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A Novel approach to Services and Fault Prediction Diagnostics of Artificial Intelligence based Smart Driver Assistant of Two-Wheeler

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ABSTRACT
This paper presents a novel approach to services and fault prediction diagnostics for an AI-based smart driver assistant system designed for two-wheelers. The system comprises a hardware ECU (Electronic Control Unit) and a Flutter-based application. Current commercial advanced driver assistance systems (ADAS) in the Indian market are limited in capability, primarily offering basic GPS navigation and simple digital dashboards. The purpose of the proposed AI- ADAS system is to integrate multi-modal sensor-based features for real-time fault detection and alert systems, navigation assistance, and predictive diagnostics. Our methodology involves designing and implementing a low-cost, mountable smart digital Flutter-based ADAS application with extensive testing and validation to ensure its efficacy in diverse riding environments. The salient features of the proposed system are Two-wheeler Health Diagnostics, Early Weather Warnings, Two-wheeler health Prediction, Rider's Risk Analysis and Behaviour Prediction, and Improved Driver Awareness. These enhancements aim to significantly improve rider safety and overall experience.

KEYWORDS
Electronic Control Unit(ECU); Advanced Driver Assistance System(ADAS); Artificial Intelligence(AI); Global Positioning System(GPS).

1. INTRODUCTION

The current commercial offerings of Advanced Drivers Assistance System(ADAS) for two-wheelers in the Indian market aimed at assisting drivers in navigating the roads are limited in their capabilities. Presently, these offerings comprise basic GPS navigation systems and simple digital dashboards that provide fundamental information like basic traffic congestion or vehicle parameters such as engine oil levels, speedometer readings, brake status, battery conditions, and mileage.

However, they fall short in providing dynamic, real-time data, including weather conditions, road conditions, instantaneous data gathered through sensors, or personalized behavioural insights to assist the driver. This deficit in comprehensive assistance not only leaves drivers vulnerable to unforeseen dangers but also misses the opportunity to harness the power of data-driven solutions. Moreover, these systems are widespread in four-wheelers, not many two-wheelers have such systems. The use of AI and machine learning (ML) for internal fault diagnostics in vehicles is becoming increasingly significant due to their ability to enhance predictive maintenance and improve vehicle reliability [1, 10]. AI-based prognostics and health management (PHM) in the automotive industry focus on data-driven methods to facilitate faster troubleshooting and better-organized logistics, moving beyond traditional symptom descriptions [1, 10]. Further, there are no established benchmark value for the sensor data of the Electronic Control Unit (ECU) in two-wheelers [16–18].

While companies like Bosch provide solutions for managing these data, the lack of standardized benchmarks in the industry is highlighted, indicating the need for further research and standardization efforts [16–18].

In light of these challenges, the work proposes a novel and cost-effective approach—an augmented, data-driven Smart Driver Assistance System utilizing Artificial Intelligence (AI) to navigate through precarious road conditions and ultimately reduce fatality. The first step in the process is the designing and assembling of the hardware module that comprises the Electronic Control Unit(ECU) containing the sensors connected to a Raspberry Pi module and a Thin Film Transistor(TFT) display. The second step is building the software module comprising of a Flutter based application which processes the data from the hardware module. The third step of developing an internal diagnostic feature includes applying Machine Learning techniques and evaluating the performance of various models on a synthetically generated dataset.[1]

The paper is organized as follows: The Introduction, which presents the context and significance of the study; the Literature Review, which surveys existing research on enhancing safety through the deployment of ADAS and related technologies; the Methodology, provides insights into the development of hardware, software modules and machine-learning-based internal diagnostics systems; the System design and

Architecture provide an overview of the blueprint of the entire system; the Design of ECU comprehensively explains the hardware module; the Data Collection detailing the challenges in obtaining the benchmark values of internal vehicle sensors and solution explored for the same; Internal Diagnostics elaborates on the machine learning techniques employed on the dataset and performs a comparative study of the models used; the User Interface highlights the front-end of the system; and the conclusion summarizing the findings. Each section methodically builds on the previous one to develop a comprehensive ADAS system for two-wheelers which enhances the safety and overall rider experience. The salient offerings of the paper can be summarized as follows:

- First, the paper explores the design and building of the hardware Electronic Control Unit(ECU). The unit consists of a Raspberry Pi module connected to various sensors. It also includes a Thin Film Transistor(TFT) display that would display the UI(User Interface).
- Second, the execution of internal diagnostics is discussed. This includes the data generation process and the application of various Machine Learning based techniques to draw insights from the data.
- Finally, the paper explores the User Interface built using Flutter and discusses it's offerings.

