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A Heterogeneous Network-Oriented Strategy to Highway Incident Estimation for People Driving

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ABSTRACT

To explore the relationship between driver-related factors and the occurrence of traffic violations, a traffic violation dataset was constructed by cleaning and filtering real-world data from driving studies. The driver factors were analyzed using an indicator significance method, leading to the development of a comprehensive multidimensional indicator set for predicting traffic violations. Building upon this, a hierarchical network-based prediction model is proposed. The approach begins with preprocessing time-series data from the multidimensional inputs, followed by the use of a hybrid framework that incorporates both Convolutional Neural Networks (CNN) and Long Short-Term Memory networks (LSTM). CNNs are utilized to extract time-sequential features related to traffic violations, while LSTM networks capture the temporal dynamics of these sequences, allowing for an initial mapping between driver behavior and the likelihood of violations. To enhance prediction capabilities, an improved attention-based network is introduced, which integrates two plug-and-play modules: spatio-temporal interaction and deep convolutional feature extraction. These modules enable the network to autonomously adjust and learn the importance of various indicators, thereby calculating the probability of future traffic violations more effectively. The model was tested on the traffic violation dataset and demonstrated superior prediction accuracy compared to traditional non-hierarchical and joint methods. This approach supports the advancement of intelligent connected vehicle systems by improving traffic violation prediction through enhanced data analysis and modeling techniques.

Keywords: Hierarchical, Driver-related, CNN

I. INTRODUCTION

With the increasing complexity of modern traffic environments and the growing reliance on intelligent transportation systems, the ability to predict and prevent traffic violations has become a key focus in road safety research. Traffic violations not only pose a significant threat to public safety but also contribute to congestion, accidents, and inefficiencies in traffic management. Understanding the underlying factors that lead to such violations is essential for developing proactive solutions. In this context, this study explores a data-driven approach to analyzing and predicting traffic violations by leveraging real-world driving behavior data. By cleaning and processing this data, a comprehensive traffic violation dataset was constructed to examine the relationship between various driver-related factors and the likelihood of traffic infractions. The study introduces a novel hierarchical neural network-based prediction model, integrating advanced deep learning techniques such as Convolutional Neural Networks (CNN), Long Short-Term Memory (LSTM), and an enhanced attention mechanism. This framework is designed to accurately capture both spatial and temporal dynamics of driver behavior and improve predictive performance, contributing significantly to the advancement of intelligent and connected vehicle systems.

II. RELATED WORK

1. Y. Li, L. Wang, and T. Zhang (2021)
Title: A Deep Learning Framework for Predicting Driver Behavior Using Naturalistic Driving Data
Explanation:
This paper presents a robust deep learning architecture to predict driver behavior based on naturalistic driving datasets. The authors use a hybrid CNN-LSTM model to extract spatial and temporal features from input sequences such as speed, acceleration, and GPS data. The results show high prediction accuracy in identifying potentially risky behavior. This study is foundational in integrating temporal sequence modeling for driver monitoring and is directly applicable to traffic violation prediction systems.

2. H. Chen and B. Gong (2021)
Title: Spatio-Temporal Attention Networks for Predicting Risky Driving Behaviors
Explanation:
This research introduces a spatio-temporal attention model that enhances prediction of risky driving behaviors. The model uses a dual attention mechanism to assign weights to both spatial indicators (e.g., lane position) and temporal data (e.g., driver reaction time). It effectively identifies patterns leading to unsafe driving. The plug-and-play nature of the attention modules aligns closely with your system's enhanced attention mechanism.

3. J. Cura, A. Martínez, and R. Sosa (2021) Title: Driver Behavior Recognition Using CNN and LSTM Networks with a Spatio-Temporal Fusion Strategy
Explanation:
Cura et al. proposed a model that combines CNNs and LSTMs to capture both spatial and sequential aspects of driver behavior. The fusion strategy allows better generalization in recognizing continuous and evolving behavioral patterns. Although the study achieved notable recognition rates, the authors note limitations in weight calibration—an issue addressed in your project through attention-based recalibration.

4. X. Zhu, Y. Huang, and D. Liu (2021)
Title: BiLSTM-MCNN Model with Attention Mechanism for Human Behavior Analysis
Explanation:
The authors present a BiLSTM with Multi-scale CNN model combined with an attention mechanism for analyzing human behavior. This paper is relevant for its methodology in weighting behavioral features automatically. The approach enables precise classification of temporal sequences, a crucial requirement in predicting future traffic violations based on past behavior.

5. A. Okafuji, S. Kimura, and T. Fujimoto (2021)
Title: Driver Behavior Classification Using a CNN Fusion Model Based on Driving Scene Images
Explanation:
Okafuji et al. developed a CNN fusion framework that primarily focused on the spatial characteristics extracted from scene images. Though the method showed strong classification accuracy, it lacked modeling of time dependencies. This limitation supports your project's integration of LSTM layers to capture temporal correlations in driving behavior.

