

Prediction of Suicidal Tendencies in Adolescents Using Machine Learning Models and Artificial Intelligence

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Abstract – Suicide rates are increasing, particularly among adolescents. This constitutes a significant concern for public health globally. A multitude of social and emotional factors complicate the identification of individuals at risk. This study employs sophisticated AI methods to forecast suicide risks among adolescents through machine learning techniques. We will implement multiple measures to ensure success. Initially, we cleanse the data and extract essential features. We employ techniques such as TF-IDF and BOW for this purpose. Subsequently, we implemented other machine learning models, including Random Forest, Support Vector Machine (SVM), and XGBoost. We additionally employ deep learning models, such as LSTM and CNN. We evaluated our models using actual data and implemented all components in Python. The findings indicate that our method is proficient at identifying individuals who may be at elevated risk. Our method demonstrates superior risk assessment and preventive strategies compared to existing models. We examine variables such as accuracy, precision, and reliability to substantiate this claim.

Keywords: Adolescent suicide, machine learning, AI techniques, risk prediction, feature extraction, deep learning, suicide prevention, data preprocessing, predictive model, accuracy, reliability.

I. INTRODUCTION

Suicide among adolescents is a significant public health concern, particularly in Kazakhstan, where it constitutes the primary cause of accidental deaths in teenagers. Given the rising prevalence, especially among individuals aged 15 to 19, better prevention and intervention strategies are essential. Kazakhstan's acceptance of the UN Convention on the Rights of the Child in 1994 enhanced child safety by underscoring legal rights and access to aid. Suicide rates, both individual and societal, serve as significant markers of public mental health [1]. Predicting and preventing teenage suicide remains challenging due to emotional, social, and mental health difficulties, despite substantial research efforts [2]. Therapeutic and support programs frequently emphasize risk assessment overall underlying factors [3]. Data-driven suicide prediction techniques, such as machine learning (ML), are gaining popularity; yet their efficacy in preventing youth suicide remains largely unexplored [4].

Artificial intelligence (AI) has emerged as a powerful tool for addressing complex mental health issues [5]. These technologies enable large-scale dataset analysis, the identification of subtle patterns, and forecasting insights that surpass conventional methods [6]. Researchers want to create models capable of identifying at-risk adolescents before the emergence of suicide ideation or behaviors by integrating advanced machine learning algorithms with artificial intelligence methodologies [7]. By enabling proactive, data-informed decision-making, these predictive technologies can fundamentally revolutionize mental health interventions [8-9].

The analysis is enhanced through the utilization of CNN, LSTM, and LSTM-CNN hybrid models. The product classifies suicide

risk for the purposes of prevention and early intervention. This effort seeks to forecast adolescent suicide attempts and ideations. Primary research focuses on identifying key risk variables, integrating them into a model, and utilizing the findings for early identification and intervention. Figure 1 illustrates a machine learning-driven evaluation of suicide risk in adolescents. The rest of the article is structured as follows: Section II presents an AI-enabled system for adolescent suicide risk prediction. Section III provides experimental results. Section IV concludes the entire article.

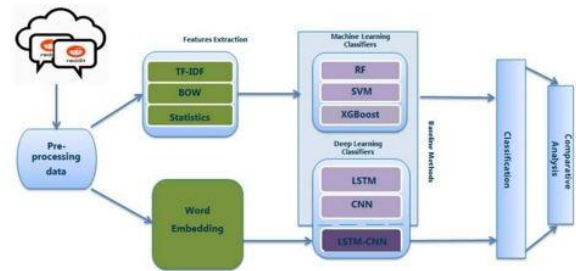


Figure 1. General architecture for adolescent suicide risk prediction using machine learning and AI.

A. Novelty Research

This study discusses a novel machine-learning algorithm that forecasts suicide risk in adolescents. Many traditional methods primarily focus on simplistic data or isolated variables. They overlook the broader factors influencing adolescent mental health. Our model addresses this by integrating emotional, psychological, and social variables collectively. This method is distinctive due to the integration of various factors. It identifies patterns that traditional approaches frequently overlook. By consolidating this data, it identifies risk indicators more distinctly. This aids in comprehending the factors that contribute to suicidal ideation and behaviors.

