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College of Science and Technology

AFRICAN CENTER OF EXCELLENCE IN INTERNET OF THINGS

# Development of an AI and IoT based system for accident prevention, detection, and real time emergency response. Case study: Rwanda

***A dissertation submitted in partial fulfilment of the requirements for the award of Master of Science degree in internet of things: wireless intelligent sensor network.***


Submitted by:
**BULONZA BASEME FABIEN (Ref. No:221030639)**


**December 2023**

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Supervised by:
**Main supervisor**: Prof. Damien HANYURWIMFURA

**Co-supervisor:** Prof. Celestin Twizere

**December 2023**

# DECLARATION

I BULONZA BASEME FABIEN, Master ‘student from African Centre of Excellence in internet of things, at University of Rwanda. I declare that this research thesis is my own original work, and it has never been presented before anywhere in the world.

**Names**: Bulonza Baseme Fabien
**Ref**: 221030639
Signed:

Date:**5 /12/ 2023**

# BONAFIDE CERTIFICATE

This is to certify that this submitted Research Thesis work report is a record of the original work done by BULONZA BASEME FABIEN (**Ref. Nu: 221030639**), MSc. IoT-WISNET Student at the University of Rwanda / College of Science and Technology / African Center of Excellence in Internet of Things, the Academic year 2022/2023.

This work has been submitted under the supervision of **Prof. Damien HANYURWIMFURA** and **Prof. Celestin Twizere**

Main Supervisor: **Prof. Damien**
Date:

Signature

Co-Supervisor: **Prof. Celestin Twizere**
Date:**5/12/2023**

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The Head of Masters and Training
Dr. James Rwigema

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Date :

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# ABSTRACT

Road incidents caused by driver distractions (such as phone usage), drunkenness, and excessive speed constitute significant dangers to public safety in Rwanda. A comprehensive study of the design and implementation of an AI and IoT-based system for accident detection, prevention, and enhanced emergency response is presented in this thesis as one of the solutions to the problem. Using Raspberry Pi microcontroller as the central server, the system incorporates several sensors and actuators connected to ESP8266, including GPS Gn801 GPS Glonass dual mode for speed detection and car localization, MQ3 alcohol gas sensor SEN42, R16 for alcohol detection, ADXL335-3 Axis compass accelerometer GY-6l for car movement changes. In addition, a Raspberry Pi 4Bl3B 5MP fisheye night vision focal camera is integrated into the system to detect driver distractions such as phone usage while driving. Sophisticated machine learning and artificial intelligence (AI) algorithms, with a specific focus on Convolutional Neural Networks (CNNs), have been utilised to identify instances of driver distraction and facilitate real-time monitoring and alert systems. By leveraging on cloud computing to store and analyse data, the system guarantees efficient and impactful correspondence with emergency response teams. Our objective is to contribute to the domain of road safety by developing an efficient solution for emergency response and accident prevention in Rwanda. Our research emphasizes the importance of utilizing technology to address critical issues related to road safety.

The study's findings demonstrate the accuracy of the integrated IoT sensors in accurately detecting accidents, speed, monitoring alcohol consumption, and identifying distractions, specifically phone usage. A remarkable 86-100% accuracy is attained by Custom Convolutional Neural Networks (CNNs) when it comes to identifying driver distractions. The combination of edge and cloud computing guarantees timely and effective communication with emergency response teams. This study highlights the critical role that technology plays in improving road safety by proposing a technologically advanced solution for emergency response and accident prevention in Rwanda. The capabilities of the system to monitor in real-time and its efficacy in accident detection and prevention demonstrate its potential to make a substantial impact on the field of road safety.

**Key words**: IoT, AI, ML, CNNs, ResNet 50, VGG 16

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# LIST OF ACRONYMS

IoT: Internet of Things

AI : Artificiel Intelligence

CNN : Convolution Neural Networks

VGG16: Visual Geometry Group 16

ResNet 50: Residual Network 50

HTTP- Hypertext Transfer Protocol

JS- JavaScript

WHO: World Health Organization

ASIRT: Association for Safe International Road Travel

PBU: Portable On-Board Unit

# CHAPTER ONE. INTRODUCTION

## 1.1 Introduction

This chapter discusses the background of the study, problem statement, objectives, scope and the significance of an accident prevention and emergency system.

## 1.2 Background

Road accidents continue to be a major concern on a global scale, resulting in substantial loss of life and property. Recent years have seen a dramatic increase in the number of traffic accidents, which is obviously highly concerning. The World Health Organization analysed traffic fatalities in detail and found that they account for the eighth leading cause of death worldwide. More than 1.35 million people die in road accident every year. The Association for Safe International Road Travel (ASIRT) predicts that by 2050, traffic fatalities will rank fifth among all causes of death worldwide[1]. According to the ASIRT, the cost of road accidents for each country accounts for 1%-2% of national budgets worldwide[2]. More than 700 people lost their lives and around 4,000 were injured in road accidents in Rwanda in 2022, according to police statistics issued on May 18th, 2023, [3].according to the police's data, there were 8000 accidents in 2021, up to 9400 in 2022 [3]. The information was shared at a forum in Kigali, Rwanda's capital, focusing on the topic of traffic safety.

According to this latest report of police of Rwanda, the most common causes of accidents in Rwanda are excessive speeding, inattentive driving, and driving under the influence of alcohol[3]. It has been noted that serious injuries frequently result in mortality due to waiting times for medical attention. The victim's chance of survival is directly related to how quickly an ambulance can reach the scene of the accident and transport the patient to a hospital. Industry and academia pay increased attention to road safety as the number of traffic incidents continues to rise. The number of people died in traffic accidents can be reduced with the help of a sophisticated accident detection, prevention, and warning system.

The system prevents accidents to happen by warning the driver in case of bad driving habits such as over speeding, alcohol consumption, distraction like using mobile phone etc. In case of an accident detection, since we cannot prevent accident at 100%, the system immediately contacts local emergency services such as hospitals, police stations, and fire departments.

In recent years, an abundance of accident prevention, detection and alert systems have been implemented. Most modern automobile tracking systems rely on GPS receivers to determine their precise locations. Certain vehicles are even equipped with global positioning systems capable of determining their precise location and subsequently transferring that information to the cloud. [4].E-Notify, one of the most prevalent accident notification systems, mandates the installation of a portable on-board unit (PBU) in each vehicle [5]. Every new vehicle manufactured in Europe after to 2015 is obligated to incorporate the eCall system, an innovation of the European Commission. Upon detecting an accident, eCall makes an immediate call to 112 [6]1ike the way we contact 113 number in Rwanda when there is traffic accident that occurs. Data from satellites, radar, and GPS systems used to be too large to analyse, but advancements in cloud computing [7]and BigData [8][9] have made this possible. A GPS is still capable of pinpointing the precise location of every individual object. In recent years, there has been a notable increase in the implementation of Internet of Things (IoT) and artificial intelligence (AI) solution development for road safety products.

These solutions are limited in their ability to provide real-time updates on accidents and to prevent accidents caused by driver distraction, over speeding and alcohol consumption.

To address these limitations, an integrated solution leveraging AI and IoT technologies was developed. The proposed system tends to prevent accidents caused by driver distraction such as phone usage, over speeding, and alcohol consumption by alert the driver or vibrating the seat in case one of these is detected. Furthermore, since accident cannot be prevented 100%, the system alerts in real time the hospitals and police stations in case of accidents that happen. The system includes Raspberry pi 4Bl3B 5MP fisheye night vision facial camera for driver distraction detection such as usage of phone, MQ3 alcohol sensor for alcohol detection. ADXL335-3 Axis compass accelerometer Gy-61 for accident detection, GPS GN801 Glonass dual module M8n for vehicle speed and its location and GSM800C for data transmission over internet, servo motors, alarm controller, ESP8266 and Raspberry pi 4 controller. The cloud server displayed the results to the dashboard report, which is useful for users to know the status of each driver.

A customized Convolutional Neural Networks (CNNs) was utilized to process visual data from camera, and detect signs of driver distraction, such as phone usage.

## 1.3 Motivation

This project is motivated by Rwanda's worryingly high rate of road accidents, which are primarily caused by excessive speeding, alcohol consumption, and driver distraction[3].These incidents result in serious injuries, fatalities, and substantial economic expenditures. Existing preventive measures and emergency response systems have proved to be insufficient to effectively address these vital issues.

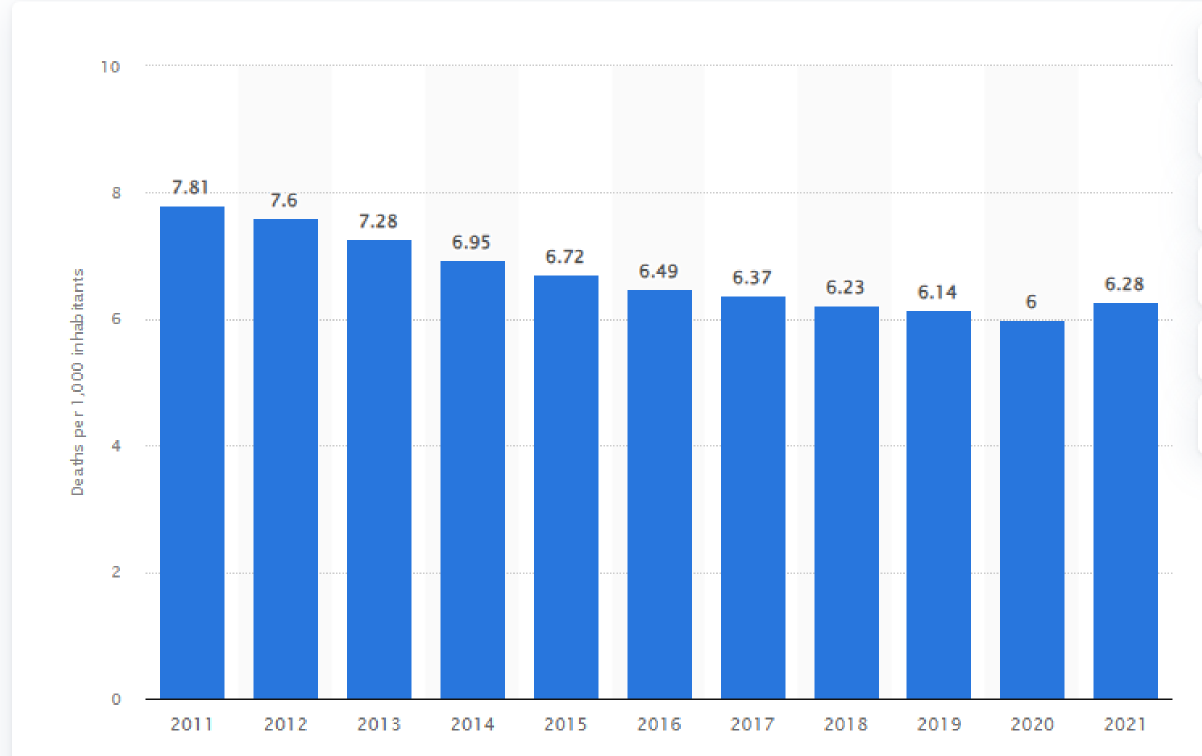



Figure 1.1 Death rate of traffic in Rwanda 2011-2021 [10]

Using the power of AI, ML and IoT technologies, we were inspired to create an advanced system that can prevent accidents and improve emergency response. The proposed system monitors real-time data from sensors, such as speed sensors, alcohol sensors, accelerometers, and camera, that are integrated into vehicles. We analysed this data using sophisticated algorithms to identify instances of driver distraction. By providing drivers with real-time alerts , we hope to raise awareness and encourage safer driving practises. In addition, the system facilitates prompt emergency response by detecting accidents with accelerometer data and alerting the appropriate department. Our ultimate objective is to save lives, reduce the social and economic costs of accidents, and promote a culture of responsible transportation. With this initiative, we hope to have a significant impact on road safety and enhance the well-being of individuals and communities all over Rwanda.

## 1.4 Problem Statement

Significant risks to public safety are posed by road incidents in Rwanda caused by driver distraction (usage of the phone), excessive speeding and alcohol consumption[3].Despite existing regulations and awareness campaigns, this rate of occurrence remains alarming. The absence of real-time monitoring and prompt intervention make worse risks and delays emergency response, resulting in increased loss of life and property.

Current accident prevention and emergency response systems lack the technological advancements necessary to effectively address these challenges. Existing methods, such as using roadside cameras to detect excessive speeding, alcohol detectors, law enforcement patrols, and manual reporting, are unable to provide timely and accurate data, resulting in ineffectual accident prevention and delayed emergency assistance [11].Proactive initiatives to reduce the possibility of accidents and improve response times are hampered by the lack of a unified system that incorporates artificial intelligence, machine learning, and the internet of things. Another thing that gets in the way of effective accident prevention is the lack of a reliable and scalable system for monitoring things like driver distraction, speeding and drunk driving, in real time.

Therefore, there is an urgent need in Rwanda to establish an AI and IoT-based system for accident prevention, detection, and emergency response. This system uses new technology to detect and address the causes of accidents quickly and correctly. It is feasible to collect real-time data on driver distraction, over speeding, and alcohol consumption by integrating IoT sensors into automobiles and applying AI and ML algorithms. This data is examined in real time to offer drivers with quick alerts and notifications, as well as to notify the appropriate authorities in circumstances when intervention is required.

Furthermore, an efficient accident detection and emergency response system was to be put in place, utilizing accelerometers to detect accidents, assess their severity, and coordinate with emergency response agencies. The proposed system intends to avoid accidents, decrease related risks, and improve emergency response capabilities in case of accident in Rwanda by addressing technical gaps and enhancing overall road safety infrastructure.

## 1.5 Study objectives

### 1.5.1 General objective

The study aimed to develop an AI and IoT-based system to prevent and detect road accidents in Rwanda caused by driver distraction such as phone usage while driving and excessive acceleration, as well as alcohol consumption.

### 1.5.2 Specific objectives

To achieve the general objective of this research, the study was guided by the following specific objectives:

1. To review the existing accidents detection and prevention with their weaknesses and limitations
2. To develop a real time accident monitoring system using IoT devices
3. To Implement AI and ML algorithms by Utilizing advanced algorithms to analyse the collected data on driver distraction for accident prevention and enable real-time driver alerts.
4. To evaluate system performance and its effectiveness by conducting rigorous evaluation and testing

## 1.6 Hypothesises

We hypothesised that by implementing an AI and IoT-based system for accident prevention and emergency response, we can reduce the number of road accidents in Rwanda caused by driver distraction, excessive speed, and alcohol consumption. This system enables real-time monitoring of driver distraction, provide drivers with timely alerts and warnings, and improve emergency response through accurate accident detection and prompt notification of authorities. We anticipated that the implementation of this system will result in enhanced driver behaviour, increased awareness of risky driving practises, and a substantial reduction in the number of road accidents.

