2024-07-22

Development of a Deep Learning-Based System for Enhanced Blind Spot Detection and Lane Departure Warning for the Kayoola Buses

Ziryawulawo, Ali

NM-AIST

DEVELOPMENT OF A DEEP LEARNING-BASED SYSTEM FOR ENHANCED BLIND SPOT DETECTION AND LANE DEPARTURE WARNING FOR THE KAYOOLA BUSES

Ali Ziryawulawo

A Project Report Submitted in Partial Fulfilment of the Requirements for the Degree of Master of Science in Embedded and Mobile Systems of the Nelson Mandela African Institution of Science and Technology

Arusha, Tanzania

July, 2024

ABSTRACT

Deep learning-based advanced driver assistance systems (ADAS) have attracted interest from researchers due to their impact on improving vehicle safety and reducing road traffic accidents. In Uganda, road accidents have continued to soar with an increase of up to 42% in 2021 due to the growing road traffic density. To curb the high rates of road accidents, especially for heavy-duty vehicles, Kiira Motors Corporation a state-owned mobility solutions enterprise needs advanced driver assistance systems for improved safety of their market entry products the Kayoola buses. This project presents an approach to vehicular safety enhancement through the implementation of a Lane Departure Warning (LDW) and Blind Spot Detection system (BSD) using advanced deep learning algorithms that will be able to alert the driver using the graphical user interface, and auditory feedback. The system was developed based on the MobileNet architecture and the Kayoola Buses manufactured by Kiira Motors Corporation were used as the project case study. A purposive sampling technique was used to select the study participants focusing on targets automotive manufacturers, bus companies, cargo truck operators, and passengers. Two distinct datasets which included the DET dataset with raw event data from 5424 images of 1280×800 pixels and the TuSimple dataset of 6,408 road images specifically captured on highways were used for model training. The resultant BSD and LDW system are realized on the Raspberry Pi platform, incorporating diverse sensors which include radar sensors, ultrasonic sensors, gyroscope and accelerometer sensors. By combining these advanced features, the study not only bridges an essential research void but also offers a practical resolution to pressing road safety concerns in the East African context. The implementation of a BSD and LDW system through deep learning techniques marks a pivotal advancement in vehicular safety. The lane detection model was tested on Dataset for Lane Extraction (DET) and TuSimple datasets. Our model attained a mean model accuracy (F1 Score) of 77.59% and a mean IoU of 65.26% on the DET and an overall accuracy of 97.96% on the TuSimple dataset. User acceptance tests were carried out to validate and ascertain whether the developed system addressed the needs of the prospective users. The tests were carried out with a total of 150 users to validate the functionality of the system. The anticipated real-world implementation is poised to substantiate the system's effectiveness, thereby contributing to safer roads regionally and inspiring innovation in automotive engineering by leveraging artificial intelligence.

DECLARATION

I, Ali Ziryawulawo, do hereby declare to the Senate of the Nelson Mandela African Institution of Science and Technology that this project report is my original work and that it has neither been submitted nor being concurrently submitted for a degree award in any other institution.

Ali Ziryawulawo		22/07/2024
Name of Candidate	**Signature**	**Date**

The above declaration is confirmed by:

Prof. Ing. Anael Elikana Sam, PhD		22/07/2024
Name of Supervisor 1	**Signature**	**Date**

Dr. Neema Mduma	N.Mdumah	22-07-2024
Name of Supervisor 2	**Signature**	**Date**

COPYRIGHT

CERTIFICATION

The undersigned certify that they have read and hereby recommend for acceptance by the Nelson Mandela African Institution of Science and Technology, a project report titled ***"Development of a Deep Learning-Based System for Enhanced Blind Spot Detection and Lane Departure Warning for the Kayoola Buses"*** in partial fulfillment of the requirements for the degree of Master of Science in Embedded and Mobile Systems of the Nelson Mandela African Institution of Science and Technology.

Prof. Ing. Anael Elikana Sam, PhD		22/07/2024
Name of Supervisor 1	**Signature**	**Date**

Dr. Neema Mduma	N.Mdumah	22-07-2024
Name of Supervisor 2	**Signature**	**Date**

ACKNOWLEDGEMENTS

I am so grateful to the God Almighty for the gift of life and for enabling me to finalize my project on time. I in a special way extend special thanks to my beloved parents for the support rendered throughout this journey.

I extend my gratitude to Kiira Motors Corporation management and staff for allowing me to undertake and complete this project. I would on a special note like to thank Eng. Richard Madanda, my industrial supervisor, for the guidance rendered throughout this project. I also in a special way appreciate Mr. Baguma Moses and Mr. Odongo Lawrence, the bus drivers at Kiira Motors Corporation, for sparing time to enable me to conduct tests on the developed system on the Kayoola buses.

Special thanks go to my academic supervisors, Prof. Anael Sam and Dr. Neema Mduma for their continuous guidance throughout the project and to DAAD GIZ and the Center of Excellence for ICT in East Africa (CENIT@EA) scholarship program for funding the project.

DEDICATION

To my loving family and loyal friends.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

LIST OF APPENDICES

LIST OF ABBREVIATIONS AND SYMBOLS

ADAS	Advanced Driver Assistance System
ANN	Artificial Neural Network
ATDD	Acceptance Test-Driven Development
BSD	Blind Spot Detection
CNN	Convolutional Neural Network
DET	Dataset for Lane Extraction
FCN	Fully Convolutional Networks
GPIO	General Purpose Input Output
GUI	Graphical User Interface
HOG	Histogram of Oriented Gradient
LDW	Lane Departure Warning
LED	Light Emitting Diode
LSTM	Long Short-Term Memory
MEMS	Micro Electro-mechanical System
MOT	Multi Object Tracking
NLTK	Natural Language Toolkit
R-CNN	Recurrent Convolutional Neural Network
ROI	Region of Interest
SCNN	Sparse Convolutional Neural Network
SLDC	Software Development Life Cycle
TDD	Test-Driven Development
V2I	Vehicle to Infrastructure
V2V	Vehicle to Vehicle
WHO	World Health Organization

CHAPTER ONE

INTRODUCTION

1.1 Background of the Problem

With reference to the World Health Organization (WHO) June 2022 report, roughly 1.3 million individuals succumb to road accidents annually (WHO, 2022). Maintaining proper lane position and distance from the vehicle in front can be challenging as extended driving is exhausting for drivers. Drivers are also susceptible to fatigue, drowsiness, inattentiveness, and other distractions like smartphones, entertainment, and navigation systems which compromise safety.

Kiira Motors Corporation (KMC) a state-owned mobility solutions enterprise is looking forward to developing advanced driver assistance systems for improved safety of their market entry products- the Kayoola buses. These include both the Kayoola Diesel buses which are designed for long-distance travel and the Kayoola EVS buses which are low-floor electric intercity buses (KMC, 2023). These buses are designed with state-of-the-art functionalities and KMC envisions advancing their level of autonomy.

One of the crucial systems found in self-driving vehicles that helps create a safer driving environment is the Advanced Driver Assistance System (ADAS). Its goal is to reduce driving errors by preventing vehicle from colliding, improving flow of traffic, hence advancing safety. The ADAS includes features such as Automatic Braking (Madhuri & UmaMaheswari, 2019), Adaptive Cruise Control (Yu & Wang, 2022), Lane-Keeping Assist (Farah *et al.,* 2021) and Drowsiness Detection (Ziryawulawo *et al.,* 2023) among others.

Driving for long periods on straight highways and good roads can cause fatigue in the driver, increasing the likelihood of accidents. To improve vehicle safety, early warning systems for lane departure and blind spots are beneficial. Lane detection is crucial in developing semi-autonomous driving technologies and is an important precursor to fully automated vehicles. By identifying the horizontal markings on painted road surfaces, lane detection draws boundaries around the lanes, making it possible for the vehicle to navigate its way through them (Keatmanee *et al.,* 2018). Subsequently, lane tracking builds on this technology by utilizing previously detected markers to adjust its position based on a motion algorithm, while using temporal consistency to detect lane markings in sequence with each new frame (Feniche & Mazri, 2019).

In this project, a BSD and LDW system using advanced deep learning techniques is developed. The prototype demonstrates the potential for improved real-time detection and enhanced vehicle safety. The Agile development approach, particularly Extreme Programming (XP), ensured efficient end-user involvement throughout the project.

1.2 Statement of the Problem

In Uganda, the number of road accidents increased by 42% according to the 2021 Annual Police Report (Walekhwa *et al.*, 2022). The task of staying in the correct lane and maintaining a safe distance from the vehicle in front can be challenging for drivers, as they must remain focused on the road for extended periods. The transport sector in East Africa, including Uganda, plays a critical role in the region's economic development. However, road accidents continue to be a major challenge, with a high number of fatalities and injuries reported each year.

According to WHO, road traffic accidents are a leading cause of fatalities globally, with significant economic and social implications. In Uganda, an increase in motorization has led to a rise in road accidents. The rate of motorization doubled from approximately 739 036 vehicles in 2012 to 1 228 425 in 2022, contributing to a staggering increase in recorded road crash fatalities. There were an estimated 1.19 million road traffic deaths in 2021; this corresponds to a rate of 15 road traffic deaths per 100 000 population (WHO, 2022).

Lane departure and blind spot events are among the major causes of road accidents in East Africa. While ADAS systems such as BSD and LDW have been developed to address these issues, majority have been implemented as separate systems using computer vision techniques which are faced with challenges like variations in lighting, object occlusions, and ineffectiveness in dealing with complex real-world scenarios. However, recent advancements in deep learning provide an opportunity to integrate these systems and improve their accuracy. Therefore, there is a need for real-time BSD and LDW systems that can detect and classify objects accurately to provide more precise warnings to drivers in critical situations.

1.3 Rationale of the Study

The transport sector in East Africa, including Uganda, is important for economic development. However, road accidents continue to be a major challenge, with many fatalities and injuries reported each year with averagely 24 people dying per 100 road crashes (Osuret *et al.,* 2021). The BSD and LDW systems have been effective in reducing accidents in developed countries, but are not widely used in East Africa due to factors such as high costs and limited access to technology.

The project aimed at developing a BSD and LDW system prototype that is affordable, reliable, and suitable for the unique driving conditions in East Africa, particularly in Uganda. The project is justified because it could enhance road safety, be more cost-effective than separate systems, be tailored to local conditions, and contribute to innovation and knowledge creation in the field of automotive engineering, particularly in the context of East Africa. By developing the BSD and LDW system prototype, the project could potentially improve road safety and save lives in the region.

1.4 Research Objectives

1.4.1 General Objective

To develop a deep learning-based system for enhanced blind spot detection and lane departure warning for the Kayoola Buses.

1.4.2 Specific Objectives

The study aimed to achieve the following specific objectives:

(i) To identify requirements for developing a blind spot detection and lane departure warning system.

(ii) To design and implement a deep learning-based blind spot detection and lane departure warning system.

(iii) To validate the developed deep learning-based blind spot detection and lane departure warning system.

1.5 Research Questions

The study intended to answer the following questions:

(i) What are the essential requirements for a blind spot detection and lane departure warning system using deep learning?

(ii) How can the deep learning-based blind spot detection and lane departure warning system be designed and implemented?

(iii) What is the validity of the developed blind spot detection and lane departure warning system in line with the end-user requirements?

1.6 Significance of the Study

The development of an effective BSD and LDW System using machine learning techniques can significantly improve road safety in East Africa, reducing the number of accidents and fatalities on the roads. By deploying a deep learning-based blind spot detection (BSD) and lane departure warning (LDW) systems, operators can continuously monitor vehicle positioning to identify potential safety hazards in real-time. This therefore allows for timely intervention and alerts to drivers, thereby reducing the risk of collisions and ensuring enhanced road safety.

Beyond the direct impact on road safety, the deployment of efficient BSD and LDW systems shall yield environmental benefits. By reducing the frequency of accidents, the system will help minimize vehicular emissions associated with traffic congestion and collisions. Furthermore, by promoting smoother traffic flow and more efficient driving behaviors, they contribute to overall reductions in carbon emissions and air pollution, aligning with sustainability goals and environmental conservation efforts. By promoting a safer driving environment, the system contributes to the overall well-being of all road users. This includes drivers of other vehicles, pedestrians, and cyclists.

By leveraging state-of-the-art deep learning techniques, the project contributes to advancing the technological landscape of automotive safety systems. The project will contribute to the growing body of knowledge on the application of deep learning techniques in the automotive industry, and can be used as a basis for further research and development of similar systems in other parts of the world.

1.7 Delineation of the Study

The project focuses on the design and development of a deep learning-based system for lane departure warning and blind spot detection. This project presents an approach to vehicular safety enhancement through the integration of BSD and LDW systems using advanced deep learning algorithms. The scope of the project was limited to development of the deep learning model as well as the graphical user interface for alerting the user in the event of detected objects in blind spots and lane departure events. The resultant BSD and LDW system are realized on the Raspberry Pi platform, incorporating diverse sensors.

CHAPTER TWO

LITERATURE REVIEW

2.1 Related Works

Several studies have emphasized the importance of utilizing technological interventions in mitigating road accidents. These interventions seek to address the causes of accidents, including but not limited to driver distraction and fatigue. Several interventions have been developed in the East African context with the prime goal of reducing road traffic accidents. Masatu *et al.* (2022) developed a smart mobile-based application aimed at mitigating road accidents in Tanzania by employing smartphone sensors to provide voice and image notifications about road signs thereby enhancing driver attentiveness. Ziryawulawo *et al.* (2023) developed an algorithm for detecting driver drowsiness with the aim of improving safety of the Kayoola Buses in Uganda.

The related works for this study focused mainly on BSD and LDW systems employing machine learning techniques.

2.1.1 Lane Departure Warning

Numerous studies employed machine learning techniques in conjunction with ADAS systems to recognize the driver's intentions for lane change control so as not to misjudge the intentions of the driver. It has been demonstrated that machine learning is useful for estimating, categorizing, and forecasting system behavior. For determining the driver's intentions, researchers have focused on classification methods including the Bayesian network, Hidden Markov Model, and Support Vector Machine (Deng *et al.,* 2020).

Lane detection tasks have witnessed significant advancements due to the application of deep learning methods (Li *et al.,* 2021). These advancements have resulted in numerous strategies meant to improve the performance of lane detection compared to previous methods. Deep learning algorithms, for instance, Convolutional Neural Networks (CNNs), are essential role in this progress, with CNNs being widely used in various tasks, including ROI generation, filtering, and tracking (Munir *et al.,* 2022). Popular CNN architectures, such as AlexNet (Xie *et al.,* 2017), have demonstrated exceptional feature extraction capabilities in computer vision, resulting in the proposal of several outstanding neural networks for lane detection. ResNeXt

(Xie *et al.*, 2017), ResNet (Zhang *et al.*, 2022), RNNs, LSTMs, and FCN (Eichelberger & McCartt, 2016) are among the other deep learning methods that have been utilized for lane detection in continuous frames and semantic segmentation. The adoption of these techniques has accelerated the development of lane detection approaches, leading to improved accuracy and performance (Lu *et al.,* 2019; Zakaria *et al.,* 2018; Zhang, *et al.,* 2020).

Du *et al.* (2015) presented a vision-based approach for detecting lanes based on adaptive thresholding of the ridge-enhanced image, using the image’s histogram. An intensity assessment is carried out to complete the operation. The major limitation of the research was the reliance on computer vision which did not adequately demonstrate the model's capability to accurately estimate vehicle pose information relative to the road, such as the camera pitch angle.

A lane detection technique was proposed by Joy *et al.* (2022) by concentrating on a collection of real-time image data. The noise is removed using a Gaussian filter after the red-green-blue (RGB) picture has been converted to grayscale. The Canny Edge Detector finds margins with notable intensity differences. The Hough Line Transform detects the edges in identified lane markings of the clever image after masking all but the area of interest in the clever image. In order to represent identified lane lines, a pixel value based on the Hough transform is superimposed onto the original picture. The study has certain limitations, as it did not include all possible scenarios with varying road and weather conditions due to the extra workload required for data collection and labelling. Additionally, the study did not incorporate the integration of blind spot detection, which could potentially improve safety.

To improve the precision of ADAS systems in recognizing the intention of the driver intention to change lanes, offer a unique preprocessing technique as a workable option (Kim *et al.,* 2017). Artificial neural network (ANN) algorithms that replicate the complex vehicle dynamics and simulations of various driving scenarios are incorporated into the model together with data from traditional onboard sensors, enhanced vehicle states, and road surface condition estimates. Sensor data is used to train these ANN models using data from a driving simulator, which offers extra road and vehicle data. A limitation of the study is that it did not test the model on real traffic scenarios of varying characteristics. Furthermore, the study did not explore other advanced deep-learning algorithms.

Irshad *et al.* (2017) proposed an on-the-spot lane recognition algorithm based on a mobile camera attached to the dashboard of a vehicle. A road image is taken, and the model then detects any lane markings that are represented by straight lines. A region of interest (ROI) is determined for the right and left lanes and lines outside ROI are removed. A point of convergence is determined using the line's right and left ROI, and some lines are discarded according to how far away from this convergence point they are. A limitation of the study is that it solely focused on low-resource platforms utilizing classical machine learning and did not explore other advanced deep-learning algorithms.

Fakhfakh *et al.* (2020) introduced a novel algorithm based on a Bayesian framework to tackle the challenge of detecting sharply curved lanes. The algorithm utilizes a unique approach to modelling the trajectory over each section of the lane using hyperbolas. Contours extracted from the preprocessed input image are then fitted to the chosen analytical model to characterize the lanes. A Bayesian framework is employed to estimate hyperparameters of N hyperbolas and delineate the curved lane throughout the image, even in challenging settings. The major limitation of the study is the inadequacy of sampling of the lane detection.

Teo *et al.* (2021) presented a cost-effective approach to lane departure warning (LDW) that leverages a combination of computer vision techniques. The system employs Adaptive Canny Edge Detection, Lane Detection, Gabor Filters, Hough Transformation, and multithreading to achieve performance by relying on Euclidean distance and departure angle calculations to determine the vehicle's position relative to lane markings. The system utilizes the directional nature of lane markings, allowing for their effective extraction from the road surface even under challenging lighting conditions caused by shadows. The major limitation of the study is the inability to cater for diverse weather changes.

2.1.2 Blind Spot Detection

Chang *et al.* (2018) developed an algorithm for detecting blind spots that can be used both during the day and at night. The algorithm makes use of Gabor feature extraction and motion analysis to identify cars in the blind spots. During the daytime, Gabor feature extraction is employed to track cars, inside and outside lane lines in the landscape. After detection, the motion of the car prospects is evaluated using the Horn-Schunck technique, which eliminates incorrect judgments. In the nighttime, the algorithm makes use of the headlights of oncoming vehicles. The image is first binarized, and the light area is divided into two groups. This study however relied on classical machine learning as opposed to deep learning for better classification.

