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Identifying Psychosocial Attributes Indicative of Violent Behavior in Students using Deep Learning

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Abstract: According to the Center for Homeland Defense and Security, in the first half of 2022, 2 active school shooter and 151 non-active shooter events resulted in 150 victims; the previous year's statistic the highest it has been since 1970. Most students displayed signs of mental illness and troubled behavior that was often overlooked. This research seeks to identify signs of a threat in order to distinguish and assist students who are at risk for violent behavior. 30 randomly selected shooters were analyzed using natural language processing with keyword extraction of news reports to identify 28 recurring psychosocial attributes described by the Federal Bureau of Investigation through a WordCloud generator. A feed forward neural network (FFNN), built on Spyder using Python, then uses these traits to recognize and categorize potential growing threats in a student body. Data is collected through deep learning graphological parameters in students' handwriting using a 2D convolutional neural network (CNN), created on Jupyter Notebook using Python. Compared to predictive models such as the Five-Factor Analysis model with an accuracy of 80.5%, the School Threat Assessment System (STAS) uses two simple neural networks to generate an accessible report that quickly identifies students in need of immediate support with an overall accuracy of 97%. STAS is available online to school systems working to increase the safety of their students from within.

Keywords: Convolutional Neural Network (CNN), Feed-Forward Network (FFN), Mental Illness, School Safety, School Threat Assessment System (STAS), Identifying

1. INTRODUCTION

The Congressional Research Service defines mass shootings as multiple, firearm, homicide incidents, involving 4 or more victims at one or more locations close to one another [1]. In the United States, mass shootings have remained on the rise. According to the Gun Violence Archive, 2022 resulted in a total of 647 mass shootings, more than doubling the 273 shootings in 2014 [2]. As the prevalence increased, classifications emerged to sort prior shooters based on the current understanding of their motives. Thomas A. Petee of the Department of Sociology at Auburn University categorizes mass shooters and murderers into 7 types [3].

The anger/revenge target shooter is driven by an internal motivation to seek justice after being wronged. Their drive is primarily targeted towards a specific person or a particular place, therefore sparing bystanders. Based upon precedent, the shooter tends to commit mass murder at a significant location or as a byproduct of targeting a single person, usually at an agency or organization that exerts control over the shooter. Anger can be targeted toward a specific person, but also a place representing how that shooter believed they were wronged. The anger/revenge diffuse target shooter, however, follows one of two victimization patterns. One involves targeting a certain group of people who the shooter believes has wronged them, mostly involving racially based shootings, those based on xenophobia, or gender. The second pattern is one where the shooter lashes out at bystanders due to a lack of a focused target for their anger. These seemingly random shootings result in a dangerous situation for bystanders.

On the other hand, the domestic/romantic shooter encompasses more personal, premeditated, intentful shootings that involve conflict between family members, normally depicting a male killing his female spouse and children in a household setting, or a male facing romantic rejection, most likely as a result of sexual harassment. These conflicts differ from the direct interpersonal conflict shooter, a result of immediate, spontaneous aggression in the face of conflict without premeditation. These murders are always due to an escalating situation i.e. cases of road rage.

Mass shootings can also occur through other premed-

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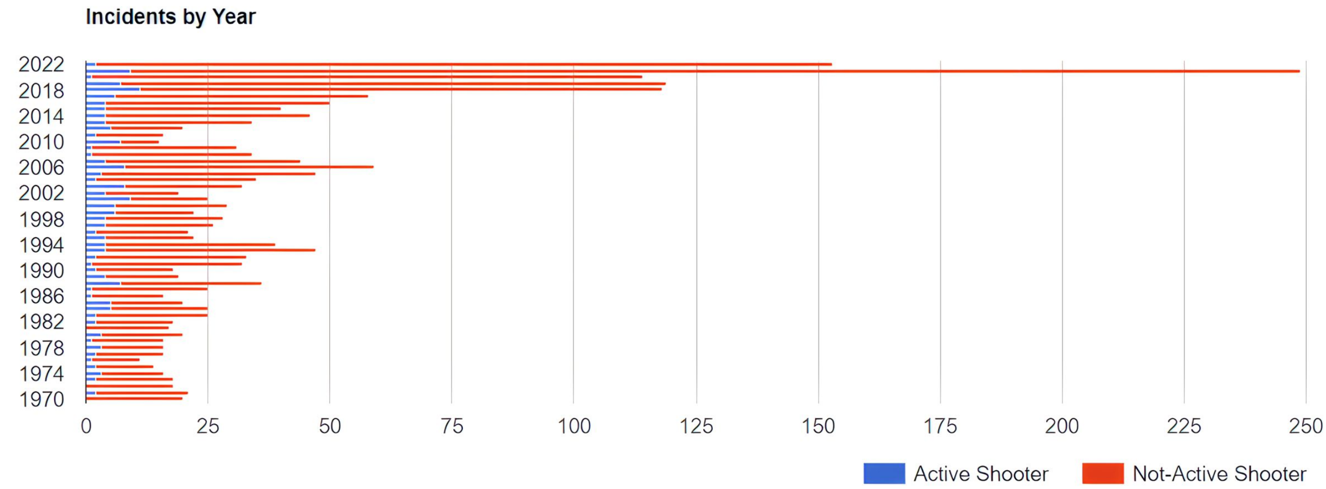

Figure 1. Number of school shooting cases per year since 1970 according to the Center for Homeland and Defense Security. [4]

itated felonies and organized crime. Felony related mass murder involves murder as a byproduct of another felony, such as robbery. The primary motivation does not involve murder, which mainly occurs as a need to eliminate witnesses. Another type, gang-motivated mass murder, occurs as a result of gang activity. Prominent examples include drive-by shootings and confrontations which are organized and premeditated. More large-scale mass murders are likely politically motivated. As an act of terrorism, shooters often intend to attract attention to a specific ideology or manifesto. These types of perpetrators are focused on magnifying the effect of their actions instead of their methodology to perpetuate their ideas.

