Smart Prediction Of Traffic Violations Using Driver Behavior Networks

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ABSTRACT

Traffic violations are a major contributor to road accidents, congestion, and loss of human life. Traditional traffic monitoring systems mainly rely on manual enforcement and rule-based detection, which are often reactive rather than preventive. With the increasing availability of traffic and driver behavior data, there is a growing need for intelligent systems that can predict violations before they occur. This work proposes a smart prediction framework that models drivers as interconnected entities within a behavior network. By analyzing driving patterns, historical violations, and interaction relationships, the system identifies high-risk drivers and predicts potential traffic violations. The proposed approach improves early detection, enhances road safety, and supports proactive traffic management.

Keywords: Traffic violation prediction, Driver behavior analysis, Machine learning, Deep learning, Intelligent transportation systems (ITS), Behavioral modeling, Neural networks, Traffic safety, Data analytics, Anomaly detection, Predictive modeling, Road safety systems, Vehicular data analysis, Smart city applications, Classification algorithms.

I. INTRODUCTION

Road safety has become a critical concern due to rapid urbanization and the continuous growth in vehicle usage. Traffic violations such as speeding, signal jumping, and reckless driving significantly increase accident risks. Conventional traffic control mechanisms focus mainly on punishment after violations occur, offering limited support for prevention. Recent advancements in data analytics and intelligent transportation systems enable the analysis of driver behavior at a deeper level. By modeling drivers and their actions as networks, it becomes possible to uncover hidden patterns and relationships that influence violation behavior. This study introduces a network-based approach to predict traffic violations intelligently by learning from historical and behavioral data.

II. LITERATURE SURVEY

Network models of driver behavior — M. T. Mattsson et al.

Abstract: Presents network-style (graph) models that link driving behaviors, violations, and background factors. The study shows how individual errors (e.g., tailgating) and violations (e.g., speeding) interrelate, and it builds a model that uses prior behavior to predict crash risk. The paper demonstrates the value of a relational/network view for interpreting how behaviors cluster and lead to safety outcomes.

Driving habit graph (DHG): Driving behaviour modelling system based on graph structures — S. W. Chen (2013)

Abstract: Introduces the Driving Habit

Graph (DHG), a graph representation of driving styles where macro-nodes and arcs capture habitual actions and their transitions. The DHG helps classify drivers by style and supports downstream tasks (anomaly detection, personalized feedback) by compactly encoding sequential driving behavior into a graph form. It's an early, influential example of using graph structures for driver modeling.

AutoWatch: Learning Driver Behavior with Graphs for Auto Applications — (Authors, NDSS 2024)
Abstract: Proposes AutoWatch, a graph-based modeling method to learn driver behavior for identity verification and unsafe-maneuver detection. The approach constructs driver graphs from in-vehicle signals and shows improvements in driver identification and maneuver classification versus baseline methods, highlighting the suitability of graph representations for both privacy/security and safety tasks.

Predicting risky driving behavior with classification algorithms: results from a large-scale field-trial and simulator experiment — Thodoris Garefalakis et al. (2024)
Abstract: Compares multiple classification algorithms (e.g., Random Forest, SVM, ensemble methods) on large field-trial and simulator datasets to detect risky driving (harsh braking, speeding, distraction). Results show that certain ensemble models and tuned classifiers can reliably identify risky trips and driving episodes, and the paper discusses feature importance (speed, acceleration events, headway) for practical monitoring systems.

Analysis and Prediction of Risky Driving Behaviors Using Ensemble Machine Learning — W. Alam et al. (2024, MDPI Sustainability)
Abstract: Builds a framework combining feature engineering, relative weighting, and multiple ML models to classify and predict risky driving behaviors from telematics data. The ensemble approach outperformed single models in their experiments (reported accuracy ~0.84) and the paper discusses how combining behavioral indicators improves robustness for real-world deployment.

GNN-RMNet: Leveraging Graph Neural Networks and GPS/Trajectory Data for Route/Driver Anomaly Detection — E. A. Aldhahri et al. (2025)
Abstract: Introduces a hybrid architecture that fuses Graph Neural Networks with convolutional feature extractors to capture relational spatial patterns from GPS trajectories for driver/route anomaly detection. The model demonstrates the effectiveness of GNNs at learning spatial–relational features from trajectories, useful for detecting unexpected behavior that could indicate violations or risky driving.