A blind-spot detection algorithm proposed by Muzammel *et al.* (2022) employed multiple CNNs and faster R-CNN as the object detector. Two different approaches/models based on CNNs were presented. Two CNNs were utilized for feature extraction, and the outputs were combined and passed through another custom-designed CNN. The semantic features from this approach were then used by faster R-CNN to detect vehicles. In another implementation, two ResNet models were combined for feature extraction. A limitation of the study is that it did not explore the combination of more than two CNNs with faster R-CNN and did not conduct a parametric study to determine the accuracy and frame rate of such integration.

A HOG-based Descriptor and Support Vector Machine-based system was proposed (Jung & Yi, 2018) with an algorithm consisting of various steps. First, a rear camera image frame sets the window for vehicle tracking in the blind spot region on either the left or right side. Estimating the direction of movement for identified cars based on previous detections is then carried out. Finally, a signal is generated to alarm in case of any vehicles in the blind spot. The basic algorithm achieved a precision of 98.62% and a recall of 99.82% for urban areas and highways, respectively. The high-speed algorithm yielded a precision of 97.26% and recall of 99.65% according to the authors' report. A limitation of the study is that it only monitored the blind-spot region based on the rear-view camera using an embedded device without any computing accelerator.

Rangesh and Trivedi (2019) proposed a multi-object tracking model that extends upon the existing framework for Multiple Object Tracking (MOT) proposed by Wu *et al.* (2018). The proposed framework can process object proposals from numerous sensors and can handle a variable number of sensors to generate continuous object tracks. Furthermore, the proposed approach tracks objects directly in the real world, as opposed to traditional techniques that track objects solely in the image plane. The study, on the other hand, did not consider integrating the lane departure and blind spot monitoring. Additionally, deep learning was not utilized to improve the classification process.

Zhao *et al.* (2019) proposed a real-time approach utilizing a camera-based system and an AlexNet-based neural network. Four distinct neural networks were used, including networks based solely on Visual Geometry Group blocks, networks combining depth-wise separable convolution with either residual learning or the squeeze-and-excitation module, and a network combining all three components. A limitation of the study is that it did not encompass all road traffic scenarios due to the added load required to gather and label data and the model's effectiveness in accounting for sloped roads did not incorporate geography data from sensing elements and adjusting the blind spot region accordingly.

De-Raeve *et al.* (2020) proposed a blind spot detection and warning system using Bluetooth Low Energy (BLE) communication, offering an alternative to camera- and radar-based systems. This BLE-based approach identifies all vulnerable road users around the truck compared to traditional camera or radar systems. The system employs five detection nodes on the truck that advertise their presence, while a wearable scanner carried by the vulnerable road user detects and interprets these signals, triggering warnings for both parties. The limitation of the system is that it requires the road users to have the BLE devices at all times and does not give visual warnings to the driver.

2.2 Technical Research Gap

While existing research has explored Advanced Driver-Assistance Systems (ADAS) for blind spot detection (BSD) and lane departure warning (LDW), these systems are typically developed and implemented independently. Furthermore, they often rely on computer vision techniques. While computer vision has played a significant role in ADAS development, it faces limitations in real-world scenarios due to factors like variations in lighting, object occlusions, and difficulty handling complex traffic situations. Recent advancements in deep learning offer an opportunity to overcome these limitations. By implementing BSD and LDW within a deep learning framework, real-time, high-precision object detection and classification is achieved, leading to more accurate and timely warnings for drivers in critical situations.

CHAPTER THREE

MATERIALS AND METHODS

3.1 Project Case Study

The study was carried out at Kiira Motors Corporation a state enterprise championing the nascent automotive industry in Uganda. The scope was to develop a deep learning-based lane departure warning and blind spot detection system that will be deployed in the Kayoola buses to improve their road safety. The system components were designed and implemented, and the system was integrated into the Kayoola buses.

3.2 Target Population

The research study targets automotive manufacturers, bus companies, cargo truck operators, and passengers. The Kayoola buses manufactured by Kiira Motors Corporation were used as the project case study.

3.3 Sampling Technique and Sample Size

The target population for this research was bus drivers, fleet operators and cargo truck operators in Uganda. A purposive sampling technique was employed to determine the study participants. Purposive sampling is a non-random sampling technique where individuals who possess specific characteristics or knowledge are selected to participate in the study (Junus *et al.*, 2023). In this case, 125 participants were selected to participate in the deployment of the system and to validate the performance of the BSD and LDW systems. This sample size was calculated from a sample of 250 drivers and passengers at Kiira Motors Corporation with a confidence interval of 95%.

3.4 System Requirements

The process of system analysis involved identifying the functional requirements that outline the tasks the system must perform, as well as the non-functional requirements that detail how the system operates. These requirements were gathered from various sources, such as potential users and stakeholders, through focus group discussions and were continually updated and improved overtime.

3.4.1 Functional Requirements

These are the requirements that outline the fundamental tasks and operations that a system should perform. This encompasses a variety of aspects such as the types of inputs that the system can accept, the output of information that the system provides, the storage of data that can be used by other systems, the computational and processing tasks that the system can perform, and the scheduling and synchronization of the processes and data involved.

3.4.2 Non-functional Requirements

These requirements encompass a wide variety of system aspects such as performance, security, usability, scalability, reliability, and maintainability. These requirements serve as a set of guidelines to ensure that the integrated lane departure warning and blind spot detection system meets the expectations of its stakeholders and performs optimally in the Kayoola buses.

3.5 Data Collection Methods

Data was gathered using a combination of methods, including document examination, observation, desktop research, a survey questionnaire, and the comparison of industry-standard practices. The data obtained consisted of both qualitative and quantitative data, and another segment comprised media files such as photos and videos.

3.5.1 Desktop Research and Benchmarking

This entailed a re-examination, interpretation, and assessment of historical information about passenger safety and security systems within the realm of public transportation. The principal aim was to discern how this historical data and the existing systems could provide insights for guiding the study and advancement of the new system. This process contributed to establishing a fundamental theoretical grasp of security and safety systems, thus serving as a basis for implementation enhancements.

3.5.2 Questionnaire

The Google Forms questionnaire was created and distributed to during the requirements gathering and system validation phases. The questionnaires included a wide variety of questions seeking to understand the user expectations during the requirements gathering and to understand the user perspective of the developed system during system validation.

3.5.3 Interviews

We conducted interview sessions with a selected number of crucial system stakeholders, primarily focusing on project owners and financiers who hold the primary decision-making authority and play a pivotal role in ensuring its integration within the organization. The insights gathered from these stakeholders played a crucial role in assessing the system's viability before proceeding with its design and development.

3.5.4 Document Review

This encompassed a thorough review of various materials and documents related to the organization, including those produced by the organization itself and related sources such as vehicle engineering drawings, specifications for different bus parts and materials, standard guidelines and procedures. The main objective was to gain insights into the organization's operations, objectives, and the products it delivers. This assessment aimed to determine the alignment of the passenger security system within the organization and to devise optimal strategies for its implementation to align with the organization's goals and fulfil end-user requirements.

3.6 Data Analysis

Python was employed as the primary tool for conducting data analysis due to its flexibility and robust support for data manipulation. For quantitative and multiple-choice data, the analysis included the generation of frequency tables and visualizations like pie charts to provide a structured summary of the data and facilitate clear interpretation.

In handling free-response data, both thematic coding and sentiment analysis techniques were employed to extract comprehensive insights from the collected information. Thematic coding, implemented using Python and the Natural Language Toolkit (NLTK) library, facilitated the identification of recurring themes and patterns within the free-response data. Simultaneously, sentiment analysis, utilizing natural language processing tools, was applied to discern the sentiments expressed in the responses. Google Analytics was also used to analyze data collected from the survey responses.

3.7 System Development

For this project, the Agile software development life cycle (SDLC) was utilized to ensure an iterative and collaborative approach to the software development process. Specifically, the focus was on Extreme Programming (XP), which emphasized continuous testing and integration, frequent releases, and customer involvement throughout the development cycle. The XP also emphasizes the importance of teamwork and communication, with developers working closely together and with customers to ensure that the software meets their needs.

3.8 System Operation

The BSD and LDW systems will work by continuously monitoring the vehicle's surroundings using a combination of sensors and cameras. The sensors will detect the proximity of the vehicle relative to other vehicles or pedestrians, while the cameras capture images of the road lanes as well as other vehicles and pedestrians. These inputs are processed by a deep learning algorithm to detect any deviations from the vehicle's lane or the presence of other vehicles and or objects in the blind spots.

If the system detects a potential hazard, it will alert the driver through a visual or auditory warning. The warning will be customizable depending on the severity of the situation, and can also be adjusted based on the driver's preferences.

The system will operate in real-time, meaning that it will continuously process the sensor and camera inputs and generate warnings as soon as a potential hazard is detected. The system will be designed to be reliable and accurate, with a low false positive rate to avoid unnecessarily alarming the driver.

3.8.1 Hardware Tools and Requirements

(i) Raspberry Pi

The Raspberry Pi serves as the main processing unit for the BSD and LDW system. This versatile single-board computer offers ample computing power and a wide range of interfaces, making it well-suited for controlling and coordinating the various components of the system. It handles data processing, decision-making, and communication with other hardware components, playing a central role in the overall system operation.

(ii) Screen

A screen was included in the system to display visual warnings to the driver. The screen provides real-time visual feedback about potential lane departure or blind spot events, allowing the driver to take prompt action to avoid collisions. The screen was integrated into the vehicle's dashboard for optimal visibility. The clarity and readability of the screen are crucial in ensuring effective communication of warnings to the driver.

(iii) Buzzer

A buzzer was used to provide auditory warnings to the driver. The buzzer sounds an alert in the event of detected lane departure or blind spot events, drawing the driver's attention to the potential hazard. The loudness and distinctiveness of the buzzer are carefully chosen to ensure it can effectively alert the driver without causing distraction or discomfort.

(iv) Camera

A camera captures images of the vehicle's surroundings, which are processed by the deep learning algorithm to detect lane departure or blind spot events. The cameras were mounted on the vehicle's exterior near the side mirrors, to provide comprehensive coverage. The resolution, field of view, and image quality of the camera were important factors in ensuring accurate detection of lane departure or blind spot events.

(v) Analogue to Digital Converters

The ADCs were used to convert analogue signals from various sensors, such as proximity sensors and accelerometers, into digital signals that can be processed by the Raspberry Pi. These converters play a critical role in ensuring the accurate and reliable conversion of sensor data, which is used by the system's algorithms for detecting lane departure or blind spot events.

(vi) The MPU6050

The MPU6050, a microelectromechanical system (MEMS), serves as a vital cornerstone in the blind spot detection system, empowering it with essential motion-sensing capabilities. This sophisticated sensor has an accelerometer and a gyroscope, enabling it to measure and track different motion-related parameters, including velocity, orientation, acceleration and displacement.

Table 1: The MPU6050 device connection

Raspberry Pi	MPU6050
Pin 6 (GND)	Ground (GND)
Pin 1 (3.3 V)	Power (VCC)
Pin 5 (SCL)	SCL
Pin 3 (SDA)	SDA

(vii) The HC-SR04 Ultrasonic Sensor

The HC-SR04 Ultrasonic distance sensor plays a pivotal role in the blind spot detection system, utilizing its two ultrasonic transducers to accurately measure distances and detect objects. One of the transducers functions as a transmitter, converting electrical signals into 40 KHz ultrasonic sound pulses. The other transducer acts as a receiver, listening for the transmitted pulses and producing an output pulse whose width correlates with the distance travelled by the pulses. This straightforward yet effective mechanism allows for non-contact range detection with an accuracy of 3 mm.

Table 2: Left ultrasonic sensor connection

Raspberry Pi	HC-SR04
Pin 14 (GND)	GND
Pin 12 (GPIO 18)	TRIG
Pin 2 (5 V)	VCC
Pin 18 (GPIO 24)	ECHO (5 V)

Table 3: Right ultrasonic sensor connection

Raspberry Pi	HC-SR04
Pin 9 (GND)	GND
Pin 4 (5 V)	VCC
Pin 13 (GPIO 27)	ECHO (5 V)
Pin 11 (GPIO 17)	TRIG

3.8.2 Software Tools and Requirements

(i) Visio Studio Code

The Visio Studio Code editor was used for writing Python scripts for both the lane detection module and the blind spot monitoring module. The editor supports intelligent code refactoring, version control and auto-completion.

(ii) Proteus

Proteus is a circuit design software which was used for designing the schematic as well as the PCB layout of the circuit.

(iii) Fritzing

Fritzing is a circuit design software which was also used in addition to Proteus for designing the schematic as well as the breadboard circuit.

(iv) Python

Python is a robust object-oriented programming language and supports deep learning tasks. The deep learning algorithms for lane detection were written in Python. The graphical user interface (GUI) for this project was also developed using Kivy which is an open-source Python framework that supports cross-platform application development.

(v) Thonny IDE

This is a Raspbian-based integrated development environment that was used for writing scripts on the Raspberry Pi. Thonny is best suited for Python and was used for running the main scripts for the lane departure warning module and the blindspot detection module.

(vi) Nvidia Geforce RTX 3050

The Nvidia Geforce RTX 3050 was the graphics card used for training the model. This high-performing GPU enabled training and optimisation of the model.

3.9 System Design

The system is designed with an array of sensors which include cameras and proximity sensors mounted on the bus as shown in Fig. 10. The sensor array is responsible for capturing environmental parameters such as lane markings and nearby objects. The deep learning algorithm processes the sensor data and detects lane departure and blind spot events in real time. The deep learning model was trained on a large dataset of annotated images using the MobileNet CNN architecture as the core neural network to learn patterns and make predictions.

The BSD and LDW system works by continuously monitoring the vehicle's surroundings using a combination of sensors and cameras. The sensors detect the proximity of the vehicle relative to other vehicles or pedestrians, while the cameras capture images of the road lanes as well as other vehicles and pedestrians. These inputs are processed by a deep learning algorithm to detect any deviations from the vehicle's lane or the occurrence of other objects in the blind spots.

If the system detects a potential hazard, it alerts the driver through a visual or auditory warning. The warning is customizable depending on the severity of the situation, and can also be adjusted based on the driver's preferences.

The system operates in real time by continuously processing the sensor and camera inputs and generating warnings as soon as a potential hazard is detected. The system was designed to be reliable and accurate, with a low false positive rate to avoid unnecessarily alarming the driver.

3.10 Lane Detection Data Collection

The dataset used in this project consisted of two open-source datasets: the TuSimple dataset and the Det dataset. The TuSimple lane detection dataset contains a large number of annotated images and corresponding lane markings. It provides diverse road scenarios and lane configurations, making it suitable for training and evaluating lane detection models. Additionally, the DET dataset, another open-source dataset, was also utilized to enhance the training process. By combining these two datasets, a more comprehensive and diverse range of lane detection scenarios was covered, contributing to the overall effectiveness and generalizability of the trained model.

The DET dataset consists of raw event data from 5424 images of 1280×800 pixels. The dataset was split into 3 sets with 3796 for training, 813 for testing, and 813 for validation. The dataset encompasses various traffic scenarios and roads. To enable evaluation and benchmarking, all images in the DET dataset are annotated using a multi-class segmentation format (Cheng *et al.,* 2019).

The TuSimple dataset encompasses a comprehensive collection of 6408 road images specifically captured on highways. Each image within the dataset possesses a resolution of 1280×720 pixels, ensuring a consistent and standardized format. To facilitate effective data management and evaluation, the dataset is divided into distinct subsets, including 3626 images assigned for training purposes, 358 images allocated for validation, and 2782 images designated for testing (Kaggle, 2023). Particularly noteworthy is the TuSimple test set, constituting the testing subset, which comprises images captured under diverse weather conditions. This inclusion of varying weather scenarios within the dataset enables a robust assessment of algorithms and models across a broad spectrum of real-world driving situations (Yoo *et al.,* 2020).

3.11 Training of the Lane Detection Model

The training of the lane departure model utilized the MobileNet architecture as the core neural network of the model. The training process was configured using the YAML file, which contained settings such as the learning rate, optimizer, and other hyperparameters. The training was conducted for 100 epochs, and a batch size of 5. The optimizer used a momentum value of 0.9 to accelerate gradient descent and dampen oscillations. Each epoch processed 5 batches, determining the number of iterations required for a complete epoch.

3.12 Implementation of the Blindspot Detection Module

This section presents the implementation details of a Blindspot Detection Module aimed at enhancing road safety, especially for buses. The system utilizes a Raspberry Pi 4 Model B and various components, including ultrasonic sensors, LEDs, an accelerometer, a camera, and a speaker. The goal is to provide real-time monitoring and alert the driver about potential hazards in the blind spot regions.

The system utilises a Raspberry Pi 4 Model B as the central processing unit. It employs proximity sensors, installed on different points of the bus, to cover the blind spots effectively.

The monitoring system can be scaled to include more sensors for additional blind spot coverage. The motion sensor used is the MPU6050 accelerometer, which detects the bus's motion to activate the system. The camera is used for capturing live feeds of objects around the bus.

The graphical user interface was designed using the Kivy python module due to it being robust and open-source and facilitating app development with innovative user interfaces, including support for multi-touch functionalities. The versatility of Kivy allows it to run on various platforms including the Raspberry Pi.

CHAPTER FOUR

RESULTS AND DISCUSSION

4.1 Findings from the Respondents

During the requirements gathering stage, a total of 122 responses were received from different respondents who included bus drivers and passengers. 85.7% of these respondents were male while the remaining 14.3% were female as shown in Fig. 1. The reason for this gap in the demographics of the respondents is because the majority of the respondents as shown in Fig. 2 were bus drivers who are predominantly male but this however doesn't affect the study findings in anyway.

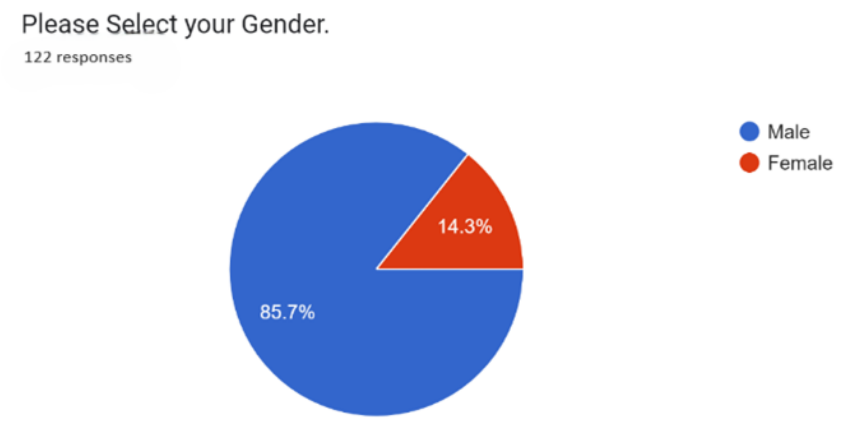


Figure 1: Demographic information of the respondents

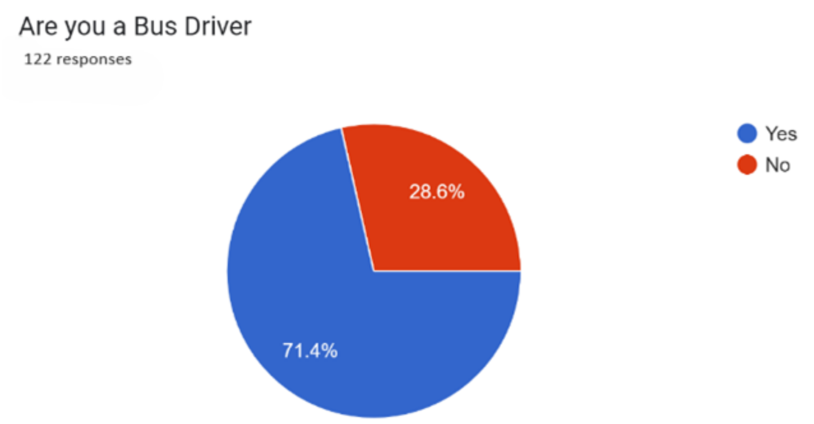


Figure 2: Responses from respondents regarding whether they are bus drivers

The respondents were asked whether their vehicles have a lane departure warning and Blindspot Detection system and it was noted that all 122 respondents did not have this system in their vehicles as shown in Fig. 3. This therefore signifies an existing gap hence the need to develop this system.

