Date available online: 30-10-2023
Vol. 1, Issue 1(January-June 2023)
This is an open-access article.

Vehicle Safety Sensory System

Noramalina Abdullah[1*] and Cui Chengjun[1]

[1] School of Electrical and Electronic Engineering, Engineering Campus, Universiti Sains Malaysia, 14300 Nibong Tebal, Pulau Pinang, Malaysia

[*]Corresponding author: Noramalina Abdullah (e-mail: eenora@usm.my)

ABSTRACT Our daily lives depend on vehicles for transportation, work, and adventure. Traffic accidents, a global issue, harm individuals, communities, and societies. Accidents often come from human errors, diversions, and judgment. This report underlines highway safety accidents' terrible consequences, from death to economic expenses. Many variables make accidents inevitable, but preventing them is crucial. Accidents are caused by human error, particularly distracted and inebriated driving. This study emphasizes driver status detecting systems' road safety benefits. These technologies evaluate drivers' safety via real-time monitoring of attentiveness, weariness, and impairment. Driver fatigue, alcohol or drug impairment, and cognitive distractions enhance accident risk. Eye tracking and facial recognition offer real-time solutions for these factors. Driver status detection devices warn drivers, preventing accidents. Tired or distracted driving can cause serious accidents. The adoption of driver status detection systems is vital. Prevention is possible with these tools that detect weariness and distraction. Addressing these concerns may reduce accidents and save lives. According to this study, the Vehicle Sensory Safety System actively analyzes drivers' physiological states using BPM and grip pressure. These dynamic data reveal the driver's emotional and physical state in real-time. The technology alerts drivers with a buzzer, vibrating steering wheel, and flashing LED strip. This project could improve road safety for all users and reduce highway accidents.

INDEX TERMS *Driver monitoring system, Heart rate, Accident prevention， Internet of things (IoT)， Sensor*

I. INTRODUCTION

Vehicles, encompassing cars, trucks, motorcycles, and various other modes of transportation, play a pivotal and multifaceted role in our modern daily lives [1]. They are essential components that form the backbone of transportation systems, serving various purposes and meeting diverse needs. Vehicles are vital for the smooth movement of goods and services, enabling the efficient transportation of products and supporting economic activities. By providing efficient transportation options, vehicles play a crucial role in connecting individuals with education, employment, and other essential services. They empower people with the freedom to explore and experience new places, fostering personal growth and enriching lives.

Given the significance of vehicles in daily life, traffic safety accidents are indeed a universal phenomenon with repercussions that impact communities and societies worldwide. Regardless of geographical location, cultural background, or economic status, the risk of traffic accidents is present everywhere [2], [3]. This universality arises from the fact that humans, irrespective of their background, are susceptible to errors, distractions, and lapses in judgment that can contribute to accidents on the road [4]. Whether it is a momentary lapse of attention, impaired driving, or reckless behaviour, the potential for human error exists within all individuals, making traffic accidents a concern that transcends boundaries [5].

Traffic safety accidents pose a significant and severe threat to individuals, communities, and societies as a whole. The severity of traffic safety accidents cannot be understated, as they result in profound consequences in terms of loss of life, injuries, and economic burdens. While traffic safety accidents are indeed a concerning and serious issue, it is crucial to acknowledge that they are not entirely unavoidable. Although accidents can happen due to various factors, such as human error, road conditions, or unforeseen circumstances, there are measures and strategies available to mitigate and prevent them [6]. Human error, which encompasses behaviours such as distracted driving, speeding, impaired driving, and reckless behaviour, stands out as a leading cause of traffic accidents [7]. Driver status detection plays a crucial role in ensuring road safety and preventing accidents. By monitoring and analysing factors such as driver attentiveness, fatigue level, and impairment, it becomes possible to assess their ability to operate a vehicle safely [8], [9]. This proactive approach of detecting and addressing driver impairment or distraction significantly improves road safety [10].

Factors like fatigue [11], alcohol [12] or drug impairment [13], and cognitive distractions [14], [15] are known to impair driving skills and increase the risk of accidents [16]. Real-time identification of these factors through driver status detection systems, employing technologies like eye-tracking, facial recognition, and monitoring devices, allows for timely interventions [17]. By providing alerts and warnings to drivers, they can regain focus, take necessary breaks, or seek assistance, thus preventing accidents before they occur [18].

