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AI-Based Hybrid System for Profiling and Predicting Traffic Offenders

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***Abstract*—** Road traffic violations remain a major challenge worldwide, contributing to accidents, injuries, and fatalities. Most existing traffic enforcement methods often rely on manual monitoring and static rule-based systems, which are inefficient in identifying repeat offenders and predicting future violations. This research proposes the design and implementation of a hybrid system for profiling and predicting traffic offenders using deep learning algorithms, aimed at enhancing law enforcement strategies and improving road safety. The system integrates unsupervised learning (K-Means clustering) for categorizing offenders into high-risk, medium-risk, and low-risk groups based on historical violation patterns, and supervised deep learning models (LSTMs) for predicting future offenses. By leveraging large-scale traffic data, the system enables proactive intervention by law enforcement agencies. The implementation utilizes Python, TensorFlow, and Scikit-learn libraries, with cloud-based infrastructure for real-time data processing and scalability. Performance evaluation using real-world traffic datasets demonstrates the system's effectiveness, with high accuracy in offender classification and future offense prediction. Compared to conventional enforcement techniques, the proposed AI-based hybrid approach enhances traffic monitoring, risk assessment, and predictive policing. This research contributes to advancing intelligent transportation systems, AI-driven law enforcement, and smart city initiatives, providing a scalable and automated framework for improving road safety.

Keywords—Traffic violation prediction, Offender profiling, machine learning, deep learning, hybrid system, smart transportation, AI in law enforcement, predictive analytics.

I. INTRODUCTSION

The World Health Organization's global status report on road safety maintains that road traffic injuries remain the leading killer of children and young people between the ages of 5 and 29 years and the 12th leading cause of death for all ages. It is estimated that 1.3 million people lose their lives in traffic accidents each year [1]. Although road traffic accidents are a global epidemic, the problem is more acute in the developing world [1]. [2] contended that developing countries especially the African region, which accounts for only 1% of the world's vehicle fleet, bear 16% of the global death toll. In Africa, Nigeria has the highest record of road traffic accidents. Road traffic accidents in Nigeria have claimed more lives than deaths resulting from all communicable diseases put together, including the dreaded acquired immunodeficiency syndrome (AIDS).

It is important to note that most traffic accidents do not happen without a traffic violation. Factors contributing to road traffic accidents include unsafe vehicles, bad road infrastructure, and road users' attitudes such as risk-taking behaviour, excessive speeding, traffic violations, and failure to comply with driving rules such as wearing motorcycle helmets and motor seat belts. It was discovered that driver age, skill, and inexperience cause road accidents. Driving under the influence of alcohol or drugs, using a cell phone while driving, poor traffic law enforcement, and poor post-crash care are all variables that have been linked to road accidents. It is also commonly known that as the economy grows, so does vehicle ownership and travel, resulting in a rise in fatalities and injuries [3].

Traffic violations have been a phenomenon that requires urgent attention. [4] described traffic violations as being perceived to be minor offenses by many motorists, with a greater potential of causing traffic crashes, leading to loss of lives and damages to property. Traffic violations, such as marked lane violations and illegal turns, are one of the leading causes of traffic accidents, undermining human safety and causing economic losses [5]. A traffic offense is a violation of traffic regulations, such as breaking the speed limit and stop sign infractions. An increase in traffic congestion is one of the major reasons for traffic violations. Road commuters tend to violate traffic rules when there is traffic congestion [6]. Table 1 lists various traffic offenses in Nigeria and their respective penalties.

