INNOVATIVE PROJECT DEVELOPMENT REPORT

CNN-LSTM DRIVING STYLE CLASSIFICATION MODEL BASED ON DRIVER OPERATION TIME SERIES DATA

Submitted by-

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In partial fulfillment of the Academic Requirements for the Degree of

BACHELOR OF TECHNOLOGY

Computer Science & Engineering

MALLA REDDY ENGINEERING COLLEGE FOR WOMEN

(Autonomous Institution-UGC, Govt. of India)

Accredited by NAAC with 'A+' Grade, UGC, Govt. of India

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National Ranking by NIRF Innovation-Rank band(151-300),MHRD, Govt. of India Approved by AICTE, Affiliated to JNTUH,ISO 9001-2015 Certified Institution

Maisammaguda, Dhulapally, Secunderabad, Kompally-500 100.

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DEPARTMENT OF COMPUTER SCIENCE AND ENGINEERING

CERTIFICATE

This is to certify that the Project work entitled **"CNN-LSTM DRIVING STYLE CLASSIFICATION MODEL BASED ON DRIVER OPERATION TIME SERIES DATA"** is carried out by **S.Rutuja (22RH1A05N5) ,P. Sravani (22RH1A05K3) ,T.Amulya (22RH1A05P7) , Y.Laxmi(22RH1A05R1)** in partial fulfillment for the award of degree of BACHELOR OF TECHNOLOGY in Computer Science and Engineering, Malla Reddy Engineering Collage For Women (Autonomous), Hyderabad during the academic year 2023-2024.

Supervisor's Signature	**Head of the Department**
Dr.Y.Geetha Reddy	**Dr.Y.Geetha Reddy**
Associate Professor	Professor and HOD

EXTERNAL EXAMINER

ACKNOWLEDGEMENT

We feel ourselves honored and privileged to place our warm salutation to our college **Malla Reddy Engineering College for Women** and Department of **Computer Science and Engineering** which gave us the opportunity to have expertise in engineering and profound technical knowledge.

We wish to convey gratitude to our Principal **Dr. Y. Madhavee Latha**, for providing us with the environment and mean to enrich our skills and motivating us in our endeavour and helping us to realize our full potential.

We express my sincere gratitude to **Dr.Y.Geetha Reddy**, Head of the Department of Computer Science and Engineering for inspiring us to take up a project to this subject and successfully guiding us towards its completion.

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With regards and gratitude,
S.Rutuja(22RH1A05N5)
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DECLARATION

We hereby declare that our project entitled **"CNN-LSTM DRIVING STYLE CLASSIFICATION MODEL BASED ON DRIVER OPERATION TIME SERIES DATA"** submitted to Malla Reddy Engineering College for Women, Hyderabad for the award of the Degree of Bachelor of Technology in Computer Science and Engineering is a result of original research work done by us.

It is declared that the project report or any part thereof has not been previously submitted to any University or Institute for the award of Degree.

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ABSTRACT

This paper presents a robust driving style recognition method with a focus on high accuracy, speed, and generalizability, addressing the challenges posed by limited data types in the driving style classification task and the suboptimal performance of conventional unsupervised clustering algorithms and single convolutional neural network (CNN) methods. The proposed approach begins by collecting and processing driver operation time sequences, even when dealing with imperfect driving data. It employs a two-layer CNN for feature extraction and incorporates a Long Short Term Memory (LSTM) module to encode and transform temporal data, enabling accurate driving style classification. The results demonstrate a recognition accuracy exceeding 95%, alongside significant speed enhancements. Additionally, an extension to the model, referred to as CNN + LSTM + BI-LSTM, leverages bidirectional LSTM to further refine performance, enhancing the overall methodology for driving style recognition.

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CHAPTER 1

INTRODUCTION ABOUT THE PROJECT

Advanced driver assistance systems (ADAS) can improve driving comfort and safety, but there are still imperfections in their powerful features that lead to distrust, prejudice and limited vision reliance on ADAS systems by drivers. The roots of ADAS at this stage are in 'assistance' and the driver is still the main operator of the vehicle. However, the behavior and driving style of different drivers varies enormously, which places greater demands on the ability to personalize the vehicle in terms of driver tuning and the threshold for triggering ADAS capabilities. Taking the above into consideration, the individual driving behavior of the driver should be considered while designing the vehicle system, which can have a significant impact on the safety performance of the vehicle. The development of vehicle intelligence also requires the vehicles to be able to adapt to the driver's driving style and provide the appropriate assistance. However, the current development of vehicle parameters using different drivers is not only time-consuming and labor-intensive, but also subjectively influenced by the different driving styles. Therefore, the development of a system that can accurately identify the driving style of the vehicle driver is of great importance for the development of intelligent vehicles. As of now, there exist many studies focusing on the driving style, and these studies generally rely on three methods, traditional questionnaire-based research methods, visual recognition-based methods, and non-visual driving signal based research methods. Basically, the mainstream research methods are based on the vehicle driving signals, since the visual-based methods suffer from inherent problems that cannot be eradicated, including invasion of driver privacy etc., and are more influenced by the environmental light.

EXISTING SYSTEM

The existing systems for driver behavior analysis and detection encompass a range of approaches and technologies. Galarza et al. utilized Android-based mobile phones to detect driver drowsiness, focusing on parameters like head posture, eye behavior, and the frequency of hiccups. This method achieved an impressive accuracy of 93.37% under natural lighting conditions. In the context of the growing online taxi industry, Ma et al. leveraged camera data to analyze the start and end of taxi-hailing tasks and subsequently assessed driver behavior using vehicle driving data.

Another existing system they introduced a method to infer driving style using vehicle dynamics data, combining inertial and GPS sensors with data from the vehicle's Electronic Control Unit (ECU). The approach was successfully tested on a bus, yielding promising results.

