Pothole Detection and Classification System for Zambian Roads: A Case Study of Lusaka

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Abstract

Potholes are a significant challenge for Zambia's road infrastructure. Posing a serious threat to vehicle safety and effectiveness of road maintenance. In order to enhance road monitoring, this project aimed to develop a real-time pothole detection and classification system utilising web technologies and artificial intelligence (AI). With the use of convolutional neural networks (CNN) for classification and for detection, the system analyses video footage to locate and map potholes using GPS coordinates. In Lusaka, a large amount of data was gathered for the study using both custom datasets and public sources. The technology offers a web-based interactive platform for dynamic road condition monitoring and delivers an 80% detection accuracy. This invention provides a scalable, automated method to improve road safety and maintenance in Zambia by solving the shortcomings of the country's present human road monitoring procedures.

Acknowledgements

We would like to express our sincere gratitude to our supervisor, Dr. Lighton Phiri, for his ongoing guidance and support throughout this project. We also extend our appreciation to the DataLab Research Group at the University of Zambia for providing invaluable resources and collaborative insights that have significantly contributed to our progress so far.

We also thank all study participants for their contributions, which continue to be essential to the development of this project. The opinions, findings, and conclusions presented here are those of the authors.

Table of Contents

List of Tables

List of Figures

List of Abbreviations

Abbreviation	**Full Form**
AI	Artificial Intelligence
CRISP-DM	Cross-IndustryCross Industry Standard Process for Data Mining
CNN	Convolutional Neural Network
RDA	Road Development Agency
ROSMA	Road Safety Mobile Application
GPS	Global Position System
UNZA	The University of Zambia
YOLO	You Only Look Once

1. Introduction

Zambia's road infrastructure faces significant challenges, with potholes being a major concern that poses significant risks to road safety. Potholes contribute to traffic accidents, vehicle damage, and endanger both passengers and pedestrians [6]. Despite the Roads and Road Traffic Act of 2002 assigning the responsibility of road maintenance to the Highway Authority and local councils, the current approach to monitoring road defects, specifically potholes, is inaccurate and often inefficient. This manual process leads to delays in identifying potholes [7], wasted resources, and increased traffic congestion.

To address these challenges, there is a growing need to automate the detection and classification of potholes using modern technologies. This project aims to develop software tools and services that utilize data mining and artificial intelligence (AI) techniques to enhance road monitoring. By leveraging AI, the system will detect and classify potholes accurately, pinpoint their locations, and improve the overall efficiency of road maintenance.

The main objective is to develop software tools and services that utilise data mining and artificial intelligence (AI) techniques to monitor and automate the detection and classification of potholes on Zambian roads.

2. Related Work

This section contains related works focusing on techniques in pothole detection and classification, highlighting their strengths and limitations, and critically analysing to identify gaps in research for future research. By synthesising existing knowledge, this review aims to contribute to ongoing efforts towards developing efficient solutions for road safety and maintenance.

2.1. Current Monitoring Techniques

The Road and Roads Act of 2002 divided Zambia's roads into six categories; these sections are inter-territorial main roads, territorial main roads, district roads, branch roads, rural roads, and estate roads as per this statute [10]. The responsibility for oversight and monitoring varies across these categories, with interterritorial main roads, territorial main roads, and district roads falling under the jurisdiction of the Road Development Agency. On the other hand, the same legislation specifies that the city and municipal councils monitor branch roads, rural roads, and estate roads [11]. This division shows a comprehensive approach to road management, with different agencies assigned to watch over particular classes of roads to ensure effective governance.

Present road monitoring procedures in Zambia are done manually through regular check-ups of roads and physical inspections conducted by the Road Development Agency and its contractors [16]. As outlined in the Public Road Act of 2002, amended by Act No. 9 of 2022, the Road

Development Agency is mandated to carry out routine and emergency maintenance, improvement, and construction of the road network across the country [12]. This includes conducting feasibility studies, enforcing axle load control, and consulting with property owners and the National Road Fund Agency on costs associated with maintaining estate roads, among other responsibilities [9]. However, the lack of advanced monitoring technologies suggests potential gaps in efficiency in road maintenance.

The current monitoring techniques place a strong emphasis on strengthened supervision by organisations like the Road Development Agency (RDA), ensuring quality road infrastructure through effective management [16]. Output performance-based road contracts like the one seen in the Chaiwa central road plan provide a structured framework with clear expectations for contractors. There are still issues to be resolved, such as reducing shoddy work and addressing community concerns as demonstrated by the Chaiwa residents [16].

Manual regular check-ups and visual inspections are among the current monitoring techniques for road maintenance, where inspectors assess defects like potholes and cracks. This process, however, is time-consuming, resource-intensive, and can vary in accuracy due to human judgement [9]. Harsh weather conditions further complicate inspections, making defect detection challenging. Though details on highway authorities' monitoring methods are limited, available information suggests they mostly use manual approaches. These challenges highlight the need for technology-driven solutions to improve the efficiency and consistency of road maintenance.

On the other hand, in the United Kingdom, potholes and other road defects are monitored using a system called SEE.SENSE [13]. This technology maps the road surface condition quickly and precisely throughout large city regions, allowing local authorities to prioritise infrastructure investment in problem areas. With the use of specialised sensors and proprietary technologies, the SEE.SENSE can produce vast amounts of hitherto unobservable data in almost real-time over the entire city [13]. The sensors are able to pick up minute changes in the state of the road surface by monitoring the cyclist's environment over 800 times per second. Following that, a grading system is used to aggregate and visualise the data in order to identify road surface quality issues in the city.

2.2. Existing Detection and Classification Systems

2.2.1. Detection System

In Abhishek Kumar's proposed system, transfer learning is employed to detect potholes in real-time photos and video clips captured by the camera. By leveraging pretrained models and performing fine-tuning on the dataset, transfer learning can reduce the time required for model training [3]. The system uses an object detection API based on the tensor flow model to identify potholes, allowing it to detect objects in images. After detecting the pothole, an Android app notifies the driver, enhancing road safety [3].

Advanced convolutional neural network models like F-RCNN and Inception v2 are used for accurate pothole detection. However, Chemikala Saisree et al mentioned that it's important to note that the RCNN-based models take more time to forecast. Additionally, models trained on roads from other countries may not achieve optimal performance on roads in a specific country due to differing damage conditions [15].

Poonam Kushwaha's proposed study involves a system that combines a user-friendly graphical interface with a deep learning CNN model and basic image processing techniques to determine the state of roads, particularly potholes. The graphical user interface built with the PyQT module allows for users and administrators to interact with the system. User details are stored in the MySQL database for secure access to the application. Image processing techniques enhance the quality of images, and the CNN model accurately predicts potholes. Subsequently, the aim is to evaluate road conditions by analysing input images and automatically notifying the government for necessary road maintenance [15].

However, the effectiveness of the system may be contingent upon factors like the robustness of image preprocessing and the reliability of automatic notifications.

2.2.2. Classification System

Once potholes are detected, they need to be classified to characterise their severity and type. Ahmad et al, developed a classification model that uses CNN to classify pavement images [1]. The model first classifies pavement images to find out images that contain potholes.It later classifies whether an image consists of a pothole or normal. Pavement images are further classified into three categories, namely, small potholes , large potholes and normal. Pavement images are then taken from a waist height of 3.5 feet using MobileNet v2, which has an accuracy of 98% for detecting potholes [1].

On the contrary, Maeda et al. proposed a system for detecting potholes utilising computer vision. While the focus is on detection, authors emphasised the use of object detection algorithms to predict bounding boxes of areas containing rod damage, which implies a classification aspect to differentiate between types of road defects [5].

Hiermath’s proposed system for pothole detection using Yolo aims to classify road anomalies such as potholes based on unique characteristics [4].

2.3. Automated Road Monitoring Tools

2.3.1. ROSMA

The Road Safety Mobile Application (ROSMA) was developed by Zambia’s Highway Authority the Road Development Agency (RDA) in an effort to reduce road traffic accidents [9]. This mobile application utilises a combination of real-time updates to inform drivers of upcoming road signs, hazards, speed limits, potential and user-reported data [9]. ROSMA also allows users to report road defects and vandalism of road signs, providing data to road maintenance teams [9]. This shows how mobile technology can be used to improve road safety through user engagements and real-time data collection.

However, the app's effectiveness is limited. Firstly, the requirement for users to pay a subscription before using the app hinders large-scale development, potentially leaving out the low income drivers who could gain the most. Additionally, the lack of images for reported defects undermines the app's effectiveness in data collection. Lastly, effectively reporting for potholes is not realistic as people will have to stop and capture the potholes and upload the images on the app, this is hard, especially for super highways.

2.3.2. Smart Patrol Pothole

The Smart Patrol Pothole system utilises smartphone-based sensing and crowdsourcing techniques to detect road surfacing conditions, particularly focusing on potholes and bumps.It leverages the inherent sensors in smartphones, such as accelerometers and GPS, to monitor road conditions [14]. This system employs dynamic Time warping (DTW) to improve classification accuracy. DTW adapts to time deformations and varying speeds in data, making it suitable for resource-constrained devices like smartphones. Road data may be concurrently collected by smartphones, which are widely used and include many sensors, including GPS, accelerometers, magnetometers, and gyroscopes. More specifically, when a car hits a bump or pothole, the accelerometer sensor notices different patterns [14].

The main challenge is in identifying a situation with shifting velocity, car state, and road kinds. It might not be able to train the models to cover all the circumstances with the current methods (machine learning and threshold).

Pothole smart patrol systems have benefits but drawbacks. Data accuracy has to be verified because it might be unreliable. Adoption of sensor technologies could be sluggish, and pothole severity might not be completely captured in sensor data. These technologies could not function effectively in places where smartphone or internet usage is restricted, which might exacerbate already existing infrastructure maintenance shortages. Effectively managing enormous volumes of pothole data and setting repair priorities is crucial [14]. Important factors to take into account include the expense of implementing and maintaining this technology as well as privacy issues with user location data.

2.3.3. Patrol Pothole App

The major goal of the pothole-patrol-app is to enable users to take pictures of potholes and their locations, upload those images to a server, and have the authorities take appropriate action [8]. The user of the Android app can add photographs from the gallery or camera after registering and logging in to a server database. Additionally, the software connects the phone's location to the taken image by uploading it to a database [8]. The app has an integrated map that allows users to view all of the places with potholes that other users have uploaded. The software also has a beta function that uses the phone's accelerometer to detect potholes when the vehicle passes them and immediately uploads that data [8].