Table 1: Federal road safety corps (FRSC) notice of offense sheet (Statista, 2023)

S/NO	TICK INFRINGEMENT (S)	CODE	POINTS	PENALTY	CATEGORY
1	Light/Sign Violation	LSV	2	2,000	2
2	Road Obstruction	ROB	3	3,000	1
3	Route Violation	RTV	5	5,000	1
4	Speed Limit Violation	SLV	3	3,000	1
5	Vehicle Licence Violation	VLV	3	3,000	2
6	Vehicle Number Plate Violation	NPV	3	3,000	1
7	Driver's Licence Violation	DLV	10	10,000	2
8	Wrongful Overtaking	WOV	3	3,000	1
9	Road Marking Violation	RMV	5	5,000	1

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10	Caution Sign Violation	CSV	3	3,000	3
11	Dangerous Driving	DGD	10	50,000	1
12	Driving Under Alcohol or Drug Influence	DUI	5	5,000	2
13	Operating A Vehicle with Forged Documents	OFD	10	20,000	2
14	Unauthorized Removal of or Tampering with Road Signs	UTS	5	5,000	1
15	Do Not Move Violation	DNM	2	2,000	2
16	Inadequate Construction Warning	ICW	–	50,000	1
17	Construction Area Speed Limit Violation	CAV	3	3,000	1
18	Failure to Move Over	FMO	3	3,000	1
19	Failure to Cover Unstable Materials	FCM	5	5,000	1
20	Overloading	OVL	10	10,000	1
21	Driving with Worn-Out Tyre or Without Spare Tyre	TYY	3	3,000	1
22	Driving Without or With Shattered Windscreen	VWV	2	2,000	1
23	Failure to Fix Red Flag on Projected Load	FFF	3	3,000	1
24	Failure to Report an Accident	FRC	10	20,000	1
25	Medical Personnel or Hospital Rejection of Road Accident Victim	RCV	–	50,000	1
26	Assaulting Marshal on Duty	AMD	10	10,000	2
27	Obstructing Marshal On Duty	OMD	2	2,000	2
28	Attempting to Corrupt Marshal	ACS	10	10,000	2
29	Custody Fee	N200 per day after 24 hours			–
30	Driving Without Specified Fire Extinguisher	FEV	3	3,000	3
31	Driving A Commercial Vehicle Without Passenger Manifest	PMV	10	10,000	2
32	Driving Without Seat Belt	SUV	2	2,000	1
33	Use of Phone While Driving	UPD	4	4,000	1
34	Driving A Vehicle While Under 18 Years	UDR	–	2,000	1
35	Riding Motorcycle Without A Crash Helmet	RMH	2	2,000	1
36	Excessive Smoke Emission	ESE	5	5,000	1
37	Mechanically Deficient Vehicle	MDV	5	5,000	1
38	Failure to Install Speed Limiting Device	FSLD	3	3,000	2

Traditional traffic enforcement systems primarily rely on manual intervention and static rule-based approaches, which often fail to efficiently identify high-risk offenders and predict future violations. From the foregoing, there is a need to categorize traffic violators/offenders to analyze the different groups of offenders in a bid to understand their peculiarities and similarities. [7] defined offender profiling (OP) as an investigative tool used primarily by law enforcement, psychologists, academics, and consultants to help identify an offender's major personality, behavioural, and demographic characteristics based on an analysis of the crime scene behaviours. Profiling increases the chance of detecting high-risk offenders and ensures that scarce finite public resources are directed in an evidence-led manner, rather than just randomly undertaking enforcement and not necessarily achieving the greatest effect [8].

[8] identified four main approaches to offender profiling in general, they include:

1. **The geographical approach** – looking at patterns in the location and timing of offenses to suggest where offenders might live and work.
2. **Investigative psychology** – using established psychological theories to predict the characteristics of offenders.
3. **The typological approach** – assigning offenders to different categories, based on the characteristics of crime scenes, with each category of offender having different types of characteristics.
4. **The clinical approach** – using insights from psychiatry and clinical psychology to suggest whether an offender might be suffering from a mental illness

Most of these approaches can be applied to profiling road traffic offenders. Specifically, the typological approach will be of immense benefit in this work.