Disadvantages:

- Limited Sensor Types: The existing systems primarily rely on a limited set of sensors and data sources, such as mobile phone sensors, camera data, and inertial sensors.
- Dependency on External Devices: Some existing systems require external devices or specific hardware components, such as mobile phones or inertial sensors, which may not be readily available in all vehicles, making their implementation and adoption more challenging.
- Task-Specific Focus: Some of the existing systems are designed for specific tasks, such as detecting driver drowsiness or analyzing taxi-hailing tasks.
- Accuracy Variability: While some existing systems achieve high accuracy in specific conditions, their performance may vary under different lighting, weather, or driving conditions, which limits their reliability and generalizability.

PROPOSED SYSTEM:

The proposed system leverages the advancements in the era of self-driving vehicles, utilizing tiny sensors to monitor the surrounding environment and driver behavior data. These sensor data are then processed by an Artificial Intelligence model, combining deep learning algorithms, specifically Convolutional Neural Networks (CNN) and Long Short Term Memory networks (LSTM). The CNN layers are employed for feature extraction from the dataset, enhancing the model's ability to capture essential patterns. These extracted features serve as inputs to the LSTM layer, which specializes in training on time-series-based temporal data. This trained model can accurately classify the driving style of the driver, improving prediction accuracy compared to previous techniques.

In the extension of this work, the system incorporates an advanced algorithm known as Bidirectional LSTM (BI-LSTM) to further enhance its performance in managing temporal time-series datasets. By introducing this additional layer, the model achieves even higher accuracy in predicting driver behavior and vehicle motion. This comprehensive approach, referred to as CNN + LSTM + BI-LSTM, represents a promising solution for the accurate and reliable prediction of driving styles and behaviors in the context of self-driving vehicles.

Advantages:

- Advanced Sensor Integration: The proposed system leverages tiny sensors to monitor both the surrounding environment and driver behavior data. This comprehensive data collection approach can provide a more holistic view of the driver's actions and their interaction with the vehicle and environment.
- Deep Learning Techniques: The use of Convolutional Neural Networks (CNN) and Long Short Term Memory networks (LSTM) in the proposed system allows for more advanced feature extraction and temporal data analysis. This can improve the model's ability to capture complex patterns in driving behavior.
- Predictive Accuracy: By combining CNN, LSTM, and Bidirectional LSTM (BI-LSTM), the proposed system offers a more accurate and reliable prediction of driver.

- Future-Proofing: The proposed system embraces the era of self-driving vehicles, positioning itself to work seamlessly with evolving automotive technologies and paving the way for the integration of driver behavior analysis with autonomous driving systems.
- Versatility: Unlike some existing systems tailored to specific tasks, the proposed system aims to provide a comprehensive solution for predicting various driving styles and behaviors, making it suitable for a wide range of driving scenarios.

Extension :

As an extension to the project voting classifier which is ensemble method , a (hybrid CNN+ Bidirectional LSTM + LSTM) is employed to improve prediction robustness and accuracy. Additionally, a Flask-based frontend interface is developed, featuring authentication for enhanced security and usability, broadening the project's scope with advanced modeling techniques and user-friendly application.

Advantages:

- Ensemble method combines models to mitigate weaknesses, enhancing prediction robustness.
- Integration of multiple modeling techniques enables comprehensive analysis of driving styles.
- Flask frontend offers user-friendly testing platform, improving accessibility.
- Authentication feature in frontend ensures secure access, safeguarding driving data.

CHAPTER 2

SYSTEM STUDY

A feasibility analysis evaluates the project's potential for success; therefore, perceived objectivity is an essential factor in the credibility of the study for potential investors and lending institutions. There are five types of feasibility study—separate areas that a feasibility study examines, described below.

1. TECHNICAL FEASIBILITY

This assessment focuses on the technical resources available to the organization. It helps organizations determine whether the technical resources meet capacity and whether the technical team is capable of converting the ideas into working systems. Technical feasibility also involves the evaluation of the hardware, software, and other technical requirements of the proposed system. As an exaggerated example, an organization wouldn't want to try to put Star Trek's transporters in their building—currently, this project is not technically feasible.

2. ECONOMIC FEASIBILITY

This assessment typically involves a cost benefits analysis of the project, helping organizations determine the viability, cost, and benefits associated with a project before financial resources are allocated. It also serves as an independent project assessment and enhances project credibility—helping decision-makers determine the positive economic benefits to the organization that the proposed project will provide.

3. LEGAL FEASIBILITY

This assessment investigates whether any aspect of the proposed project conflicts with legal requirements like zoning laws, data protection acts or social media laws. Let's say an organization wants to construct a new office building in a specific location. A feasibility study might reveal the organization's ideal location isn't zoned for that type of business. That organization has just saved considerable time and effort by learning that their project was not feasible right from the beginning.

4. OPERATIONAL FEASIBILITY

This assessment involves undertaking a study to analyze and determine whether—and how well—the organization's needs can be met by completing the project. Operational feasibility studies also examine how a project plan satisfies the requirements identified in the requirements analysis phase of system development.

5. SCHEDULING FEASIBILITY

This assessment is the most important for project success; after all, a project will fail if not completed on time. In scheduling feasibility, an organization estimates how much time the project will take to complete.

When these areas have all been examined, the feasibility analysis helps identify any constraints the proposed project may face, including:

Internal Project Constraints: Technical, Technology, Budget, Resource, etc.

Internal Corporate Constraints: Financial, Marketing, Export, etc.

External Constraints: Logistics, Environment, Laws, and Regulations, etc.