Challenges of this app, according to the reviews of users who have interacted with it is the image process has a lot of challenges, which include some important information which may be useful in pothole detection (such as location). They have to stop to capture potholes, which are dangerous. There is a need to create an automated system that will be used to take videos as they monitor roads by the highway authorities.

2.4. Exploring the Consequence of Potholes

Potholes pose serious safety risks to road users, particularly vehicles, passengers, and pedestrians. For example, the March 2022 Ministerial Statement on "Rise in the Number of Road Traffic Crashes and Measures the Government is Putting in Place to Curb Road Crashes." reported on a big bus travelling towards Lusaka from Nakonde hit a pothole, leading to the driver losing control of the bus. Sadly, seven people died and thirty-three others sustained injuries. The Ministerial Statement further identified the poor state of roads as the cause, which is characterised by potholes [6].

3. Methodology

3.1. Current Monitoring Techniques

To address the challenges associated with the current road monitoring practices , we conducted site visits to the Road Development Agency and Lusaka city council to determine specific departments that are actively involved in road monitoring. With the qualitative approach, we used interviews for the collection of data.

Participant recruitments , data collection methods, data transcription , and data analysis

3.1.1. Lusaka City Council

3.1.1.1. Participant Recruitment

The interview participants were purposely recruited based on their expertise and involvement in road monitoring within Lusaka city council. The main interviewee was Mr.Kanneth Futi, a civil engineer in the road maintenance and drainage engineering department . His key responsibilities include monitoring road safety , installing and maintaining road furniture, setting speed limits , and patching potholes. The key interviewer was Harris Shikapande , who was tasked with exploring the road monitoring process and the challenges faced by the Lusaka city council.

3.1.1.2. Data Collection Method

The data collection method employed in the study was a semi structured interview that was conducted on August 28th, 2024 , at the Civic Center in Lusaka. It consisted of a series of open-ended questions which allowed Mr.Kanneth Futi the interviewee, to elaborate on his role in road monitoring and, the day to day operations , the methods and tools employed , the challenges they face. The interview was recorded using mobile phones and manually through notes to capture key information from Mr.Futi's responses.

3.1.1.3. Data Transcription

The interview transcript contained verbatim dialogue between the interviewer Mr Harris Shikapande, and the interviewee, Mr.Kanneth Futi. Thematic analysis of the transcribed data revealed several key themes. Lusaka City Council primarily relies on manual, visual inspections for road monitoring, with no modern technological tools in place. Resource limitations, such as insufficient vehicles, fuel shortages, and the absence of a proper digital system for tracking road conditions, present significant challenges. Additionally, the council collaborates with subcontracted companies to monitor roads in designated zones, highlighting the cooperative nature of road maintenance efforts. Despite these challenges, there is openness to adopting new technologies, such as DashCams with automatic detection systems, indicating a willingness to improve current practices and enhance efficiency. The data was transcribed using Google Docs, ensuring accurate and efficient capture of the interview content.

3.1.2. Road Development Agency

3.1.2.1. Participant Recruitment

Participants for this study were recruited from the Road Development Agency (RDA). The interview involved key personnel directly responsible for road monitoring and maintenance: Gaston Meleki and Kangoma Immanuel from the periodic maintenance department, and Lubuto Siame, an engineer from the Network Planning department. These participants were selected purposely based on their experience and roles in overseeing and executing the road monitoring activities across different regions.

3.1.2.2. Data Collection Method

Data was collected through a semi-structured interview conducted in person at the RDA headquarters on August 29, 2024. The open-ended questions allowed for a thorough exploration of the RDA's road monitoring techniques, challenges, and potential technological improvements. The flexible interview structure provided insights into both current practices and areas for improvement in road monitoring.

3.1.2.3. Data Transcription

The interview was transcribed word for word from an audio recording that was recorded using a mobile phone to ensure a precise and accurate reflection of the responses. Key exchanges between the interviewer, Harris Shikapande, and the interviewees were documented. Non-verbal cues were excluded to focus on the substantive content of the discussion, ensuring clarity in the transcribed data

3.2. Model Development

Data gathering, data preparation, model training, validation, and evaluation were all crucial stages in the creation of the AI-based classification and detection model for pothole monitoring.

3.2.1 Gathering and Preparing Data

The photos utilised in this study were gathered from two sources: a custom dataset made from video footage of potholes in Lusaka and publicly accessible datasets from Kaggle. The Python library FFmpeg was used to extract frames from video footage in order to create the custom dataset. Roboflow was used to label the retrieved images, which were then divided into two classes: pothole and no pothole

Figure 1: shows Normal Road

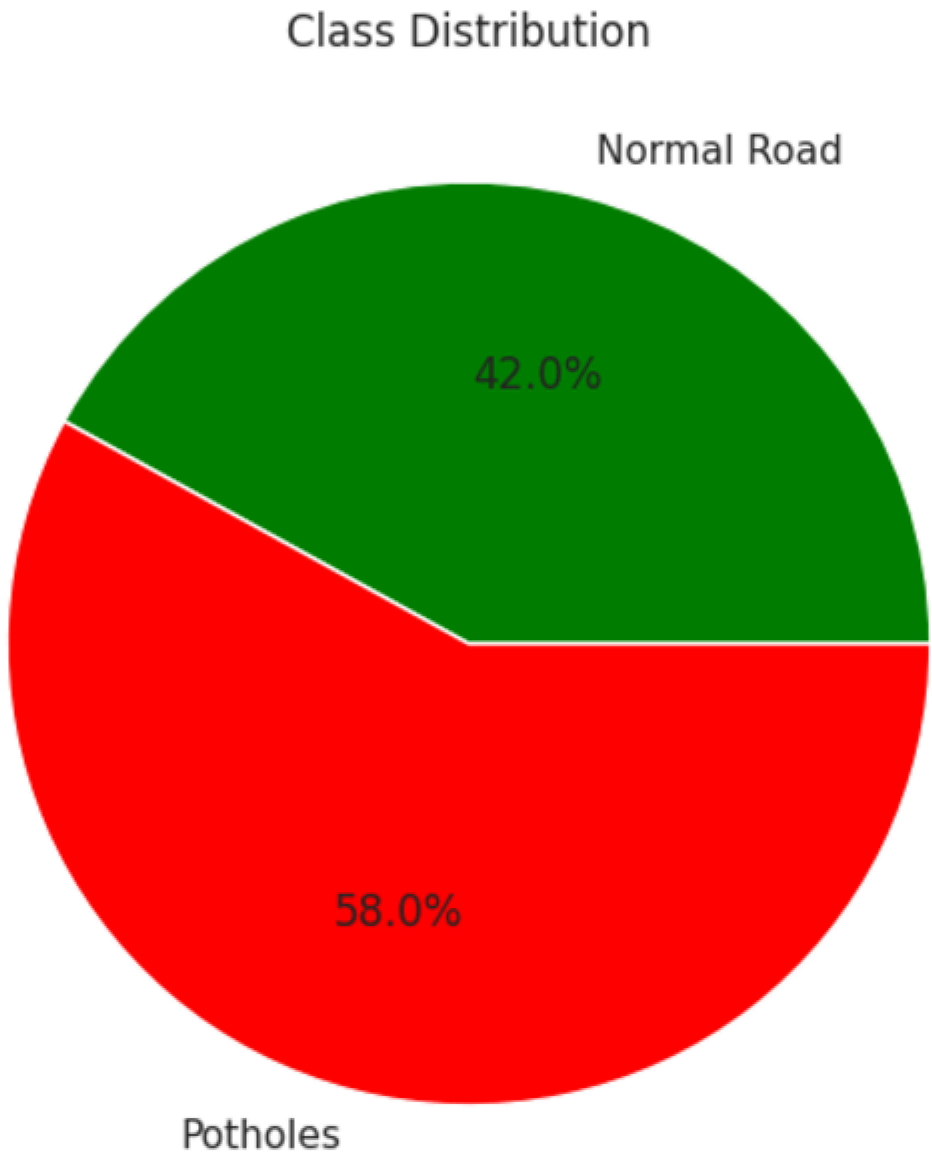

Figure 2: shows class class distribution

3.2.2 Training of Models

For binary classification, a Convolutional Neural Network (CNN) was designed and implemented using Keras. The model was specifically tailored for detecting potholes in images, with the following architectural components:

- Input Layer: The input layer is configured to accept images with a resolution of 224 x 224 pixels and three RGB colour channels.

- Convolutional Layers: The model utilises two convolutional layers with 3x3 kernels to extract local features from the input images. Each convolutional layer is followed by a max-pooling layer, which reduces the spatial dimensions and minimises overfitting.

- Fully Connected Layers: After the convolutional layers, the feature maps are flattened into a one-dimensional vector.
  The flattened data is passed through a dense layer with a dropout layer applied to prevent overfitting by randomly deactivating some neurons during training.

- Output Layer: The final layer uses a sigmoid activation function for binary classification, producing a probability score indicating the presence or absence of potholes in an image.

Training Process, the model was trained for 10 epochs using a labelled dataset of pothole and non-pothole images.

Evaluation Metrics, during training, loss and accuracy metrics were monitored and plotted to evaluate the model's performance over epochs.

- Confusion MatrixA confusion matrix was generated to evaluate the model's classification performance, providing a detailed breakdown of true positives, true negatives, false positives, and false negatives.
- Classification ReportA classification report was generated, offering insights into precision, recall, F1-score, and overall accuracy. These metrics highlighted the model's effectiveness in distinguishing between the two classes.

3.3. Web Mapping Tool

The web-based monitoring application was developed by combining several frameworks and technologies to allow for the mapping and real-time detection of potholes using camera footage. To guarantee smooth data processing and visualisation across client and server components, the system was built with a modular architecture. The technologies listed below were used:
Frontend (Leaflet React)
React was used in the development of the client-side interface to provide a responsive and dynamic user experience. Map tiles and overlay location markers were rendered using the Leaflet package, making it possible to visually represent the locations of identified potholes in an approachable way.

Server (Express with Node.js)

Node.js and Express were used to construct the server-side functionality, which made it easier for the client and backend to handle requests effectively.

