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Time Series-based Driving Event Recognition for Two Wheelers

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***Abstract*—Classification of a motorcycle's driving events can provide deep insights to detect issues related to driver safety. In order to perform the above, we developed a hardware system with 3-D accelerometer/gyroscope sensors that can be deployed on a motorcycle. The data obtained from these sensors is used to identify various driving events. We firstly investigated several machine learning (ML) models to classify driving events. However, in this process, we identified that though the overall accuracy of these traditional ML models is decent enough, the class-wise accuracy of these models is poor. Hence, we have developed time-series-based classification algorithms using LSTM and Bi-LSTM to classify various driving events. The experiments conducted have demonstrated that the proposed models have surpassed the state-of-the-art models in the context of driving event recognition with better class-wise accuracies. We have also deployed these models on an edge device (Raspberry Pi) with similar prediction accuracies. The experiments demonstrated that the proposed Bi-LSTM model showed a minimum of 86% accuracy in the case of a Left Turn (LT) event and a maximum of 99% accuracy for the event Stop (ST) in class-wise prediction when implemented on Raspberry Pi for a two wheeler driving dataset.**

***Index Terms*—Driving events, classification, time-series data, LSTM, Machine Learning**

I. Introduction

Transportation has become one of the basic needs of human life. Driving patterns on roads in cities of developing countries are very different from those in cities in developed countries. In India, two wheelers are popularly used [1] for reasons such as 1) best mobility solution for 1 or 2 people, 2) requires less parking space, 3) easy maneuvering through traffic, and 4) low purchase and running cost. With the increasing urbanization, the two wheeler users are increasing in numbers, resulting in a greater risk of accidents. The two-wheeler users are directly exposed and come in direct contact with the impacting vehicle or obstacle during a collision resulting in severe injuries and fatality [2]. Three factors impacting the cause of accidents are human, vehicle and road conditions. Human behavior is something that can be altered and acted upon in terms of accident prevention and mitigation. Therefore, understanding human behavior while driving becomes very crucial.

Firstly, understanding driving behavior becomes vital for the safety of other commuters as it can cause high risk to them on the road. Secondly, the safety point of view of the rider, feedback and driving assistance systems are essential for improving individual driving behavior and creating awareness regarding the impacts of the way they drive. Drivers differ in the way they choose to accelerate and decelerate, and use body weight while taking turns. Unlike four wheelers, identifying the driving patterns of two wheelers is even more difficult due to their highly transient dynamics during operation, which is heavily dependent on riding conditions and rider behaviors. This can help in detecting events that can potentially result in accidents. However, in order to detect an accident scenario, the first step is to recognize driving events, a combination of which could lead to accident scenarios. Therefore our contributions in this space are as follows: 1) Due to the unavailability of two wheeler driving data, we have developed the hardware system and deployed it on the two wheeler. 2) We have collected the driving data using this system to understand the driver's behavior. 3)We have compared various traditional machine learning algorithms using the data acquired. 4) We propose time-series-based DL models for driving event recognition and demonstrate its superiority over traditional machine learning models in terms of accuracy. 5) We deployed the time-series-based DL models on the Raspberry Pi platform and demonstrated their trade-offs between accuracy, memory usage and inference time.

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II. Methodology

In this work, we have implemented the end-to-end framework for recognizing various driving events. The overall problem can be addressed in four phases. Phase 1 comprises of design and development of the hardware followed by data collection. In the 2nd phase, the dataset is labeled and pre-processing is performed before feeding it as input to the model. In this work, the proposed time series-based classification models have been developed and trained in Phase 3. In the 4th phase, the models are optimized and deployed on an edge device Raspberry Pi. The deployed models have been analyzed w.r.t. memory usage and inference time.

A. Hardware setup

The proposed system consists of a microcontroller, ac-accelerometer, gyroscope, GPS module and an SD card module. The sensors are interfaced using an Arduino Nano 33 IoT controller board. The data is collected for various driving events from the hardware system deployed on the two wheeler. The system is placed near the footrest area of the two wheeler.

B. Data collection and pre-processing

The data from the accelerometer and gyroscope sensors are continuously logged in the SD card. Simultaneously, the entire ride is recorded with the help of a camera. Later, by matching the timestamps between the sensor data and the video, the dataset is labeled manually. The dataset consists of 7 features,

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namely Ax, Ay, Az (accelerometer data on the x, y and z-axis), Gx, Gy, Gz (Gyroscope data on the x, y and z-axis) and speed. The sampling rate of the sensors is 104 Hz. We have performed five driving events, such as Left Turn (LT), Right Turn (RT), Straight Line (SL), Speed Bump (SB), and Stop (ST). A pre-processing step is essential to replace the missing values to ensure data continuity and synchronization with the video. The database contains a total of 2,22,857 data points which contain 1,42,138 SL instances, 9729 RT instances, 5937 LT instances, 13163 SB instances and 7316 ST instances. The dataset is divided into training and test set consisting of 80% and 20% of the original data respectively.