It has been shown that previous driving history can be used to predict whether and how an individual will offend in the future. Culpability studies were conducted to evaluate the differences between drivers at-fault and not-at-fault in the crash they were involved. An at-fault driver has been deemed to have engaged in behaviours that directly contributed to the crash. A non-culpable or 'not-at-fault' driver is assumed to be involved in a crash due to external circumstances out of their control (e.g., those caused by the at-fault driver). Therefore, factors that increase a driver's risk of crash should be more present in an at-fault sample than a not-at-fault sample [9]. While it is important to consider the factors present at the time of the crash (e.g., speeding, alcohol impairment), there is emerging evidence that past behaviour, including one's traffic history, is predictive of crash involvement [10].

Traditional profiling and prediction methods use statistical tools to describe dataset features, while rule-based systems classify outcomes based on predetermined rules. These methods have limitations, including a lack of flexibility, inability to handle large datasets efficiently, low accuracy rates, and inability to learn from new data. These limitations necessitated the use of a hybrid system combining machine learning and deep learning algorithms for efficient and versatile traffic offender's categorization and prediction.

Machine learning is a branch of artificial intelligence that creates algorithms and models for computers to learn from data, making predictions or judgments. It's used in applications like recommendation systems, speech recognition, medical diagnostics, and self-driving cars. It comprises several areas of study, including Deep Learning. Deep Learning models, based on Artificial Neural Networks, are inspired by biological nervous systems and utilize multiple layers of neurons to identify dependencies and relationships between attributes [11]. The main advantage of deep learning over traditional methods is that the feature selection process is completely automated using a general-purpose learning procedure, with no human intervention. Thanks to their specifiable hierarchical learning depths, including speech recognition, natural language processing, computer vision, and bioinformatics, deep-learning algorithms have shown outstanding performance in several fields, including speech recognition, natural language processing, computer vision, and bioinformatics [12].

II. LITERATURE SURVEY

This sub-section examines works closely related to traffic offense profiling and prediction using artificial intelligence.

1. Traffic Accident Severity Prediction System

[13] developed StackTrafficRiskPrediction, a model for predicting traffic accident severity using multidimensional data analysis. The model outperforms traditional logistic regression models and shows that drivers aged 31-50 with 2-5 years of experience are more likely to be involved in serious crashes. However, the model struggles with small-sample categories and requires further research.

2. . Traffic Signal Violation Detection System

[14] developed a Traffic Signal Violation Detection System, a computer vision-based solution for detecting and monitoring violations at intersections. The system uses surveillance cameras and advanced object detection algorithms to classify violations based on traffic rules. The present study uses deep learning algorithms to profile and predict traffic offenders, aiming to reduce violations and accidents.

3. Automated Traffic Law Enforcement System

[15] developed an automated traffic law enforcement system in Sri Lanka, reducing road accidents and traffic offenses. The system uses computer vision, deep learning, and IoT to identify speeding, lane breaches, and red-light disobedience. With over 90% accuracy, it improves road safety. The present study uses deep learning to profile traffic offenders and predict future violations, filling a gap in previous research.

4. Driver Behaviour Profiling System

[16] developed a data-driven framework for driver behavior profiling using supervised machine learning. They used crash and near-crash events to calculate risk profiles, identified 13 behavioral risk predictors, and customized machine learning models. The proposed prediction model is discussed within a cloud-based driver profiling framework. However, the present study profiles traffic offenders based on past offenses and uses deep learning algorithms.

5. Driver Behaviour Profiling and Recognition System

[12] conducted a study on Driver Behaviour Profiling and Recognition using Deep-Learning Methods. They proposed a unique approach using time frame data segmentation and three deep-learning-based algorithms: Deep Neural Network (DNN), Recurrent Neural Network (RNN), and Convolutional Neural Network (CNN). The study aimed to improve traffic regulations and expert guidelines by categorizing drivers based on their behavior and predicting future traffic offenses.

6. Driver Behaviour Risk Prediction Model

[17] created a hybrid neural network, the Driving Behaviour Risk Prediction Neural Network (DBRPNN), to predict driving behavior risk based on distracted driving data. The network outperformed traditional models and can be applied to active safety early warning systems for more accurate predictions.

