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Improving Driver Style Detection Using Cnn And Bidirectional Lstm

[1]Rajana Naresh, Student in Dept. Of Master of Computer Applications, at Miracle Educational Society Group of Institutions
[2]Mrs. P. Sridevi, Assistant Professor at Miracle Educational Society Group of Institutions
[3]Pottam Mukesh, Assistant Professor at Miracle Educational Society Group of Institutions

ABSTRACT
The need for efficient and effective classification of drivers has arisen due to the growing usage of autonomous vehicles and enhanced telematics systems. A CNN-LSTM hybrid model is proposed in this paper to assess how drivers' operational time series data can be clustered into driving behaviors of normal, aggressive, or conservative within the context of time series. CNN encodes important information in the dataset while LSTM modules identify trends in longitudinal datasets. The extension of the model with Bidirectional LSTM (BI-LSTM) is also explained in the work to warrant further improvements in performance. The model is trained and tested on the Driver Style Classification dataset obtained from Kaggle. Many trials have been conducted and results have shown that the CNN-LSTM model has an accuracy of 99.03% while the accuracy of the implanted CNN-LSTM-BI-LSTM model is 99.58%. This research proposes a satisfying solution to the problem of driving styles' classification with its possible implement in self-driving cars or in driver's security systems.

Keywords: LSTM, BI-LSTM, CNN

INTRODUCTION:

This essay highlights the increasing role of individualized operation for control and drive assistance in any Advanced Driver Assistance System (ADAS). While ADAS have contributed much to the improvement of the safety and comfort of driving, the problem of the ability of the ADAS to deal with different driving patterns is always a concern. Customizing ADAS to suit an individuals' style of driving would be of great importance in increasing the level of both safety and user experience in the vehicle. However, common driving style recognition approaches such as questionnaires and visual recognition techniques are often subjective and time consuming and also affected by external factors like illumination. This project advances STAPI which aims to change driving style recognition approach by using vehicle driving signals. This method does not raise privacy issues and at the same time do not have external environmental restraints but rather present a strong non-visual means. With studies of both classic and recent research methods, the project aims to support the development of new intelligent vehicles with increased safety and adaptive driving technologies in the future.

GAP IDENTIFIED BASED ON LITERATURE SURVEY:

Drivers and user studies involving group classifications of different types of driver behavior rely a lot on question or image based models which is an unsatisfactory resolution and is too environmental dependant. On the other hand, while machine learning models improved predictive capabilities, implementation of those is still lacking resilience when coping with data that has a time dimension.

Key Gaps

1. Limits Imposed by the Environment: Consumable and occupant based techniques are largely dependent on the external telematics and illumination making them less dependable overall.
2. The incorporation of time into the data: Time series data is one of the weakest points of machine learning models because they are poor at dealing with sequential dependencies.
3. Suppressed feature extraction: Older techniques tried too but they could not extract the key features which would help improve the model.
4. Absence of hybrid model: There are only a few papers that have employed both convolutional and recurrent layers for the analysis of driving behavior.
5. Comparative Analysis: Previously conducted research has not been able to provide adequate comparisons of their results against the very best techniques available.

PROBLEM STATEMENT:

Classifying driving styles accurately is vital for fostering the deployment of new technologies relating to autonomous vehicles as well as enhancing road safety. It has been stated that the available models do not make these approaches use spatial and temporal data efficiently which leads to poor output models.

Key Challenges

1. **Temporal Analysis:** A suitable solution to the problem of time series data classification of most complex driver behavior.

2. **Feature Extraction:** All significant patterns in the complex data have to be located and extracted.