CHAPTER 3

REQUIREMENT ANALYSIS

REQUIREMENT SPECIFICATIONS

The following are the hardware and software requirements that have used to implement the proposed system

Functional Requirements

1. Data Collection
2. Data Pre-processing
3. Training and Testing
4. Modelling
5. Predicting

Non-Functional Requirements

1. Usability requirement
2. Serviceability requirement
3. Manageability requirement
4. Recoverability requirement
5. Security requirement
6. Data Integrity requirement
7. Capacity requirement
8. Availability requirement
9. Scalability requirement
10. Interoperability requirement
11. Reliability requirement
12. Maintainability requirement

Software Requirements

For developing the application the following are the Software Requirements:

Operating Systems supported

1.Windows 7

2.Windows 8

3.Windows 10

Technologies and Languages used to Develop

1. Software : Anaconda
2. Primary Language : Python
3. Frontend Framework : Flask
4. Back-end Framework : Jupyter Notebook
5. Database : Sqlite3
6. Front-End Technologies : HTML, CSS, JavaScript and Bootstrap4

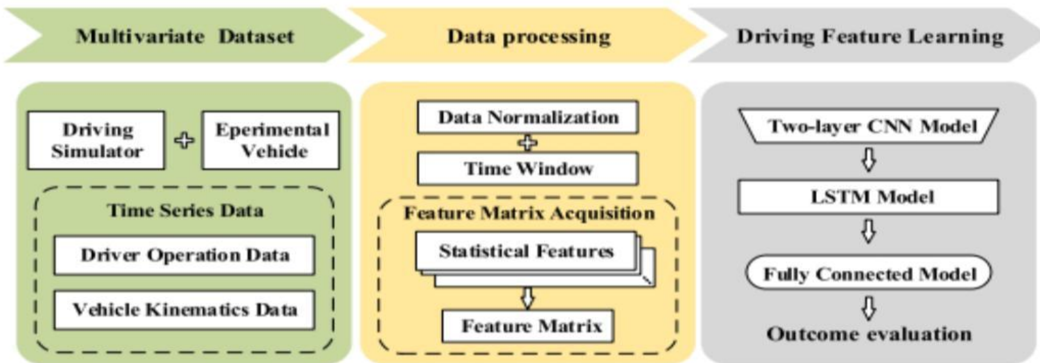
Hardware Requirements

1. Operating System : Windows Only
2. Processor : i5 and above
3. Ram : 8GB and above
4. Hard Disk : 25 GB in local drive