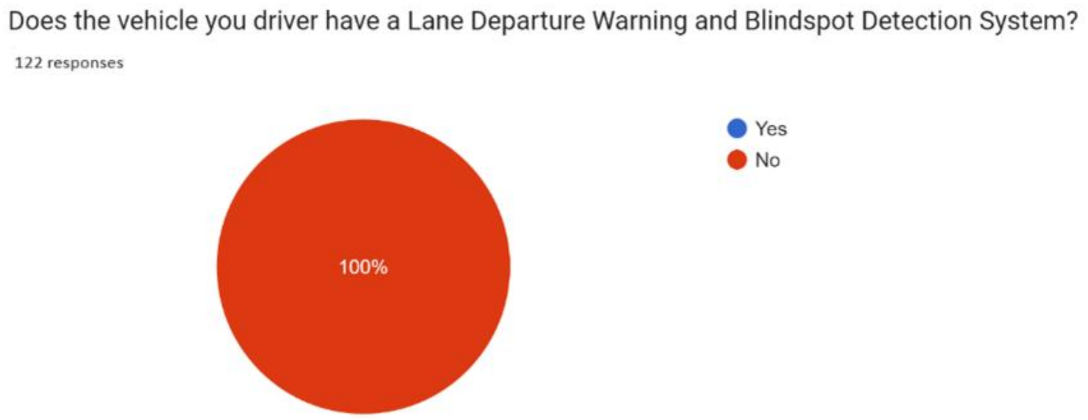


Figure 3: Respondents on whether their vehicles have a lane detection and blind spot monitoring system

The project also went out to understand whether the respondents believed that unintended lane departures and objects in blind spots have led to several road accidents. 96.8% of the respondents believed that it's true while 3.2% believed that it's not the case as shown in Fig. 4. This therefore presented a significant need to develop the BSD and LDW system that would reduce these road accidents and improve road safety.

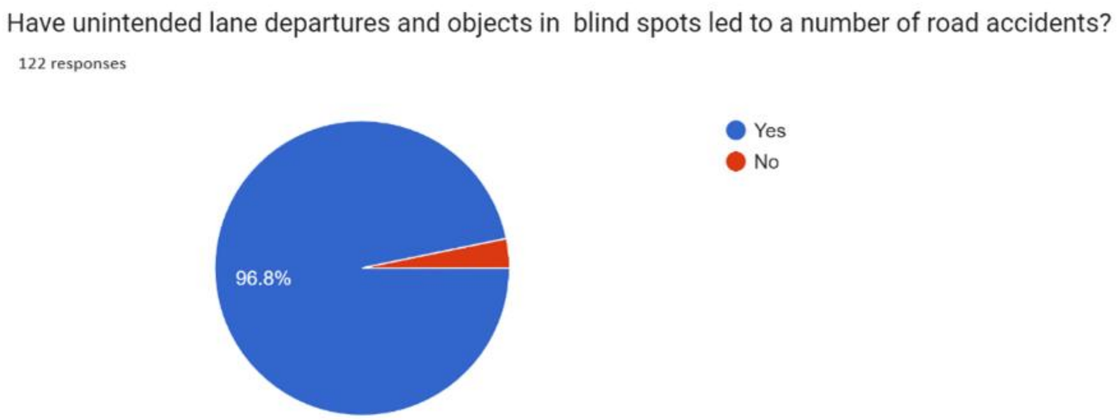


Figure 4: Responses on whether unintended lane departures and objects in the blind spots have led to road accidents

The respondents were also asked whether it was necessary to have deep learning-based BSD and LDW system where 83.9% believed that it was necessary and answered with “Yes” while the remaining 16.1% believed that it was “Maybe” necessary to have this system as shown in

Fig. 5. This result therefore demonstrated the need to develop this system owing to the fact that the majority of the respondents found it necessary.

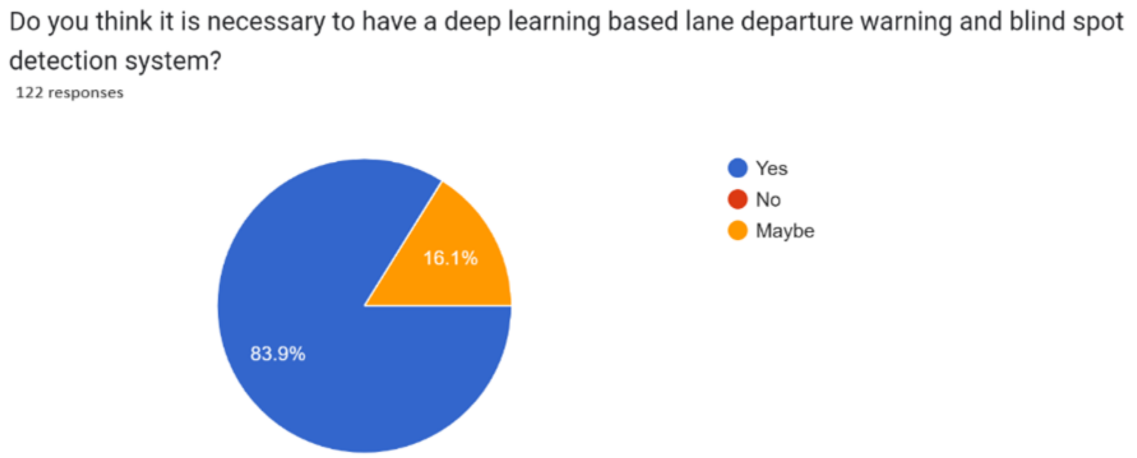


Figure 5: Responses on the necessity of the developed system

The 87.1% of the respondents believed that the project would impact road safety while the other 12.9% answered "Maybe" to this question as shown in Fig. 6. Thus, most of the survey participants believed that this project would impact the safety of all road users.

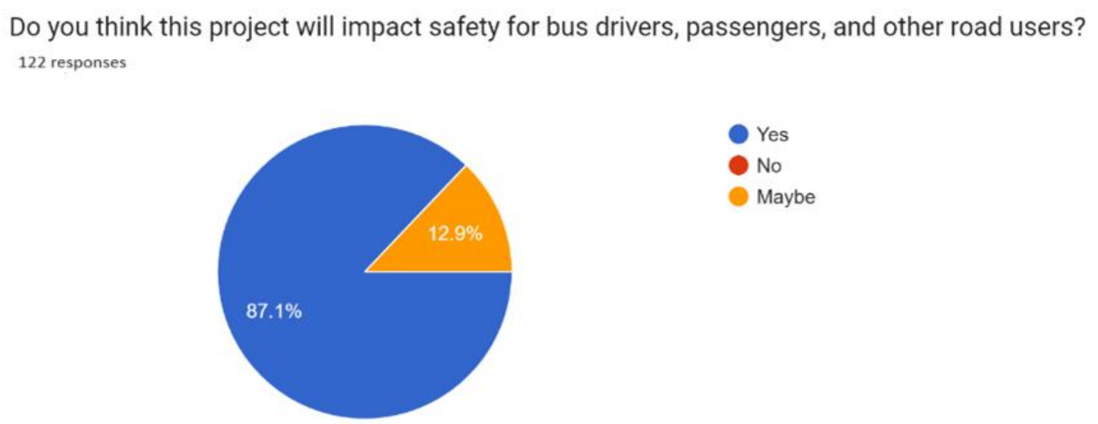


Figure 6: Responses on whether the developed system impacts safety of drivers and other road users

Respondents were asked whether they had been involved in an accident caused by lane departure and or blind spots. The study found that 51.6% of the respondents had previously been involved in an accident caused by lane departure and or blind spots. Figure 7 represents a significant portion of the sampled population and demonstrates a critical need for developing this system.

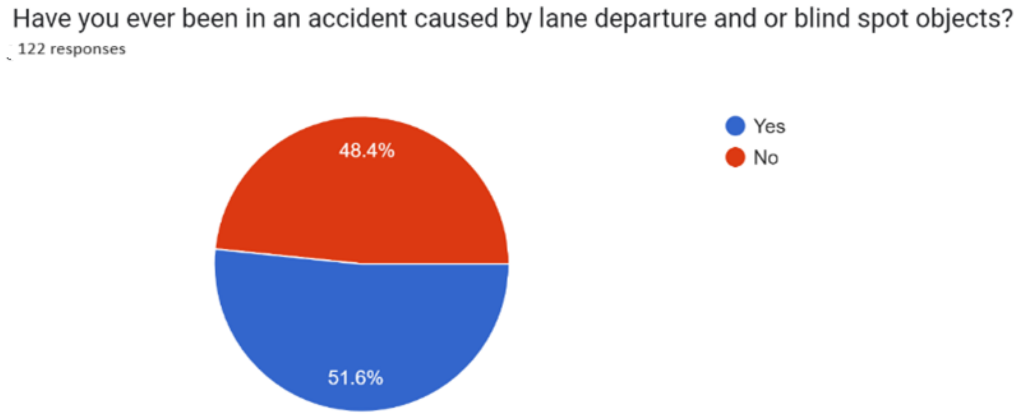


Figure 7: Respondents on whether they have been involved in an accident caused by lane departure and or blind spots

Respondents were also asked about the types of roads that they often drive on as shown in Fig. 8. From the findings, most respondents representing 96.8% normally used Highways followed by city streets (80.6%), residential streets (48.4%) and lastly rural roads at 9.7%.

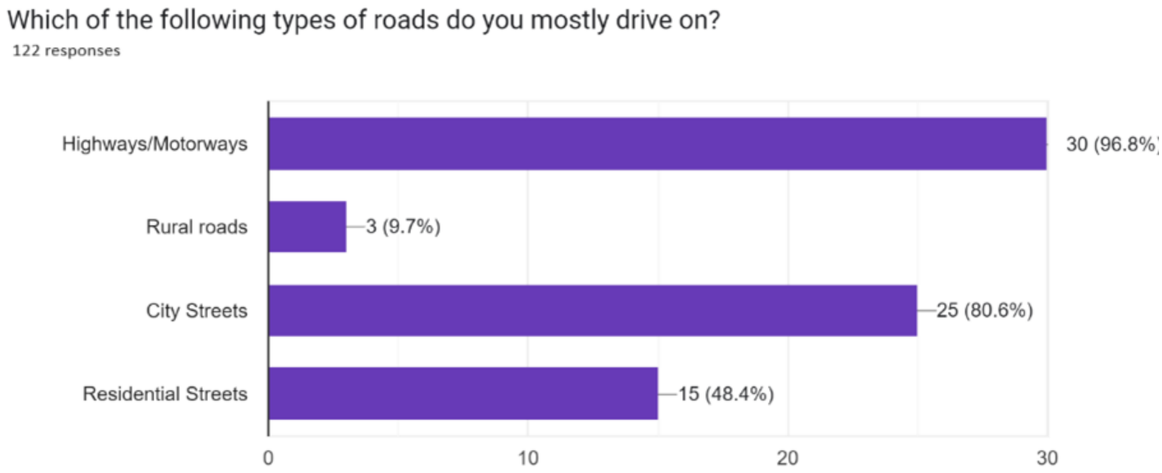


Figure 8: Responses on the most often used roads

Respondents were also asked how important it is for ADAS systems to provide feedback to the driver. The majority of the respondents representing 80.6% believed that this was very important while 16.1% believed that it was somewhat important. The 3.3% of the respondents remained neutral on this particular question (Fig. 9).

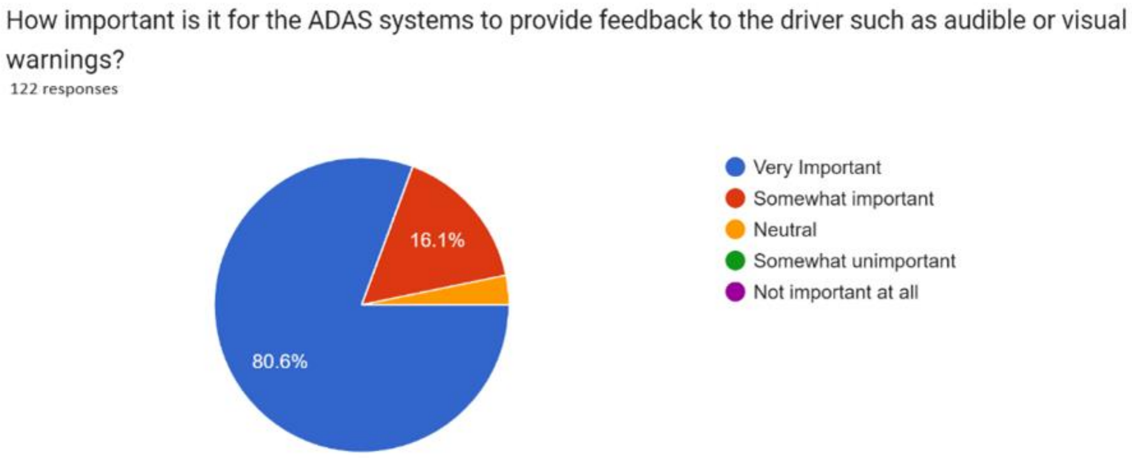


Figure 9: Responses on how important it is for ADAS systems to provide feedback

4.2 System Requirement Results

4.2.1 Functional Requirements

The functional requirements for the BSD and LDW system are outlined. In Table 4 to 7.

(i) Use Case – 001: Lane Departure Warning

Table 4: Requirements for lane departure warning

Purpose	To continuously monitor the vehicle's position within the lane and detect potential lane departure events.	
Requirements Traceability	REQ-LDW-001	The system shall be able to detect and classify lane markings on the road.
	REQ-LDW-002	The system shall be able to determine the vehicle's position relative to the detected lane markings.
	REQ-LDW-003	The system shall be able to calculate deviation from the lane centre and evaluate the severity of departure.
	REQ-LWD-004	The system shall be able to provide timely and accurate warnings to the driver, such as audible alerts to prompt corrective action.
Priority	High Priority	

(ii) Use Case – 002: Blind Spot Detection

Table 5: Requirements for blind spot detection

Purpose	To continuously detect the presence of other vehicles or objects in the blind spots.	
Requirements Traceability	REQ-BSD-001	The system shall monitor areas adjacent to the vehicle, typically the sides and rear.
	REQ-BSD-002	The system shall be able to detect and identify other vehicles or objects in the blind spots.
	REQ-BSD-003	The system shall be able to provide timely and accurate warnings to the driver, such as audible alerts to prompt corrective action.
Priority	High Priority	

(iii) Use Case – 003: User Interface

Table 6: Requirements for the user interface

Purpose	To provide a user-friendly interface that displays warnings and system status to the driver	
Requirements Traceability	REQ-UI-001	The system shall be able to present clear and intuitive visual feedback, such as icons or graphical overlays, to indicate lane departure or blind spot alerts.
	REQ-UI-002	The system shall be capable of displaying relevant information, such as the position of detected objects or the vehicle's current lane status.
	REQ-UI-003	The user interface shall be easy to understand and minimally distracting to the driver.
Priority	High Priority	

(iv) Use Case – 004: System Integration

Table 7: Requirements for system integration

Purpose	To seamlessly integrate the BSD and LDW system with the vehicle's existing electrical and control systems, ensuring compatibility and smooth operation.	
Requirements Traceability	REQ-SI-001	The system shall be capable of interfacing with the vehicle's CAN bus or other communication protocols to exchange data and commands.
	REQ-SI-002	The system shall be integrated with the vehicle's power supply and electrical architecture to ensure reliable operation.
Priority	High Priority	

4.2.2 Non-functional Requirements

The non-functional requirements for this system are outlined in Table 8.

Table 8: Non-functional requirements

Requirement	**Description**
Security	The system and its subcomponents shall ensure secure protection and encryption for purposes of safeguarding the data being processed, stored and transmitted.
Performance	The system shall be able to process computations in real-time with no delays. Lane and Blindspot detection shall be in real-time.
Usability	The system shall be easy to use by bus drivers and other system operators.
Availability	The system shall be available always whenever required.
Robustness	The system shall have failsafe mechanisms in events of loss of connectivity or loose connections.

4.3 System Design Results

The system comprises of ultrasonic sensors, MEMS, Raspberry Pi, Camera, Display Screen, Buzzer and LEDS as illustrated in Figs. 12 and 13

Figure 10 shows the system design with an alert mechanism to alert the driver as well as a display dashboard to show the monitor, analyse and show the status of the system.

