Time-Series based Fall Detection in Two-Wheelers

Sai Usha Goparaju, Keerthi Pothalaraju, Shriya Dullur, Arihant Jain, Deepak Gangadharan
Computer Systems Group, IIIT Hyderabad, India
Email: {ushasai.g, arihant.jain}@research.iiit.ac.in, {keerthi.pothalraju, shriya.dullur}@students.iiit.ac.in, deepak.g@iiit.ac.in

***Abstract*—Driving event recognition plays a crucial role in understanding and enhancing road safety. This research focuses on developing efficient time-series based models for Fall detection in two-wheelers. Traditional machine learning models proved inadequate in accurately classifying Fall scenarios due to their inability to capture temporal transitions in kinematic states. To address this limitation, time-series based Deep Learning (DL) models are proposed, utilizing Long Short-Term Memory (LSTM) networks. These networks enable direct learning from raw time series data, eliminating the need for manual feature engineering. Additionally, Bi-LSTMs were employed to capture contextual information from both past and future timesteps, further improving the model's understanding of driving events. The architecture was enhanced with an attention mechanism to boost accuracy. Experimental results showcased that the proposed Bi-LSTM model achieved an overall accuracy of 97%, with a specific accuracy of approximately 92% in detecting Fall scenarios. This research contributes to the development of an accurate Time-series based system for Fall detection, facilitating improved road safety in the context of two-wheelers.**

***Index Terms*—Driving events, Fall detection, classification, time-series data, LSTM, Deep Learning**

I. Introduction

Transportation plays an indispensable role in our lives, and as advancements continue to shape this sector, certain challenges have emerged. One significant issue faced by developing countries is the higher proportion of two-wheeler accidents. Motorcycles and scooters are widely used as primary modes of transportation in these regions, but unfortunately, they pose a greater risk to riders due to their inherent vulnerability. Unlike enclosed vehicles, two-wheelers lack structural protection, leaving riders significantly more exposed to injuries in the event of a Fall. This vulnerability is reflected in the statistics, as highlighted in a recent report published by the Ministry of Road Transport and Highways. According to the report [1], more than a third (37%) of road accident fatalities in 2019 involved two-wheeler riders. The problem extends beyond developing countries, as motorcycle and moped fatalities account for a considerable proportion (17.7%) of the total number of road accident fatalities in Europe [2]. Comparatively, the likelihood of a motorcycle rider dying in a Fall is 26 times higher than that of a passenger car occupant, considering the distance traveled. These distressing figures clearly indicate that riders are among the most vulnerable road users [3].

Every day as many as 1,40,000 people are injured on roads across the world, of which more than 3000 die and around 15,000 are disabled for life [4]. The implications of such accidents are not limited to the individual riders alone; they also pose a significant risk to the general population. When an accident occurs, the response time to provide medical assistance and minimize harm is crucial. Unfortunately, the inherent risks associated with two-wheelers, coupled with the lack of structural protection, often result in severe injuries or fatalities. This increased reaction time, compounded by the vulnerability of riders, further contributes to the alarming number of deaths on the roads.

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II. Motivation

The frequency of two-wheeler Fall poses a serious threat to road safety, needing a thorough understanding of the underlying causes. Numerous factors, including rider behavior, vehicle attributes, road conditions, weather, and traffic circumstances, have an impact on these collisions [5]. The intricate interactions between human behavior, infrastructure, and environmental elements that cause these incidents can be better understood by thoroughly examining these factors. However, regardless of the specific causes behind the occurrence of Falls, the early detection and timely notification of accidents hold immense potential for saving lives. Therefore, implementing a Fall detection system in two-wheelers is of great importance as a safety precaution.

To the best of our knowledge, there has been very little work on identifying Fall scenarios, specifically in two-wheelers utilizing deep learning techniques. To address this gap, we propose the development of a Time-series based Fall detection system for two-wheelers as an extension of our previous work [6]. By training the system on a comprehensive dataset of two-wheeler Fall scenarios, it will learn to recognize and differentiate between normal riding behavior and instances of Fall. This system will leverage time-series based DL algorithms to detect and classify falls accurately, enabling prompt communication with nearby hospitals or emergency services.