2. LITERATURE REVIEW

The literature showcases a burgeoning interest in enhancing transportation safety and efficiency through the deployment of advanced driver-assistance systems (ADAS) and related technologies. The research landscape reveals a multifaceted approach, leveraging innovations in IoT, artificial intelligence (AI), machine learning (ML), and multisensory alert systems.

A substantial body of work focuses on the development and implementation of ADAS solutions tailored to diverse environments. Tang and Ball (2019) highlight the integration of machine learning and embedded computing in ADAS, emphasizing its potential to revolutionize road safety [6]. Additionally, Abhilasha Singh's analysis (2022) of ADAS for motorcycles underscores a market trend towards comprehensive rider assistance systems [21].

Machine learning and AI techniques are increasingly prominent in fault diagnosis and real-time driver assistance features. Studies by Dettinger et al. (2023) and Alzayed and Chaoui (2023) delve into machine-learning-based fault detection in electric vehicle power-trains, showcasing the efficacy of these methods in ensuring vehicle reliability [1, 10]. Ding et al. (2021) further explore real-time anomaly detection using long short-term memory (LSTM) and Gaussian Mixture Models (GMM), highlighting their role in preempting potential failures [11].

Challenges persist, including limited processing power in mobile platforms and the need for balanced training datasets. Quinonez et al. (2021) discuss the development of a Flutter-based mobile application for controlling IoT devices, addressing concerns regarding platform compatibility and user interface design [19]. Chen et al. (2015) contribute insights into abnormal driving behaviors detection using smartphone sensors, illustrating ongoing efforts to refine fault diagnosis mechanisms [8].

Moreover, research extends beyond urban settings, with endeavors to adapt ADAS for rural roads and highways. Studies by Eren et al. (2020) and Huang et al. (2022) explore time series forecasting of traffic data and auxiliary ADAS modules for electric power-assisted bicycles, respectively, demonstrating a holistic approach to transportation safety [12, 15].

Sun et al. (2011) present a comprehensive in-vehicle physiological signal monitoring system for driver fatigue detection, emphasizing the importance of real-time health monitoring to enhance driving safety [22]. Wang et al. (2014) survey the modeling and recognition of driver behavior based on driving data, highlighting the use of advanced algorithms to interpret complex driving patterns [23].

Research by Filev et al. (2009) investigates real-time driving behavior identification using driver-in-the-loop vehicle dynamics and control, showcasing the integration of driver inputs with vehicle system responses to enhance driving safety [13]. De-Las-Heras et al. (2021) emphasize the use of machine learning techniques for detecting and transcribing variable message signs on roads, illustrating the potential of AI to improve road communication systems [9].

The application of AI in automotive systems is further explored by the Telecommunication Engineering Center (2020), which discusses the broader implications and potential of AI in the automotive industry, particularly in enhancing vehicle intelligence and connectivity [7]. Springer (2021) compiles various research on machine learning applications in the automotive industry, providing a comprehensive overview of current trends and future directions [4].

A comprehensive review on automotive ADAS by ScienceDirect (2023) delves into the latest advancements and challenges in the field, emphasizing the critical role of ADAS in modern vehicles [5]. Shinde and Mane (2015) explore an advanced vehicle monitoring and tracking system based on Raspberry Pi, highlighting the use of low-cost computing solutions in enhancing vehicle monitoring capabilities [20].

ResearchGate (2021) discusses the classification of driving behavior based on oversampled signals of smartphone-embedded sensors using optimized stacked-LSTM neural networks, showcasing the integration of mobile sensing technologies with advanced neural network algorithms [3]. MDPI (2019) presents a study on in-vehicle physiological signal monitoring systems for driver fatigue detection, emphasizing the importance of continuous health monitoring for safe driving [2].

Studies by Gharib et al. (2020) and Mdpi (2023) further highlight the efforts towards implementing fault diagnosis mechanisms, preventing accidents, and optimizing vehicle performance through advanced ADAS technologies [1, 14].

Reference	Approach	Key Features	Novelty/Contributions	Advantages of Our Project
[1][2] Dettinger et al. (2023), Alzayed and Chaoui (2023)	Machine learning-based fault detection in EV powertrains	Real-time fault detection, anomaly detection	Improved predictive maintenance, preemptive failure detection	Integrates real-time adaptive learning, advanced hybrid models for better accuracy
[3][5] Ding et al. (2021), Chen et al. (2015)	Real-time driver assistance, abnormal driving behavior detection	Fault diagnosis, driver assistance using smartphone sensors	Enhanced real-time assistance, refined diagnosis	Comprehensive driver behavior analysis, robust sensor fusion approach
[4] Quinonez et al. (2021)	Flutter-based mobile application for IoT devices	Platform compatibility, user interface design	Addressed platform compatibility and UI design	Seamless integration with multiple platforms, enhanced user experience
[6][7] Eren et al. (2020), Huang et al. (2022)	Time series forecasting, auxiliary ADAS modules	Traffic data forecasting, enhanced safety for electric bicycles	Improved transportation safety	Predictive analytics, V2X communication for better safety

Table 1. Comparative Study of existing research and our approach

In conclusion, the literature underscores a concerted effort towards implementing fault diagnosis mechanisms, preventing accidents, and optimizing vehicle performance. As the field continues to evolve, interdisciplinary collaborations and technological innovations will drive further advancements in ADAS technology and related domains [1, 14].