CHAPTER 4

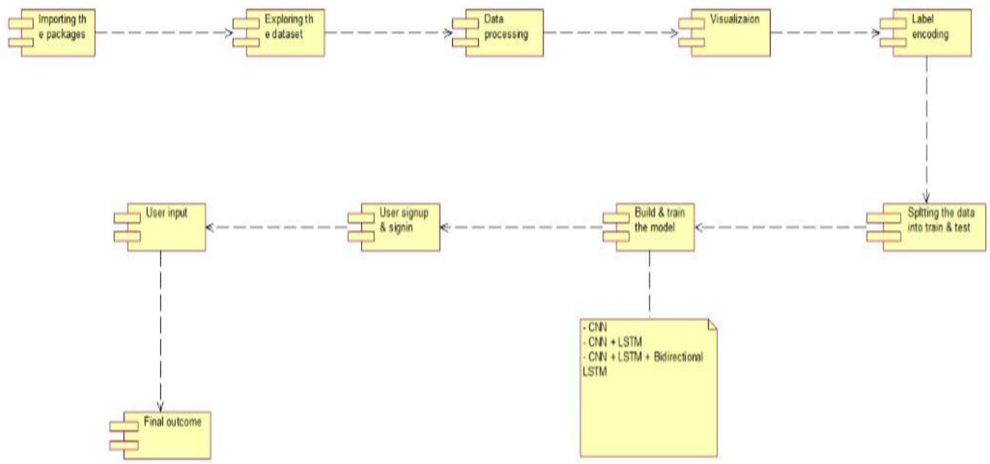
SYSTEM ARCHITECTURE

ARCHITECTURE DIAGRAM

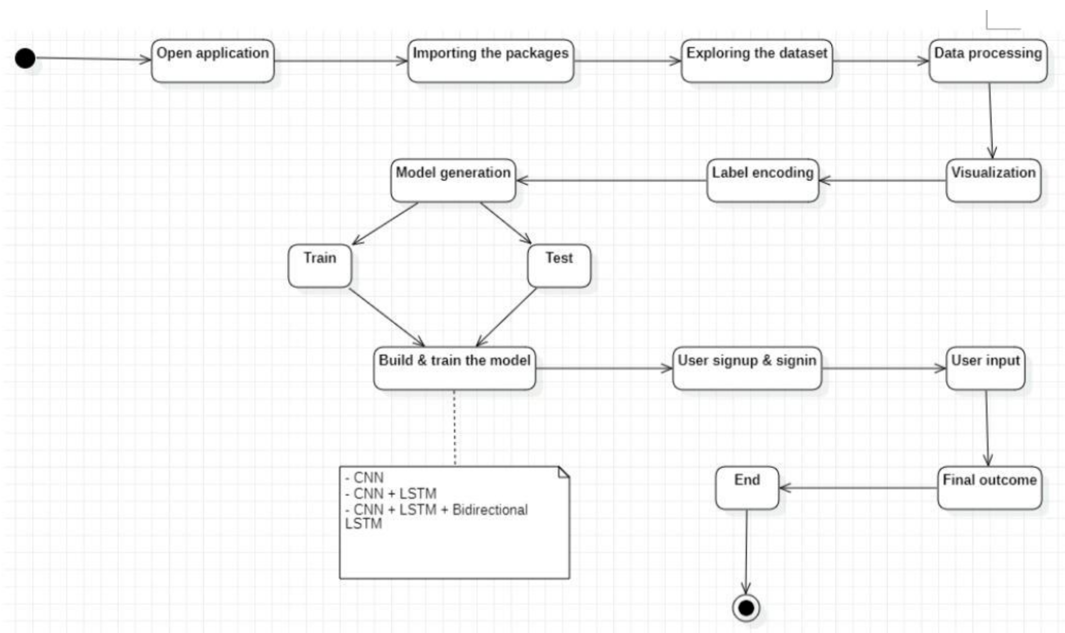


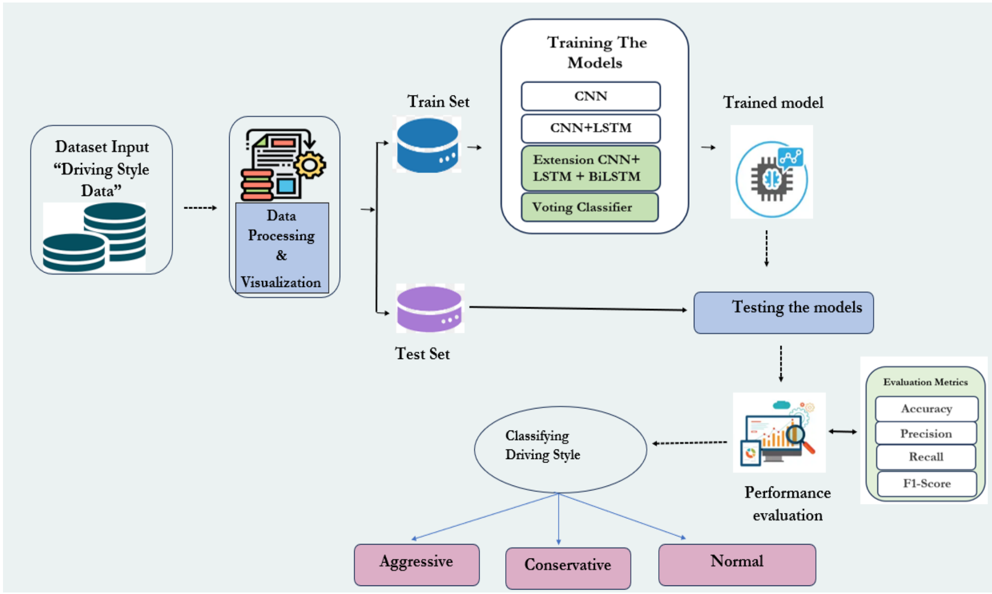
USE CASE DIAGRAM

CLASS DIAGRAM

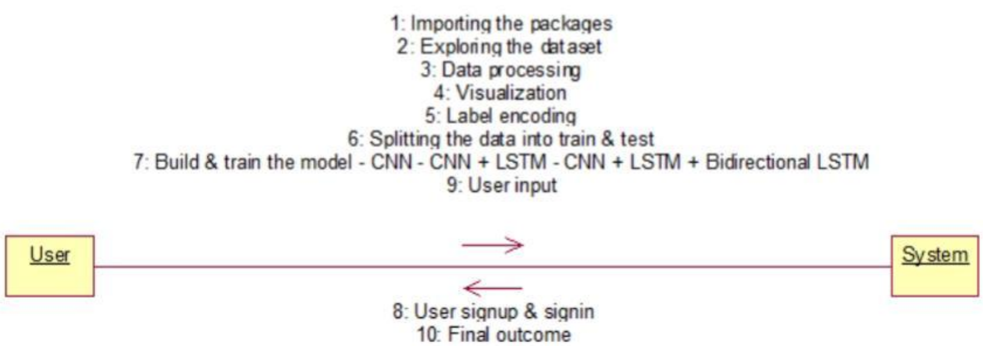


ACTIVITY DIAGRAM

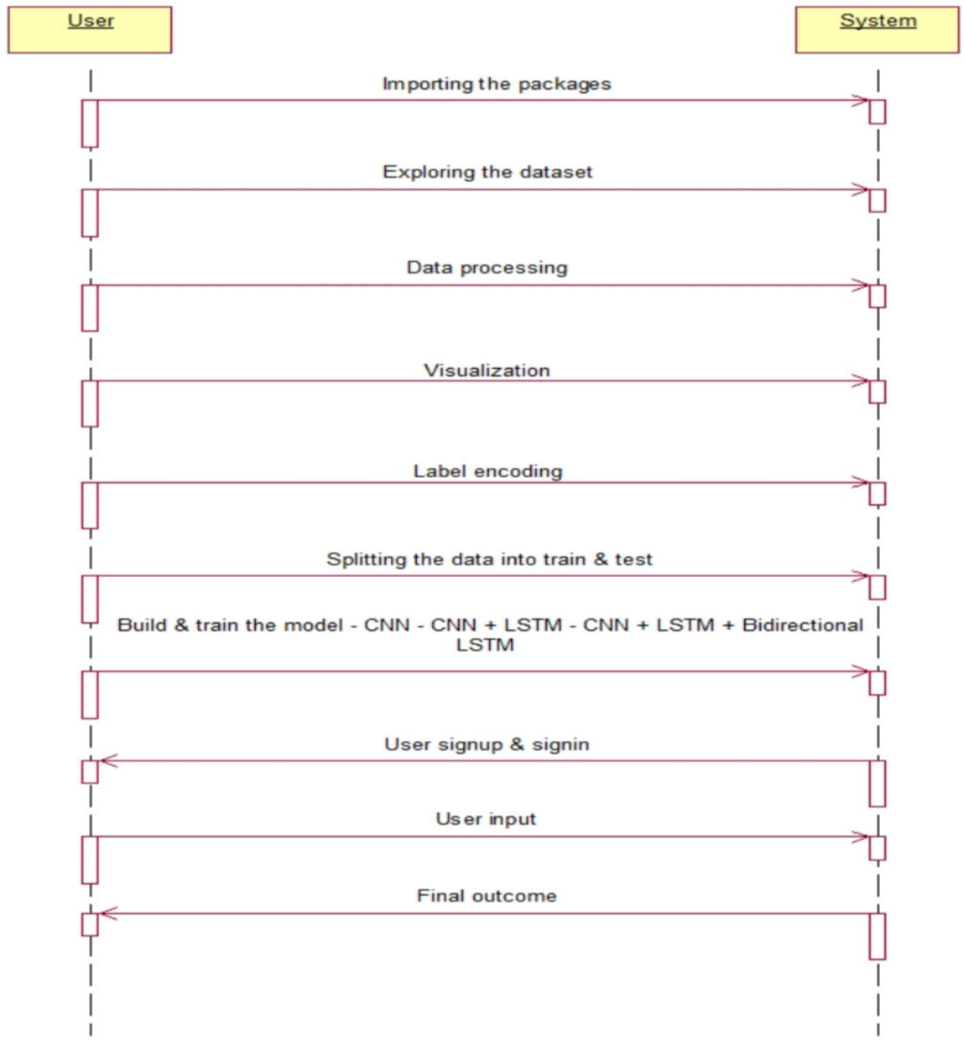




COLLABORATION DIAGRAM



SEQUENCE DIAGRAM



CHAPTER 5

WORKING MODULES AND WORK FLOW

MODULE DESCRIPTION

- Data loading: using this module we are going to import the dataset.
- Data Processing: Using the module we will explore the data.
- Splitting data into train & test: using this module data will be divided into train & test
- Model generation: Model building – CNN – CNN + LSTM – CNN + LSTM + Bidirectional LSTM. Algorithms accuracy calculated
- User signup & login: Using this module will get registration and login
- User input: Using this module will give input for prediction
- Prediction: final predicted displayed
- Note: Extension
- In the base paper the author mentioned to use different deep learning like CNN and CNN + LSTM got 95% of accuracy,
- As an extension we applied an ensemble method combining the predictions of multiple individual models to produce a more robust and accurate final prediction.