The research holds significant potential to revolutionize two-wheeler safety and emergency response systems. Additionally, with the increasing usage of Electric Vehicles (EVs), the fall detection system can play a crucial role in improving the safety and reliability of electric two-wheelers, thereby promoting their adoption in sustainable transportation. Leveraging deep learning capabilities, the proposed fall detection system offers a proactive approach to mitigate risks for two-wheeler riders. Hence, our contributions in this field can be summarized as follows:

1) Due to the unavailability of two-wheeler Fall data, we have used a simulator to generate various Fall scenarios and collect the data.
2) We have compared various traditional machine learning algorithms using the data acquired.
3) We propose time-series-based DL models for Fall detection and demonstrate their superiority over traditional machine-learning models in terms of accuracy.

III. Related work

Driver behavior is the primary cause of two-wheeler accidents. There have been works on studying driving event recognition in the case of four-wheelers using classical and machine learning approaches. In this context, there are various frameworks [7], [8], [9] that use unsupervised, semi-supervised and supervised models for the multi-class classification of driving maneuvers and also identify the specific types of abnormal driving behaviors from sensor fusion data of four-wheelers. A few works on driving behavior studies for two-wheelers are presented next.

A. Driver behavior studies for two-wheelers

There are some frameworks developed using traditional machine learning models for two-wheelers. Mitrovic proposed a simple system based on accelerometers, gyroscopes, and GPS data to recognize patterns using HMMs [10]. In [11], a machine learning framework was proposed to identify the class of riding patterns using data collected from 3-D accelerometer/gyroscope sensors mounted on motorcycles. Additionally, they also proposed an approach for sensor selection to identify the significant measurements for improved riding pattern recognition. But this work does not capture the kinematic state change of moving vehicles. Hence, to capture those dynamic transitions, we have proposed time-series-based classification models for two-wheelers. In [12], the authors adopted a Machine Learning based movement identification process with an Artificial Neural Network (ANN) algorithm.

There are some studies based on deep learning as well in the context of time-series classification in general. LSTMs are proven to excel in learning, processing and classifying such types of data. Schalk Wilhelm Pienaar [13] proposed an LSTM-RNN Deep Neural Network Architecture for human activity recognition signifying the importance of the usage of RNN for time-series data. A prior work [14] deals with collision and hazard detection for motorcycles. This is usually done by setting absolute thresholds on the accelerometer measurements, which is not intuitive. In [15], they have used to GMMs and KNN to identify fall and near fall scenarios. In [16], the authors have proposed an airbag system using LSTM to decide on the deployment of a wearable bike airbag in case of an accident.

The paper is further organized into the following sections. In Section IV, we discussed the proposed methodology. Section V provides a detailed experimental procedure. Section VI consists of the conclusion and future scope.

IV. Proposed Methodology

The focus of this study is to develop a Fall detection system using time-series based deep learning techniques. Our prior work [6], which involved the development of time-series based models for the analysis and classification of different driving events. In this current study, we extend our research to address the critical scenario of Fall detection. By leveraging deep learning techniques and analyzing time-series data, we intend to create a robust system capable of accurately detecting and identifying Falls. This work represents an important step forward in enhancing the understanding and response to Fall events, thereby saving precious lives.

A. Data Collection

Given the unavailability of a real-world Fall scenario dataset and the challenges associated with collecting real-time data due to safety risks, we employed a simulator called BikeSim [17] to generate diverse Fall scenarios that closely resemble real-world situations. BikeSim is a highly regarded tool for simulating the performance of two and three-wheeled vehicles, offering high accuracy, detail, and efficiency. With over two decades of real-world validation, BikeSim has become the industry standard for analyzing motorcycle dynamics. Therefore, we utilized this simulator in our research to create a range of Fall scenarios.

Our simulations consists of various scenarios commonly encountered during motorcycle rides, including left and right turns, traversing speed bumps, riding straight, swaying and coming to a stop. In the case of Fall scenarios, we specifically simulated situations that are prone to lead to Fall. For instance, taking steep turns at high speeds can result in Fall. To ensure a comprehensive understanding of Fall dynamics, we generated Fall scenarios with varying intensities, such as rolling over and falling.