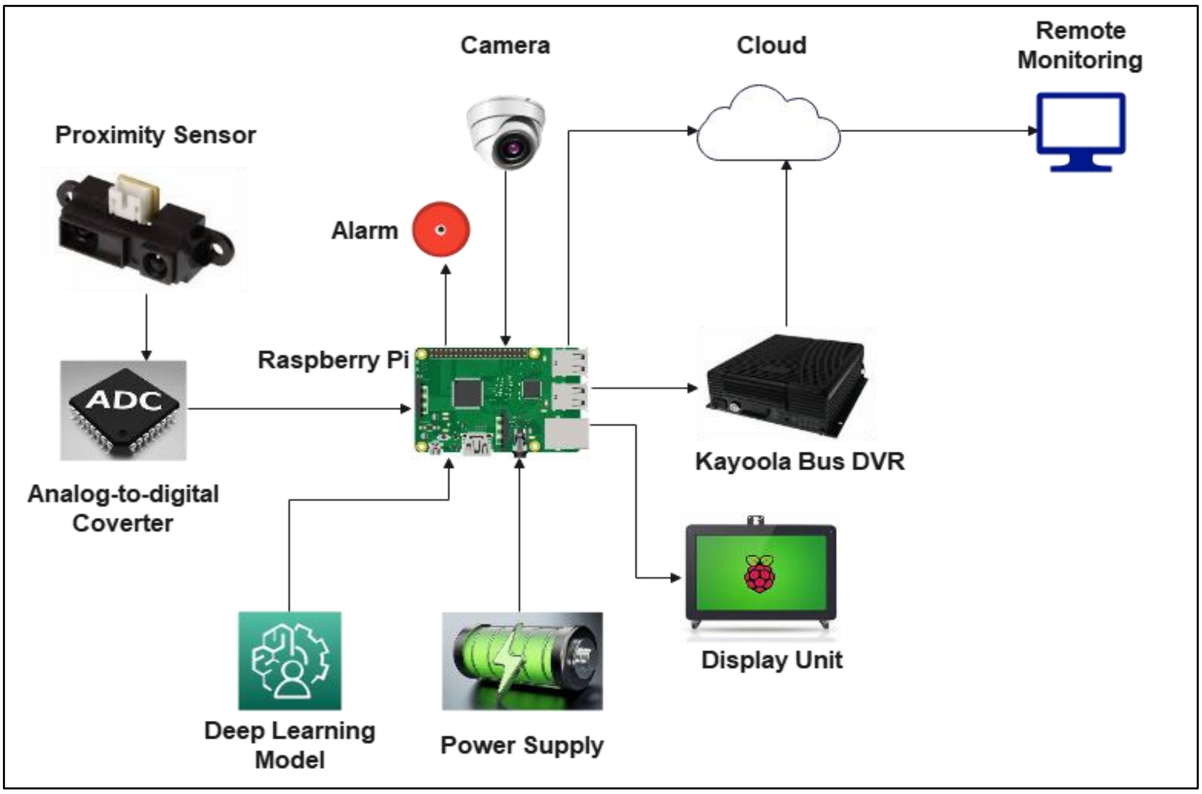


Figure 10: System design

The BSD and LDW system works by continuously monitoring the vehicle's surroundings using a combination of sensors and cameras. The sensors detect the proximity of the vehicle relative to other vehicles or pedestrians, while the cameras capture images of the road lanes as well as other vehicles and pedestrians. These inputs are processed by a deep learning algorithm to detect any deviations from the vehicle's lane or the occurrence of other objects in the blind spots.

If the system detects a potential hazard, it alerts the driver through a visual or auditory warning. The warning is customizable depending on the severity of the situation, and can also be adjusted based on the driver's preferences.

The system operates in real time by continuously processing the sensor and camera inputs and generating warnings as soon as a potential hazard is detected. The system was designed to be reliable and accurate, with a low false positive rate to avoid unnecessarily alarming the driver.

Figure 11 shows the conceptual diagram of the system demonstrating how the different components are mounted in the Kayoola Bus.

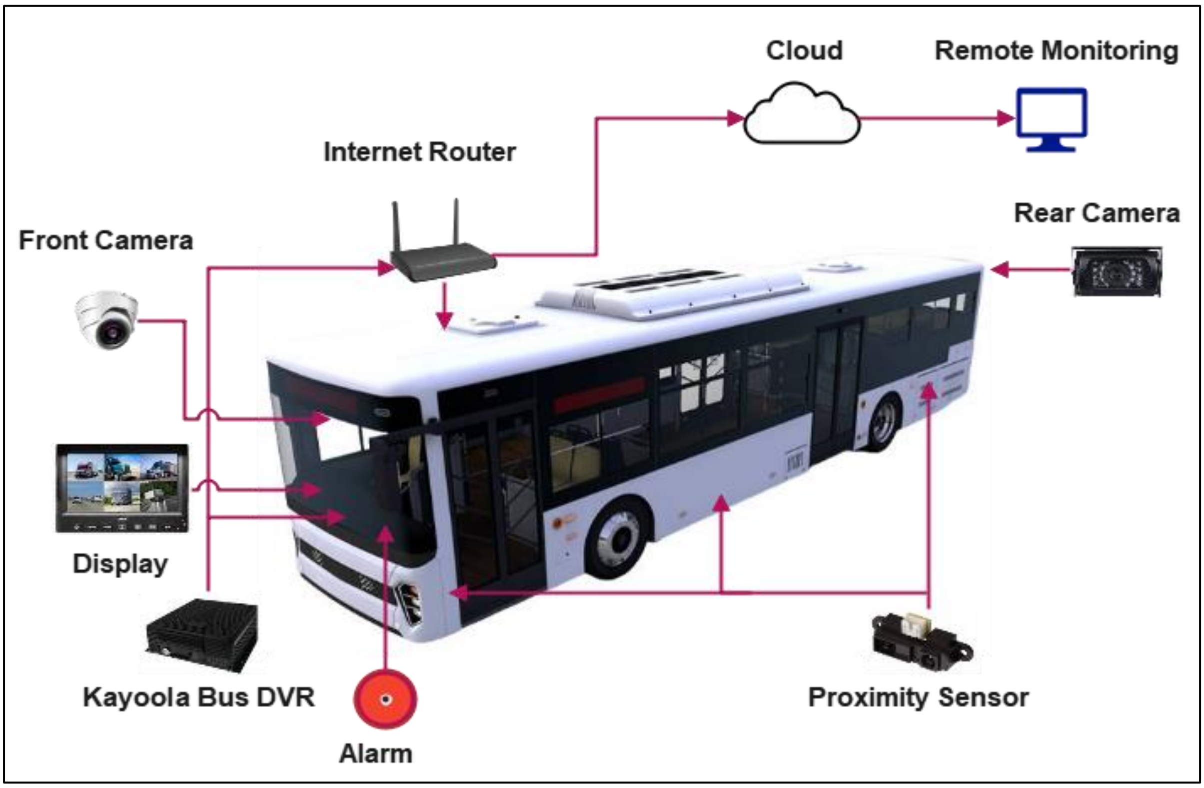


Figure 11: Conceptual diagram of the system

The ultrasonic sensors constantly detect objects within the 1m proximity of the bus. The object coordinates are mapped internally to determine whether the detected object is within the 1m range of detection.

The objected detection model running in the background thread is used to detect the type of object. This model is trained to accurately detect and classify pedestrians, motorcycles and vehicles. Other objects can be detected but are not classified by the model.

The detected objects are displayed on the Graphical User Interface with their approximate positions relative to the bus. The GUI also shows the number of detected objects during the active mode of operation.

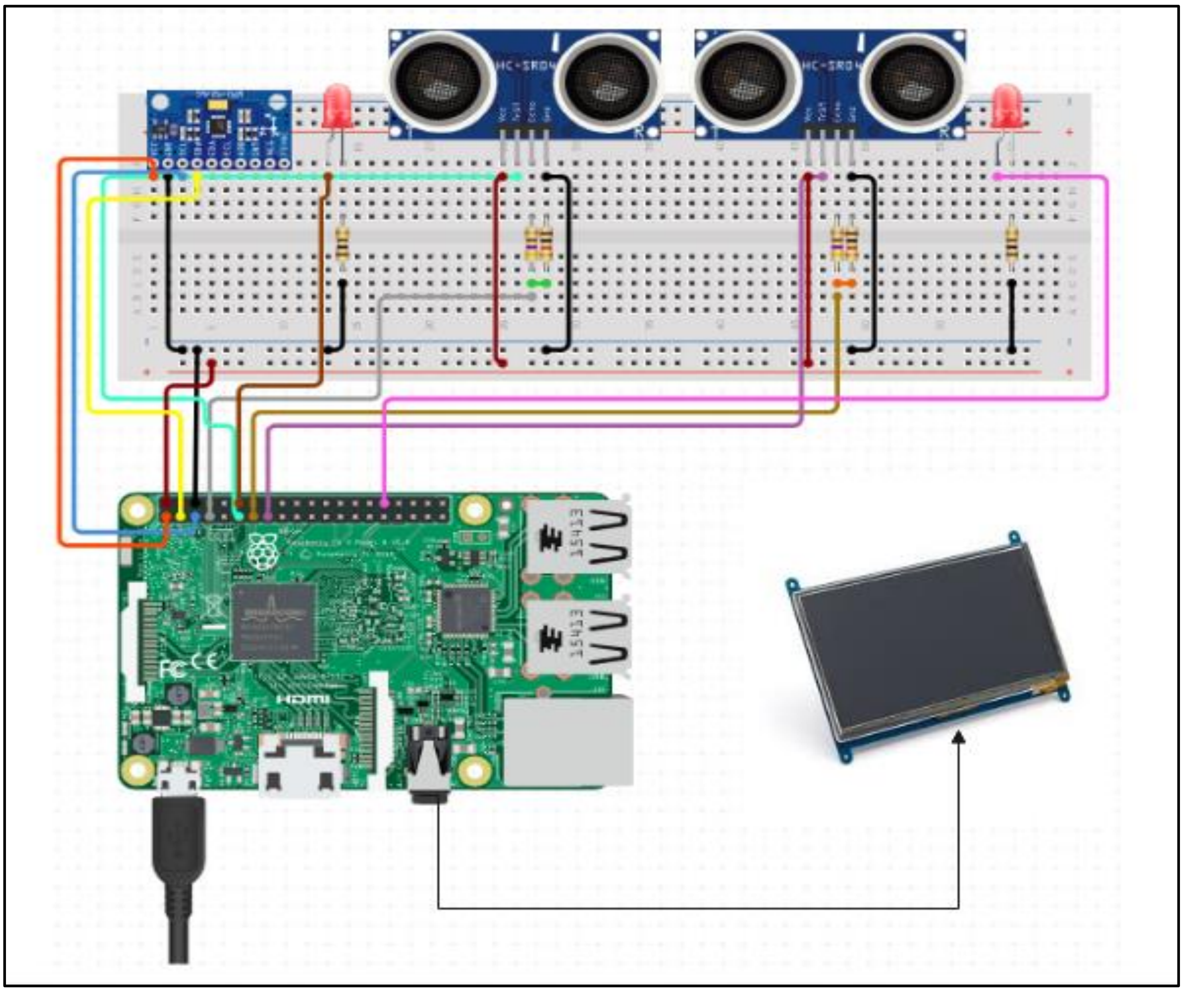


Figure 12: Breadboard circuit

The hardware implementation of the above breadboard circuit is shown in Fig. 13. The Raspberry Pi is used as the main processor responsible for running the deep learning models as well as the Graphical User Interface.

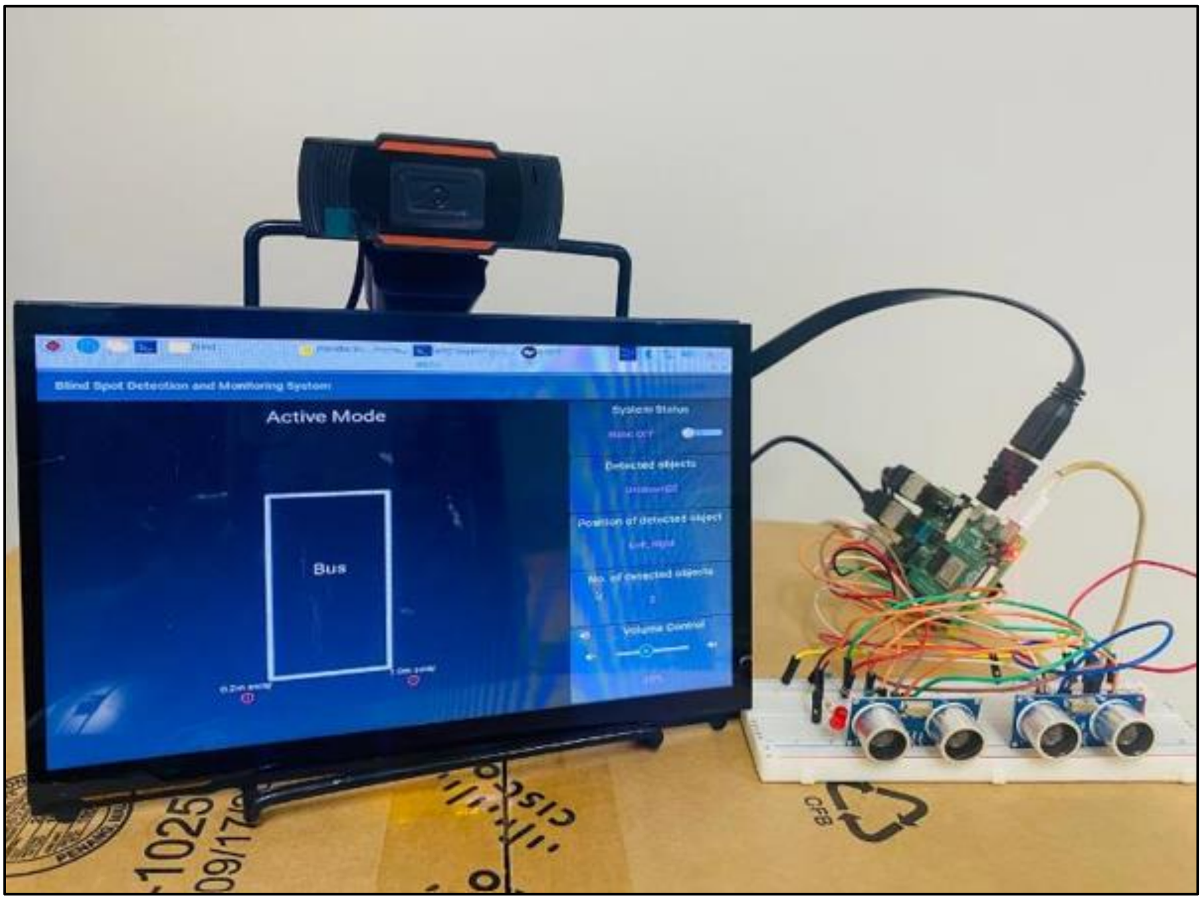


Figure 13: Hardware setup

4.4 System Development Results

4.4.1 Training Process

During the training process, several steps were followed to optimize the model. Firstly, the random seed value of 125 was used to ensure reproducibility of the results. The torch backends were configured with deterministic behaviour, while the benchmark mode was disabled to prioritize consistency over efficiency.

The training loop consisted of a total of 100 epochs, with the option to resume training from a specific epoch. The model optimization utilized the Adam optimizer at an initial learning rate of 1e-7. The beta values of (0.9, and 0.999) were used for computing the moving averages, and an epsilon value of 1e-08 was added for numerical stability. Additionally, a weight decay of 5e-4 was applied to regularize the model's weights.

For logging and visualization, the TensorboardX library was utilized to track the training progress. Training and validation losses were logged for each epoch, allowing for the assessment of model convergence and performance.

By following this training process, the model was optimized and trained to accurately detect lanes in images or video frames, providing valuable insights for autonomous driving and other computer vision applications. Figs. 14 and 15 show the training process for the first and one hundredth epoch respectively.

```
Training Network...
Kayoola-mobilenet-lane detection
Found 2716 train images
Found 873 val images
[Epoch: 0, numImages:  2716]
Loss: 15822.923547
Execution time: 647.585083300015

Validation:
[Epoch: 0, numImages:   873]
Loss: 6111.992131
Predicted iou (tensor(0.3073, dtype=torch.float64), tensor([0.9652, 0.0029, 0.1545, 0.3371, 0.07
67], dtype=torch.float64))

Best F1 till now =  0.3804734832245839
Correspond OA=  0.9654081329310746
Correspond IOU=  0.3072717566928306
Best F1 Iter till now=  1
Best IOU till now =  0.3072717566928306
Correspond F1=  0.3804734832245839
Correspond OA=  0.9654081329310746
Correspond IOU=  0.3072717566928306
Best IOU Iter till now=  1
[Epoch: 1, numImages:  2716]
Loss: 5990.458766
Execution time: 604.5192044000141
```

Figure 14: Training process for the first epoch

```
Validation:
[Epoch: 99, numImages:   873]
Loss: 7410.816982
Predicted iou (tensor(0.6175, dtype=torch.float64), tensor([0.9768, 0.5070, 0.5491
, 0.5697, 0.4847], dtype=torch.float64))

Best F1 till now =  0.7497700722571367
Correspond OA=  0.9772331526189325
Correspond IOU=  0.6174627330962632
Best F1 Iter till now=  100
Best IOU till now =  0.6174627330962632
Correspond F1=  0.7497700722571367
Correspond OA=  0.9772331526189325
Correspond IOU=  0.6174627330962632
Best IOU Iter till now=  1
Save model at C:\Users\USER\Project\Lane3\experiments\experiment_2023-10-03_08_16\
models\Kayoola-mobilenet-lane detection_epoch-99.pth
```

Figure 15: Training process for the 100th epoch

4.4.2 Lane Detection Training Results

The training was done for a total of 100 epochs using the MobileNet backbone and the Cross-Entropy loss function for optimizing the model's parameters. The training progress was tracked, and the model's performance was determined every 5 epochs. Training and validation losses were plotted over the epochs, allowing for the visualization of the model's convergence and the identification of any overfitting or underfitting issues.

The evaluation of the lane detection model was carried out on two distinct datasets, DET and TuSimple while benchmarking against state-of-the-art algorithms. The Convolutional Neural Network for the detection of lane lines was trained for 100 epochs on 12 344 images and validation of the model was carried out on 873 images as shown in Figs.16 and 17. The training loss was computed per iteration and the loss plot is as shown in Fig. 16.

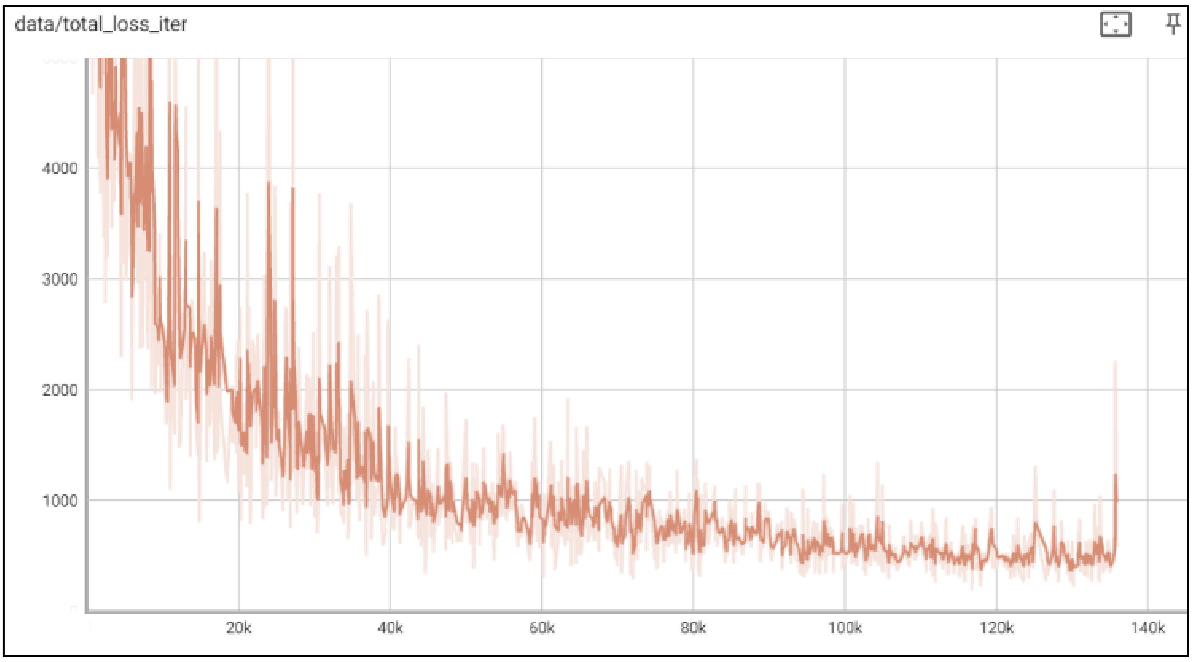


Figure 16: Training loss per iteration

The training loss was also computed for each entire epoch and the plot in Fig. 17 shows the training loss per epoch for the 100 epochs.

