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Artificial Neural Network-Based Prediction of Violent Behaviour Using Psychosocial and Behavioural Indicators

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ABSTRACT

The increasing prevalence of violence among young people highlights the urgency of empirical, data-driven approaches capable of identifying early behavioural risk indicators. Understanding the behavioural and psychosocial factors that contribute to violent tendencies is critical for early identification and prevention. This study develops a predictive framework using an Artificial Neural Network (ANN) to classify the likelihood of violent character based on a structured survey of 1,277 respondents aged 13–30 years. The dataset incorporated key predictors, including emotional disposition, peer influence, family environment, media exposure, socioeconomic conditions, and psychological traits. After data preprocessing, the ANN was trained using a 70/30 split and further validated through 5-fold cross-validation, yielding strong and consistent performance with an average accuracy of 98.2%, precision of 96.9%, recall of 98.9%, and F1-score of 97.9%. The Receiver Operating Characteristic (ROC) analysis demonstrated excellent ability, indicating a highly reliable model. The results and findings demonstrate that violent behavioural tendencies can be reliably inferred from structured psychosocial indicators, highlighting the utility of machine learning for early detection and intervention planning. This study contributes to the body of knowledge by integrating behavioural science and machine learning to provide a practical, evidence-based tool for violence prevention initiatives.

Keywords: Violent Behaviour, Machine Learning, Artificial Neural Networks, Psychosocial, Cross-Validation, Predictive Model

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1. Introduction

Violence is broadly defined as the intentional use of physical force or power, whether threatened or actual, against oneself, another individual, or a community, resulting in or having a high likelihood of causing injury, death, psychological harm, developmental impairment, or deprivation [1,2]. It manifests in diverse forms, including collective violence, warfare, interpersonal conflicts, abuse, street crimes, and neglect [3]. The emergence of violent tendencies often begins during adolescence, with some individuals escalating to severe criminal behaviour, while others remain engaged in less aggressive antisocial acts throughout adulthood [4,5]. Historically, violence has been a persistent feature of society, contributing to millions of deaths and countless injuries annually from self-inflicted, interpersonal, and collective forms of aggression [6,7].

Human behaviour is shaped by the duality of instinct, both the life-driving self-preservation and the death that may lead to destruction and harm [8]. Violence exists along a broad continuum that includes economic, psychological, interpersonal, and emotional abuse, extending to physical, domestic, social, environmental, and self-directed forms such as suicide and self-harm [9].

Various social and psychological factors, including poverty, limited education, family instability, abuse, personality traits, and belief systems, have been identified as precursors to violent or antisocial behaviour [10]. Studies further reveal a correlation between lower intelligence quotient (IQ) and increased predisposition to violent conduct [11]. Moreover, environmental and domestic conditions play a critical role in shaping behaviour across age groups, from children to the elderly [12]. Different manifestations of abuse, physical, verbal, emotional, economic, religious, reproductive, and sexual, can evolve from subtle coercive actions to extreme violence, resulting in severe injury, disfigurement, or death [13–15].

Globally, violence remains a leading cause of mortality, particularly among individuals aged 15–45 years [16]. Its economic and social costs are immense, with billions of dollars spent annually on healthcare, law enforcement, lost productivity, and post-conflict reconstruction. In West Africa, regional conflicts have displaced over 300,000 people in recent years, exacerbating instability and economic decline despite significant investment in peacekeeping and reconstruction [16,17]. Given these global implications, the ability to accurately predict and mitigate violent tendencies would hold tremendous value for public safety, governance, and social welfare.

In response, this study proposes the development of a violent character predictive model using an Artificial Neural Network (ANN) to enhance the accuracy of predicting human behaviour. ANNs are computational models inspired by the biological structure and functionality of the human brain, where interconnected neurons process information in parallel [18]. Deep learning models such as neural networks have demonstrated strong capability in pattern recognition, classification, and behavioural prediction tasks [19,20]. By leveraging these strengths, this study aims to construct an ANN-based predictive framework capable of identifying potential violent behavioural patterns.

The primary objective of this study is to design and implement a predictive model capable of identifying individuals with a propensity for violent behaviour using an Artificial Neural Network. The research seeks to (i) examine the key social, psychological, and environmental variables influencing violent tendencies, (ii) train and validate an ANN model using relevant behavioural datasets, and (iii) evaluate the model's predictive performance using standard metrics.

Research Questions (RQ)

The proposed model is predictive, not diagnostic. It does not verify, establish, or rule out any diagnosis or present state of health. Instead, it offers probabilistic estimates, risk ratings, or forecasts based on patterns in the input data. The model's outputs are only offered for informational and decision-supporting purposes. Therefore, the research set out to answer the following questions:

1. RQ1: Psychosocial and behavioural indicators can statistically discriminate between individuals classified as violent and non-violent.
2. RQ2: An ANN can learn non-linear interactions among indicators more effectively than linear statistical models.

2. Literature Review

Research on violent behaviour prediction has evolved through several methodological phases, ranging from traditional approaches to the application of advanced artificial intelligence models. Each stage has contributed valuable insights into the understanding of human aggression, yet also revealed limitations that continue to motivate the pursuit of more adaptive and data-driven predictive systems.

2.1. Traditional and Clinical Predictive Approaches

Early studies on violent behaviour largely relied on statistical and clinical assessment techniques. Dressel and Farid [21] applied logistic regression to identify key biological predictors of violence, introducing the concept of incremental validity where new measures add predictive power beyond existing variables. Although insightful, their model suffered from an insufficient sample size, limiting its generalizability. Recent studies have increasingly explored the use of predictive techniques for violent and antisocial behaviours, as proposed in Dobbins et al. [22] and van der Put et al. [23], by formulating retrospective clinical equations to forecast future violent acts among specific populations. Berk et al. [24] expanded this approach by analysing the relationship between exposure to violence and later aggressive behaviour, integrating fairness variables such as risk assessment and environmental context. These studies outlined the importance of multifactorial analysis in violence prediction but were constrained by static assumptions that fail to capture behavioural dynamics.

