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Research Article

Development of an AI-enabled smart ambulance system for real-time emergency response and traffic navigation

Sani Saminu[1], Olaosebikan Samuel Tunmise[1], Suleiman Abimbola Yahaya[1], Idris Oladele Muniru[1], Kazeem Olawale Salaudeen[1], Muhammad kabir Abdulkadir[2], Sanusi Abdulrazaq[3], Hauwa Mohammed Hambali[4]

[1]*Department of Biomedical Engineering, University of Ilorin, Ilorin, Nigeria*
[2]*Department of Medical Radiography, University of Ilorin, Ilorin, Nigeria.*
[3]*Department of Pharmaceutical and Medicinal Chemistry, University of Ilorin, Ilorin, Nigeria.*
[4]*Department of Physiotherapy, University of Ilorin, Ilorin, Nigeria.*

Corresponding Author: saminu.s@unilorin.edu.ng

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Abstract
Delay in ambulance arrival during an emergency remains a major cause of avoidable damage, especially in congested areas and under-resourced regions. This project presents the design and development of an artificial intelligence ambulance detection and alert system using public space CCTV cameras. The system uses a Raspberry Pi as the central processing unit, running a deep learning model built on TensorFlow and trained with MobileNetV2 to identify an ambulance. Upon successful detection, an integrated buzzer is triggered for immediate local alert, while a GSM module sends SMS notifications to the nearby hospital or emergency response unit. The system was mechanically designed using TinkerCAD, with a 3D model that optimally arranges the camera, Raspberry Pi, and peripheral components. Circuit design and simulation were conducted using Cirkit Designer to ensure electrical stability and compatibility. This AI-enabled system demonstrated 96% detection accuracy and high precision, providing a reliable, cost-effective, and scalable alternative to GPS or a manual tracking approach. It offers a vital improvement to emergency medical response workflow, particularly in developing environments where smart healthcare infrastructure is still emerging.

Nomenclature and units

1.0 Introduction

In medical emergencies, ambulances serve as the initial point of contact, providing critical pre-hospital care and rapid transport to healthcare facilities (Selvan et al., 2025). Emergency medicine has been established globally as a vital component of healthcare, with demand surging due to the need for time-sensitive interventions. This urgency was starkly evident during the COVID-19 pandemic, when overwhelmed Emergency Departments exposed systemic limitations in preparedness and coordination (Kularathne et al., 2022). A defining factor in patient outcomes, particularly in time-critical cases like out-of-hospital cardiac arrests is the speed of ambulance navigation through traffic and delivery to hospitals. Delays in Emergency Medical Services (EMS) activation can increase mortality risk by 7-10% per minute, underscoring the life-saving potential of swift responses (Darginavicius et al., 2023; Bhatia et al., 2024).

Historically, ambulance services evolved from battlefield transport systems for injured soldiers to comprehensive civilian EMS frameworks. Today, a new era is unfolding with the integration of intelligent technologies. Ongoing research on Smart Ambulance Systems highlights their capacity to enhance response times, operational efficiency, and patient survival rates (Hampiholi, 2024). Proper detection of ambulances enables emergency services to manage incoming calls effectively (Neira-Rodado et al., 2022; Li et al., 2022), relying on robust data collection and model training to distinguish ambulances from other vehicles (Yu & Marinov, 2020; Shamrat et al., 2020; Noor et al., 2024). AI-driven innovations, including machine learning, deep learning, computer vision, and the Internet of Things (IoT), now enable real-time vehicle tracking and classification along urban streets (Kong & Woods, 2018; Bajwa, 2025). These advancements not only optimize ambulance routing but also facilitate pre-hospital preparedness through warnings, enabling coordinated responses (Mahalakshmi et al., 2022). In densely populated cities, where traffic congestion exacerbates delays, AI integration with public surveillance networks, such as CCTV cameras, allows for automatic ambulance detection, speed and location monitoring, and seamless hospital notifications (Darginavicius et al., 2023; J. H. Kim et al., 2025; Peelam et al., 2024). Pioneering efforts in cities like London and Bangalore demonstrate the viability of AI-enhanced EMS systems that prioritize ambulance detection via surveillance feeds, marking a global shift toward automated, reliable pre-hospital care (Selvan et al., 2025; Peelam et al., 2024). At the core of these systems lies computer vision, a pivotal AI subdomain that emulates human visual processing by analyzing digital images and videos for tasks like capture, screening, identification, and extraction (Ahmed et al., 2024; Bisio et al., 2022; Desai et al., 2021). Deep learning has revolutionized this field, powering applications in image segmentation (Eesaar et al., 2023; H. J. Kim et al., 2024), classification (Hussain et al., 2019; Guo et al., 2017), and object detection (Ren et al., 2017). Recent transitions toward visual-language and large language models, collectively termed foundation models, further amplify these capabilities, enabling nuanced, context-aware interpretations.