Accidents caused by driver-related factors such as drowsy driving or distracted driving can have severe consequences [19], [20]. Therefore, the implementation of driver status detection systems is crucial. These systems help identify signs of fatigue or distraction, enabling preventive measures to be taken[21]. By addressing these issues, accidents can be mitigated, potentially saving lives, and preventing injuries [22].

II. METHODOLOGY

In this research, the development and modification of a Vehicle Sensory Safety System for 4-wheeled vehicles such as cars, vans, and lorries are proposed. This system aims to monitor the biological responses of the driver to ensure road safety for all road users. The System Design concept is shown in Figure 1.

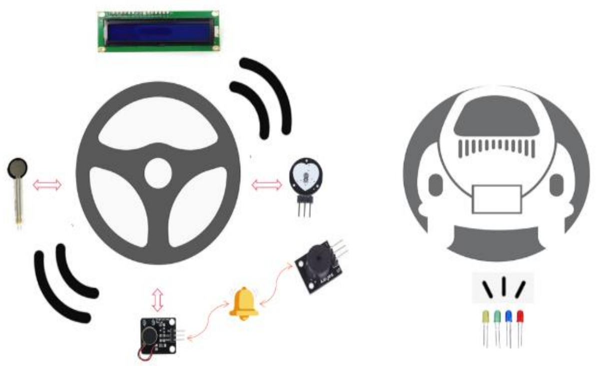

Figure 1 System Design Concept Drawing

The overall flowchart that was utilized to demonstrate the approach that was applied to this research may be seen in Figure 2.

The pulse sensor is responsible for detecting and collecting the beats per minute (BPM) of the driver's heart rate, while the force-sensitive resistor measures the grip pressure of the driver on the steering wheel. These readings, specifically the BPM and grip pressure, are influenced by the driver's emotional and physical state at that moment. For example, if the driver is feeling sleepy or under the influence of alcohol, their grip force and heart rate may decrease. Conversely, if the driver is agitated or affected by drugs, their grip force and heart rate may increase.

When the system detects abnormal levels of BPM and grip pressure, indicating potential driver impairment, it activates alerts to notify the driver of their reckless driving behaviour. This is done through a ringing buzzer and a vibrating steering wheel, which provide stimuli for the driver to respond to. The driver is prompted to take corrective actions. If the driver continues to ignore the alerts and fails to respond, an additional safety measure is activated. The LED strip located at the back of the vehicle lights up to alert other road users of the potential danger posed by the reckless driver. Figure 3 shows the block diagram of the proposed system.