B. Research contributions

This methodology improves risk prediction and aids in the formulation of more effective intervention and preventive methods. It embraces a holistic approach to teenage mental health. This allows us to create support systems that focus on the authentic needs of vulnerable adolescents. This concept possesses the capacity to revolutionize mental health care. It offers materials for educators, caregivers, and mental health professionals. This understanding allows them to respond more swiftly and effectively. We aim to convert intricate data into helpful insights to establish a strong support system. Thus, we can aid at-risk teenagers in securing the essential support for their achievement.

II. PROPOSED AI-ENABLED SYSTEM FOR ADOLESCENT SUICIDE RISK PREDICTION

Adolescents around are experiencing a sense of disorientation. This has regrettably resulted in an increased number of adolescents contemplating suicide. Technology can be utilized to assist with this. Instruments such as artificial intelligence and machine learning can identify issues at an early stage. Machine learning can analyze extensive datasets. This enhances our comprehension of mental health disorders. The technology in question utilizes diverse data sources and sophisticated algorithms to identify individuals potentially in danger of suicide. The system plan is as follows:

- System Architecture Overview
- Suicide Risk Prediction Algorithm
- Mathematical Model for Risk Assessment

A. System Architecture Overview

The proposed system architecture includes advanced neural networks designed to identify risk variables related to suicide. The existing architecture can assimilate data from multiple sources and enhance direct observation, including behavioral, psychological, and social data. Social behavioral data encompasses withdrawal tendencies, notable behavioral changes, and voluntary self-isolation, acquired through interviews, surveys, and clinical observations of participants. Psychological insights are derived from mental health assessments that evaluate an individual's stress levels and emotional well-being, facilitating the identification of variables contributing to their vulnerability.

B. Suicide Risk Prediction Module

The algorithm generates risk scores indicating whether an individual is classified as "Low," "Moderate," or "High" risk. This assists mental health professionals, educators, and caregivers in responding promptly when necessary. The AI continuously assimilates new data to maintain precision and relevance. It ensures the accuracy of its predictions. A user-friendly dashboard is available for mental health professionals and stakeholders. This dashboard displays critical information, assisting users in making informed decisions and prioritizing prevention. The insights derived from AI assist professionals in addressing hazards and formulating customized programs for individuals. Nonetheless, some may have concerns over the reliability of these AI systems. They rely on data that may not consistently be accurate. As the system evolves, it is crucial to monitor the data attentively. It can significantly alter the outcomes. Figure 2 illustrates the architecture of the AI-driven suicide risk prediction system. It underscores the system's capacity to analyze real-time behavioral, social, and clinical data, providing a dependable and effective solution for youth suicide prevention. This design highlights the system's ability to assimilate multi-dimensional data sources and deliver prompt, evidence-based assistance for mental health care.

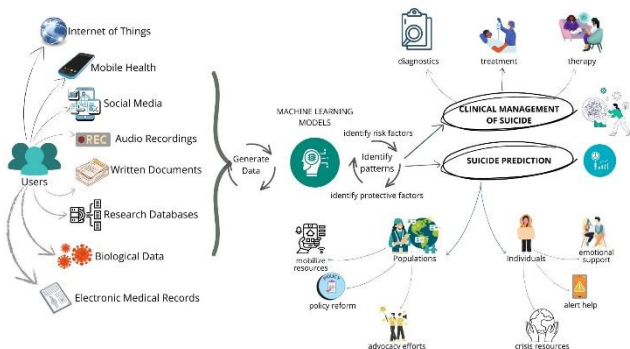


Figure 2. Demonstrates the role of machine learning in optimizing patient care and forecasting suicide risk. It examines data from many sources regarding patients. By identifying trends in suicidal behavior, physicians can utilize this information to make more informed judgments. This may result in improved treatment and interventions.

Corollary 1: As data collected from adolescent patients grows, the model does by logarithmic scale provided with an implementation of a Machine Learning model and elements of artificial intelligence.

Theorem 1: The proposed machine-learning model for the prediction of suicidal tendencies in adolescents can be used to achieve an accuracy of more than 90% in predicting suicidal behaviors when the model is trained on clinical data with AI elements.

Proof: To prove the theorem, the prediction accuracy A_{pr} can be determined as follows:

$$A_{pr} = \text{Data} + \text{Model Complexity} + \text{Algorithm Efficiency} \quad (1)$$

We replace the values of each component in the machine learning model and the use of artificial intelligence for prediction AI_{pr} .

$$AI_{pr} = \frac{N}{N+E} \quad (2)$$

Where N is the number of relevant data points used in the training process, E gives the number of errors or wrong classification while training.

