Application of Machine Learning Techniques for Risk Assessment of School Violence

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***Abstract*** ***—* School violence defines violent activities that interfere with learning and are detrimental to students, schools, and the community. School violence can lead to depression, anxiety, and many other psychological issues. Those who experience or witness violence at school are at a higher risk of engaging in substance abuse, including alcohol and drug misuse, as a means to cope with the traumatic experiences they have endured. To address this issue, we developed a web-based application using machine learning techniques to help parents figure out whether their children are at risk of being violent to their colleagues or not. Machine learning algorithms are utilized to analyze various factors and indicators associated with potentially violent behavior. These algorithms are applied to data collected from a questionnaire submitted to students at different schools in Egypt. The questionnaire encompasses various risk factors including behavioral history, social interactions, academic performance, and emotional well-being. The accuracy measure is calculated for three machine learning algorithms. The Random Forest algorithm achieved an accuracy of 93%, while Support Vector Machine (SVM) achieved 95% accuracy, and Logistic Regression achieved the highest accuracy of 97.5%. These accuracy measures indicate the performance of the respective algorithms in accurately predicting and assessing the risk of school violence.**

***Keywords*** ***—*** *School violence, Risk factors, questionnaire, Machine Learning Algorithms.*

# Introduction

School violence exposure can result in a variety of unhealthy behaviors and outcomes, such as alcohol and drug abuse and suicide[1].

School violence can take on various forms, including physical violence, bullying, verbal violence, cyberbullying, sexual violence, gang violence, weapon-related violence, and hate crimes. Physical violence involves acts of aggression such as fights, assaults, or attacks using weapons. Bullying is a persistent form of aggression that can be physical, verbal, or psychological and occurs over an extended period. Verbal violence entails the use of abusive language, threats, insults, or derogatory remarks targeting individuals within the school environment [2].

Cyberbullying, on the other hand, involves using electronic communication platforms to harass, intimidate, or humiliate others. Sexual violence encompasses unwanted sexual behavior or harassment within the school setting, including assault, inappropriate touching, coercion, or verbal harassment. Gang violence can arise from conflicts between different gangs or gang-associated individuals, leading to physical altercations or threats in the school environment. Weapon-related violence refers to incidents involving the possession or use of weapons within the school premises, posing a significant threat to the safety of students, teachers, and staff members. Hate crimes involve acts of violence or harassment motivated by bias or prejudice against certain characteristics, such as race, religion, ethnicity, gender, or sexual orientation. These forms of violence can have a detrimental impact on targeted individuals and the overall school climate[2].

School violence has a profound and lasting impact on students. It can result in physical injuries, emotional trauma, hindered academic performance, decreased school attendance and engagement, damaged social relationships, long-term effects, and mental health consequences such as anxiety, depression, and low self-esteem[3].

In Washington, there were a total of 93 violent deaths related to schools between June 2021 and June 2022. Students, teachers, and non-students were among those who perished in these school-related accidents. 12 homicide victims and 8 suicide victims (or 42%) of these fatalities were between the ages of 5 and 18. Students between the ages of 12 and 18 experienced more violent victimization in school in 2019 than outside of it [4]. The effects of school violence are extensive, affecting both students and staff as well as the entire student body. Youth who experience the most violent schools have worse academic achievement, lower school attendance, and higher dropout rates, according to studies [5]. Moreover, it demonstrates that cyberbullying in public schools increased to 16% in 2019–20 from 8% in 2009–2010[6].

To address this issue, we developed a web-based application using machine learning techniques to help parents figure out whether their children are at risk of being violent to their colleagues or not. The web-based application utilizes machine learning algorithms to analyze various factors and indicators associated with potentially violent behavior. These factors may include a student's behavioral history, social interactions, academic performance, and emotional well-being. The application can mitigate the long-term consequences of childhood violence and promote healthier outcomes for both individuals and society as a whole.

# Literature Review

In this section, we compare systems that are similar to our system and describe the tools, processes, and results of each system.

In[7], authors employed various machine learning algorithms to predict risk levels in an inpatient forensic psychiatry setting. Specifically, Seven machine learning methods Bagging, J48, Jrip, Logistic Model Trees (LMT), Logistic Regression, Linear Regression, and Support Vector Machine (SVM) were used to identify the combination of dictionaries and algorithms that best-predicted risk assessment scores. These algorithms were applied in conjunction with natural language processing techniques to analyze electronic mental health records. The dataset used in the study consisted of electronic mental health records from an inpatient forensic psychiatry setting. The records contained textual information, such as clinical notes and assessments. The model's ensemble approach can predict risk in an inpatient forensic psychiatry setting with an accuracy between 68% and 75%.