2.2. Machine Learning in Behavioural Prediction

The limitations of traditional methods encouraged the adoption of machine learning (ML) techniques for more flexible, data-driven prediction. Perry [25] pioneered this transition by applying Random Forest and Naïve Bayes algorithms for conflict prediction using historical population data. The study demonstrated that machine learning models outperform baseline statistical predictors, though they remained limited by coarse temporal resolution. Farrington et al. [26] extended ML application to adolescent behaviour, predicting violent acts among urban youths with an accuracy of 77%. Despite this progress, dataset limitations and the narrow demographic scope restricted model robustness. Subsequent work by Cheng et al. [27] employed four machine learning algorithms, finding Random Forest superior in predicting aggressive behaviours in hospitalised schizophrenia patients. Similarly, Tate et al. [28] integrated genetic data into ML-based models to predict suicidal and aggressive tendencies, reinforcing the role of hybrid behavioural-genetic approaches. These efforts mark a clear shift toward leveraging computational intelligence for behavioural forecasting, yet they highlight persistent challenges.

2.3. Neuro-Predictive and Psychobiological Models

A distinct research stream focused on neuroscientific and biological correlations of violence, offering a mechanistic understanding of aggression. Poldrack et al. [29] explored neuro-prediction using neuroimaging markers to assess violence risk, emphasising the proximity of these markers to causal processes in the brain. Their findings advanced the integration of neuroscience into behavioural prediction but raised ethical and methodological concerns regarding imaging bias and intentional subject interference. Yu et al. [17] built upon this paradigm by employing Support Vector Machine (SVM) classifiers on Magnetic Resonance Imaging (MRI)-derived brain structure data from patients with schizophrenia, achieving a balanced accuracy of 82%. The results validated the presence of measurable neuroanatomical differences in violent individuals.

2.4. Behavioural Modelling and Deep Learning

In parallel with clinical and computational research, scholars have examined psychological and environmental predictors of violence. The General Aggression Model by Cavalcanti and Pimentel [30] synthesised multiple theoretical frameworks, demonstrating both direct and indirect relationships between personality traits and violent tendencies among adolescents. Likewise, Varela et al. [31] used structural equation modelling to link school attachment and violent attitudes, showing that social context significantly mediates aggression. Complementary studies, such as those by Grumm et al. [32], Harsh et al. [33], and Chanchlani et al. [34], utilised non-traditional behavioural cues, social media text and handwriting analysis, to infer personality traits and predisposition to aggression. Although innovative, such approaches faced issues of data authenticity, privacy, and susceptibility to manipulation. Advancements have increasingly favoured deep learning for automatic feature learning and scalable violence detection. Parsaei et al. [35] analysed several machine learning and deep learning frameworks for detecting violent acts demonstrating and analysing reasons for improved accuracy in real-time identification tasks. Similarly, Martinez et al.[36] analysed movie scripts using language models to classify violent content, illustrating the versatility of deep learning in multimodal behavioural analysis. Dunne et al.[37] also conducted a comprehensive review of computational methods for human behaviour prediction, identifying key datasets such as MavHome, Centre for Advanced Studies in Adaptive Systems (CASAS), and Reference Energy Disaggregation Data Set (REDD), and proposing the integration of audio and time-series prediction models. These contributions emphasise the transition from traditional data structures to network-based representations of human behaviour, marking the next frontier in predictive modelling for violence dominance.

While significant progress has been made, several challenges persist in the prediction of violent character. Traditional, statistical and clinical approaches lack adaptability to nonlinear behavioural patterns, while existing machine learning methods are often limited by demographic bias and insufficient feature generalisation. Neuro-predictive models, though promising, face ethical and scalability constraints. Furthermore, most existing frameworks focus narrowly on specific contexts such as clinical or surveillance environments rather than developing generalised behavioural models.

To address these limitations, this study proposes the development of a Violent Character Predictive Model using Artificial Neural Networks (ANNs), leveraging their capacity for nonlinear mapping, adaptive learning, and pattern generalisation. The ANN-based approach is designed to integrate multidimensional behavioural indicators, enabling more accurate and generalizable predictions.

3. Research Methodology

This study adopts an artificial neural network machine learning approach. For the objectives of this research work to be achieved, the following procedures/phases were executed: data collection, preprocessing, modeling and evaluation (**Figure 1**).

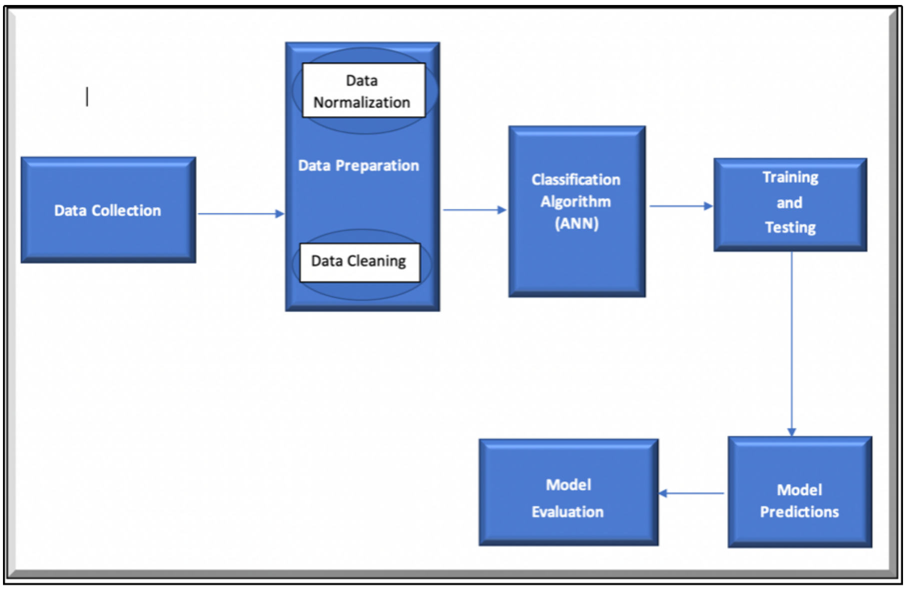

Figure 1. Architecture.