The following research focuses on the anger/revenge - diffuse target type shooter with ”randomly” patterned victimization in order to better understand the underlying motivations of their crime. In 2021 alone, 9 different schools across the country experienced an active-shooter event that posed significant damage to both their community’s physical and mental well-being [4]. At the center of each of these events was a single distraught student who exhibited countless signs foreshadowing their actions, all overlooked by their community. Current efforts to mitigate this issue, such as by the Federal Bureau of Investigation (FBI), conclude that it is the community’s job to be alert for these signs [5]. This is due to a high percentage of active-school shooter incidents perpetrated by current or former students of the school, who displayed specific, identifiable, warning signs prior to the incident. But despite the awareness, shootings continue to occur, having taken the lives of 277 victims last year alone [4]. Figure 1 displays the exponential growth of school shootings since 1970.

This research aims to create an Artificial Intelligence (AI) system with a simple feed-forward neural network that can use student records and objective, recordable psychosocial attributes to perform a threat-level assessment for school shootings. It creates a concrete system through which all students can be analyzed free of human bias or error, leaving no one overlooked. Previously, the FBI has conducted a thorough analysis of past school shooters, and combined with the previous research from O’Toole [5], this information is used by our model, the School Threat Assessment System (STAS) to classify cases (or students) based on 28 predetermined covariates using a feed forward neural network through analysis of handwriting using a 2D convolutional neural network. It then generates a summary report that identifies students at risk for violent behavior in order to provide them with access to mental health resources.

This paper begins with an analysis of current systems created to interpret abnormal psychology, then describes the methods of data collection and preprocessing, including natural language processing with keyword extraction and handwriting analysis using a 2D convolutional neural network. Following this, the proposed method of classifying students within threat levels using a feed forward neural network is described. Experimentation with this method is then detailed, preceding results and conclusion.

2. Literature Review

Handwriting exposes the genuine personality, including emotional outpouring, phobias, honesty, defenses, and much more. Graphologists, who are trained to study handwriting professionally, frequently recognize the author from a piece of handwriting. The analyst’s level of proficiency affects how accurate the analysis is. Despite the effectiveness of human assistance in handwriting analysis, it is expensive and prone to weariness, human bias, and subjectivity. So, the suggested techniques including baseline, slant, pressure, and lead-in and end strokes are centered on creating a tool for behavioral analysis that can predict personality traits

TABLE I. Literature Review Comparison.

Paper	Methods Used	Results
[6]	Polygonization, grey-level thresholding algorithms, template matching, and Generalized Hough Transforms are used for automated handwriting analysis [7]. Handwriting represented using a Feature Vector Matrix and K Nearest Neighbors (KNN) classifier is used to classify samples based on traits identified from handwriting.	Prediction Accuracy: 68%
[8]	Automated Five-Factor Analysis of baseline, slant, pressure, connecting stroke features and lowercase letters using feed-forward neural networks.	Prediction Accuracy: 80.5%
[9]	Predicted the five factor model personality traits (Openness to Experience, Agreeableness, Neuroticism, Extraversion, Conscientiousness) through the use of handwriting analysis and text features such as character shape, size, length, and slant.	Prediction Accuracy: 91.3%
[10]	Analyzing behavior, handedness, authorship, and gender-based on handwriting analysis of incline, shape, and form using NEUROSCRIPT, WANDA, CEDAR-FOX, and a Gaussian Mixture Model.	Not tested.
[11]	Identification of critical warning signs by applying psychometric network analysis to a dataset of crises observed in mass shooters before their attack, as assessed by a Poisson Distribution.	Isolation, agitation, mood swings, depression, and abusiveness towards others were identified as contributors toward shooting severity.
STAS	Deep learning of graphological features in students' handwriting to identify psychosocial attributes to create a data-informed feed-forward neural network for a school threat level assessment.	Prediction Accuracy: 97.43%

automatically with the help of a computer and without the involvement of a human. In the paper [7], the author uses a person's handwriting to make predictions about their personalities based on the baseline, pen pressure, letter 't,' lower loop of letter 'y,' and tilt of the writing. Where they obtained accuracy ratings of 88% for predicting the 't' bar, 86% for predicting the lower loop of the letter 'y,' and 87% for predicting the writing's slant. While the authors in [6] have used Artificial Neural Networks with the Widrow-Hoff learning rule and the sigmoid activation function to predict the above technique. Table I provides a summary of, and comparison between, previous neural network and network analysis models created to analyze handwriting and identify contributing factors to violence in a potential shooter.

The following sections detail the method by which the contributing factors to violent behavior in students were determined through the analysis of local and national news reports as well as the architecture of the data flow through the system. This study also explores the applicability of handwriting analysis in practical scenarios and discusses how it can be used in an efficient, ethical, and accurate way to analyze and make predictions about students' behavior. Following this, the paper also details the testing, training, and experimentation with the system and methods that helped to arrive at the current system architecture. The validity of the system is expressed in the results section through the measure of system accuracy, and the conclusions drawn and discussed.

3. Dataset Collection and Preprocessing

The first step towards this system was to determine what factors to consider. Similar to the organization of the personality traits employed by Zhi Chen and Tao Lin in [12], this was done through the analysis of an FBI report which uses a 4-pronged approach to analyze a shooter: psychological, social, behavioral, and familial. This report exemplifies the eclectic biopsychosocial approach to psychological analysis. The list of objective, recordable attributes was then cross-referenced with a separate analysis of local and national news reports of past school shooters after the shooting had occurred, utilizing keyword extraction techniques from natural language processing.

31 indiscriminate school shooters - those that align with anger/revenge - diffuse target mass murderers - were selected from a pool of 2069 shootings between January of 1970 to June of 2022 from the Center for Homeland Defense and Security School Safety Compendium database.

40 credible articles and reports from local and national news agencies following the shootings committed by these shooters were collected and conjoined into a single PDF document for language processing using keyword extraction like the following articles. This PDF can be found at https://shorturl.at/puI13.