Despite these advancements, emergency healthcare faces critical bottlenecks in ambulance detection and response. Traditional systems predominantly rely on radio communication and GPS tracking, which are hampered by connectivity issues, limited visibility, and operational complexity (Nayak & Patgiri, 2020). These methods often incur delays from traffic congestion, situational unawareness, and communication breaches between ambulances and hospitals (Linderoth et al., 2015). In urban environments, where infrastructure strains under high vehicle density, manual monitoring or human-perceived dispatch exacerbates these issues, leading to suboptimal patient outcomes. The absence of automated, real-time detection systems means hospitals frequently lack advance notice for preparation, resulting in disorganized patient transfers and heightened risks in critical scenarios (Darginavicius et al., 2023). This disconnect not only prolongs response times but also amplifies mortality in conditions like cardiac arrests, where every minute counts.

In healthcare, AI's roles span diagnostics, monitoring, and administrative streamlining. Applications include online scheduling, digitized records, dosage algorithms, and adverse effect alerts (Amisha et al., 2019). Radiology exemplifies AI's impact, with deep learning achieving superior accuracy in image analysis for quantitative assessments (Zhou et al., 2019; Huang et al., 2022). Beyond diagnostics, AI facilitates precise monitoring via wearable devices and predictive analytics, replicating diary functions for longitudinal patient management and proactive interventions (E. Kim et al., 2023; Jeddi & Bohr, 2020). Virtual assistants (e.g., Siri, Alexa) and automated systems further integrate AI into daily care, enhancing efficiency and personalization (Mintz & Brodie, 2019; Briganti & Le Moine, 2020).

In emergency medicine and ambulance services, AI addresses urban challenges, including congestion. Real-time detection via CNNs and object models (e.g., YOLO, ResNet) identifies ambulances using visual cues like sirens and lights, enabling traffic prioritization and pre-notification (Myagmar-Ochir & Kim, 2023; Kaladevi et al., 2025; Ezzat et al., 2021; Dong Chae et al., 2021). Surveillance-integrated systems reduce response times by creating dynamic green corridors and alerting departments early (Giachali et al., 2018; Roy & Rahman, 2019; Suthahar et al., 2025). Intelligent transportation frameworks, including AI dispatch and signal control, foster EMS-hospital synergy (Qi et al., 2024; Patel et al., 2022; Sarapirom & Poochaya, 2021).Vehicle detection methods fall into three categories: sensor-based (e.g., radar, LiDAR), vision-based (e.g., CCTV with deep learning), and hybrid approaches (Yang & Pun-Cheng, 2018). Vision-based methods dominate for scalability, using AI to process streams for emergency vehicle prioritization (Alruwaili et al., 2025; Bajwa, 2025).

While literature on smart ambulance systems and vehicle detection abounds, key gaps persist in scalable, real-world deployment. GPS-centric tracking falters in urban signal-degraded areas like tunnels or high-rises, lacking precision for dynamic environments (Alruwaili et al., 2025; Selvan et al., 2025). AI-based CCTV detection remains largely experimental, with infrequent integration into hospital alerts, perpetuating manual delays and errors (Bajwa, 2025; Roy & Rahman, 2019; Darginavicius et al., 2023; J. H. Kim et al., 2025). Resource-heavy models (e.g., GPU-dependent) limit adoption in low-income regions, where congestion amplifies risks (Ahmed et al., 2024; Noor et al., 2024; Mahalakshmi et al., 2022). Optimization for edge devices and context-aware routing under variable conditions remains underexplored (Dong Chae et al., 2021; Kaladevi et al., 2025). This work bridges these voids by proposing an end-to-end, lightweight system for ambulance detection, automated notifications, and efficient deployment, advancing toward resilient EMS infrastructures.