3.1. Detailed Architecture Analysis

3.1.1. Data Collection

Data for this study were obtained through a structured survey questionnaire designed to capture respondents' opinions across a set of predefined behavioural and psychosocial predictors of violent character. The sample population consisted of individuals aged 13 to 30 years. This age range was deliberately selected because adolescence to early adulthood represents the developmental period in which behavioural tendencies, particularly aggression, risk-taking, and social influence, are most pronounced and most likely to manifest. The final dataset, comprising a total of 1,277 records, was then imported into Python and preprocessed for training the baseline models and artificial neural network classifier. Representative samples of the dataset are presented in **Figure 2**.

Respondent_ID	Anger_Control	Aggressive_Reaction	Impulsivity	Stress_Level	Emotional_Regulation	Substance_Use	Past_Confrontations	Risk_Taking	Social_Isolation	Frustration_Tolerance
1	2	3	4	5	1	2	3	4	5	1
2	3	4	5	1	2	3	4	5	1	2
3	4	5	1	2	3	4	5	1	2	3
4	5	1	2	3	4	5	1	2	3	4
5	1	2	3	4	5	1	2	3	4	5
6	2	3	4	5	1	2	3	4	5	1
7	3	4	5	1	2	3	4	5	1	2
8	4	5	1	2	3	4	5	1	2	3
9	5	1	2	3	4	5	1	2	3	4
10	1	2	3	4	5	1	2	3	4	5
11	2	3	4	5	1	2	3	4	5	1
12	3	4	5	1	2	3	4	5	1	2
13	4	5	1	2	3	4	5	1	2	3
14	5	1	2	3	4	5	1	2	3	4
15	1	2	3	4	5	1	2	3	4	5
16	2	3	4	5	1	2	3	4	5	1
17	3	4	5	1	2	3	4	5	1	2
18	4	5	1	2	3	4	5	1	2	3
19	5	1	2	3	4	5	1	2	3	4
20	1	2	3	4	5	1	2	3	4	5
21	5	1	2	3	4	5	1	2	3	4
22	1	2	3	4	5	1	2	3	4	5
23	2	3	4	5	1	2	3	4	5	1
24	3	4	5	1	2	3	4	5	1	2
25	4	5	1	2	3	4	5	1	2	3
26	5	1	2	3	4	5	1	2	3	4
27	1	2	3	4	5	1	2	3	4	5
28	2	3	4	5	1	2	3	4	5	1
29	3	4	5	1	2	3	4	5	1	2
30	4	5	1	2	3	4	5	1	2	3
31	5	1	2	3	4	5	1	2	3	4
32	1	2	3	4	5	1	2	3	4	5
33	2	3	4	5	1	2	3	4	5	1
34	3	4	5	1	2	3	4	5	1	2
35	4	5	1	2	3	4	5	1	2	3
36	5	1	2	3	4	5	1	2	3	4
37	1	2	3	4	5	1	2	3	4	5

Figure 2. Sample Dataset.

- **Questionnaire Design**

The questionnaire development followed a multi-stage methodological process:

1. Construct Identification: Key psychosocial and behavioural constructs associated with violent behaviour were identified from peer-reviewed literature and forensic risk assessment studies.
2. Item Formulation: For each construct, multiple questions were formulated to capture observable behavioural tendencies rather than subjective moral judgments.
3. Scaling and Encoding: A uniform scale structure was adopted to reduce ambiguity and facilitate numerical encoding for machine learning.
4. Content Refinement: Redundant or ambiguous items were removed to reduce noise and respondent fatigue.
5. Pilot Review: The questionnaire was pilot-reviewed to ensure comprehension and consistency, and minor wording adjustments were made before final deployment.

This systematic design approach ensured that the collected data reflected theoretically grounded constructs suitable for computational analysis. The questionnaire (see **Appendix A**) included key features such as age, gender, emotional stability, peer influence, family background, exposure to violent content, impulsiveness, anger response, conflict involvement and many more. Some of which are explained below:

1. School Factor: The school environment influences behavioural development through academic engagement, disciplinary structure, and peer interactions. Poor school attachment, frequent disciplinary actions, and exposure to bullying may increase frustration and aggressive tendencies. Supportive school climates, on the other hand, can reduce the likelihood of violent behaviour.
2. Cultural Factor: Cultural norms and societal values shape attitudes toward aggression, conflict resolution, and acceptable behaviour. Cultural environments that tolerate or normalise violence may influence aggressive tendencies, while those promoting restraint can act as protective factors. This variable provides a broader social context for behaviour modelling.
3. Community Factor: Community factors reflect neighbourhood conditions, social cohesion, and exposure to crime or violence. Environments characterised by insecurity or limited social support may reinforce aggressive behaviour. Including community indicators allows the model to account for environmental stressors beyond individual control.
4. Parental Factor: Parental influence is captured through supervision quality, disciplinary consistency, and emotional support. Inadequate monitoring or harsh parenting styles may contribute to impulsiveness and aggression. This factor isolates the specific role of parenting in be-

havioural outcomes.

5. Psychological Factor: Psychological factors represent internal emotional and cognitive states such as stress, anxiety, impulsiveness, and emotional instability. Individuals with poor psychological regulation may respond aggressively to perceived threats. These indicators are critical for modelling nonlinear behavioural patterns.
6. Religion: Religion may influence moral judgement, self-control, and social behaviour through belief systems and ethical values. Religious engagement can discourage violent actions, while weak or conflicting moral frameworks may increase vulnerability. This factor is treated as a contextual behavioural influence.
7. Peer Influence: Peer influence reflects the impact of social networks and group behaviour on individual actions. Association with aggressive peers can normalise violence and reinforce risky behaviour. This factor captures socially driven reinforcement of violent tendencies.
8. Family Background: Family background includes long-term socioeconomic conditions, household structure, and early-life experiences. Adverse backgrounds may increase exposure to stress and behavioural risks. This variable supports an understanding of developmental influences on violence.
9. Impulsiveness: Impulsiveness refers to acting without adequate forethought or consideration of consequences. High impulsivity increases the likelihood of aggressive reactions, particularly under emotional stress. This factor is strongly associated with violent behaviour.
10. Anger: Anger response describes how individuals perceive and manage anger-inducing situations. Poor anger control or heightened reactivity may lead to aggressive behaviour. This indicator captures emotional response patterns linked to violence.