3. NOVELTY OF OUR WORK

Our proposed system is an innovative solution for two-wheeler riders, integrating multiple sensor-based features for real-time fault detection and navigation assistance using a Flutter-based mobile application. The key novelties of our AI-powered Advanced Driver Assistance System (AI-ADAS) are:

1. Comprehensive Vehicle Diagnostics and Alerts: The system utilizes IoT and sensor technologies to monitor critical parameters such as battery level, temperature, motor speed, and brake pressure. It provides timely diagnostics and alerts to the rider, ensuring a safer and more reliable riding experience.
2. Early Weather Alerts: The application notifies riders about upcoming weather conditions, enabling them to plan their rides more effectively and avoid adverse weather scenarios.
3. Two-Wheeler Health Prediction: By processing data from internal sensors, the system offers regular health updates of the vehicle, identifying faulty components before they lead to significant issues.
4. Rider Risk Analysis: An overall rider score is generated, assessing the performance of the rider based on various parameters. This feature helps in enhancing rider safety by promoting better riding practices.

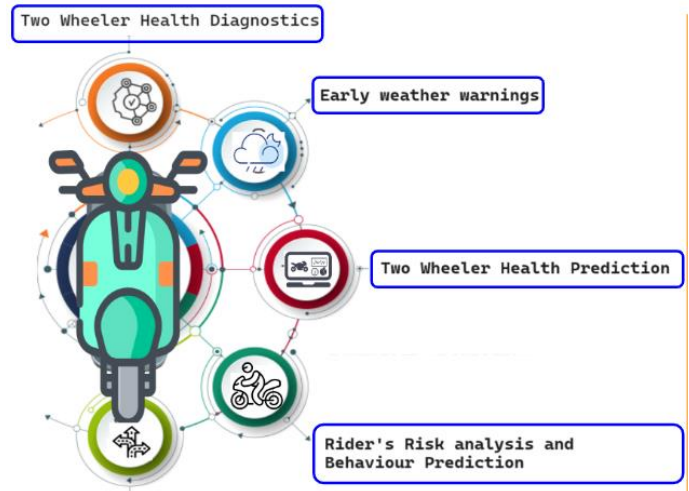

Fig 1. Features of proposed ADAS system

Fig.1 provides a visual summary of the features incorporated in the AI-ADAS system. All these features are managed through a seamless Flutter application, ensuring ease of use and accessibility for the rider.

4. METHODOLOGY

Our methodology comprises the design, development, deployment, and optimization of an AI-powered Advanced Driver Assistance System (AI-ADAS) for two-wheelers. It includes both the hardware and software modules of the system. The methodology employed is as follows:

1. System Design and Architecture: A detailed system architecture design and overview is performed. It includes defining the flow of the system and finalizing the hardware and software tools to be used.
2. Design of ECU of Two-Wheeler: A Raspberry Pi-based ECU (Electronic Control Unit) is developed to interface with various sensors. This includes Adafruit BNO055 Sensor captures acceleration, gyroscope, and orientation data. GPS Module captures latitude and longitude data.
3. Synthetic Data Generation: Due to the lack of benchmark value ranges of the internal sensors of the two-wheeler, a synthetic time series dataset is generated using a Python Script. The readings are simulated over two years from 2021 to 2023.
4. Internal Diagnostics: Machine Learning models including Long Short Term Memory(LSTM), Gated Recurrent Unit(GRU), and Exponential Smoothing are implemented for forecasting the time series synthetic sensor data. The individual models are trained on the synthetic dataset,

followed by stacking used as an ensemble learning technique. The performance of all the models is compared using metrics like Root Means Squared Error(RMSE) and the best-fit model is identified.

5. User Interface: The user interface is designed using Flutter, offering a seamless and responsive experience. The app includes:

- GPS-based Rider Alert System: Utilizes MapMyIndia to provide real-time notifications about hazards such as accidents, road closures, and oil spills.
- Vehicle Health Monitoring (VHM): Displays current status, alerts for various vehicle parameters, and the results from the internal diagnostics enhancing rider awareness of potential issues.
- Risk Assessment Graphs: Presents statistical graphs on weekly and monthly assessments of rider performance and vehicle health.
- Rider Risk Assessment: An AI-based predictive model calculates a rider score displayed on the dashboard, grading overall performance.