This study is a conceptual/system design focuses on developing an AI-powered ambulance detection system using a shortest-path decision approach that leverages public space CCTV feeds to identify incoming ambulances in real time and automatically notify hospitals for pre-arrival preparation. The scope encompasses data collection from urban surveillance streams, training deep learning models (e.g., TensorFlow-based architectures) for accurate vehicle classification, and integrating alert mechanisms for seamless EMS-hospital coordination. By emphasizing scalable deployment on edge devices, the system aims to enhance patient transfer efficiency without relying on resource-intensive infrastructure, targeting reductions in response times within congested cityscapes.

2.0 Materials and Methods

2.1 System Workflow

The AI model, trained using machine learning, analyzes video stream captured using a public space camera to monitor ambulance movement and to detect incoming ambulances by recognizing patterns specific to ambulances. These cameras continuously record and transmit video data to the AI-powered processing unit. The AI-based detection system was developed using a deep learning technique, particularly the TensorFlow framework, which helps classify ambulance and no ambulance. Image processing techniques are applied to enhance detection accuracy while minimizing false positives (raising false alarms). Once an ambulance is detected, an alert system will be triggered immediately. There is then the notification system to initiate a timely response. A GSM module and buzzer, which has been interfaced with Raspberry Pi, was programmed to send an alert. The SIM800A modem was connected to a Raspberry Pi, through which the AI detection system communicated well with the GSM module. Figure 1 shows the data flow between ambulance, traffic system, and hospital. Figure 2 shows the block diagram for the ambulance detection system, while the methodology flowchart is shown in Figure 3.

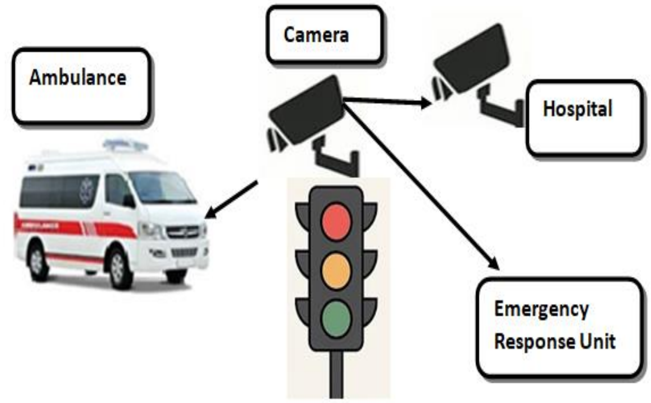

Figure 1 Data flow for ambulance detection system.

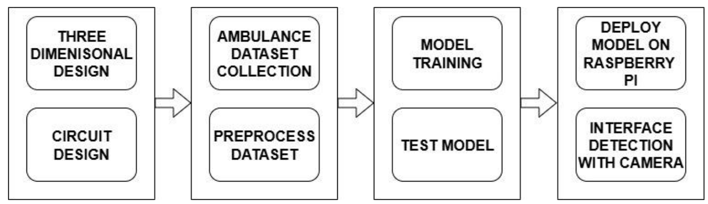

Figure 2 Block diagram for ambulance detection system.