## 1.7 Study Scope

The scope of this study is the development and deployment of a system that utilises artificial intelligence (AI) and Internet of Things (IoT) technologies to address accident prevention, detection, and emergency response in Rwanda. The primary focus of the study is on mitigating driver distraction, specifically related to phone usage as well as addressing issues of excessive speeding and alcohol consumption. The research uses Internet of Things (IoT) devices, such as speed sensors, alcohol sensors, accelerometers, and cameras, to collect real-time data on driving behaviours. Artificial intelligence (AI) and machine learning (ML) algorithms were employed to evaluate the data and identify occurrences of dangerous driver distraction, such as prolonged phone usage. This facilitated the prompt transmission of real-time alerts and notifications to relevant authorities. Furthermore, the study offers recommendations for the installation and modification of the system, in addition to analysing its performance, efficacy, and user satisfaction.

## 1.8 Significance of the study

The significance of this work is numerous. The primary purpose of this study is to address a significant concern regarding road safety in Rwanda. Specifically, it aims to examine the primary factors contributing to accidents, including excessive speed, alcohol consumption, and driver distraction. The study aims to achieve a substantial reduction in the occurrence of road accidents, injuries, and fatalities by implementing an AI and IoT-based system specifically intended for the detection and prevention of such behaviours. These findings have significant implications for the overall safety of the public as well as the well-being of individuals and communities.

Second, the significance of the study extends beyond its immediate impact on road safety. By utilising cutting-edge technologies such as AI, ML, and IoT, this initiative demonstrates the innovative use of cutting-edge solutions to address real-world problems. The successful implementation of the proposed system could serve as a model for other regions and nations dealing with comparable road safety issues. In addition, the study's findings, recommendations, and lessons learned can contribute to the development of automated transportation systems, influencing future policies and interventions to create safer road environments worldwide. The study has the potential to save lives, enhance road safety practises, and inspire innovation in accident prevention and emergency response.

## 1.9 Organization of the study

The chapter 1 started with introduction of the research study, the chapter 2 gives a review of the related work (literature review) and the gaps identified. Chapter 3 describes the methodology applied in this study and Chapter 4 explains the system model and design, prototype, and parameters. The Chapter 5 presents the results and findings analysed from the research study carried out. The last is Chapter 6, which provides the conclusion and recommendations of the study.

## 1.10 Summary

This chapter presented an introduction of the study, provides background information on road safety issues in Rwanda, concentrating specifically on excessive speeding, alcohol consumption, and driver distraction. It defines the problem statement and research objectives with precision, emphasising the need for an AI and IoT-based system for accident prevention and emergency response. The chapter highlights the importance of the study in addressing these critical road safety challenges and its potential to have a significant impact on reducing accidents, injuries, and fatalities. It provides the context, motivation, and justification for developing an innovative solution to enhance road safety in Rwanda.

# CHAPTER TWO. LITERATURE REVIEW

## 2.0 Introduction

The second chapter presents the relevant existing literature for this investigation. The review of related work assisted in identifying gaps and determining how to address the resulting issues. It provides and demonstrates how IoT and AI technologies utilised on the existing research works**.** Over the past few decades, many different approaches to accident detection, prevention and alerting have been developed. Detection, prevention, and warning systems for accidents are often divided into three groups: smart phone-based systems, hardware-based systems and integrated accident prevention and detection systems.

## 2.1 Smartphone based systems.

In these setups, multiple sensors on a smartphone are utilized to detect, prevent, and report traffic incidents. The location of accidents was tracked using an accelerometer and GPS data by Zhao et al. [12]. The method employed herein is limited to accident detection and does not provide any rescue operations, in other words. Using a GPS module to pinpoint the incident's precise location, the accident detection approach proposed by Reddy et al [13].instantly alerts nearby medical facilities. The single sensor used is the paper's primary shortcoming. Thus, the sensor is crucial to the success of the system. In addition, it could lead to a higher rate of false alarms.

A system for detecting accidents and sending alerts via smartphones was proposed by Hamid M. et al. [14]. Vehicle collisions can be detected through analysis of the combined G-force, noise, and speed data. Both gravity strength and background noise can be extracted with the use of the mobile sensor and accelerometer (microphone). When an accident is identified, an alert is sent to the appropriate authorities. Due of the importance of speed in accident detection, the gadget may give false positives if the collision occurs at low speeds and no warning alert was taken into consideration.

Patel et al. [15] developed an Android software that can detect and report accidents. They have detected an accident simply using a mobile sensor with an accelerometer and a GPS module. In the event of an accident, it will dial 108 and play a pre-recorded message. The biggest drawback of this study is that they only employ a single sensor, an accelerometer, which means the whole system is useless if the sensor fails and no warming message was taken into consideration.

The primary issue of the smartphone-based system is its reliance on the smartphone itself. The accident detection app must be pre-installed on each user's smartphone. The accuracy of the system will depend on the quality of sensors embedded into the smartphone. It could have a greater potential for erroneous accident detection in the case of when a car goes with l low speeds.

## 2.2 Hardware based systems.

To detect, prevent accidents and alert the appropriate parties, these systems employ a wide variety of sensors. These sensors are typically installed in the vehicle's exterior.

D. Bindu Tushara et al. [16]suggested a vibration sensor and microcontroller-based system for detecting and preventing automobile accidents. The Atmel microcontroller AT89S52 is linked to everything else in the system, including sensors, a GSM module, a GPS module, and so on. Acceleration, force, vibration, and other sensor data are often interpreted and sent to all saved emergency numbers until the source of the event is determined. The rescue operations are not supported by this system and Driver distraction.

An IoT-based accident alarm and rescue system was proposed by A. Shaik et al. [17], which employs a GPS sensor and accelerometer to collect data and upload it to the cloud. In the event of an accident, a notification will be sent to any saved emergency contacts. The severity and location of the accident are communicated in this message to speed the arrival of the ambulance the limitation of this system is that does not use machine learning techniques to determine the false alarm and real time detection and prevention of accidents. And it can't detect driver's distraction.

An Internet of Things-based automobile accident detection and rescue system was discussed by C. Nalini et al. [18]. In this project, an accident detection and warning system is built using a vibration sensor, a buzzer, and a GPS module. When an accident is detected, a buzzer goes out for one minute; if the buzzer is still going after that time, a web service message is sent to the appropriate authorities.

C. Dashora et al. [19] presented an Internet of Things–based accident detection and warning system analogous to [18]. The primary shortcoming of this work is that once an accident has been identified, the location data will be transmitted to the customer service department, and a representative will manually contact the nearest hospital. It needs to be done by a person. It's not a real time system.

These IoT-based systems have one major drawback which is less accuracy however, using some AI-based techniques, the system's accuracy can be increased.

## 2.3 integrated accident prevention and detection systems

An integrated system for accident detection and rescue was developed by Fogue et al. [20] This system makes use of an on-board unit (OBU) to identify and alert about vehicle accidents. All information related to accidents like speed, the type of vehicles involved, the deployment status of airbags, and so on, is collected by various sensors and uploaded to the cloud.

After that, methods like machine learning are utilized in order predict the accident. The fact that not all cars can support an OBU is the primary constraint of this strategy. And it can't detect accidents related to driver distraction to prevent this.

In [21]Rajesh, G et al. presented an accident detection and rescue system built on deep learning. Pre-installed on the roadway, a Wi-Fi web camera keeps constant watch over traffic and uploads its findings to the cloud. In the cloud, a deep neural network analyses the video data. If an incident occurs, the data is transmitted to a nearby control centre. S.

An accident detection system using convolutional neural networks (CNN) was proposed by Ghose et al.[22]. The two categories in this approach are accidents and non-accidents. The camera's picture stream is constantly uploaded to the server, where CNN is utilized to determine whether an incident occurred. Their dataset, which was created from the YouTube videos, will be used to train a model. The authors claim that the accident detection model has a 95% success rate. This approach is designed to identify accidents but does not consider subsequent rescue efforts. and does not use real driver alert to prevent accident that may be cause by some risky behaviour such as driver distraction.

To detect accidents and trigger the rescue module, Akash Bhakat et al. [23]combined Internet of Things (IoT) technology with machine learning methods. At first, they gather data from the IoT kit about the accident and transfer it to the server for analysis. This method utilizes fog computing to process data locally as opposed of sending it to a remote server. Due to the complexity of the input video data, the accuracy of this method, which uses a machine learning methodology to detect accidents, may not be satisfactory. Driver distraction and prevention of accidents caused by over speeding; alcohol was not covered.

To identify crashes using footage captured by the car's dashboard camera, Choi, J. G., Kong et al. [24]proposed a deep learning-based ensemble method. This method employs gated recurrent unit (GRU) and convolutional neural networks (CNN) to analyse data from the car's dashboard camera and identify the cause of an accident. The camera's location on the dashboard, which could be destroyed in an accident, is the method's main drawback. Since no Internet of Things (IoT) modules are used in this method, the false positive rate may be higher.

An automatic car accident detection method was introduced by Hozhabr Pour et al. [25] which combines a convolutional neural network (CNN) and a support vector machine (SVM) to detect the accident. This work uses different feature selection approaches to select the most prominent features from the available features set. The author claims the highest 85% accuracy at the testing time, which is not acceptable in the real-world applications. The first big limitation with this project is that they only used one data set because there wasn't much data for this application. This makes it hard to use their results in other situations. Second, it's hard to compare their results to those of other studies because there are different ways to define accidents and different kinds of sensor channels. Their system cannot be integrated in every car and driver distraction was not taken into consideration.

The leading cause of road accidents and its pattern were identified using data mining techniques by Comi, A et al. [26]. The author gathered information on traffic accidents that occurred in 15 different areas of the Rome Municipality from 2016 to 2019 to complete the analysis. Based on their findings, the authors propose using Kohonen networks and k-means algorithms for descriptive analysis and neural networks and decision trees for predictive analysis. The limitation of this work is no system was developed which combine IoT and ML to solve the issue of accident. Only data mining techniques which are suitable to analyse road accidents were given. And information on traffic accidents was based on accidents that occurred in different areas in Rome which causes are not the same as Rwanda's causes.

A straightforward approach based on deep learning was suggested to forecast traffic accidents by Singh, G et al. [27] For making predictions, this model employs a single input layer, a single output layer, and a pair of hidden layers. A real-time dataset with only 148 samples was used to train the model, which is insufficient for deep learning and the limitations is they could not prevent accidents and no IoT was used. Only approach was given for prediction.

Nikhlesh Pathik et al [28] proposed AI Enabled Accident Detection and Alert System Using IoT and Deep Learning for Smart Cities Once an accident has been identified by the IoT module, which utilizes a force sensor to measure the impact on the vehicle and a GPS module to determine the vehicle's speed, it uploads all relevant data to the cloud. In the second phase, pre-trained models, namely VGGNet and InceptionResNetV2, are utilized to reduce the rate of false positives and activate the rescue module. The limitations of this system are that it cannot detect driver distraction and real time alerting driver who over speeding to prevent accident which may be due to this.

## 2.4 Gaps identified.

Several gaps in the existing literature and research were identified during the investigation. These gaps illustrate areas where additional research and knowledge are required. Among the identified gaps are:

- ✓ Insufficient Emphasis on Driver Distraction
- ✓ Absence of comprehensive approaches that incorporate multiple risk factors, including excessive acceleration, alcohol consumption, and driver distraction.
- ✓ Relevance in Context: Many studies conducted in other regions may not consider Rwanda's specific contextual factors, road conditions, and regulatory frameworks. There is a need for research that addresses the unique obstacles to road safety in Rwanda and provides solutions that are tailored to the local context.

## 2.5 Research Contributions

This study's contribution stands out in various aspects when compared to previous research:

- ✓ **Driver distraction consideration**: While other studies may have examined excessive speeding and alcohol consumption, the incorporation of driver distraction as a significant factor in this study is a significant contribution. By incorporating cutting-edge techniques such as Convolutional Neural Networks (CNNs), the system seeks to detect distracted behaviours such as cell phone use, which is frequently ignored by conventional road safety systems.
- ✓ **Comprehensive approach**: This study takes a more holistic approach by considering multiple risk factors, as opposed to many extant studies that focus on a single factor, such as speeding or alcohol consumption. By incorporating detection of excessive speed, analysis of alcohol consumption, and detection of driver distraction, the proposed system addresses a broader range of accident causes and provides a more comprehensive solution to improve road safety.
- ✓ **Real time monitoring and response**: The proposed system provides drivers with immediate notifications and real-time monitoring of their driving behaviour. Accelerometer data allows for accurate accident detection and prompt emergency response. This study differs from others that may focus just on data analysis or post-accident response due to its emphasis on real-time analysis and proactive intervention.

## 2.6 Summary

The literature review provided a summary of existing studies and research on road safety, accident prevention, and emergency response systems. It emphasises the gaps and limitations in the existing literature, particularly regarding the inclusion of driver distraction as a major risk factor. While prior research has primarily focused on a single factor, the review exposes a lack of comprehensive approaches that incorporate multiple risk factors. In addition, the literature review highlights the need for real-time monitoring and proactive intervention systems, as well as the significance of contextual relevance in road safety research. By addressing these gaps, the study hopes to contribute to the existing corpus of knowledge and provide valuable insights for the development of an AI- and IoT-based system for accident prevention and emergency response in Rwanda.

# CHAPTER THREE. METHODOLOGY

## 3.0 Introduction

This chapter provides a comprehensive overview of the methodology used to design and implement the AI and IoT-based system for accident prevention and emergency response. This chapter outlines the key steps taken to capture data, develop algorithms, integrate hardware components, and enable real-time monitoring and alerts during the practical implementation of the proposed system.

This study's methodology entails a systematic approach to the development and implementation of an AI- and IoT-based system for accident prevention and emergency response. The methodology is broken down into the following steps:

## 3.1 System design and architecture

We designed the overall system architecture by considering the integration of IoT devices, data flow, and component communication. It was to determine the functions and roles of each component, including sensors, microcontrollers, data storage, AI algorithms, and user interfaces. And then we determined the connectivity options and protocols necessary for seamless data transmission and device-to-device communication.

The primary components of the design are the sensing data, communication, and data visualisation. The sensors used to collect data are processed, analysed, and the results are displayed on a dashboard. The data is then sent to the cloud server via Internet and the SIM800C GSM communication protocol, where it is further processed, analysed, and displayed in a web-based dashboard.

Figure 3.1 illustrates the system architecture. Data transmission, processing, storage and dashboard, sensing, and alerting are its five primary components. All these components are essential to the system's overall operation. Hardware or software may comprise the components of the units.