- **Ground Truth Definition and Labelling Procedure**

The class labels used in this study were determined based on an operational definition of violent behavioural tendency derived from responses to a structured psychosocial and behavioural questionnaire (0 to 5). Specifically, respondents were categorised according to predefined scoring criteria based on validated behavioural indicators, including aggression-related behaviours, impulsivity markers, and self-reported history of violent or threatening actions. Individuals whose cumulative scores exceeded a defined threshold were labelled as exhibiting violent behavioural tendencies, while those below the threshold were labeled as non-violent. It is important to emphasise that these labels do not represent objectively verified forensic or clinical diagnoses. Rather, they constitute proxy ground-truth labels constructed from self-reported data and established behavioural measurement frameworks. The supervised learning models were therefore trained to predict consistency with this operational categorisation, rather than to infer definitive violent behaviour.

- **Respondent Verification Process**

Participant verification was conducted to ensure the authenticity and validity of collected responses. Data collection was restricted to voluntary participants who met predefined inclusion criteria, including age eligibility and informed consent. Duplicate submissions were prevented through controlled data collection procedures, and incomplete or inconsistent responses were excluded during preprocessing. To enhance data reliability, attention-check mechanisms were incorporated within the questionnaire to identify random or careless responses. Responses failing consistency checks were removed before analysis. It is important to note that behavioural class labels were derived from operationalised thresholds based on questionnaire responses rather than independent forensic records. Therefore, the classification reflects statistically inferred behavioural tendencies within the surveyed population and should not be interpreted as a formal forensic diagnosis. This methodological constraint is acknowledged as a limitation of the study.

- **Statistical Analysis of the Questionnaire Responses**

Preliminary statistical analyses were conducted to examine the structural properties of the dataset and ensure its suitability for supervised classification. First (see **Figure 3**), class distribution analysis was performed to evaluate the balance between labelled behavioural categories. The dataset consisted of 1,277 respondents, with a relatively balanced representation of non-violent (n = 652) and violent (n = 625) cases. This near equal distribution reduces the risk of class imbalance bias and supports reliable supervised training without the need for synthetic resampling. Second (see **Figure 4**), correlation analysis was conducted to assess relationships among psychosocial, environmental, and behavioural indicators. The correlation matrix revealed meaningful positive associations among several theoretically related constructs to violent character. These moderate interrelationships are consistent with established behavioural risk frameworks, suggesting that violent tendencies may emerge from interacting psychosocial dimensions. While correlations were observed among related variables, no excessive multicollinearity was detected, indicating that the feature set retained sufficient independence to support stable model training.

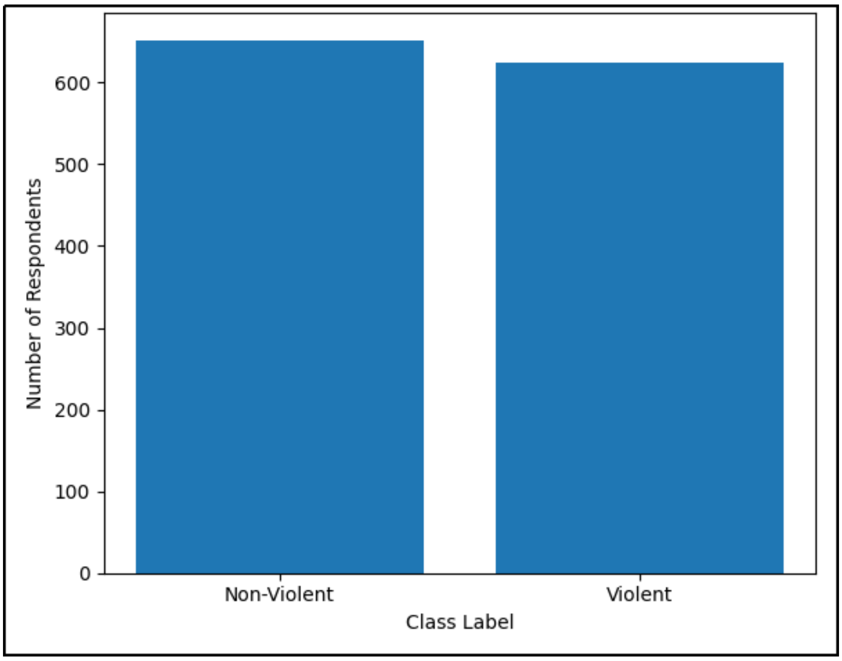

Figure 3. Class Distribution.

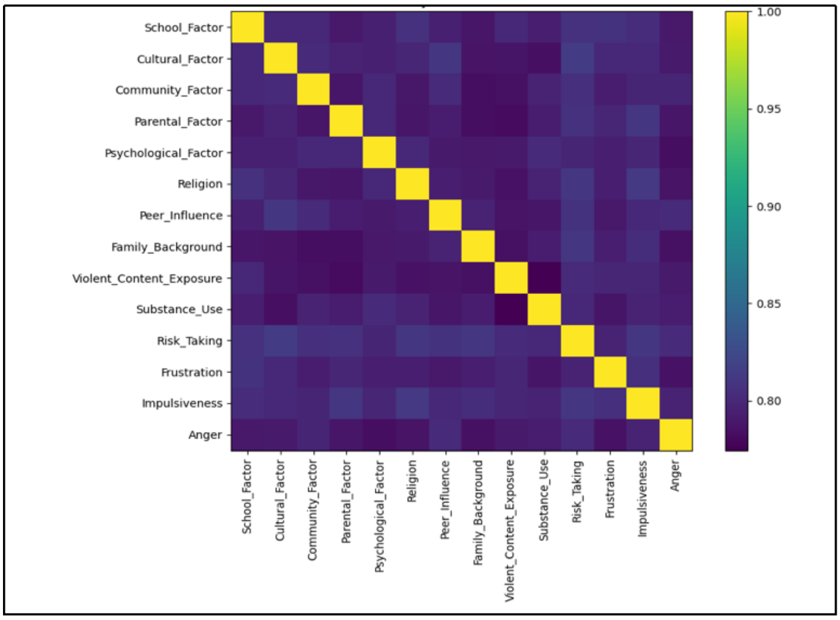

Figure 4. Correlation Analysis.