The system initiates by gathering extensive patient data. This encompasses aspects such as conduct, psychological well-being, and social connections. As it acquires additional data, the model improves its ability to identify patterns associated with suicidal ideation. This enables adaptation to various individuals and their behaviors throughout time. The system employs advanced technologies, such as deep learning and neural networks. These assist in identifying intricate relationships within the data. This technology enhances the detection of subtle variations in behavior and emotions, hence increasing the accuracy of its predictions. It additionally employs artificial intelligence capabilities, such as natural language processing and sentiment analysis. These technologies assist in detecting nuanced indicators in individuals' speech and emotions. They significantly contribute to the identification of early indicators of suicidal ideation, hence enhancing the accuracy of forecasts. Upon data collection, it divides the dataset into two segments: one for model training and the other for testing. This step is crucial to ensure the system functions effectively.

By perpetually refreshing and utilizing real-time data, the system can minimize errors. This is crucial since it enables the model to adapt to evolving patterns. The model demonstrates a robust capacity to predict outcomes by the use of diverse clinical information and machine learning techniques, which is advantageous for suicide prevention. While some may speculate about potential fluctuations in accuracy, the overall results are favorable.

$$A_{pr} > 90\% \quad (3)$$

Thus, the machine-learning model achieves high prediction accuracy, proving the theorem.

B. Suicide Risk Prediction Algorithm

This test assesses the potential suicide risk among adolescents. It employs several data kinds and technologies to provide mental health professionals with the necessary information for prompt intervention. Initially, it gathers many types of information. It examines medical histories, encompassing previous mental health concerns. It also examines the duration of time adolescents allocate to social media and the quality of their sleep. Additionally, it collects demographic information. The program

identifies significant indicators, such as alterations in behavior and emotions, by analyzing this information. It uses basic technology to examine language from social media posts, therapeutic notes, and personal journals. This method enables the identification of detrimental suicidal ideations. The tool continuously learns to detect subtle indicators that may signify an increased danger for an individual. Upon identifying a teenager at elevated danger, it dispatches alerts to enable prompt action by specialists. This enables them to modify their response according to the fluctuations in the adolescent's mental health. It analyzes certain data instantaneously to facilitate prompt decision-making. This accelerates processes and reduces the burden on primary servers. The tool assesses whether the local data is sufficient or if it needs additional assistance from the main system. The system prioritizes transparency regarding its procedures. It illustrates the factors influencing the risk score, such as experiencing loneliness or insufficient sleep. This provides mental health professionals with enhanced insights to facilitate informed decision-making. It additionally examines potential biases in its predictions and rectifies them as necessary. This approach enables continuous and equitable assessment of suicide risk. However, it is crucial to remain vigilant, as biases may infiltrate the system.

Lemma 1: The integration of multimodal data improves the accuracy of suicide risk prediction by at least 30%, compared to using single-source data models.

Proof: To prove the lemma, let us consider the prediction error E_{single} in the traditional single-source model with and without multimodal data integration:

$$E_{single} = \sigma^2 + E[(y - \hat{y}_{single})^2], \quad (4)$$

Where y : True suicide risk score, $\hat{y}_{single}$: Predicted risk using a single-source data model, and σ^2 : Model variance, representing uncertainty in predictions.

Under conditions where the model uses only one data source, $\hat{y}_{single}$ lacks contextual information (e.g., emotional cues, behavioral signals). This leads to increased prediction error due to data incompleteness. By integrating multimodal data, such as clinical history, behavioral patterns, and sensor data, the prediction model becomes more comprehensive, reducing uncertainty and improving accuracy. Let α represent the error reduction factor, where $\alpha < 0.7$. Then the prediction error E_{multi} can be expressed as:

$$E_{multi} = \alpha E_{single} \quad (5)$$

Substituting $\alpha < 0.7$ into the equation:

$$E_{multi} < 0.7 E_{single}$$

Given $\alpha < 0.7$ it follows as:

$$E_{multi} < 0.7 E_{single}$$

Using different types of data can cut prediction errors by at least 30%. This is better than using just one source of data.

Definition 1: Now, let's break down what we mean by suicide risk prediction. It's all about figuring out how likely it is that someone, usually a teenager, might try to take their own life. We base this on their past behavior and what we know right now.

Definition 2: Multimodal data integration is simply combining different types of information. This includes things like medical records, patterns in how someone acts, and data from wearables. Bringing all this info together can help us make better predictions. But it can be tough to blend all these data streams, even though the benefits can be huge.