3. Model Performance: The models should be able to operate with multiple real world data sets.

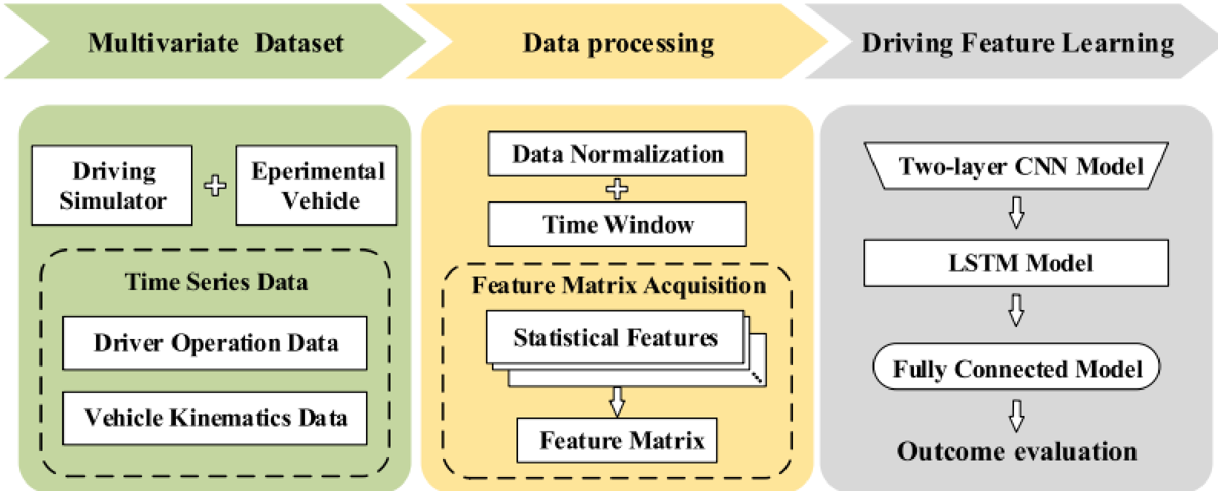
4. Robustness: Building models that would be able to analyze massive and ever-changing data sets.

5. Fidelity: Predicting driving behavior accurately but with a lower chance of false predictions.

PROPOSED METHOD:

This project proposes a hybrid CNN-LSTM model for driving style classification. CNN layers extract meaningful features from the dataset, and LSTM layers analyze temporal patterns, enabling robust classification. The model is trained on the Driver Style Classification dataset from Kaggle, with classes labeled as Normal, Aggressive, and Conservative. Data preprocessing includes normalization and label encoding. Performance is benchmarked against standalone CNN models, demonstrating the superiority of the CNN-LSTM approach. As an extension, a Bidirectional LSTM (BI-LSTM) is integrated to further enhance temporal data analysis. This extension achieves improved accuracy, highlighting the model's scalability and applicability in autonomous driving systems.

ARCHITECTURE:



DATASET:

In this project we consider the use of CNN-LSTM architecture as a neural network that takes the best of both 3D convolutional NTM for the spatio-temporal features and long short term memory for the temporal features. The intention is to classify driving behaviors such as normal, aggressive and conservative within an across driver systems of temporal frames. This was shown to be efficient with previous works which used LSTM as a classifier for ECG signals and for autonomous vehicles. The backbone of the architecture is integrated within the driver databases as well as the driver systems available on Kaggle.

METHODOLOGY:

This section covers dataset exploration, preprocessing, analysis, and feature identification for the classification problem.

First, the data for the model is uniform by normalizing it.

Third, with a Label Encoding technique any non-numeric class labels are converted to numeric values.

Data was split into two parts; an eighty percent part was designated to training and twenty percent for testing as noted at the start.

The data was then shuffled to mitigate any form of bias that may have cropped in during collection or from the model under construction.

Two convolutional layers are used for feature extraction in the standalone CNN model.

This model is tested in terms of accuracy, and confusion matrices.

This section describes the LSTM Model and how it will be implemented starting with the architecture, the combination of the LSTM network and CNN.

Component: CNN Layers. The convolutional neural network is second to the feed-forward one.

Component: LSTM Layer. Where information derived from temporal dependencies present within LSTM's time-series are analyzed.

The accuracy of the model, as well as various error measurements were obtained after training it on a pre-cleaned dataset.

After constructing the CNN-LSTM model, the ability of a Bidirectional LSTM to add future predictions to past predictions was explored.

This enables the model to gain better accuracy since temporal patterns that it can observe are both forwards and backwards.

This incorporates another bidirectional LSTM layer that respects the LSTM model.

The performance of the model is assessed using Categorical Cross Entropy as the loss function and the adam optimizer to speed up convergence.

The model optimization involves adjusting hyperparameters including optimial batch size and learning rate for training better results.

Models:

All models constructed were verified against, accuracy, precision, recall and confusion matrices (baseline, Bi-LSTM, LSTM).

Make sure to stress how the models utilizing hybridization and extrapolation did achieve some improvements.

Visualisation and Insights

For some of the predictions, provide visualization, such as using graphs to show accuracy performance, using bar graphs and confusion matrices.