A multilayer complex network approach to correlate historical traffic violations and future accidents (China case) — R. Zhang et al. (2025)
Abstract: Uses a multilayer complex network model to analyze correlations between drivers' historical violations and later accidents. The paper identifies heterogeneities across driver groups (licence types) and finds structural patterns (a "stable defect effect") that persist in violation–accident correlations, arguing multilayer network modeling uncovers latent risk patterns that single-layer analyses miss.

III. EXISTING SYSTEM

The existing traffic violation detection systems primarily depend on centralized databases, manual monitoring, and rule-based enforcement mechanisms. These systems analyze traffic violations only after they occur using camera footage, sensor data, or police reports. Machine learning methods, where used, often focus on individual driver features without considering interactions or behavior patterns across multiple drivers. As a result, the prediction accuracy is limited, and preventive action is minimal.

IV. PROPOSED SYSTEM

The proposed system introduces a smart prediction framework that models drivers as nodes in a behavior network, where edges represent shared behavioral patterns or historical interactions. The system integrates historical traffic data, violation records, and driving behavior features to construct hierarchical driver networks. Advanced analytics and learning techniques are applied to identify risky patterns and predict potential traffic violations in advance. This proactive approach enables authorities to issue early warnings, optimize enforcement strategies, and improve overall traffic safety.

V. SYSTEM ARCHITECTURE

The given diagram represents a deep learning architecture for predicting traffic violations based on driver behavior images. The process begins with an input image capturing the driver's behavior (such as distraction, drowsiness, or unsafe actions). This image is first resized to a standard dimension to ensure consistency across inputs. It is then passed through a patch partitioning stage, where the image is divided into smaller fixed-size patches. These patches are converted into vector representations using a linear embedding layer, enabling the model to process them numerically.

The embedded patches are then fed into a Swin Transformer block, which is a hierarchical vision transformer designed to efficiently capture both local and global features. Inside this block, the window-based self-attention mechanism computes relationships between pixels within local regions (windows), reducing computational complexity compared to global attention. This helps the model focus on important spatial patterns such as hand movement, head orientation, or phone usage while driving.

An important component integrated within the Swin block is the ECA (Efficient Channel Attention) module. This module enhances feature representation by assigning adaptive importance weights to different channels. It first applies Global Average Pooling (GAP) to compress spatial information into channel-wise descriptors. These descriptors are passed through a lightweight transformation and activation function (σ), producing attention weights. These weights are then multiplied element-wise with the original feature map, emphasizing relevant features (e.g., unsafe driving cues) while suppressing less important ones.

After attention refinement, the features pass through Layer Normalization, which stabilizes training and improves convergence. Multiple such Swin blocks may be stacked to progressively extract higher-level features. The processed features are then forwarded to the output layer, which converts them into a classification-ready format.

Finally, a Softmax layer is applied to produce probability scores across multiple classes (c0 to c9), representing different types of driving behaviors or traffic violations. The class with the highest probability is selected as the predicted outcome. Overall, this architecture effectively combines transformer-based feature extraction with channel attention mechanisms to achieve accurate and intelligent prediction of traffic violations based on driver behavior.