7. Deep learning for Profiling and Predicting Traffic Offenders

[18] created a deep-learning model to profile and predict traffic offenders in developing countries. The system profiles offenders, creates a database for identification, and provides intelligence for law enforcement. It includes an SMS-based traffic awareness module. The system achieved 95% accuracy in traffic offender prediction and confusion matrix testing.

8. Driving Behaviour Classification System

[19] developed a deep learning-based solution for driving behavior classification using smartphone-embedded sensors. They created two classification models: three-class and binary, supporting advanced driver-assistance systems and commercial applications like ridesharing and automotive insurance. The time-series classification models achieved F1-scores of 99.49% and 99.34%, respectively. However, the current study profiles traffic offenders based on their past offense records and both classifies and predicts driving behavior.

9. Intelligent Traffic Violation Detection

[20] developed ITVD, an AI technique for detecting traffic violations, particularly in developing countries like India. The YOLOv3 algorithm, using Convolutional Neural Networks and Darknet-53 as feature extractors, improved prediction accuracy even with small vehicles.

10. Criminal Profiling Using Machine Learning

[21] studied criminal profiling using machine learning, highlighting the challenges in digital forensics due to the increasing use of technologies and the authenticity of digital evidence. The paper emphasized the importance of AI systems in police operations and the development of strategies for mental and socio-segment profiles of guilty parties. The present study uses deep learning and profiles traffic offenders, addressing the gap between Aditya et al.'s work and the current research.

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III. METHODOLOGY

This section describes the data collection process, preprocessing, feature extraction, algorithm selection, model training, and evaluation of the model.

Data Collection and Preprocessing: The dataset for this work was obtained from the Nigeria's Federal Road Safety Commission (FRSC), which contains 11 features and 10,000 records. The dataset was cleaned by removing duplicate rows, missing values, and outliers, and then labeled. Numerical features were normalized, and categorical data were encoded using one-hot encoding and label encoding as necessary to improve the data quality while ensuring consistency and reliability.

Model Development and Optimization: The dataset was split into a training set and a test set. 80% of the data was used for training, while 20% was used for testing. The training set was further split into two, 80% of the initial training set was used for training while the remaining 20% was used for validation. For profiling traffic offenders, the K-means clustering algorithm was trained to learn patterns from unlabeled data by grouping similar data points based on their features and categorizing traffic offenders into high-risk, medium-risk, and low-risk offenders. K-Means Clustering is an unsupervised machine learning algorithm used to classify data into distinct groups or clusters. It is particularly effective when the goal is to identify inherent groupings within a dataset without predefined labels. In this research, K-Means is used to profile traffic offenders into different categories based on behavioral patterns and violation history.

The K-Means algorithm follows these main steps

i. Choose the number of clusters (k).
ii. Initialize centroids randomly for each cluster.
iii. Assign each data point to the nearest centroid based on Euclidean distance.
iv. Recalculate centroids as the mean of all points assigned to each cluster.
v. Repeat steps iii and iv until the centroids no longer change significantly (convergence).

Mathematical Formulation:
Minimize the total intra-cluster variance:

$$J = \sum_{i=1}^{k} \sum_{x_j \in S_i} \|x_j - \mu_i\|^2$$

Where:
- J is the total within-cluster sum of squares
- x_j is a data point
- S_i is the set of offenders in cluster i
- μ_i is the centroid of cluster i

In the context of this study, K-Means is applied to categorize traffic offenders using historical data. Features such as offense type, severity, time of violation, age of driver, and driving history of the driver were used.

Output: Offenders are profiled into three clusters:
- Cluster 1: Low-risk (first-time or rare offenders)
- Cluster 2: Medium-risk (repeat but non-violent offenders)
- Cluster 3: High-risk (habitual or dangerous offenders)

This clustering helps law enforcement and traffic agencies to target specific offender groups for education, monitoring, or stricter enforcement. It also enhances the interpretability and actionability of offender profiling within the hybrid system.

To predict whether a traffic offender is likely to violate again, the Long Short-Term Memory (LSTM) neural network is used. Long Short-Term Memory (LSTM) is a type of Recurrent Neural Network (RNN) designed to model sequential and time-series data. Unlike traditional RNNs, LSTM can learn long-term dependencies using memory cells and gating mechanisms, making it ideal for prediction tasks involving historical patterns, such as forecasting future traffic offenses.