The Flutter application is deployed on a mountable TFT screen, ensuring easy accessibility and visibility for the rider. By integrating these components, our AI-ADAS system aims to significantly enhance the safety and reliability of two-wheeler rides, providing a comprehensive and user-friendly solution through its innovative deployment on a mountable TFT screen.

5. SYSTEM DESIGN & ARCHITECTURE

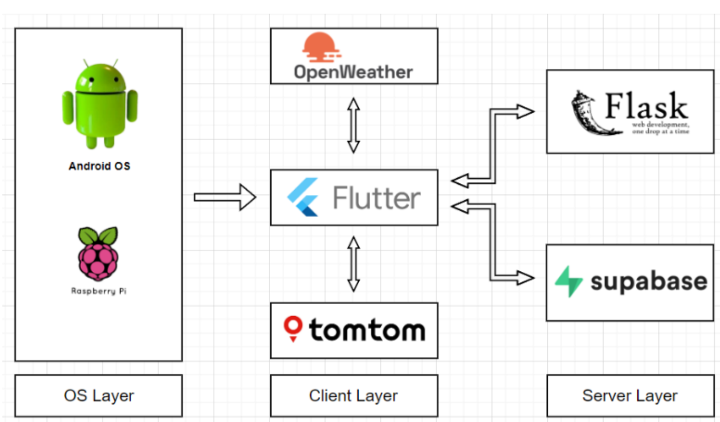

Fig. 2 System Design

Figure 2 shows the flow diagram of the proposed system. There are three broad layers: OS, Client and Server Layer. The OS Layer consists of the Raspberry Pi running Emteria Android 13 OS; the Client layer comprises the Flutter app, weather(OpenWeather) and traffic(TomTom) APIs; the Server layer consists of a flask server and Supabase as the database

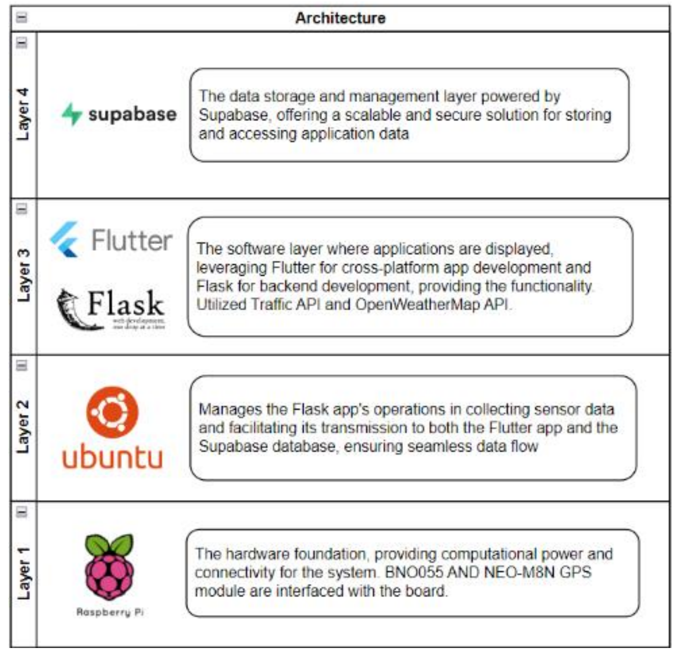

Fig. 3 System Architecture

Figure 3 shows the system architecture highlighting the various layers in detail and the tools used.

The NEO-M8N module has high sensitivity, meaning it can effectively receive and process weak GPS signals. This enables it to obtain accurate location data even in challenging environments such as urban canyons or dense foliage where GPS signals may be obstructed or attenuated.

The Flask server seamlessly interfaces with OpenWeather and Tom-Tom APIs to procure pertinent weather and traffic data corresponding to the received coordinates.

Post data aggregation, the combined dataset is persistently stored locally on an SD card, ensuring reliable access to information even in offline scenarios.

Simultaneously, leveraging Supabase as a cloud storage, the amalgamated data is securely stored, Since Supabase encrypts data both in transit and at rest, facilitating seamless synchronization and accessibility across multiple platforms.

To enhance user experience, a Flutter-based mobile application interfaces with Supabase, dynamically fetching and presenting the aggregated data through an intuitive and aesthetically pleasing user interface.