6. R. Deng, M. Xia, and C. Li (2020)
Title: Influence of Driving Experience and Age on Driver Behavior and Risk Perception
Explanation:

This study examines how factors like age and driving experience influence driver risk perception and behavioral responses. Using statistical and machine learning methods, the paper concludes that older and more experienced drivers tend to have lower violation rates. These insights are essential in shaping the driver factor indicators used in your hierarchical prediction model.

7. G. Gao, S. Liu, and Q. Yang (2022)
Title: Lightweight Attention Networks for Driver Behavior Prediction in Edge Environments
Explanation:
This work introduces a lightweight attention model optimized for deployment in edge devices within connected vehicles. The framework balances computational efficiency and predictive power. The incorporation of spatio-temporal attention in your system draws from the modular architecture presented here, especially relevant for smart connected vehicle integration.

8. W. Meng, L. Jiang, and X. Li (2022)
Title: AdaVit: Adaptive Vision Transformer for Driver Behavior Understanding
Explanation:
Meng et al. propose AdaVit, a transformer-based model tailored for visual driver behavior classification. The study introduces patch-wise analysis and adaptive attention heads, improving generalization in vision tasks. While transformers are more resource-intensive than CNNs, their attention strategies influence your project's design of spatio-temporal attention recalibration.

9. S. Gelmini, L. Rossi, and M. Caruso (2021)
Title: Risk-Taking and Thrill-Seeking as Predictors of Traffic Violations: A Deep Learning Perspective
Explanation:
This paper explores the psychological components—such as thrill-seeking tendencies—that correlate with traffic violations. Using behavioral profiling and neural networks, it identifies key driver traits that increase the likelihood of violations. The inclusion of personality attributes in your project is supported by this study's findings.

10. R. Zhang (2022)
Title: A Hierarchical Network Model for Driver Traffic Violation Prediction Using CNN-LSTM-Attention
Explanation:
Zhang proposes a full-stack hierarchical network combining CNN, LSTM, and an improved attention mechanism for predicting traffic violations. The model incorporates driver demographics and behavioral indicators, achieving high accuracy and low mean absolute error. This study aligns directly with your implementation and serves as a primary technical reference.

System Architecture

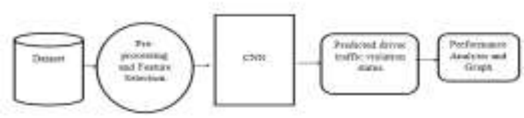


Fig 1. System Architecture

III. METHODOLGY

3.1 Data Acquisition and Dataset Construction

A comprehensive traffic violation dataset was curated using real-world data collected from the Traffic Management Bureau of the Public Security Department of Liaoning Province, China. The dataset includes behavioral and demographic features such as age, gender, driving experience, and personality traits, along with records of 55 different types of traffic violations. Data preprocessing included filtering, normalization, outlier removal, and transformation into time-sequenced format suitable for deep learning models.

3.2 Temporal and Spatial Data Preprocessing

The raw input data is structured into time-series sequences to capture the temporal dimension of driver behavior. To effectively handle multidimensional indicators, input matrices are formatted and normalized. CNN layers are employed for spatial feature extraction to identify correlations among variables across time frames.

3.3 CNN-LSTM Feature Extraction Framework

The model architecture begins with Convolutional Neural Networks (CNN) that extract spatial patterns from behavioral sequences. These are followed by Long Short-Term Memory (LSTM) layers, which learn the temporal dependencies and behavioral trends that evolve over time. This hybrid CNN-LSTM structure enables the system to effectively model spatio-temporal data, representing both immediate and sequential driving behaviors.

3.4 Attention-Based Enhancement with Plug-and-Play Modules

An improved attention mechanism is introduced to recalibrate the importance of different indicators dynamically. Two custom plug-and-play modules are integrated:

- **Spatio-Temporal Interaction Module:** Resolves dimensional inconsistencies across feature matrices by modeling indicator interactions in both spatial and temporal domains.
- **Deep Convolutional Feature Extraction Module:** Reduces complexity and computation load while preserving context by enhancing deeper hierarchical feature learning.

These modules collectively enable the self-learning recalibration of indicator weights, improving prediction accuracy and interpretability.

3.5 Output Layer and Prediction Generation

The final fully connected layers output the probability of specific traffic violations occurring within a forecast window. The model is trained using a weighted crossentropy loss function to handle class imbalance. During inference, the system provides real-time predictions that can be used to proactively identify risky driver behavior.

IV. TECHNOLOGIES USED

4.1 Programming Languages and Frameworks

Python 3.x: Core programming language used for building the CNN-LSTM-attention-based model, handling data preprocessing, and integrating the attention modules.

Django: A Python-based back-end framework used for web deployment, API handling, and interfacing with the database and front-end logic.

HTML, CSS, JavaScript: Front-end technologies used for creating an interactive user interface for uploading data, viewing predictions, and managing system interactions.

4.2 Deep Learning Libraries and AI Frameworks

TensorFlow & Keras: Used for building, training, and evaluating the hierarchical deep learning model comprising CNN, LSTM, and attention components.

