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Driving Behaviors Recognition Using Deep Neural Networks

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Abstract[1]— Road accidents are skyrocketing, and traffic safety is a severe problem around the world. Many road traffic deaths are related to drivers’ unsafe behaviors. In this paper, we propose two different deep-learning models which classify the driver’s actions in a 60-second time frame into two main categories: Normal and Aggressive driving based on GPS data collected at 1 Hz, which is later preprocessed and passed to the proposed models to identify dominant driving behavior in each time frame. The models achieved an accuracy of 93.75 percent in real-world tests, which proves the efficiency of this method in driving behavior recognition.

Keywords—Driving behaviors; deep learning; Global Positioning System (GPS); deep neural networks; time series classification.

INTRODUCTION

Driver behavior recognition has gained increasing interest recently due to the importance of this process in many domains, such as safety and insurance premiums. Driver behaviors are among the main factors in road traffic accidents that can lead to devastating losses on the human and economic levels. According to The Global status report on road safety 2018 [1], launched by WHO, the number of road traffic deaths continues to climb, reaching 1.35 million yearly. Therefore research in this field is very critical nowadays, especially with the large amount of data collected via multiple instruments and sensors. Such data analysis can help develop a method to identify driving behaviors, which can be beneficial in many applications, like adjusting insurance premiums according to real driving patterns rather than flat rates [2], or warning the driver when he behaves aggressively, which can work with other solutions such as collision avoidance systems to prevent road accidents and maximize driving safety [3][4].

We can extract hidden essential features for driving behavior recognition from multi-dimensional time series data [5], such as speed, acceleration, steering angle, trajectory, etc. Our paper suggests two different deep-learning models which classify driver behavior in 60 second time window into two main categories: Normal Driving and Aggressive Driving, based on real-world Global Positioning System (GPS) data.

II. UAH-DRIVERSET DATASET

UAH-DriverSet [6] is a public dataset that provides a large amount of driving data captured by a smartphone monitoring app called DriveSafe [7][8]. The dataset contains about 500 minutes of driving data from six drivers, where the drivers tried to perform three distinct behaviors (normal, aggressive, and drowsy) on both motorway and secondary roads. The resulting dataset offers Raw real-time data (GPS log and accelerometer readings), and semantic information represents an evaluation of different maneuvres and behaviors in each trip.

METHODOLOGY

We have proposed two supervised deep learning models that extract hidden patterns from training data and match them with the labels to identify aggressive behavior in real-world data. Applying deep learning techniques to GPS data to characterize driving styles is motivated by the application of those techniques in speech recognition [9]. We can interpret GPS data as a time series because each data point corresponds with the preceding and next ones. So we have applied Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) to identify driving behaviors.

A. 1 Dimensional Neural Network (1D CNN)

1D CNNs are an alternative version of traditional CNNs that can handle 1D signals like speech data. 1D and 2D CNNs have the same architecture since both consist of CNN (convolutions, activation, subsampling) and MLP layers, but the main differences are the input data and computational complexity. Although 1D CNNs require much less computational power, they perform well in real-time applications that deal with 1D time series signals, such as GPS data [10].

B. Long Short-Term Memory (LSTM)

LSTM is a type of recurrent neural networks that uses memory cells to deal with the vanishing gradients problem. Each LSTM cell consists of four parts: three gates (input, forget, and output) and a memory cell state. The memory state is forgotten and updated by the forget and input gates, while the output gate decides which part of the memory state will be used as output. LSTM neural networks are good at handling time series data like the one we are working with in this paper [11].

DATA PREPROCESSING

A paper published by Talebloo et al. (2021) suggested that we need at least 60 seconds to classify driving behavior accurately. But they needed more time steps (120 and 180) to achieve better results. So we decided to use different preprocessing techniques and features engineering on the 60 seconds time window to improve classification accuracy significantly.