This architecture ensured efficient data processing and optimised communication by supporting asynchronous operations and routing.
Backend (supporting libraries in a flask)

Flask was used to implement the backend, and it carried out the following essential tasks:

Frame Extraction: FFmpeg was used to extract frames from uploaded video files, allowing snapshots to be taken at predetermined intervals for further study.
Optical Character Recognition (OCR): Pytesseract was used to extract text from video frames, with a particular emphasis on GPS information that was contained.
Data Parsing: To precisely collect GPS coordinates and parse the recovered text, regular expressions (Regex) were used. To facilitate integration with the mapping interface, these coordinates were saved in JSON format.

AI Model Integration: To make pothole identification easier, a CNN (Convolutional Neural Network) AI model was incorporated into the backend. After processing the retrieved frames, the model detected and categorised potholes according to their level of severity. Locations and classifications of the resultant data were sent to the server for display.

4. Results and Discussion

4.1. Road Monitoring in Zambia

4.1.1 Lusaka City Council

The Lusaka City Council, through its team of engineers, oversees the monitoring and maintenance of roads within the city. Their process involves manual inspections by engineers and technicians, often constrained by limited resources and transportation.

4.1.1.1 Monitoring Process

Engineers at the Lusaka City Council conduct regular visual inspections to assess road conditions. This process is often carried out once a week, depending on the availability of vehicles and resources. Due to transport and fuel challenges, engineers sometimes rely on contractors or community reports to identify areas requiring immediate attention.

4.1.1.2 Techniques Used

Unlike the RDA, the Lusaka City Council does not have advanced equipment for road monitoring. Engineers and technicians visit road sites manually, documenting defects using record books. The data collected is stored in laptops by engineers on-site, though there is no centralised information system for long-term storage. This lack of digital infrastructure presents challenges in retaining critical data.

4.1.1.3 Challenges in Road Monitoring

The biggest challenges engineers face at the Lusaka City Council are the lack of sufficient vehicles and fuel, which limit their ability to inspect roads consistently. Furthermore, the absence of an electronic record-keeping system makes it difficult to track maintenance efforts and historical data. When information is lost due to hardware issues, such as a stolen or damaged laptop, it is difficult to recover the recorded data, hindering future planning and road repairs.

4.1.1.4 Community Involvement and Contractors

The Lusaka City Council works closely with community members and contractors in their road maintenance efforts. Engineers receive reports from the public, which can include images and videos of road defects. Additionally, the council employs performance contractors responsible for maintaining and monitoring roads in designated zones.

4.1.2 Road Development Agency (RDA)

The Road Development Agency, led by teams of engineers, is responsible for coordinating road maintenance activities, including both routine and periodic maintenance. An interview with key representatives provided insights into the road monitoring processes, techniques, and challenges faced by the agency.

4.1.2.1 Monitoring Process

The road monitoring process at RDA involves multiple engineers working across various departments, including inventory and planning. Surveys are conducted using specialised vehicles equipped with GPS, cameras, and other tools to capture road conditions. Engineers also conduct visual inspections as part of the regular maintenance strategy. The agency performs monthly inspections on selected core roads to maintain safety and identify defects.

4.1.2.2 Techniques Used

Engineers at the RDA use road surface survey vehicles mounted with equipment to measure road defects, such as potholes, lane width, and road roughness. These vehicles operate at specific speeds during surveys, allowing for accurate data collection, including GPS coordinates for defect locations. The information is stored electronically in the Project Management System (PMS), which engineers refer to during future maintenance operations.

Figure 3: showcasing Road surface survey vehicle-mounted camera and GPS mapping antenna

Figure 4: showcasing Road surface survey vehicle pavement camera

4.1.2.3 Challenges in Road Monitoring

The RDA's engineers face challenges such as inadequate funding and resource limitations, which delay the timely repair of road defects. Another challenge is the reliance on post-survey analysis, as the monitoring vehicles do not automatically detect defects in real-time. Engineers also deal with equipment fragility and occasional server downtime, further complicating the road monitoring process.

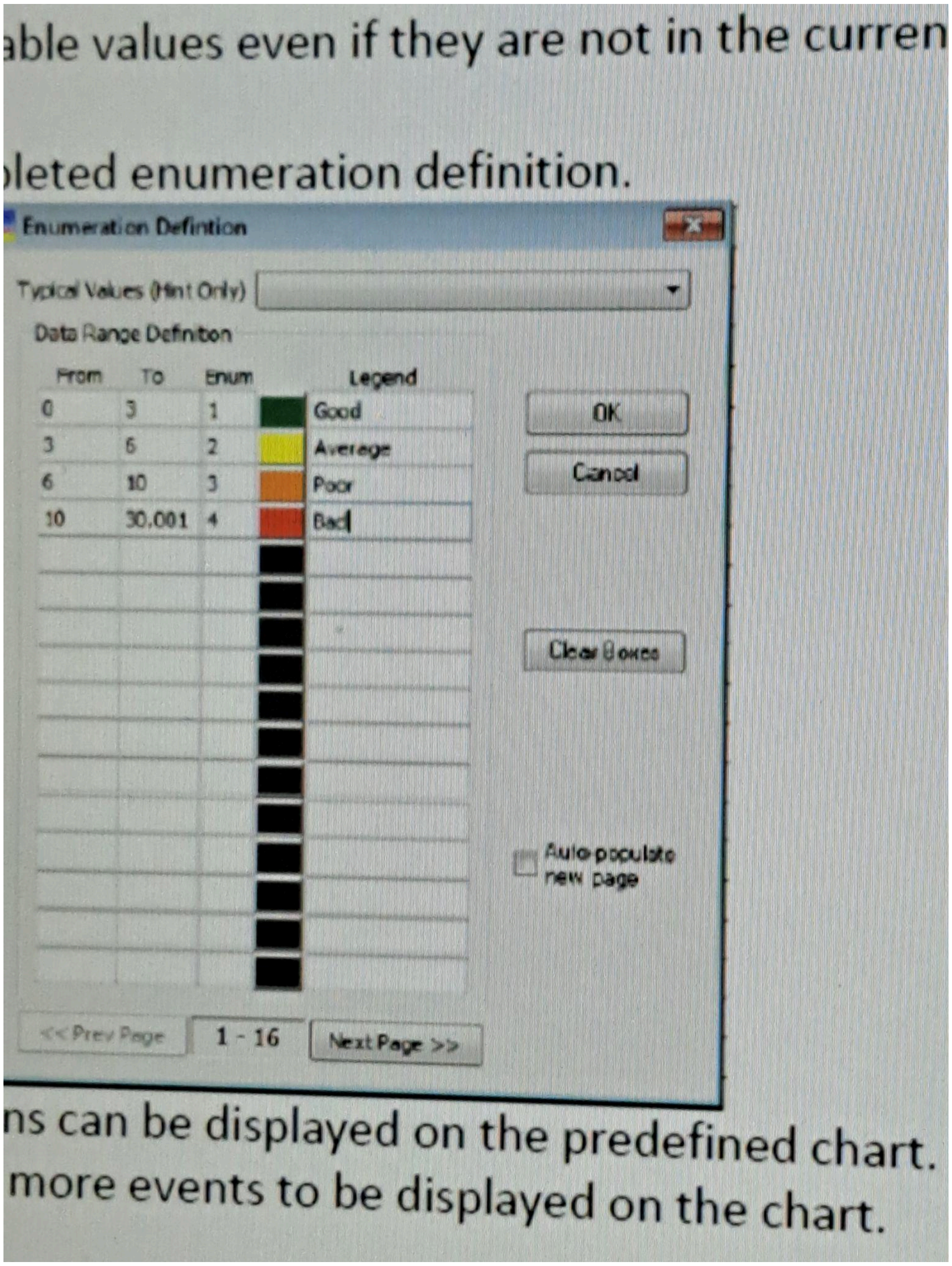

Figure 5: showing post-survey analysis phase in data view

4.2. Model Development: Model Performance Metrics

The CNN model’s performance was evaluated on the test dataset using multiple metrics to assess its ability to accurately classify pothole images.

4.2.1 Base Model Performance

The base model Compact Convolutional Transformer (CCT) was tested alongside other CNN models, with their classification reports summarised. It achieved moderate accuracy and served as a valuable baseline for performance comparison.

Confusion Matrix

The confusion matrix below provides insight into models performance, showing the counts of true positives, true negatives, false positives, and false negatives:

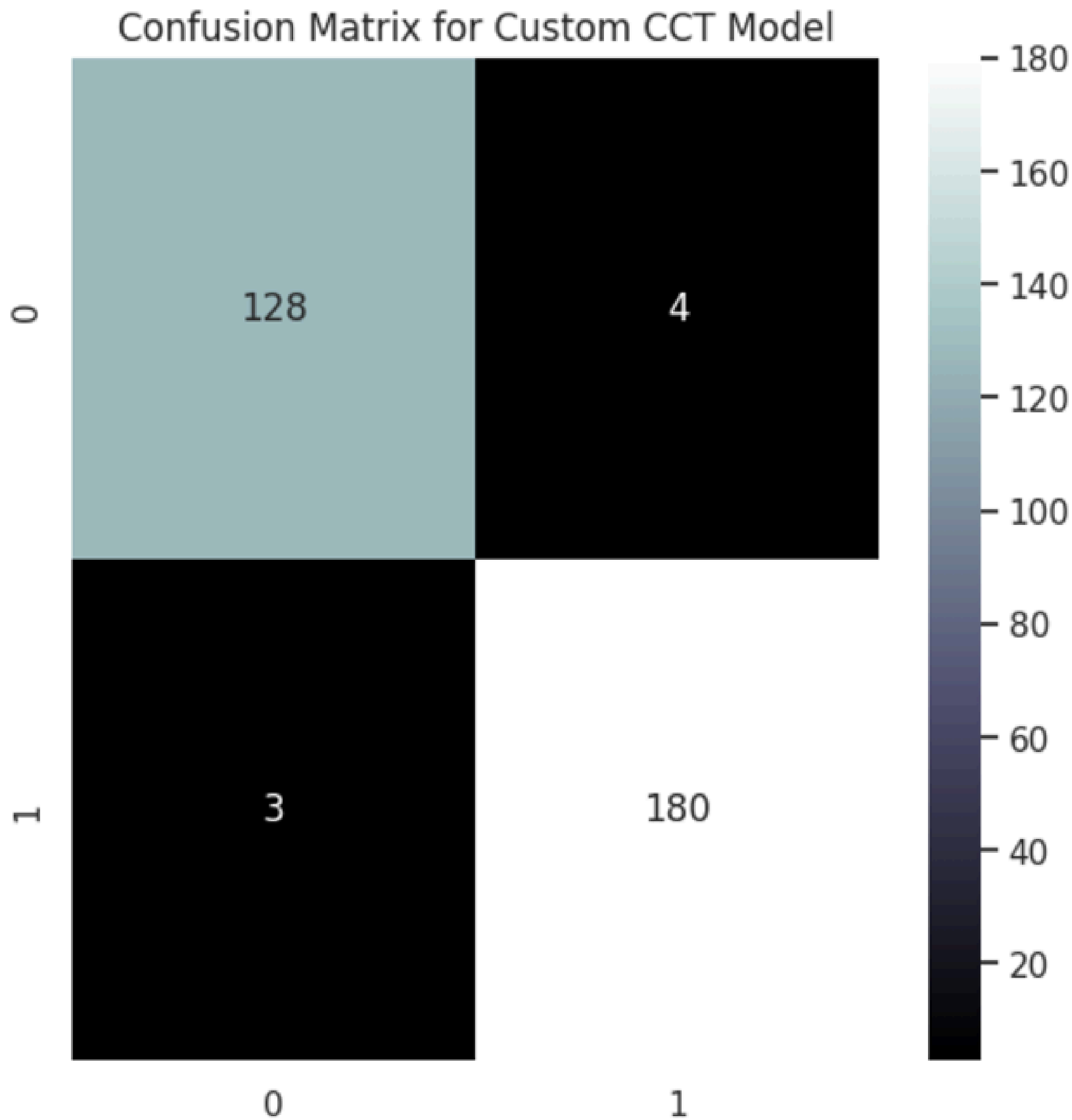

Figure 6: showing confusion matrix for custom CCT Model

ROC Curve

An overall representation of the trade-off between the true positive rate (TPR) and false positive rate (FPR) is offered by the receiver operating characteristic (ROC) curve. With an Area under the Curve (AUC) score of 1.0, the model with flawless prediction capabilities performs exceptionally well. In this instance, an AUC of 1.0 was attained during testing, and the ROC curve validates great discriminating between the two classes.