In[8], authors implemented a natural language processing (NLP) pipeline in previous research to extract information from clinical narratives. In this pipeline, the transcribed interviews underwent tokenization and lemmatization, with the removal of punctuation marks. Four machine learning methods, namely Logistic Model Trees (LMT), Logistic Regression, Linear Regression, and Support Vector Machine (SVM) were employed to identify the optimal combination of dictionaries and algorithms for accurately predicting risk assessment scores. The dataset was collected from a Psychiatric Response Center (PIRC) questionnaire that collects basic information including the subject's personality, school, and social and family dynamics. The model's ensemble approach can detect the risk of school violence with an accuracy between 90% and 94%.

In[9], the authors focus on conducting a pilot study to develop an automated risk assessment system for school violence. they used Logistic Model Trees (LMT), Logistic Regression, Linear Regression, and Support Vector Machine (SVM) was used to find the set of dictionaries and algorithms that most accurately predicted risk assessment scores using statistical analysis and four machine learning techniques. The dataset was collected from Cincinnati Children’s Hospital Medical Center (CCHMC) from psychiatry outpatient clinics, the inpatient units, and the emergency department. Participants (ages 12–18) were active students in 74 traditional schools (i.e. non-online education). The model's ensemble approach can detect the risk of school violence with an accuracy between 88% and 91%.

# Methodology

The process of applying machine learning models for risk assessment is shown in Fig. 1. It is composed of multiple sequential processes, that handle everything from data collection and pre-processing through model training and testing.

## Data Collection & Preparation Phase

To assess the risks of violence in adolescents, a comprehensive questionnaire was designed, incorporating the identified risk factors from a related study in [10]. To ensure the validity and relevance of the included risk factors, an interview was conducted with Dr. Tarek at the Psychiatric Health Resort at Ain Shams University, Egypt. During the interview, specific attention was given to assigning appropriate weights to each question in the questionnaire. The collaboration with Dr. Tarek not only confirmed the accuracy of the collected risk factors but also provided valuable insights into their significance. This collaborative approach enhanced the overall robustness and credibility of the research findings.

For this study, data collection was conducted by submitting the questionnaire to users/friends on various social media platforms, in addition to the direct collection from students at selected schools. Direct data collection was obtained through visits to Gamal Abdel Nasser Elementary School and Ahmed Shawky Preparatory School, which are both administered by East Shubra El-Kheima. These particular schools were chosen as primary locations for collecting data directly from the students. The questionnaire used in the study is depicted in Figures 2 and 3, and it served as a sample for gathering information from the participants.

A diagram of a data processing process

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Fig. 1: Automated Risk Assessment Process

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Fig. 2: Sample 1 From Created Questionnaire

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Fig. 3: Sample 2 From Created Questionnaire

## Data Pre-Processing Phase

Data Preprocessing includes the following steps that are necessary to transform or encode data so that it may be easily parsed by machine learning: Identifying and handling the missing values, Feature scaling, Splitting the dataset, and Encoding the categorical data.

The dataset collected for this work, as illustrated in Figure 4, was in textual format. After preprocessing the data, was transformed into numerical format depicted in Figure 5.

Table

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Fig. 4: Original Dataset

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Fig. 5: Weighted Dataset

## Feature Extraction Phase

Feature extraction refers to the process of transforming raw data into numerical features that can be processed while preserving the information in the original data set. It yields better results than applying machine learning directly to the raw data.



## Machine Learning Phase

In this study, three machine learning techniques were employed to predict the risk level based on the input data.

1. Logistic Regression

Logistic Regression is a supervised learning algorithm used for binary classification tasks. It models the relationship between the dependent variable and independent variables using the logistic function, which allows the output to represent the probability of the input belonging to a certain class[11]. The logistic regression equation for binary classification is as follows:

z is the linear combination of the input features and their corresponding coefficients. It is given by:

z = β₀ + β₁x₁ + β₂x₂ + ... + βₚxₚ

β₀, β₁, β₂, ..., βₚ are the coefficients or weights associated with each input feature.

x₁, x₂, ..., xₚ are the input features.

The logistic regression function is defined as:

Y = 1 / (1 + e^(-z))

1. Random Forest

This algorithm aims to provide accurate predictions rather than explicitly explaining the underlying relationships in the data. The focus is on leveraging the collective knowledge of the ensemble of decision trees to make robust predictions[12].

Random Forest has several parameters that can be tuned to optimize its performance. Some common parameters include the number of trees in the forest, the maximum depth of each tree, the number of features considered for splitting at each node, and the criterion used for measuring the quality of a split (e.g., Gini impurity or information gain)[12].

A random forest is an ensemble of decision trees. This is to say that many trees, constructed in a certain “random” way form a Random Forest[12].