6. DESIGN OF ECU (ELECTRONIC CONTROL UNIT) OF TWO WHEELER

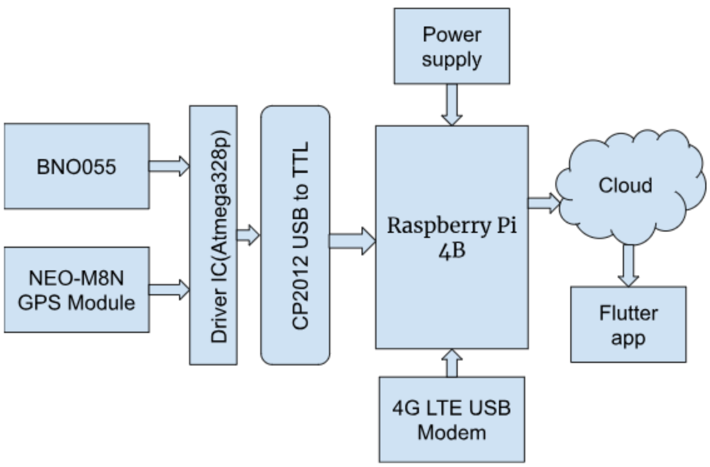

Fig. 4 Block diagram of ECU (Electronic Control Unit)

Figure 4 shows the block diagram of the ECU model. The project is a real-time data acquisition system that collects and logs data from a GPS module and a BNO055 IMU sensor. Raspberry Pi is used as a controller. Adafruit BNO055 Sensor captures acceleration (x, y, z), gyroscope (x, y, z), and orientation (roll, pitch, yaw) data. GPS Module captures latitude and longitude data. ATmega328P receives data from the GPS module and the BNO055 sensor via UART and I2C respectively. It also processes, extracts and formats the data. The formatted data is then sent to a Raspberry Pi 4 using UART, with a CP2102 USB-to-serial bridge driver enabling the data transfer to the Raspberry Pi.

4G LTE USB modem offers fast and reliable internet connectivity, making it suitable for high data transfer rates and real-time monitoring. Using a 4G LTE USB modem allows devices to connect to the internet in locations where traditional wired internet is unavailable or impractical. This is useful for remote applications as it offers flexibility and portability. They can be used with laptops, single-board computers (like Raspberry Pi), or embedded systems that support USB connectivity.

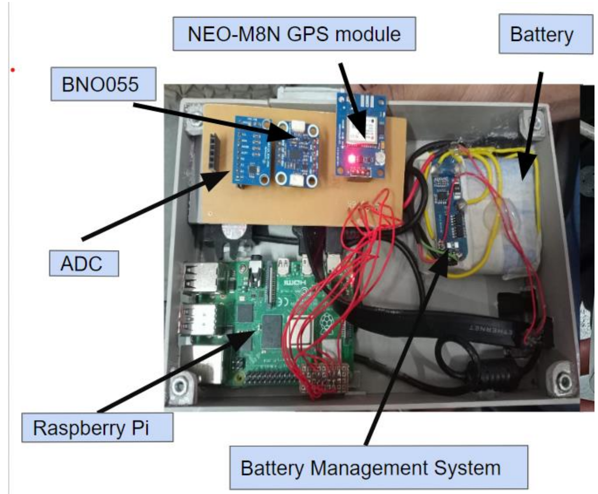

Fig. 5 ECU Setup

Figure 5 Illustrates the ECU unit that would installed on the vehicle. It includes all the sensors mentioned above.

Fig. 6 TFT Screen

Figure 6 illustrates the TFT Screen that would display the app with all the sensors connected to it.

7. SYNTHETIC DATA GENERATION

The internal diagnostics system depends on data from six sensors: Battery Voltage Sensor, Battery Current Sensor, Battery Temperature Sensor, Wheel Speed Sensor, Brake Sensor, and Motor RPM Sensor. Accurate forecasting of the time series data from each of these sensors is essential for performing internal diagnostics. However, a significant challenge arose because the data from these sensors is proprietary to the two-wheeler manufacturers and is not publicly accessible. Furthermore, the sensors are directly attached to the two-wheelers, making direct access infeasible.

To address this issue, several EV two-wheeler manufacturers, including Ather, Tata.ev, Ola Electric, and Emflux, were contacted to obtain benchmark values for these sensors in their respective vehicles. Due to a lack of satisfactory responses, Large Language Models(LLMs) were used as an alternative method to obtain a standardized range of values for these sensors in EV two-wheeler vehicles. The range of values for these sensors is as follows.