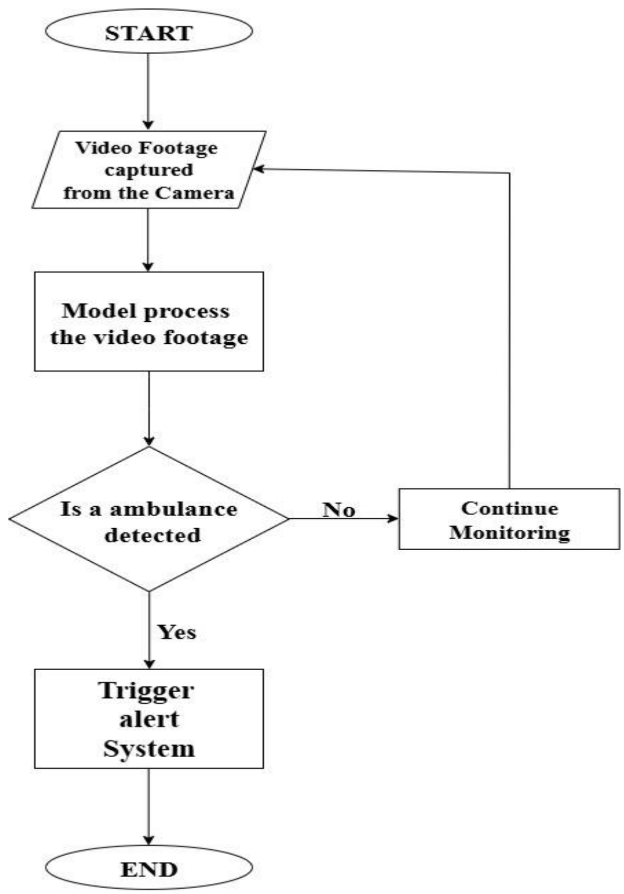

Figure 3 Flow chart for the ambulance detection system.

2.2 System Device Design

The device design includes the hardware and software components. The main components include the camera, raspberry pi, GSM Module, and the Buzzer. The three-dimensional (3D) design was done using Tinker cad software, the model shows the various parts of the device which includes the mounting frame, a camera and a compartment that houses the electrical circuit. Figure 4 shows the components part of the design, Figure 5 shows the side view of the ambulance detection system device design, Figure 6 shows the top view of the device and Figure 7 depicted the front view of the ambulance detection system device design.

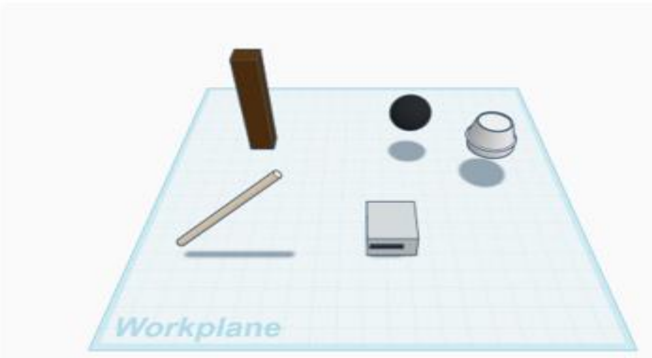

Figure 4 3D Parts of the Device Design.

Figure 6 Top View of the Device Design.

2.2.1 Components Selection

The CCTV camera was selected based on high-definition imaging (at least 1080p), a wide field of view (up to 120° coverage), and infrared night vision, to enable accurate and reliable ambulance detection in different public space conditions, day or night. The Raspberry Pi 4 (8GB RAM model) is utilized as the main processing core, which is capable of managing video stream analysis, executing the ambulance detection model, and coordinating the communication with the peripheral modules. A buzzer generates immediate audible alerts when ambulance is detected, enabling rapid local response. The GSM module supports automatic notification through SMS or voice call, facilitating rapid intervention in the event of an emergency. The choice of components, especially the use of Raspberry Pi, GSM module, and surveillance camera, is in line with best practice reported in recent studies, such as (Gowtham et al., 2020; Mahalakshmi et al., 2022), who emphasized the importance of localized processing, real-time alerting, and scalable hardware in a smart ambulance solution.

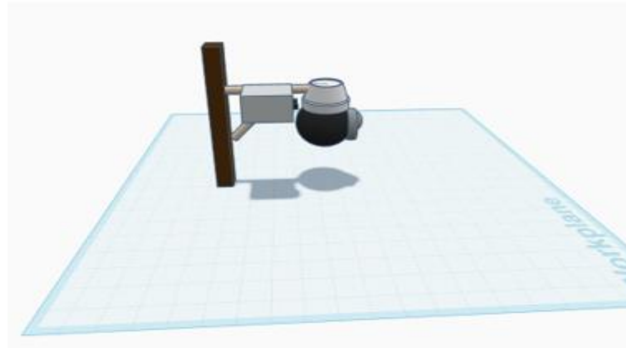

Figure 5 Side View of the Device Design.