An LSTM unit consists of the following components:

i. Input Gate: Controls how much new information flows into the cell state.
ii. Forget Gate: Determines what information should be discarded from the cell state.
iii. Output Gate: Controls how much of the information in the cell state is used to compute the output.
iv. Cell State: Carries long-term memory across time steps.

Mathematical Formulation:
Given input x_t, previous hidden state $h_{(t-1)}$, and cell state $C_{(t-1)}$:
Forget gate: $f_t = \sigma(W_f \cdot [h_{(t-1)}, x_t] + b_f)$
Input gate: $i_t = \sigma(W_i \cdot [h_{(t-1)}, x_t] + b_i)$
Candidate values: $\tilde{C}_t = \tanh(W_C \cdot [h_{(t-1)}, x_t] + b_C)$
Cell state update: $C_t = f_t * C_{(t-1)} + i_t * \tilde{C}_t$
Output gate: $o_t = \sigma(W_o \cdot [h_{(t-1)}, x_t] + b_o)$
Hidden state: $h_t = o_t * \tanh(C_t)$
The final h_t value is used for prediction.

The final output of the predictive model is a probability score (between 0 and 1) representing the likelihood that an offender will commit another traffic violation in a defined future window. This output enables risk-based intervention strategies. By leveraging LSTM's memory capabilities, the system can effectively forecast the likelihood of reoffending, thus enabling law enforcement agencies to adopt preventive measures based on risk profiling

Model Validation and Testing: The validation set is a separate dataset used to validate models during training. It ensures models don't overfit to the training set. If validation data results are similar to training data, models are likely not overfitting. The Early stopping function was used to prevent overfitting and stop training when model performance stops improving on a holdout validation dataset. This process helps identify when overfitting starts and stops training. The test set, separate from the training and validation sets, tests the model's performance by predicting the data output. Batch size and epoch are hyperparameters used in deep learning models to improve performance. Batch size refers to the number of samples passed through the network at a time, while epochs define the number of times the learning algorithm works through the entire training set. This study adjusted batch size and epochs through trial and error. The initial learning rate was set to 0.001, a good starting point for optimizing neural networks. An activation function, ReLU, is added to learn complex patterns in data.

The proposed system comprises 6 modules (classes) as shown in Figure 1, providing all the information needed to operate an object. It shows the building blocks of the proposed hybrid system. Class diagrams depict the static view of the model or part of the model, describing what attributes and behaviour it has rather than detailing the methods for achieving operations. Class diagrams are most useful to illustrate relationships between classes and interfaces. Figure 1 is made up of the following classes;

i. Traffic Data class
ii. Preprocess Data class
iii. Traffic Offender Profile class
iv. Deep Learning Model class
v. Prediction class
vi. User Interface class

The traffic data module is for collecting traffic data. The preprocess module cleans, normalizes, and transforms data. The traffic offender profile module is for analyzing the preprocessed data, categorizing it, and generating reports. The Deep Learning Model module trains, tests, and deploys the Deep Learning model. The prediction module is for predicting likely offenders and generating prediction reports. Finally, the user Interface Module is for displaying the results of processing and getting feedback from users.