- However, we can further enhance the performance by exploring other ensemble techniques such as CNN + LSTM + BiLSTM , which got 99% of accuracy,
- As an extension we can build the front end using the flask framework for user testing and with user authentication.

CHAPTER 6

ALGORITHMS

The algorithms used are -

- CNN
- CNN + LSTM
- CNN + LSTM + Bidirectional LSTM

CNN:

A convolutional neural network (CNN or ConvNet) is a network architecture for deep learning that learns directly from data. CNNs are particularly useful for finding patterns in images to recognize objects, classes, and categories. They can also be quite effective for classifying audio, time-series, and signal data.

CNN + LSTM:

The CNN + LSTM algorithm combines Convolutional Neural Networks (CNN) and Long Short Term Memory (LSTM) networks. The CNN extracts spatial features from input sequences, and the LSTM processes temporal dependencies, enabling accurate classification of time series data like driver operations.

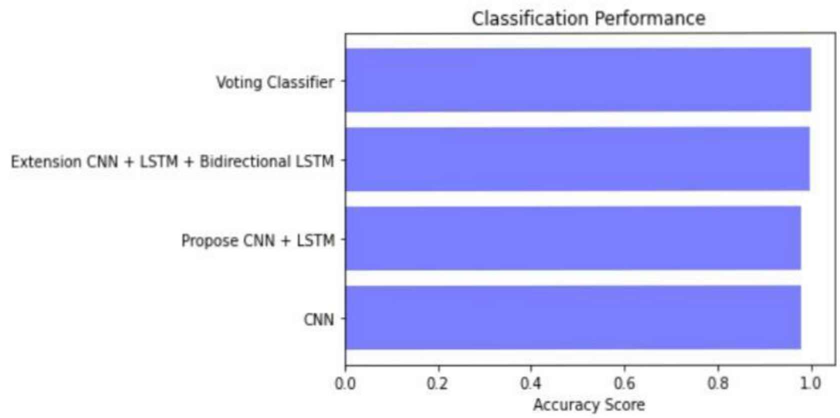
CNN + LSTM + Bidirectional LSTM:

The CNN + LSTM + Bidirectional LSTM algorithm extends the model by adding Bidirectional LSTM layers, allowing the network to consider information from both past and future time steps. This bidirectional approach further refines performance in capturing complex temporal patterns for driving style recognition.