2.2.2 Circuit Design and Connection

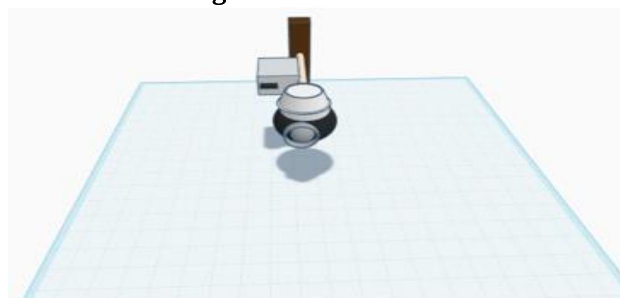

Figure 7 Front View of the Device Design.

The camera module is used for video surveillance and ambulance detection. The pin1 of the camera is connected to the VCC (5V) pin of the Raspberry Pi, the pin2 of the camera is connected to the GND pin of the Raspberry Pi, and the Data/Control pin3 of the camera is connected to the GPIO17 of
the Raspberry Pi. The SIM800A GSM module was used to send an SMS alert when an ambulance is detected.

The VCC pin on the SIM800A was connected to the positive terminal of the battery, and the GND pin on the SIM800A was connected to the negative terminal of the battery. The TX pin of the SIM800A was connected to GPIO15 of the Raspberry Pi, and the RX pin of the SIM800A was connected to GPIO14 of the Raspberry Pi. The buzzer was used to trigger an alarm when an ambulance was detected. The positive terminal of the buzzer is connected to GPIO17 on the Raspberry Pi that controls the ON/OFF state. The GND terminal of the buzzer is connected to the GND pin on the Raspberry Pi. Figure 8 shows the electrical connection of the component system.

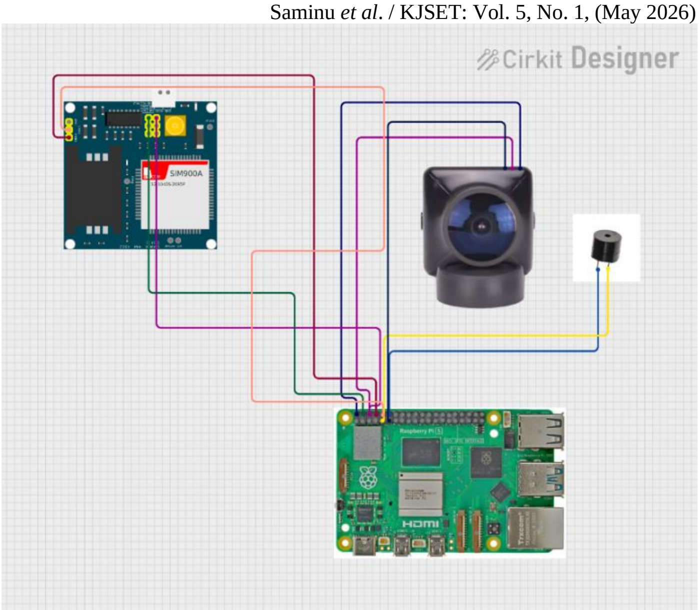

Figure 8 Electrical Circuit Design of the ambulance detection system.

2.3 Model Training

The development of the ambulance detection system employed a deep learning image classification using the TensorFlow framework and Keras API, implemented in the Python 3.x environment. The system was trained using a preprocessed image dataset categorized into three subsets: train, validation, and test. This section outlines the entire software configuration, model training, evaluation, and conversion used to build the AI model.

2.4 Data Preparation and Directory Structure

The dataset used for training the model was manually arranged and organized into a structured folder. Each subfolder (train, val, test) contains two classes: ambulance and no ambulance. A custom Python script was developed to verify the number of images per class and ensure dataset integrity. Image preprocessing and augmentation techniques were applied using Image Data Generator. These include:

1. Rescaling pixel values to (0, 1)
2. Random rotation (up to 30°)
3. Zooming (up to 30%)
4. Horizontal flipping
5. Brightness variation
6. Width and height shift .

These augmentations improve the generalization ability of the model by simulating real-world variability in camera feed.