The IAM Handwriting Top50 dataset is a publicly available set [13] of 4,900 lines of handwriting from 50 de-identified common writers and authors. With close to 9,500 downloads, this dataset has 17 unique contributors and is owned and created by Tejas Reddy. Curated from a greater set of 13,353 lines of writing by the FKI Research Group on Computer Vision and Artificial Intelligence, this dataset was intended to be used to classify writers based on writing styles but is used in the system to train a 2D convolutional neural network to identify indicators for psychosocial attributes in students' handwriting.

A. Keyword Extraction

Natural Language Processing leverages the use of keyword extraction to analyze text files, and in this case, determine the frequency characteristics found across a set of 31 independent cases of school shooters. A WordCloud generator on the integrated development environment Jupyter Notebook was used to extract keywords from local and national news reports of these cases and was matched against the characteristics described in the FBI report. The resulting characteristics are displayed in the WordCloud, where larger words indicate a higher frequency of occurrence of that word within the analyzed news reports. The proportion of frequencies of each characteristic, or the number of times each covariate was mentioned in an article, was plotted in the distribution below, and it was apparent that the proportions fell into four groups as shown in Figure 2: very low, low, medium, and high weighted covariates. However, two anomalies can be seen in the high-weighted category in red. Criminal records and evidence of the homicidal triad, which includes arson and animal cruelty, were moved to the top level due to evident practical reasons.

Psychological covariates identified include 3 subcategories of mental illness, suicidal risk, and prescribed counseling such as court-ordered counseling. Behavioral factors, however, are more varied and prone to interpretation. Covariates such as the Homicidal Triad (arson, bed-wetting, and animal cruelty during young ages) and verbal shooting threats are more concrete and identifiable than those such as a lack of empathy or attention seeking. Social and familial covariates are analogous to the environmental component of the biopsychosocial approach. Social covariates describe a student's interpersonal relationship with their school environment such as with peers and teachers. Examples include bullying, disciplinary records with suspension and expulsion, and more observation-oriented variables such as social isolation and antisocial tendencies. The last prong the STAS takes into account is familial relationships, ranging from parental abuse to a student's access to weapons.

Data supporting covariates in Figure 3 can be gathered through various sources of data including school medical records, criminal records, disciplinary records, student/teacher reports, depression screening surveys, and county-level community surveys. However, these data collection methods can be unreliable due to the invalidity and inaccuracy in self-reporting, or unethical due to data privacy laws preventing the creation of a centralized database and students' status as a protected class of minors.

B. Handwriting Analysis

To combat problems faced in data collection, handwriting analysis was used to draw inferences regarding specific psychosocial attributes as emotional states of mind often manifest in one's handwriting [14]. Handwriting analysis is becoming an increasingly popular area of research due to its applications in a myriad of fields from healthcare and medical diagnoses and to education and development [15]. It is also often used in forensic analysis and the U.S criminal justice system as both structural and symbolic analysis of handwriting are used for personality analysis [16]. Past literature indicates that specific parameters in handwriting, such as baseline, slant, pressure, lead-in and ending strokes, spacing, and writing size can be used as indicative measures for contributing factors to violent behaviors in students including mental illness and depression, physical aggression, isolation, antisocial tendencies, substance abuse, and an affinity for violence [17] [18]. A 2D convolutional neural network was then trained to identify these parameters in handwriting samples to classify students based on the presence or absence of these six covariates.

In order to train this 2D CNN, six feature identification functions were engineered to flag a dataset of 4,900 handwriting samples on the presence or absence of these parameters.

1) Baseline

Baseline refers to the imaginary line underlying a single line of writing as it progresses across a page. A falling baseline, where the angle between the baseline of the writing and the horizontal x-axis at 0 is negative, is suggestive of mental illness, specifically depression. The baseline of each sample was calculated by constructing a rectangular boundary around each naturally separable block of letters and calculating the y value of the base. After plotting each value on a scatter plot, a linear regression was applied. Based on the threshold calculated by applying this technique to handwriting samples of prior school shooters diagnosed with a form of mental illness, either before or after the mass shooting, handwriting samples that have a linear regression slope of less than -2.196 were flagged, suggesting mental illness due to a falling baseline. Figure 4 represents a sample from the handwriting of the Sandy Hook School Shooter and the subsequent baseline regression generated.

2) Slant

While baseline refers to the angle at which a line of writing progresses, slant refers to the angle of each

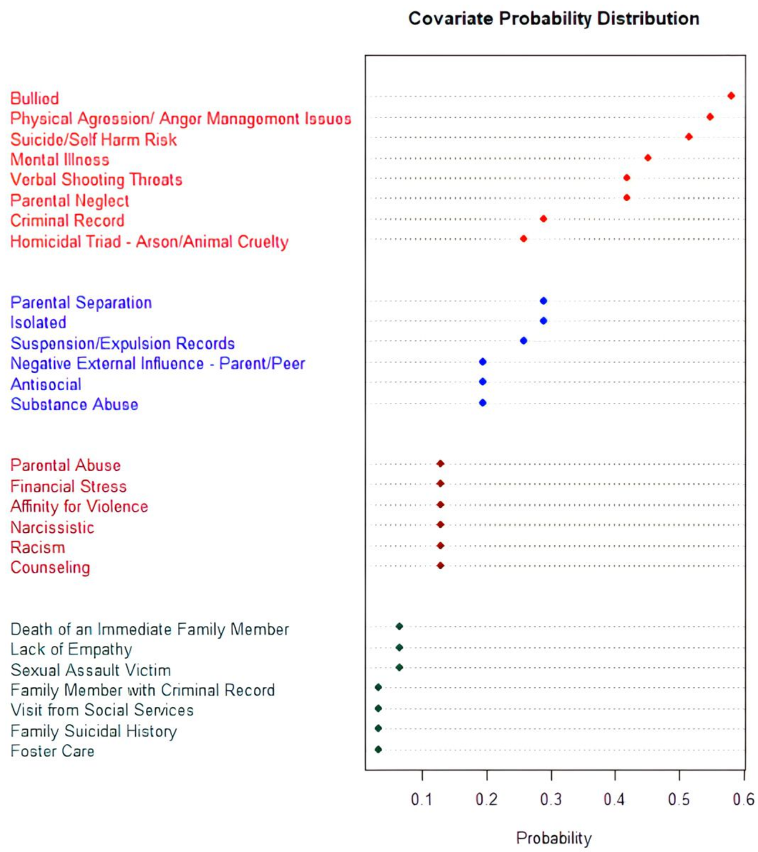

Figure 2. Frequency of words identified by WordCloud across a set of 40 local and national news reports. This probability distribution displays the frequency of each covariate within 40 news reports of past indiscriminate shootings. The frequency values fell into 4 groups, with two exceptions. "Criminal Record" and "Homicidal Triad" were associated with the most probable set of characteristics due to the dire nature of these covariates.