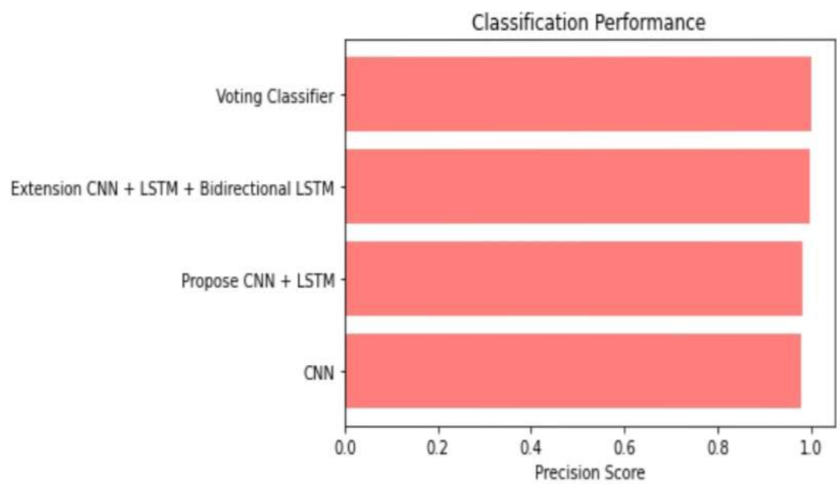
CHAPTER 7

PERFORMANCE EVALUATION

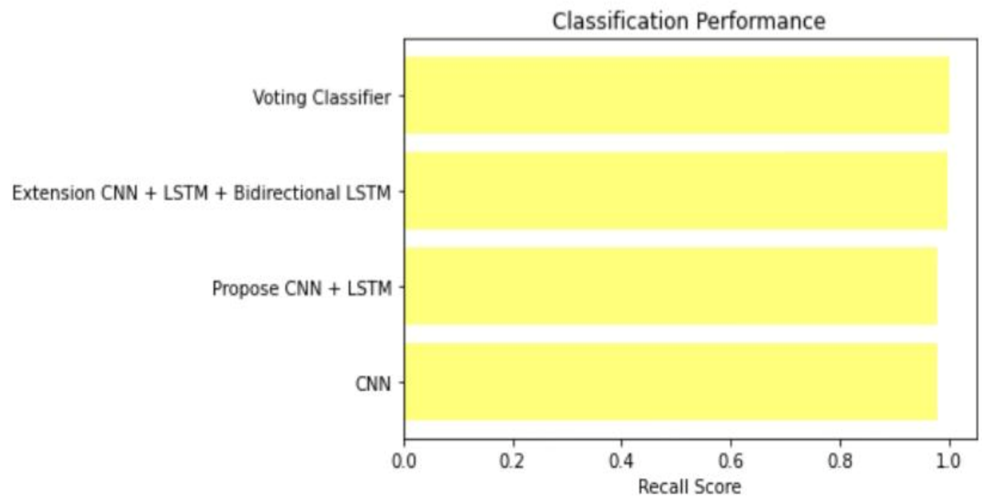
COMPARISON GRAPHS



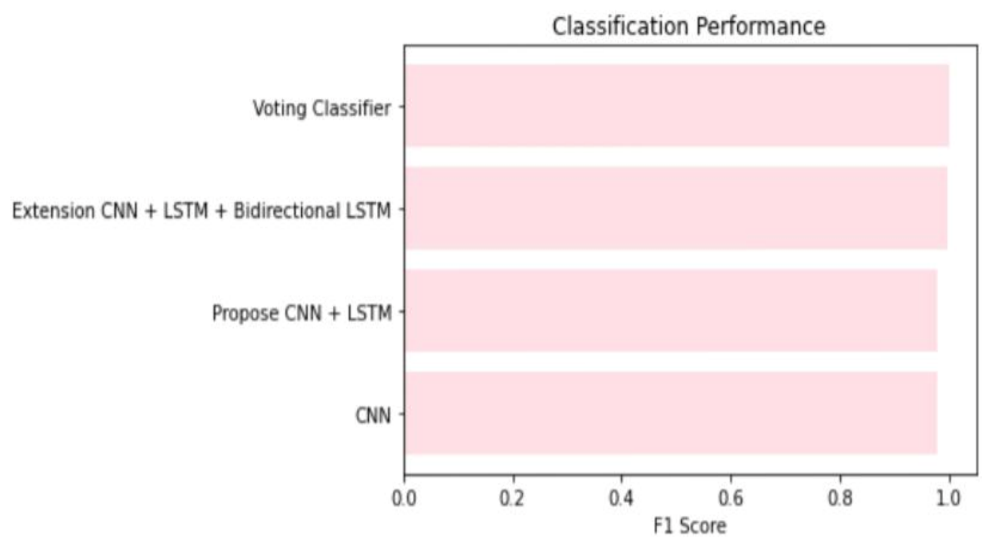
ACCURACY Comparison Graphs



PRECISION Comparison Graphs



RECALL Comparison Graphs



F1 SCORE Comparison Graphs

CHAPTER 8

INPUT AND OUTPUT DESIGN

INPUT DESIGN

Input design is a critical part of system design, especially for a CNN-LSTM model based on time series data. The design of the input layer and preprocessing of the data significantly impacts the performance and efficiency of the model. Below is a detailed approach to input .

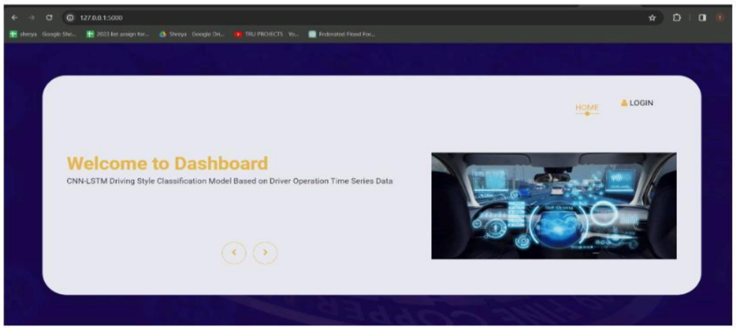
- Time Stamps: Essential for capturing time-based patterns.
- Steering angle
- Vehicle speed
- Acceleration (longitudinal and lateral)
- Brake
- Each of these data points forms a feature for each time step in the series.

OUTPUT DESIGN

1. **Aggressive Driving :** The output classifies the driver's behavior as aggressive, meaning the model has detected driving patterns such as sudden acceleration, sharp braking, or rapid steering changes. Aggressive driving can be associated with higher risk and lower fuel efficiency.
2. **Conservative Driving Style:** The model categorizes the driving behavior as conservative, indicating a smooth, cautious approach. The system recognizes that the driver is maintaining a calm and steady pace, contributing to fuel-efficient and safe driving.
3. **Normal Driving Style:** The driving behavior is labeled as normal, indicating a balanced style without extremes in acceleration or braking. The model detects that the driver follows typical driving patterns, neither overly aggressive nor overly cautious.