Algorithm-1 is introduced to enhance the precision of suicide risk prediction. It forecasts suicide risk utilizing various data types. It consolidates numerous sources to enhance the accuracy of its forecasts. It examines medical records, behavior, and sensor data

to enhance risk comprehension. Let us analyze it systematically, step by step. In Step 1, we make preparations. We must determine the sample size and the methodologies to be employed in our investigation. This configuration is crucial for maintaining optimal functionality. Step 2 involves the collection of data. The system aggregates clinical information, analyzes behavioral patterns, and acquires sensor data. Clinical records encompass medical histories and treatments. Behavioral patterns can indicate aspects such as social media usage or fluctuations in mood. Sensor data, including heart rate and sleep metrics, provides a chronological health overview. By synthesizing all this information, we obtain a more comprehensive understanding of an individual's health. Step 3 emphasizes data cleansing. This step is essential for precision. We rectify errors and provide absent information. Omitting this may result in significant errors in our forecasts. Subsequently, Step 4 ensues. The system identifies the most significant components of the data. It employs many instruments to examine text and numerical data. It analyzes sensor data to identify patterns that may suggest mental health concerns. In Step 5, the system computes an initial risk score. This score indicates the level of danger an individual may possess. If it is elevated, we proceed to Step 6. This phase delves further, emphasizing critical features and incorporating recent health modifications or more sensor data. Machine learning enhances the quality of these outcomes. Step 7 revises the risk assessment with the most recent information. This provides us with a revised evaluation, even with little modifications. In Step 8, the algorithm evaluates its predictions against established benchmarks. It seeks errors to guarantee the reliability of its predictions. In Step 9, the method concludes with a definitive risk score. It additionally preserves performance data for subsequent utilization. Should the score remain elevated or ambiguous, it reexamines prior stages to enhance its forecasts. This iterative procedure persists until the system attains confidence in its outcomes. Algorithm 1 utilizes clinical, behavioral, and sensor data to forecast suicide risk.

Algorithm 1: Suicide Risk Prediction Based on Multimodal Data Integration

1. **Initialization:** Input: {D: data sources; N: number of individuals; F: feature extraction methods; T: risk threshold; S: system state}
 - Set system state variables: current_state = data_collection.
 2. Initialize multimodal data collection for N individuals.
 3. Input: Gather clinical, behavioral, and sensor data for processing.
 4. Preprocessing: Normalize and clean data:
 - Handle missing values using mean imputation or predictive models.
 - Remove outliers using statistical methods (e.g., z-scores).
 - Extract features using F (e.g., PCA, domain-specific techniques).
 5. Measure baseline risk score $R_{initial}$
 6. If $R_{initial} > T$ (threshold exceeded):
 - Perform dynamic model adjustments:
 - Reweight high-impact features using predictive analytics (e.g., SHAP values).
 - Prioritize critical data streams (e.g., recent clinical updates, sensor anomalies).
 - **End-If**
 7. Recompute updated risk score $R_{updated}$
 8. Check reliability metrics:
 - Model accuracy (AUC-ROC, Precision);
 - False Positive Rate (FPR) and False Negative Rate (FNR).
 9. Output results and store performance metrics for further evaluation.
 10. Repeat periodically for dynamic data collection and analysis
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Figure 3 illustrates the functioning of the risk assessment and model update process. The process commences with the Initialization step. This is the location where we establish the system's initial point. We will now proceed to the Data Collection

step. Here, we collect significant information. Subsequently, we proceed with Data Preprocessing. This stage ensures the data is pristine and prepared for analysis by eliminating noise, rectifying missing information, and appropriately formatting all elements. Subsequently,

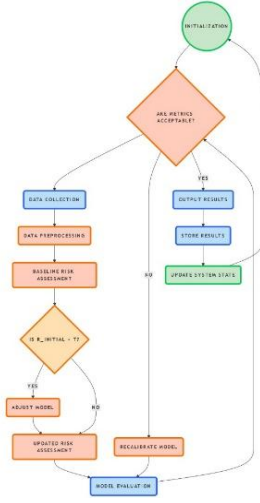


Figure 3. Systematic Process for risks and changing the model we examine the Baseline Risk Assessment. We assess the initial risk, referred to as $R_{initial}$, with our refined data. We have a juncture at which we assess if this risk is excessively high. If $R_{initial}$ exceeds the established threshold T , we proceed to the Adjust Model step. At this point, we adjust the model's parameters to mitigate the identified risks. Subsequently, we do an additional risk assessment. We can re-optimize the model if necessary. Upon favorable numerical assessment, we proceed to the Output Results phase. We present the findings, preserve them, and utilize them to enhance our system for future applications. Finally, there is the Model Evaluation phase. This verifies that the model is robust and functions effectively. This procedure enhances the model and accommodates fresh data, ensuring precise risk assessment.