naturally separable block of letters, relative to the word's baseline. A slant of more than 35 degrees from the positive vertical y-axis is indicative of a tendency towards isolation [17]. For each sample, the slant was calculated by first constructing rectangular boundaries around each naturally separable block of letters. The rectangle with the largest area was selected, for which the midpoint and bottom right corners were connected. The angle between this line and the connecting line was then measured. Samples with an angle less than 55 degrees would be indicative of a tendency towards isolation, and would subsequently be flagged. Figure 5 exhibits the original handwriting sample from the Oxford High School Shooter, 2022, and the methodology of the slant calculated.

3) Pressure

Writing pressure is indicative of two major contributors to violent behavior in students. Highly irregular pressure is associated with a tendency towards physical aggression, whereas excessive heavy pressure is associated with an affinity for violence. For the analysis of pressure, all images are converted to Grayscale as done by Syeda Asra and D. C. Shubhangi in [19]. Highly irregular pressure was assessed in samples through the variance of all nonzero RGB pixels, after setting all background pixels to zero. Samples with a variance of more than 900 were flagged to show a tendency towards physical aggression based on a threshold calculated by applying this technique to handwriting samples of shooters reported to be physically aggressive. Excessive pressure was identified based on the mean RGB value of all nonzero pixels in the sample. Samples with averages greater than 120 were flagged to have an affinity for violence. Figure 6 shows a heat map of the variations in pressure in the handwriting sample.

Another form of pressure can be identified through pastiosity. Pastiosity is defined as the repeated retracing of strokes through the progression of a line of writing. Extreme pastiosity, however, can be indicative of substance abuse. This function measures pastiosity using a different technique than previous methods. Handwriting samples are dilated to identify individual strokes, increasing pixel value. The original pixel values are then subtracted, revealing areas with high pixel values due to repeated strokes. If more than 50% of the dilated pixel values are different from the original pixel values, then the sample is flagged for extreme

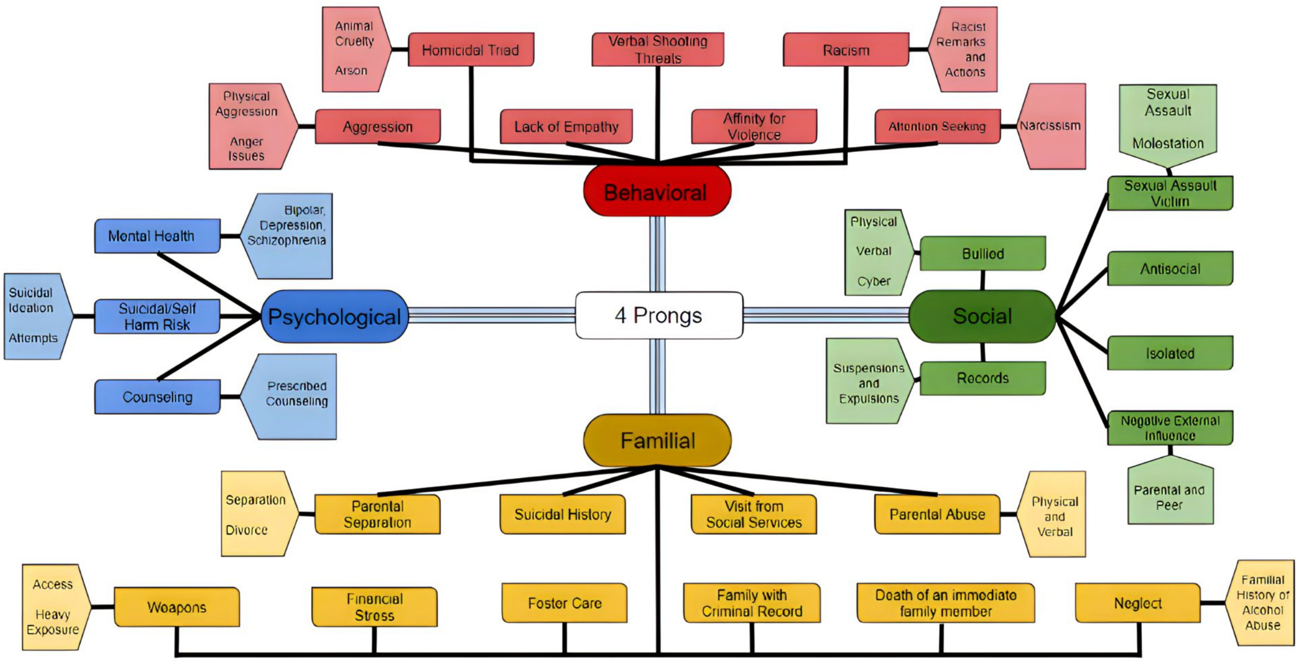

Figure 3. Conceptual data diagram of all 28 covariates organized according to the 4-Pronged approach.