2.5 Model Architecture and Transfer Learning

The core of the ambulance detection system is a convolutional neural network on MobileNetV2, a lightweight and efficient model optimized for mobile and edge computing devices. Transfer learning was employed by loading pre-trained weights from ImageNet, followed by freezing the base layers and appending a custom classification head:

1. Global Average Pooling 2D layer.
2. Dropout (0.3) for regularization.
3. Dense (1, sigmoid activation) for binary classification.

Initial training was performed with the Adam optimizer, binary cross-entropy loss, and accuracy metric. After the initial 10 epochs, the base model was partially unfrozen (from layer 100 onward), and fine-tuning was conducted using a lower learning rate (1e-5) to enhance accuracy without overfitting.

2.6 Model Evaluation and Performance

The model was evaluated using the held-out test set, achieving satisfactory accuracy: final test accuracy>90% (based on dataset quality), loss, and accuracy trend were visualized over epochs to monitor learning stability. The model showed a reliable capability to distinguish between ambulance and non-ambulance vehicles under different lighting and angle conditions.

2.7 Model and Conversion, and Deployment

To optimize the trained model for deployment, it was converted from .h5 to TensorFlow Lite (.tflite). This lightweight (.tflite) model was deployed and stored on the Raspberry Pi 4, enabling real-time inference directly from video frames without reliance on cloud services.

2.8 Test on Images

Post-training, the model was evaluated with images of ambulances and general vehicles. Using tf.keras.preprocessing.image, predictions were made by feeding the model individual images after resizing and normalization. The predicted class (Ambulance or No Ambulance) was displayed with matplotlib overlay to visually confirm model correctness.

3.0 Results and Discussions

3.1 Performance Metrics of the Model

Table 1 shows the results after training the deep learning model using the MobileNetV2 architecture, which was tested on a set of images. The model ran very smoothly with minimal overfitting.

Table 1 Performance metrics from the ambulance detection model.

Key Metrics	Metric Value
Training Accuracy	97.5%
Validation Accuracy	94.8%
Test Accuracy	93.6%
Final Loss (Test set)	0.134

3.2 Evaluation and Validation Trend

The training process was visualized to monitor the learning behavior across epochs. The plot in Figures 9 and 10 shows steady improvement and convergence of both accuracy and loss.