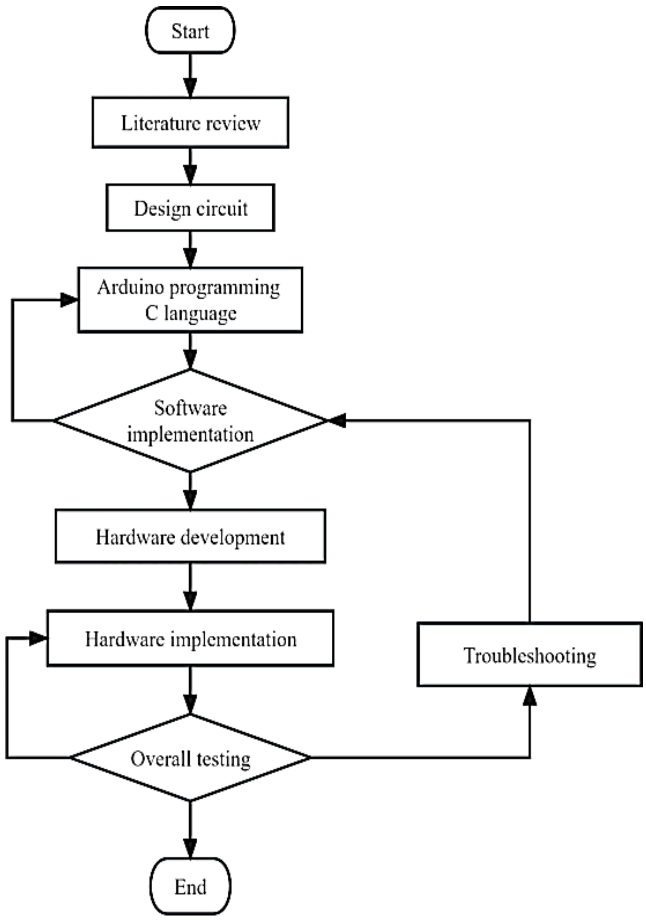

Figure 2 Overall flowchart of the research

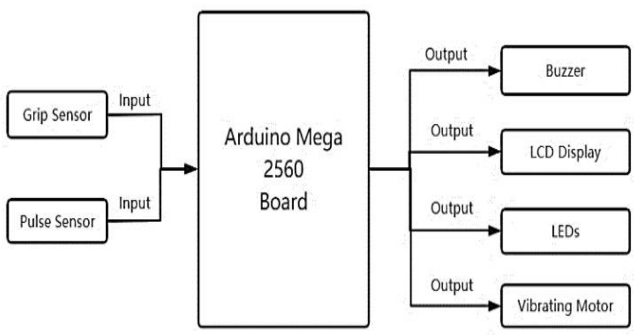

Figure 3 Block Diagram of Proposed System

The flowchart of Data Collection is shown in Figure 4. As depicted in the diagram, the data collection process begins when the system is initiated. Initially, a dataset comprising heart rate and grip strength information is obtained. This real-time data is transmitted to a computer for further processing.

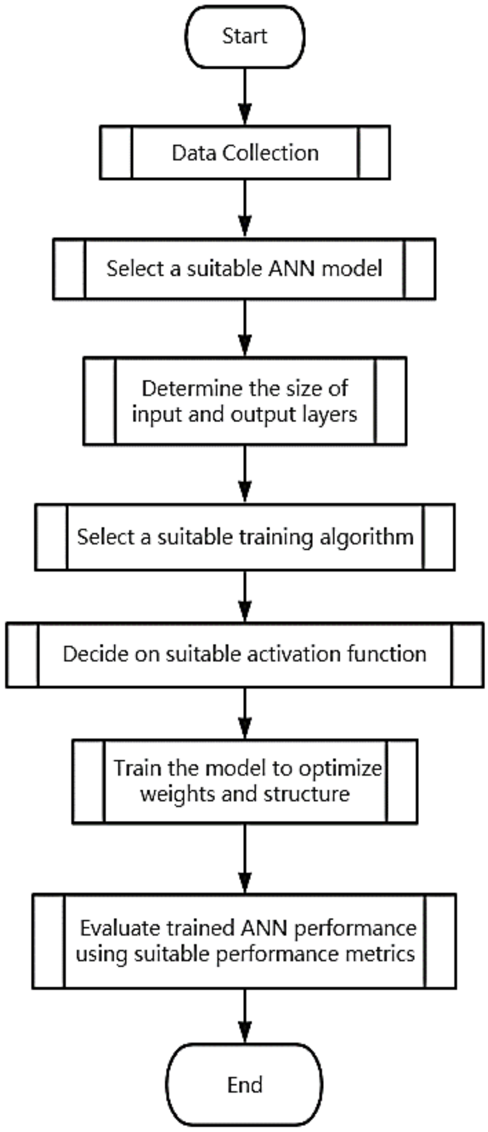

Figure 4. The flowchart of Data Collection

The Flowchart of Data Progress is shown in Figure 5. The collected data is initially transmitted to the computer and processed using a compiled classification model. This processing step aims to obtain the classification results based on the data. Once the classification results are obtained, they are then sent to the Vehicle Sensor Safety System. Within the Vehicle Sensor Safety System, the received classification results trigger the execution of functional functions. These functions may include various safety measures or actions based on the specific classification. Additionally, the system executes preset commands that correspond to the classification results. After executing the functional functions and preset commands, the process concludes, indicating the end of this particular cycle or iteration. Subsequently, the data is manually classified into specific categories, as outlined in Table 1. Once this classification task is completed, the collected data is automatically stored in a folder within the same directory. At this stage, a dataset has been gathered.