1. Each tree is created from a different sample of rows and at each node, a different sample of features is selected for splitting.
2. Each of the trees makes its prediction.
3. These predictions are then averaged to produce a single result.

The averaging makes a Random Forest better than a single Decision Tree hence improving its accuracy and reducing overfitting as shown in Fig 6.

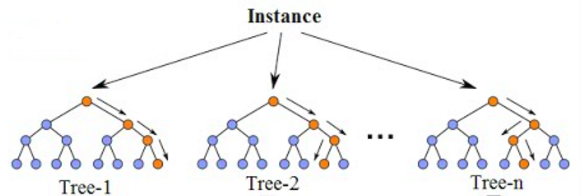


Fig. 6: Random Forest Equation [12]

1. Support Vector Machine

SVM is a supervised machine learning algorithm used for classification and regression tasks. It works by finding an optimal hyperplane that separates the data into different classes. The goal is to maximize the margin (distance) between the hyperplane and the closest data points of different classes[13].

The decision function of SVM is represented as follows for a binary classification problem as shown in Fig 7. In this equation, X represents the input features, w is the weight vector, b is the bias term, and f(X) represents the predicted class[13].A picture containing diagram, line, screenshot, text

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Fig. 7: Support Vector Machine Equation[13]

## Evaluation Phase

The evaluation of a learning process involves assessing the extent to which knowledge or skills have been acquired and applied, using predefined criteria.

# Experimental Results

The data collected consists of 1400 records summarized in Table I.

Table I: Requirement gathering technique

|  |  |
| --- | --- |
| Question | Percentage |
| Gender | 51.6%- Male  49% -Female |
| Age | 27.2% of individuals belong to the age group of 11-13 years.  30.6% of individuals belong to the age group of 14-16 years.  42.2% of individuals belong to the age group of 17-19 years. |
| Do you feel happy when others suffer? | 44.6% -Yes  55.4% -No |
| Do you prefer games that are based on violence? | 50.4% -Yes  49.6% -No |
| Do you have severe emotional outbursts? | 53.6% -Yes  46.4% -No |
| Do you bully others physically or online? | 46.1%-Yes  53.9%-No |
| Do you feel angry or lose your temper often? | 50.1%-Yes  49.9%-No |
| When you get into a fight, what do you use? | 29.5%-use brick or stone  29.8-use white weapons such as knife  40.7%-use your power |
| Have you ever been cruel to an animal? | 41.4%-Yes  58.6%-No |
| Are your parents wanted by the police or have they committed a crime before? | 45.4%-Yes  54.6%-No |
| Have any of these actions you have done before or are still doing them?   * Trespassing * School Escape * Threatening Your Colleagues * You have physical injuries from fights * You're hitting your Colleagues or others in fights * Frequent refusal to command parents or others in authority * Drug abuse, cigarettes, hookah, or drinking alcohol | 47.5%-Yes  52.5%-No |
| What would you do if you witnessed someone being abused? | 54.7%-you will help him/her  45.3%-you will ignore him/her |
| What is your parental education level? (either of them)? | 22.3%-uneducated  30.5%-at least one of the parents has a university education  24.4%- both parents have a high school diploma  22.8%-parents have less than a high school diploma |
| Did your father lose his job sometime for a long time? | 45.8% -Yes  54.2% -No |
| Is there a family member addicted to alcohol or drugs? | 44.8% -Yes  55.2% -No |

One commonly used method for evaluation is the utilization of a confusion matrix. The confusion matrix provides a structured representation of the performance of a learning model by presenting the counts of true positive, true negative, false positive, and false negative predictions. This matrix helps in measuring the accuracy and effectiveness of the learning process by comparing the predicted and actual outcomes[14].

Accuracy measure is calculated for each algorithm using the following equation:

Accuracy = (TP + TN) / (TP + TN + FP + FN)

where:

1. TP (True Positive) is the number of correctly predicted positive instances.
2. TN (True Negative) is the number of correctly predicted negative instances.
3. FP (False Positive) is the number of falsely predicted positive instances.
4. FN (False Negative) is the number of falsely predicted negative instances.

The dataset was divided equally into training and testing sets. Logistic regression achieved the highest accuracy at 97.5%, as demonstrated by the confusion matrix in Figure 2. Random forest achieved an accuracy of 93.7%, as shown in the confusion matrix in Figure 3. Support vector machine (SVM) achieved an accuracy of 95.5%, as depicted in the confusion matrix in Figure 4. Both logistic regression and SVM performed well and yielded similar results, surpassing random forest in terms of accuracy. Based on these findings, logistic regression was selected as the preferred model for violence risk assessment classification.

