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DriveC: Web Application for Classification of Driving Events

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Abstract: - This paper presents a web application designed to analyze and classify driving behaviors using data from gyroscope and accelerometer sensors embedded in smartphones. By harnessing real-time sensor data, the tool accurately calculates driving risk, enabling continuous and comprehensive driver behavior assessment. An advanced Long Short Term Memory neural network model was implemented, chosen for its superior capability to capture temporal dependencies in sequential data and effectively identify complex driving patterns. The model achieved a notable accuracy of 86.36 percent, underscoring its reliability and strong potential for real-time deployment. This innovative approach provides a practical and precise method for driving risk assessment, with significant implications for enhancing safety in the insurance industry and road management systems.

Keywords: Driving rating, Aggressive Driving Detection, Gyroscope and Accelerometer Data.

I. INTRODUCTION

Pricing in vehicle insurance faces significant challenges due to the standardization of rates, which overlook the specific driving behavior of each user. This approach results in an unequal distribution of costs, where responsible drivers end up subsidizing higher-risk individuals, leading to dissatisfaction among policyholders. The absence of personalized rates can lead drivers with impeccable records to pay more than they should, perpetuating market inequity. For instance, in the United States, the average cost of full-coverage auto insurance has reached $2,543, representing a 26% increase from the previous year. This rise, combined with slower wage growth, underscores a mismatch that particularly affects responsible drivers [1], [2].

Research [3] has demonstrated that behaviors such as speeding and driving in heavily trafficked urban areas are correlated with an increased risk of accidents. By employing a Poisson model applied to a monthly data panel encompassing both telematic data from drivers and contextual factors such as weather conditions, it has been possible to analyze the frequency of insurance claims. Nevertheless, applying this model to rare events, such as serious accidents, and its real-time implementation still present significant limitations and challenges [3].

Furthermore, studies on usage-based pricing models, such as "Pay-As-You-Drive" (PAYD) and "Pay-How-You-Drive" (PHYD), have shown the potential of these strategies for offering fairer rates [4]. Building on these approaches, this study proposes a web application that utilizes gyroscope and accelerometer data to analyze driving behavior and provide insurers with a tool for customizing rates based on each driver's actual risk. This solution aims to address the shortcomings of traditional methods by providing more detailed analyses and fair, efficient pricing.

The structure of the document is as follows: Section II reviews related work; Section III outlines the system design, including architecture, methodology, and evaluation; Section IV presents the results obtained; Section V discusses the findings and their significance; Section VI concludes with a summary of findings and recommendations for future research; and Section VII acknowledges the entities and individuals who supported this research.

II. RELATED WORKS

Research [5] compares machine learning classification methods (Logistic Regression, Artificial Neural Networks, Gradient Boosting, and Random Forest) to detect driving behaviors (normal, drowsy, aggressive) using the UAH-DriveSet. Gradient Boosting demonstrated the highest accuracy: 0.60 (normal), 0.67 (aggressive), and 0.62 (drowsy), with F1-Scores of 0.62, 0.72, and 0.69, respectively. Logistic Regression showed accuracies of 0.44, 0.55, and 0.53, with F1-Scores of 0.53 (normal) and 0.05 (aggressive). Random Forest achieved 0.53 (normal), 0.62 (aggressive), and 0.56 (drowsy), with F1-Scores of 0.58 (normal) and 0.31 (aggressive). The performance of Artificial Neural Networks did not exceed 30% accuracy, emphasizing the effectiveness of Gradient Boosting. The