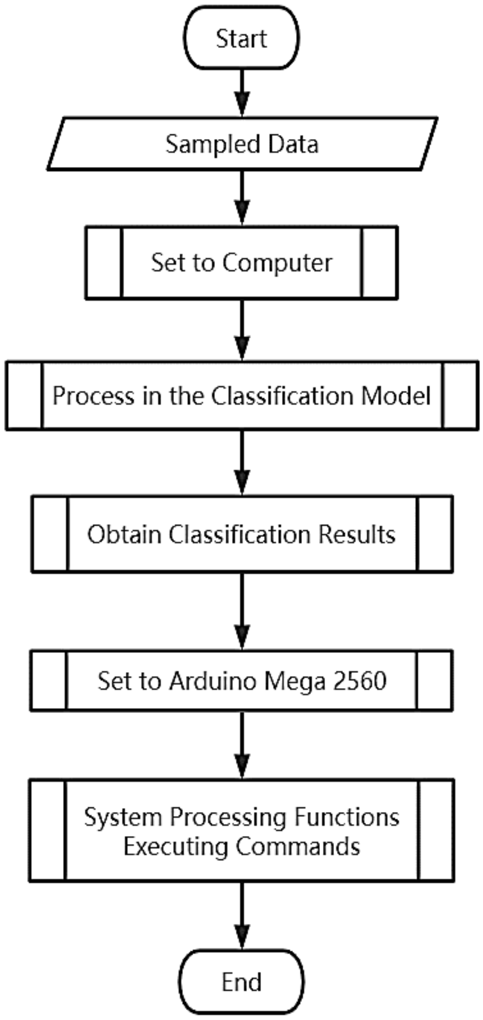

Figure 5 The Flowchart of Data Progress

TABLE I
Classification Situation

Indicator	Driving status
1	Drunk Driving
2	Fatigue Driving
3	Road Rage Driving
4	Normal

To determine whether the amount of collected data is adequate, an assessment is performed. If the data is deemed insufficient, the data collection process continues according to the flowchart. Conversely, if the collected data is deemed sufficient, the process is concluded, and the required data is obtained.

This safety system utilizes pulse and grip strength measurements to monitor the driver's health condition, triggering alerts through a vibration motor and buzzer. It also provides real-time information on an LCD module, displaying BPM and grip pressure. Additionally, LED strips at the back of the vehicle activate when detecting unusual health conditions, alerting other drivers on the road.

In the proposed system, the Arduino Mega 2560 is selected as the main processor due to its capabilities and compatibility with the integrated sensors. The Arduino Mega 2560 is equipped with 54 digital input/output pins and 16 analog inputs, providing sufficient connectivity for the various sensors used in the project. The key feature of this safety system is its ability to detect the user's health condition by measuring their pulse and grip strength. Using these measurements, the system can effectively monitor the driver's physical well-being. In case of any abnormalities, the system promptly activates a vibration motor and a buzzer to alert the driver, ensuring they are aware of the detected issue. The heart rate sensor detects the driver's heart rate, while the force sensor measures the grip pressure exerted by the driver. The sensor can transmit the collected analog signal to microcontroller unit (MCU) and then analog signal will be converted into digital signal. These sensors play a vital role in monitoring the driver's health condition and focus while driving.

To provide real-time information, the safety system includes an LCD module that displays two important metrics: BPM (Beats Per Minute), indicating the driver's pulse rate, and grip pressure, which reflects the strength of the driver's grip. This allows the driver to monitor their vital signs during the drive and stay informed about any changes in their health condition.

To enhance the visibility of the driver's health status to others on the road, LED strips are installed at the back of the vehicle. These LED strips are designed to activate when the sensors detect any unusual health condition in the driver. By doing so, they serve as a visual indicator for other drivers, signaling the need for extra caution and potentially encouraging assistance.

A. DATA COLLECTION PROCESS

The following procedures can be carried out in order to carry out an investigation into simulated driving:

1. Find ten willing participants aged between 20 and 30 who fall within the volunteer age range and recruit them for the study. In order to guarantee the accuracy of the data collected, you must check that the participants are of the required age and are in good health.

2. Establish a setting that can be monitored and managed for the driving simulation sessions. The participants will have a more pleasurable time if you give them with a room that is air-conditioned and has a temperature that is kept at 24 degrees Celsius throughout the entire event.

3. Set aside a predetermined amount of time, typically between thirty and forty-five minutes, for each session of simulated driving. Within this time range, an accurate assessment of driving behavior as well as physiological responses can be performed.

4. Plan the sessions of simulated driving to take place in the afternoon, when people are more likely to be experiencing feelings of tiredness. This time period has been chosen so that the potential impacts of tiredness on driving performance and physiological data can be investigated.

5. After each driving session, keep the gathered physiological data in a safe place and organize it so that it may be used for subsequent analysis and interpretation.