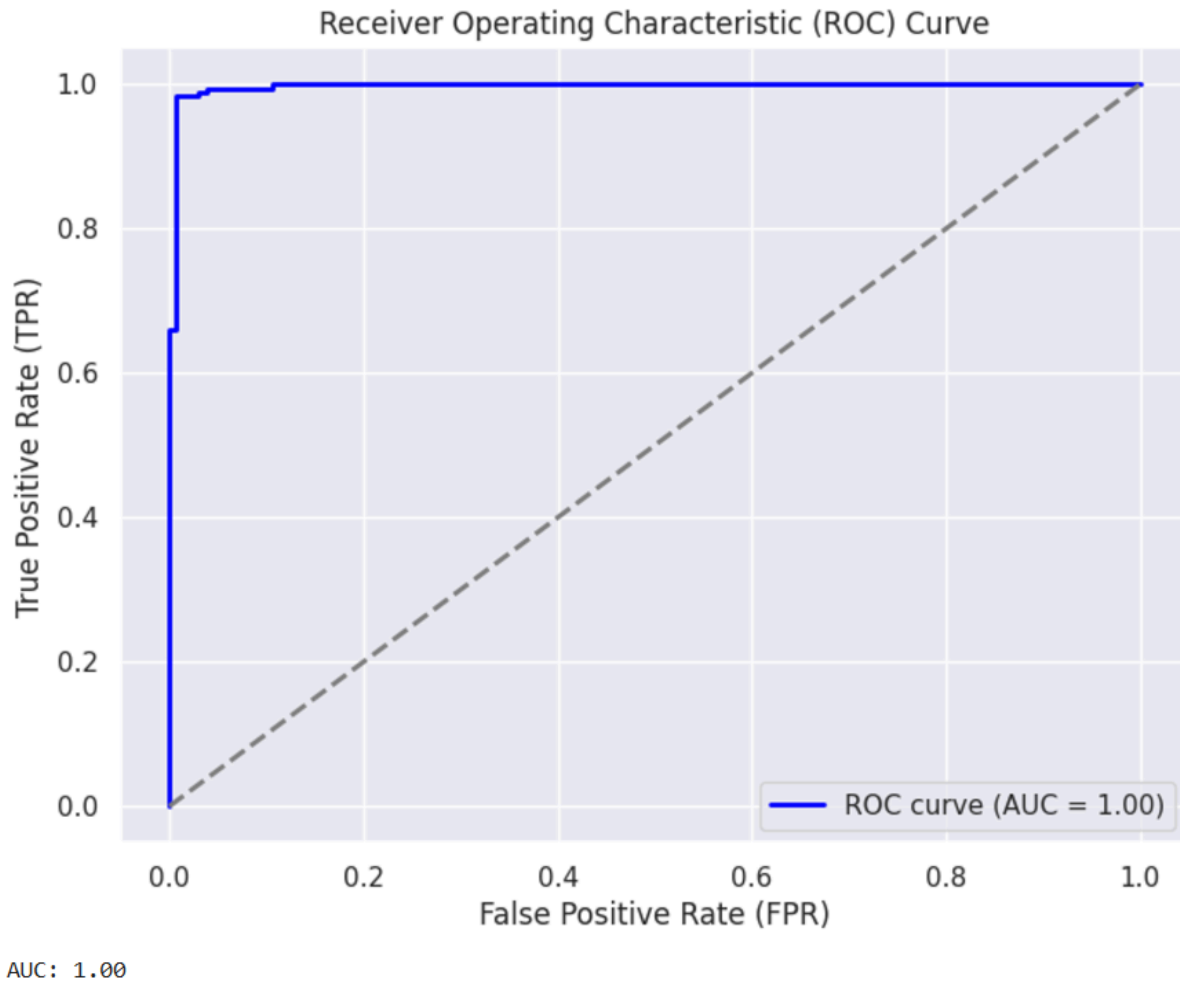

Figure 7: shows (ROC) Curve

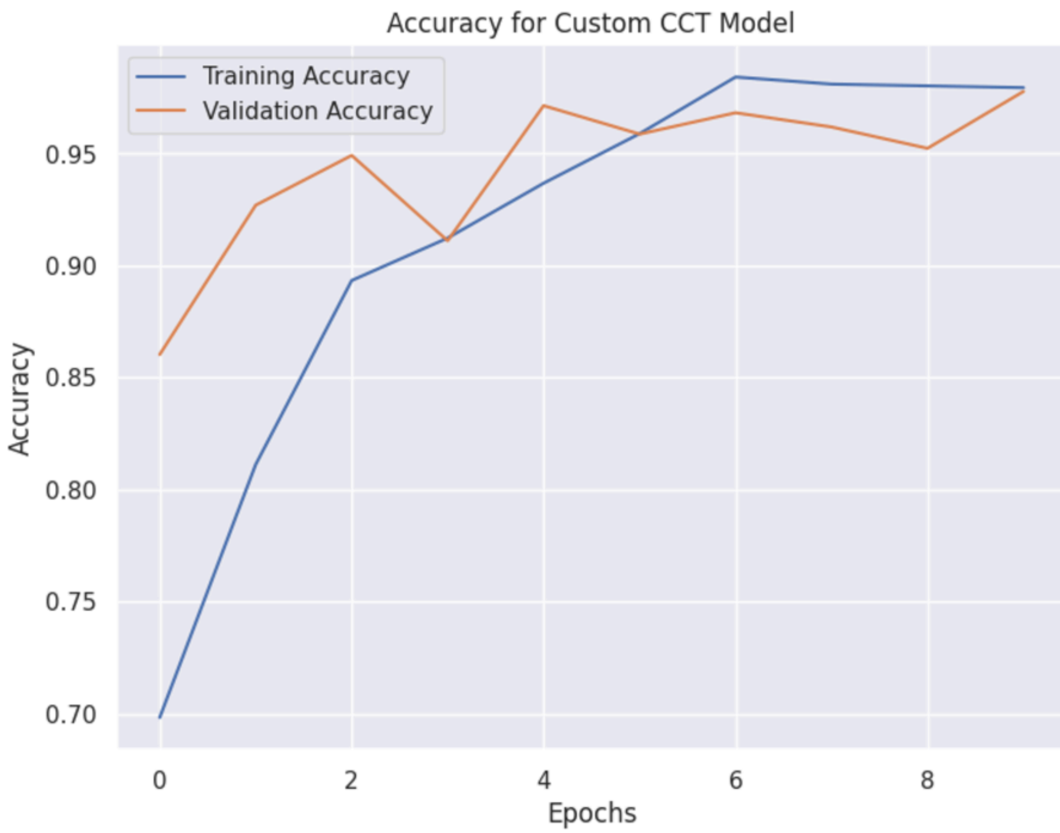

Figure 8: showing accuracy for Custom CCT Model

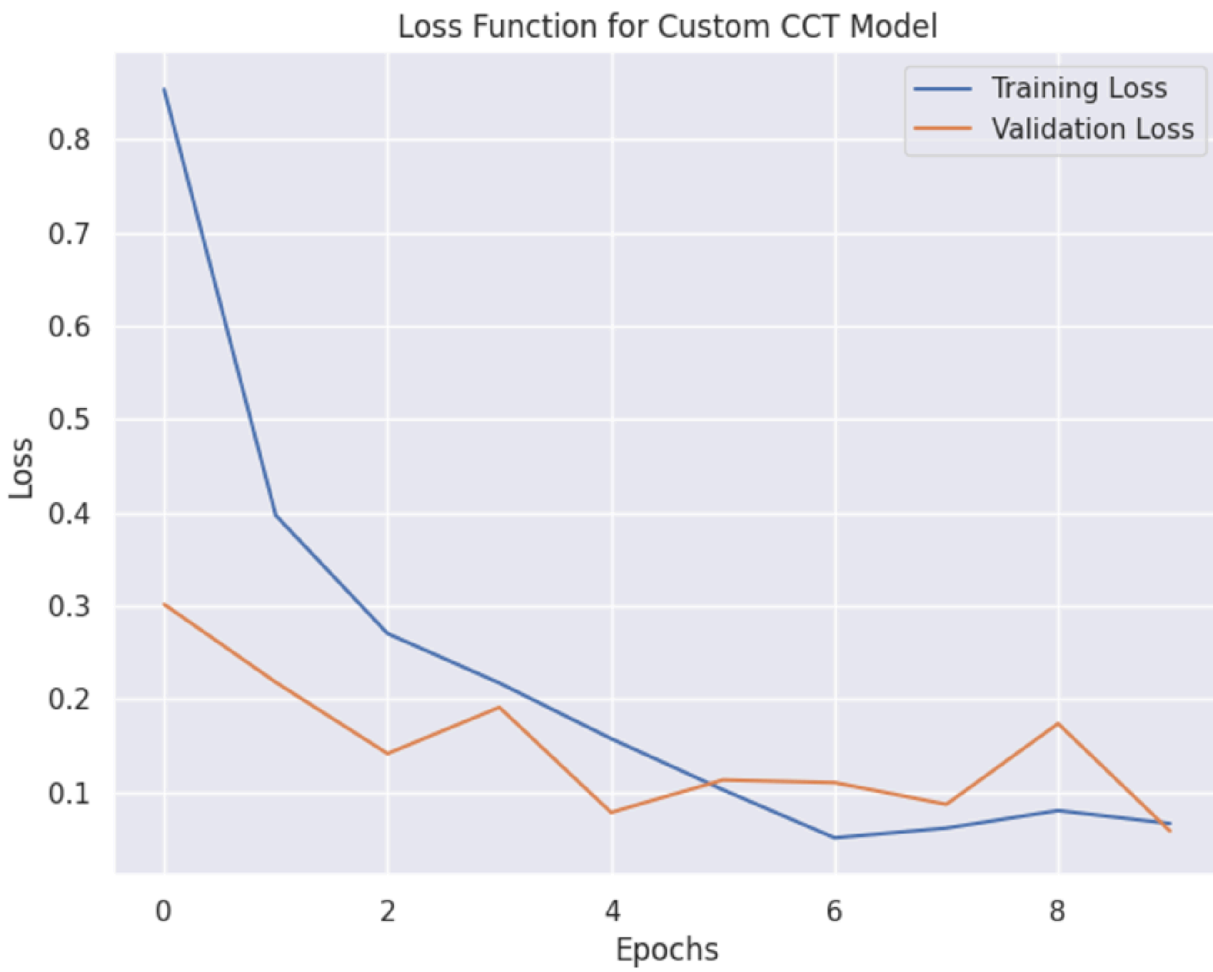

Figure 9: showcases loss function for custom CCT Model

4.2.2 Other CNN ModelC Performance

Below are the classification reports for the performance of the individual models, and confusion matrix.

1. VGG16

Classification Report for VGG16:

	precision	recall	f1-score	support
No_Pothole	0.47	0.47	0.47	132
Pothole	0.62	0.61	0.61	183
accuracy			0.55	315
macro avg	0.54	0.54	0.54	315
weighted avg	0.55	0.55	0.55	315

Accuracy: 97.78%

Figure 10: shows classification report for VGG16

Confusion Matrix

The confusion matrix below provides insight into models performance, showing the counts of true positives, true negatives, false positives, and false negatives:

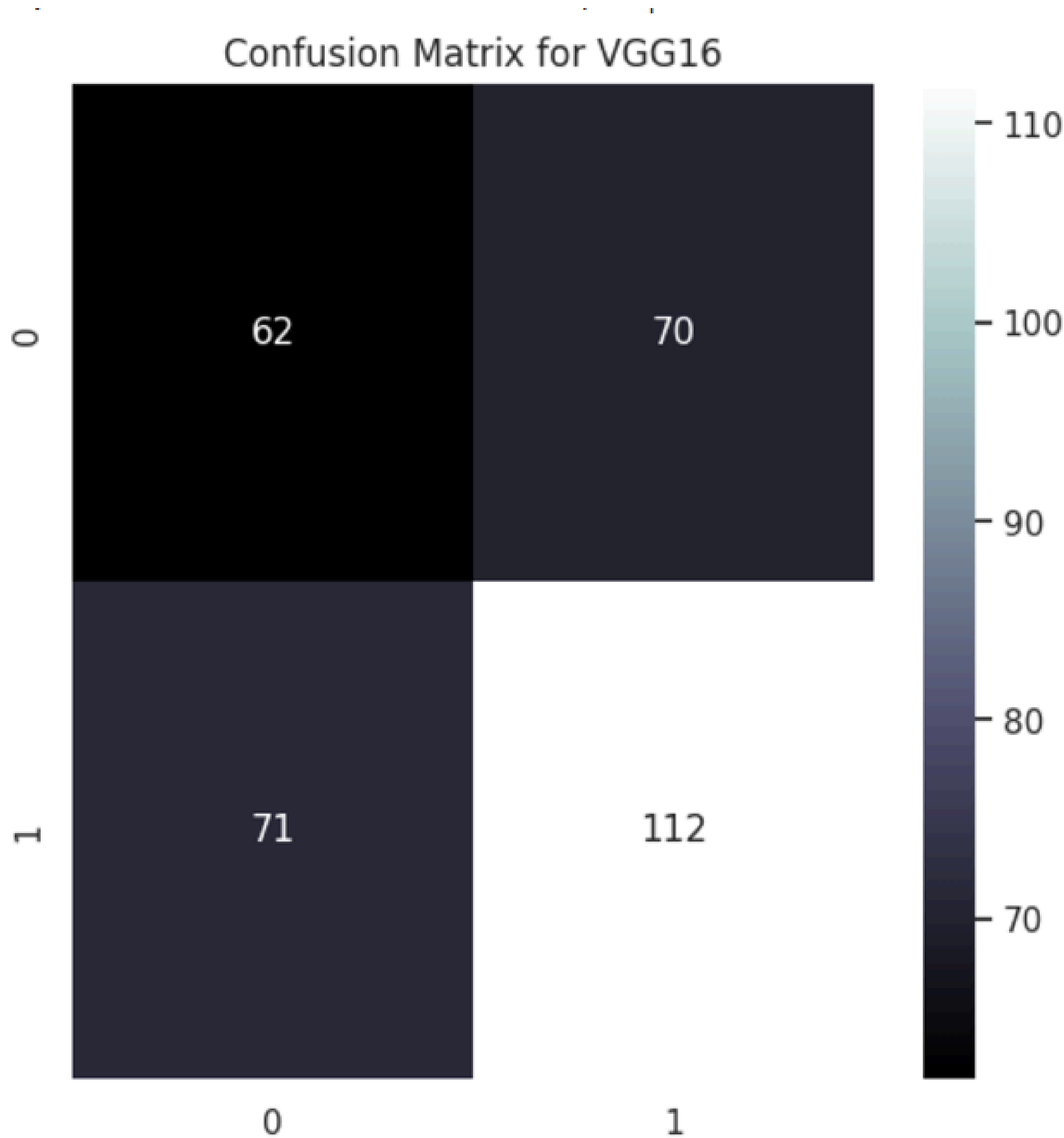

Figure 11: shows confusion matrix for VGG16

2. ResNet50

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Classification Report for ResNet50:
              precision    recall  f1-score   support

  No_Pothole       0.41      0.11      0.17       132
     Pothole       0.58      0.89      0.70       183

    accuracy                           0.56       315
   macro avg       0.50      0.50      0.44       315
weighted avg       0.51      0.56      0.48       315