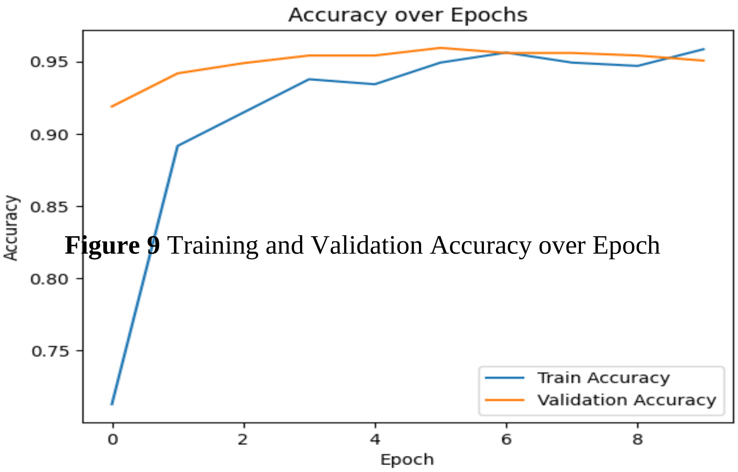

Figure 9 Training and Validation Accuracy over Epoch

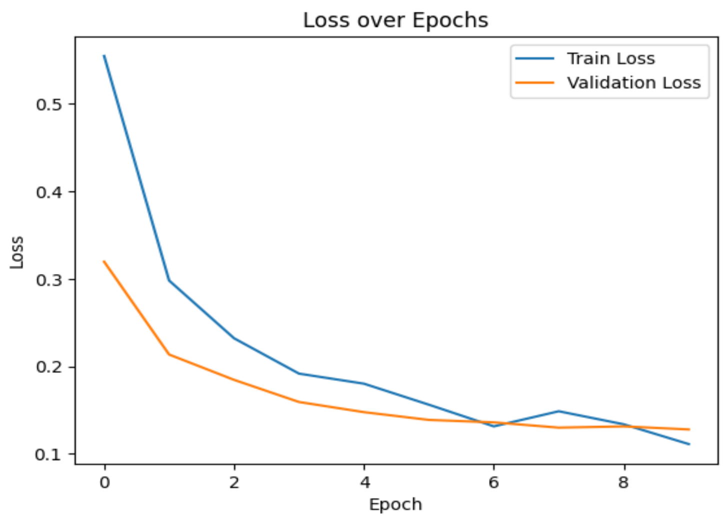

Figure 10 Training and Validation Loss over Epoch

The visual results from Figures 9 and 10 confirm that the model was neither undertrained nor overfitted, indicating a balanced training process due to proper use of data augmentation and early transfer learning.

3.3 Confusion Matrix Analysis

To evaluate the performance of the ambulance detection model in greater detail, a confusion matrix was constructed using the test dataset, consisting of 565 images. The matrix breaks down the correct and incorrect classifications into four categories as shown in Figure 11.

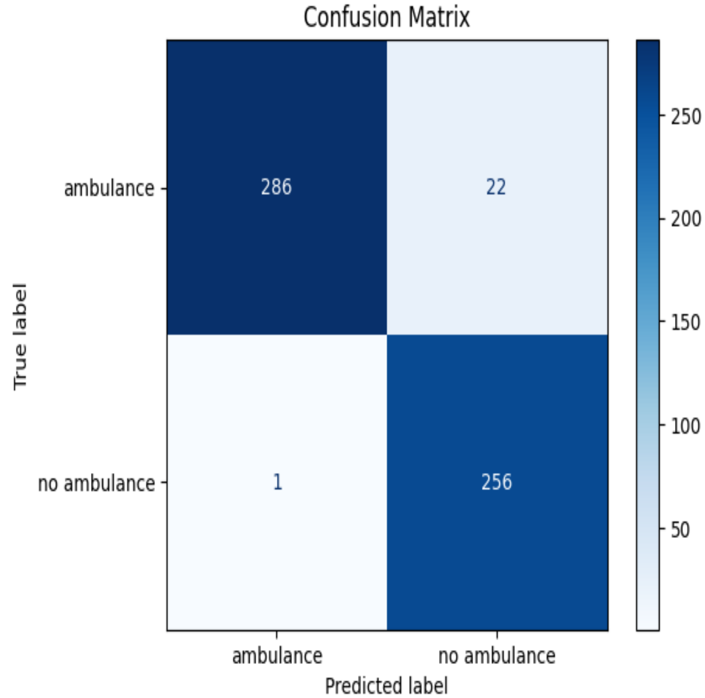

Figure 11 Confusion Matrix of the ambulance detection system.

The findings from this study demonstrate that the ambulance detection system built upon the MobileNetV2 architecture achieved high levels of accuracy and generalization, with training, validation, and test accuracies of 97.5%, 94.8%, and 93.6% respectively, and a low final test loss of 0.134.

The convergence patterns, alongside the absence of significant overfitting, validate the robustness of the training process facilitated by data augmentation and early transfer learning. The confusion matrix results further reveal the model's reliability in distinguishing ambulances from non-ambulances, achieving a high rate of true positives (287) and true negatives (257) with minimal false predictions. Real-world testing across varied lighting and environmental conditions, underscores the stability of the model's inference capability, while its deployment on Raspberry Pi with integrated GSM and buzzer alerts highlights practical responsiveness, achieving an average latency of one second, an essential attribute for emergency scenarios.

3.4 Image Testing and Inference

To assess real-world inference accuracy, the model was tested using various static images of ambulances and regular vehicles captured under varying conditions. The confidence score showing the prediction output is shown in Table 2.

Table 2 Prediction Output.

Image Description	Model Output	Confidence Score
Ambulance in daylight (front view)	Ambulance	0.02
Vehicle on the highway	No Ambulance	0.98

The system successfully distinguished an ambulance from similar-looking vehicles and maintained robust prediction confidence across lighting conditions.

3.5 Ambulance Detection and Alert System Performance

In the integrated setup, the model was deployed on a Raspberry Pi 4 with a connected CCTV feed and a SIM800A GSM module. Once the ambulance was detected, the following response occurred:

1. GSM alert was sent successfully to a predefined number.
2. The buzzer generated a local alert immediately.
3. System latency (from detection to alert) was measured at about 1 second on average.