Table 2: Range of values of the six sensors

Sensor name	Sensor functions	Range of values
1. Battery Voltage Sensor	Measures the voltage of the battery pack	40V to 48V
2. Battery Current Sensor	Measures the current flowing in and out of the battery pack	6A to 10A
3. Battery Temperature Sensor	Measures the temperature of the battery cells	30°C to 60°C
4. Motor RPM Sensor	Measures the rotational speed of the electric motor	2000rpm to 10000rpm
5. Motor Temperature Sensor	Measures the temperature of the motor	30°C to 100°C
6. Brake Pressure Sensor	Measures the pressure applied in the braking system	1psi to 145psi

Table 2 shows the range of values of the six sensors used in the two-wheelers. Using this range, a synthetic dataset was generated using a Python script encompassing data from all six sensors. The readings span over two years, from December 1, 2021, to November 30, 2023. The dataset was created under the assumption that a ride occurred daily, lasting an average of 30 to 40 minutes, with sensor readings recorded every 10 seconds during these rides. The data was then smoothened using the moving average technique with a window size of 10 to reduce the randomness in the data. To simulate faults in the sensors, anomalies are introduced into the dataset to enhance the systems 'ability to predict vehicle health accurately. The anomalies introduced are as follows.

- For the Battery Temperature and Motor Temperature sensors, anomalies were added to simulate overheating, with temperatures close to or exceeding the maximum permissible value.
- For the Battery Voltage and Battery Current sensors, anomalies were introduced to show erratic fluctuations in their readings.
- For the Motor RPM and Brake Pressure sensors, anomalies were designed to show sudden zero readings, indicating sensor failure.

Anomalies comprise 8 per cent of the total dataset. The final generated dataset comprises 197802 rows.

8. INTERNAL DIAGNOSTICS

To conduct internal diagnostics for an electric two-wheeler, we utilized time series data from our six sensors. The use of time series data facilitates forecasting, allowing for the prediction of the vehicle's future health. To achieve accurate predictions, it is essential to employ machine learning models that excel in analyzing sequential data and identifying trends and patterns. Therefore, we selected the following machine learning models for our forecasting tasks.

8.1. LSTM

Long Short Term Memory(LSTM) is a type of recurrent neural network (RNN) that analyzes sequential data. LSTM networks are well-suited for our time series data forecasting because they can effectively remember information over extended periods. The architecture includes memory cells and three types of gates: input, output, and forget gates. These gates regulate the flow of information, allowing the network to maintain, update, or discard cell states as necessary.

In our implementation, we reshape the training and testing data for each sensor's data into a 3D format suitable for LSTM input. The LSTM model, built with 50 units and a dense layer, is compiled using the Adam optimizer and trained over 20 epochs with a batch size of 32. This process is repeated for each of the six sensors, resulting in six LSTM models tailored to their respective time series data.

The graph in Figure 7 shows us the plot of the actual values and the predictions made by the LSTM model for the Brake Pressure Sensor for the rides taken between December 1, 2023, 14:31:00 to December 6, 2023, 16:48:50. From this graph we can infer that the LSTM model can forecast the values of the brake pressure sensor easily. The model achieved a Root Mean Squared Error (RMSE) of 5.375. Considering the sensor's range of 0-145, these results are relatively good.

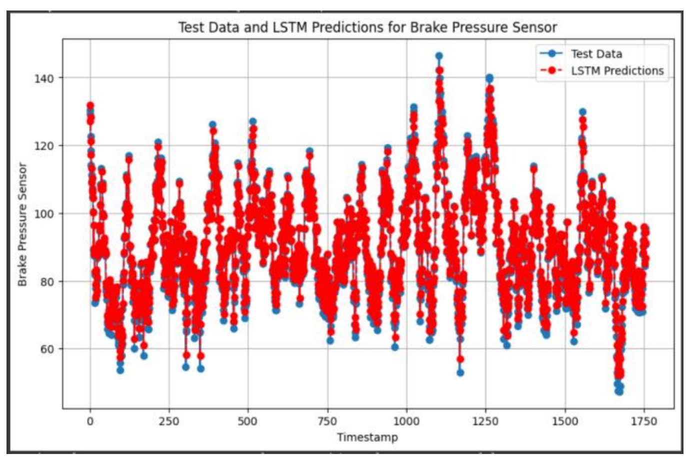

Fig 7: LSTM model predictions

8.2. GRU

Similar to LSTM, Gated Recurrent Units (GRUs) are a type of Recurrent Neural Network (RNN) architecture designed to handle sequential data. GRU is a simplified variant of LSTM that aim to address the vanishing gradient problem that traditional RNNs face, making them more effective at capturing long-term dependencies in sequences. GRU has a more efficient architecture as compared to LSTM. It makes use of the update and reset gates to control information flow making it less computationally intensive while still effectively capturing dependencies in sequential data.