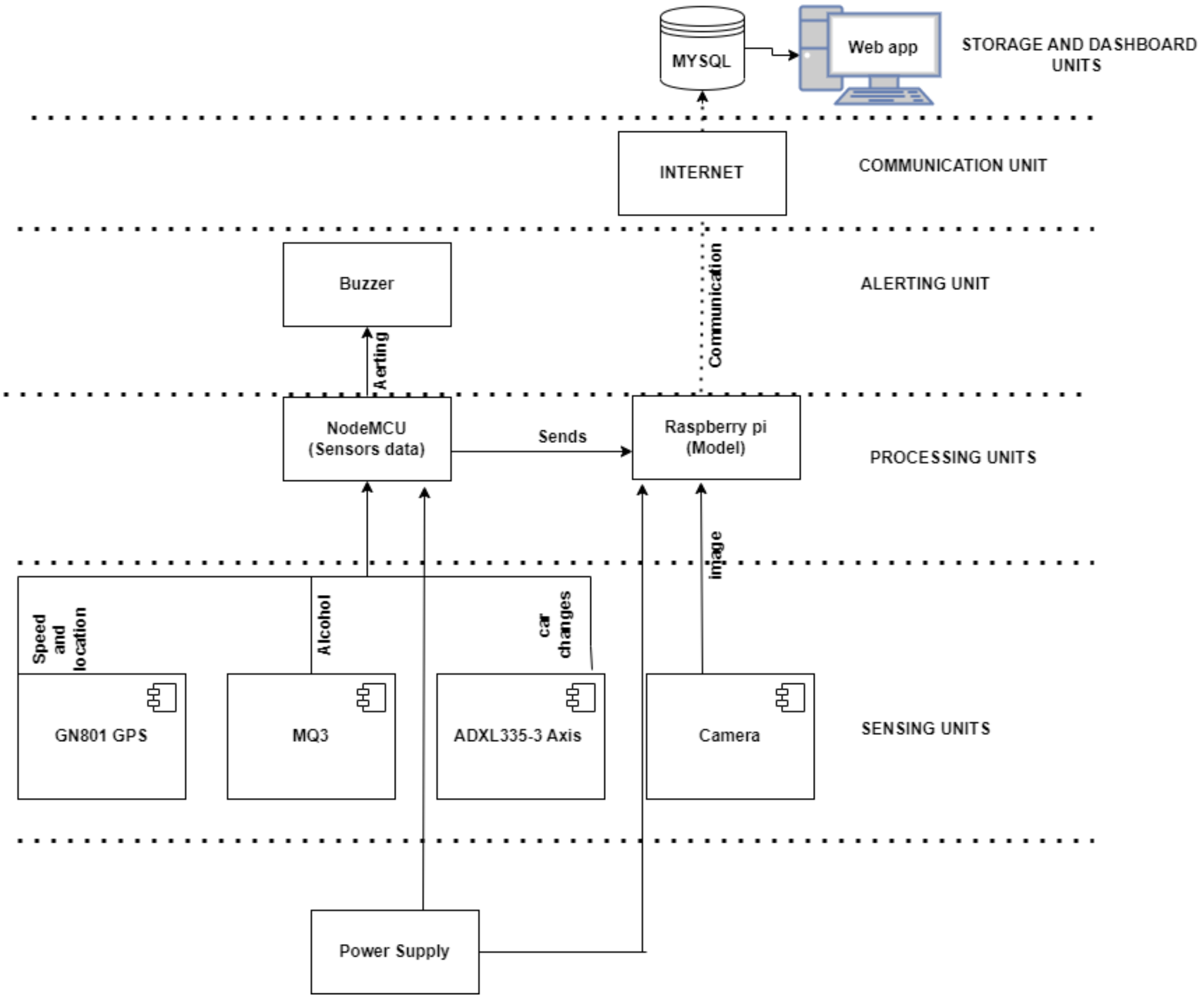



Figure 3.1 System Architecture

### 3.1.1 Sensing units

The sensing devices utilised in this endeavour serve as vigilant protectors of road safety. These devices conscientiously collect real-time data that is of the greatest significance for our mission. Comprising the ensemble of sensing devices are the following:

**i. Camera (Raspberry Pi 4B/3B 5MP Fisheye Night Vision Focal Camera)**

The camera is utilised to record visual data. It monitors driver behaviour, such as distractions, and assists in identifying actions such as cell phone use.

Figure 3.2 Raspberry Pi 4B/3B 5MP camera

### ii. GPS (GN801 GPS Glonass Dual-Mode Speed Sensor)

This component is responsible for providing precise location and speed information. It enables the system to monitor the vehicle's location in real-time and determine its speed, which is essential for detecting incidents of excessive speeding. It continuously measures the car's speed from 0 to 80 km/h for normal speed, 100 km/h to 120 km/h for excessive speed, and if the speed exceeds 120 km/h for abnormal, the accident risk is high.

Figure 3.3 GN801 GPS Glonass Dual-Mode Speed Sensor

### iii. Alcohol Sensor (MQ3 Alcohol Gas Sensor SEN42, R16)

The alcohol sensor detects alcohol vapours in proximity of the driver. It measures alcohol concentration and alerts the system if alcohol consumption is detected, thereby aiding in the identification of driving under the influence. In the case the alcohol level is too high, it alerts.


Figure 3.4 MQ3 Alcohol Gas Sensor SEN42, R16

### iv. Accelerometer (ADXL335-3 Axis Compass Accelerometer GY-61)

The accelerometer measures the acceleration of the vehicle and detects sudden motion changes. By monitoring acceleration data, the system identifies potential collisions and differentiate them from normal driving manoeuvres.

Figure 3.5 ADXL335-3 Axis Compass Accelerometer GY-61

### 3.1.2 Processing units

Our IoT and AI-driven accident prevention system utilises two integral processing units, each of which serves a distinct purpose in guaranteeing the smooth functioning of the system and the achievement of our objective to improve road safety. The Raspberry Pi and the ESP8266 constitute these components.

#### i. ESP8266

As the dynamic coordinator of our sensing devices and actuators, the ESP8266 is utilised. The software effectively handles the data acquired from various sensors, including the MQ3 alcohol sensor, accelerometer, and GPS. By means of its diminutive size and potent capabilities, this microcontroller interprets sensor data and maintains our system's vigilance against potential road hazards. Additionally, it assumes a critical function in triggering the alert mechanism, which includes the buzzer, upon detecting indications of driver distraction such as phone usage and drowsiness.

Figure 3.6 NodeMCU ESP8266 module

### ii. Raspberry pi 4

Owing to its powerful processing capabilities, the Raspberry Pi functions as the primary hub of our complete system. Assigning the task of data reception and processing from the ESP8266, it functions as an intermediary connecting the sensing devices with the sophisticated AI and ML algorithms. The core of our system, this central processing unit implements the algorithms necessary for detecting driver distractions. Furthermore, it oversees the integration process involving the camera, thereby assuring vigilant surveillance of driver conduct.

Figure 3.7 Raspberry pi 4 8GB Ram

### 3.1.3 communication unit

The processed data, comprising alcohol readings, driver distraction detection outcomes, speed and location information, and accelerometer data, is transmitted in a secure and real-time manner to a MySQL database via the Wi-Fi module of the phpMyAdmin web server. The previously mentioned data transmission procedure guarantees prompt availability of the gathered information, enabling its subsequent examination, visualisation, or application in the context of decision-making.

In the event of an accident, the GSM800c module sends immediate alerts and pertinent information, such as the accident's location, to the emergency contact numbers that have been programmed. This enables for prompt assistance and response in the event of an accident.

Figure 3.8 SIM800C GSM GPRS module

### 3.1.4 storage and dashboard unit

In addition to serving as an interface for interacting with the intelligent accident detection and prevention device, the dashboard provides real-time monitoring and data visualisation capabilities. The dashboard was developed employing a blend of web technologies, such as JavaScript, Cascading Style Sheets (CSS), and Hypertext Markup Language (HTML). Through HTTP, this web interface establishes a connection with a cloud server over the internet. It retrieves and displays data stored in the cloud in a format that is intuitive and easy to comprehend. The user interface, which can be accessed through a standard web browser, provides real-time monitoring of driver distractions, including but not limited to phone usage, speed, alcohol consumption, and accelerometer-detected incidents.

Users can stay informed and receive notifications regarding potential hazards, including driver distraction, excessive driving, and alcohol consumption, via this intuitive and user-friendly interface.

Furthermore, secure access to the MySQL database, which stores backups, system records, and historical data, is provided by the interface. This feature ensures the conservation of critical data for subsequent examination and thorough evaluation, enabling more knowledgeable choices and actions to be taken in accordance with the system's observations.

### 3.1.5 Alert Unit

A sophisticated safety component of our AI and IoT-based accident prevention system, the alert device consists of an embedded vibration motor located in the driver's seat and a buzzer. The purpose of this two-part system is to give drivers with comprehensive notifications, thereby heightening their awareness regarding possible hazards to safety. The tactile aspect of the alert system is introduced by the vibration motor. Upon activation, it produces tactile vibrations that are tangibly incorporated into the driver's seat. In circumstances where the driver might be distracted or drowsy, this tactile feedback is especially beneficial.

Certain safety-related occurrences, including driver distraction, drowsiness, and alcohol consumption, elicit audible warnings from the buzzer. A buzzer emits a loud and attention-grabbing sound to notify the driver whenever the system detects any of these risky behaviours. Refocusing the driver's attention on safe driving practises is prompted by this audible alert.

The vibration motor will generate vibrations in the driver's seat, serving as a tangible reminder to the driver to maintain attentiveness and vigilance, if the system detects indications of phone usage or drowsiness. The buzzer is shown in figure 3.9 while the vibration motor is shown in the figure 3.10.

Figure 3.9 Buzzer

Figure 3.10 Vibration motor

The success of the implementation of this this system included not only gathering components but also data collection, data preprocessing, ML model development, hardware development, data transmission, web application development, and testing and validation. The architecture enables real-time monitoring, data analysis, and alerting, empowering users to make informed decisions and take timely actions.

## 3.2 System integration

The hardware components, including the sensors, IoT devices, and central processing unit, were integrated into an interconnected system. Figure 3.11 shows the system block diagram which demonstrates the components of our system and their interconnections.

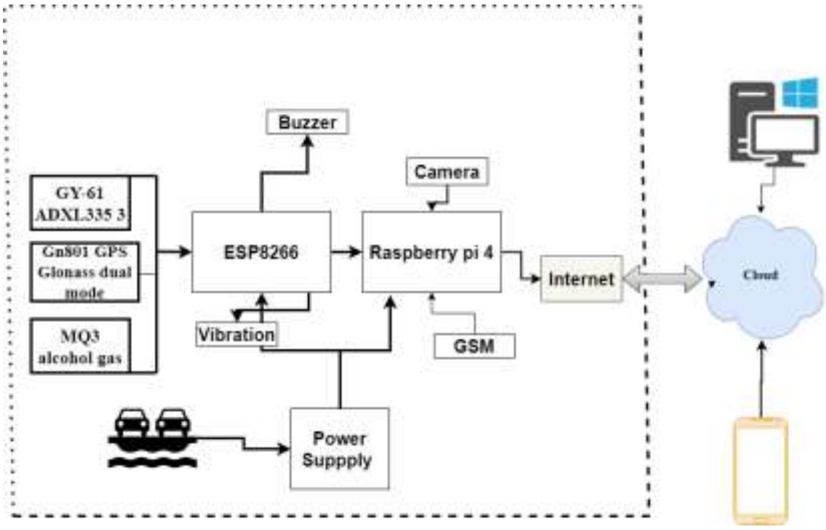



Figure 3.11 System block diagram

## 3.3 Data collection

Selecting and integrating IoT devices into vehicles to capture real-time data on distracted drivers was the initial step. This includes GPS Gn801 GPS Glonass dual mode speed sensor, an alcohol sensor (MQ3 alcohol gas sensor SEN42, R16), an accelerometer (ADXL335-3 Axis compass accelerometer GY-6l), and a camera (raspberry pi 4Bl3B 5MP fisheye night vision focal Camera). Data transmission protocols were established to ensure seamless communication between devices and esp8266 with the Raspberry pi 4 8GB RAM central processing unit.

Our study relies on the How drive 3d driver distraction and our personal images dataset to train and evaluate the suggested system. With 11745 samples, the dataset provides enough data for robust model training. It collects a variety of real-world driving distractions for phone holding and not holding to ensure the model can distinguish between distractions and non-distracted states.

## 3.4 Algorithm development

To analyse the collected data on driver distraction such as phone usage, AI and ML algorithms were developed. This incorporates the use of a customized Convolutional Neural Networks (CNNs) algorithm.

### 3.4.1 Data preprocessing

The collected images were pre-processed to make them suitable for the model. This involved normalization, resizing, label encoding and equalization to ensure that the images meet the necessary requirements for the model to learn effectively.

**Image Resizing**

To assure compatibility with the selected CNN architecture, all images in our dataset were resized to a resolution of 256x256 pixels using TF. image library. This resizing procedure ensured that the model received consistent input sizes.

**Data Normalization**

During model training, normalization plays a crucial function in ensuring uniformity and numerical stability. By rescaling pixel values to a standard range of [0, 1], we reduced the potential for variation in images with different pixel value scales. This step speeds up model convergence improves numerical stability during back propagation and enhances the model's ability to generalize to new data. To accomplish this, we used the 'ImageDataGenerator' class with the 'rescale' parameter set to '1. /255', effectively mapping pixel values from the original range [0, 255] to the normalized range [0, 1]. This preprocessing technique enhanced the dependability and robustness of our CNN model for precise driver distraction detection.

**Label Encoding**

Each image of a drivers was assigned a binary label to signify its overall destruction. Specifically, 'non-phone-holding' driver were labelled 0 and 'holding phone' driver was labelled 1. This binary labelling system was employed to facilitate the classification of drivers based on their distraction status, enabling efficient analysis and training of the detection model.

**Histogram Equalization**

Histogram equalization is a method for improving images by reshaping the distribution of pixel intensities within each image. This method enhanced the overall reliability and Adaptability of our CNN model by increasing image contrast and enabling the machine to recognize subtle patterns associated with distraction (phone holding and not-holding) across the dataset. In this technique, we use the formula below to calculate the equalization [29]. Each pixel's value in the output image (g (x, y)) is adjusted based on its original intensity (T) and the cumulative distribution function of pixel intensities in the input image. The result is an image with improved contrast and enhanced visual features, which aids in the accurate identification of a driver who is using a phone or not.

$$g(x, y) = (L - 1 \sum_{r=0}^{T} \text{Prdr}$$

Where:

- ✓ **g (x, y)** is the pixel value of the output image at coordinates (x, y).
- ✓ L is the number of intensity levels. In our case 256
- ✓ **p(r)** is the normalized cumulative distribution function of the input image.
- ✓ **T** is the pixel value of the input image at coordinates (x, y).