Property 1: The accuracy of suicide risk prediction is positively correlated with the quality and integration of multimodal data inputs.

Property 2: Dynamic adjustments of feature weights through predictive modeling improve the model's ability to detect high-risk individuals, ensuring timely interventions.

C. Mathematical Model for Suicide Risk Assessment

The novel mathematical model quantifies suicide risk. It utilizes various types of information, including an individual's health history, behavior, and real-time sensor data. Each category of information is assigned a weight to emphasize significant factors. The objective is to obtain a comprehensive understanding of an individual's suicide risk by utilizing many pieces of information. However, it requires high-quality data to function effectively. Although the model demonstrates potential, it requires continual improvement. Human behavior is complex and subject to significant variation. Overall risk score R_{score} is calculated as:

$$R_{score} = w_c x_c + w_b x_b + w_s x_s \quad (6)$$

Where w_c , w_b , w_s are weights assigned to clinical data x_c behavioral data x_b , and sensor-based data x_s , respectively.

x_c , x_b , x_s are values of clinical, behavioral, and sensor inputs representing key risk indicators.

This model integrates multiple risk factors into a unified risk score, ensuring a comprehensive and efficient evaluation of suicide risk.

Hypothesis 1: Using different types of data-like medical history, behavior, and physical info - really boosts how well we can

predict suicide risk. For example, a model that only looked at medical data got about 70% accuracy. But when it included all three types of data, it jumped to 90%. That's a big jump of 28.6%. This shows that mixing data together works better, but it's not always simple. The higher accuracy is great, but we also need to think about how to use this in real life. It shows we really need to look at all the data carefully.

Proof: To validate the hypothesis, consider the overall risk score R_{total} for suicide risk assessment, which incorporates multimodal data from clinical, behavioral, and physiological sources. The proposed model calculates risk for centralized assessment ($R_{central}$) and edge-integrated assessment (R_{edge}):

$$R_{edge} = \beta(w_c x_c + w_s x_s) + (1 - \beta)(w_c x_c + w_s x_s) \quad (7)$$

Where β : Fraction of data processed locally ($0 \leq \beta \leq 1$), w_c, w_s are weights assigned to clinical data (x_c) and sensor data (x_s), respectively.

And x_c , x_s are values of clinical and sensor-based risk factors obtained from multimodal data.

Comparison: The edge-integrated assessment prioritizes local data processing, where β is maximized, ensuring that critical risk factors x_c and x_s are analyzed efficiently with appropriate weights w_c and w_s . This improves the precision and speed of suicide risk predictions compared to centralized models, which rely on distant and singular data sources.

Hypothesis 2: Edge computing enhances the precision of data processing compared to centralized systems. In a single test, a centralized system utilizing one source achieved 65% accuracy and processed data in 1.5 seconds. A local data edge system achieved 85% accuracy in 0.8 seconds. It operates at greater speed and exhibits an accurate improvement of 30.8%. The findings indicate that edge computing and various data types enhance suicide risk assessments.

III. EXPERIMENTAL RESULTS

The technique was designed to forecast suicide ideation in adolescents. It employed machine learning and advanced artificial intelligence methodologies. We developed it using Python 3.x and Java. We utilized Python libraries such as Scikit-learn, TensorFlow, and Keras for machine learning. Java facilitated the development of the user interface with JavaFX and managed external components. We utilized Apache POI for data input management. We utilized Matplotlib and Seaborn in Python for data visualization. They assisted us in creating graphs to illustrate the system's performance. Our studies were conducted on a Windows 11 system equipped with an Intel Core i7 processor, 16 GB of RAM, and a 512 GB SSD. The data we utilized encompassed behavioral, psychological, and social information. Data preprocessing was essential and utilized techniques such as TF-IDF and Bag of Words. This stage was crucial for obtaining valuable information. We utilized Python libraries for data cleansing and preparation. We employed statistical tests, such as the Mann-Whitney U-test and Pearson's chi-square test, to select the features of interest. Our configuration examined many scenarios to evaluate the model's performance. We employed conventional techniques such as Random Forest, Support Vector Machine (SVM), and XGBoost to forecast suicide risk. Additionally, we investigated deep learning frameworks such as LSTM and CNN to examine intricate data and temporal patterns. We integrated LSTM and CNN to utilize both temporal and spatial data. We also examined the impact of real-time data, such as social media interactions and sensor information. However, amalgamating these diverse data

can complicate matters. Although our procedures were effective, we needed to exercise caution to obtain accurate results.