B. ANN MODEL ESTABLISHMENT

Data processing in Artificial Neural Networks (ANN) begin with, the collected data is preprocessed and organized into a worksheet. Subsequently, an appropriate ANN model is selected for the data processing task. For a simple nonlinear classification problem, the Multilayer Perceptron (MLP) model proves to be a suitable choice. MLP is a Feedforward neural network comprising interconnected nodes or neurons. In this study, the MLP architecture is adopted, featuring the establishment of a hidden layer. The number of neurons in the input layer is set to match the number of features in the input data, while the number of neurons in the output layer aligns with the number of classes in the classification problem. In this particular research, the input layer consists of 2 nodes, and the output layer comprises 4 nodes.

To optimize the performance of the ANN, various parameters can be adjusted. These include the number of nodes in each layer, the activation function used in each layer, the activation function used in each layer, and the

learning rate. During training, the optimizer updates the weights of the neural network based on the gradient of the loss function. This process helps the network to learn and improve its performance. It is essential to monitor the model’s performance on the validation set during training and make adjustments to hyperparameters such as the learning rate or the number of neurons to prevent overfitting. Overfitting occurs when the model becomes too specialized in the training data and performs poorly on new, unknown data. After training the ANN, evaluating its performance is crucial to assess its generalization ability for

new, unseen data. Various performance indicators can be

used depending on the specific task and output types. These indicators may include metrics such as accuracy, precision, recall, F1 score, mean squared error, or mean absolute error.

III. RESULTS AND DISCUSSION

Table 2 summarizes the personal information and data results of the ten recruited volunteers. The table provides a concise overview of the collected data for each volunteer. TABLE presents the data obtained from parallel experiments conducted by the identical group of ten volunteers.

TABLE I

Volunteer Information and Physiological Data Results

No	Sex	Age	Heart rate (BPM)				Pressure (mmHG)			
1	Female	24	102	72	121	78	418	176	523	368
2	Female	24	98	67	98	81	425	162	612	399
3	Female	23	105	62	105	76	449	97	531	268
4	Female	24	121	69	103	83	451	98	549	369
5	Female	29	98	65	145	85	405	93	420	396
6	Male	24	142	66	80	97	498	87	530	398
7	Male	25	92	66	83	73	410	79	546	321
8	Male	24	110	79	97	76	440	115	596	231
9	Male	29	99	70	113	96	423	187	612	349
10	Male	29	123	75	131	85	431	195	639	306

TABLE II

Volunteer Information and Physiological Data Results (Parallel Experiment)

No	Sex	Age	Heart rate (BPM)				Pressure (mmHg)			
1	Female	24	145	63	143	86	482	163	720	372
2	Female	24	87	67	135	71	403	198	699	201
3	Female	23	85	55	126	79	387	162	548	332
4	Female	24	98	63	132	83	388	178	566	371
5	Female	29	118	59	116	80	487	169	569	312
6	male	24	131	66	123	81	445	189	612	326
7	male	25	146	78	95	71	521	231	559	196
8	male	24	122	80	79	79	476	203	505	265
9	male	29	128	59	137	80	456	168	632	352
10	male	29	99	72	116	82	410	199	598	361