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analysis in [6] reviews the application of deep learning methods to detect aggressive driving behaviors. The authors developed a system that processes sensor data using DNN, RNN, and CNN architectures, achieving an accuracy of 96.1% in aggressive driving classification with CNN. The system incorporates temporal segmentation and normalization of key variables, yielding accuracies of 93.6% (DNN) and 93.1% (RNN). This system is intended for use by insurers and traffic authorities to monitor aggressive behavior. A method for classifying five types of driving behaviors (normal, aggressive, distracted, drowsy, and drunk) is presented in [7], employing vehicle signals converted into images through recurrence plots and analyzed using a CNN. The model achieved 99.98% accuracy with a computational complexity of 0.043 MFLOP, making it suitable for in-vehicle applications with rapid training convergence. In [8], the focus shifts to real-time identification of driving behavior by integrating data from multiple sources, including kinematic data and driver facial expressions. A driving dataset collected over 12 days during a naturalistic test on an online transport platform in Nanjing, China, was utilized. The data included GPS position information and non-intrusively captured driver video. From this data, an S-LSTM model was developed, which identified five types of driving behaviors (lane keeping, acceleration, deceleration, turning, and lane changing) and outperformed ANN and XGBoost models with an average F1 score of 0.877 using a 3.5-second window.

To enhance road safety, [9] combines geographic information and vehicle sensor data to detect risky driving behaviors. The methodology involves image extraction using GIS and GPS to identify specific traffic scenes and data collection through OBD-II and CANbus sensors to capture driver metrics. Techniques such as sparse autoencoders (SAE) and K-means are employed to classify levels of driver aggression. A negative binomial regression associates aggressive behaviors with road infrastructure characteristics. The results show that the model classifies between 80% and 100% of normal and aggressive behaviors, with factors such as inadequate signage and speed limits at intersections being significantly linked to aggressiveness. Proposed infrastructure improvements aim to reduce incidents and enhance safety. An innovative approach for creating driver behavior profiles using dynamic driving data is outlined in [10]. The methodology employs clustering techniques, such as K-means for kinematic data and map matching for GPS data, constructing a "driver profile" represented as a state-transition graph. Results validated with the UAH-DriveSet and Hcilab datasets show a low false discovery rate (6% and 8%) and an average rate of change (RoC) of 20%, suggesting strong representation of driving patterns and moderate stability, with potential for customization in intelligent vehicle systems. Safety profiles using smartphone sensor data are explored in [11], where behaviors such as aggressiveness, distraction, and speeding are analyzed through a two-stage clustering approach. The K-means algorithm, validated using indices such as Dunn and Calinski-Harabasz, categorizes trips into safe, aggressive, risky, and distracted behaviors. In the first stage, aggressive trips are separated from non-aggressive ones (Dunn = 1.36), and in the second stage, sub-behaviors within both groups are identified (Dunn = 1.32 for aggressive and 0.99 for non-aggressive). The findings reveal that 51% of the trips were safe, 23.5% involved speeding, and 7.5% involved distraction.

The Vision-Sensor Fusion Transformer (V-SFT) proposed in [12] is a multimodal fusion method designed to classify driving risk into four categories: safe driving, mild risk, moderate risk, and severe risk. Data from 36 individuals were collected on a simulation platform under urban and suburban scenarios involving distractions. The V-SFT model achieved 92% accuracy in classifying distraction risks, surpassing traditional methods, particularly in detecting mild and severe distractions. This approach supports the development of advanced driver assistance systems (ADAS) and enhances road safety by reducing accidents associated with distracted driving. In [13], risk quantification in vehicle tracking is examined by considering driving style. Potential field theory is employed to assess risk in real-time based on acceleration, speed, and inter-vehicle distance. The Fuzzy C-Means algorithm categorizes risk into four levels: safe, low, medium, and high. LightGBM is used for risk prediction, achieving 86% accuracy in identifying medium and high-risk levels, contributing to real-time warning systems and vehicle safety.

Finally, [14] introduces a system based on fuzzy ontologies for classifying driver behavior into profiles (very passive, passive, normal, aggressive, and dangerous) to improve road safety. Integrating an ontology and a set of driving rules, the system infers decisions in various traffic situations. Experimental evaluation in a simulated environment showed an F1 score of 0.84, outperforming classifiers such as Random Forest (0.69) and Naive Bayes (0.42). Drivers receiving alternative route recommendations experienced an average time gain of 66.4%, demonstrating the system's effectiveness in optimizing traffic flow and enhancing the driving experience. The tools used include a 3D driving simulator, Java, and a genetic algorithm for learning fuzzy rules.