By utilizing the BikeSim simulator, we were able to accurately replicate real-world riding conditions and generate Fall scenarios that closely resemble actual events as shown in Fig. 1. This approach allowed us to study and analyze the dynamics and patterns associated with different Fall scenarios, providing valuable insights into the factors contributing to Falls and the potential consequences for riders. The simulated Fall provides a controlled environment for investigating Fall detection methodologies and developing effective algorithms that can be used in detecting Falls and ultimately enhance motorcycle safety.

The dataset collected from BikeSim consists of several parameters, including A_x, A_y, A_z(acceleration in the x, y, and z directions), G_x, G_y, G_z (angular velocity around the x, y, and z axes). During our preliminary data analysis, we observed significant variations in these parameters over time specifically in the context of Fall scenarios.

In the case of Fall scenarios, the acceleration parameters (A_x, A_y, A_z) exhibited notable fluctuations that deviated from typical riding patterns. These fluctuations can indicate sudden changes in the vehicle's motion, such as sharp deceleration or unusual lateral movements, which are indicative of a Fall event. Similarly, the angular velocity parameters (G_x, G_y, G_z) captured the rotational movements of the vehicle. The Fig. 2 depicts the variations of various physical parameters such as longitudi-

Fig. 1: Snapshots of various scenarios simulated in Bikesim during simulations.

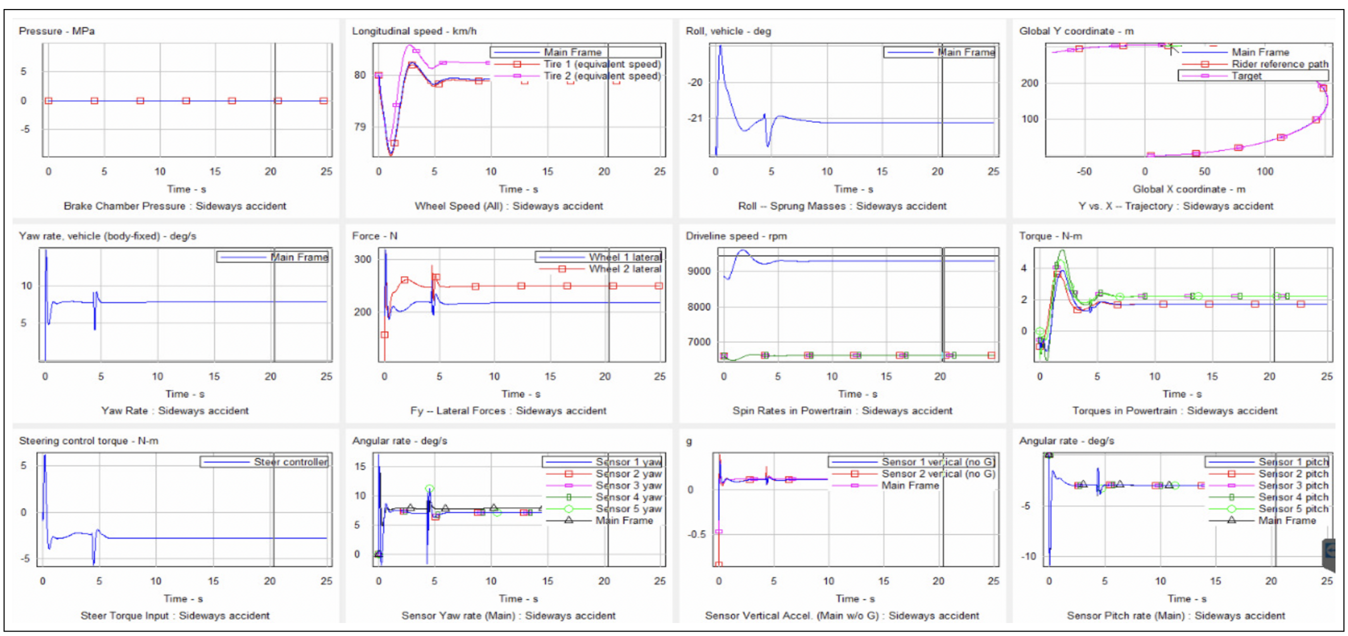

Fig. 2: Graphs depicting the variations of different parameters during a simulation in Bikesim

nal speed, angular velocities (yaw, pitch, roll), Force, vertical acceleration, torque, etc. All these parameters have been captured during the simulation, but only Acceleration and angular velocity values in the x, y, and z directions have been used for training the models. In Fall scenarios, these parameters demonstrated irregular patterns, deviating from the expected smooth and controlled movements observed during regular riding.