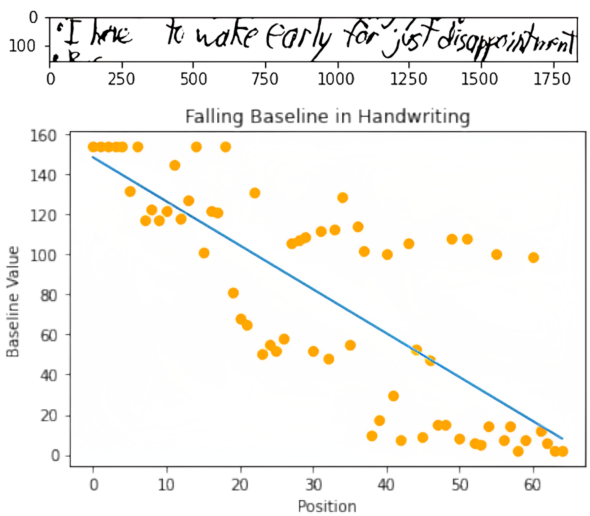

Figure 4. Real-time sample displaying baseline regression. A linear regression (blue line) was calculated using the y values of the base of each naturally separable block of letters in the sample above.

pastiosity, indicating substance abuse. Figure 7 displays the output image following the methodology of quantizing pastiosity.

4) Lead-in and Strokes Out

Lead-in and end strokes are defined using the nature of the beginning and last strokes of a word or letter. Two characteristics of end strokes can be used to make inferences about students' tendencies toward violent behavior. Angular

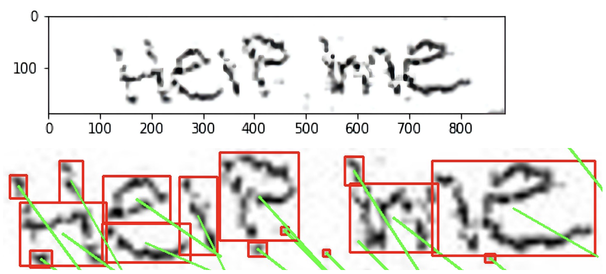

Figure 5. Real-time sample with slant methodology. The original sample was written by the Oxford High School shooter in Michigan, in 2022 (top). The slant of letters is calculated and visualized (bottom).

endings refer to end strokes that finish at a significant angle when compared to the baseline. These endings are suggestive of a tendency towards physical aggression. Weak

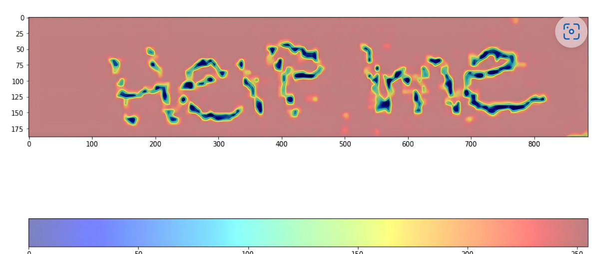

Figure 6. Real-time sample displaying heat map of pressure in writing.

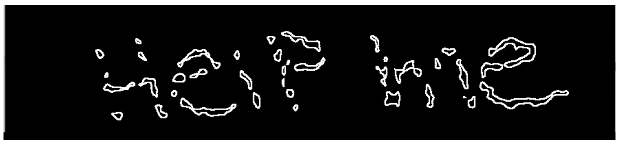

Figure 7. Real-time sample analysis of pastiosity in handwriting.

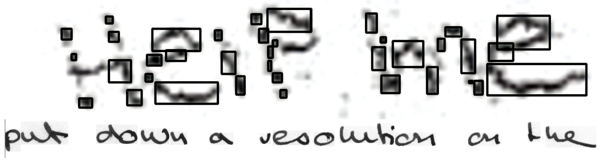

Figure 8. Real-time sample displaying angular endings (within rectangles), and weak endings.

endings, on the other hand, refer to endings that are significantly extended off the letter and do not create a significant angle with the baseline. Weak endings are indicative of mental illness, specifically depression.

Angular endings were measured by constructing rectangular boundaries around individual letter segments, connecting the top right and bottom left corners, and calculating the slope of the resulting line. If the slope is greater than 0.7 - a threshold calculated off of writing samples from prior shooters who were known to exhibit physical aggression - then the image is flagged. Weak endings were measured using the same method, with the threshold set to less than 0.1. Figure 8 provides visualization of the methodology used to identify angular and weak endings in samples.

5) Spacing

Spacing refers to the average distance between isolated letters in a word. The main characteristic that can be inferred from spacing is a tendency toward isolation. Spacing was calculated using a similar technique as previous parameters. A rectangular boundary was constructed around each letter before subtracting the x value of the closest sides between letters, producing the distance between each rectangle. The average distance was then subtracted from the average width of the word. If the value is positive, the sample was flagged for excessive spacing as the majority of handwriting samples tend to have negative values. Figure 9 displays the calculation of the average distance between letters.

6) Writing Size

Writing size, as measured in this system, refers to the consistency in the size of letters, case-wise. Uneven margins above and below a word demonstrate an inconsistency in the writing size of letters within that word, suggesting the presence of antisocial tendencies. To determine the presence of significantly uneven margins, as in other methods, a rectangular boundary was constructed around each letter. To measure the degree to which the upper margin of a set of letters is uneven, the variance of the height of the

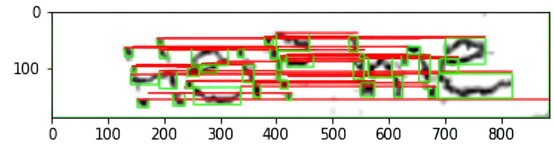

Figure 9. Real-time sample displaying the distance between rectangular boundaries.

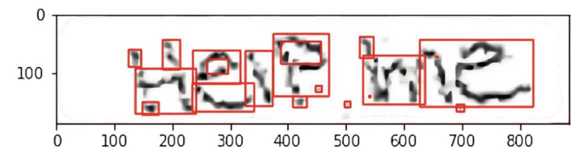

Figure 10. Real-time sample displaying rectangular boundaries used to analyze writing size.

rectangles was calculated. The threshold for comparing this value was determined based on applying this method to handwriting samples from prior shooters who displayed antisocial tendencies. Samples with a variance higher than 2000 were flagged for this characteristic. Figure 10 exhibits this process.