### 3.4.2 Data splitting

After the preprocessing, driver distraction dataset was divided into three distinct subsets following data preprocessing to facilitate the training, validation, and testing of our CNN model for driver distraction detection. 75% of the pre-processed images were assigned to the training dataset, 15% to the validation dataset, and the remaining 10% to the testing dataset. The training set was used to train the model, the validation set was used to fine-tune hyperparameter and monitor training progress, and the testing set was used to evaluate the model’s performance on previously unseen data.

### 3.4.3 Data augmentation

To improve the accuracy of the model, we employed image enhancement techniques such as random rotation, scaling, cutout, brightness and flipping to the collected images. Through these techniques, the model was exposed to a wider variety of examples, allowing it to generalize to new data more effectively. The completion of data augmentation efforts resulted in a dataset with 11745 driver distraction images, of which 2,489 were not distracted driving and 9,256 were distracted drivers.

**Vertical and Horizontal Flipping**

Both vertical and horizontal rotating transformations were applied to images. This enhancement introduced mirrored images of driver distraction to simulate possible variations in the orientation of driver distraction in case of phone usage while driving in real-world situations.

**Random Rotation**

Images were randomly rotated to simulate driver distraction images captured from different position while holding a phone and not holding.

**Scaling**

A fundamental technique for augmenting data is scaling, also known as resizing. It entailed enlarging images within our dataset without compromising their aspect ratio. Incorporating varying input quantities into the network was principally the objective of scaling.

### 3.4.4 Model development (Customized CNNs)

Keras was utilised in conjunction with a TensorFlow backend to facilitate the development of our model, thereby guaranteeing a dependable and effective framework. The development of the neural network's construction is illustrated in Figure 3.12, which shows the architecture of our custom developed model.

```
Model: "sequential_2"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 conv2d (Conv2D)             (None, 254, 254, 32)      896

 max_pooling2d (MaxPooling2D  (None, 127, 127, 32)     0
 )

 conv2d_1 (Conv2D)           (None, 125, 125, 64)      18496

 max_pooling2d_1 (MaxPooling  (None, 62, 62, 64)       0
 2D)

 conv2d_2 (Conv2D)           (None, 60, 60, 128)       73856

 max_pooling2d_2 (MaxPooling  (None, 30, 30, 128)      0
 2D)

 flatten (Flatten)           (None, 115200)            0

 dense (Dense)               (None, 512)               58982912

 dense_1 (Dense)             (None, 256)               131328

 dense_2 (Dense)             (None, 1)                 257

=================================================================
Total params: 59,207,745
Trainable params: 59,207,745
Non-trainable params: 0
_________________________________________________________________
```

Figure 3.12 CNNs model Architecture

Our process of developing our custom model begins by integrating a convolutional layer consisting of 32 filters, each measuring 3x3 pixels. By utilising the rectified linear unit (ReLU) activation function, the network's capability to discern complex patterns in the input data is improved. Furthermore, the model takes into consideration the input geometry (256, 256, 3), thereby recognising the dimensions of the input images.

Following this, a max-pooling layer is implemented, which aids in the reduction of feature map dimensions while preserving their most prominent attributes. The process mentioned earlier is repeated by integrating an additional convolutional layer that consists of 64 filters, after which another max-pooling layer is incorporated.

Prior to constructing a series of densely connected layers, the feature maps generated by the convolutional layers are flattened. To facilitate feature abstraction and representation, two dense layers consisting of 512 and 256 neurons are utilised. The sigmoid activation function is finally applied to the output layer, which consists of a single neuron. The precise function of this last layer is binary classification, which uses the input image data to differentiate between distracted and undistracted driving states.

A CNN model was trained in jupyter Notebook utilising TensorFlow, a Python machine learning framework. Our CNN model was developed utilising the Keras library, a Python package containing an API for high-level neural networks. The TensorFlow machine learning framework was also used as a backend to Keras for efficient computation.

The CNN model was then trained on the pre-processed image dataset to accurately classify driver distraction as either distracted by phone usage or not usage.

Various techniques such as data augmentation was utilized during the training process to improve the model's performance and generalization ability. The accuracy of the model was evaluated using metrics such as precision, recall, and F1 score to ensure that they met the desired performance threshold. The major steps taken to achieve our classification goal are shown in figure 3.13 below. And some steps have been explained above.

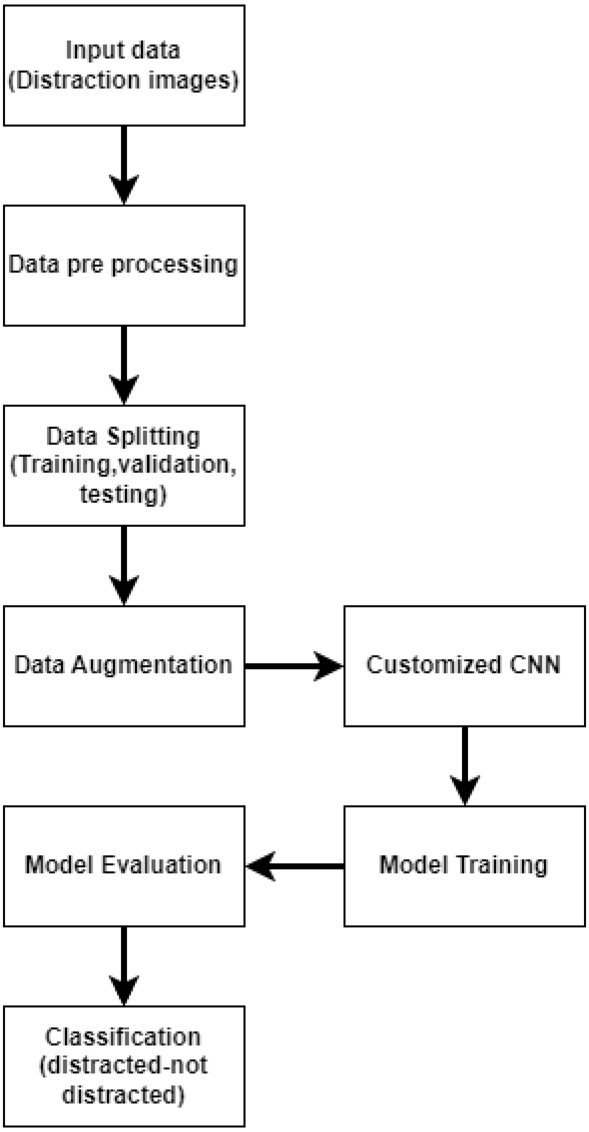


Figure 3.13 Classification steps

### 3.4.5 Model Training and optimization

We optimised and fine-tuned our customised CNNs for precise driver distraction detection during the critical phase of model training and optimisation. Precautions were taken to prevent overfitting and optimise model performance during this rigorous process, including adjusting learning rates, batch sizes, and dropout rates.

### 3.4.6 Model Evaluation criteria

Several binary evaluation criteria were utilised to determine the reliability and accuracy of the model while evaluating the performance of the driver distraction detection system in preventing accidents. Determining the system's capability to distinguish between drivers who aren't distracted by their phones and those who are while using their phones requires the establishment of these criteria.

#### 3.4.6.1 Accuracy

The proportion of accurately classified instances relative to the total number of instances in the dataset is the accuracy metric. It serves as a foundational metric for evaluating the overall efficacy of the model. The calculation of accuracy is illustrated by the formula below:

$$ACC = \frac{\mathrm{TP} + \mathrm{TN}}{\mathrm{TP} + \mathrm{TN} + \mathrm{FP} + \mathrm{FN}}$$

Where:

**True Positive (TP):** The model accurately predicted "phone_holding" when the true class was "phone_holding," demonstrating the model's effectiveness in recognising the positive class.

**True Negative (TN):** When the model correctly recognised "non_phone" when the actual class was "non_phone." This demonstrates the model's ability to accurately predict the negative class.

**False Positive (FP)**: When the model did not misclassify any "non_phone" occurrences as "phone_holding," demonstrating the model's accuracy in avoiding Type I mistakes.

**False Negative (FN)**: Similarly, no occurrences were predicted as "non_phone" when they were “phone_holding,".

#### 3.4.6.2 Precision

Precision measures the proportion of true positive predictions among all positive predictions made by the model. It assesses the model’s ability to avoid false-positive predictions. The formula below shows how it is calculated:

$$PREC = \frac{\mathrm{TP}}{\mathrm{TP} + \mathrm{FP}}$$

#### 3.4.6.3 Recall

Recall calculates the proportion of true positive predictions among all actual positive instances in the dataset. It quantifies the model’s ability to identify all positive cases.

$$RECALL = \frac{\mathrm{TP}}{\mathrm{TP} + \mathrm{FN}}$$

#### 3.4.6.4 F1 score

The F1-Score is the harmonic mean of precision and recall. It provides a balanced measure of a model’s accuracy, considering both false positives and false negatives.

$$F1 = \frac{2(\mathrm{PREC} \ \times \mathrm{RECALL})}{\mathrm{PREC} + \mathrm{RECALL}}$$

## 3.5 Real time monitoring and alerts

A user-friendly interface was developed to provide real-time monitoring and alerts to drivers. The trained CNN was integrated into the raspberry pi so that computation and analysis is done at device level for quick actions. As driver's face image will be captured by the camera system, they will be sent to database for real-time analysis. The model processes the images, detecting and predicting distracted or not distracted. If it detects distracted, immediate alerts will be generated, notifying the driver to focus on driving.

Real-time communication mechanisms to deliver alerts to drivers such as audio was implemented.

## 3.6 Accident detection and emergency response

Using accelerometer data, accidents are detected, allowing for accurate differentiation between normal vehicle manoeuvres and collision events. In the event of an accident, the system promptly notifies emergency response teams and relevant authorities, providing accurate information about the accident's location to facilitate a prompt and effective response.

## 3.7 Testing the prototype.

A series of simulations of diverse driving scenarios and environmental conditions that may influence road safety were performed to test and validate the developed system for enhanced emergency response and accident prevention. The challenges consisted of simulating authentic driving conditions by introducing variables such as driver distraction by using a phone, various speeds of travel, and fluctuations in alcohol concentration. Strict monitoring and evaluation were conducted on the system's performance in such scenarios.

## 3.8 Summary

The approach taken in the design and implementation of the AI and IoT-based road safety system is described in detail in the methodology chapter. The project consists of several key components: establishment of a cloud storage, data collection from sensors, development of an algorithm for driver distraction detection, system integration, real-time monitoring, accident detection, and a literature review to ascertain the present state of the art. By monitoring driver distraction, alcohol consumption, and excessive speed, this comprehensive approach accentuates the system's capacity to improve road safety through accident prevention.

## CHAPTER FOUR. AI AND IOT BASED SYSTEM FOR ACCIDENT PREVENTION, DETECTION AND REAL TIME EMERGENCY RESPONSE

### 4.0 Introduction

In this chapter, we present the complex architecture and design of the proposed system that utilises AI and IoT to prevent, detect, and improve emergency response in the event of an accident.

#### 4.1 System Architecture of the proposed system

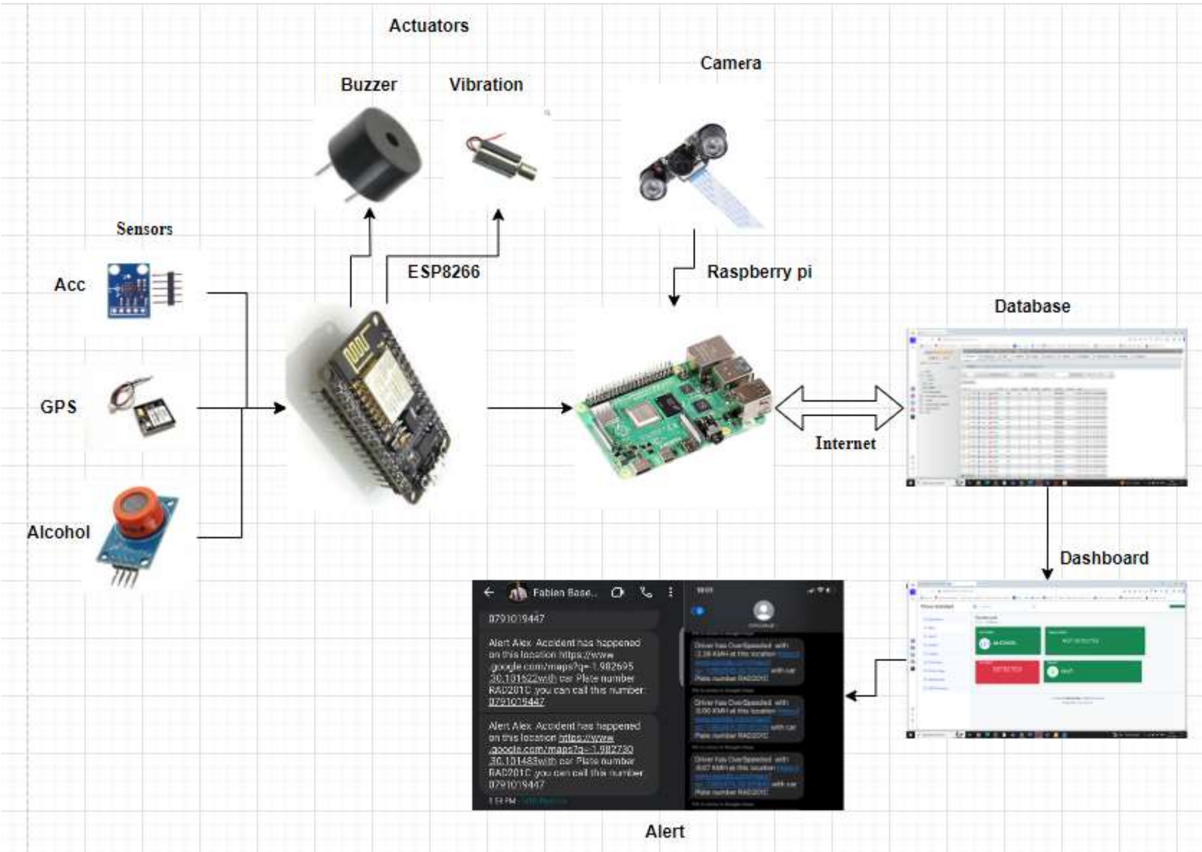



Figure 4.1 Data Flow diagram

We have strategically incorporated important IoT sensors like a GPS, accelerometer, and camera into our state-of-the-art accident detection and prevention system that was developed with instantaneous emergency response in mind. This high-tech system constantly tracks critical metrics like blood-alcohol content, vehicle speed, and the presence of potential distractions for the driver. The system promptly generates alerts whenever an accident or over speeding incident is detected, ensuring instant notification via SMS messages. When a distraction is detected, a special alert system goes into action, sounding a buzzer to get the driver's attention.