B. Classification using traditional machine learning models

We initially employed traditional machine learning models, such as Support Vector Machines (SVM), K-Nearest Neighbors (KNN), and Random Forests (RF) for classification. While these models achieved high overall accuracy, their performance in classifying Fall scenarios was notably poor. The discrepancy arises from the dynamic nature of the vehicle, where kinematic states like acceleration, deceleration, and angular velocity undergo significant changes during driving events such as turns, Fall, and braking. Traditional machine learning models struggle to effectively capture these transitional patterns.

In contrast, neural network models exhibit the ability to learn complex temporal relationships, making them well-suited for capturing the dynamic changes in kinematic states during driving events. By training these models on the time-series data collected from the vehicle, they can effectively detect and classify different driving events, including Fall scenarios. The inclusion of temporal information enables the models to capture nuanced variations in the data, enhancing their accuracy in identifying Fall events.

C. Proposed DL-based time-series classification Models

To address the above limitation, we propose time-series based classification models that are capable of capturing and understanding the temporal transitions in kinematic states. By leveraging neural network models, we can train classifiers that have the capacity to capture and learn these intricate transitions. Time-series-based models offer the advantage of considering the sequential nature of the data, enabling them to recognize patterns and dependencies over time that eventually lead to Fall.

1) LSTM

In addition to the rationale mentioned earlier, the reason for choosing LSTM [18] to perform driving event classification is its ability to learn from the raw time series data directly thereby eliminating the need to manually engineer input features. LSTM is an efficient recurrent neural network that can hold information from the time series data for a longer duration of time. It can be used to model sequential data and is hence used to learn complex human behavior while riding two-wheelers.

2) Bi-LSTM

Bidirectional LSTMs are an extension of traditional LSTMs that can improve model performance on sequence classification problems. The input sequence given to the network consists of the six features (A_x, A_y, A_z, G_x, G_y, G_z) of the dataset. In problems where all timesteps of the input sequence are available, Bidirectional LSTMs train two instead of one LSTM's on the input sequence [19]. The first LSTM traverses on the input sequence in the given order, whereas the second one on the reversed copy of the input sequence. This can provide additional context of the driving event to the network and result in faster and even fuller learning on the problem.

D. Attention mechanism

The attention mechanism [20] emerged innately from problems that deal with time-varying data (sequences). The main objective of the attention mechanism is to filter the critical representations out for the purpose of recognition. An attention mechanism is used to redistribute the weights of representations. It can 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. In time-series problems, all sequence elements generally contribute equally to the result, but this may not be the case. For example, a sudden change in acceleration along one direction could better indicate a particular driving event. Hence, capturing those features contributing to recognizing a particular event is critical. Hence, we have enhanced the LSTM and Bi-LSTM models by focusing on specific features that have more impact in recognizing a particular event by embedding an attention layer.

1) LSTM with attention mechanism

LSTM cells can't understand long terms dependencies from arbitrary lengths. Therefore, their performance degrades as the sequence length increases. As the name suggests, attention furnishes a mechanism where output can *attend to* a particular input time step for an input sequence of arbitrary length. Hence, an attention layer is embedded on the LSTM layer. The simple LSTM model cannot capture these critical features.

2) Bi-LSTM with attention mechanism

An attention mechanism focuses on the information fed out from the hidden layers of Bi-LSTM. The simple Bi-LSTM structure allows the networks to have both backward and forward information about the sequence at every time step. In this work, we have added an attention layer over the Bi-LSTM layer for enhanced feature extraction. The output of the attention layer is given to the dense layers.