Similar to the LSTM implementation, the data for each sensor is reshaped to fit the GRU's requirements. Our GRU model, consisting of 50 units and a dense layer, is compiled with the Adam optimizer and trained for 20 epochs with a batch size of 32, optimizing for mean squared error. This procedure is applied separately to each sensor, resulting in six GRU models.

The graph in Figure 8 shows us the plot of the actual values and the predictions made by the GRU model for the Brake Pressure Sensor for the rides taken between December 1, 2023, 14:31:00 to December 6, 2023, 16:48:50. From this graph we can infer that similar to the LSTM model, GRU can forecast the values of the brake pressure sensor easily as well. This model also achieved a Root Mean Squared Error (RMSE) of 5.371. Considering the sensor's range of 0-145, these results are relatively good.

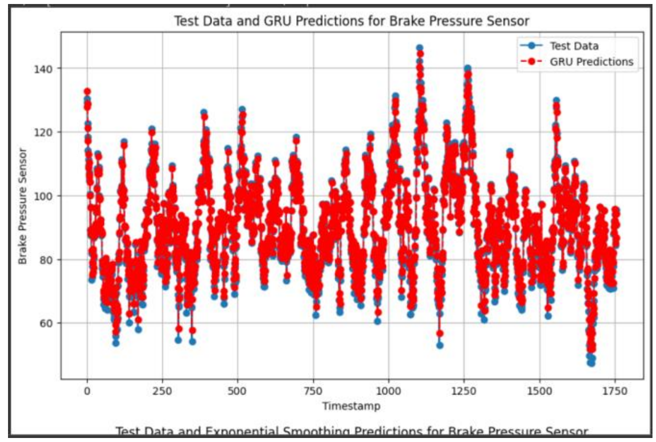

Fig. 8 : GRU Model Predictions

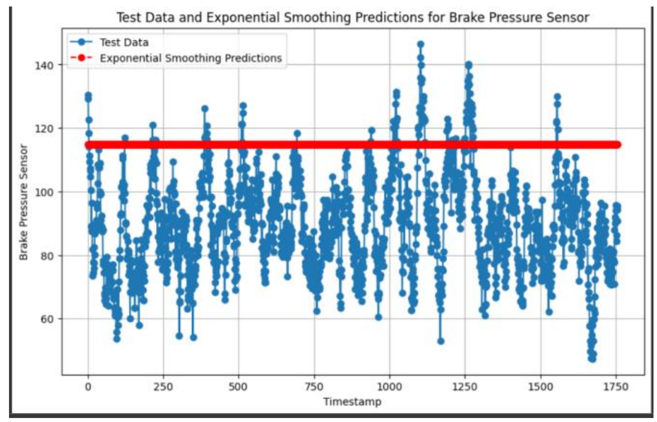

Fig. 9: Exponential Smoothing Model Predictions

8.3. Exponential Smoothing

Exponential Smoothing (ES) is a time series forecasting method introduced by Brown (1959) and later expanded by Holt (1960) and Winters (1960). Exponential Smoothing methods are particularly effective for data with a clear trend and seasonal patterns. The Exponential Smoothing approach assigns exponentially decreasing weights to past observations, emphasizing more recent data points and allowing for trend and seasonal components to be captured in the forecast.

For each sensor's data, we use the Holt-Winters Exponential Smoothing model with additive seasonality and a seasonal period of 12. The model is fitted on the training data for each sensor and used to forecast the test data, capturing seasonal variations effectively. This process is repeated for all six sensors, resulting in six Exponential Smoothing models.

The graph in Figure 9 shows us the plot of the actual values and the predictions made by the Exponential Smoothing model for the Brake Pressure Sensor for the rides taken between December 1, 2023, 14:31:00 to December 6, 2023, 16:48:50. From this graph we can infer that unlike the LSTM and GRU models, Exponential Smoothing is not able to forecast the values of the brake pressure sensor that easily. This model also achieved a Root Mean Squared Error (RMSE) of 29.60. Considering the sensor's range of 0-145, these results are poor compared to the other models.

8.4. Ensemble

Each model was trained using the time series data from individual sensors. However, no single model consistently provided excellent results across all sensors. While one model might perform well for a specific sensor, another model would outperform it for different sensors. Hence to leverage the strengths of the individual models, we employ a stacking ensemble approach.

Stacking involves combining the predictions of multiple models to enhance overall prediction accuracy and robustness. In our approach, we utilized a stacking regressor, with linear régression as the meta-learner, to integrate the strengths of various models. This method improved the reliability of forecasts across the different sensors, providing more accurate and consistent predictions.

The graph in Figure 10 shows us the plot of the actual values and the predictions made by the ensemble model for the Brake Pressure Sensor for the rides taken between December 1, 2023, 14:31:00 to December 6, 2023, 16:48:50. This model achieved a Root Mean Squared Error (RMSE) of 5.35. Considering the sensor's range of 0-180, the ensemble models have slightly outperformed the individual models 'results.