4. Proposed Method

Following preprocessing data for handwriting analysis, the next step was to prepare the data into a systematic, logical setup. The proposed method for this model structurally resembles the prosposed framework of Samsuryadi et al in [20] and of Aditya Chitlangia and G. Malathi in [21]. After preprocessing and extraction of handwriting features, each case was assigned a vector, or set, of 28 '0's and '1's to identify the presence of each covariate. Figure 11 depicts a decision tree created for manual classification, in which the level of threat is based on a combination of a student's access to weapons and high, medium, and low weighted covariates. Based on the tree, cases would be classified from 0 (no threat) to 3 (high threat). In [9], personality scores based upon surveys were used as labels to train a neural network. Similarly, 200,000 case vectors were randomly generated to train the following neural network with a large proportion of possible combinations of the 28 covariates. Each generated case was designated a gold label for classification training based on this tree.

The basic structure of the neural network needed 4 layers. First, an input layer for a case vector, then a set of hidden layers, a dropout layer (included to prevent overfitting of the model), and an output layer with four classes for the four categories. The initial batch of 200,000 randomly generated cases was split into 80% testing and 20% training batches. The model was used to classify each case. Figure 12 is a flowchart of the path the data takes through the system. Covariates are initially determined by the keyword extraction model, from which psychosocial attributes are passed to the handwriting analysis convolutional neural network. Characteristics are extracted from

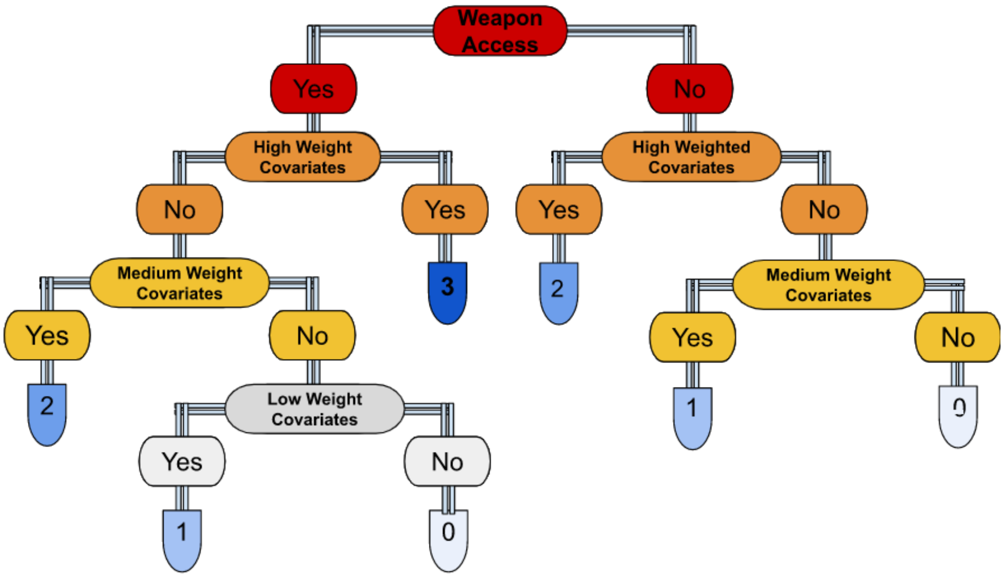

Figure 11. Decision tree for original classification - "gold label". The feed forward neural network uses case vectors classified using this decision tree for training. Cases are first classified according to access to weapons, and are then subsequently classified based on the presence or absence of high, medium, and low weighted covariates, determined based upon the probability distribution in figure 2.

students' handwriting and passed to a feed-forward neural network along with non-psychosocial attributes. The data for psychosocial and non-psychosocial covariates were then assembled into case vectors and provided to the feed-forward neural network as input and were classified based on the covariates. The accuracy of the feed-forward neural network was then calculated in two different ways.

The first-way accuracy was calculated through the generation of an overall accuracy score, comparing the predicted classification to the cases' gold labels and calculating the percent correct. The second method generated a confusion matrix comparing the true and predicted labels to calculate precision, recall, and F1-score. Finally, STAS generated a PDF summary with the number of cases in each category, identifying students in category 3 as in need of immediate mental health support.

In summary, The process begins with the FBI school safety threat assessment report combined with news articles and reports on past indiscriminate shootings. Using natural language processing with keyword extraction, the frequency of covariates listed by the FBI and cross-referenced with the news reports were visualized using a WordCloud. The most prominent covariates were selected from the WordCloud and classified as either objective or psychosocial. Psychosocial covariates, such as physical aggression and antisocial tendencies are assessed using handwriting analysis by a CNN whereas objective covariates, such as verbal shooting threats and bullying are assessed using teacher reports and disciplinary records. The presence or absence of these characteristics, represented as a 1 or 0 respectively, is then assembled into case vectors. A FFNN was then used to classify each case based upon the decision tree in figure 11. A report is then generated detailing the number of case vectors within each threat level.

A. Convolutional Neural Network

A Convolutional Neural Network is a category of artificial neural networks used to analyze and classify digital images. A 2D Convolutional Neural Network takes a two-dimensional image (RGB, Grayscale, etc.) as input and segments it to read various details associated with the image to differentiate. In a traditional CNN, the input is an array of multiple dimensions used to represent an image.

A convolutional layer is then applied to the input array, where a filter, or kernel, detects features within the input image, represented by the array, quantifying its details and extracting features such as edges, gradients, color, etc.

Following convolutions, an activation function provides the ability for the CNN to learn and analyze complex relationships within the data presented within the input array. Without this function, the network is severely limited to linear relationships within data.

The image then undergoes a pooling layer. This essentially summarizes details within a specific, localized sections of images and produces the most important information within that section. Max pooling selects the maximum values of the quantified features within an image in order to extract that feature in an efficient manner.