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Fig. 8: Accuracy for Logistic Regression

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Fig. 9: Accuracy for Random Forest

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Fig. 10: Accuracy for Support Vector Machine

After splitting the dataset into 70% for training and 30% for testing, Table (II) presents the accuracy results for logistic regression, random forest, and support vector machine. Both logistic regression and support vector machine achieved impressive performances, with their outcomes being relatively similar. Notably, they outperformed random forest in terms of accuracy. Logistic regression was chosen for classifying the risk assessment of violence.

Table II: Experimental and Results 1 for accuracy for each algorithm

|  |  |
| --- | --- |
| **Model Name** | **Accuracy** |
| Logistic Regression | 0.9708 |
| Random Forest | 0.9250 |
| Support Vector Machine | 0.9667 |

Following the division of the dataset into 70% for training and 30% for testing, Table (III) presents the precision, recall, and f1-score results specifically for the low-risk category. This table provides insights into the performance of logistic regression, random forest, and support vector machine algorithms in accurately predicting low-risk outcomes. The precision, recall, and f1-score metrics were calculated to assess the effectiveness of each algorithm in this particular category.

Precision, recall, and F1-score can be calculated using the following formulas:

1. Precision:

Precision measures the proportion of correctly predicted positive instances out of all instances predicted as positive. It focuses on the accuracy of positive predictions[15].

Precision = TP / (TP + FP)

1. Recall:

Recall measures the proportion of correctly predicted positive instances out of all actual positive instances. It focuses on the coverage of positive instances[16].

Recall = TP / (TP + FN)

1. F1-score:

The F1-score is a metric that combines precision and recall into a single value. It provides a balanced measure of the model's performance[17].

F1-score = 2 \* (Precision \* Recall) / (Precision + Recall)

Table III: Experimental and results 1 for the precision, recall, and f1-score specifically for the low-risk category

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Model Name** | **Accuracy** | **Precision** | **Recall** | **F1 Score** |
| Logistic Regression | 0.9708 | 0.97 | 1.00 | 0.98 |
| Random Forest | 0.9250 | 0.92 | 0.99 | 0.96 |
| Support Vector Machine | 0.9667 | 0.96 | 1.00 | 0.98 |

Following the division of the dataset into 70% for training and 30% for testing, Table (IV) presents the precision, recall, and f1-score results specifically for the high-risk category.

Table IV: Experimental and results 1 for the precision, recall, and f1-score specifically for the high-risk category

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Model Name** | **Accuracy** | **Precision** | **Recall** | **F1 Score** |
| Logistic Regression | 0.9708 | 1.00 | 0.83 | 0.91 |
| Random Forest | 0.9250 | 0.93 | 0.61 | 0.74 |
| Support Vector Machine | 0.9667 | 1.00 | 0.80 | 0.89 |

Following the division of the dataset into 50% for training and 50% for testing, Table (V) presents the precision, recall, and f1-score results specifically for the low-risk category.

Table V: Experimental and results 2 for the precision, recall, and f1-score specifically for the low-risk category

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Model Name** | **Accuracy** | **Precision** | **Recall** | **F1 Score** |
| Logistic Regression | 0.975 | 0.97 | 1.00 | 0.99 |
| Random Forest | 0.9375 | 0.90 | 0.63 | 0.74 |
| Support Vector Machine | 0.9550 | 0.96 | 0.99 | 0.97 |

Following the division of the dataset into 50% for training and 50% for testing, Table (VI) presents the precision, recall, and f1-score results specifically for the high-risk category.

Table VI: Experimental and results 2 for the precision, recall, and f1-score specifically for the high-risk category

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Model Name** | **Accuracy** | **Precision** | **Recall** | **F1 Score** |
| Logistic Regression | 0.975 | 0.98 | 0.84 | 0.91 |
| Random Forest | 0.9375 | 0.94 | 0.99 | 0.96 |
| Support Vector Machine | 0.9550 | 0.93 | 0.74 | 0.82 |

# Conclusion and Discussion

The web-based application utilizes machine learning algorithms to analyze various factors and indicators associated with potentially violent behavior. Three widely employed machine learning algorithms, namely logistic regression, random forest, and support vector machine (SVM), were utilized. These algorithms were applied to the collected dataset to predict and assess the risk of violence in adolescents. To evaluate the risk of violence in adolescents, a thorough questionnaire was developed based on the research titled "Assessing the Risk of Violence in Adolescents in the Pediatric Emergency Department". The questionnaire encompassed various risk factors identified in the study. Data for this research was collected from two primary sources: social media platforms and direct surveys conducted with students from specific schools. The accuracy results of different algorithms for automated risk assessment of school violence. The Random Forest algorithm achieved an accuracy of 93%, while Support Vector Machine (SVM) achieved 95% accuracy, and Logistic Regression achieved the highest accuracy of 97.5%. These accuracy measures indicate the performance of the respective algorithms in accurately predicting and assessing the risk of school violence.

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