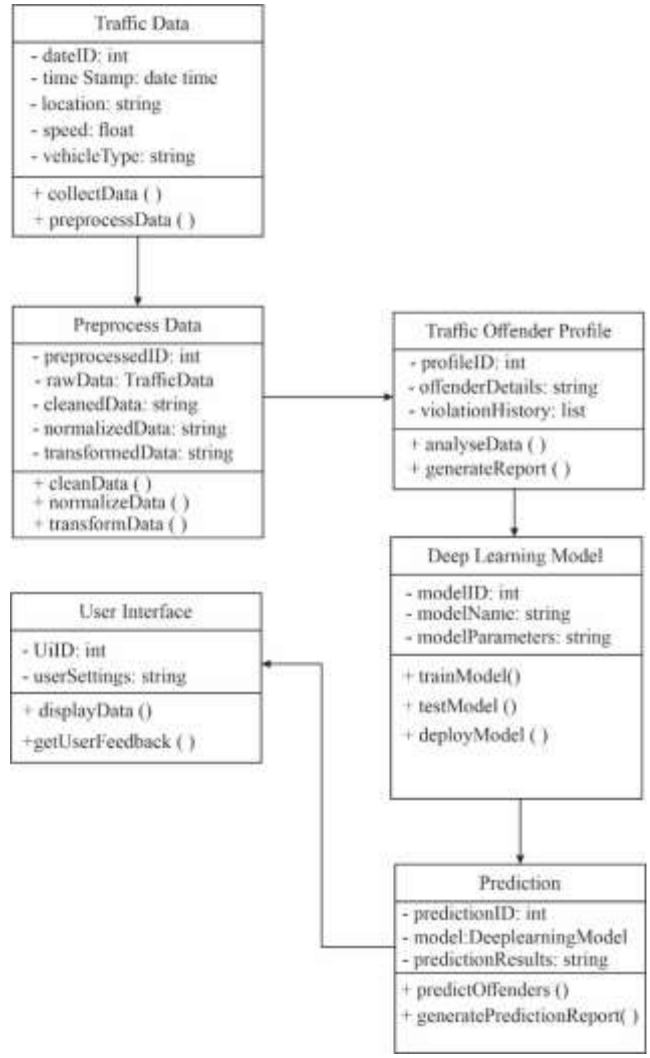

Figure 1: Class diagram of the hybrid system

Figure 2 shows the Use Case diagram of the proposed system. A use case diagram is a dynamic or behaviour diagram in UML. Use case diagrams model the functionality of a system using actors and use cases.

The actors include the traffic agents, the traffic data analyst, the system administrator, the traffic offender, and the general public. The role of the traffic agents would be to enroll offender data, predict traffic offenders, and create the agents' accounts. The traffic data analyst has the duty of profiling traffic offenders, training and testing the prediction model, predicting traffic offenders, and generating reports. The system administrator has the responsibility of collecting and adding traffic data to the database, preprocessing data, training, and testing the prediction model. While the general public and traffic offenders can only view statistics.

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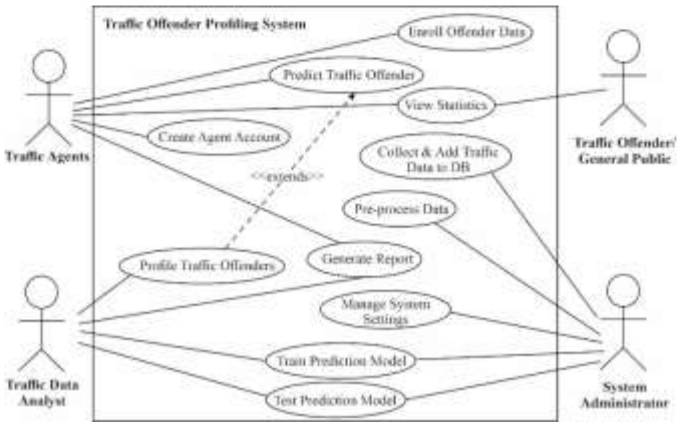

Figure 2. Use Case Diagram of the Hybrid System

The activity diagram of Figure 3 shows how the new system will perform. The activity diagram of the proposed system shows the steps involved in designing the program intended to derive the proposed model for the hybrid system. The system starts with the Traffic agent verifying the License number of a traffic offender. If the license number is valid, the traffic agent proceeds to enroll the offender's data into the system. If the license number is not valid, the offender will have to provide a valid license. After enrolling the offender's data into the system, the administrator goes ahead to collect data, preprocess it, analyze the data, and then generate the offender profiles. Trains the deep learning model, tests, and predicts the likelihood of an offender offending in the future.