Data Flow Diagrams (DFDs) presented in figure4.1 are used to graphically depict the system's architecture by showing how data flows from one part of the system to another without any interruptions. The vehicle, Internet of Things (IoT) sensors, and cameras all contribute to the data flow. The camera records in real time while Internet of Things (IoT) sensors gather vital environmental data, giving drivers a full picture of the road ahead.

This data undergoes two primary operations:

- ✓ **Real-time Data Processing**: Real-time processing is executed by the system to detect accidents, instances of driver distraction, alcohol and overspeeding. Rapid alert generation guarantees prompt reactions to critical incidents that may occur while driving.
- ✓ **Data Transmission and Storage:** Real-time transmission of processed data to a remote MySQL database via a secure Wi-Fi connection function as a centralized repository for the purposes of analysis and monitoring. The system's user interface is a user-friendly web-based dashboard that provides instantaneous access to data storage, enabling users to make well-informed decisions.

Besides facilitating dashboard interaction, our system integrates a multi-modal alert system as well. Users are promptly notified and alerted via vibration and buzzer, thereby guaranteeing prompt reactions to critical occurrences. By incorporating real-time data processing and multi-modal alerting, this all-encompassing solution improves transportation safety and facilitates informed decision-making in a dynamic environment.

Figure 4.2 physical architecture of the proposed system

## 4.2 IoT and AI modules for accident prevention and detection

In this AI and IoT-based accident prevention and emergency response system, capturing real-time data from vehicles and facilitating communication with the central processing unit and cloud infrastructure are both dependent on the IoT modules. The entire system requires 5volts. The AI part of this project includes complex algorithms, with a focus on Convolutional Neural Networks (CNNs), which are made to intelligently process the image data from a camera. Its job is to find and sort driving distractions like talking on the phone or being sleepy in real time. The AI module has a deep learning model which is trained to detect signs of distraction with accuracy of 86-100%. It sends instant alerts to the driver to encourage safe driving in case of phone usage detection. This AI-driven intelligence is an important part of the system because it helps keep people safe on the roads by avoiding accidents caused by phone usage while driving and letting people help in time.

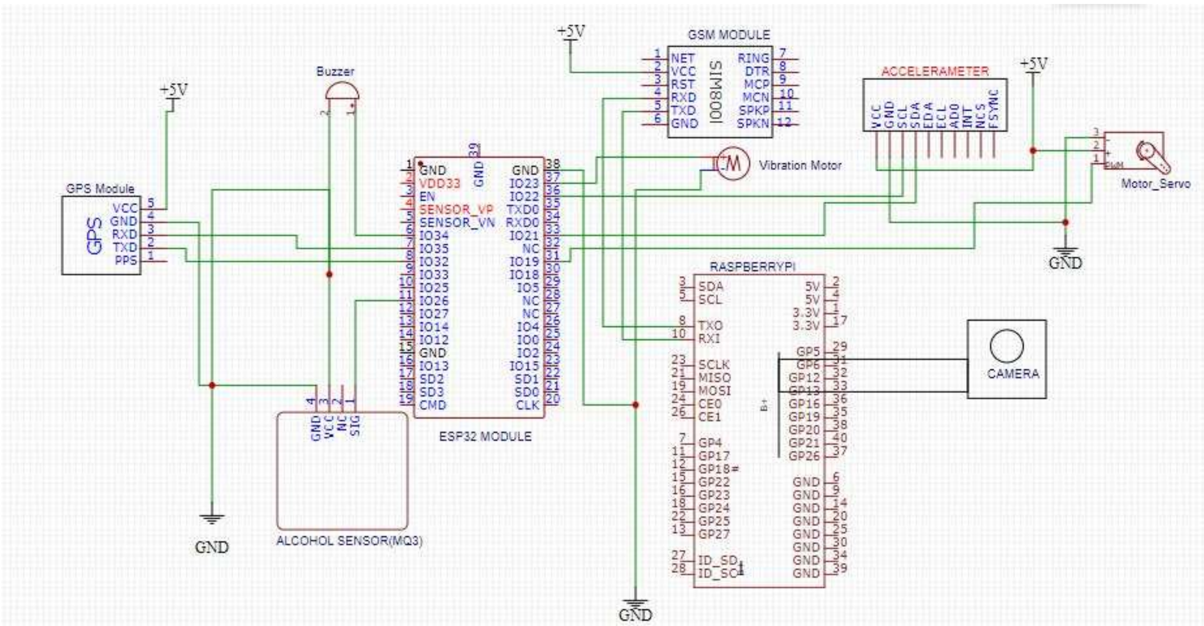



Figure 4.3 Schematic diagram

In figure 4.3 above, the NodeMCU functions as the primary controller, coordinating the operations of every sensor and actuator. It performs an essential function in the context of our project's Internet of Things (IoT). Furthermore, we have incorporated a Raspberry Pi as a critical element, serving primarily to power the camera module, which is indispensable for capturing images to identify instances of driver drowsiness and phone usage.

The input terminal of the NodeMCU establishes connections with three crucial sensors: a GPS module, an accelerometer sensor, and an alcohol sensor. Further elaborate on the connections:

the VCC and GND pins of the NodeMCU are connected to the first alcohol sensor, which receives power and ground from the 5V and GND pins, respectively. Its data pin is connected to the analogue pin (A0) of the NodeMCU, which enables data transmission. The accelerometer, the second sensor, is connected in the same manner and utilises I2C communication. It is grounded via GND and powered via VCC, drawing power from the NodeMCU's 5V.

Furthermore, in conjunction with the SDA and SCL pins of the NodeMCU, its SDA and SCL pins are linked. Through a GPIO pin, the third input device, the GPS receiver, is seamlessly connected to the NodeMCU.

The output end of the NodeMCU establishes connections with three crucial output components, namely a vibration motor, a servo, and a buzzer. A complex interconnection exists between these devices and the GPIO pins on the NodeMCU.

The Raspberry Pi functions as a critical component of the system, concurrently utilising its camera module to perform face recognition and machine learning operations. The integration of this computational capability with a GSM module enhances the overall functionality of our pioneering system, facilitating efficient communication.

## 4.3 Experimental Setup

Effective experimental design was critical to the implementation and evaluation of our AI and IoT-based system for accident prevention. The experimental setup was purposefully constructed to incorporate a diverse range of hardware and software elements, coordinated in a manner that facilitates smooth operation and generates significant findings. A centralized computing unit, a network of IoT devices integrated into test vehicles, and cloud infrastructure for data storage and processing comprised our configuration. The deployment of a GPS (GN801 GPS Glonass Dual-Mode Speed Sensor), an alcohol sensor (MQ3 Alcohol Gas Sensor SEN42, R16), an accelerometer (ADXL335-3 Axis Compass Accelerometer GY-61), and a camera (Raspberry Pi 4B/3B 5MP Fisheye Night Vision Focal Camera) constituted the fundamental components of our system. These devices were tasked with acquiring real-time data from within the vehicles. The sensory network comprised of these devices was collectively accountable for acquiring vital data concerning driving behavior. The gathered information was transmitted without interruption to the system's central processing device, a Raspberry Pi 4 equipped with 8GB RAM, which was crucial to its operation. The Raspberry Pi implemented advanced machine learning and artificial intelligence algorithms, such as Convolutional Neural Networks (CNNs), to detect driver distractions and preprocess data. In addition, a camera was integrated into the system to monitor driver distractions, including phone use by means of a SIM800L GSM GPRS module, the system's generated alerts and insights were transmitted to the cloud for additional analysis. This facilitated communication with emergency response teams in a timely manner and allowed for real-time monitoring. The experimental configuration we developed was optimized to facilitate the smooth transmission of data, commencing with the acquisition of sensory data from vehicles and concluding with the rigorous analysis of this data utilizing AI and ML algorithms. This architecture ultimately empowered us to identify driver distraction and promptly respond to potential accidents. The developed prototype is shown in figure 4.4 below.

Figure 4.4 developed prototype

### 4.3.1 Real time monitoring of Alcohol and Speed data

Our prototype demonstrates exceptional real-time monitoring capabilities, which are critical for ensuring the safety of drivers while driving. This requires precise and real-time monitoring of critical parameters, including speed and alcohol concentration in different scenarios such as normal speed, over speeding, normal alcohol less than 300 and drunk >=300. Our system employs a variety of sophisticated sensors, such as the GN801 GPS sensor for precise vehicle speed and location determination, the MQ3 alcohol sensor for immediate detection of alcohol vapours in the driver's area, and the dashboard that gives real-time feedback. This methodology guarantees that instances of speeding and alcohol consumption can be promptly detected, thereby enabling the activation of immediate alerts through an integrated buzzer.

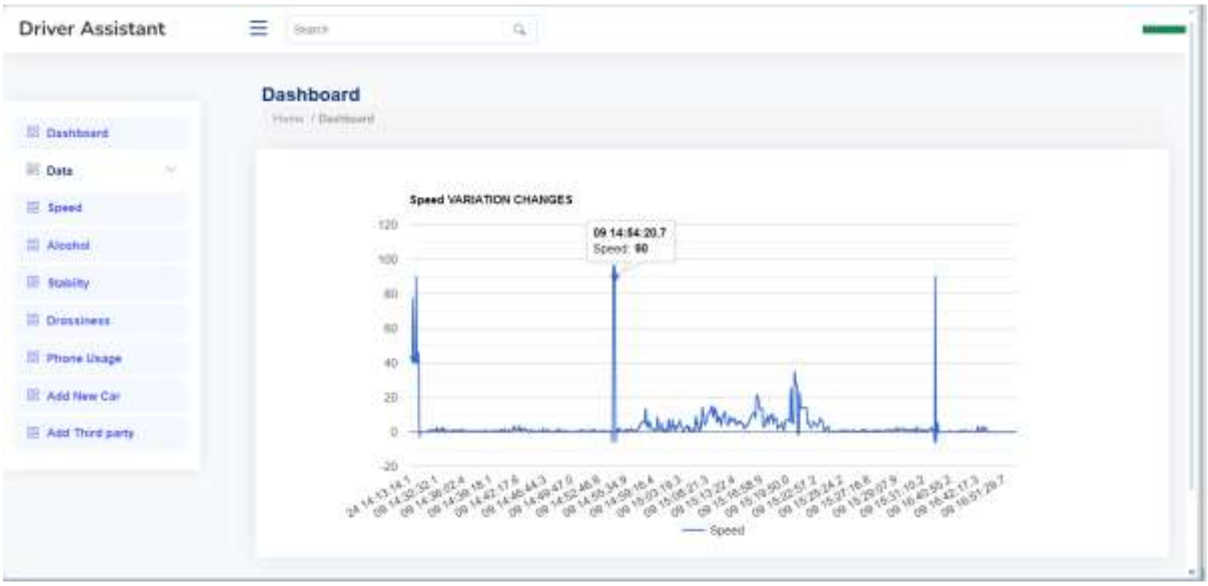


Figure 4.5 Speed Monitoring

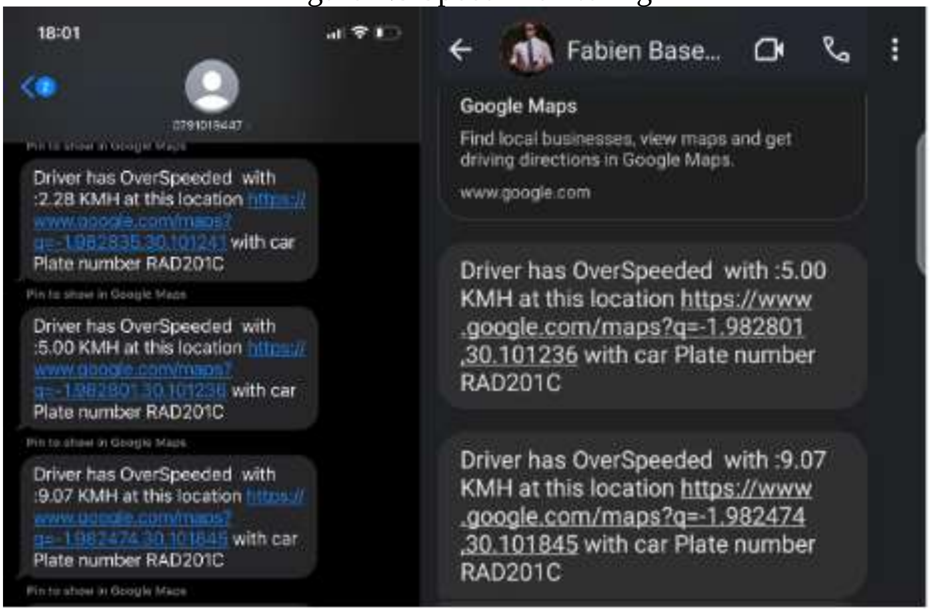


figure 4.6 overspeed Alerts

The figure 4.6 above shows the alert via SMS whenever the overspeed is detected and it also send the link where the driver has over speeded.