Let It Be Known That the Accuracy Reached by CBC is the Highest of its Kind at 99.58 Percent.

Scalability and Deployment

Verify the ability of the model to scale to wider datasets and confirm that the model is suitable for real world analysis of how a driver behaves.

Make sure that the system can accommodate all forms of integration aimed at supporting autonomous vehicle.

EVALUATION:

Precision:

Formula: $\text{Precision} = \frac{\text{True Positives}}{\text{True Positives} + \text{False Positives}}$

Recall (Sensitivity):

Formula: $\text{Recall} = \frac{\text{True Positives}}{\text{True Positives} + \text{False Negatives}}$

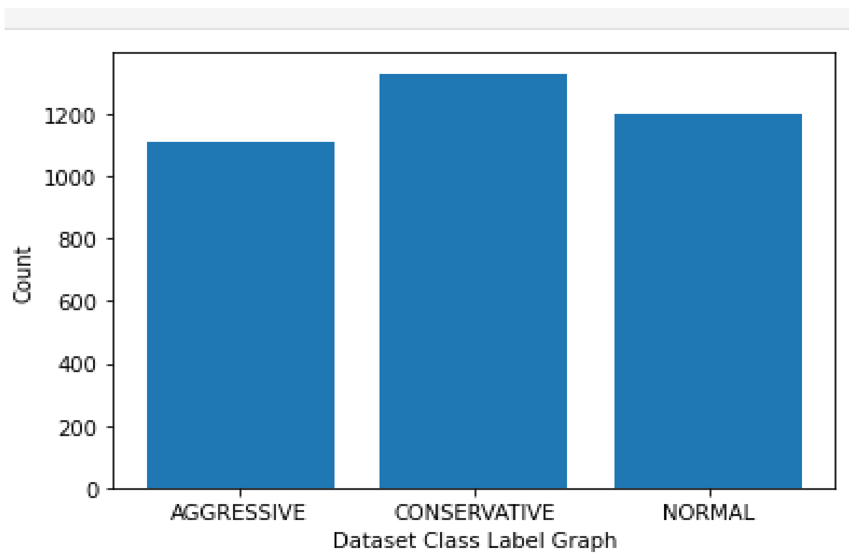
F1 Score:

Formula: $F1 = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$

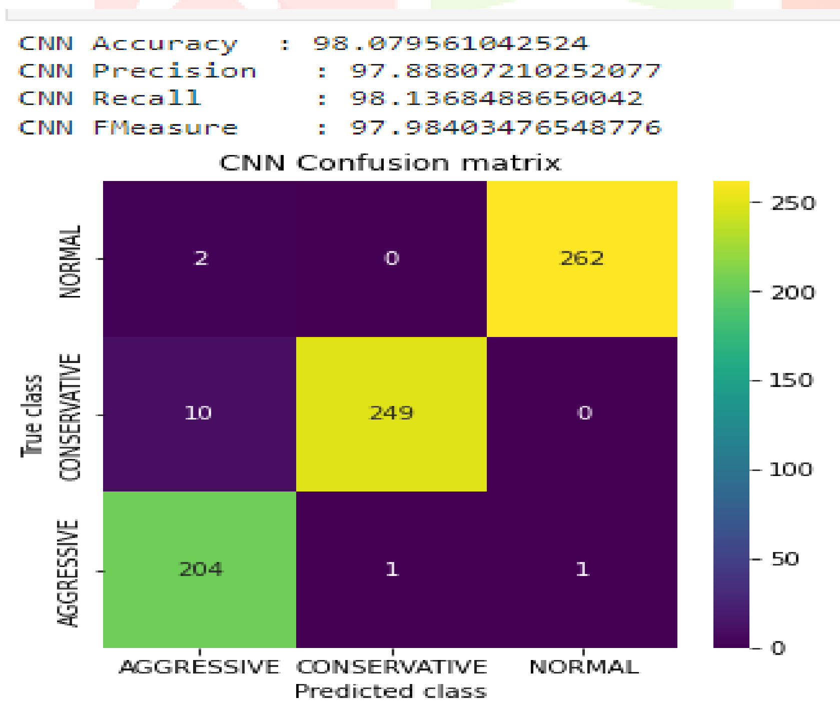
Accuracy:

Formula: $\text{Accuracy} = \frac{\text{Correct Predictions}}{\text{Total Predictions}}$

RESULTS:

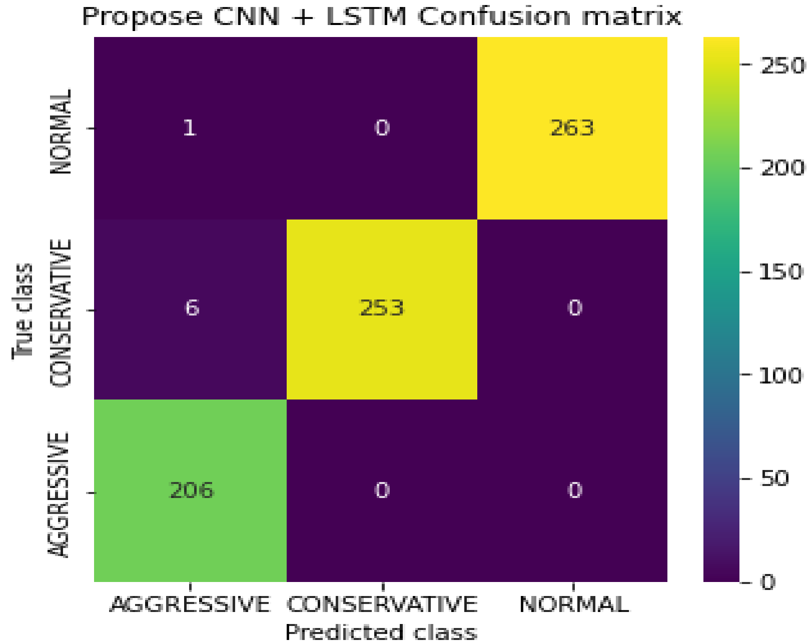


In above screen we are finding and plotting graph of various class labels found in dataset



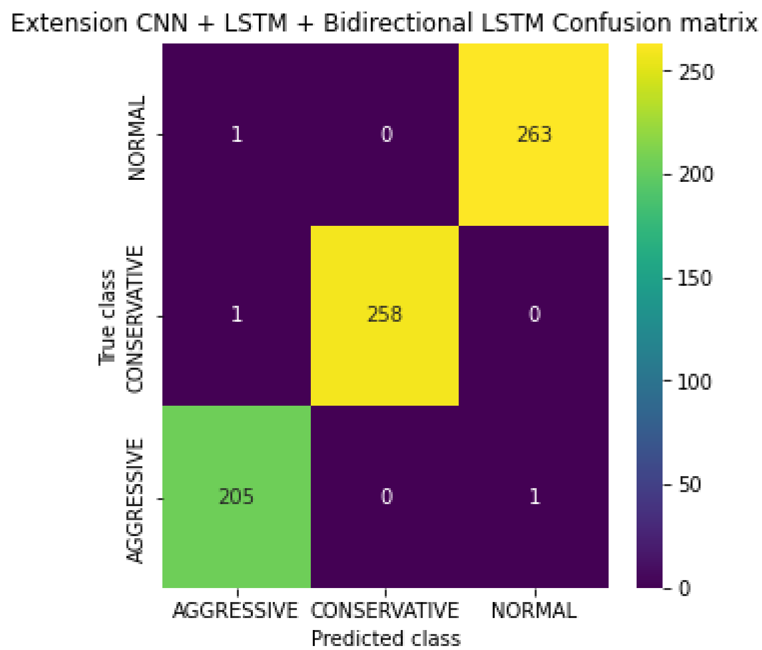
CNN got 98% accuracy

```
Propose CNN + LSTM Accuracy   : 99.039780521262
Propose CNN + LSTM Precision   : 98.90453834115806
Propose CNN + LSTM Recall      : 99.1015366015366
Propose CNN + LSTM FMeasure    : 98.98924242930292
```