A. DATA SET EXPANSION RESULTS

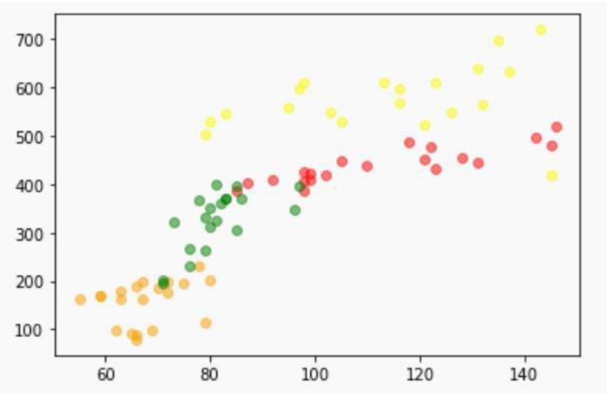

Figure 6 Scatter plot of raw data

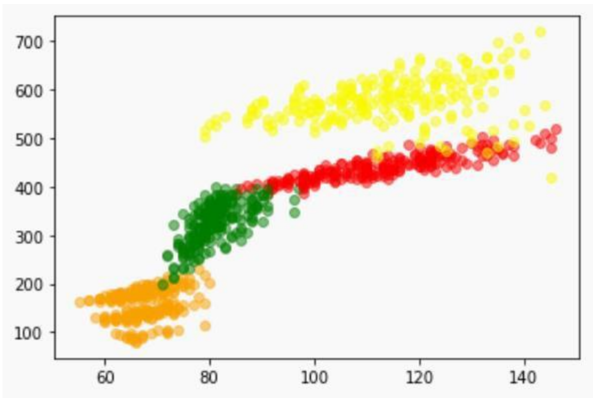

Figure 7 Extended Data Scatter Char

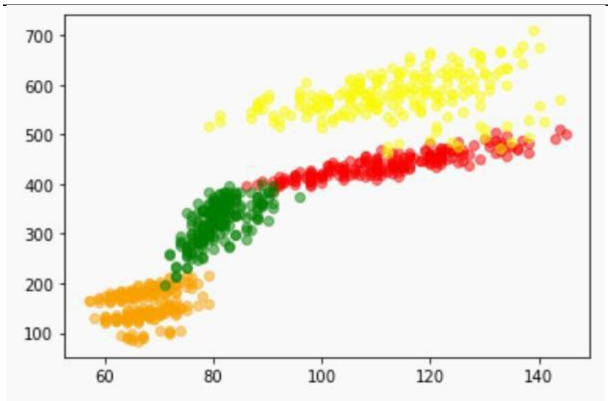

Figure 8 Combined Dataset Scatter Chart

Figure 6 and Figure 7 present scatter plots illustrating the raw data and extended data, respectively. The original dataset comprises 80 data points, with 20 points for each type. To enhance the dataset, interpolation was conducted between different points within the same class, resulting in the insertion of a total of 760 data points. As a result, a comprehensive database containing 840 data points is formed, encompassing the original 80 data points. Figure 8 showcases the scatter plot of the combined dataset.

B. ANN TEST RESULTS

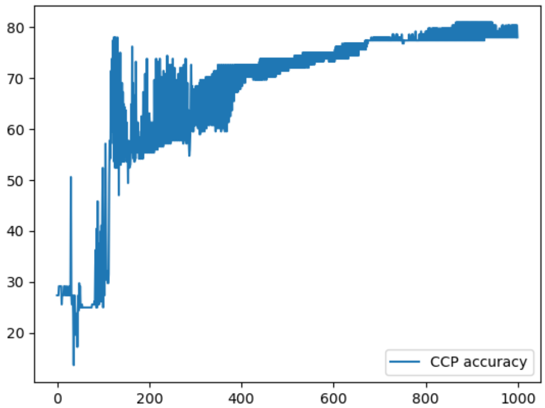

Figure 9 Accuracy variation chart

Figure 9 demonstrates the variation in accuracy as the number of iterations increases during the classification task. With 1000 iterations, the accuracy fluctuates and displays an overall increasing trend. The most substantial changes in accuracy occur within the initial 200 iterations. After this point, the fluctuations become less pronounced, and the rate of increase gradually slows down. Ultimately, the accuracy stabilizes at over 70%. The stable accuracy above 70% indicates that the classification task can be accomplished relatively well.

Figure 10 depicts the iterative Mean Squared Error (MSE) diagram for the data processed using the ANN architecture. The ANN is configured to iterate 1000 times. The graph illustrates that as the number of iterations.