A. Raw GPS data generalization

In this research, we have only used the raw GPS data collected at 1Hz as our training data. This data includes information about the exact coordinates of the vehicle (latitude and longitude), direction, and speed. But dealing with such data was challenging since we needed a method to standardize GPS coordinates while preserving geospatial features of the trajectories to build robust models that perform well without geographical limitations. To do so, we have suggested relating each point of route coordinates to the first point of it using the formula:

Relative Latitude[i]=Latitude[i]-Latitude [0]

Relative Longitude[i]=Longitude[i]-Longitude [0]

B. Data Labeling

The second problem with UAH-DriverSet was labeling the training data into one of two classes (Normal or Aggressive). We could not give each route one label as a whole, Since we have a limited number of variable-length trajectories to simulate each behavior. And the same behavior may differ from one driver to another. Furthermore, simulated behaviors would not be persistent all the time. For example, a driver's behavior can be normal for some time while simulating aggressive behavior. To solve the problem, we have segmented each trajectory into fixed-length segments of 60-time steps (1 minute) with overlapping windows to oversample aggressive behavior [12]. Then we labeled each data segment based on semantic information provided with the dataset, which gives the data real-time and overall scores for various actions (accelerating, braking, turning, weaving, drifting, overspeeding, and car following) and behaviors ratio based on the scores.

C. Normalization

Since there is no definitive answer to which normalization technique will work better, we tried both Min-Max Normalization and Standardization (Z-score normalization) [13]. Through experimentation, we found that Z-score Normalization is the most effective method for our dataset. This is due to the varying ranges and presence of outliers among the features.

D. Training data features

As we mentioned earlier, our models will depend on GPS data only. Therefore we have the following features:

- Speed (m/s)
- Acceleration between two points (m/s2)
- Heading (degrees)
- Heading change (degrees)
- Relative latitude coordinate
- Relative longitude coordinate
- Latitude change (degrees)
- Longitude change (degrees)

DATASET SPLIT AND MODEL CONFIGURATION

After data preprocessing and excluding the D5 driver data to use it as unseen validation data, we had a training dataset consisting of 355 minutes of driving data, 222 minutes of non-aggressive driving (62.5%), and 133 minutes of aggressive driving (37.5%).

TABLE I. DATASET SPLIT

Dataset	Source	Length
Training	DriverSet D1, D2, D3, D4, D6	355 minutes
Validation	DriverSet D5	40 minutes
Test	Real-world data collected by 4 drivers	32 minutes

Furthermore, we have collected real-world test data rather than depending only on the UAH-DriverSet data in the model evaluation process.

A. Real-World test data

In order to collect real-world test data, we have asked four different drivers to simulate aggressive and normal behaviors on the motorway and secondary road while logging GPS data at a 1Hz rate using an open-source free Android application called BasicAirData GPS Logger.

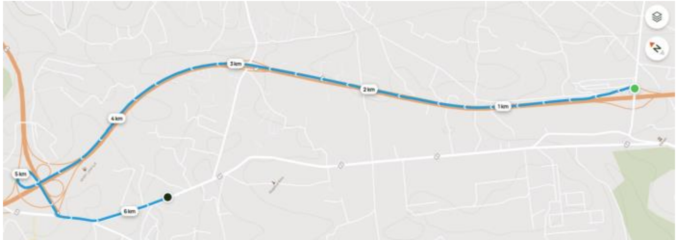

Figure 1: One of the routes in motorway road tests

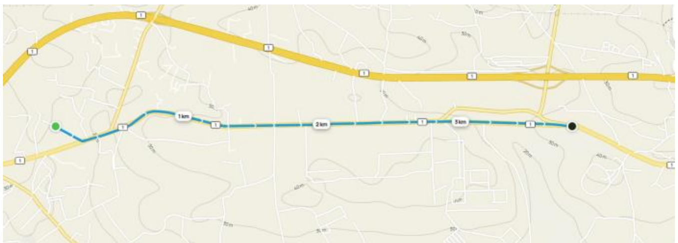

Figure 2: One of the routes in the secondary road test

The GPS Logger app allows users to record and visualize trip data such as position coordinates (latitude and longitude), speed, altitude, direction, and many statistics using the device's GPS receiver [14].

TABLE II. LIST OF DRIVERS AND VEHICLES THAT COLLECTED TEST DATA

Driver	Age range	Vehicle
D1	20-30	Hyundai Accent (2011)
D2	30-40	Kia Rio (2007)
D3	30-40	Hyundai Avanti (2010)
D4	50-60	Hyundai Accent (2011)

B. Deep Learning Models

We have experimented with multiple models and tried different configurations to achieve the best outcomes. And the best models were:

1) 1D-CNN Model: A simple 1D-CNN model consists of 4 layers: 2 Convolution layers (1D convolution, activation function, drop out, and max pooling) followed by 2 fully connected (Dense) layers as shown in the following figure:

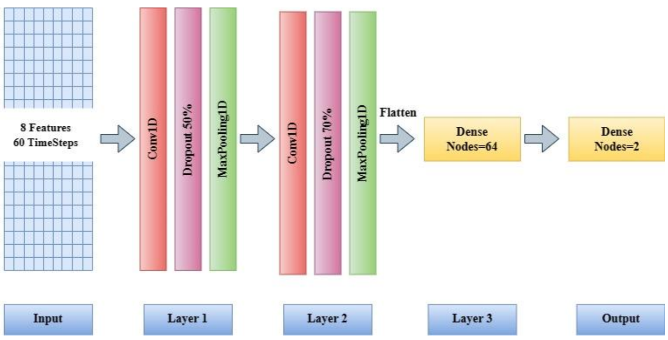

Figure 3: 1D-CNN architecture

2) LSTM Model: One LSTM layer consists of 64 LSTM cells followed by a fully connected layer with a Sigmoid activation function to classify the discovered patterns.

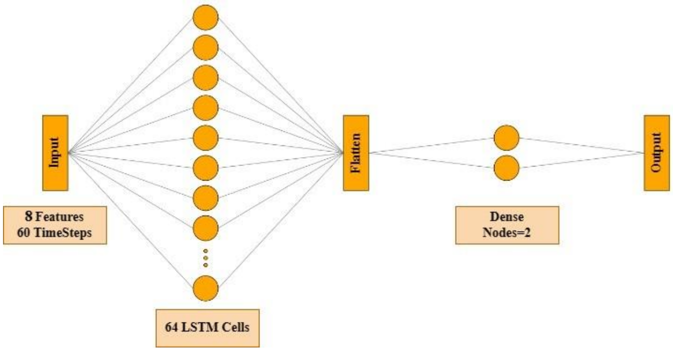

Figure 4: LSTM architecture

RESULTS AND CONCLUSION

We could not depend on accuracy as the only evaluation metric for our models because the training dataset is imbalanced, so in addition to accuracy, we have used the f1-score metric. We had a validation accuracy of 92.5 percent and an f1-score of 92.45 in one minute, which is very good compared to the 84.6 percent accuracy and 71 percent f1-score achieved by Talebloo et al. (2021) in the sixty-second time frame, taking into consideration that we have validated our models using the same unseen data.

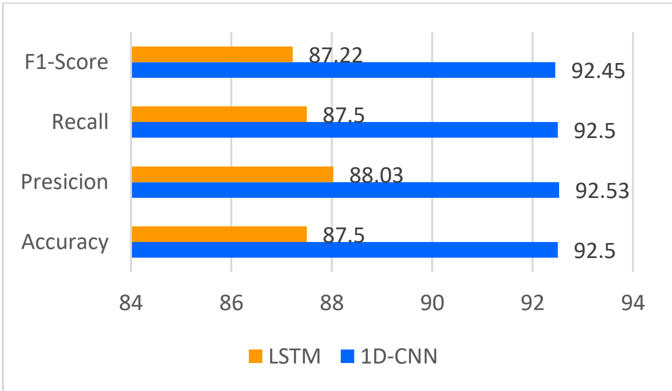

Figure 5: Models evaluation

In real-world tests, our model achieved an accuracy and f1-score of 93.75 percent with 1 minute of driving. Figure 6 shows the confusion matrix of the 1d-CNN model.

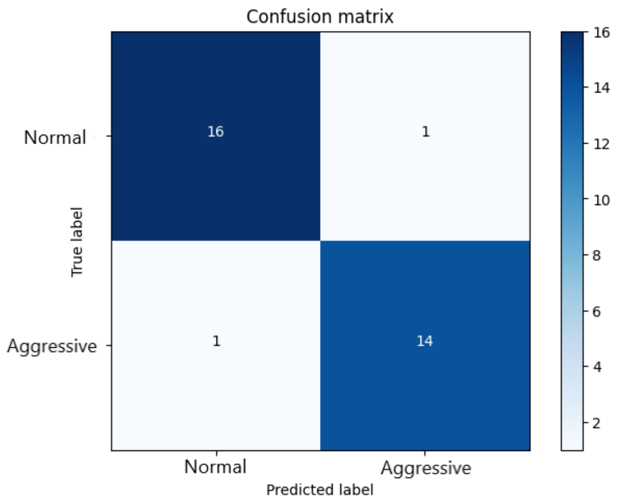

Figure 6: Confusion matrix of the 1D-CNN model

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