OUTPUT SCREENS

WEB PAGE



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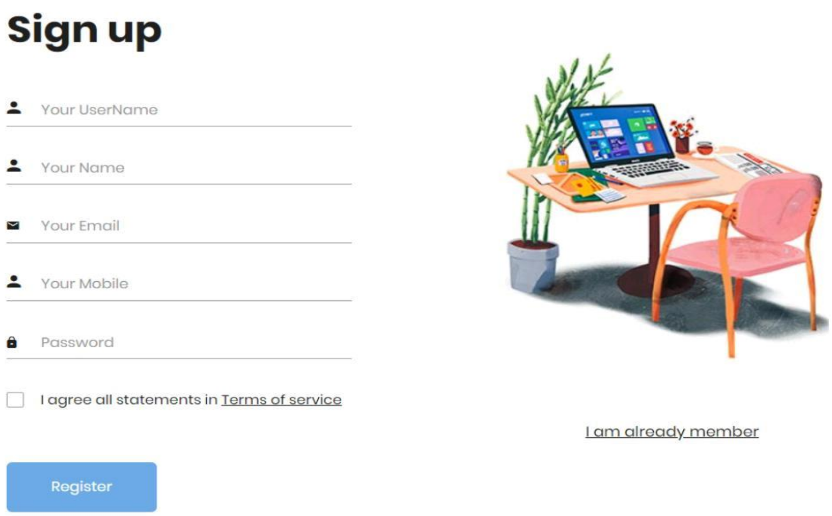
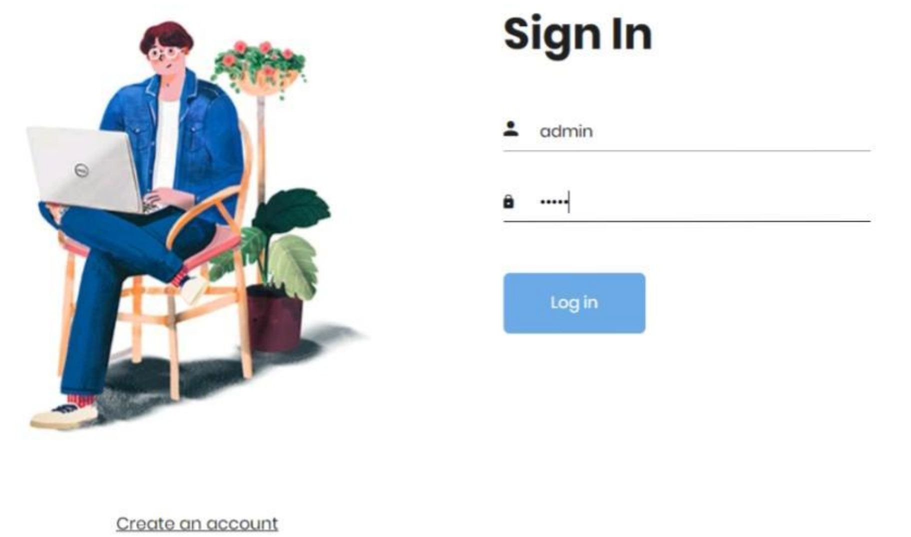
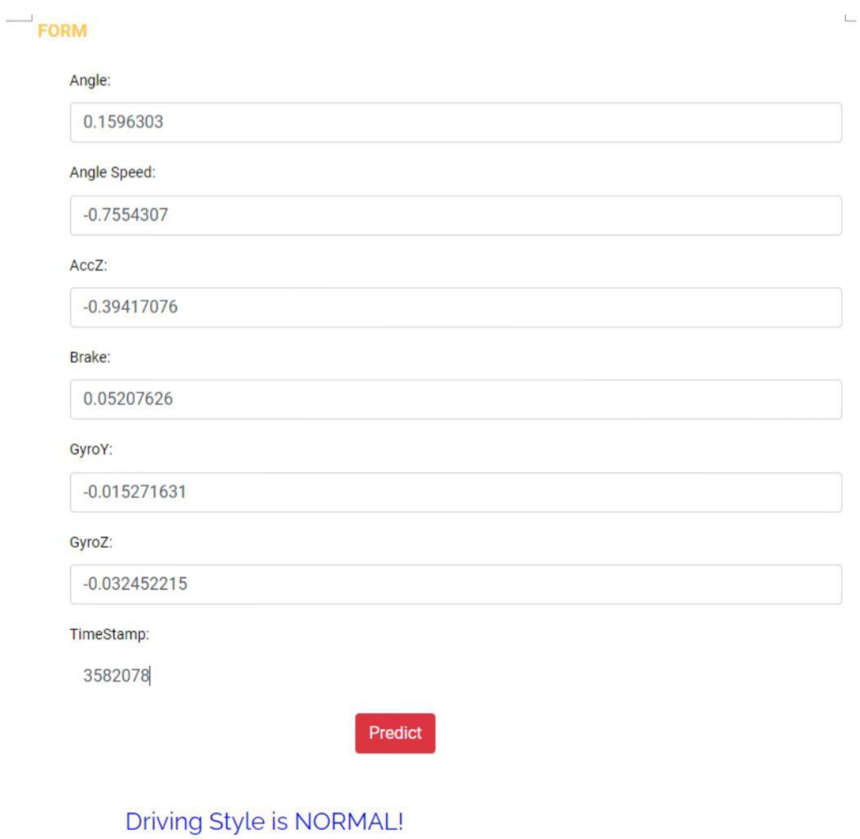