III. System Design

3.1 Architecture

The application comprises two main components: a frontend and a backend. The frontend provides users with an intuitive interface for uploading vehicle data in CSV format, facilitating user interaction. Once the data is submitted, the backend processes it with an LSTM model. Prior to analysis, the data undergoes cleaning and preparation, including the removal of incomplete records and normalization of values to ensure analytical accuracy. The LSTM model then analyzes the time series data to identify patterns and accurately classify driving events. The analysis results are displayed to the user through the frontend and stored in an SQL database for future queries and analysis.

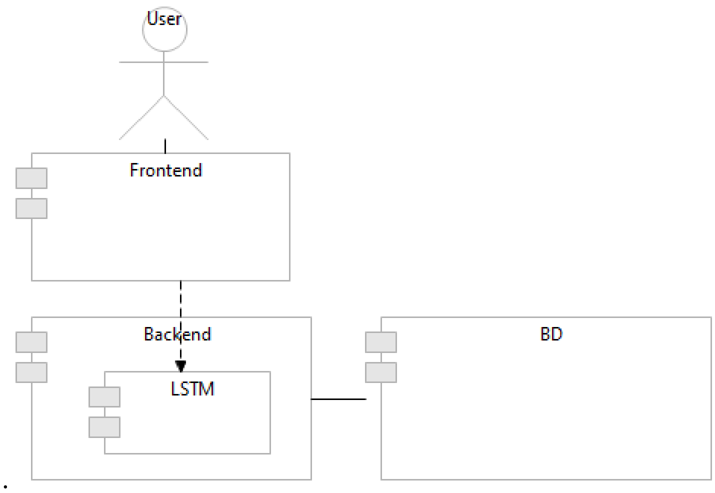

Fig.1. Application Architecture

Fig. 1 presents the structure of the application in four key components:

1. Frontend: An interface where users intuitively upload vehicle data in CSV format, enabling direct and straightforward interaction with the system.
2. Backend: Processes the uploaded CSV files and manages the classification of driving events.
3. LSTM Model: The classifier for driving events.
4. SQL Database: Stores both the original data and the analysis results, facilitating subsequent queries and further analysis.

3.2 Methodology

3.2.1 Dataset

This study employed a dataset published in [15], collected using a Samsung Galaxy S10 Android smartphone installed in a Dacia Sandero 1.4 vehicle, enabling the capture of acceleration and gyroscope data. The collected data includes measurements on the X, Y, and Z axes for both acceleration and rotation, with the aim of classifying driving behavior into three categories: 'slow,' 'normal,' and 'aggressive.' To simplify the classification and emphasize cases of 'aggressive' driving, the 'slow' and 'normal' categories were combined into a single 'safe behavior' category.

The dataset was structured into two main parts: a training set consisting of 3644 records (1331 'slow,' 1200 'normal,' and 1113 'aggressive') and a test set with 3084 records (1273 'slow,' 997 'normal,' and 814 'aggressive'). This structure allowed for an accurate assessment of the model's ability to generalize and maintain performance under diverse conditions.

3.2.2 Model

The proposed model is based on a Long Short-Term Memory (LSTM) neural network architecture, chosen for its ability to capture temporal dependencies in data sequences, a crucial feature for classifying driving behaviors using sensor time series. The architecture comprises two LSTM layers with 64 and 48 units, respectively, followed by a fully connected layer with 64 units and ReLU activation, and an output layer with two neurons and softmax activation for binary classification. Regularization techniques, such as dropout, were applied with rates of 50% in the LSTM layers and 40% in the dense layer to mitigate overfitting and enhance the model's generalization capacity.

3.2.3 Training

The model was trained using the Adam optimizer with a learning rate of 0.001, effectively balancing convergence speed and optimization stability. Batches of size 64 were employed, enabling efficient management of computational resources and frequent model weight updates. To prevent overfitting, an early stopping scheme was implemented based on validation loss, with a patience criterion of 5 epochs. This ensured that training stopped when validation improvement became insignificant, thus optimizing training time and maximizing efficiency.