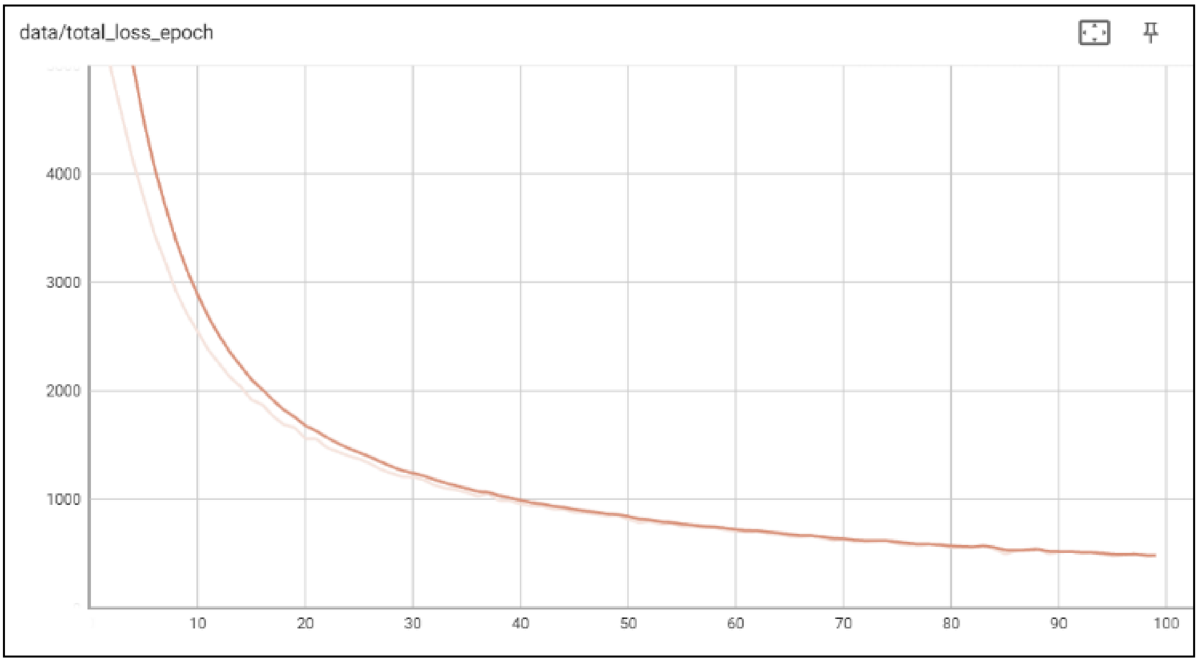


Figure 17: Training loss per epoch

Figure 18 shows the IoU plot calculated on the validation dataset per epoch. This illustrates the measure of the accuracy of the model's segmentation predictions.

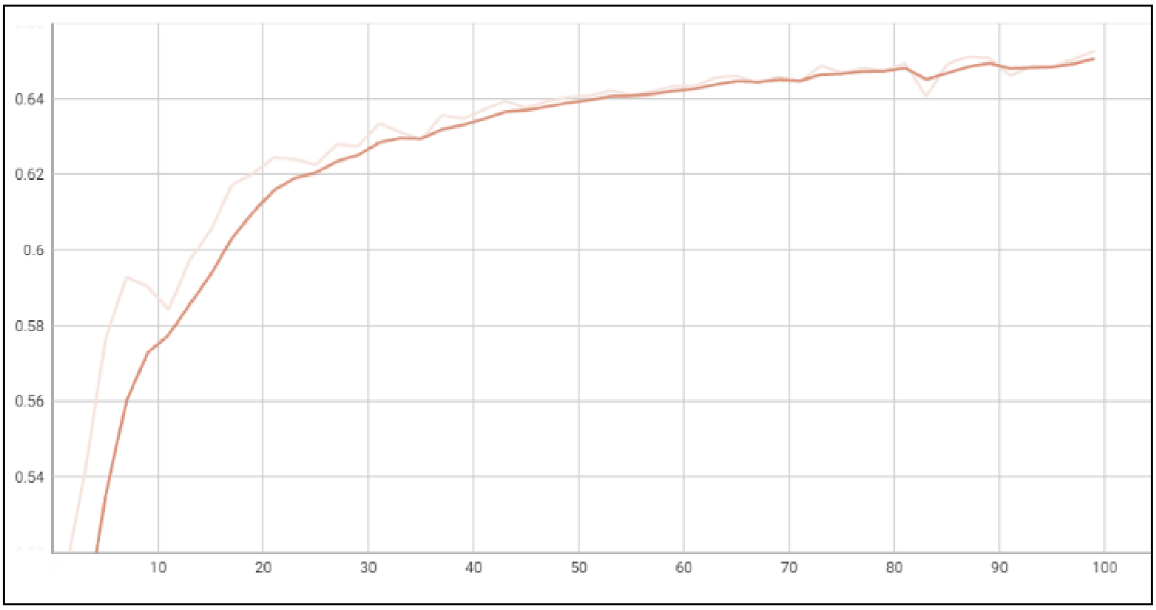


Figure 18: Mean intersection over union (IoU) plot

4.4.3 Evaluation Metrics

To assess the model's performance, the project employed several key metrics: F1 score, Intersection Over Union (IOU) and Accuracy. These metrics were calculated from the true positives and true negatives during training. IOU quantifies the overlap between predicted and actual bounding boxes, while the F1 score balances precision and recall. Our model achieved an F1 score of 0.7759. Overall Accuracy, a measure of the model's correctness across all classes, was determined as the ratio of correct predictions to total instances.

In this study, a comparative analysis of the model was conducted with the current state-of-the-art methods. Table 9 presents the evaluation results of our model on the DET Dataset alongside other state-of-the-art approaches.

Table 9: Comparative analysis of the model's performance with the state-of-the-art on the DET dataset

Model	Mean F1 Score (%)	Mean IoU (%)
FCN (Cheng *et al.*, 2019)	60.39%	47.36%
SCNN (Pan *et al.*, 2017)	70.04%	56.29%
RefineNet (Cheng *et al.*, 2019)	63.52%	50.29%
DeepLabv3 (Cheng *et al.*, 2019)	59.76%	47.30%
LaneNet (Cheng *et al.*, 2019)	69.79%	53.59%
Our model	77.59%	65.26%

With a mean F1 Score of 77.59% and a mean IoU of 65.26%, our model compares favourably with other works in literature such as FCN, DeepLabv3, RefineNet, LaneNet, and SCNN on the DET dataset.

We further assessed the model's performance using the TuSimple dataset, and the outcomes were compared to the current state-of-the-art, as outlined in Table 10.

Table 10: Comparative analysis of the model's performance with the state-of-the-art frameworks on the TuSimple dataset

Model	Accuracy (%)
ResNet-18 (Hou *et al.*, 2019)	92.69%
LaneNet (Neven *et al.*, 2018)	96.38%
SCNN (Pan *et al.*, 2017)	96.53%
Our Model	97.96%

Table 10 provides a comparative analysis of our model's performance against state-of-the-art frameworks on the TuSimple dataset, with a focus on accuracy. With an overall accuracy of 97.96%, our model compares favourably with the state-of-the-art models ResNet-18, LaneNet and SCNN.

These metrics reflect the model's ability to accurately identify and track lanes, crucial for preventing lane departures and ensuring safe driving behaviour. The obtained detection accuracy implies that the model correctly classifies 97% of the road lanes accurately which is a key requirement in ensuring an effective lane departure warning system. The F1 score balances precision and recall ensuring that our model correctly identifies lanes (precision) and does not miss any lanes (recall). The IoU measures the overlap between the predicted and ground truth lanes ensuring that the lanes predicted by the model align closely with the actual lanes on the road. Together, these metrics underscore the model's direct impact on road safety, ensuring a reliable advanced driver assistance system.

4.4.4 Blindspot Detection and GUI Implementation

The graphical user interface was designed using the Kivy python module due to it being robust and open-source and facilitates app development with innovative user interfaces, including support for multi-touch functionalities.

The GUI encompasses three primary display screens: the landing screen, the passive mode screen, and the active mode screen. The landing screen serves as an initial view when the system starts, giving the user the impression, that background initializations are occurring.

The active mode screen has a vertical stack of interactive widgets that offer valuable information and enable user interactions. These include system status, categories of the detected objects, detected objects, and volume control.

The passive mode screen represents the state of the GUI when the system is not yet running fully. The system logic governing the ultrasonic sensors and LED indicators remains inactive. However, the accelerometer logic continuously senses motion and transitions the system into active mode once the vehicle starts moving. By interacting with the system status switch on the GUI, the system user also has the option to switch to the Active mode.

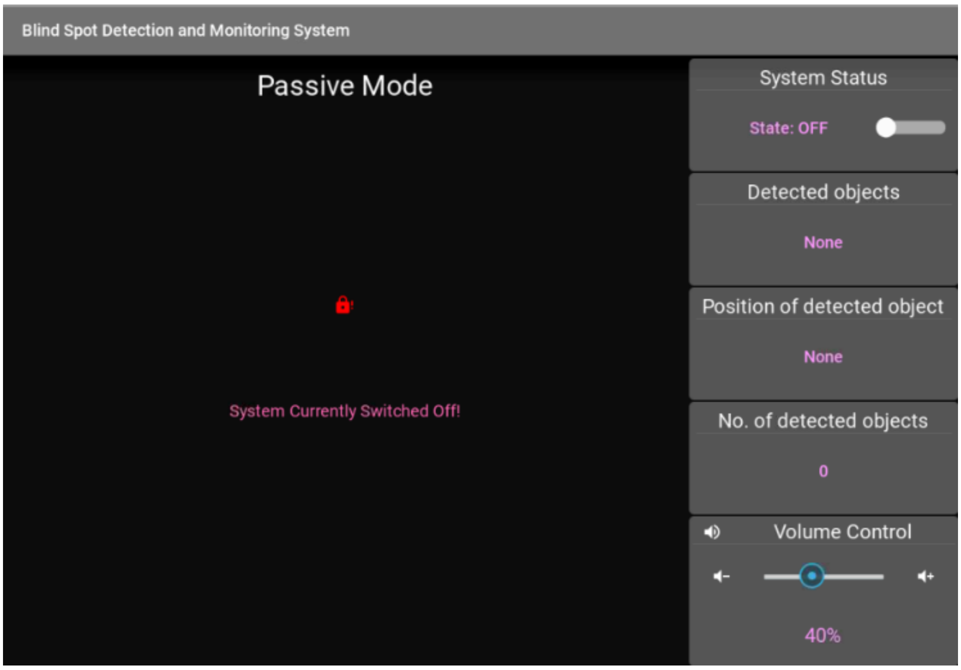


Figure 19: Passive mode screen

The active mode screen is the central focus of the GUI, where the main functionalities of the system are carried out. It displays a 2D map of a bus on a large canvas, featuring a green dashed boundary line placed at a distance of 1 meter away from the bus. As objects are detected by the ultrasonic sensor, their identities are retrieved from a thread running the object detection model. The icon displayed for each object corresponds to the type of object detected by the model.

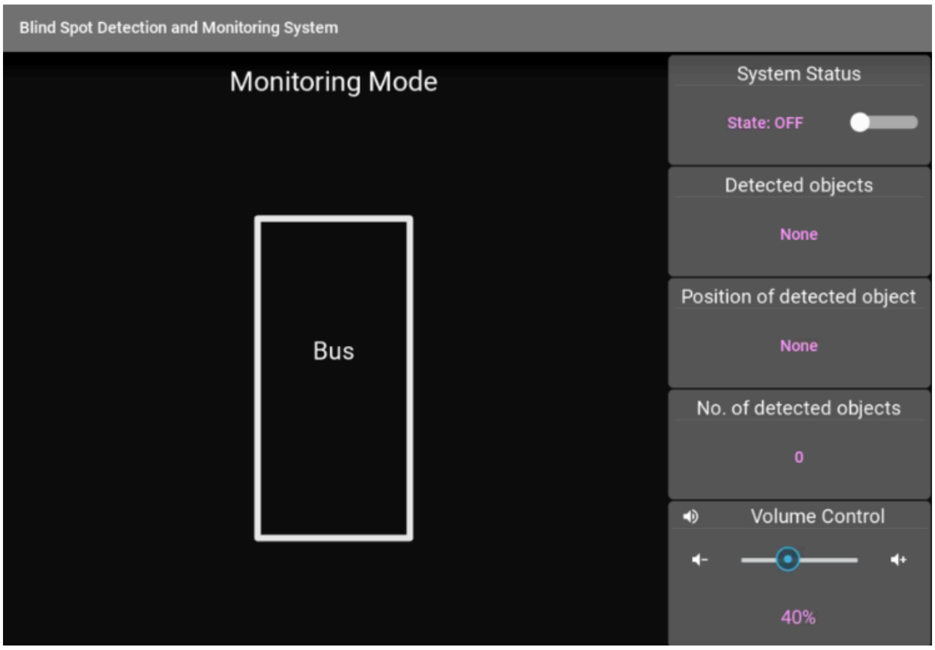


Figure 20: Active Mode Screen

The blind spot detection module was integrated with the object detection model capable of identifying objects within images, recorded videos, or live streams. The primary objective of this model is to accurately recognize and categorize objects located in the blind spot area, enabling the driver to make informed decisions. The model was trained to accurately identify humans, vehicles, and bikes (including bicycles and motorcycles).

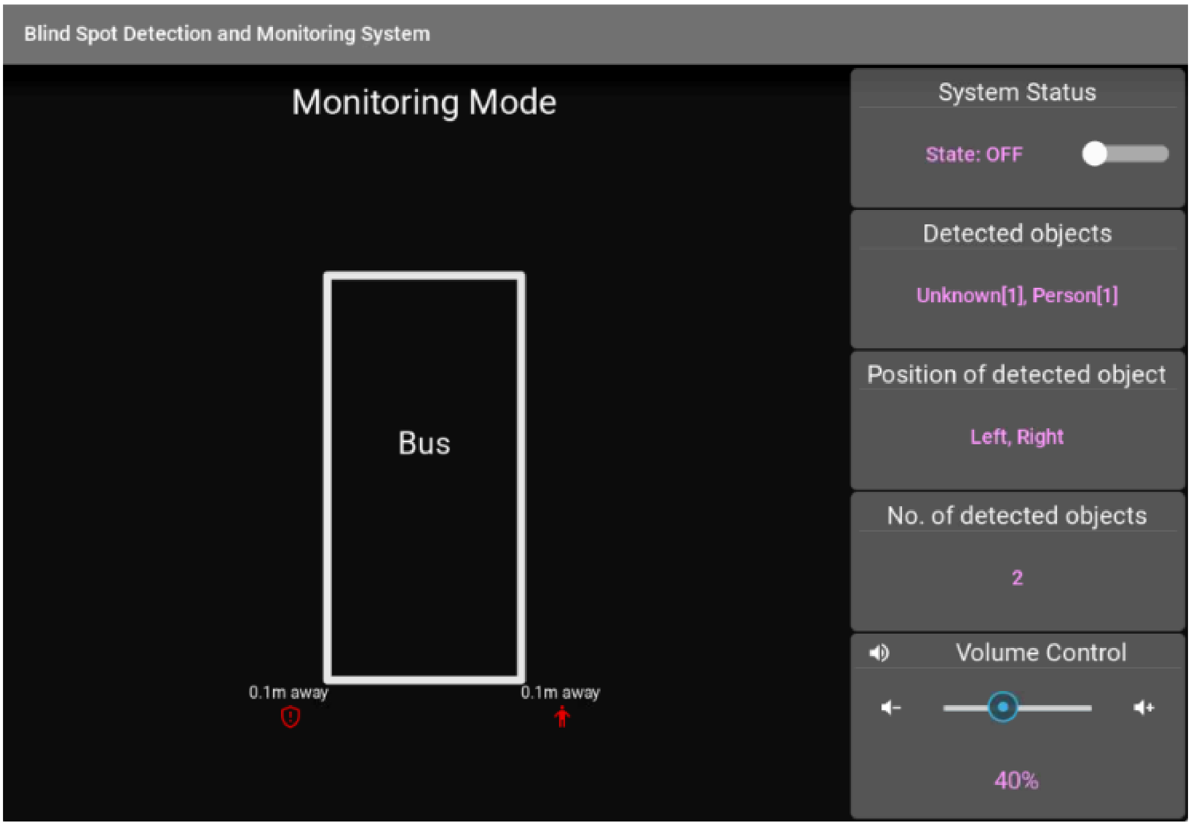


Figure 21: Monitoring mode with object detection

4.4.5 Prototype Development

The prototype of the developed system was set up and tested in the Kayoola EVS. This included offboard tests that were aimed at ensuring that the prototype was ready for deployment in the Kayoola EVS. The setup of the offboard tests is shown in Fig. 22.

Figure 22: Offboard testing in the Kayoola EVS

The setup of the prototype included the integration of the different system components in the Kayoola EVS. These components included the system control unit, the cameras, proximity sensors, display unit among others.

Integration of the system cameras included the installation of 3 camera modules on the bus. Two cameras were installed on the right and left-hand side of the vehicle just around the side mirrors. These were installed in such a way that they give the widest camera angle for detecting objects in the blindspots. Figure 23 shows the installation of the side cameras on the bus.

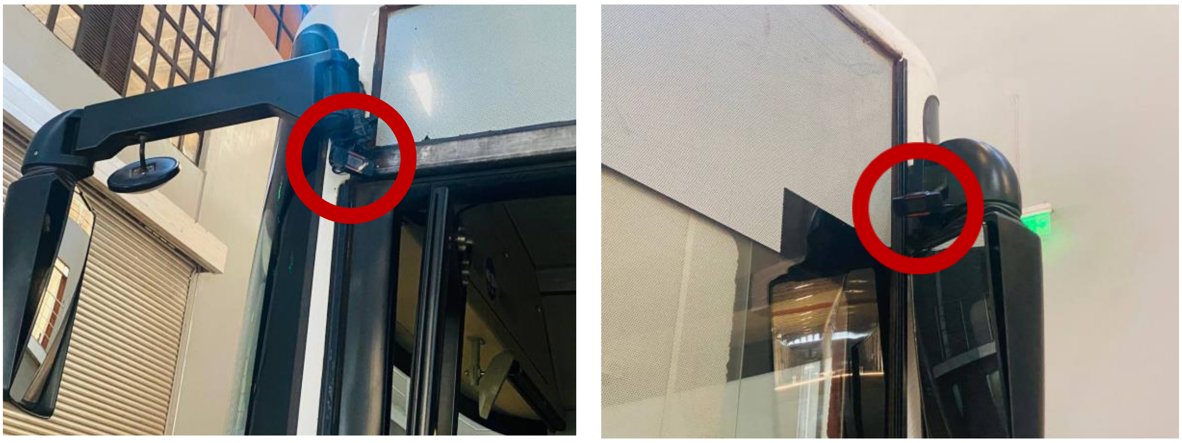


Figure 23: Installation of the right and left-hand side cameras

The third camera was installed on the dashboard mainly for lane departure detection. This camera was mounted in such a way that it captures the entire road profile as shown in Fig. 24.