Accuracy: 68.89%
```

Figure 12: showing classification report for ResNet50

Confusion Matrix

The confusion matrix below provides insight into models performance, showing the counts of true positives, true negatives, false positives, and false negatives:

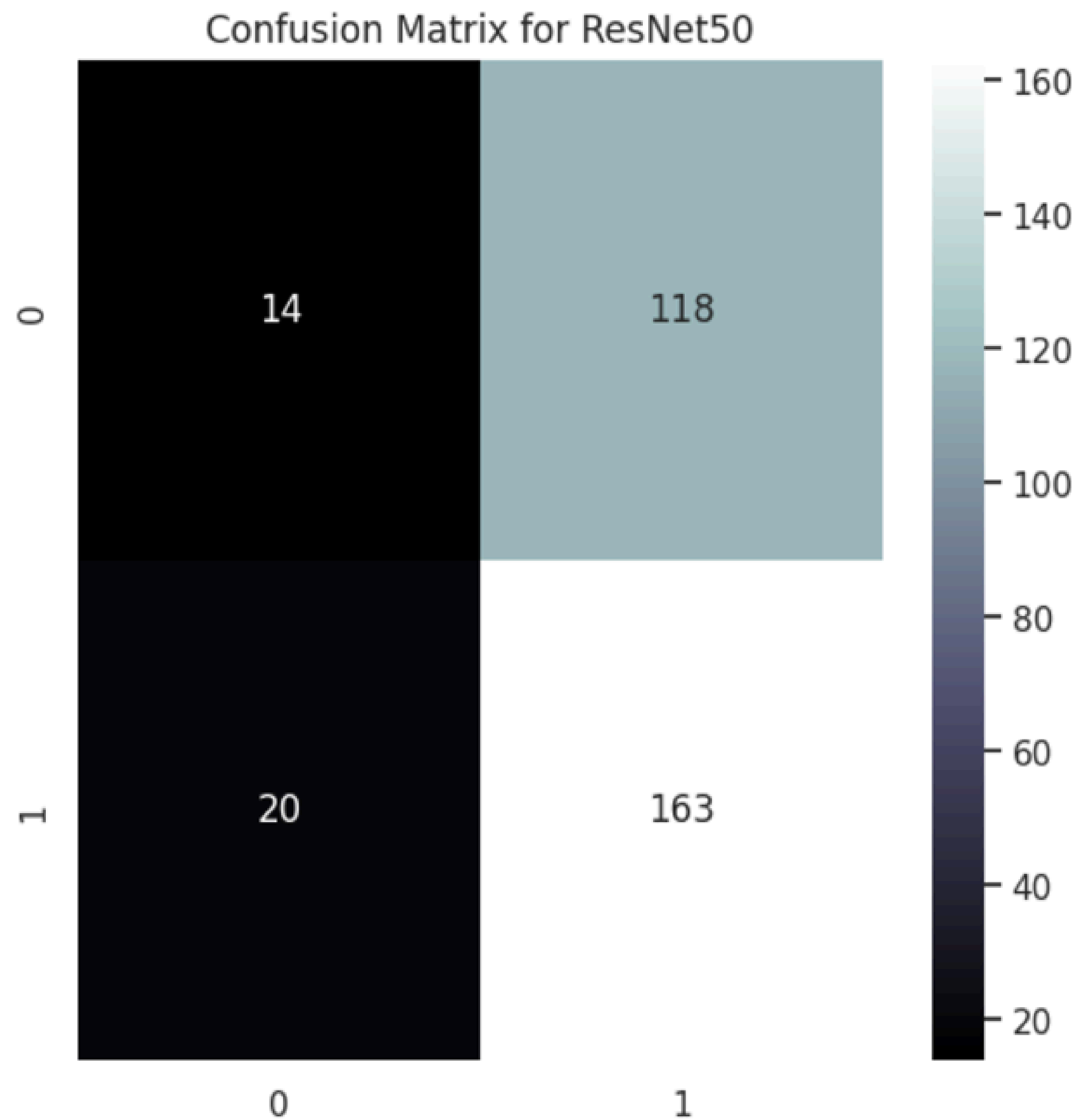

Figure 13: showing confusion matrix for ResNet50

3. InceptionV3

Classification Report for InceptionV3:

	precision	recall	f1-score	support
No_Pothole	0.42	0.42	0.42	132
Pothole	0.58	0.58	0.58	183
accuracy			0.51	315
macro avg	0.50	0.50	0.50	315
weighted avg	0.51	0.51	0.51	315

Figure 14: shows classification results for incetionV3

Confusion Matrix

The confusion matrix below provides insight into models performance, showing the counts of true positives, true negatives, false positives, and false negatives:

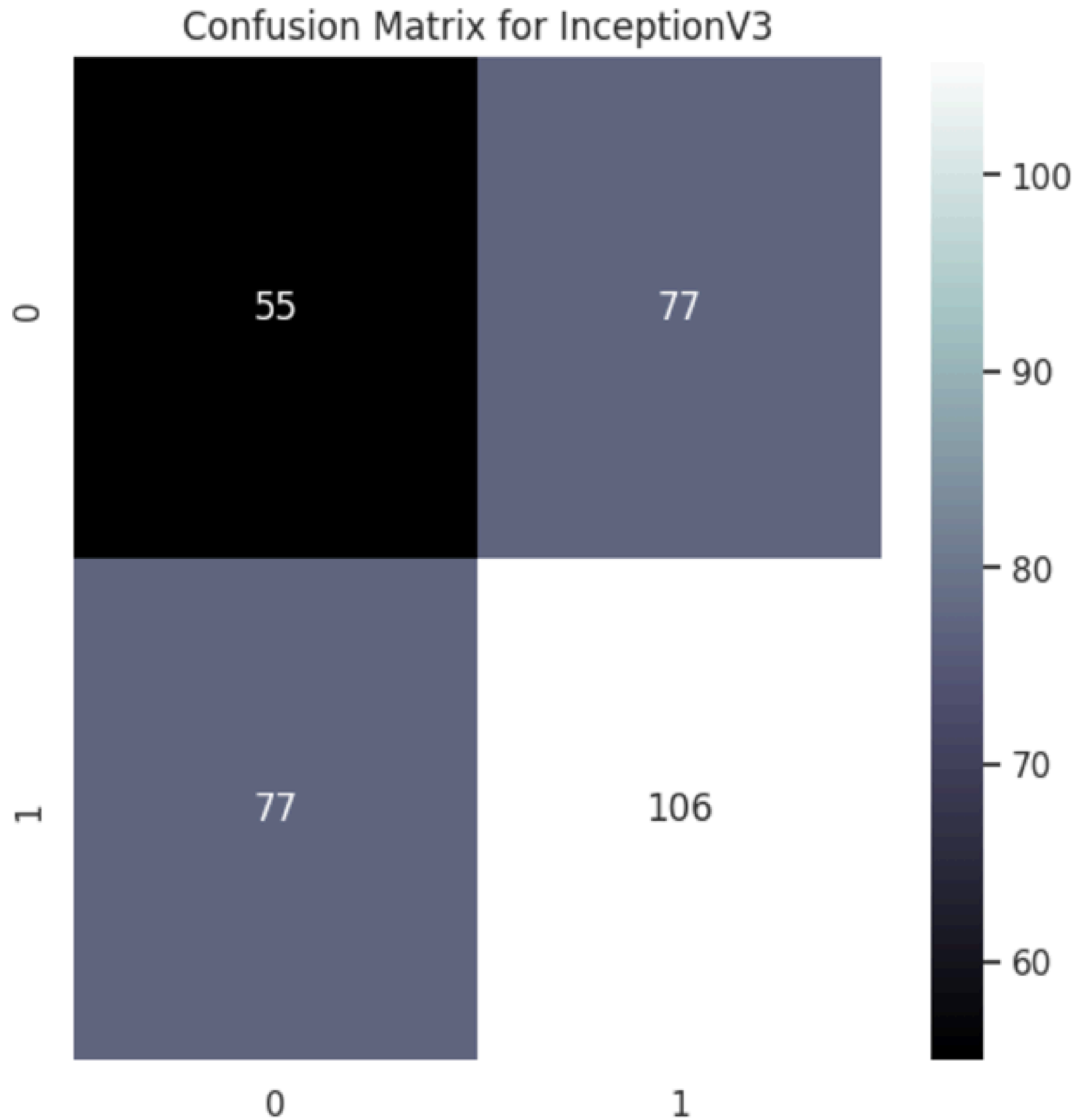

Figure 15: showcases confusion matrix for InceptionV3

4. EfficientNetB0

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Classification Report for EfficientNetB0:
              precision    recall  f1-score   support

  No_Pothole       0.00      0.00      0.00       132
     Pothole       0.58      1.00      0.73       183

    accuracy                           0.58       315
   macro avg       0.29      0.50      0.37       315
weighted avg       0.34      0.58      0.43       315

Accuracy: 58.10%
```

Figure 16: shows classification report for EfficientNetB0

Confusion Matrix

The confusion matrix below provides insight into models performance, showing the counts of true positives, true negatives, false positives, and false negatives:

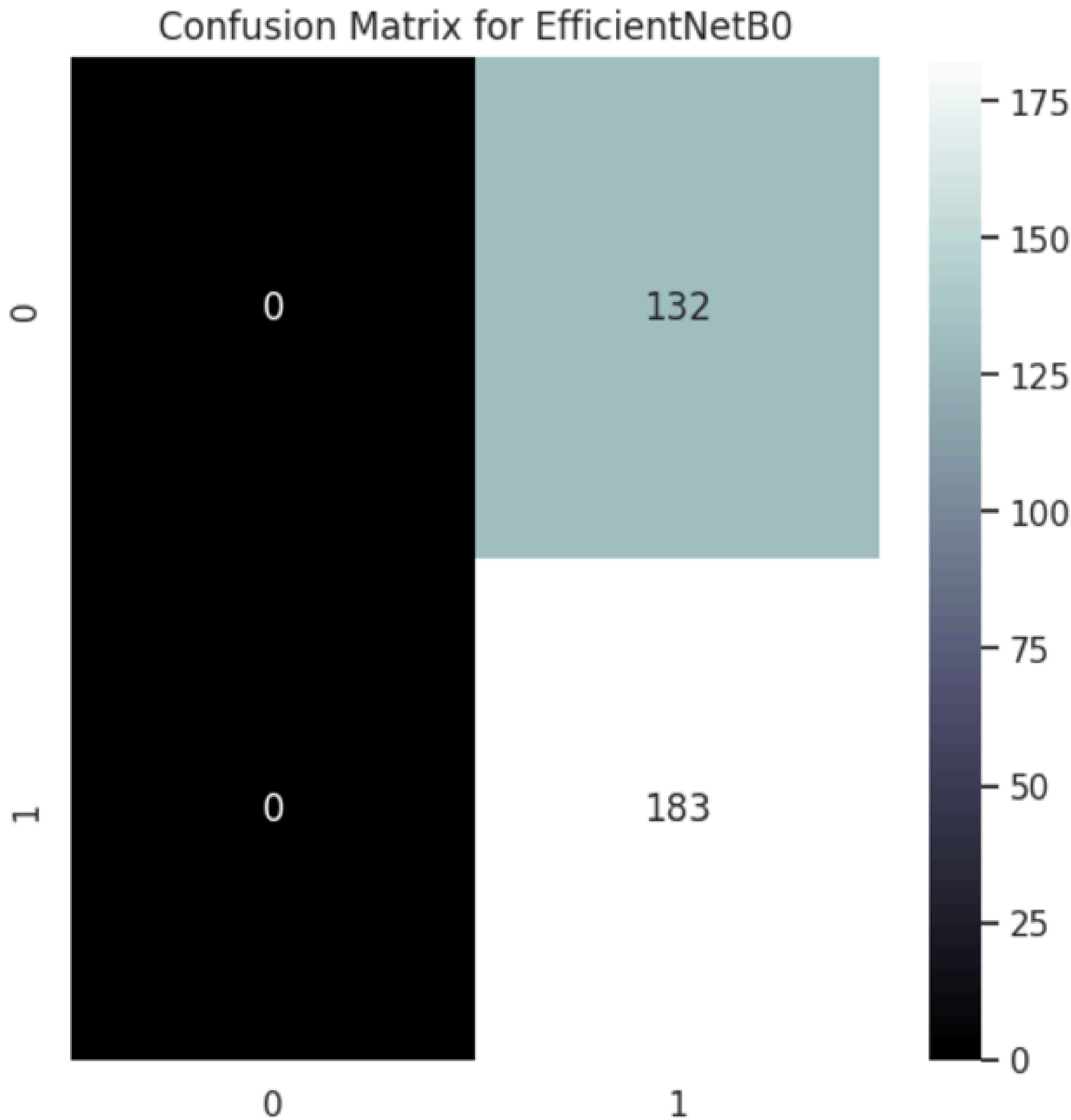

Figure 17: shows confusion matrix for EfficientNetB0

5. DenseNet121

Classification Report for DenseNet121:

	precision	recall	f1-score	support
No_Pothole	0.42	0.41	0.41	132
Pothole	0.58	0.59	0.59	183
accuracy			0.51	315
macro avg	0.50	0.50	0.50	315
weighted avg	0.51	0.51	0.51	315