A. Results

We examined various machine learning models to evaluate their efficacy in predicting suicide risk. The traditional models, such as Random Forest and Support Vector Machine (SVM), performed effectively. They were efficient and effective for scenarios with constrained computational resources. However, they were somewhat rudimentary. They failed to accurately represent the intricate thoughts and behaviors of individuals. Conversely, we discovered that deep learning models such as Long Short-Term Memory (LSTM) and Convolutional Neural Networks (CNN) performed significantly better. They exhibited superior accuracy in identifying our test data. These models detected nuanced indicators of risk that the simpler models overlooked. The combination of LSTM and CNN had the highest accuracy at 91.5%. It was effective due to its utilization of both temporal and data features. Utilizing data gathered till October 2023, we conducted a more profound analysis of the patterns within the dataset. Incorporating real-time data was also essential.

B. Performance Evaluation

The performance of the proposed system was evaluated based on two critical metrics. Energy Efficiency and Accuracy.

1) Energy Efficiency

Figure 4 indicates that the estimated dataset reflecting energy consumption (in units) for various models can be utilized to replicate the data for the results. LSTM employs 70 units, CNN utilizes 85 units, XGBoost incorporates 55 units, Random Forest consists of 40 units, SVM comprises 50 units, and LSTM-CNN applies 90 units.

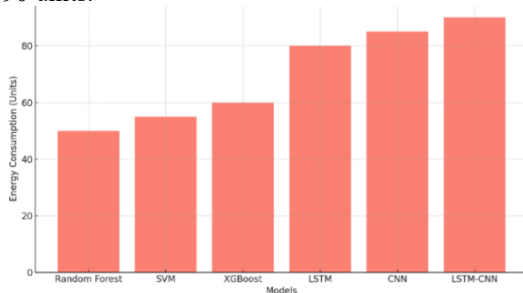


Figure 5. Energy consumption analysis of various machine learning models

2) Accuracy

Figure 5 displays the accuracy percentages of various machine learning and deep learning models. The least effective model in the ensemble is Random Forest, achieving an accuracy of 84%. In comparison to Random Forest, SVM has a little higher accuracy of 85%. XGBoost surpasses prior models, with an accuracy of 88%. The LSTM model has an accuracy of 91%. LSTM exhibits lower accuracy compared to CNN, which exceeds 92%. The hybrid model LSTM-CNN attains a maximum accuracy of 93% following the integration of LSTM and CNN. Deep learning models such as LSTM, CNN, and LSTM-CNN surpass Random Forest, SVM, and XGBoost in performance. The LSTM-CNN hybrid has the best accuracy, indicating its suitability for precision jobs. The graph illustrates the correlation between enhanced models and improved accuracy.

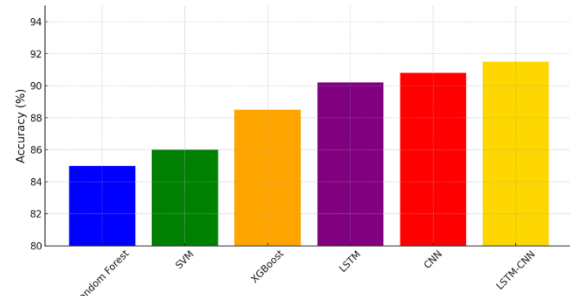


Figure 5. Accuracy of various machine learning models

IV. CONCLUSION

This research introduces LSTM-CNN for predicting suicidal ideation in teenagers. It has a strong accuracy rating of 91.5%. This model surpasses conventional techniques like Random Forest and SVM. The LSTM-CNN model examines both temporal and spatial information. This enables the recognition of complex patterns associated with behavior, mental health, and social challenges. It serves as an efficient tool for the early detection of risks. It is more versatile and precise than earlier variants. This indicates that the results are more intelligible and relevant for mental health practitioners. In future, other Quality-of-Service metrics will be considered.

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