3.1.2. Preprocessing

Survey-derived behavioural data, similar to most real-world social data, often contains inconsistencies such as categorical variables, missing values, and heterogeneous attribute scales. If left unprocessed, these issues can increase noise, inflate dimensionality, and reduce the interpretability of machine learning models, as they enhance data quality and ensure that the neural network receives structured and meaningful inputs. Although several pre-processing techniques exist, such as feature engineering, dimensionality reduction, feature selection, and data transformation, this study applies two essential methods aligned with the nature of the collected data:

a) Label Encoding: Used to convert categorical survey responses into numerical representations appropriate for neural network computation. This is necessary because ANN models operate on numerical data tensors and cannot directly interpret qualitative or nominal data. In our case, the encoding was done automatically for each response from the respondents.

b) Feature Scaling: After encoding, feature values are normalised to a common scale to prevent attributes with larger numeric ranges from disproportionately influencing the learning process and to ensure less noisy data. The data pre-processing workflow followed in this study comprises the following steps:

1. Import the raw dataset
2. Convert to categorical values to numerical weights
3. Generate labels for each data point per sample provided
4. Check for missing or inconsistent values
5. Check for duplicate values
6. Check the dimensions of the final table to ensure consistency
7. Splitting the dataset into training and testing subsets

3.1.3. Modelling (ANN Building)

This framework consists of two algorithms, namely Forward Propagation and Backward Propagation, designed for executing feedforward networks Qamar and Zardari [38]. In this model, the chosen neural network family is the Multilayer Perceptron (MLP) classifier. The selection of ANN as the model for this study is motivated by its capacity to comprehend and represent non-linear associations between input and output. This characteristic enables addressing problems even in the absence of extensive prior knowledge about the specific problem at hand. The mathematical model is as follows:

- **The Forward Propagation (Forward Pass):**

The activation function of the artificial neurons in ANNs implements the forward propagation and the sum of the inputs (x_i) multiplied by their respective weights (w_{ji}), where (x_i) are attributes and (w_{ji}) is the weight of attributes in each case.

$$A_j(x,w) = \sum_{i=0}^{n} x_i w_j \tag{1}$$

The activation function depends only on the inputs and the weights. The most common output function is the sigmoidal function:

$$O_j(x,w) = 1/(1+e^{Ai(x,w)}) \tag{2}$$

The goal of the training process is to achieve a desired output when specific inputs are provided. The error depends on the weights; hence, the weights of each attribute are adjusted to minimise the error. The total error of the model will simply be the sum of all errors of each neuron. We can define the error function for the network output:

$$E_j(x,w,d) = \sum \left(O_j(x_i, w_{ji}) - d_j\right)^2 \tag{3}$$

- **The Backward Propagation (Backward Pass):**

The backpropagation algorithm now calculates how the error depends on the output, inputs, and weights. After this is found, the weights are then adjusted.

$$\Delta w_{ji} = \partial E / \partial w_{ji} \tag{4}$$

$$\partial E / \partial w_{ji} = 2(O_i - d_j) \tag{5}$$

And then how much the output depends on the activation, which also depends on the weights (from Equations (1) and (2)):

$$\partial O_j / \partial w_{ji} = (\partial O_j / \partial a_j) \times (\partial a_j / \partial w_{ji}) = O_j (1 - O_j)\, x_i \tag{6}$$

Then (from Equations (5) and (6)):

$$\partial E / \partial w_{ji} = (\partial E_j / \partial O_j) \times (\partial O_j / \partial w_j) = 2(O_j - d_j) \times O_j\,(1 - O_j)\, x_i \tag{7}$$

Therefore, the adjustment to each weight will be (from Equations (4) and (7)):

$$\Delta w_{ji} = 2(O_j - d_j) \times O_j(1 - O_j) x_j \tag{8}$$

Finally, the backward propagation process updates the weights of each attribute by computing the gradient of the loss function with respect to the network parameters. The error is propagated from the output layer to preceding layers, allowing the model to adjust its internal representations and minimise prediction error. This iterative optimisation ensures that the network learns meaningful nonlinear relationships within the behavioural data.

3.1.4. Training and Testing

The model is executed using the training dataset, generating results that are then compared with the target for each input vector within the training dataset. The test set serves as a collection of observations employed to assess the model's performance using specific performance metrics. No observations from the training set must be incorporated into the test set. In this particular study, 70% (893 samples) of the data is allocated for the training stage, while the remaining 30% (384 samples) is reserved for the test set. The hyperparameter values used for each model training are shown in **Table 1**.

Table 1. Hyperparameter Values.

