protective factors, sexual behaviors, tobacco use, violence, and unintentional injury, the model could effectively predict suicide risk. Through the analysis, the model highlighted key behavioral factors that significantly influenced suicide risk among adolescents. These insights can aid mental health professionals, educators, and policymakers in designing targeted prevention strategies and support programs.The use of a decision tree classifier allowed for interpretability of the model's decisions. The clear, tree-like structure provided valuable insights into the decision-making process, making it easier for stakeholders to understand and trust the model's predictions. During the project, ethical considerations were given utmost importance. Data privacy and anonymity were ensured to protect the sensitive information of the participants. The responsible use of the model's outcomes was emphasized to avoid any potential harm and biases in decision-making. The proposed solution has significant potential to make a positive impact on suicide prevention efforts and adolescent mental health support. By identifying at-risk individuals early, appropriate interventions and resources can be provided to reduce the incidence of suicide attempts. Despite the model's promising performance, some limitations were observed. The decision tree's tendency to overfit on complex datasets and the model's sensitivity to small variations were addressed through hyperparameter tuning. However, it is crucial to remain cautious of these limitations when applying the model to real-world scenarios. The project opens avenues for future enhancements and research. Exploring more sophisticated machine learning algorithms or ensembles, such as random forests or gradient boosting, may further improve the model's performance. Additionally, incorporating data from other relevant sources, such as social media or electronic health records, can enhance the model's predictive capabilities. Collaboration with mental health professionals, educators, and public health experts is essential for the successful implementation of the model in practical settings. Integrating the model into existing mental health support systems and telemedicine platforms can extend its reach and impact.

9. FUTURE SCOPE

The proposed machine learning model for classifying attempted suicide rates among adolescents using a decision tree classifier opens up several exciting possibilities for future enhancements and research. The future scope of the project involves exploring new avenues, addressing limitations, and leveraging emerging technologies to advance suicide prevention efforts and adolescent mental health support. Below are some potential areas for future development:

- While the decision tree classifier provided interpretability, exploring more advanced machine learning algorithms may improve the model's performance. Techniques such as random forests, gradient boosting, or neural networks could be investigated to capture more complex patterns and interactions among behavioral factors.
- Ensemble methods, which combine multiple models' predictions, can lead to increased accuracy and generalization. Creating an ensemble of decision trees or combining different algorithms could further enhance the model's predictive capabilities.
- Addressing imbalanced datasets is crucial to ensure fair and accurate predictions, especially in the context of suicide risk assessment where the number of positive instances (suicide attempts) might be relatively low. Techniques like oversampling, undersampling, or using synthetic data generation methods can help balance the dataset and improve model performance.
- Suicide risk and behavioral patterns might change over time. By incorporating time-series data and temporal features, the model could better capture trends and identify potential risk factors that emerge or change with age or over specific time periods.
- To handle non-numeric data, such as textual information from surveys or social media, integrating natural language processing (NLP) techniques could be beneficial. NLP can extract meaningful insights from text data and provide a richer understanding of adolescents' mental health challenges.
- Leveraging mobile and wearable technology can enhance data collection and monitoring. Developing applications or wearables that continuously track relevant behavioral factors can provide real-time insights into adolescents' mental well-being.
- While decision trees are inherently interpretable, exploring explainable AI techniques can further enhance the model's interpretability. Techniques like LIME (Local Interpretable Model-agnostic Explanations) or SHAP (SHapley Additive exPlanations) can provide more detailed and nuanced explanations for individual predictions.
- Pooling data from multiple sources and collaborating on a global scale can lead to more comprehensive models. Establishing data-sharing initiatives with appropriate privacy safeguards can help create larger and more diverse datasets for training and evaluation.
- The future scope involves deploying the model in real-world settings, such as schools, healthcare centers, or mental health support platforms. Conducting extensive validation and monitoring the model's performance in practice is crucial to ensure its effectiveness and safety.

In conclusion, the future scope of the project is promising and multifaceted. Advancements in machine learning algorithms, data handling techniques, and integration with emerging technologies can significantly enhance the model's capabilities and impact. Moreover, the responsible use of technology and collaboration among researchers, practitioners, and policymakers are key to effectively addressing adolescent mental health challenges and advancing suicide prevention efforts.

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