After passing through a dense layer, which performs traditional neural network operations (classification, etc.), the output layer produces the final product, depending on

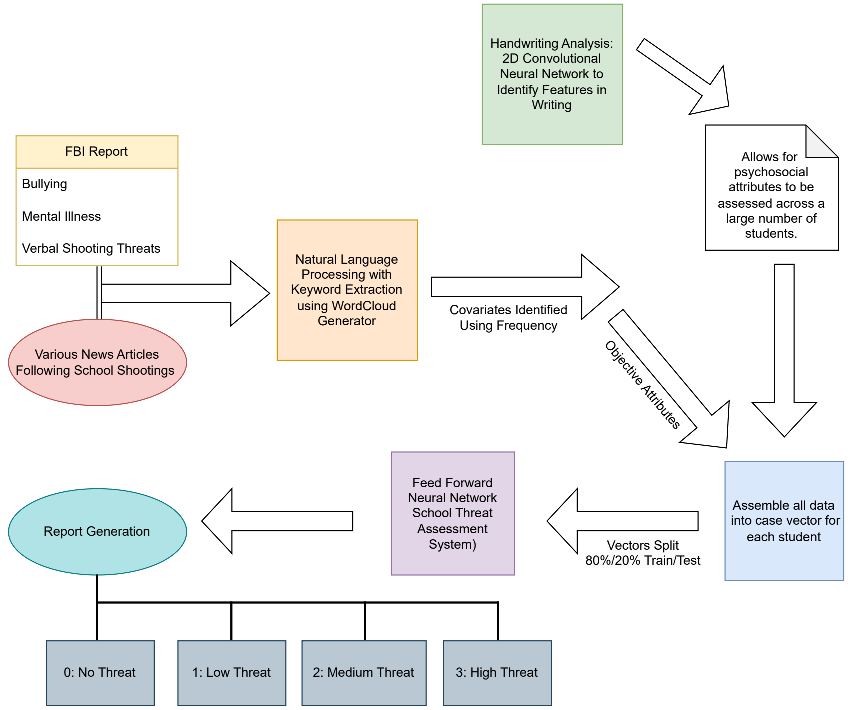

Figure 12. Data flow diagram depicting whole system process.

what the CNN was architected to do.

The proposed model created for this system includes two 2D convolutional layers using the ReLU activation function, followed by two max pooling layers and a single dropout layer. A dropout layer is optional; it is used to prevent overfitting of the model by retraining the network on multiple iterations, each time removing a small percentage of images to readjust weightage assigned to each training batch image. As described in table II, the components in the model map a 150 X 2000 X 3 input array to a 32 convolutional layer 2D CNN followed by a 2 X 2 max pool layer and sequentially into a 64 convolutional layer 2D CNN followed by another 2 X 2 max pool layer and a dropout layer. A fully connected embedded layer using softmax classifies the images into 6 different categories.

B. Feed Forward Neural Network

A Feed Forward Neural Network is relatively more basic. This type of artificial neural network does not process images but can analyze numerical data. In FFNNs, the input moves only in the forward direction through the hidden layer and to the output layer without going through any loops in the network. The general equation for an FFNN is as follows:

$$\sum_{i=1}^{\infty} X_n W_n \tag{1}$$

where X is the input, and W is the weight assigned.This equation represents how weightages assigned for each input value are cumulatively summed for all given inputs.

The proposed model includes one input layer, 60 hidden nodes, activated by ReLU, followed by a dropout layer, and classified by an output layer. The input vectors of dimension 1×21 are transformed by two linear layers, weights initialized by xavier_uniform_, from input to

TABLE II. Convolutional Neural Network Architecture.

Layer	Architecture
Input dimensions	$150 \times 2000 \times 3$
Conv1	$32 \times (3, 3)$
Maxpool	(Max 2×2)
Conv2	$64 \times (3, 3)$
Maxpool	(Max 2×2)

TABLE III. Display of overall accuracy, precision, recall and F1 Score calculated from the accuracy.

Accuracy Measure	Value
Precision	96.32%
Recall	95.766%
F1-Score	95.12%
Overall Accuracy	97.43%

TABLE IV. Sample table included in counselor report with students identified in the highest threat level classification.

High Threat Level				
Student ID	Depression & Other Mental Illnesses	Social Isolation	Verbal Threats	Shooting
1562433	1	1	0	
1563142	1	1	1	
1539495	1	0	1	

TABLE V. Comparison among existing models.

Paper	**Methods Used**	**Results**
[22]	Image-to-Sequence and layout agnostic architecture-based model trained to recognize full pages of handwriting without segmentation for increased practical application of handwriting text recognition.	Average error rate: 7.6%
[23]	This decoupled attention network bypasses the use of historical decoding information and relies solely on visual information from the image for alignment for text recognition.	Average error rate for characters in the IAM data set: 6.4%
[24]	This model uses encoders to create feature maps of paragraphs and uses an attention module to follow text line features. Finally, it uses a decoder module to recognize the associated character sequence.	Average error rate: 1.91%.
[25]	This model identifies writers through handwriting styles and patterns using global context features as well as local fragment-based features. A recurrent neural network is used to assess the spatial relationship between fragments, proposed as the Global-Context Residual Recurrent Neural Networks.	Prediction Accuracy: 97.4%.
STAS	Deep learning of graphological features in students' handwriting to identify psychosocial attributes to create a data-informed feed-forward neural network for a school threat level assessment.	Prediction Accuracy: 97.43%

hidden, and hidden to output. The output layer, activated by LogSoftmax classifies the input into 4 threat levels by assigning probabilities to each case vector.

5. Experiments

Initially, this system was approached through a statistical lens. The initial path was to classify cases with a scoring method. Following a study of 31 various indiscriminate school shooters, similar characteristics listed by the FBI that were identified multiple times were recorded and organized. The frequency of each characteristic occurring was then calculated and the proportion was recorded. The score was then determined by calculating the sum of all the covariates' probabilities that were found to be present in each case. As these sums were calculated, certain ranges were identified upon which bounds were then determined by the minimum or maximum of each category.

This system did not work, as it did not account for various practical scenarios, for example: "the responsible gun owner." It became apparent that the most common characteristic across all mass indiscriminate school shooters is their access to weapons with a probability of .96. However, this must not imply that every student with access to weapons will pose a threat to a school, leading to the decision tree in figure 8, where the level of threat is based on a students access to weapons in combination with high, medium, low and very low weighted covariates.

A. *Testing and Training Stages*

The following section details the methods used to train and test the handwriting analysis convolutional neural network as well as the methods used to determine the quantitative thresholds used to infer certain covariates from handwriting.