Model	Value
Logistic Regression (LR)	C: [100, 10, 1.0, 0.1, 0.01], penalty: L2 solver: saga, max_iter: 1000
Multinomial Naïve Bayes (MNB)	alpha: [0.01, 0.05, 0.1, 0.5, 1.0] fit_prior: True
Decision Tree (DT)	_estimators: [50,100,300,500] max_depth: [10,30,50,100], max_features: sqrt
ANN	Chidden_layer_sizes=(100,), activation='relu',solver='adam', alpha=0.0001,batch_size='auto', learning_rate='constant', learning_rate_init=0.001

3.1.5. Evaluation Metrics and Results

The predictions of the test set are evaluated against the original classes of the data samples to assess the model's performance using standard machine learning metrics, including accuracy score, precision, recall, F1-score, and error rate, which are considered the model's results. For this phase, two experiments were conducted: (i) the dataset was loaded at a single epoch, and (ii) using cross-validation stratified k-fold scores. The figures and tables for each result are given below (**Figures 5** and **6**, **Table 2**):

```
Accuracy Score: 0.9921875

              precision    recall  f1-score   support

           0       1.00      0.99      0.99       229
           1       0.98      1.00      0.99       155

    accuracy                           0.99       384
   macro avg       0.99      0.99      0.99       384
weighted avg       0.99      0.99      0.99       384
```

Figure 5. Accuracy Score and Classification Report (ANN).

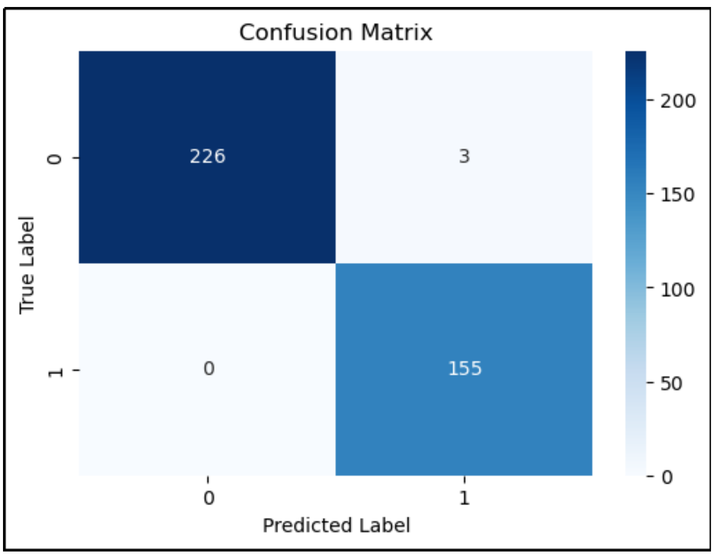

Figure 6. Confusion Matrix (ANN).

Table 2. Evaluation Metrics (ANN full epoch).

SN	Model	Accuracy	Precision	Recall	F1-Score	Error Rate
1	ANN	99.2%	99%	99.5%	99%	0.08%

- **Cross Validation**

This determines the accuracy of the model by partitioning the data into two different groups, called a training set and a testing set. The results are presented below in **Figures 7** and **8** and **Table 3**:

```
Training Fold 1...
8/8 [==============================] - 0s 1ms/step
Fold 1 Completed -> Accuracy: 0.9727, F1: 0.9677
Training Fold 2...
8/8 [==============================] - 0s 1ms/step
Fold 2 Completed -> Accuracy: 0.9766, F1: 0.9732
Training Fold 3...
8/8 [==============================] - 0s 1ms/step
Fold 3 Completed -> Accuracy: 0.9647, F1: 0.9596
Training Fold 4...
8/8 [==============================] - 0s 1ms/step
Fold 4 Completed -> Accuracy: 1.0000, F1: 1.0000
Training Fold 5...
8/8 [==============================] - 0s 1ms/step
Fold 5 Completed -> Accuracy: 0.9961, F1: 0.9954

==== Final 5-Fold Cross Validation Results ====
Accuracy: 0.9820 ± 0.0137

Precision: 0.9699 ± 0.0237

Recall: 0.9890 ± 0.0147

F1-score: 0.9792 ± 0.0158
```

Figure 7. Cross-Validated Scores.

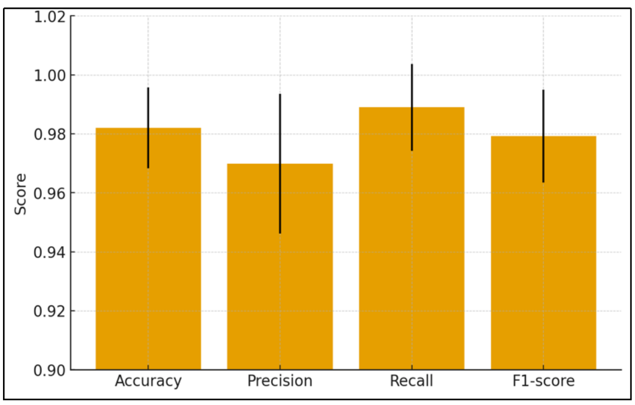

Figure 8. Performance Metrics (Cross-Validation).

Table 3. Evaluation Metrics (Cross-Validation).

Epoch	Accuracy Score	Mean Accuracy Score
1	97.27%	
2	97.66%	
3	97.47%	98.20%
4	100%	
5	99.61%	

- **Receiver Operating Characteristics: ROC/Area Under the Curve (AUC)**

The ROC curve (**Figure 9**) demonstrated a rise toward the top-left corner, indicating high sensitivity at low false-positive rates. The model achieved an AUC of 0.8537, showing excellent ability. This indicates that the model can reliably distinguish individuals with violent tendencies from non-violent individuals, with an 85.4% probability of correctly ranking a violent case higher than a non-violent case.

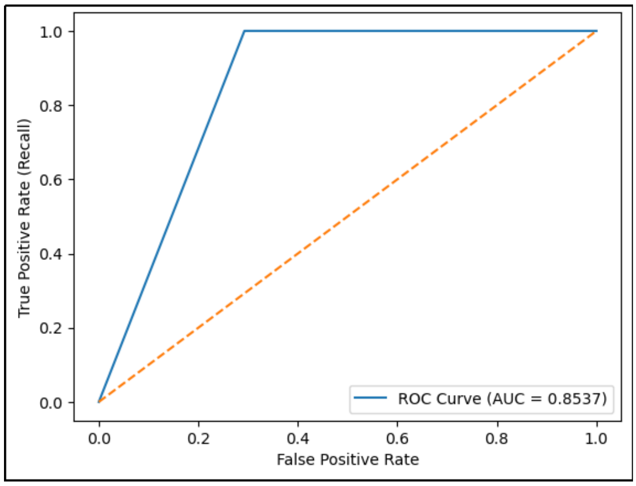

Figure 9. ROC Curve.