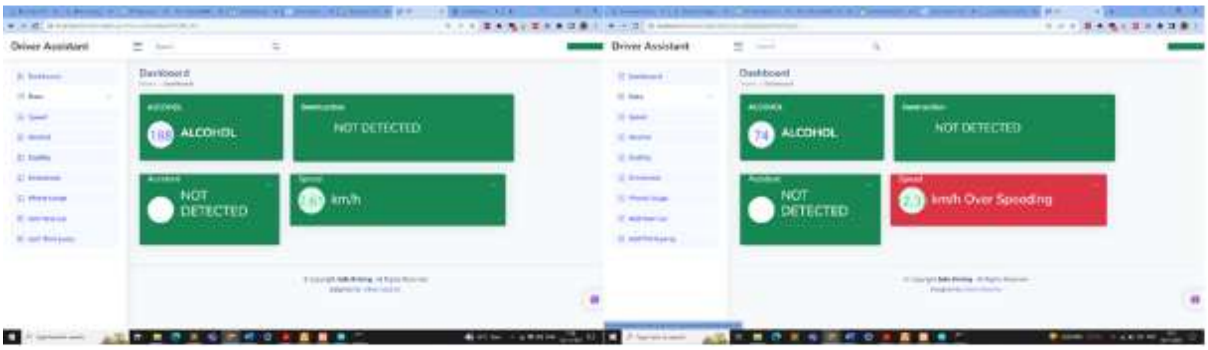


figure 4.7 Normal speed and overspeed visualization alert


Figure 4.8 Alcohol Monitoring

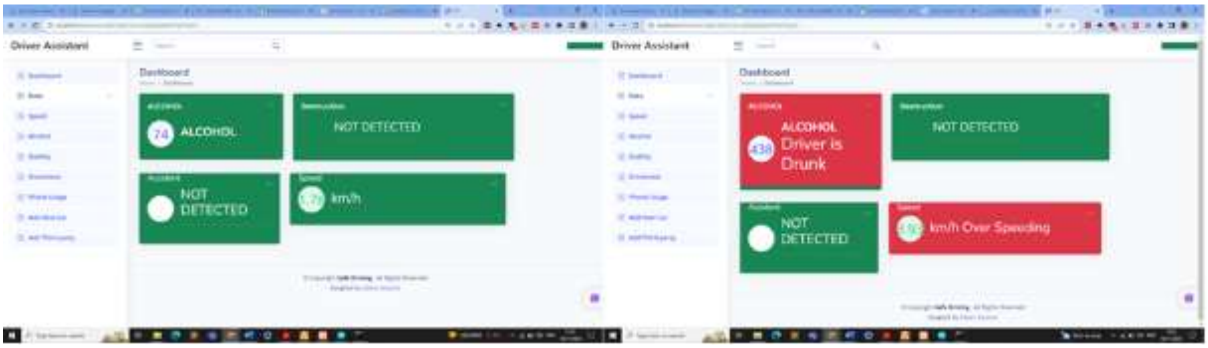



Figure 4.9 Normal vs Drunk Driver visual Alert

### 4.3.2 Real time monitoring of accelerometer data

Our prototype is highly effective at detecting and evaluating changes in a vehicle's motion in real time. By employing the ADXL335 3-Axis Compass Accelerometer (GY-61), it was possible to monitor acceleration data with pinpoint precision in real-time. The real-time representation of the vehicle's motion is depicted in Figure 4.10 which shows when accident is detected and it is represented by 1 and figure 4.11 shows when there is no accident, represented by 0. This immediate assessment is of the utmost importance to detect sudden alterations in the vehicle's motion, which may serve as indicators of approaching collisions or accidents. When these changes are identified, the system promptly issues alerts via an integrated buzzer and transmits an SMS to an emergency team such as a police station.

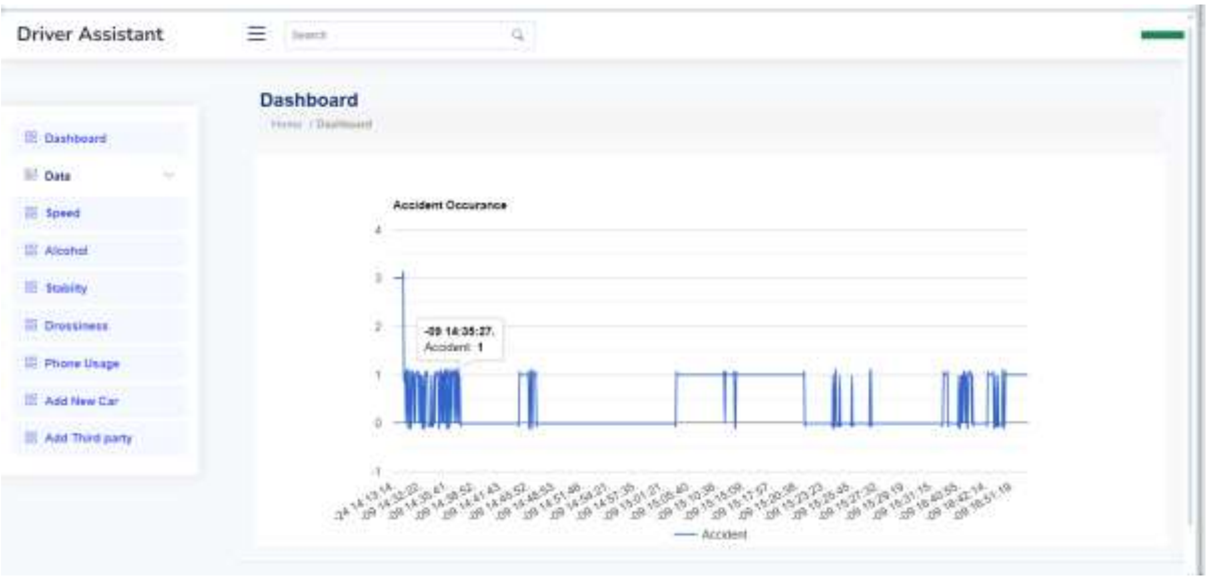



Figure 4.10 Accident detection: 1

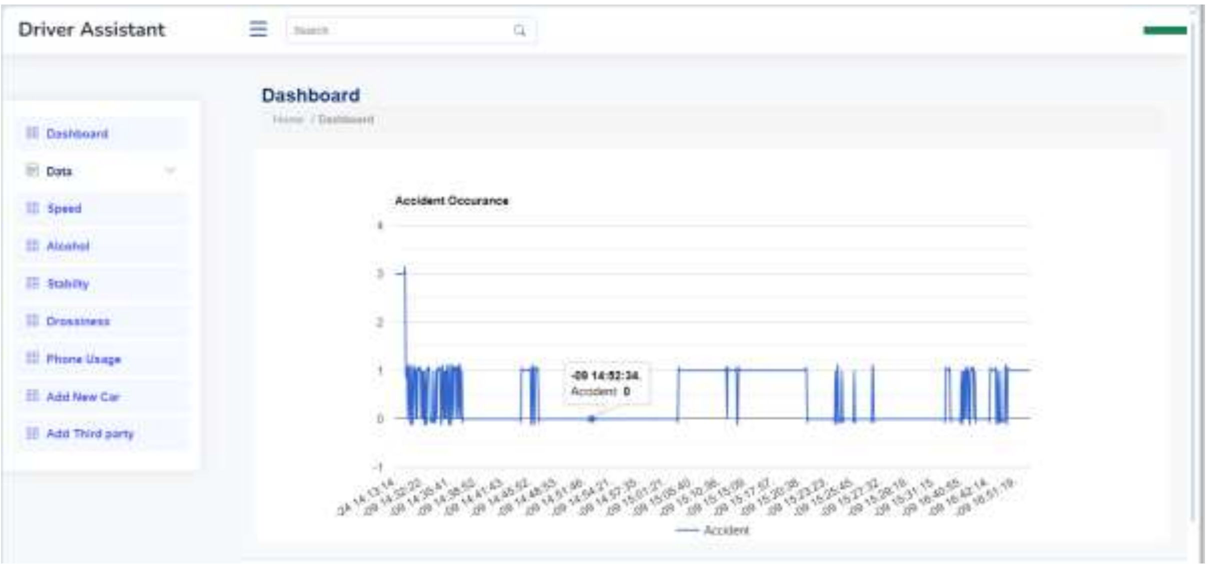



Figure 4.11 No accident: 0

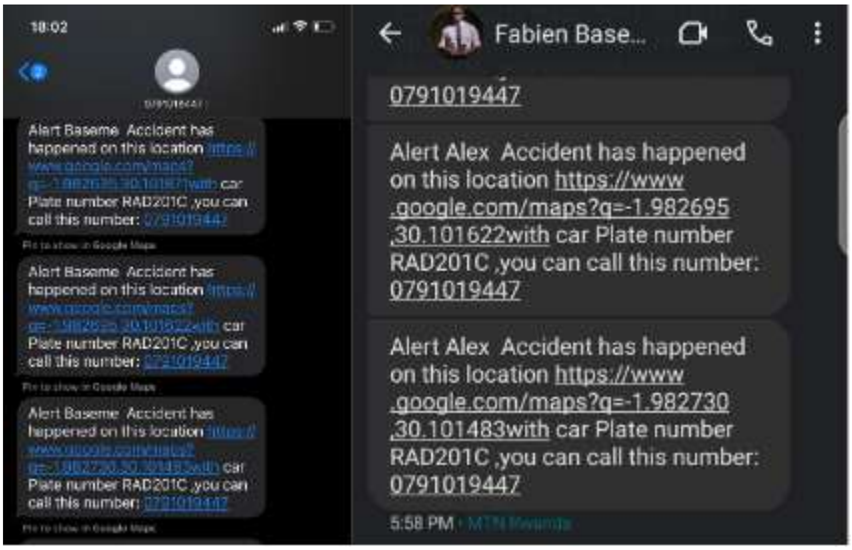



Figure 4.12 SMS Alerts for accident detection

The figure 4.12 above shows the alert via SMS whenever the accident is detected, and it also send the link where the accident has happened and the driver number.

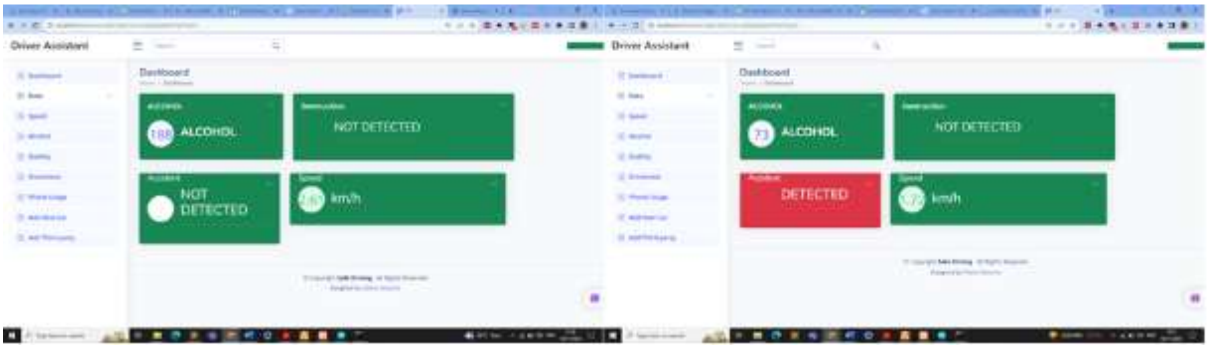



figure 4.13 Accident vs not accident detection visual Alert

### 4.3.3 Real time data storage

The system has been carefully engineered to facilitate the storage and transmission of data in real-time. We orchestrate a well-structured data transmission following the processing of an assortment of sensor data by the Raspberry Pi, including the GPS Gn801 GPS Glonass dual-mode speed sensor, the MQ3 alcohol gas sensor SEN42, R16, ADXL335-3 Axis compass accelerometer GY-6l, and the Raspberry Pi 4Bl3B 5MP fisheye night vision focal Camera. Two discrete data streams are involved in this transmission: sensor data and image results. Sensor data, which includes critical indicators of driver distraction, alcohol levels, vehicle speed, and acceleration, is compiled and transmitted at consistent time intervals, usually on a minutely basis. Concurrently, upon the completion of the analysis, the results of the image analysis are transmitted. The transmission employs the HTTP protocol, and the data is formatted efficiently in JSON, a widely recognised and flexible format for exchanging data.

Our systematic methodology guarantees the protection and availability of the amassed data, thereby facilitating its access from any geographical location. As the central repository of data, our cloud-based infrastructure streamlines the retrieval and administration of information for users and stakeholders. By utilising a resilient data storage and retrieval mechanism, our system's dependability and effectiveness are fortified. This enables us to make timely decisions regarding vital information, which is essential in our endeavour to improve road safety and avert collisions.

### 4.3.4 Real time data visualization on web application.

#### 4.3.4.1 Backend development of the web app

Developing a robust database architecture constituted the primary objective during the development of our system. The tables and structure necessary for the storage of our data entities and their relationships were meticulously designed and determined. We successfully developed a user-friendly interface by integrating PHP, HTML, and Bootstrap for the frontend. PHP, which is widely recognized for its ability to execute server-side scripting, was instrumental in optimizing database operations.

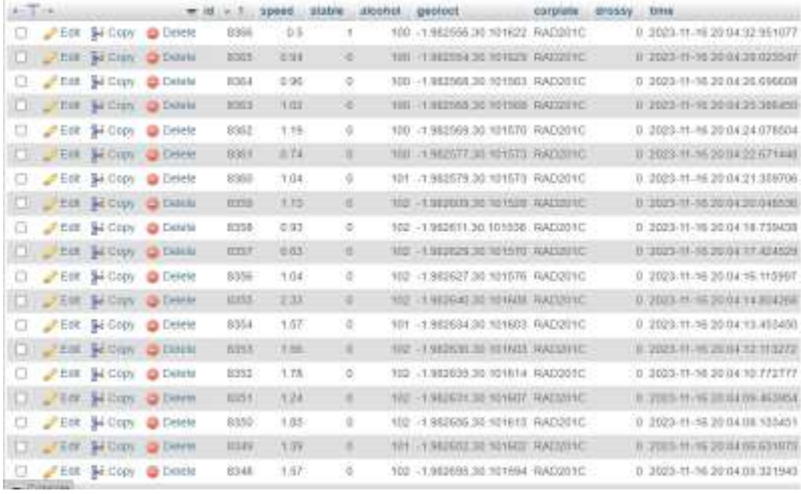
A responsive and aesthetically pleasing design framework was obtained through the intentional selection of Bootstrap. The versatility with which PHP could be interfaced with MySQL databases influenced our decision to utilize it. A smooth transition and enhanced performance were achieved by migrating our database structure to MySQL. We could develop a meticulously organized and effective system for our undertaking by leveraging the responsiveness of HTML, the simplicity and efficiency of PHP, and the styling functionalities of Bootstrap.