Figure 24: Installation of the dashboard camera

The integration of the proximity sensors involved 4 radar sensors installed at the rear of the bus and 2 sensors installed at the sides. These sensors were positioned in such a way as to be able to detect objects in the blindspot regions along the bus profile as shown in Fig. 25.

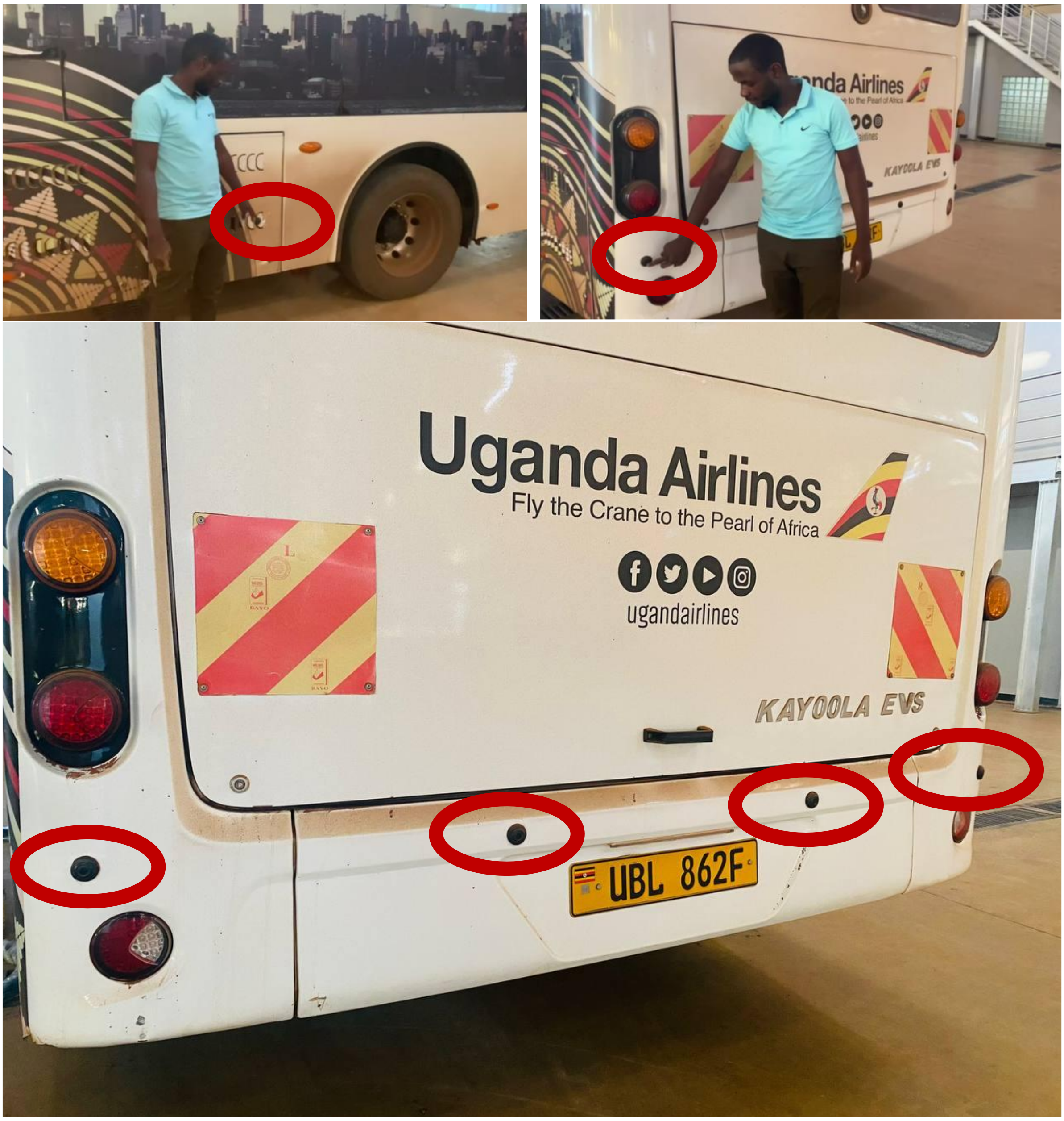


Figure 25: Integration of proximity sensors

The system control unit consisting of the Raspberry Pi as the central processing unit was installed in the vehicle dashboard. The components were firmly installed in the dashboard as shown in Fig. 26.

Figure 26: Integration of the system processing unit in the dashboard

The display of the system was connected to the already installed 4-inch display of the Kayoola EVS. The display is well-fitted in the dashboard and offers an excellent view for the driver. Figure 27 shows the integration and graphical user interface implementation of the system.

Figure 27: Integration of the display in the Kayoola EVS Bus

4.5 System Testing Results

Extreme Programming (XP) offered several testing techniques that were utilized to improve software quality. These include Acceptance Test-Driven Development, Exploratory Testing and Test-Driven Development. The TDD involved writing a test case before the code was implemented and continuously testing throughout development. The ATDD ensured the involvement of stakeholders in the creation of acceptance criteria and tests to ensure that the software meets requirements.

The hardware testing involved unit and integration tests which were iteratively carried out during each sprint. Unit testing was performed for each use case, and integration testing ensured that the different subsystems worked together correctly. Finally, the entire system testing ensured that the system functions correctly and is usable by the target users as shown in Table 11.

Table 11: System testing results

Requirement	Test Case	Precondition	Purpose	Post Condition	Test Score
REQ-LDW-001	Identification and Classification of Road Lane Markings	The vehicle is in motion on a road with clearly visible markings The system is powered on The system is in the Active mode	Verify that the system detects and classifies lane markings on the road.	The system accurately classifies the detected lane markings	Pass
REQ-LDW-003	Calculation of the deviation from the lane centre	The system has accurately detected the road lane markings	Verify that the system can calculate the deviation from the lane centre and evaluate the severity of departure.	The system accurately calculates the deviation from the lane center	Pass
REQ-LDW-004	Lane departure alarms Test	The vehicle has deviated away from the lane	Verify Alarm Triggers are enabled and disabled	The system can provide timely and accurate audio and visual warnings to the driver	Pass
REQ-BSD-001	Blind Spot Monitoring Test	The system is in active mode and the cameras are powered	Verify that the system can monitor the areas adjacent to the vehicle, typically the sides and rear.	The system can monitor the areas adjacent to the vehicle	Pass
EQ-BSD-002	Object Detection Test	The presence of objects in the blind spots	Verify that the system can detect and identify other vehicles or objects in the blind spots.	The system detects the objects in the blind spots	Pass

Requirement	Test Case	Precondition	Purpose	Post Condition	Test Score
REQ-BSD-004	Blind spot alarm test	Detected objects in the Blind spots	Verify that the system can provide timely and accurate warnings to the driver, such as audible alerts to prompt corrective action.	The system triggers audio and visual alarms	Pass
REQ-UI-001	Alarm display test	Detected objects in the Blind spots	The system shall be able to present clear and intuitive visual feedback, such as icons or graphical overlays	The GUI displays the visual alert and feedback	Pass
REQ-UI-002	GUI display test	Detected lanes and objects in the Blind spots	The system shall be able to display relevant information, such as the position of detected objects or the vehicle's current lane status.	The GUI displays the position and number of detected objects and lane status	Pass
REQ-UI-003			The user interface shall be easy to understand and minimally distracting to the driver.		Pass
REQ-SI-001	CAN integration test	The vehicle is in start mode	Verify that the system can interface with the vehicle's CAN bus and other communication protocols to exchange data and commands.	The system can communicate with other vehicle systems	Pass
REQ-SI-002	Power on test	The Vehicle is in start mode	The system shall be integrable with the vehicle's power supply and electrical architecture to ensure reliable operation.	The system powers on using the vehicle's low-voltage supply	Pass

4.6 System Validation Results

User acceptance tests were carried out to ascertain whether the developed system addressed the needs of the prospective users. The tests were carried out with a total of 125 drivers and passengers from Kiira Motors Corporation to validate the functionality of the system. Teble 12 shows the summary of the system validation results.

Table 12: System validation results

Criteria	**Purpose**	**Evaluation Metrics**	**Test Score**
Ease of Use	To verify whether the system is ready for use	User interface clarity, intuitiveness, ease of interaction	Pass
Impact on Road Safety	To verify whether the system will positively impact road safety	Reduction in accidents, improved safety measures	Pass
Willingness to use the system	To verify whether the participants are willing to use the system	User feedback on system usability and acceptance	Pass
Readiness for deployment	To verify whether the system is ready for deployment	System stability, reliability, successful integration	Pass
Willingness to recommend the system	To verify whether the participants will be willing to recommend the system to others	User satisfaction, the likelihood of recommending to others	Pass

The first validation question was aimed at ascertaining whether the respondents believed that the developed system was ready for use. All the respondents believed that the developed system is easy to use as shown in Fig. 28.

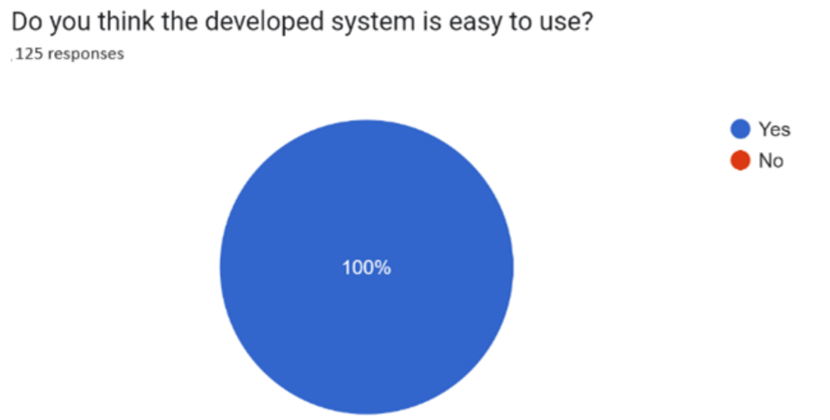


Figure 28: Respondents regarding the ease of use of the system

The respondents were also asked whether the system would improve road safety. The 86.7% of the respondents believed that the developed system would improve road safety. The remaining 13.3% of the respondents were neither in disagreement but also believed that the developed systems might maybe improve road safety as shown in Fig. 29.

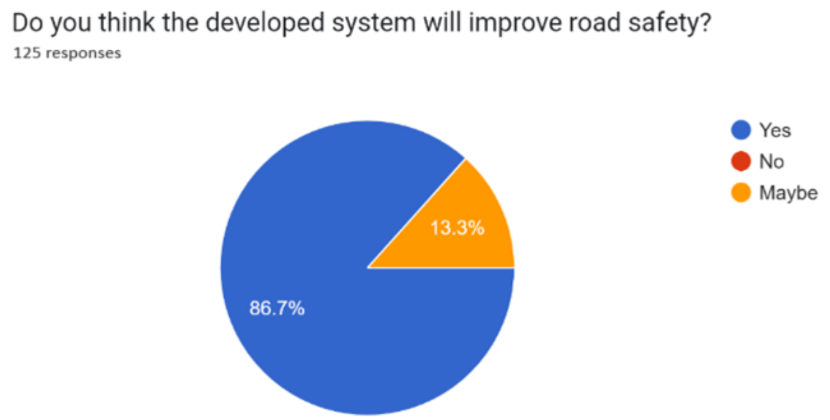


Figure 29: Respondents on whether the developed system will improve road safety

The respondents were also asked about their willingness to use the developed system. The 100% of the respondents were all willing to use the developed system in a bus as shown in Fig. 30. This data shows that the majority of the stakeholders are willing to adopt the developed system to improve the safety of the vehicles.

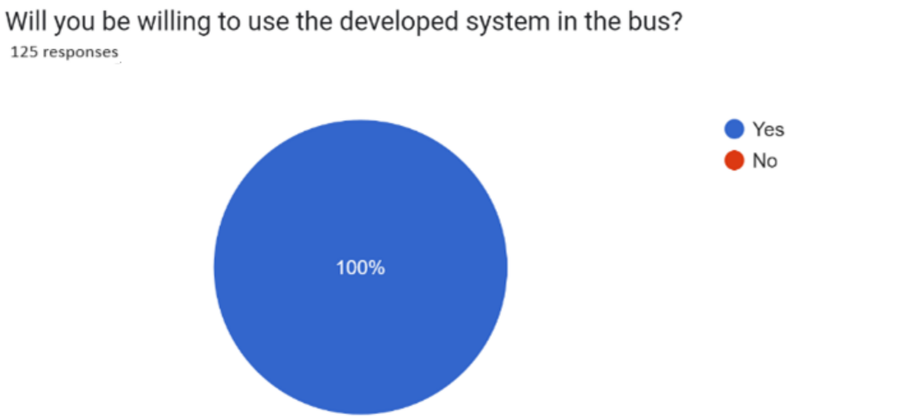


Figure 30: Respondents regarding their willingness to use the developed system

On the sufficiency of the alert mechanisms integrated into the system, 92.3% of the respondents suggest that the mechanisms are sufficient while 7.7% suggest that there is a need for improvement of the alert mechanisms deployed as shown in Fig. 31. This feedback indicates that the alert mechanisms integrated into the developed system are considerably sufficient.

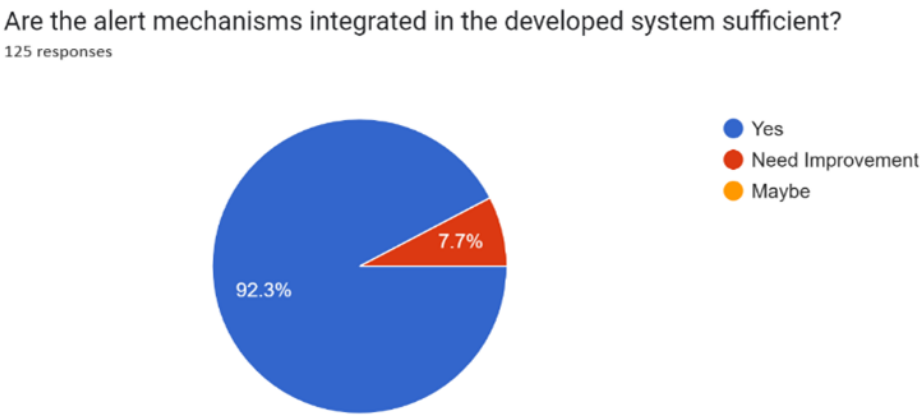


Figure 31: Respondents Regarding Sufficiency of the Alert Mechanisms

Regarding the system readiness for deployment, 80% of the respondents strongly agree and 20% agree that the system is ready for deployment as shown in Fig. 32. This illustrates that the developed system as validated by the end-users is ready for deployment in the real-world environment.

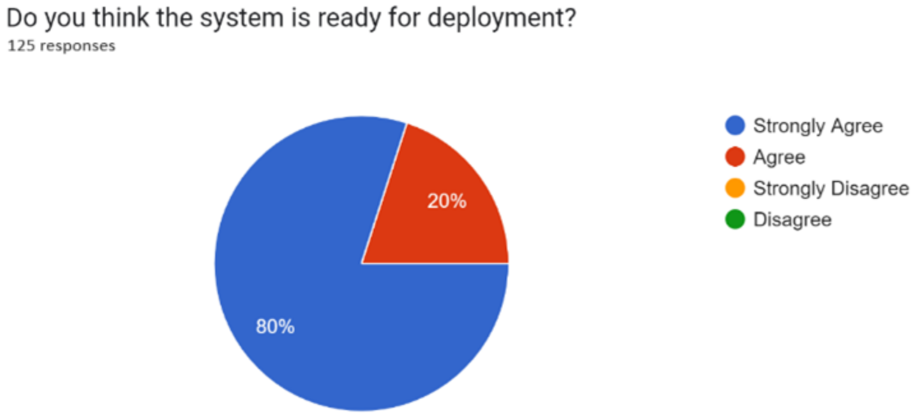


Figure 32: Respondents regarding the system readiness for deployment

The 100% of the respondents were willing to recommend the developed system to others as shown in Fig. 33. This implies that the system meets the user's needs and thus is ready to recommend it to other users.

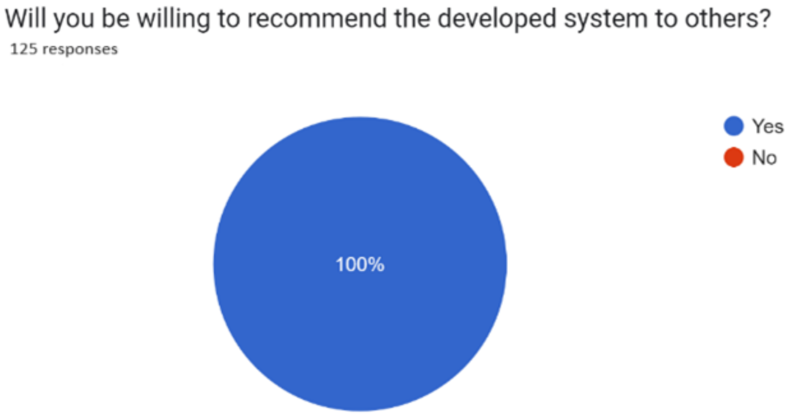


Figure 33: Respondents regarding their willingness to recommend the developed system

4.7 Discussion

During the requirements gathering phase, all participants unanimously agreed on the importance of incorporating a deep learning-based Blind Spot Detection (BSD) and Lane Departure Warning (LDW) system. However, none of the respondents had such a system installed in their vehicles. This data highlighted a significant gap, emphasizing the necessity of implementing the system with the primary objective of enhancing road safety. Furthermore, all participants unanimously agreed that the project would enhance the safety of bus drivers, passengers, and other road users.

Every respondent in the study recognized the absence of BSD and LDW systems in their vehicles, with a striking 96.8% indicating their belief that unintended lane departures and blindspot obstructions have contributed to numerous road accidents. This crucial statistic underscores the urgency and importance of developing the BSD and LDW system.The developed BSD and LDW system comprises a number of subsystems which include a sensing unit, camera monitoring, alerting, display unit and the central processor. The sensing unit is responsible for proximity sensing of the objects in the blindspots. The proximity sensor works by identifying the relative position of the object near the vehicle and triggering the respective camera which then captures the object. The detected object is then displayed on the GUI. Once the object is detected to be within the defined 1m from the bus, an audio and visual alert is sounded to notify the driver. The camera monitoring system is responsible both for monitoring the road lanes as well as tracking and identification of the objects in the blindspots. The alerting unit ensures that real-time alerts are triggered in the event of detected objects in the blindspots or unsafe lane departures. The alarms are both audio through the buzzers and visual through the graphical user interface. The graphical user interface relays real-time visual information to the driver and thus serves as the interface through which the driver interacts with the BSD and LDW system. The GUI displays information about detected objects, their distance from the vehicle, the position of the detected objects, the lane detection status, auditory volume controls and other relevant data. When an object is detected within the predefined 1-meter proximity, the visual alerts are triggered on the GUI ensuring that the driver is informed in real time.