3.2.4 Evaluation

The model evaluation was conducted using an independent test set, enabling the assessment of the model's performance on unseen data and ensuring its generalizability. Metrics such as accuracy, precision, and recall were used to provide a comprehensive overview of the model's ability to correctly identify aggressive and safe behaviors. The evaluation process was carried out under controlled conditions to ensure result consistency and comparability with other studies in the field.

Table I: Model Performance Metrics

Metric	**Description**	**Formula**
Precision	Measures the proportion of positive predictions that were correct relative to all positive predictions made by the model.	$\frac{TP}{TP + FP}$
Recall	Measures the proportion of actual positive instances that were correctly identified by the model.	$\frac{TP}{TP + FN}$

Table I presents the metrics used to evaluate the model's performance, detailing the formulas and the following abbreviations: TP (True Positives), FP (False Positives), and FN (False Negatives).

IV. Results

The model achieved an accuracy of 86.36%, with precision and recall metrics also at 86.36%, highlighting its robust ability to correctly classify driving behaviors. These results indicate that the LSTM-based approach is effective for detecting aggressive driving behaviors, providing a promising solution for applications in road safety monitoring and accident prevention. The consistency of the metrics demonstrates that the model is reliable and can be a valuable tool for implementing real-time analytics systems.

V. Discussion

The performance of the LSTM model, with an accuracy of 86.36%, highlights its ability to capture temporal dependencies in acceleration and gyroscope data, which is crucial for classifying driving behaviors. This performance is comparable to traditional machine learning methods, such as Gradient Boosting and Random Forest, as discussed in [5]. In that study, Gradient Boosting achieved accuracies of 60% (normal), 67% (aggressive), and 62% (drowsy), with F1-scores of 62%, 72%, and 69%, respectively. Random Forest, on the other hand, achieved a maximum accuracy of 62% when classifying aggressive events, emphasizing that these methods do not excel at capturing temporal dependencies. Conversely, CNNs, as reported in [6], reached 96.1% accuracy in classifying aggressive behaviors but relied on multimodal data, including imagery and additional sensor inputs, which increased the complexity and computational demands. These differences in approach complicate direct comparisons, as the data types and classified events vary significantly.

The study in [8] employed an S-LSTM model to classify complex driving behaviors such as lane keeping, acceleration, and turning, integrating kinematic and visual data and achieving an F1-score of 0.877. While this approach is effective, it targets different behavior classifications than those in our study and relies on multiple data sources, adding to the complexity of implementation. Similarly, studies such as [12], which introduced the Vision-Sensor Fusion Transformer (V-SFT), focus on classifying driving risk into detailed categories like 'safe,' 'mild risk,' and 'serious risk,' using visual and sensor data. Although this approach achieves high accuracy, it does not classify specific driving events as 'aggressive' or 'safe' based solely on accelerometer and gyroscope data. It is essential to consider that the studies reviewed use datasets with different characteristics and objectives. For instance, [9] classifies aggressive driving behaviors and their relationship with road infrastructure using geographic data and vehicle sensors, while [10] and [11] employ clustering techniques to profile driver safety. These differences in methodologies and types of classified events make direct comparisons difficult and should be considered when interpreting the results and applications of each model.

VI. CONCLUSIONS

This study proposed an LSTM model for the classification of driving events, emphasizing its effectiveness in identifying temporal patterns from acceleration and gyroscope data. The choice of a sensor-based approach using accelerometers and gyroscopes achieves an optimal balance between simplicity and performance, ensuring that the model is not only accessible and easy to deploy but also maintains high levels of accuracy and reliability. This quality makes it a valuable tool, particularly for applications that require real-time monitoring and operate in environments with limited computational resources. The model demonstrates that robust performance can be achieved without relying on overly complex or multimodal data-dependent architectures, underscoring its potential for effective integration into practical and sustainable systems.

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