Figure 18: shows classification report for DenseNet121

Confusion Matrix

The confusion matrix below provides insight into models performance, showing the counts of true positives, true negatives, false positives, and false negatives:

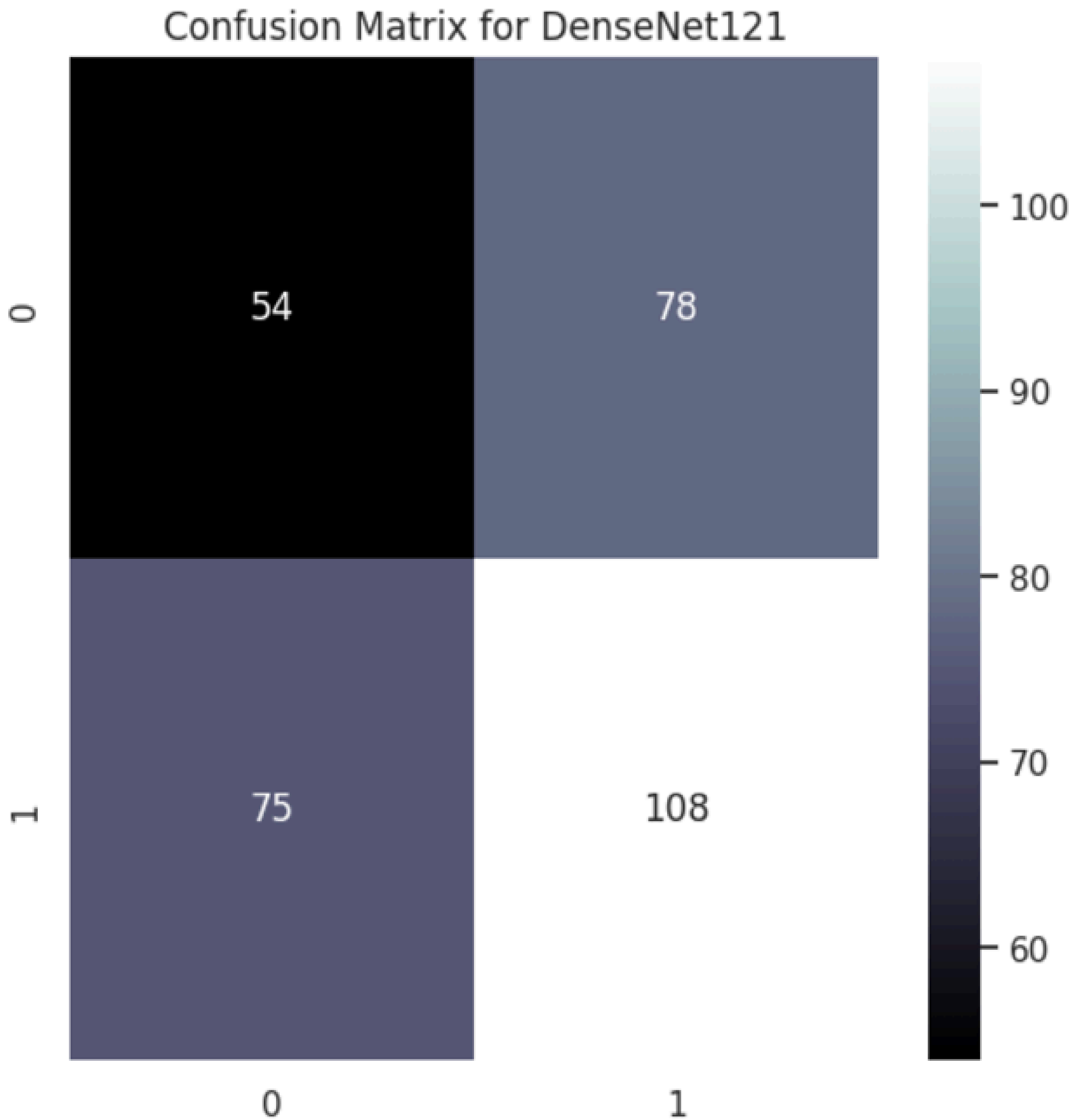

Figure 19: showing confusion matrix for DenseNet121

6. MobileNetV2

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Classification Report:
              precision    recall  f1-score   support

      Normal       0.00      0.00      0.00       145
    Potholes       0.54      1.00      0.70       172

    accuracy                           0.54       317
   macro avg       0.27      0.50      0.35       317
weighted avg       0.29      0.54      0.38       317

Accuracy: 54.26%
```

Figure 20: shows classification report

Confusion Matrix

The confusion matrix below provides insight into models performance, showing the counts of true positives, true negatives, false positives, and false negatives:

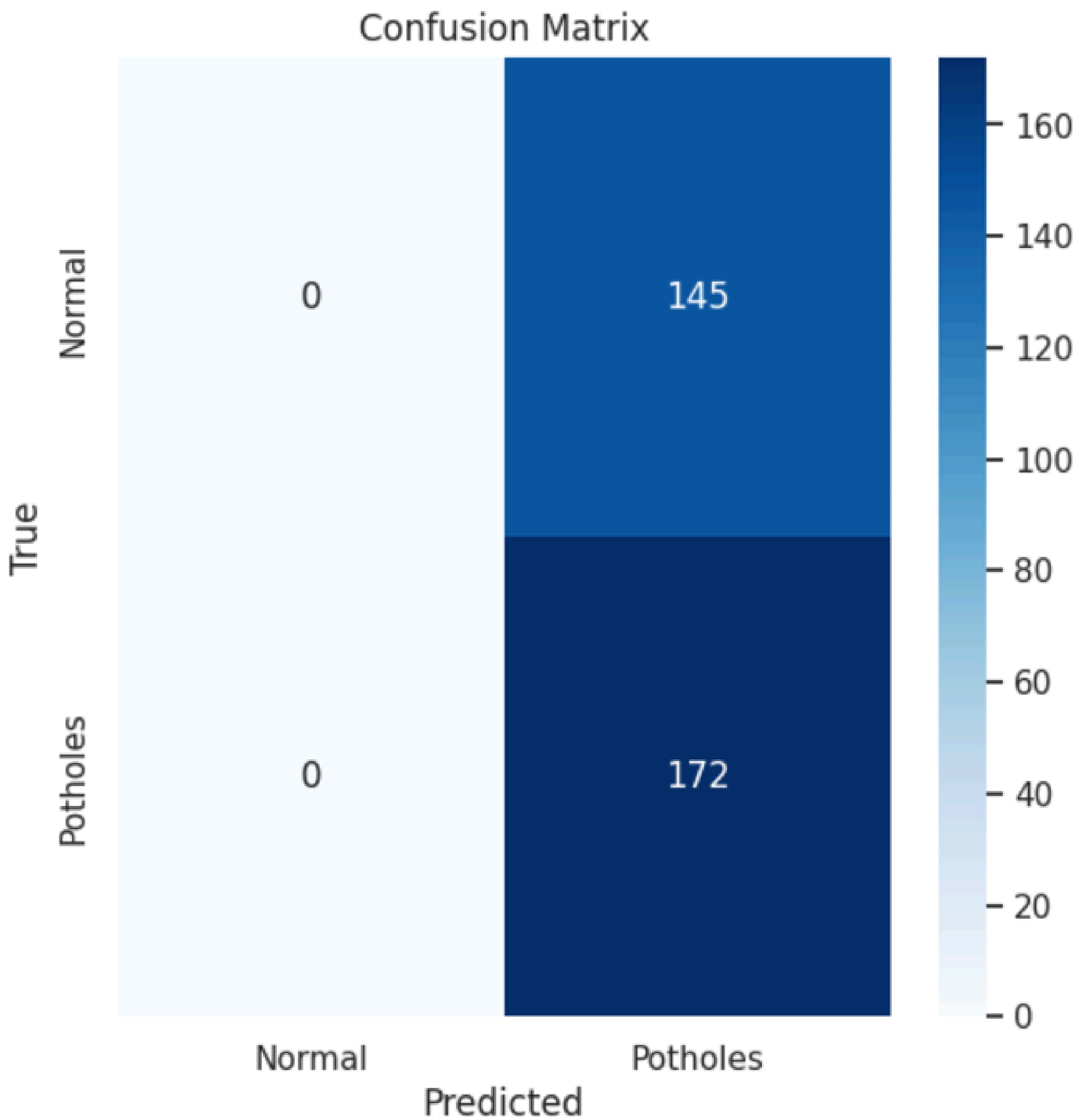

Figure 21: shows confusion matrix

7. Xception

```
Classification Report for Xception:
              precision    recall  f1-score   support