The developed system has stood out compared to the previous works in literature with a high level of accuracy and a non-intrusive alerting mechanism and GUI design. As opposed to the previous works where the BSD and LDW systems are developed and implemented independently, this study integrated both systems. The dual functionality of the proximity sensing and camera monitoring system for lane detection as well as tracking of objects in blind spots ensures that the driver is not only alerted to potential lane departures but is also provided with timely warnings about objects in immediate proximity, thereby improving road safety and reducing on accidents. The integration of a dual-alert system, comprising both audio alerts through buzzers and visual alerts on the Graphical User Interface (GUI), adds an extra layer of reliability. This multi-modal approach ensures that drivers receive alerts through different channels enhancing the timely response.

The outcomes of the system validation revealed a significant level of satisfaction among the respondents regarding the implemented system, with all respondents expressing willingness to utilize it. A majority (86.7%) of participants agreed that the system would enhance road safety, while a minority (13.3%) neither disagreed nor fully endorsed its potential for improving road safety. Furthermore, all participants found the system user-friendly and expressed readiness to recommend it to others. Their feedback highlighted the system's intuitive design and user-friendliness, which facilitates its adoption. Participants acknowledged the system's potential to enhance road safety and appreciated the effectiveness of its alert mechanisms in providing timely audio and visual cues to drivers, enabling informed decision-making while driving. This positive feedback underscores participants' confidence in the system's functionality, reliability, and its ability to meet their Advanced Driver Assistance Systems (ADAS) requirements effectively.

CHAPTER FIVE

CONCLUSION AND RECOMMENDATIONS

5.1 Conclusion

The project addressed a crucial gap in current automotive safety systems by developing an integrated Lane Departure Warning and Blind Spot Detection system using advanced deep learning techniques. Our prototype demonstrates the potential for improved real-time detection and enhanced vehicle safety. The Agile development approach, particularly Extreme Programming (XP), ensured efficient development progress throughout the project.

Our model attained a mean F1 Score of 77.59% and a mean IoU of 65.26% on the DET dataset and an overall accuracy of 97.96% on the TuSimple dataset. These results compared favourably with other works in literature. On the TuSimple dataset, Hou *et al.* (2019) proposed a system based on ResNet-18 achieving an accuracy of 92.69%, Neven *et al.* (2018) proposed a system based on LaneNet achieving an accuracy of 96.38% and Pan *et al.* (2017) proposed a system based on SCNN achieving an accuracy 96.53%. With an accuracy of 97.96%, our model compares favourably with the state of the art on the TuSimple dataset. On the DET dataset, Cheng *et al.* (2019) proposed a model based on FCN achieving a mean F1 score of 60.39% and a mean IoU of 47.36%, RefineNet achieved a mean F1 score of 63.52% and a mean IoU of 50.29%, DeepLabv3 achieved a mean F1 score of 59.76% and a mean IoU of 47.30%, LaneNet achieved a mean F1 score of 69.79% and a mean IoU of 53.59%, and Pan *et al.* (2017) proposed a model based on SCNN achieveing a mean F1 score of 70.04% and a mean IoU of 56.29%. With a mean F1 Score of 77.59% and a mean IoU of 65.26%, our model compares favourably with the state of the art on the DET dataset.

The system was designed to be non-intrusive to the driver with the alert mechanisms integrated in such a way that the driver gets real-time notifications through sound alerts as well as via the display screen. The system was successfully tested in the Kayoola EVS and was able to achieve the intended purpose. This study addresses a substantial research gap and provides a tangible solution to urgent road safety issues, benefiting not only Kayoola Buses but also the broader East African region.

5.2 Recommendations

Kiira Motors Corporation should ensure further development of this system to ensure that the technology is mature enough for rollout in all the Kayoola buses. The system being a camera based requires infrared cameras to improve the accuracy of detection during low light and night conditions. This will further improve the accuracy of the system and ensure accurate alerts are sent to the driver during these driving scenarios. This system has been tested and is premised to improve the safety of drivers, passengers and other road users. The future works should therefore explore and analyse the impact of the developed system and how it has improved pedestrian and vehicle safety.

The developed system employs deep learning methodology which has demonstrated great results across different road traffic scenarios. Researchers can explore the implementation of the system using Internet of Things (IoT) approach to explore potential benefits and drawbacks in comparison with the developed system.

5.3 Future Works

Further research should be carried out to implement Vehicle-to-Vehicle (V2V) and Vehicle-to-Infrastructure (V2I) communication. Interconnected communication networks between vehicles and infrastructure elements will significantly enhance the accuracy and overall reliability of the system. The V2V communication will allow vehicles to exchange critical information, such as position, speed, and intentions, in real-time while V2I communication will ensure the exchange of information between vehicles and infrastructure components like traffic signals and road signs. This communication will ensure that vehicles are not only aware of each other but also the surrounding infrastructure, contributing to a more comprehensive and responsive ADAS.

Future research should also consider integrating the ADAS system with the rest of the vehicle's electronic components through the Controller Area Network (CAN) to facilitate seamless communication between the ADAS and various electronic components within the vehicle, allowing for real-time data exchange. This integration will enable a more holistic approach to data gathering, analysis, and decision-making, contributing to improved accuracy.

REFERENCES

Chang, S. M., Tsai, C. C., & Guo, J. I. (2018). A blind spot detection warning system based on Gabor filtering and optical flow for E-mirror applications. *2018 IEEE International Symposium on Circuits and System,* 1-5. https://doi.org/10.1109/ISCAS.2018.8350927.

Cheng, W., Luo, H., Yang, W., Yu, L., Chen, S., & Li, W. (2019). DET: A high-resolution DVS dataset for lane extraction. *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition Workshops,* 1-10.

De-Raeve, N., De-Schepper, M., Verhaevert, J., Van-Torre, P., & Rogier, H. (2020). A bluetooth-low-energy-based detection and warning system for vulnerable road users in the blind spot of vehicles. *Sensors*, *20*(9), 2727. https://doi.org/10.3390/s20092727.

Deng, Q., Wang, J., Hillebrand, K., Benjamin, C. R., & Söffker, D. (2019). Prediction performance of lane changing behaviors: a study of combining environmental and eye-tracking data in a driving simulator. *IEEE Transactions on Intelligent Transportation Systems*, *21*(8), 3561-3570. https://doi.org/10.1109/TITS.2019.2937287.

Devi, I., Karpagam, G. R., & Kumar, B. V. (2017). A survey of machine learning techniques. *International Journal of Computational Systems Engineering*, *3*(4), 203-212. https://doi.org/10.1504/ijcsyse.2017.10010099.

Du, X., Tan, K. K., & Htet, K. K. K. (2015, May). Vision-based Lane line detection for autonomous vehicle navigation and guidance. *2015 10th Asian Control Conference*, 1-5. https://doi.org/10.1109/ASCC.2015.7244831.

Eichelberger, A. H., & McCartt, A. T. (2016). Toyota drivers' experiences with dynamic radar cruise control, pre-collision system, and lane-keeping assist. *Journal of Safety Research*, *56*, 67-73. https://doi.org/10.1016/j.jsr.2015.12.002.

Fakhfakh, M., Chaari, L., & Fakhfakh, N. (2020). Bayesian curved lane estimation for autonomous driving. *Journal of Ambient Intelligence and Humanized Computing*, *11*(10), 4133-4143. https://doi.org/10.1007/s12652-020-01688-7.

Farah, H., Bhusari, S., Van-Gent, P., Babu, F. A. M., Morsink, P., Happee, R., & Van-Arem, B. (2020). An empirical analysis to assess the operational design domain of lane keeping system equipped vehicles combining objective and subjective risk measures. *IEEE Transactions on Intelligent Transportation Systems*, *22*(5), 2589-2598.

Feniche, M., & Mazri, T. (2019). Lane detection and tracking for intelligent vehicles: A survey. *2019 International Conference of Computer Science and Renewable Energies*, 1-4. https://doi.org/10.1109/ICCSRE.2019.8807727.

Home - Kiira Motors Corporation. (2023). Retrieved September 20, 2023, from https://www.kiiramotors.com.

Hou, Y., Ma, Z., Liu, C., & Loy, C. C. (2019). Learning lightweight lane detection CNNS by self-attention distillation. *Proceedings of the IEEE/CVF International Conference on Computer Vision*, 1013-1021. https://doi.org/10.1109/ICCV.2019.00110.

Irshad, A., Khan, A. A., Yunus, I., & Shafait, F. (2017). Real-time lane departure warning system on a lower resource platform. *2017 International Conference on Digital Image Computing: Techniques and Applications*, 1-8.

Joy, S., Mamta, B. S., Mukesh, T. B., Ahmed, M. M., & Kiran, U. (2022). Real time road lane detection using computer vision techniques in Python. *2022 International Conference on Automation, Computing and Renewable Systems*, 1228-1232. https://doi.org/10.1109/ICACRS55517.2022.10029238.

Jung, K. H., & Yi, K. (2018). Vision-based blind spot monitoring using rear-view camera and its real-time implementation in an embedded system. *Journal of Computing Science and Engineering*, *12*(3), 127-138. https://doi.org/10.5626/JCSE.2018.12.3.127.

Junus, A., Hsu, Y. C., Wong, C., & Yip, P. S. (2023). Is internet gaming disorder associated with suicidal behaviors among the younger generation? Multiple logistic regressions on a large-scale purposive sampling survey. *Journal of Psychiatric Research*, *161*, 2-9. https://doi.org/10.1016/J.JPSYCHIRES.2023.02.038.

Keatmanee, C., Jakborvornphan, S., Potiwanna, C., San-Uml, W., & Dailey, M. N. (2018). Vision-based Lane keeping: A Survey. *2018 International Conference on Embedded Systems and Intelligent Technology & International Conference on Information and Communication Technology for Embedded Systems*, 1-6.

Kim, I. H., Bong, J. H., Park, J., & Park, S. (2017). Prediction of driver's intention of lane change by augmenting sensor information using machine learning techniques. *Sensors, 17*(6), 1350. https://doi.org/10.3390/s17061350.

Li, J., Jiang, F., Yang, J., Kong, B., Gogate, M., Dashtipour, K., & Hussain, A. (2021). Lane-DeepLab: Lane semantic segmentation in automatic driving scenarios for high-definition maps. *Neurocomputing*, *465*, 15-25.

Lu, Y., Chen, Y., Zhao, D., & Chen, J. (2019). Graph-FCN for image semantic segmentation. *International Symposium on Neural Networks*, 97-105. https://doi.org/10.1007/978-3-030-22796-8_11.

Madhuri, K., & UmaMaheswari, B. (2019). Adaptive steering control and driver alert system for smart vehicles. *2019 3rd International Conference on Computing Methodologies and Communication*, 208-213. https://doi.org/10.1109/ICCMC.2019.8819636.

Masatu, E. M., Sinde, R., & Sam, A. (2022). Development and Testing of Road Signs Alert System Using a Smart Mobile Phone. *Journal of Advanced Transportation*, *2022,* 1-14. https://doi.org/10.1155/2022/5829607.

Munir, F., Azam, S., Jeon, M., Lee, B. G., & Pedrycz, W. (2021). LDNet: End-to-end Lane marking detection approach using a dynamic vision sensor. *IEEE Transactions on Intelligent Transportation Systems*, *23*(7), 9318-9334.

Muzammel, M., Yusoff, M. Z., Saad, M. N. M., Sheikh, F., & Awais, M. A. (2022). Blind-Spot Collision Detection System for Commercial Vehicles Using Multi Deep CNN Architecture. *Sensors*, *22*(16), 6088. https://doi.org/10.3390/s22166088.

Neven, D., De-Brabandere, B., Georgoulis, S., Proesmans, M., & Van-Gool, L. (2018). Towards end-to-end lane detection: An instance segmentation approach. *2018 IEEE Intelligent Vehicles Symposium,* 286-291. https://doi.org/10.1109/IVS.2018.8500547.

Osuret, J., Namatovu, S., Biribawa, C., Balugaba, B. E., Zziwa, E. B., Muni, K., Ningwa, A., Oporia, F., Mutto, M., Kyamanywa, P., Guwatudde, D., & Kobusingye, O. (2021). State of pedestrian road safety in Uganda: A qualitative study of existing interventions. *African Health Sciences*, *21*(3), 1498-1506.

Pan, X., Shi, J., Luo, P., Wang, X., & Tang, X. (2017). Spatial As Deep: Spatial CNN for Traffic Scene Understanding. *32nd AAAI Conference on Artificial Intelligence*, 7276–7283. https://doi.org/10.1609/aaai.v32i1.12301.

Rangesh, A., & Trivedi, M. M. (2019). No blind spots: Full-surround multi-object tracking for autonomous vehicles using cameras and lidars. *IEEE Transactions on Intelligent Vehicles*, *4*(4), 588-599. https://doi.org/10.1109/TIV.2019.2938110.

Teo, T. Y., Sutopo, R., Lim, J. M. Y., & Wong, K. (2021). Innovative lane detection method to increase the accuracy of lane departure warning system. *Multimedia Tools and Applications*, *80*(2), 2063-2080. https://doi.org/10.1007/s11042-020-09819-0.

Walekhwa, A. W., Mulolo, F., Achiro, C., Nantongo, M., Nakazibwe, B., & Masanza, M. M. (2022). A Rapid Assessment of Road Crashes in Uganda: Notes from the Field. *Dr. Sulaiman Al Habib Medical Journal*, *4*(4), 174-181. https://doi.org/10.1007/s44229-022-00018-7.

World Health Organization. (2022). Global Status Report on Road Safety 2022 Summary. *World Health Organization*, *1*, 20. http://apps.who.int/bookorders.

Wu, C., Sun, H., Wang, H., Fu, K., Xu, G., Zhang, W., & Sun, X. (2018). Online multi-object tracking via combining discriminative correlation filters with making decision. *IEEE Access*, *6*, 43499-43512. https://doi.org/10.1109/ACCESS.2018.2858853.

Xie, S., Girshick, R., Dollár, P., Tu, Z., & He, K. (2017). Aggregated residual transformations for deep neural networks. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, 1492-1500. https://doi.org/10.1109/CVPR.2017.634.

Yoo, S., Lee, H. S., Myeong, H., Yun, S., Park, H., Cho, J., & Kim, D. H. (2020). End-to-end lane marker detection via row-wise classification. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition Workshops*, 1006-1007. https://doi.org/10.1109/CVPRW50498.2020.00511.

Yu, L., & Wang, R. (2022). Researches on Adaptive Cruise Control system: A state of the art review. *Proceedings of the Institution of Mechanical Engineers, Part D: Journal of Automobile Engineering*, *236*(2-3), 211-240.

Zakaria, N. J., Zamzuri, H., Ariff, M. H., Shapiai, M. I., Saruchi, S. A., & Hassan, N. (2018). Fully convolutional neural network for Malaysian road lane detection. *International Journal of Engineering & Technology*, *7*(4.11), 152-155.

Zhang, H., Wu, C., Zhang, Z., Zhu, Y., Lin, H., Zhang, Z., Sun, Y., He, T., Mueller, J., Manmatha, R., Li, M., & Smola, A. (2022). Resnest: Split-attention networks. *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, 2736-2746. https://doi.org/10.1109/CVPRW56347.2022.00309.

Zhao, Y., Bai, L., Lyu, Y., & Huang, X. (2019). Camera-based blind spot detection with a general purpose lightweight neural network. *Electronics*, *8*(2), 233.

Ziryawulawo, A., Kirabo, M., Mwikirize, C., Serugunda, J., Mugume, E., & Miyingo, S. P. (2023). Machine learning based driver monitoring system: A case study for the Kayoola EVS. *SAIEE Africa Research Journal*, *114*(2), 40-48.

APPENDICES

Appendix 1: Requirements Gathering Questionnaire

Final Project- Requirements

1. Please select your gender

   Mark only one oval.

   - ⬭ Male
   - ⬭ Female

2. Have you ever been in an accident caused by lane departure and or blind spot objects?

   Mark only one oval.

   - ⬭ Yes
   - ⬭ No

3. How do you feel about the potential for this system to reduce accidents?

   Check all that apply.

   - ☐ Optimistic
   - ☐ Pessimistic

4. Which of the following types of roads do you mostly drive on?

   Check all that apply.

   - ☐ Highways/Motorways
   - ☐ Rural roads
   - ☐ City Streets
   - ☐ Residential Streets

5. How important is it for the ADAS systems to provide feedback to the driver such as audible or visual warnings?

Mark only one oval.

- Very Important
- Somewhat important
- Neutral
- Somewhat unimportant
- Not important at all

Appendix 2: System Validation Questionnaire

Final Project- System Validation

1. Do you think the system is ready for deployment?

Mark only one oval.

- Yes
- No

2. Have you ever been in an accident caused by lane departure and or blind spot objects?

Mark only one oval.

- Yes
- No

3. How do you feel about the potential for this system to reduce accidents?

Mark only one oval.

	1	2	3	4	5	
Very						Very Optimistic

4. How do you feel about the potential for this system to reduce accidents?

Check all that apply.

- Optimistic
- Pessimistic

5. Which of the following types of roads do you mostly drive on?

Check all that apply.

- [ ] Highways/Motorways
- [ ] Rural roads
- [ ] City Streets
- [ ] Residential Streets

6. How important is it for the ADAS systems to provide feedback to the driver such as audible or visual warnings?

Mark only one oval.