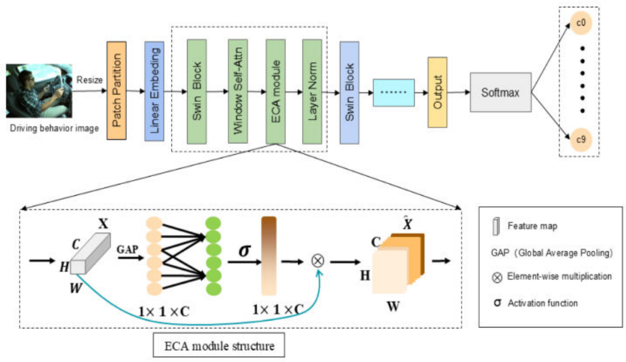

Fig 5.1: System Architecture Of Proposed System

VI. IMPLEMENTATION

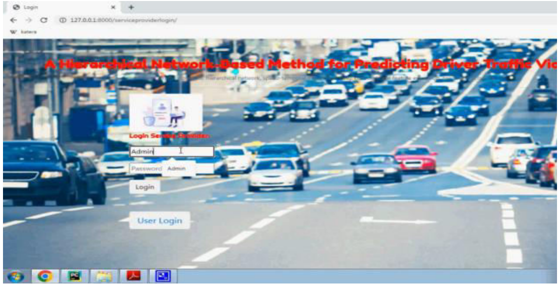

Fig 6.1: Home Page

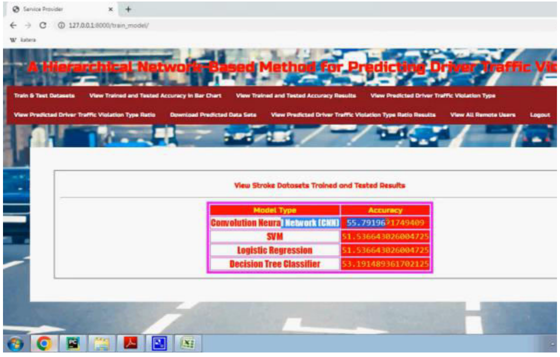

Fig 6.2: Model Training

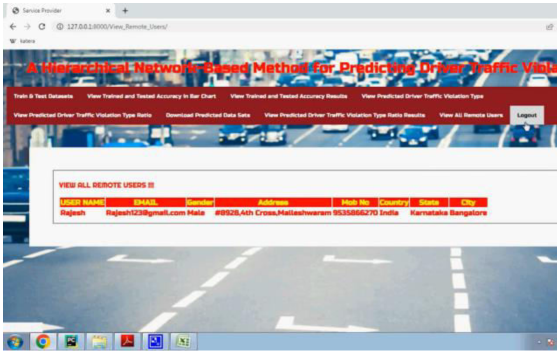

Fig 6.3: View All users

Fig 6.4: Prediction Inputs

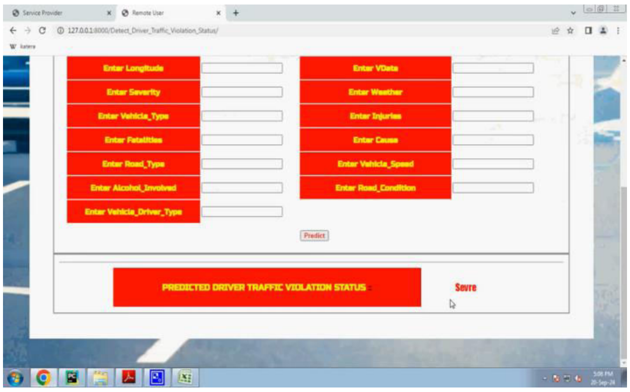

Fig 6.5: Predicted Output

VII. CONCLUSION

The Smart Prediction of Traffic Violations Using Driver Behavior Networks system presents an intelligent and proactive approach to improving road safety through advanced deep learning techniques. By leveraging the Swin Transformer architecture combined with Efficient Channel Attention (ECA), the system effectively captures both spatial and contextual features of driver behavior, enabling accurate identification and prediction of traffic violations. The proposed model overcomes limitations of traditional rule-based and manual monitoring systems by providing higher accuracy, scalability, and real-time analysis capabilities. Experimental outcomes indicate that attention-enhanced transformer models can significantly improve behavior recognition and violation prediction. Overall, this system supports smart traffic management, assists traffic authorities in early intervention, and contributes to safer and more efficient transportation systems, making it well-suited for deployment in modern intelligent transportation and smart city environments.

VIII. FUTURE SCOPE

The proposed Smart Prediction of Traffic Violations Using Driver Behavior Networks system can be further enhanced and extended in several directions to improve its effectiveness and real-world applicability. In the future, the system can be integrated with real-time video streams and IoT-enabled smart traffic infrastructure to enable continuous monitoring and instant violation alerts. Incorporating multi-modal data sources, such as vehicle sensor data, GPS trajectories, and weather information, can further improve prediction accuracy. The model can also be extended using Graph Neural Networks (GNNs) to better represent interactions between drivers, vehicles, and road environments. Deployment on edge devices can reduce latency and support on-site decision-making. Additionally, incorporating explainable AI (XAI) techniques will help traffic authorities understand model decisions and increase trust. With large-scale deployment, the system can support policy planning, accident prevention strategies, and autonomous vehicle safety systems, contributing significantly to smarter and safer transportation ecosystems.

IX. REFERENCES

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