The table created was named ‘destdriver’ and contains three tables namely:

- ✓ **Car table**: this table contains all the information related with the car such as car owner with his/her detail, number plate, etc. It’s shown in figure 4.14 below:

Figure 4.14 Car table

✓ **Data table**: This table contains all data collected by the system such as speed, alcohol, accident, etc. It’s shown in figure 4.15 below:



| id | speed | stable | alcohol | geoloct | carplate | drossy | time |
|---|---|---|---|---|---|---|---|
| 8366 | 0.5 | 1 | 100 | -1.982556 30.101622 | RAD201C | 0 | 2023-11-16 20:04:32.951077 |
| 8365 | 0.94 | 0 | 101 | -1.982554 30.101629 | RAD201C | 0 | 2023-11-16 20:04:28.023047 |
| 8364 | 0.96 | 0 | 100 | -1.982568 30.101563 | RAD201C | 0 | 2023-11-16 20:04:26.696608 |
| 8363 | 1.03 | 0 | 101 | -1.982565 30.101568 | RAD201C | 0 | 2023-11-16 20:04:25.386450 |
| 8362 | 1.19 | 0 | 100 | -1.982569 30.101570 | RAD201C | 0 | 2023-11-16 20:04:24.078504 |
| 8361 | 0.74 | 0 | 101 | -1.982577 30.101573 | RAD201C | 0 | 2023-11-16 20:04:22.671440 |
| 8360 | 1.04 | 0 | 101 | -1.982579 30.101573 | RAD201C | 0 | 2023-11-16 20:04:21.359706 |
| 8359 | 1.13 | 0 | 102 | -1.982603 30.101528 | RAD201C | 0 | 2023-11-16 20:04:20.048536 |
| 8358 | 0.93 | 0 | 102 | -1.982611 30.101536 | RAD201C | 0 | 2023-11-16 20:04:18.739438 |
| 8357 | 0.63 | 0 | 102 | -1.982629 30.101570 | RAD201C | 0 | 2023-11-16 20:04:17.424529 |
| 8356 | 1.04 | 0 | 102 | -1.982627 30.101576 | RAD201C | 0 | 2023-11-16 20:04:16.115997 |
| 8355 | 2.33 | 0 | 102 | -1.982640 30.101608 | RAD201C | 0 | 2023-11-16 20:04:14.804266 |
| 8354 | 1.57 | 0 | 101 | -1.982634 30.101603 | RAD201C | 0 | 2023-11-16 20:04:13.493400 |
| 8353 | 1.56 | 0 | 102 | -1.982630 30.101603 | RAD201C | 0 | 2023-11-16 20:04:12.113272 |
| 8352 | 1.78 | 0 | 102 | -1.982639 30.101614 | RAD201C | 0 | 2023-11-16 20:04:10.772777 |
| 8351 | 1.24 | 0 | 102 | -1.982631 30.101607 | RAD201C | 0 | 2023-11-16 20:04:09.463954 |
| 8350 | 1.85 | 0 | 102 | -1.982606 30.101613 | RAD201C | 0 | 2023-11-16 20:04:08.133451 |
| 8349 | 1.39 | 0 | 101 | -1.982602 30.101602 | RAD201C | 0 | 2023-11-16 20:04:06.631979 |
| 8348 | 1.57 | 0 | 102 | -1.982695 30.101694 | RAD201C | 0 | 2023-11-16 20:04:03.321943 |

Figure 4.15 Data table

✓ **Third part table**: this contains the information about the stakeholders such as police station, hospital with their details and phone number for alerting purposes. It’s shown in figure 4.16 below:

Figure 4.16 Third party table

**4.3.4.2 Frontend**

By utilising an intuitive web-based dashboard, we have implemented an advanced data visualisation solution for our comprehensive accident detection system. The interface of this skilfully designed dashboard, which was created utilising HTML, CSS, and JavaScript, is both user-friendly and intuitive, facilitating the continuous monitoring of critical environmental factors. The parameters encompass information obtained from a diverse range of specialised sensors. For instance, the GPS Gn801 GPS Glonass dual mode sensor is utilised to detect and localise speed, the MQ3 alcohol gas sensors are employed to detect alcohol, the ADXL335-3 Axis compass accelerometer GY-6l is employed to monitor changes in vehicle movement, and the Raspberry Pi 4B/3B 5MP fisheye night vision focal Camera is implemented to identify driver distractions. Significantly, the web interface of the dashboard is intelligently engineered to promptly generate notifications if specified limits associated with these sensors are surpassed. This ensures that potential accident risks are promptly addressed. Furthermore, our system delivers instantaneous image analysis outcomes. green driver distraction not detected and red detected. he previously mentioned dynamic characteristics greatly improve the effectiveness of accident prevention and detection.

The figure 4.17 shows the visualization of all data on dashboard.

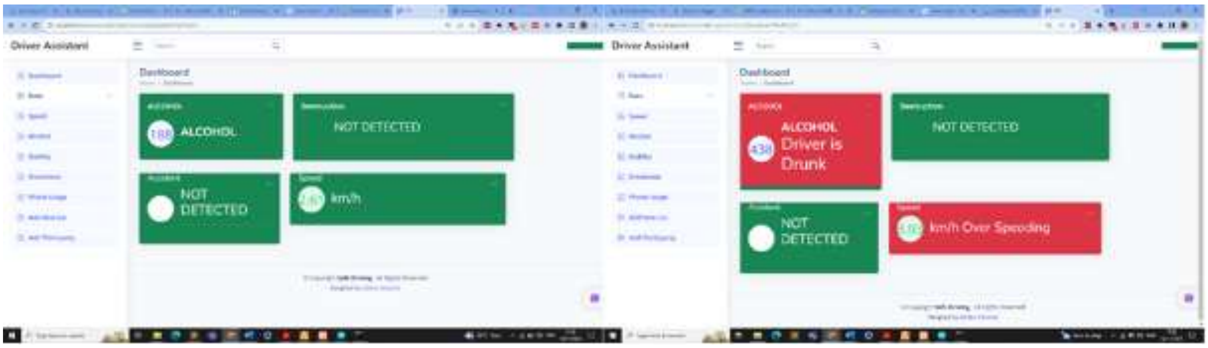



Figure 4.17 Visual representations of transmitted data on home dashboard

Throughout its extensive testing, the device that we proposed generated data in an efficient manner. The information was transmitted without any interruptions to a web-based interface that was specifically developed for thorough management and monitoring. The detection process and the smooth transmission of data to the interface for simple analysis are visually depicted in Figure 4.18.


Figure 4.18 Device with Dashboard Data Visualization

## 4.4 Deep learning module for the accident prevention

The primary objective of utilizing deep learning in this Work was to facilitate accurate and instant identification of driver distraction, an essential component in augmenting road safety and preventing accidents. Central to this deep learning module are Convolutional Neural Networks (CNNs), which are optimized for the analysis of images and video frames captured by our system's camera. The efficacy of this module is dependent upon thorough data preparation, which includes defining and resizing images and employing data augmentation methods to improve the model's capacity to extrapolate from various real-life situations. After the data is prepared, the CNN model is subjected to extensive training, during which it acquires knowledge from a labelled dataset that contains examples of inattentive and non-distracted driving. Ongoing improvement is critical for ensuring the accuracy of the model and may require hyperparameter adjustments or the collection of supplementary data to improve generalization. After having training, the deep learning module involves seamlessly into the architecture of the system, where it analyses real-time data from the driver monitoring camera continuously.

Upon detection of a driver distraction, the module promptly issues alerts in the form of auditory stimuli, encouraging the driver to take immediate corrective measures. The implementation of continuous monitoring and adaptation is crucial to maintain the efficacy of the deep learning module in identifying emerging distractions and making a substantial contribution towards the project's objective of promoting road safety and preventing accidents.

### 4.4.1 Datasets

**Table 1 Dataset details**

| DataSet Sample Type | | Number of images | Images format |
|---|---|---|---|
| 1 | Not distracted (No phone holding) | 2089 | jpg |
| 2 | Distracted (Phone holding) | 8 756 | jpg |
| 3 | Personal images (No phone holding) | 400 | jpg |
| 4 | Personal images (phone holding) | 500 | jpg |


Figure 4.19. Dataset sample of distraction and not distraction

The table 1 above summarizes the dataset we used to design and test an AI and IoT-based driver attention detection and accident prevention system. Our study relies on the How drive 3d driver distraction dataset to train and evaluate the suggested system. With 11745 of which 2,489 were not distracted driving and 9,256 were distracted drivers. Within the not distracted images 400 images where our personal images taken into the car and within the distracted images 500 were our images taken into the car to match with other images, the dataset provides enough data for robust model training. It collects a variety of real-world driving distractions for phone holding and not holding to ensure the model can distinguish between distractions and non-distracted states.

### 4.4.2 Data formatting

Our two classes dataset—phone holding and not holding, required careful organization for data formatting. The dataset repository carefully organizes class data into directories. Data processing is clear and accessible with this framework. For example, the dataset repository has two subfolders for each class: 'Phone Holding,' and 'Not Holding,' ' For easy model training and evaluation, these subfolders' images samples are labelled by class.We use a common naming scheme and file format for all class pictures to ensure uniformity. This systematic technique simplifies data retrieval and labelling, streamlining the data processing pipeline and aiding model training and evaluation. The file also contains metadata like image timestamps, geolocation data, and contextual data. This metadata augmentation helps researchers analyse driver distraction.

### 4.4.3 Model training and testing

The efficacy of our driver distraction detection and accident prevention system, which is built upon AI and IoT, is contingent upon the rigorous training of machine learning models, specifically Convolutional Neural Networks. The training of a model comprises two crucial stages. To commence, data preprocessing is performed to guarantee that the dataset is formatted, normalized, and augmented in a suitable manner to facilitate optimal model learning. This procedure encompasses activities such as standardizing pixel values, resizing images to a uniform format, and implementing data augmentation methods to improve the generalizability of the model. To facilitate model evaluation, the data is partitioned into training, validation, and testing sets once it has been prepared. During the second phase, which consists of our customized CNN training, the model acquires the ability to identify patterns and characteristics that are linked to distracted driving situations, such as phone holding. The training procedure consisted of forward and backward cycles, with techniques such as stochastic gradient descent utilized to optimize model parameters. The models undergo training with the objective of reducing classification errors and improving their precision in identifying driver distractions.

Figure 4.20 Image classification during training phase and testing phase. A) Training phase B) Testing phase

As illustrated in Figure 4.4, the customised model demonstrated exceptional performance in the classification of driver distractions during the training phase. The model accurately and reliably identified a diverse range of distraction cues present in the training dataset, attaining a perfect score of one hundred percent. During this phase, the model effectively showcased its capacity to learn and generalise from the training data.

The model kept its exceptional accuracy in driver distraction classification during the testing phase, during which my personal images were used. The model effectively detected distracting behaviours in the test dataset, demonstrating its resilience and practical utility with an equally remarkable level of precision. The efficiency of the model in identifying and resolving distraction-related concerns can be seen by the smooth transition from training to testing, which demonstrated its dependability in real-world situations.

## 4.5 Summary

In this chapter the system architecture and all algorithms used from data collection to the final stage (system alert) for AI and IoT based system for accident prevention, detection and real time emergency response were presented.

# CHAPTER FIVE. PERFORMANCE ANALYSIS

## 5.0 Introduction

In this section, we present the performance analysis of our work.

## 5.1 Model performance metrics

The primary objective of our Work was to develop and deploy a Convolutional Neural Network (CNN) architecture designed to identify driver distractions via image analysis. The CNN model experienced rigorous design and training to accurately detect a wide range of distracting driver behaviours, including phone usage, using images obtained from our camera. By implementing this novel methodology, our objective was to augment road safety by promptly issuing alerts and warnings regarding identified distractions. The evaluation comprised an extensive array of performance metrics, namely F1 score, accuracy, precision, recall, and precision. These metrics played a critical role in determining the efficacy of our deep learning solution in real driving situations.

### 5.1.1 Confusion matrix

The confusion matrix, as shown in the figure 5.1, provides a thorough representation of the performance evaluation for a binary classification model charged with differentiating between two classes: "non_phone" and "phone_holding." This matrix, which is an important tool in machine learning evaluation, assesses the model's classification accuracy by categorising its predictions into four separate outcomes.

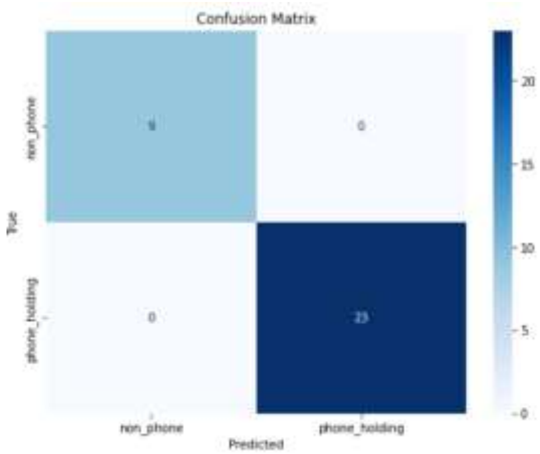


Figure 5.1 Confusion matrix for our customized CNN

### 5.1.2 Model efficacity

To accomplish our goal, from the confusion matrix, we calculated four metrics for evaluation of our distinct customized CNN architectures. These metrics helped in understanding of our model's performance in terms of accuracy, precision, recall and the trade-off between them the table 2 below shows the efficacity of our model across these metrics which was 1.00 in all the metrics.

**Table 2** Model efficacity

| Model | Accuracy | Precision | Recall | F1 Score |
|---|---|---|---|---|
| Customized CNN | 1.00 | 1.00 | 1.00 | 1.00 |

Our custom CNN demonstrated exceptional classification performance, with accuracy, precision, recall, and F1 scores consistently 1.00. This high level of performance indicated the robustness and reliability of our model in accurately classifying phone holding and non-phone. To account for the details of driver distraction detection, we were constrained to utilise a custom CNN model for our project. Although pre-existing models such as VGG16 and ResNet-50 demonstrate commendable efficacy in general image classification project, our objective was to develop a model that was precisely optimised to recognise driver distractions from in-car camera images, owing to its distinctive characteristics and complexities. Through the utilisation of this methodology, we successfully developed a model architecture that was precisely adapted to the complexities present in our dataset, thereby guaranteeing its ability to detect behaviours such as phone holding. Aligned perfectly with the objective of our project, which was to develop real-time road safety applications, a custom model also provided increased adaptability to changing road conditions and the possibility of future improvements.

## 5.2 Model training results

The foundation of our system, the customized Convolutional Neural Networks (CNNs) algorithm has demonstrated outstanding performance in detecting driver distractions (phone usage). A remarkable accuracy rate of 100% was attained by the model throughout the training phase, and the loss function converged to an exceptionally small value of 0.