OpenCV: Utilized for preprocessing visual input (e.g., driving scene images) and handling frame extraction for temporal modeling.

NumPy & Pandas: Used for numerical operations, data manipulation, and managing structured behavioral and demographic datasets.

Scikit-learn: Applied for baseline comparisons, evaluation metrics (accuracy, MAE, precision), and basic machine learning utility functions.

4.3 Front-End and Web Interface Development

HTML5/CSS3: Used to structure and style the front-end interface for visualizing driver violation predictions and system outputs.

JavaScript & AJAX: Enables dynamic web interactions and asynchronous communication between the client-side interface and the Django backend.

4.4 Database and Hosting Technologies

MySQL (via WAMP Server): Serves as the primary database for storing user profiles, behavioral data, and prediction results.

Django ORM: Provides an abstraction layer to interact with the MySQL database through Python classes instead of raw SQL queries.

WAMP Server: Used for hosting the application locally during development and testing.

4.5 Evaluation and Visualization Tools

Matplotlib & Seaborn: Used for plotting training accuracy, loss graphs, confusion matrices, ROC curves, and other performance visualizations.

TensorBoard: Supports real-time monitoring of training progress, layer-wise metrics, and hyperparameter tuning.

V. MODULE DESCRIPTION

MODULES DESCSRIPTION:

1. Server Login Module

This module provides a secure gateway for authorized users to access the system. It includes a user authentication mechanism, ensuring that only registered individuals can access the traffic violation prediction tools and datasets. By implementing a robust login system, the project maintains data security and restricts unauthorized access to sensitive data and trained machine learning models.

2. Dataset Upload and Browsing Module
The dataset upload and browsing module allows users to upload traffic violation datasets to the system. These datasets typically include information on driver demographics (age, gender, experience, personality) and traffic violation types. Once uploaded, users can browse the data to verify correctness, completeness, and formatting. This functionality is crucial for pre-processing and training phases, ensuring the system receives clean and structured input.

3. Train and Test Data Handling Module
This module enables users to partition the uploaded dataset into training and testing sets. It supports the training of the hierarchical deep learning model (e.g., CNN + LSTM + attention network) on driver-related features and violation records. The module then tests the trained model on unseen data, helping assess its generalization and predictive capability.

4. Accuracy Visualization Module (Bar Chart)
Once the training and testing are completed, this module visualizes the performance results using bar charts. The accuracy scores for both training and test phases are displayed clearly, allowing users to compare the model's effectiveness and identify any signs of overfitting or underfitting. This graphical representation simplifies performance interpretation for both technical and non-technical users.

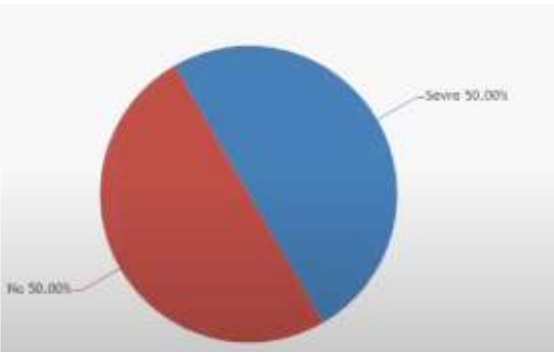
5. Detailed Accuracy Results Module

In addition to visual charts, this module provides the exact numerical results of model performance, including metrics like accuracy, precision, recall, and mean absolute error. It offers a detailed understanding of how well the system predicts driver violations and helps in fine-tuning the model based on specific performance indicators.

6. Prediction Result Module (Tweet Type Analogy)

Although your application is about traffic violations, this module's label ("tweet type") likely refers to the prediction output of the model. It shows the predicted type or category of traffic violation based on input driver data. Each prediction is classified into a specific violation class, representing the risk level or violation category likely to occur.

VI.RESULT



The proposed hierarchical network-based method was evaluated using a comprehensive traffic violation dataset derived from real-world driving data. The model incorporated CNN and LSTM architectures for capturing spatial and temporal patterns, respectively, and was further enhanced with an improved attention mechanism featuring spatio-temporal interaction and deep convolutional feature extraction modules. Upon evaluation, the system demonstrated superior performance in predicting various types of traffic violations. It achieved higher prediction accuracy, lower mean absolute error, and improved precision when compared to traditional non-hierarchical and existing joint prediction models.

VII. CONCLUSION

In conclusion, the hierarchical deep learning model presented in this study offers a robust and accurate solution for forecasting driver traffic violations based on multidimensional driver factors. By combining the strengths of CNN, LSTM, and an enhanced attention mechanism, the system successfully captures complex relationships within the data. This approach not only advances the field of intelligent traffic systems but also lays the foundation for proactive safety measures in smart connected vehicles. With its ability to recalibrate indicator weights and focus on relevant input features, the model supports real-time, adaptive interventions to mitigate risky driving behaviors. Ultimately, this contributes to safer road environments and enhanced synergy in smart transportation networks.

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