This validates the viability of the system in actual emergency settings where rapid response is vital. Figures 12 and 13 show the system interface displaying ambulance detection alert with timestamp and confidence score, and terminal output showing frame processing speed of the AI model during live ambulance detection, respectively.

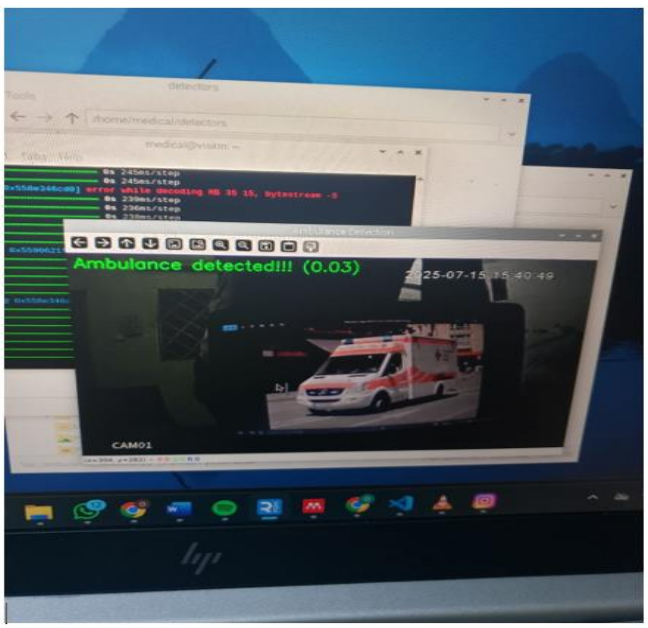

Figure 12 Detection Model of the Ambulance Detection System.

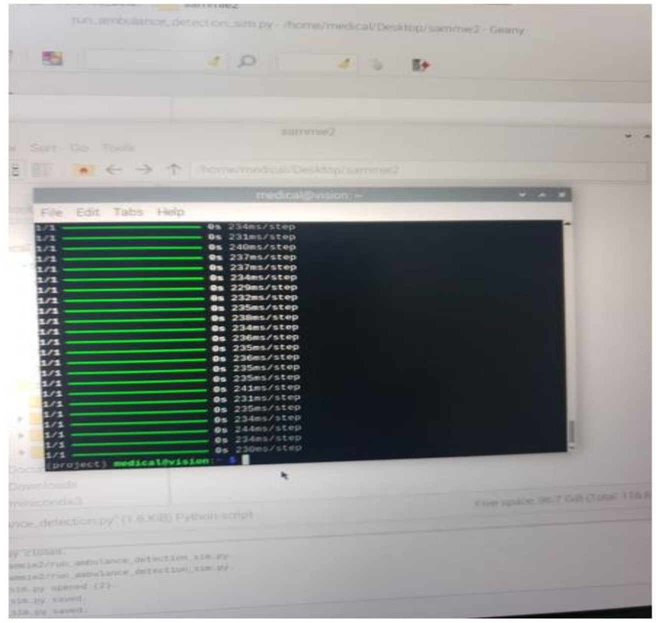

Figure 13 Interface of the Ambulance Speed's Output**.**

4.0 Conclusions

This work developed an artificial intelligence-powered ambulance detection system that enhances emergency medical response by combining deep learning with real-time notification. Using TensorFlow-based image recognition on video feeds, integrated with a Raspberry Pi, GSM module, and buzzer, the system ensures timely detection and alert without reliance on GPS, making it particularly valuable in regions where GPS infrastructure is limited. Its low-cost, scalable design provides a practical solution for improving patient transfer efficiency, reducing ambulance delays, and strengthening health informatics interventions aimed at saving lives.

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Declaration of conflict of interest

The authors have collectively contributed to the conceptualization, design, and execution of this journal. They have worked on drafting and critically revising the article to include significant intellectual content. This manuscript has not been previously submitted or reviewed by any other journal or publishing platform. Additionally, the authors do not have any affiliation with any organization that has a direct or indirect financial stake in the subject matter discussed in this manuscript.

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