3.1.6. Baseline Statistical Models

This section presents three different statistical baseline model comparisons. The goal is to compare their evaluation results with the ANN performance. We trained three classification algorithms (Logistic Regression, Decision Tree and Naïve Bayes) with the same dataset.

- **Logistic Regression**

The results in **Figure 10** demonstrate that the logistic regression model provides a decent performance for the behavioural classification task, achieving a 79.4% accuracy, 78.5% precision, 76% recall, and 77% F1-score on the test set, which shows the efficiency of the model. The confusion matrix further reinforces this performance, showing only 79 misclassifications.

```
====== Outputing for Logistic Regression ======

 ======== Accuracy Score ========

0.7942708333333334 or 79.4%

 ======== Confusion Matrix ========

[[218  27]
 [ 52  87]]

 ======== Classification Report ========

              precision    recall  f1-score   support

           0       0.81      0.89      0.85       245
           1       0.76      0.63      0.69       139

    accuracy                           0.79       384
   macro avg       0.79      0.76      0.77       384
weighted avg       0.79      0.79      0.79       384
```

Figure 10. Logistic Regression Metrics.

- **Decision Tree**

The decision tree model also provides a decent performance for the classification task, achieving a 78.9% accuracy, 78% precision, 75% recall, and 76% F1-score on the test set, which shows the efficiency of the model. The confusion matrix shows that 81 classes were misclassified, as shown in **Figure 11**.

```
==== Outputing for Decision Tree =====

 ======== Accuracy Score ========

0.7890625 or 78.9%

 ======== Confusion Matrix ========

[[218  27]
 [ 54  85]]

 ======== Classification Report ========

              precision    recall  f1-score   support

           0       0.80      0.89      0.84       245
           1       0.76      0.61      0.68       139

    accuracy                           0.79       384
   macro avg       0.78      0.75      0.76       384
weighted avg       0.79      0.79      0.78       384
```

Figure 11. Decision Tree Metrics.

- **Naïve Bayes**

The Naïve Bayes (GaussianNB) is the closest to the ANN model proposed in this study. It provided a reliable performance for the classification task, achieving an 86.2% accuracy, 85% precision, 86% recall, and 85% F1-score on the test set, which shows the notable efficiency of the model. The confusion matrix shows that 53 classes were misclassified, as shown in Figure 12.

```
======== Outputing for Naive Bayes ========

 ======== Accuracy Score ========

0.8619791666666666 or 86.2%

 ======== Confusion Matrix ========

[[219  26]
 [ 27 112]]

 ======== Classification Report ========

              precision    recall  f1-score   support

           0       0.89      0.89      0.89       245
           1       0.81      0.81      0.81       139

    accuracy                           0.86       384
   macro avg       0.85      0.85      0.85       384
weighted avg       0.86      0.86      0.86       384
```

Figure 12. Naïve Bayes Metrics.

3.1.7. General Discussion of Results

The comparative evaluation of baseline classifiers (see Figure 13 and Table 4) and the proposed Artificial Neural Network (ANN) provides important insight into the predictive structure of the psychosocial and behavioural dataset. Overall, all evaluated models demonstrated reasonable discriminatory ability, suggesting that the selected indicators contain meaningful information relevant to behavioural classification. However, notable performance differences were observed across models, reflecting their varying capacity to capture relationships within the data.

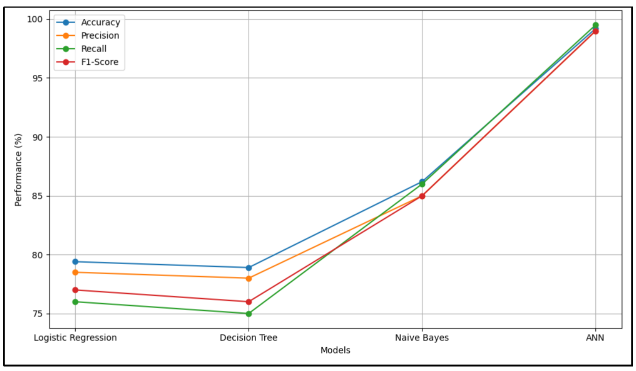

Figure 13. Model Metrics Comparison.

Table 4. Performance Comparison.

Models	Accuracy	Precision	Recall	F1 Score
Logistic Regression	79.4%	78.5%	76%	77%
Decision Tree	78.9%	78%	75%	76%
Naïve Bayes	86.2%	85%	86%	85%
Artificial Neural Network	99.2%	99%	99.5%	99%

The logistic regression model achieved a test accuracy of 79.4%, with balanced precision, recall, and F1-score values. This performance indicates that linear combinations of the input features are capable of separating violent and non-violent behavioural classes to a reasonable extent. Nevertheless, the number of misclassifications observed in the confusion matrix suggests that the linear decision boundary imposed by logistic regression may be insufficient for fully modelling the complex interactions among psychosocial and behavioural variables.

Similarly, the decision tree classifier yielded comparable results, with an accuracy of 78.9%. While decision trees can model non-linear relationships, their performance in this study suggests potential sensitivity to local feature splits and limited generalisation capacity given the available data. The observed misclassification count further indicates that single-tree structures may struggle to capture higher-order behavioural patterns embedded within the dataset.

The Naïve Bayes classifier demonstrated notably stronger performance relative to the other baseline models, achieving an accuracy of 86.2% and a balanced precision–recall profile. This suggests that probabilistic modelling of feature distributions is well-suited to the dataset, despite the conditional independence assumption inherent in Naïve Bayes. Its comparatively low misclassification rate indicates that the statistical structure of the data aligns reasonably well with generative probabilistic assumptions.