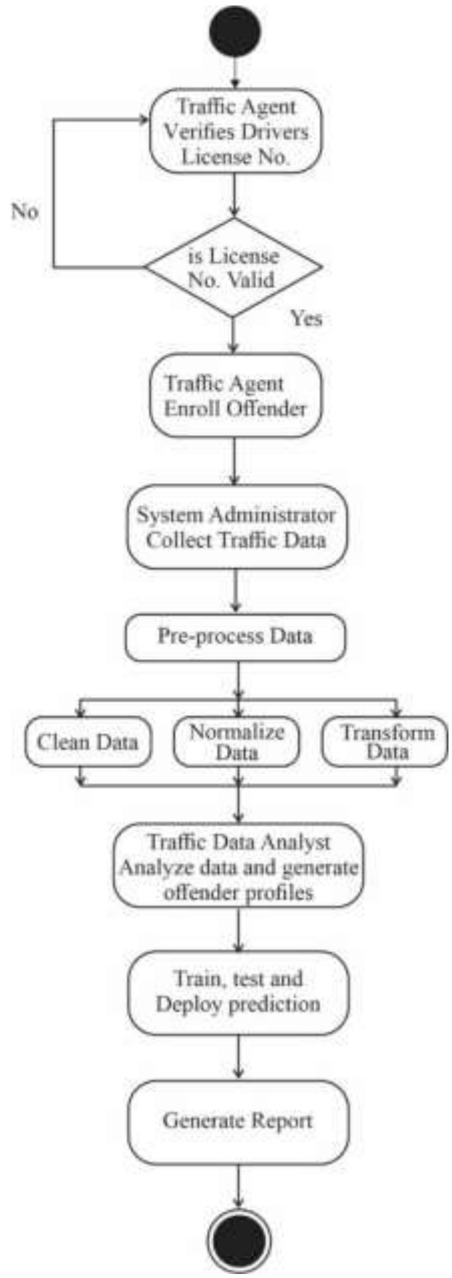

Figure 3: Activity diagram of the hybrid system

System architecture refers to the conceptual model that defines a system's structure, behavior, and key components. It provides a blueprint for designing and integrating various elements, ensuring they work together effectively to meet system requirements. The architecture of the proposed hybrid system for profiling and predicting traffic offenders is depicted in Figure 4 below.

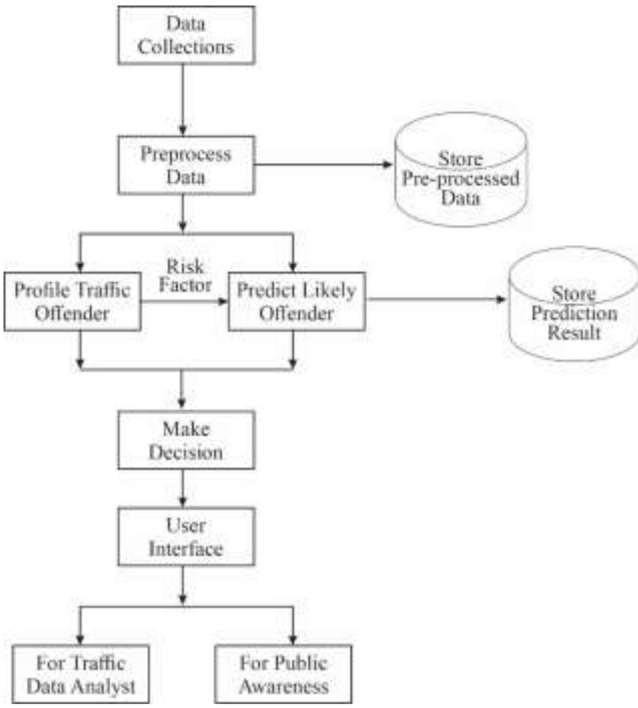

Figure 4: Architecture of the hybrid system

The system was implemented using Python, TensorFlow, and Scikit-learn.