1) *Determining Thresholds*

In order to determine the degree to which a handwriting trait would indicate contributing factors of tendencies towards violent behavior, a threshold needed to be determined for each measure using the handwriting traits. The

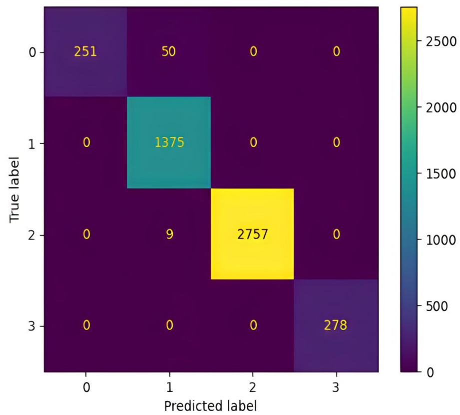

Figure 13. Confusion matrix displaying accuracy of cases using precision and recall.

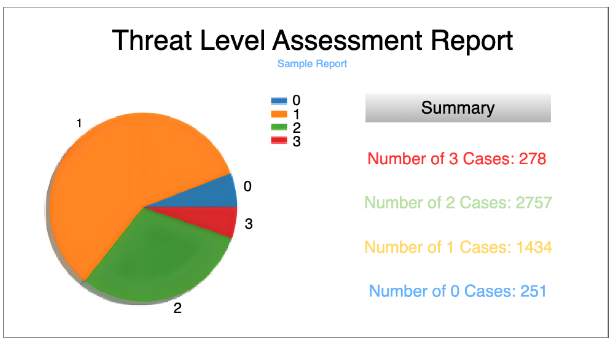

Figure 14. Results in the report for counselor accessibility to identify at-risk students using system

preprocessing modules were used to determine the actual slant pressure baseline, writing size, spacing, and lead-in and end strokes with real-time data from actual perpetrators. The values determined from images of these handwriting samples were used as thresholds in order to evaluate the available data.

2) Data Validation

The IAM Top50 Handwriting dataset was used for preprocessing to determine labels in order to train and test the module. Following this, the data collected, along with the predetermined labels, were split with $\frac{60}{40}$ proportion. However, due to system limitations in processing power, only 200 data points were initially used to train the 2D convolutional neural network for handwriting analysis. As a result, the test accuracy following training with such a sparse number of data points was 40%. To improve this result, we then increased the total number of data points to 600, while still maintaining a $\frac{60}{40}$ training/testing split. However, the accuracy remained at 40%. Since there was a limited change, the split proportion was increased to $\frac{70}{30}$ while remaining at 600 data points. This increased the test accuracy to 65%. As accuracy tended to increase with an increase in data points, it was concluded that system processing power needed to be improved in order to obtain a higher accuracy level. Thus, in a GPU environment, 4899 data points were split into a $\frac{70}{30}$ proportion, increasing test accuracy to 90%. The final trial with 4899 data points with an $\frac{80}{20}$ split yielded a 100% test accuracy.

6. Results

Once the model's parameters were tuned, two batches of 5000 randomly generated cases were used to test the system. All of the following metrics were collected from ten trials. The mean overall accuracy was 97.43%, with errors mostly occurring in categories 1 and 2. The precision of the system was 96.32%, the recall was calculated to be 95.76%, and the F1-score was calculated to be 95.12%, as displayed in table III.

Figures 13 and 14, display the results, confusion matrix, and report generated by the 10th and final trial run, consisting of 5000 data points.

These numbers indicate, with these 28 objective features, we can successfully predict potentially violent behavior in students with 97.43% accuracy while accounting for overfitting with a dropout layer along with various unique practical combinations of features. As previously stated, a value of 96.32% was calculated for precision meaning that 96.32% of the cases classified in a certain predicted category will be correct. Next, a recall value of 95.76% was calculated indicating that 95.76% of the cases in each gold label category will be classified correctly. The F1-score of 95.12% represents the harmonic mean of the precision and recall values to determine their balance.

A. Comparison among existing models

In order to determine the validity of the data set used, 5 different models created based on the IAM handwriting dataset were compared based on goal, method, and result. Table V exhibits the comparison conducted between 5 separate models trained using the IAM handwriting dataset.

7. Conclusions

Our model, STAS, aims to work around the political blockade regarding gun control and school safety. While the political approach toward a solution for this issue is possible, it is clear that much deliberation is needed before an effective societal change is implemented. However, until such a change is administered, the status of school safety remains uncertain. Using data from student records and handwriting samples from daily assignments, STAS can analyze the combinations of 28 factors that are known contributors to previous school shooters, having been distilled from characteristics identified by the FBI, in order to predict potentially violent behavior in current students, all using two simple neural networks. This allows school staff such as counselors to provide support for students in need. Though STAS may indicate that a student may be susceptible to potentially violent behavior, it must not be used as evidence for an accusation; it must only be used to deliver mental health support to those who need it.

Counselors and school officials may also use this system to help identify students who need additional social-emotional support, thereby aiding suicide prevention efforts.

With a runtime of 25 minutes on the average laptop, and an overall accuracy of 97% with a precision of 96.32%, a recall of 95.76% and an F1 score of 95.12% using easily accessible integrated development environments such as Spyder and Jupyter Notebook, STAS has the capability to be implemented efficiently at any individual school. This model, compared to previously rendered models such as the Automated Five-Factor Analysis which has a prediction accuracy of 80.5%, contains both an in depth analysis of students' behaviors, but also has a high prediction accuracy. User-friendly summary reports are also generated with each run of the system, easily identifying and organizing the status of the school for that day. It is the hope that, with this system, the warning signs exhibited by a student before every potential event will be impossible for their community to overlook, drastically reducing the number of school shooting incidents.

Further research into STAS will be necessary in order to better tune, not the parameters of the network, but the actual covariates used for classification, as only practical use will point out some of the limitations the features can pose. Research will also be necessary in order to analyze potential indirect, correlated bias towards race, gender, and socioeconomic class, and extend its implementation to the county level to encompass homeschooled students.

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