The experimental results demonstrate that the developed Artificial Neural Network (ANN), which is the best performing model, provides highly reliable performance for the behavioural classification task, achieving a 99.2% accuracy, 99% precision, 99.5% recall, and 99% F1-score on the test set, which shows the effectiveness of the ANN model. These values indicate that the model can identify positive behavioural cases with high sensitivity while maintaining strong specificity. The confusion matrix further reinforces this observation, showing only 3 false positives and zero false negatives, a characteristic desirable in safety-critical and behavioural risk prediction domains, where missing a true positive (false negativev or FN) can have severe implications.

The 5-fold cross-validation results, Table 3, Figures 7 and 8 (Accuracy of 0.9820 with 0.0137 error rate), further show that the model generalises well across different data splits, which speaks directly to how dependable the model is. The low variance across folds indicates stability, reliability and reduces the likelihood of overfitting, consistent with the role of cross-validation as a reliable generalisation estimator as explained in Yang et al.[39]. The ROC curve, with an AUC of 0.8537, indicates strong discriminative power and robustness along with other metrics (precision, recall, f-measure) already highlighted above. The steep curve demonstrates that the model effectively separates the classes with minimal false positives at most thresholds. This behaviour is typical in behavioural datasets where threshold-based metrics can appear stronger than threshold-free metrics like AUC.

Although the ANN operates as a black-box model, the inclusion of emotional disposition, peer influence, family environment, media exposure, socioeconomic conditions, and psychological traits as input features collectively enabled the model to learn complex nonlinear relationships that strongly contribute to predictive performance, consistent with behavioural risk modelling literature. The combination of high recall, low false positives, narrow cross-validation variance, and strong AUC performance positions the model as a healthy solution for deployment in real-world behavioural assessment systems.

4. Contribution

This study developed and validated an Artificial Neural Network (ANN)-based framework for predicting violent behavioural tendencies among people aged 13–30 years using structured psychosocial and behavioural indicators. The proposed model demonstrated excellent and efficient predictive performance, achieving an accuracy of 99.2%, precision of 99.0%, recall of 99.5%, and an F1-score of 99.0% on the test dataset. The confusion matrix revealed only three false positive cases and zero false negatives, highlighting the model's strong sensitivity and suitability for behavioural risk detection scenarios where missing true cases can have serious implications.

The robustness and generalizability of the model were further confirmed through 5-fold cross-validation, yielding an average accuracy of 0.9820 with a low error rate of 0.0137, indicating consistent performance across different data partitions and reduced risk of overfitting. Additionally, the ROC analysis produced an AUC value of 0.8537, demonstrating strong discriminative capability across classification thresholds. These findings confirm that violent behavioural tendencies can be reliably inferred from psychosocial and behavioural factors such as emotional disposition, peer influence, family environment, media exposure, socioeconomic conditions, and psychological traits when modelled using Artificial Neural Networks. The strong predictive performance observed across multiple evaluation metrics demonstrates the ANN's ability to capture complex, nonlinear interactions among these interrelated factors.

5. Conclusions

This study presented an Artificial Neural Network-based approach for predicting violent behavioural tendencies using psychosocial and behavioural indicators. The results demonstrate that the proposed model achieves high predictive performance compared to traditional machine learning techniques, highlighting the capability of neural networks to capture complex, non-linear behavioural patterns. Through the integration of behavioural science principles with machine learning techniques, this study provides an evidence-based predictive framework that can support early identification of at-risk individuals and inform targeted, data-driven intervention strategies for youth violence prevention. In practical terms, such models may assist educators, social workers, and policymakers in prioritising preventive measures before violent behaviours escalate. However, despite the promising predictive performance observed in this study, some limitations must be acknowledged. First, the proposed model is based on proxy ground-truth labels derived from reported psychosocial and behavioural indicators rather than independently verified forensic or clinical assessments. As such, the model should not be interpreted as providing diagnostic or causal explanations of violent behaviour, but rather as a computational decision-support tool that identifies statistical patterns within the available data. Furthermore, the dataset was not independently examined or annotated by forensic or behavioural experts, which limits the extent to which the model's predictions can be validated against domain-specific judgment. This study is best understood as a preliminary computational investigation intended to explore the feasibility of machine learning approaches for behavioural risk prediction. Future work will focus on interdisciplinary validation involving forensic professionals, the use of externally verified or longitudinal datasets, and the integration of expert-driven behavioural frameworks to strengthen the scientific and applied relevance of the proposed approach.

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Institutional Review Board Statement

This study was conducted using anonymised primary data that contained no identities, and all analytical procedures complied with standard guidelines for data handling and research integrity. No direct human or animal subjects' personal identifiers were involved, and therefore, formal ethical approval was not required. The research adhered to responsible data use practices, ensuring confidentiality, transparency, and accuracy throughout the analysis and reporting process.

Informed Consent Statement

This study involves a survey that includes human inputs. Therefore, informed consent was obtained from all subjects (respondents) involved in this study.

Data Availability Statement

Data are available from the corresponding author upon reasonable request.

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Conflicts of Interest

The author declares that no financial, personal, or institutional conflict of interest could have influenced the outcomes, interpretation, or presentation of this research. All results and conclusions were derived objectively and remain independent of any external influence.

AI Use Statement

During the preparation of this work, the author utilised GROK and OpenAI to perform some rephrasing of the literature. After using this tool/service, the author reviewed and edited the content as needed and take full responsibility for the content of the published article.

Appendix A

1. I find it difficult to control my anger in stressful situations.
2. I often react aggressively when I feel provoked.
3. I have been involved in physical or verbal confrontations in the past.
4. I engage in risky or impulsive behaviours without considering consequences.
5. I feel easily frustrated by minor inconveniences.
6. I have experienced prolonged emotional stress in recent months.
7. I consume alcohol or substances when feeling emotionally distressed.
8. I have witnessed or experienced violence in my environment.
9. I struggle to calm down quickly after becoming upset.
10. I feel socially isolated or unsupported.

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