C. Proposed DL-based time-series classification Models

As a preliminary part of this work, we implemented various ML models [3]. Though the overall accuracy of these models is decent, the class-wise accuracy (accuracy to classify a specific driving event) is pretty low. Hence, we propose time-series-based classification models to classify various driving events. In this work, firstly, we test the efficiency of the time series-based DL models on driving event recognition, which has not been done earlier for two wheelers. The rationale behind using time series-based DL models is that the driving events have a dependency on the immediate historical data pattern. Therefore, we implement LSTM [4] and Bi-LSTM [5], two widely popular time-series-based DL models. An attention mechanism is used to redistribute the weights of representations that highlight the vital information from the contextual information by setting different weights. Our attention function is straightforward; it takes the dot product of weights and inputs followed by adding bias terms. After that, we add a tanh followed by a softmax layer. For the data set we have collected, the events were better detected with some window sizes as the appropriate amount of information for event detection was present in that window. We have identified that the best window size for detecting all the events in this dataset is 80 for LSTM model. To evaluate the models, we have used the 'accuracy', the most commonly used evaluation metric which is defined as the number of true positives and true negatives divided by the number of true positives, true negatives, false positives, and false negatives.

D. Deployment of Proposed models on Rapspberry Pi

In this work, we have implemented the above proposed time-series classification models to classify various events on Raspberry pi. Before deploying on the Raspberry Pi, the models have been quantized w.r.t. model size. There is a significant reduction in model size in exchange for minimal impact to accuracy. We achieved a more than four times reduction in model size, which ensured a feasible model capable of fast inference on edge devices.

III. Results and Discussion

The overall and class-wise accuracies of the deployed proposed models on Raspberry Pi have been tabulated in Table I. From the table, we can observe that the Bi-LSTM with attention mechanism has the highest accuracy as well as equally distributed class-wise accuracy without having any bias towards a particular class. The LSTM and Bi-LSTM models with attention mechanism have achieved better overall and class-wise accuracies, implicitly showing the importance of attention mechanism and time series-based classification.

TABLE I
COMPARISION OF ACCURACY OF PROPOSED MODELS IN %.

Model	LSTM	LSTM with attention	Bi-LSTM	Bi-LSTM with attention
Overall Accuracy	**95.72**	**96.58**	**97.12**	**98.92**
Straight (SL)	**99.11**	**97.23**	**97.18**	**98.36**
Left Turn (LT)	**90.64**	**86.38**	**86.92**	**96.27**
Right Turn (RT)	**93.22**	**94.56**	**97.19**	**99.99**
Bump (SB)	**74.33**	**88.23**	**88.56**	**91.49**
Stop (ST)	**99.99**	**99.98**	**99.99**	**99.98**

TABLE II
COMPARISION OF ACCURACY, MEMORY USAGE AND INFERENCE TIME FOR THE PROPOSED MODELS AFTER OPTIMIZATION.

Model	Accuracy (%)	Memory required (MB)	Prediction time (sec)
LSTM	95.19	434.96	0.93
LSTM with attention	96.05	583.66	1.68
Bi-LSTM	96.76	448.83	2.3
Bi-LSTM with attention	97.84	648.84	3.36

The Table II, shows the accuracy, memory required and prediction time of the proposed models after optimization. We have calculated the % reduction of accuracy, memory required and prediction time after optimizing. Among the optimized models, Bi-LSTM has the highest accuracy while LSTM has the most diminutive model size and inference time. The % reduction in accuracy, model size and inference time in the case of Bi-LSTM are 0.37%, 43.44% and 54.27% respectively. In the case of Bi-LSTM with attention the % reduction in model size and inference time is 21.73% and 39.67%, respectively, at the cost of 1.09% reduction in accuracy. In the context of driving event recognition, if the edge deployed two wheeler has no power supply constraints, Bi-LSTM with attention can be used though it consumes more RAM but provides the best possible accuracy values for all the classes. However, in two wheelers where power supply is a critical resource (e.g., electric vehicles), models such as LSTM with smaller sizes are preferred with lesser classification accuracy.

IV. Conclusion and Future scope

We proposed time-series-based DL models that mitigate the problems persisting in the machine learning models which shows the importance of adapting time-series-based classification models in the context of driving event recognition. We have also deployed these models on Raspberry Pi to check the performance on an edge device. This work is just the beginning of a more comprehensive vision. In future work, we plan to classify several other critical driving events to facilitate the greater safety of two wheelers.

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