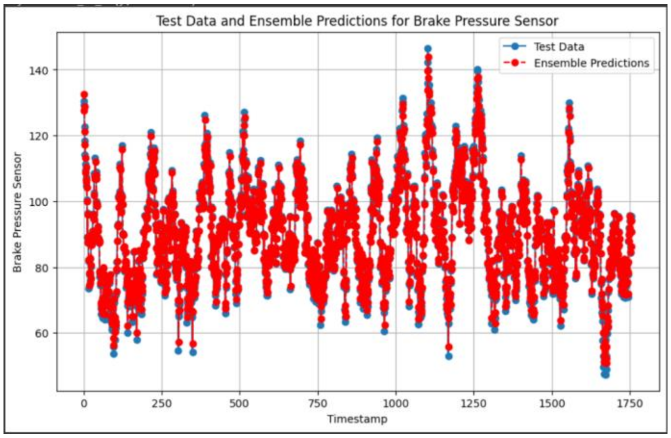

Fig 10: Ensemble Model Predictions

Table 3: Model Parameters and Sensor Prediction RMSE

Model Name	Parameters	Battery Voltage Sensor	Battery Current Sensor	Battery Temperature Sensor	Motor RPM Sensor	Motor Temperature Sensor	Brake Pressure Sensor
LSTM	Units: 50 Epochs:20 Batch size: 30 Optimizer: adam	1.7468625	1.6993968	4.863332478	1629.399	10.94670183	5.3753283
GRU	Units: 50 Epochs:20 Batch size: 30 Optimizer: adam	1.7779129	1.6942491	4.835250157	1713.543	10.98084955	5.3712379
Exponential Smoothing	Seasonality: Additive Period: 12	1.7875015	1.7112233	5.161905439	1945.165	11.67783231	29.607232
Ensemble	Meta-learner: Linear Regression	1.7242209	1.6815238	4.825510027	1625.602	10.93835291	5.3561704

Table 3 presents the parameters used and the Root Mean Square Error (RMSE) for various sensors predicted by different models: LSTM, GRU, Exponential Smoothing, and an Ensemble approach.

9. USER INTERFACE

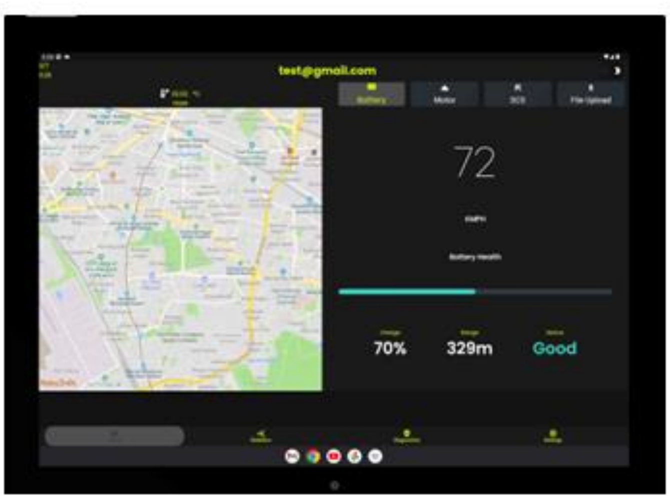

Fig.11 Home Page

The UI (User Interface) is composed of a Flutter-built application, consisting primarily of four sections: the Dashboard Statistics page, the Diagnostic page, and the Settings page. The Dashboard presents basic information such as speed, battery life, and a navigation map. The Statistics page offers an overview of the rider's driving behavior and provides details about taken rides. The Diagnostics page displays information regarding the current health and performance of various systems of the two-wheeler. Finally, the Settings page includes essential features like the profile setup, Wi-Fi and Bluetooth connectivity, display and sound settings, among others.

Fig.12. Vehicle Diagnostic

Fig. 13: Vehicle Diagnostics Page

10. CONCLUSION

The development of the proposed AI-DAS, driven by a comprehensive analysis of driver behavior and road conditions, holds the potential to be a transformative step towards enhancing road safety and the overall driving experience in India. In conclusion, the smart AI-DAS offers potential to enhance road safety in India substantially. The data-driven, AI-powered approach, combined with the integration of various data sources, positions the Ai-DAS as a valuable tool for both individual drivers and authorities responsible for road safety. It represents a vital step towards a safer and more efficient road ecosystem in India.

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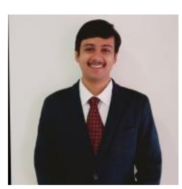

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