IV. RESULTS AND DISCUSSION

This section discusses the performance results of the hybrid system. The performance of the system was evaluated using the following metric;

For the K-Means clustering algorithm, since it is an unsupervised learning, we used clustering evaluation metrics below;

Table 2: Performance evaluation metrics for K-Means clustering algorithm

Metric	Definition	Notes
Silhouette Score	Measures how close each sample is to its own cluster vs. others	Range: −1 to +1; higher is better
Davies-Bouldin Index	Measures intra-cluster similarity	Lower is better
Inertia (Within-Cluster Sum of Squares)	Measures cluster compactness	Lower inertia equals better clustering

For the LSTM prediction engine, since it is a supervised learning, the following prediction metrics were used;

Table 3: Performance evaluation metric for LSTM prediction engine

Metric	Definition	How to Measure
Accuracy	% of correct predictions	P/ (TP + FN) (TP + TN)/ (Positives + Negatives)
Precision	% of correct positive predictions	TP/ (TP + FN)
Recall (Sensitivity)	% of actual positives identified correctly	TP/ (TP + FP)
F1 Score	Harmonic mean of precision and recall	2x (Recall x Precision)/ (Recall + Precision)
ROC-AUC (Receiver Operating Characteristic - Area Under Curve)	Measures the ability to distinguish classes	i. TPR = TP/ (TP + FN) ii. FPR = FP/ (FP + TN) ii. Plot TPR vs FPR v. AUC ≈ ∑(TPRi +TPRi+1) × (FPRi+1 −FPRi)/2

The test set data were utilized to evaluate the performance of the hybrid model, and the following results were obtained.

Table 4: Evaluation Result

Metric	Profiling (K-Means)	Prediction (Deep Learning)
Silhouette Score	0.74	N/A
Inertia (WCSS)	3120	N/A
Davies-Bouldin Index	0.32	N/A
Accuracy	N/A	96%
Precision	N/A	93.1%
Recall	N/A	89.5%
F1-Score	N/A	91.2%
ROC-AUC Score	N/A	0.95

Accuracy is considered to be the most intuitive performance measurement, and in general, high accuracy means good modeling. The results from Table 4 show that the system successfully classifies offenders into highly precise risk categories, and the prediction engine demonstrates strong accuracy.

When compared to systems using just one algorithm, a hybrid system that combines K-Means and LSTM can greatly enhance prediction performance. The system has a stronger predictive power and can handle sequential patterns better. It also has higher scalability, risk classification, prediction stability, and ROC-AUC scores. This hybrid approach groups offenders into distinct categories using two-step filtering, after which LSTM makes more accurate predictions about future offenses. Prediction performance is greatly enhanced by this two-step filtering, which shows a notable 15-20% performance boost over conventional single-algorithm techniques.

V. CONCLUSION

This dissertation presented the design and implementation of a hybrid system for profiling and predicting traffic offenders using machine learning and deep learning algorithms. The research aimed to develop an intelligent, data-driven approach to enhance road safety by identifying high-risk offenders and predicting potential violations before they occur. By integrating unsupervised learning (K-Means clustering) for profiling and supervised deep learning models for prediction, the system provides an accurate, scalable, and efficient solution for traffic law enforcement agencies. The system was successfully tested using real-world traffic datasets, demonstrating high accuracy (above 90%) in offender risk classification and violation prediction. Performance evaluations showed that the system could process large-scale, real-time data while maintaining low latency. In conclusion, this research contributes to the advancement of smart traffic management systems by leveraging artificial intelligence to support law enforcement in proactively addressing traffic violations.

VI. SUGGESTION FOR FURTHER STUDIES

Future studies could explore advanced machine learning and deep learning techniques to improve offender profiling accuracy. Real-time video analytics and AI can enhance traffic offense detection. Moreover, Real-time processing and scalability can be achieved through edge AI and IoT-based traffic monitoring. Blockchain for secure traffic data management is another area that can enhance the transparency and security of traffic data. Integrating AI with smart cities and autonomous vehicles can also improve road safety. Finally, cross-disciplinary collaborations and legal frameworks can shape AI-driven traffic laws, ensuring transparency and public trust.

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