V. Experimental results and discussions

A. Experimental setup

The aim of this work is to develop a system and efficient DL models that outperform existing approaches in driving event classification. The training was conducted on a MacBook Air M1, which features an Apple M1 chip with an 8-core CPU and 8-core GPU. We have used Jupyter notebook to perform the experiments. The framework used in our work to build various models is TensorFlow-Keras. In order to evaluate the models, we have used the 'accuracy', the most commonly used evaluation metric as denoted in Eq. (1).

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{1}$$

where true positives (TP) and true negatives (TN) denote the correct classifications of positive and negative examples, respectively. False positives (FP) represent the incorrect classification of negative examples into the positive class, and false negatives (FN) are positive examples incorrectly classified into the negative class.

B. Data pre-processing

A pre-processing step is essential to replace the missing values to ensure the continuity of data and synchronization with the video. The database comprises approximately 25,000 data points, consisting of various driving events such as left turns, right turns, straight rides, and stops categorized as 'Normal'.

Model	Overall accuracy	Normal	Fall
SVM	0.904	1.00	0.243
RF	0.934	0.93	0.765
LSTM	0.941	0.973	0.807
LSTM-attn	0.969	0.981	0.846
Bi-LSTM	0.968	0.943	0.884
Bi-LSTM-attn	**0.976**	**0.962**	**0.923**

TABLE I: Comparison of accuracies of the proposed models.

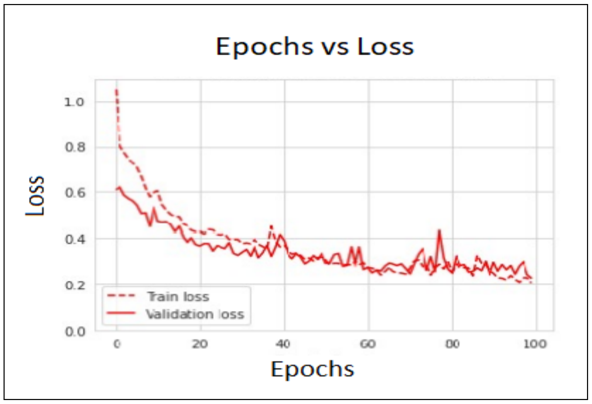

Fig. 3: Epochs vs Loss

Additionally, it consists of critical scenarios like 'Fall'. The dataset is divided into training and test set consisting of 80% and 20% of the original data, respectively.

C. Results

The obtained results are presented in Table I, showcasing the overall and class-wise accuracies of the proposed models. The table reveals that the Bi-LSTM model with an attention mechanism exhibits the highest accuracy, particularly in Fall detection. Both the LSTM and Bi-LSTM models with attention mechanisms demonstrate higher overall and class-wise accuracies compared to other models. This highlights the importance of attention mechanisms and their ability to capture relevant patterns and features within the temporal data. Although the Bi-LSTM model has slightly lower overall accuracy than the LSTM model with attention, it exhibits superior performance in detecting Fall scenarios. This indicates its sensitivity towards Fall-specific patterns. On the other hand, the LSTM model with attention, while achieving decent overall accuracy, does not perform as well in detecting Fall scenarios. This indicates limitations in capturing the distinctive features or patterns associated with Falls.

The variation of accuracy and loss over the number of epochs for the training and validation dataset for the LSTM model is demonstrated by Fig. 3. Initially, the validation accuracy increases then slows down. After 80 epochs, the accuracy and loss values become stable. At 100 epochs, the model has converged.

VI. Concluding Remarks and Future scope

In this work, we have addressed the challenge of critical driving event classification, with a specific focus on Fall detection. We have simulated various critical scenarios using a simulator. The proposed time-series-based models exhibited superior accuracy in detecting fall scenarios compared to traditional machine learning models, highlighting the significance of considering temporal factors in classification. The proposed models, particularly the Bi-LSTM with attention mechanism, demonstrated superior performance in detecting Fall scenarios, highlighting the importance of attention mechanisms and time-series-based classification. Implementing this fall detection system can potentially reduce response time for medical help, ultimately decreasing fatalities. There are several avenues for further exploration and enhancement of this work. The performance of the proposed models can be evaluated on larger and more diverse datasets, including real-world driving data, to validate their effectiveness in practical scenarios. In addition to the proposed fall detection system, there is potential for further advancements in developing models for fall prediction to predict potential fall events before they occur and alarm the rider.

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