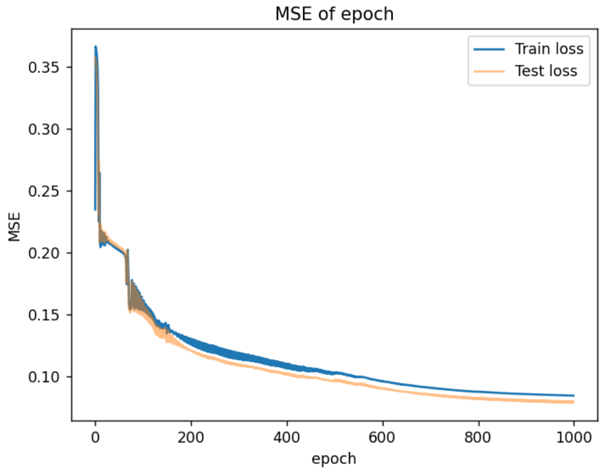

Figure 10 Iterative Mean squared error diagram

IV. CONCLUSION

Design and implementation of a comprehensive vehicle safety sensing system with driver state detection are the subject of this work. To determine driver health, the technology monitors and analyzes heart rate and fingertip pressure in real time. It may identify abnormal driving circumstances and alert drivers. The system collects volunteer data and processes it with ANN. The system performs well in classification tasks using ANN, proving its ability to analyze and comprehend driver status data. The approach and findings show that this research achieved all its goals. The research fulfilled its goals by gathering and processing real human bodily data, extending the dataset, and training the artificial neural network model. The system processes and filters data well, and the trained model performs well in accuracy, performance metrics, and other criteria. The vehicle safety sensing system monitors and ensures driver safety by integrating many sensing technologies and using ANN for data processing. The system's anomalous driving detection and response can improve road safety and driver awareness.

ACKNOWLEDGEMENT

Gratitude and thanks are given to the authority of the School of Electrical and Electronic Engineering for providing support and facilities to complete this work.

REFERENCES

[1] K. Shah, C. Sheth, and N. Doshi, "A Survey on IoT-Based Smart Cars, their Functionalities and Challenges", *Procedia Comput. Sci.*, vol. 210, pp. 295–300, 2022, doi: 10.1016/j.procs.2022.10.153.

[2] T. Jannusch, D. Shannon, M. Völler, F. Murphy, and M. Mullins, "Cars and distraction: How to address the limits of Driver Monitoring Systems and improve safety benefits using evidence from German young drivers", *Technol. Soc.*, vol. 66, p. 101628, Aug. 2021, doi: 10.1016/j.techsoc.2021.101628.

[3] V. Saritha, S. L. Chandana, U. S. B. K. Mahalaxmi, D. Shamia, P. Chawla, and A. Chaturvedi, "An intelligent sensing and detection system for accident preventions in four wheeler vehicles", *Mater. Today Proc.*, vol. 80, pp. 1713–1716, 2023, doi: 10.1016/j.matpr.2021.05.353.

[4] P. Gershon, S. Seaman, B. Mehler, B. Reimer, and J. Coughlin, "Driver behavior and the use of automation in

real-world driving", *Accid. Anal. Prev.*, vol. 158, p. 106217, Aug. 2021, doi: 10.1016/j.aap.2021.106217.

[5] H. Singh and A. Kathuria, "Analyzing driver behavior under naturalistic driving conditions: A review", *Accid. Anal. Prev.*, vol. 150, p. 105908, Feb. 2021, doi: 10.1016/j.aap.2020.105908.

[6] H. Singh and A. Kathuria, "Profiling drivers to assess safe and eco-driving behavior – A systematic review of naturalistic driving studies", *Accid. Anal. Prev.*, vol. 161, p. 106349, Oct. 2021, doi: 10.1016/j.aap.2021.106349.

[7] R. A. Zaidan *et al.*, "Comprehensive driver behaviour review: Taxonomy, issues and challenges, motivations and research direction towards achieving a smart transportation environment", *Eng. Appl. Artif. Intell.*, vol. 111, p. 104745, May 2022, doi: 10.1016/j.engappai.2022.104745.

[8] A. J. Gonzalez *et al.*, "Detection of driver health condition by monitoring driving behavior through machine learning from observation", *Expert Syst. Appl.*, vol. 199, p. 117167, Aug. 2022, doi: 10.1016/j.eswa.2022.117167.

[9] L. Li, B. Zhong, C. Hutmacher, Y. Liang, W. J. Horrey, and X. Xu, "Detection of driver manual distraction via image-based hand and ear recognition", *Accid. Anal. Prev.*, vol. 137, p. 105432, Mar. 2020, doi: 10.1016/j.aap.2020.105432.

[10] K. Lu, A. Sjörs Dahlman, J. Karlsson, and S. Candefjord, "Detecting driver fatigue using heart rate variability: A systematic review", *Accid. Anal. Prev.*, vol. 178, p. 106830, Dec. 2022, doi: 10.1016/j.aap.2022.106830.

[11] P. Boyraz, M. Acar, and D. Kerr, "Multi-sensor driver drowsiness monitoring", *Proc. Inst. Mech. Eng. Part J. Automob. Eng.*, vol. 222, no. 11, pp. 2041–2062, Nov. 2008, doi: 10.1243/09544070JAUTO513.