- ( ) Very Important
- ( ) Somewhat important
- ( ) Neutral
- ( ) Somewhat unimportant
- ( ) Not important at all

Appendix 3: Sample Code for Blind Spot Detection

```python
import sys
from kivy.lang import Builder
from kivy.properties import ObjectProperty, BooleanProperty, ListProperty, NumericProperty, DictProperty
from kivy.uix.boxlayout import BoxLayout
from kivy.uix.scrollview import ScrollView
from kivymd.app import MDApp
import time
from kivy.clock import Clock
from kivy.core.window import Window
from BSDS_firmware.accelerometer import Accelerometer
import pygame
import threading
import queue
import RPi.GPIO as GPIO
from optimized_detector import ObjectDetectionModel


class MessageItem(BoxLayout):

    def __init__(self, **kwargs):
        super(MessageItem, self).__init__(**kwargs)


class StandbyMode(BoxLayout):

    def __init__(self, monitor_screen=None, **kwargs):
        super(StandbyMode, self).__init__(**kwargs)
        self.monitor_screen = monitor_screen


class ActiveMode(BoxLayout):
    monitor_screen = ObjectProperty(None)

    def __init__(self, monitor_screen=None, **kwargs):
        super(ActiveMode, self).__init__(**kwargs)
        self.monitor_screen = monitor_screen

class SplashScreen(BoxLayout):
    screen_manager = ObjectProperty(None)
    app_window = ObjectProperty(None)
    monitor_screen = ObjectProperty(None)

    def __init__(self, **kwargs):
        super(SplashScreen, self).__init__(**kwargs)
        Clock.schedule_interval(self.update_progress_bar, .2)

    def update_progress_bar(self, *args):
        if (self.ids.progress_bar.value + 5) < 100:
            raw_value = self.ids.progress_bar_label.text.split('[')[-1]
            value = raw_value[:-2]
            value = eval(value.strip())
            new_value = value + 5
            self.ids.progress_bar.value = new_value
            self.ids.progress_bar_label.text = 'Loading.. [{:} %]'.format(new_value)
        else:
            self.ids.progress_bar.value = 100
            self.ids.progress_bar_label.text = 'Loading.. [{:} %]'.format(100)
            time.sleep(2)
            self.screen_manager.current = 'main_screen'
            # self.resize_window(800, 600)
            Window.borderless = False
            Window.maximize()
            return False
```

Appendix 4: Sample code for Training the Lane Detection Model

```python
import socket
import timeit
from datetime import datetime
import os
import glob
from collections import OrderedDict
import numpy as np
import yaml
from addict import Dict
import argparse

# PyTorch includes
import torch
from torch.autograd import Variable
import torch.optim as optim
from torchvision import transforms
from torch.utils.data import DataLoader

# Tensorboard includefro
▶ Launch TensorBoard Session
from tensorboardX import SummaryWriter

# Custom includes
# from dataloaders import cityscapes
from dataloaders import lane_detect
from dataloaders import utils
from dataloaders import augmentation as augment
#from dataloaders import ImageFolder
from models.LDnet_network import LDNet_network
from utils import loss as losses
from utils import iou_eval
from utils.metrics import runningScore, averageMeter


#To make reproducible results
torch.manual_seed(125)
torch.backends.cudnn.deterministic = True
```

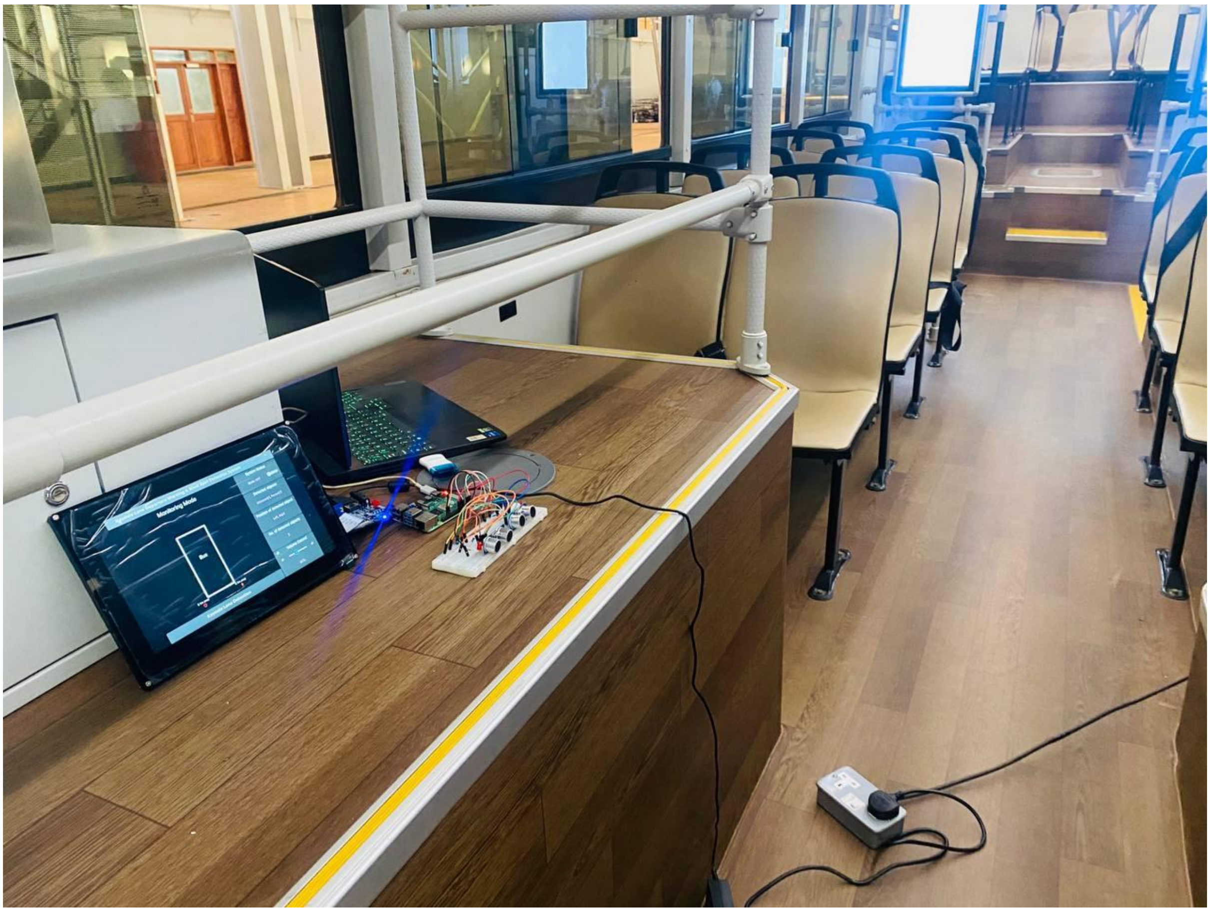
```python
#To make reproducible results
torch.manual_seed(125)
torch.backends.cudnn.deterministic = True
torch.backends.cudnn.benchmark = False
np.random.seed(125)
CONFIG=Dict(yaml.load(open("./config/training.yaml"),Loader=yaml.FullLoader))


ap = argparse.ArgumentParser()
ap.add_argument('--backbone_network', required=False,
                help = 'name of backbone network',default='mobilenet')
ap.add_argument('--model_path_resume', required=False,
                help = 'path to a model to resume from',default='./experiments')

args = ap.parse_args()
backbone_network=args.backbone_network
model_path_resume=args.model_path_resume





# Setting parameters
```

Appendix 5: Sample code for Testing the Lane Detection Model

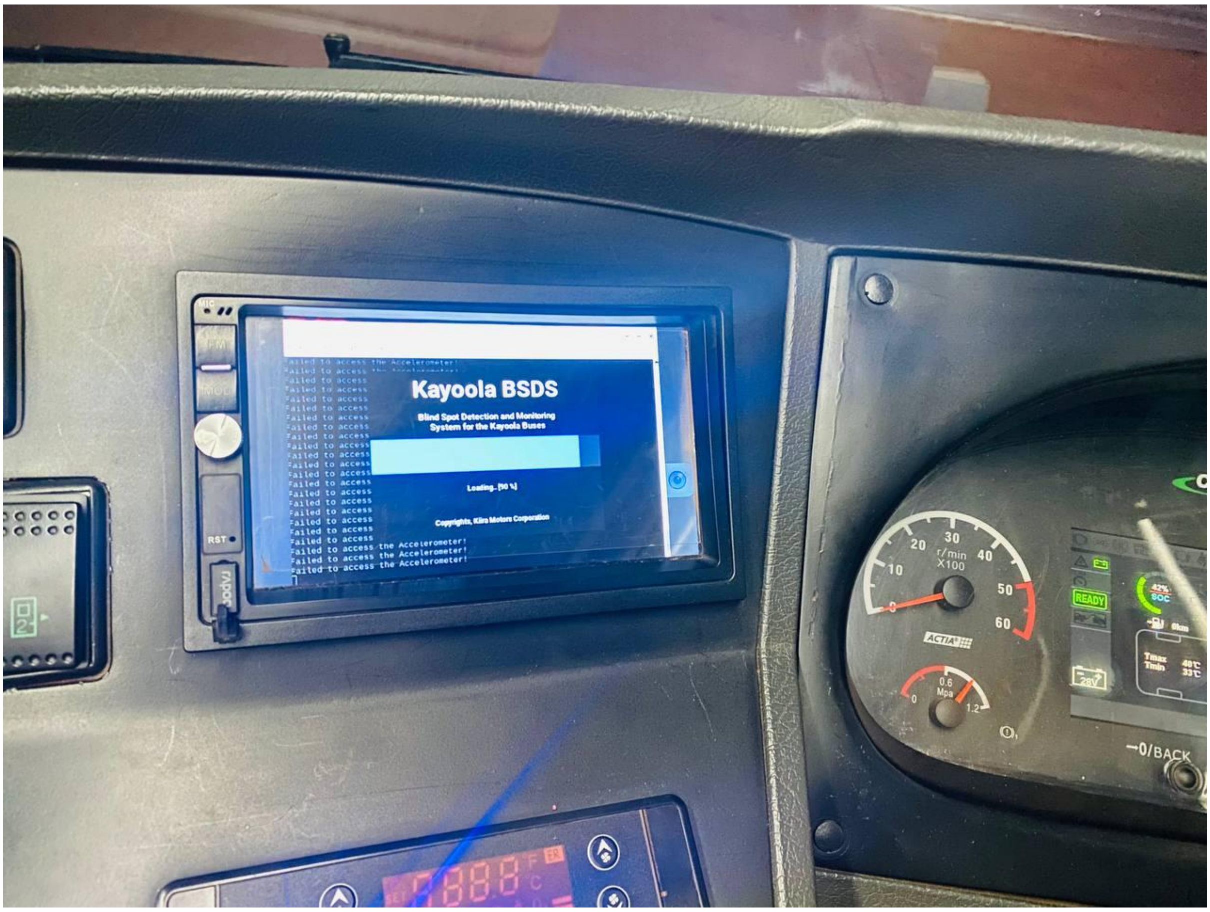
```python
import socket
import timeit
from datetime import datetime
import os
import glob
from collections import OrderedDict
import numpy as np
import yaml
from addict import Dict
import argparse
import cv2
# PyTorch includes
import torch
from torch.autograd import Variable
import torch.optim as optim
from torchvision import transforms
from torch.utils.data import DataLoader
from torchvision.utils import make_grid



from dataloaders import lane_detect
from dataloaders import utils
from dataloaders import augmentation as augment

from models.LDnet_network import LDNet_network
from utils import loss as losses
from utils import iou_eval
from utils.metrics import runningScore, averageMeter

from dataloaders.utils import *
#To make reproducible results
torch.manual_seed(125)
torch.backends.cudnn.deterministic = True
torch.backends.cudnn.benchmark = False
np.random.seed(125)
CONFIG=Dict(yaml.load(open("./config/testing.yaml"), Loader=yaml.FullLoader))

ap = argparse.ArgumentParser()
ap.add_argument('--backbone_network', required=False,
                help = 'name of backbone network',default='mobilenet')
ap.add_argument('--model_path_resume', required=False,
                help = 'path to a model to resume from',default= './experiments/lane_epoch-17.pth')

args = ap.parse_args()
backbone_network=args.backbone_network
model_path_resume=args.model_path_resume





# Setting parameters
nEpochs =1  # Number of epochs for training 150
resume_epoch = 0  # Default is 0, change if want to resume 0

p = OrderedDict()  # Parameters to include in report
p['trainBatch'] =4  # Training batch size
p['lr'] =1e-7# Learning rate  1e-8 for darknet and 1e-7 shufflenet and mobilenet
p['wd'] = 5e-4  # Weight decay
p['momentum'] = 0.9  # Momentum
```

Appendix 6: Installation of cameras on the Kayoola EVS

Appendix 7: Benchtop Tests in the Kayoola EVS Bus

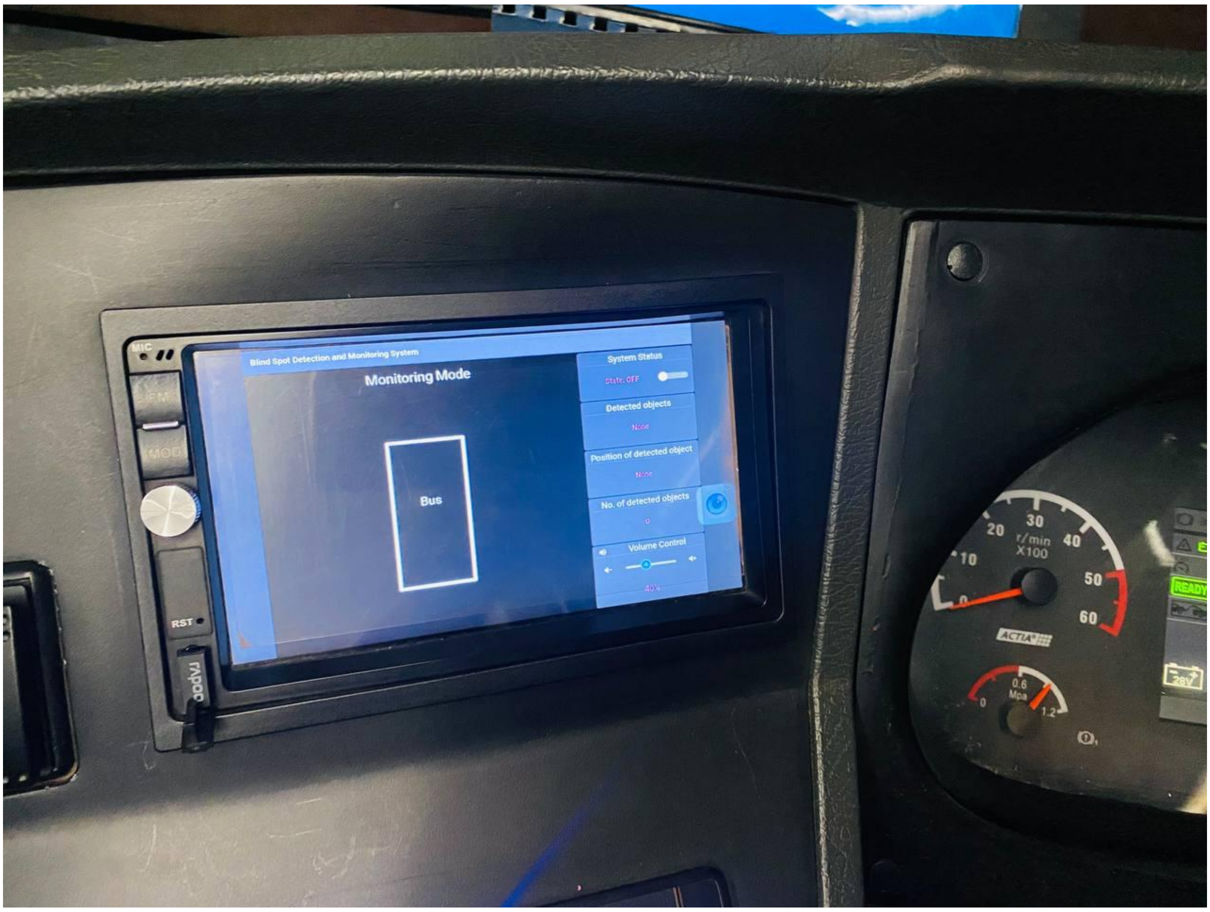


Appendix 8: System Initialization in the Kayoola EVS Bus



Appendix 9: Passive Mode in the Kayoola EVS

Appendix 10: Monitoring Mode in the Kayoola EVS



RESEARCH OUTPUTS

(i) Research Paper

Ziryawulawo, A., Mduma, N., Lyimo, M., Mbarebaki, A., Madanda, R., & Sam, A. (2023). An Integrated Deep Learning-based Lane Departure Warning and Blind Spot Detection System: A Case Study for the Kayoola Buses. In *2023 First International Conference on the Advancements of Artificial Intelligence in African Context*, 1-8.

(ii) Poster Presentation

Appendix 11: Poster Presentation

A DEEP LEARNING-BASED LANE DEPARTURE WARNING AND BLIND SPOT DETECTION SYSTEM FOR IMPROVED VEHICLE SAFE

[1]Ali Ziryawulawo, [1]Neema Mduma, [1]Martine Lyimo, [2]Adonia Mbarebaki, [2]Richard Madanda, [1]Anael Sam
[1]The Nelson Mandela African Institution of Science and Technology , [2]Kiira Motors Corporation

Abstract

In Uganda, road accidents have continued to soar with an increase of up to 42% in 2021 due to the growing road traffic density. This project presents a system that alerts the driver using the graphical user interface, and auditory feedback. The model was tested on the DET and TuSimple datasets attaining an F1 Score of 77.59% and a mean IoU of 65.26% on the DET and an overall accuracy of 97.96% on the TuSimple dataset.

Introduction

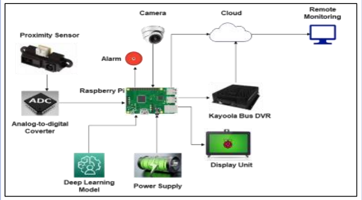
In Uganda, the number of road accidents increased by 42% according to the 2021 Annual Police Report. Lane departure and blind spot events are among the major causes of road accidents in East Africa.

Kiira Motors Corporation a state-owned mobility solutions enterprise is looking forward to developing advanced driver assistance systems for improved safety of their market entry products- the Kayoola buses.

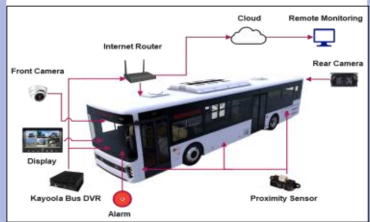
The main objective is to develop a deep learning-based lane departure warning and blind spot detection system for improved vehicle safety.

Methodology

The system is designed with sensors which include cameras and proximity sensors mounted on the bus. The sensor array captures environmental parameters such as lane markings and nearby objects. The deep learning algorithm processes the sensor data and detects lane departure and blind spot events in real-time.

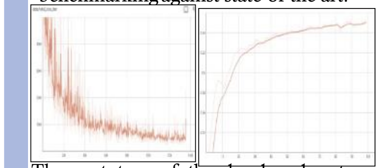


The LDW and BSD system works by continuously monitoring the vehicle's surroundings using a combination of sensors and cameras.



Results

Training was done for 100 epochs using the MobileNet backbone and the Cross-Entropy loss function for optimizing the model. The evaluation of the lane detection model was carried out on two datasets, DET and TuSimple, while benchmarking against state-of-the-art.



The prototype of the developed system was tested in the Kayoola EVS.

Conclusion

The project addressed a crucial gap in current automotive safety systems by developing a Lane Departure Warning and Blind Spot Detection system using advanced deep learning techniques. Our prototype demonstrates the potential for improved real-time detection and enhanced vehicle safety.

Our model attained a mean F1 Score of 77.59% and a mean IoU of 65.26% on the DET dataset and an overall accuracy of 97.96% on the TuSimple dataset. These results compared favorably with other works in literature. The system was designed with the alert mechanisms integrated in such a way that the driver gets real-time notifications through sound alerts and the display screen.

The system was tested in the Kayoola EVS and was able to achieve the intended purpose.

Bibliography

Chang, S. M., Tsai, C. C., & Guo, J. I. (2018). A Blind Spot Detection Warning System based on Gabor Filtering and Optical Flow for E-mirror Applications. Proceedings - IEEE International Symposium on Circuits and Systems, 2018-May.