STEP 2


Sign In
admin
Log in
Create an account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Predict
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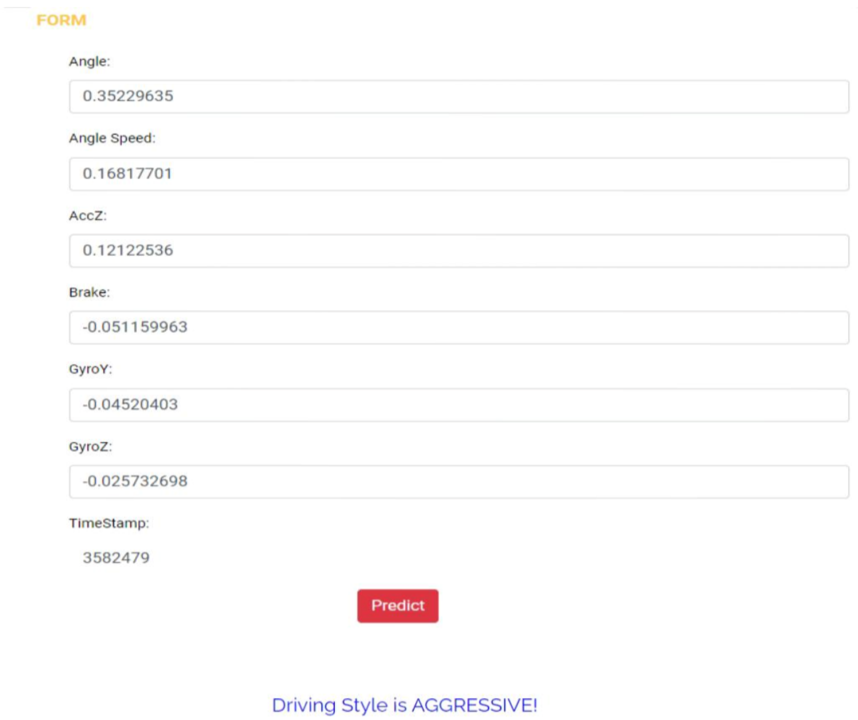
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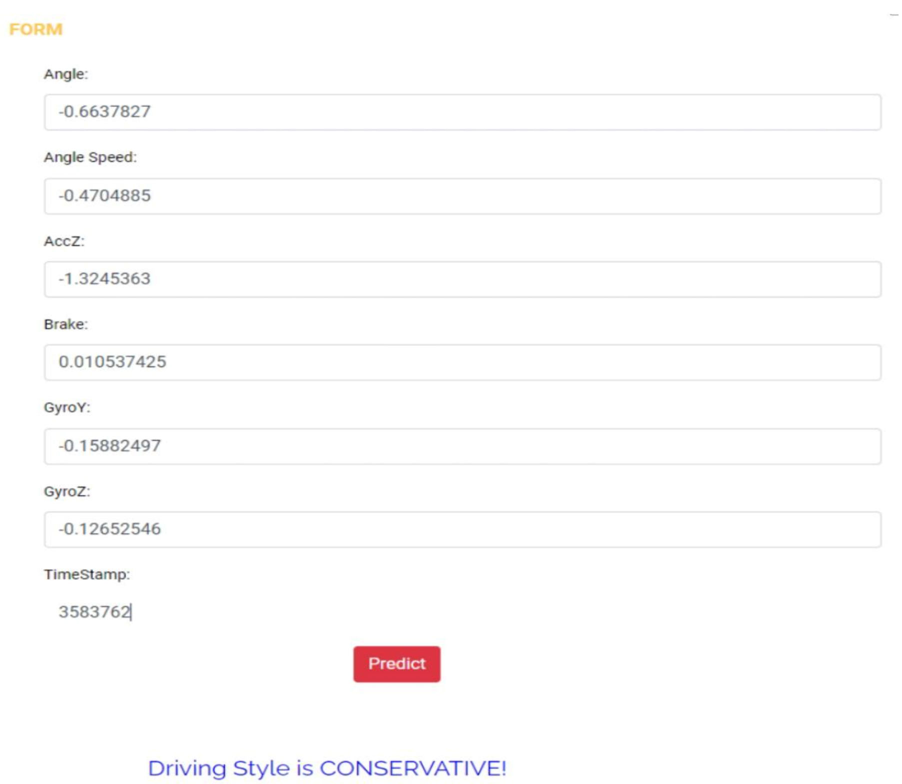
Driving Style is AGGRESSIVE!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GyroZ:
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Predict
Driving Style is CONSERVATIVE!

CHAPTER 9

CONCLUSION

In conclusion, this paper introduces a robust driving style classification method based on the analysis of driver operating signals and vehicle dynamics. The study collects driving data from diverse road conditions and different drivers in a simulator environment and employs a combination of unsupervised clustering and voting methods to obtain driving style labels. Subsequently, a CNN+LSTM network is trained using these labels and driving data, achieving impressive results in the detection of driving styles. The system's application to real car data showcases high generalization capabilities, low cost, and efficiency.

Furthermore, the paper suggests the potential for signaling both the driver of the vehicle and surrounding vehicles to plan driving routes effectively, enhancing overall efficiency. Future work should focus on optimizing the network structure to further improve recognition accuracy and generalization across various driving scenarios. Additionally, the incorporation of driving style information into the vehicle's Advanced Driver Assistance Systems (ADAS) could enhance driver acceptance and road safety. Notably, the achieved accuracy levels, with CNN+LSTM+BI-LSTM reaching 99%, underscore the potential of this approach for driving style classification and real-world applications.

CHAPTER 10

FUTURE SCOPE

Future research can concentrate on refining the network structure to enhance recognition accuracy and ensure robust performance across diverse driving scenarios, contributing to improved driving style classification.

Incorporating driving style information into Advanced Driver Assistance Systems (ADAS) holds promise for enhancing driver acceptance and road safety, offering opportunities for further exploration and development in real-world applications.

Exploring methods to effectively communicate driving style information to both the driver and surrounding vehicles could optimize driving routes, thereby improving overall efficiency on the road.

Efforts should be directed towards enhancing the model's ability to generalize across various driving scenarios, ensuring its applicability in real-world settings beyond the training data.

Further research should focus on the practical deployment of the proposed approach, considering factors such as scalability, reliability, and integration with existing transportation infrastructure to facilitate widespread adoption and impact.

CHAPTER 11

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