[12] C. Ahlström, R. Zemblys, S. Finér, and K. Kircher, "Alcohol impairs driver attention and prevents compensatory strategies', *Accid. Anal. Prev.*, vol. 184, p. 107010, May 2023, doi: 10.1016/j.aap.2023.107010.

[13] M. Alcañiz, M. Guillen, and M. Santolino, "Differences in the risk profiles of drunk and drug drivers: Evidence from a mandatory roadside survey", *Accid. Anal. Prev.*, vol. 151, p. 105947, Mar. 2021, doi: 10.1016/j.aap.2020.105947.

[14] N. Zangi, R. Srour-Zreik, D. Ridel, H. Chassidim, and A. Borowsky, "Driver distraction and its effects on partially automated driving performance: A driving simulator study among young-experienced driver"', *Accid. Anal. Prev.*, vol. 166, p. 106565, Mar. 2022, doi: 10.1016/j.aap.2022.106565.

[15] M. Bassani *et al.*, "Do driver monitoring technologies improve the driving behaviour of distracted drivers? A simulation study to assess the impact of an auditory driver distraction warning device on driving performance", *Transp. Res. Part F Traffic Psychol. Behav.*, vol. 95, pp. 239–250, May 2023, doi: 10.1016/j.trf.2023.04.013.

[16] J. M. Morales *et al.*, "Monitoring driver fatigue using a single-channel electroencephalographic device: A validation study by gaze-based, driving performance, and subjective data", *Accid. Anal. Prev.*, vol. 109, pp. 62–69, Dec. 2017, doi: 10.1016/j.aap.2017.09.025.

[17] C. Jacobé De Naurois, C. Bourdin, C. Bougard, and J.-L. Vercher, "Adapting artificial neural networks to a specific driver enhances detection and prediction of drowsiness", *Accid. Anal. Prev.*, vol. 121, pp. 118–128, Dec. 2018, doi: 10.1016/j.aap.2018.08.017.

[18] K. Mohammed, M. Abdelhafid, K. Kamal, N. Ismail, and A. Ilias, "Intelligent driver monitoring system: An Internet of Things-based system for tracking and identifying the driving behavior", *Comput. Stand. Interfaces*, vol. 84, p. 103704, Mar. 2023, doi: 10.1016/j.csi.2022.103704.

[19] P. Josephinshermila, S. Sharon Priya, K. Malarvizhi, R. Hegde, S. Gokul Pran, and B. Veerasamy, "Accident detection using Automotive Smart Black-Box based Monitoring system", *Meas. Sens.*, vol. 27, p. 100721, Jun. 2023, doi: 10.1016/j.measen.2023.100721.

[20] P. I. J. Wouters and J. M. J. Bos, "Traffic accident reduction by monitoring driver behaviour with in-car data recorders", *Accid. Anal. Prev.*, vol. 32, no. 5, pp. 643–650, Sep. 2000, doi: 10.1016/S0001-4575(99)00095-0.

[21] I. Jegham, I. Alouani, A. Ben Khalifa, and M. A. Mahjoub, "Deep learning-based hard spatial attention for driver in-vehicle action monitoring", *Expert Syst. Appl.*, vol. 219, p. 119629, Jun. 2023, doi: 10.1016/j.eswa.2023.119629.

[22] V. G. Menon, S. Jacob, S. Joseph, P. Sehdev, M. R. Khosravi, and F. Al-Turjman, "An IoT-enabled intelligent automobile system for smart cities", *Internet Things*, vol. 18, p. 100213, May 2022, doi: 10.1016/j.iot.2020.100213.

Cuichengjun completed her Bachelor's degree in Vehicle Engineering at North University of China in 2020. Subsequently, she embarked on a journey of academic advancement by pursuing a master's degree in Materials and Chemical Engineering in China, starting in 2021. Presently, she is furthering her educational pursuits at the Universiti Sains Malaysia (USM), where she is enrolled in the master's program for Electronic System Design Engineering.

Noramalina Abdullah received her Bachelor's degree in Quality Control and Instrumentation (B. Tech) from Universiti Sains Malaysia in 2000. Then, she pursued her Master degree in Mechatronic and Automation Engineering from Universiti Teknologi Malaysia in 2009. She received her PhD in Electrical Power System in 2015 from Chulalongkorn University, Thailand. Her research interest is power system, electrical fault detection and Internet of things (IoT)