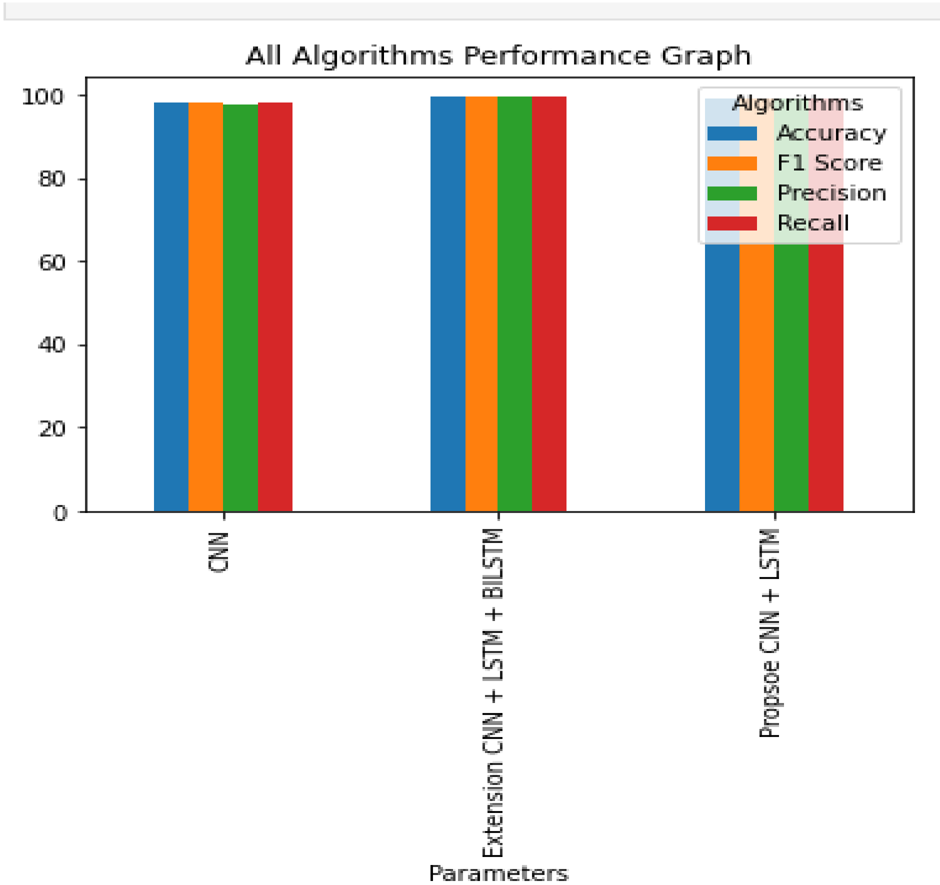


CNN +LSTM got 99.03% accuracy

```
Extension CNN + LSTM + Bidirectional LSTM Accuracy  : 99.58847736625515
Extension CNN + LSTM + Bidirectional LSTM Precision   : 99.55167618211095
Extension CNN + LSTM + Bidirectional LSTM Recall      : 99.58322494730261
Extension CNN + LSTM + Bidirectional LSTM FMeasure    : 99.5671320905724
```



Extension algorithm got 99.58% accuracy which is higher than all algorithms



In all algorithms extension got high accuracy

	Algorithm Name	Precison	Recall	FScore	Accuracy
0	CNN	97.888072	98.136849	97.984035	98.079561
1	Propose CNN + LSTM	98.904538	99.101537	98.989242	99.039781
2	Extension CNN + LSTM + BI-LSTM	99.551676	99.583225	99.567132	99.588477

Displaying all algorithms performance

Prediction:

```
Test Data = [ 2.5347030e-01 -4.1313040e-01  3.2444763e-01 -7.5594574e-02
 -8.9186326e-02 -1.9089539e-03  3.5833270e+06] Predicted Style ====> CONSERVATIVE

Test Data = [-6.3623285e-01  1.1276133e+00 -5.0986860e-01 -7.3151110e-02
 -3.2803464e-01  3.5117117e-01  3.5819320e+06] Predicted Style ====> NORMAL

Test Data = [-1.4737010e+00  1.1309308e-01  5.8971310e-01  2.5961774e-03
 -1.5760323e-01  1.1453723e-03  3.5828250e+06] Predicted Style ====> AGGRESSIVE
```

Predicted Driving Style as Normal, Aggressive or Conservative

CONCLUSION

This particular project has managed to show how driving styles can be classified using a hybrid CNN-LSTM architecture. Feature extraction mesh and CNN-LSTM which are fused together performs temporal data analysis making the architecture very effective at over 90% (99.03%), It is safe to say that CNN algorithms alone do not have that kind of level. Coupled with a Bidirectional LSTM, the architecture's performance takes off, reaching just under 100%, a mark of 99.50%. These are benchmarks which show the assurance the model has on it being robust, scalable as well as real-time usage benchmarks especially for self-driven cars, or cars deployed for road safety purposes. Future work will be able to look at more datasets and better architectures to change the reliability and scope of the system to a wider scale.

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