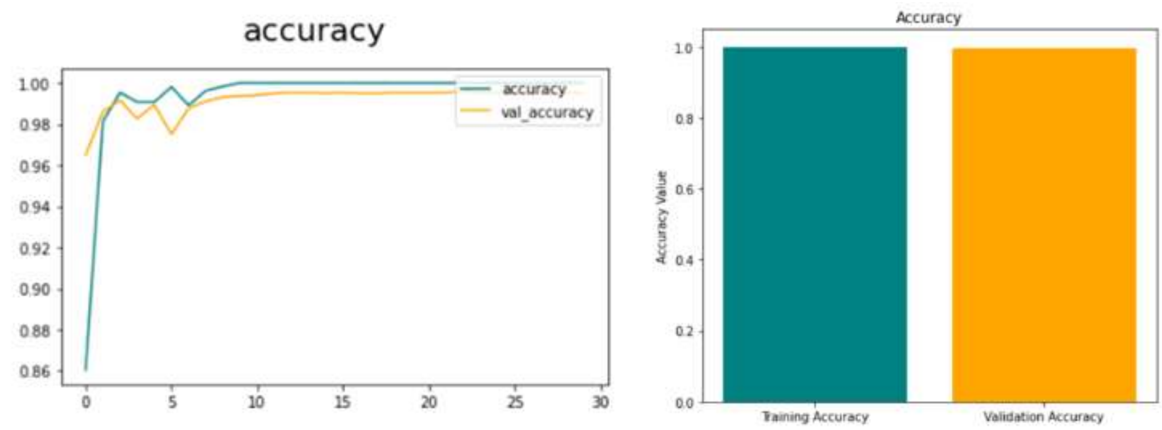
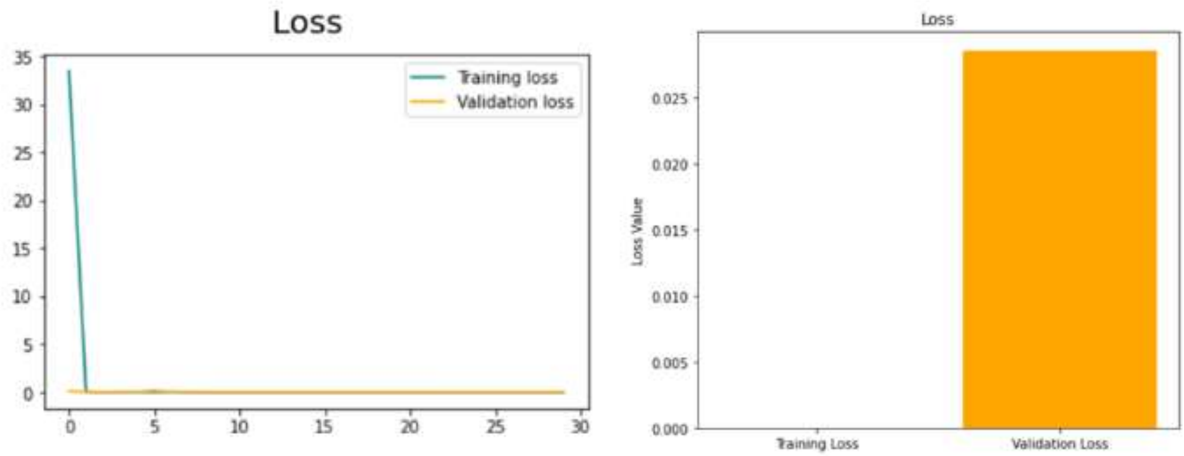



Figure 5.2 training accuracy v/s validation accuracy for our customized model

The training accuracy versus validation accuracy graph (in figure 5.2) of our customised model shows an exceptional accuracy of 1.00 (equivalent to 100%) for both curves. The remarkable correspondence observed between the training and validation accuracies indicates the model has successfully generalised and is not susceptible to overfitting. This indicates that the model acquires and predicts driver distraction patterns from our dataset in an efficient manner, guaranteeing reliable results when implemented in real-world scenarios. The strong correlation observed between the two accuracy curves indicates that our customised CNN model has been effectively optimised, thereby exhibiting a notable level of dependability and precision in identifying driver distractions.




**F**igure 5.3 training loss v/s validation loss for our customized CNNs

The customised CNNs model exhibits an exceptional loss of zero in both the training and validation loss curves as shown in Figure ***5.3*** above. This represents a perfect scenario in which our model has achieved error minimization throughout the training phase, thereby efficiently capturing and assimilating the nuances present in our dataset. The fact that the alignment of training and validation losses is zero indicates that the model effectively predicts driver distraction without yielding to overfitting. This serves as a robust validation of the model's ability to detect driver distractions with minimal error and high precision, establishing it as a dependable device for use in real life.

The visual representation of the distraction and not distraction detection on our dashboard is shown in the figure 5.4 below.

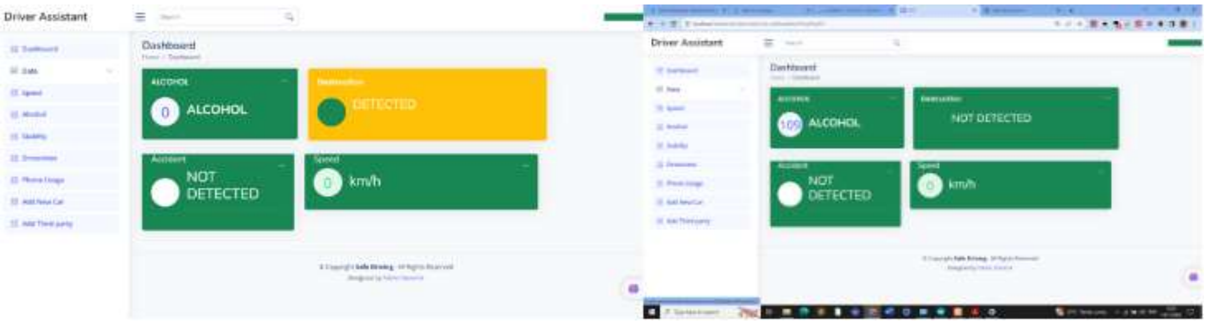



Figure 5.4 distraction and not distraction

## 5.3 Comparison of exiting solutions with our solution

**Table 3: solutions comparison**

| Solutions | Real-time monitoring | Monitor-driver distraction (phone usage) | Tracking and notification | integration capability | Used IoT |
|---|---|---|---|---|---|
| AI accident detection and alert system using IoT and D[28]. | YES | NO | YES | NO | YES |
| Automatic car accident prevention and detection [25]. | YES | NO | NO | NO | NO |
| Vehicle accident detection and alert system.[23] | YES | NO | YES | NO | YES |
| Our System | YES | YES | YES | YES | YES |

The table 3 presents a comparative analysis of various accident detection and prevention solutions, assessing their respective attributes including real-time monitoring, driver distraction monitoring (such as phone usage), tracking and notification functionalities, integration capabilities, and Internet of Things (IoT) implementation. While the initial solution prioritizes real-time tracking and monitoring, it is deficient in functions such as driver inattentive monitoring and integration. Although the second solution prioritizes real-time monitoring and automatic car accident prevention, it is deficient in tracking, notification, and IoT integration. Regarding the detection of vehicle accidents, the third solution integrates real-time tracking, monitoring, and the Internet of Things.

In conclusion, our suggested system demonstrates exceptional performance across all domains, encompassing extensive real-time monitoring, driver distraction monitoring, tracking capabilities, notification features, integration capabilities, and an optimization of IoT potential to adopt a holistic approach towards accident detection and prevention.

## 5.4 Summary

In this chapter the performance results of our model and comparison of existing solutions were presented.

# CHAPTER 6. CONCLUSION AND RECOMMANDATIONS

In summary, our investigation has revealed the capacity of an Internet of Things (IoT) and artificial intelligence (AI) system to improve road safety through the efficient identification of driver distraction and the prevention of collisions resulting from negligent driving, excessive acceleration, and drunkenness. In real-world transportation scenarios, the proposed system has been shown to be viable through our experiments and findings. By employing cloud-based processing, IoT device integration, data collection, AI and ML algorithms, and real-time driver distractions monitoring, we have demonstrated that suitable alerts can be generated to mitigate the dangers associated with distracted driving.

Our research emphasizes the importance of utilizing technology to address critical issues related to road safety. The implementation of Convolutional Neural Networks (CNNs) has proven to be an effective method in detecting driver distractions with 86-100% accuracy, thereby contributing significantly to the prevention of accidents. The infrastructure of our system, which is comprised primarily of the Raspberry Pi, Internet of Things devices, camera, and GSM/GPRS communication, has effectively showcased the potential for instantaneous response and real-time monitoring in the case of an accident. The implications of this research for the implementation of practical solutions that can substantially mitigate road accidents and improve driver safety are extremely encouraging.

## Recommendations

- Enhancing efficacy, we recommend incorporating the latest AI and IoT advancements and collaborating with experts for ongoing algorithm refinement.
- To implement periodic surveys or feedback mechanisms to gauge user satisfaction with the system.
- To prioritize the implementation of robust security protocols to safeguard user data and protect against potential cyber threats.
- The study emphasizes collaboration with research institutions and stakeholders for continuous improvement, creating a feedback loop that incorporates user and expert insights into the system's evolution.

## Future Work

Future AI and IoT road safety research will focus on several key areas. This study may expand and enrich its dataset to include more driving circumstances and distractions. The system will be robust and adaptable to changing road safety concerns by collecting diverse and representative data.

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# REFERENCES


[1] Aswir and H. Misbah, "Global status report on road safety 2018," *Photosynthetica*,

[2] "No Title." https://police.gov.rw/media/news-detail/news/media-plays-key-role-in-road-safety-digp-sano/.

[3] G. Street and D. C. Washington, "Rwanda National Congress," p. 20005, 2019.

[4] J. Cuena, J. Hernández, and M. Molina, "Knowledge oriented design of an application for real time traffic management: The TRYS system," 1996.

[5] M. Fogue, P. Garrido, F. J. Martinez, J.-C. Cano, C. T. Calafate, and P. Manzoni, "Automatic accident detection: Assistance through communication technologies and vehicles," *IEEE Veh. Technol. Mag.*, vol. 7, no. 3, pp. 90–100, 2012.

[6] M. S. Amin, M. A. S. Bhuiyan, M. B. I. Reaz, and S. S. Nasir, "GPS and Map matching based vehicle accident detection system," in *2013 IEEE Student Conference on Research and Developement*, 2013, pp. 520–523.

[7] R. K. Gupta and R. K. Pateriya, "Balance resource utilization (BRU) approach for the dynamic load balancing in cloud environment by using AR prediction model," *J. Organ. End User Comput.*, vol. 29, no. 4, pp. 24–50, 2017.

[8] M. M. Rathore, A. Paul, A. Ahmad, and G. Jeon, "IoT-based big data: From smart city towards next generation super city planning," *Int. J. Semant. Web Inf. Syst.*, vol. 13, no. 1, pp. 28–47, 2017.

[9] B. Jan *et al.*, "Deep learning in big data analytics: a comparative study," *Comput. Electr. Eng.*, vol. 75, pp. 275–287, 2019.

[10] Statista, "Global fertility rate from 2011 to 2021," *Aaron O'Neill*, vol. 2021, pp. 2021–2024, 2023, [Online]. Available: https://www.statista.com/statistics/805064/fertility-rate-worldwide/.

[11] A. Gumaei *et al.*, "A deep learning-based driver distraction identification framework over edge cloud," *Neural Comput. Appl.*, pp. 1–16, 2020.

[12] Y. Zhao, "Mobile phone location determination and its impact on intelligent transportation systems," *IEEE Trans. Intell. Transp. Syst.*, vol. 1, no. 1, pp. 55–64, 2000.

[13] M. Reddy and J. Tulasi, "Accident detection depending on the vehicle position and vehicle theft tracking, reporting systems," *Int. J. Sci. Eng. Technol. Res*, vol. 3, no. 9,

pp. 2359–2362, 2014.

[14] H. M. Ali and Z. S. Alwan, *Car accident detection and notification system using smartphone*. Lap Lambert Academic Publishing Saarbrucken, 2017.

[15] K. Patel, "Utilizing the emergence of android smartphones for public welfare by providing advance accident detection and remedy by 108 ambulances," *Int. J. Eng. Res. Technol.*, vol. 2, no. 9, pp. 1340–1342, 2013.

[16] D. B. Tushara and P. A. H. Vardhini, "Wireless vehicle alert and collision prevention system design using Atmel microcontroller," in *2016 International Conference on Electrical, Electronics, and Optimization Techniques (ICEEOT)*, 2016, pp. 2784–2787.

[17] A. Shaik *et al.*, "Smart car: An IoT based accident detection system," in *2018 IEEE global conference on internet of things (GCIoT)*, 2018, pp. 1–5.

[18] C. Nalini and R. N. Swapna, "IoT based vehicle accident detection & rescue information system," *Eurasian J. Anal. Chem*, vol. 13, pp. 911–916, 2018.

[19] C. Dashora, P. E. Sudhagar, and J. Marietta, "IoT based framework for the detection of vehicle accident," *Cluster Comput.*, vol. 23, pp. 1235–1250, 2020.

[20] M. Fogue, P. Garrido, F. J. Martinez, J.-C. Cano, C. T. Calafate, and P. Manzoni, "A system for automatic notification and severity estimation of automotive accidents," *IEEE Trans. Mob. Comput.*, vol. 13, no. 5, pp. 948–963, 2013.

[21] G. Rajesh, A. R. Benny, A. Harikrishnan, J. J. Abraham, and N. P. John, "A deep learning based accident detection system," in *2020 International Conference on Communication and Signal Processing (ICCSP)*, 2020, pp. 1322–1325.

[22] M. S. Supriya, S. P. Shankar, H. J. BJ, L. L. Narayana, and N. Gumalla, "Car crash detection system using machine learning and deep learning algorithm," in *2022 IEEE International Conference on Data Science and Information System (ICDSIS)*, 2022, pp. 1–6.

[23] A. Bhakat, N. Chahar, and V. Vijayasherly, "Vehicle Accident Detection & Alert System using IoT and Artificial Intelligence," in *2021 Asian Conference on Innovation in Technology (ASIANCON)*, 2021, pp. 1–7.

[24] J. G. Choi, C. W. Kong, G. Kim, and S. Lim, "Car crash detection using ensemble deep learning and multimodal data from dashboard cameras," *Expert Syst. Appl.*, vol. 183, p. 115400, 2021.

[25] H. Hozhabr Pour *et al.*, "A machine learning framework for automated accident detection based on multimodal sensors in cars," *Sensors*, vol. 22, no. 10, p. 3634, 2022.

[26] A. Comi, A. Polimeni, and C. Balsamo, “Road accident analysis with data mining approach: evidence from Rome,” *Transp. Res. procedia*, vol. 62, pp. 798–805, 2022.

[27] G. Singh, M. Pal, Y. Yadav, and T. Singla, “Deep neural network-based predictive modeling of road accidents,” *Neural Comput. Appl.*, vol. 32, pp. 12417–12426, 2020.

[28] N. Pathik, R. K. Gupta, Y. Sahu, A. Sharma, M. Masud, and M. Baz, “AI enabled accident detection and alert system using IoT and deep learning for smart cities,” *Sustainability*, vol. 14, no. 13, p. 7701, 2022.

[29] M. Abdullah-Al-Wadud, M. H. Kabir, M. A. A. Dewan, and O. Chae, “A dynamic histogram equalization for image contrast enhancement,” *IEEE Trans. Consum. Electron.*, vol. 53, no. 2, pp. 593–600, 2007.