  No_Pothole       0.40      0.39      0.40       132
     Pothole       0.57      0.57      0.57       183

    accuracy                           0.50       315
   macro avg       0.48      0.48      0.48       315
weighted avg       0.50      0.50      0.50       315
```

Figure 22: showing classification report for Xception

Confusion Matrix

The confusion matrix below provides insight into models performance, showing the counts of true positives, true negatives, false positives, and false negatives:

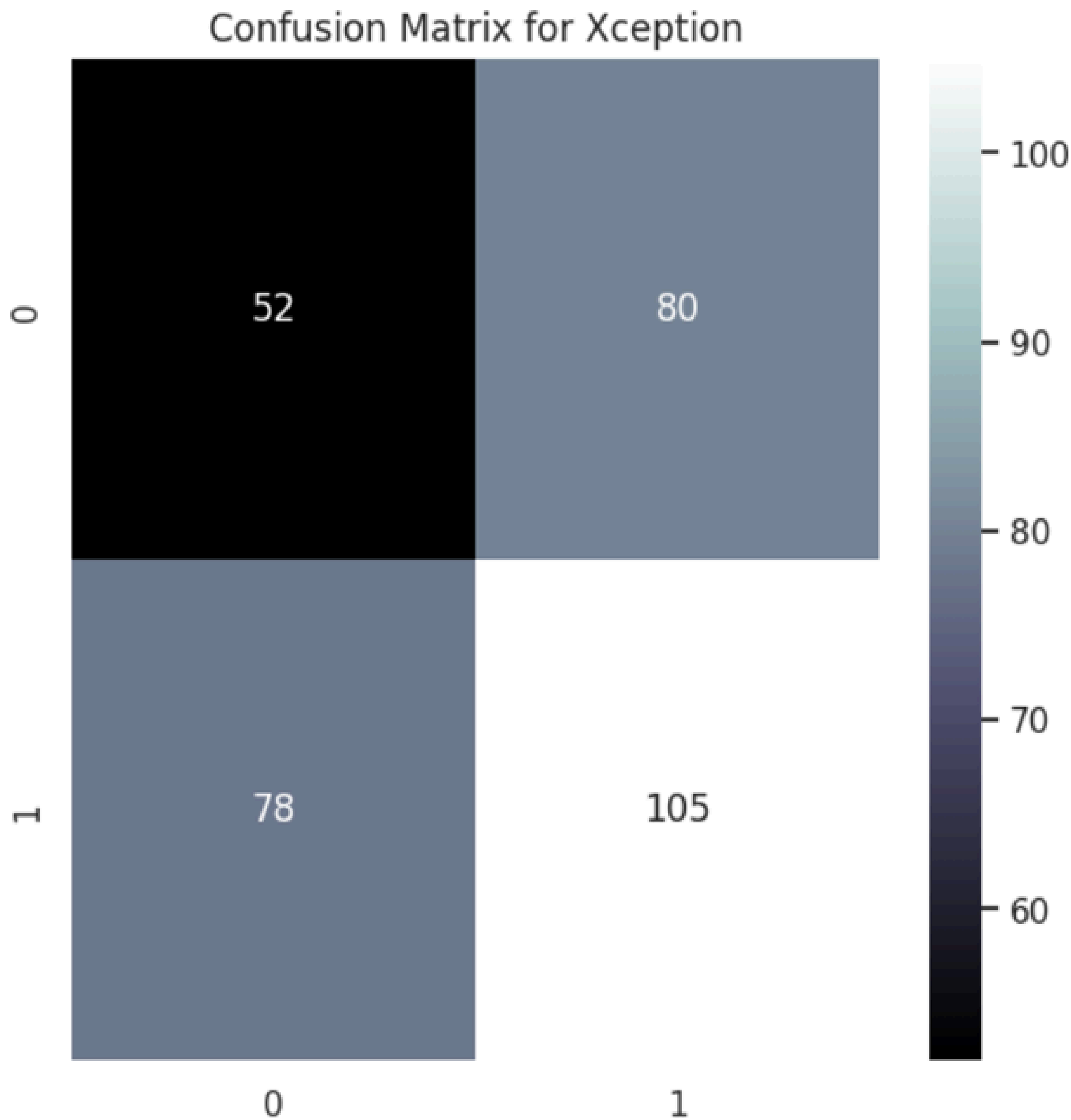

Figure 23: showing confusion matrix for Xception

4.3. Web Mapping Tool

The developed web-based monitoring application successfully incorporated all necessary components for real-time pothole detection and mapping. The modular architecture ensured seamless communication between the client and the backend. The following outcomes were attained:

4.3.1 Frontend Functionality

Pothole sites were dynamically and accurately represented as markers using a leaflet-based map interface. Users can interact with the map (e.g zooming, panning, and seeing the location of potholes as markers pin-point the exact location of potholes on the map) without latency, resulting in a seamless user experience.

4.3.2 Backend Integration

Frames were extracted from the uploaded video files at exact intervals using FFmpeg, which processes about 30 frames per second. With an average processing of 1.5 seconds per frame, the GPS data embedded in the video was successfully parsed and saved in JSON format using Pytesseract and Regex.

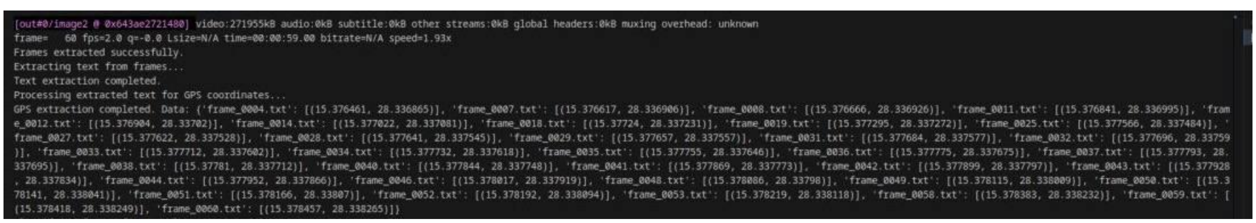

Figure 15: Shows extraction of frames

4.3.3 Mapping Pothole Locations

The map correctly displayed the coordinates that were extracted from the video metadata. Clicking on each marking revealed details about the pothole's severity, the location and the detection time. A 10-minute video file on average produced approximately 450 mapped pothole locations. Plotting marks at intervals of at least two metres allowed the tool to distinguish between potholes that were closely spaced.

4.4. Risk Analysis

Several risks could potentially impact the successful completion and deployment of this project. These risks have been classified and analysed in terms of their impact, likelihood, and mitigation strategies.

Table 1: Risks

Classification	Impact	Likelihood	Mitigation Plan
Communication	High	Very High (>70%)	Encourage open and transparent communication, and maintain constant communication with team members to ensure everyone is clear with their duties.
Disputes	Medium	Low (11-3-%)	Stop and cool off, acknowledge the conflict and list all assumptions based on each position
Skill resource	Medium	Low(11-30)	Considering training to address skill gaps
Schedule	Medium	High (51-70%)	Develop a trained project schedule and contingency plan for potential delays
Operational	Medium	Medium (31-50%)	Develop contingency plans to address potential disruptions
Healthy and Safety	Low	Low (11-30%	Assign another team member to help when other member is sick
Legal	Low	Low (11-30%)	Prioritise ethical clearance approval
Scope creep risk	Low	Low (11-30%)	Define clear project scope boundaries
Data Quality	Low	Very Low (<10%)	Implementation data validation to identify and correct labelling errors

4.5. Timeline

The project timeline details each phase's estimated duration, from initial planning to final deployment. As shown in the appendix A section.

4.6. Resources

The following resources will be required to successfully carry out the project:

Table 2: Resources

Resource	Description
Human Resources	
Project Team	The personnel needed to complete the project.
Stakeholders	Input from the Road Development Agency (RDA) and Lusaka City Council experts to provide contextual information and validate project outcomes
Software	
Database Management System (DBMS)	For handling the labelled dataset
Programming Language	For developing the software service, including relevant libraries like Matplotlib for data visualisation, and Pandas for data manipulation and analysis
Google Collab or Jupyter Notebooks	For interactive development and experimentation with code, providing an environment to write and test python code
Project Management Tools	To track progress, manage timelines and assign tasks. Tools like Trello.
Hardware and Technical Resources	
Dash Cam	To capture video footage for data collection
Transport	Travelling to various sites for image capture and stakeholder engagements.
Fuel	For driving around to collect footage to add to the dataset, and testing the system
Communication Resources	
Data Bundles	For internet connectivity.
Airtime	For communication via phones calls

4.6. Deliverables

The following deliverables are expected to be produced after successful completion of the project:

- A comprehensive understanding of road monitoring methods

- The approach utilised in implementing the automation of road monitoring can be extended and applied to further projects.
- Final Report: Detailed project report, covering methodology, results, analysis, and recommendations for scaling the application.
- Web-Based Mapping Application: An interactive platform for real-time road condition monitoring, integrated with the AI classifier.

4.7. Milestones

The following is a chronologically ordered list of milestones the project:

- Project Proposal and Approval
- Literature Review
- Research and Data Collection:
  - Conducted interviews with road maintenance professionals in Zambia.
  - Collected initial image and video datasets for model training and testing.
- Model Development:
  - Designed and trained a Convolutional Neural Network (CNN) for pothole detection.
  - Evaluated the binary classifier using metrics like precision, recall, F1 score, and accuracy
- Feature Development:
  - Developed the frame extraction capability to process video data.
  - Implemented a mapping interface to visualise.
- Integration Planning:
  - Began planning the integration of the detection model, frame extraction, and mapping interface.
- Preliminary Testing:
  - Tested individual components (AI detection, frame extraction, and mapping) independently.
- Prototype Demonstration

- Final Testing and Optimization
- Report and Presentation Preparation
  - Documented methodology, results, challenges, and limitations.
  - Prepared the final project report and presentation materials.
- Submission of Final Deliverables
  - File Project Website Setup
  - Final Project Presentation
  - Final Project Report
- Final Project Presentation

5. Conclusion

This research effectively created a real-time pothole detection and classification system by combining web-based mapping tools with AI technologies like CNN and YOLOv8. The technology offers a dynamic platform for visualising the locations and severity of potholes and has achieved considerable accuracy in identifying and classifying road defects, specifically potholes. The initiative overcomes the drawbacks of human approaches by automating road monitoring, providing a scalable way to improve the effectiveness of road repair. To get even higher accuracy, further work can concentrate on extending the dataset, increasing processing efficiency, and fine-tuning the model for a variety of circumstances. This study supports continuing initiatives to use technology to modernise road infrastructure monitoring.

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6. Appendix A: Gantt Chart Study Timeline

	Name	Duration
1	PROJECT DURATION	145 days?
2	RESEARCH DESIGN AND PLANNING	39 days?
3	Project Desription Specified	1 day
4	Team Roles Indentification	2 days?
5	Literature Synthesis Draft	8 days?
6	Literature Synthesis	0 days?
7	Proposal Documnet Draft	20 days?
8	Project Website Setup	0 days
9	Project Proposal	0 days
10	Presentation Rehearsal	4 days?
11	Proposal Presentation	1 day?
12	Revised Project Proposal	3 days?
13	REQUIREMENT ENGINEERING	12 days?
14	Road Monitoring Information Inquiry	5 days?
15	Data Analysis	12 days?
16	Data Preprocessing Of The Model	3 days?
17	ITERATION 1	15 days?
18	Iniatial Models Prototype Development	5 days?
19	Initial Project Feasibility Demonstration	0 days?
20	Prototype Refinement	5 days
21	Testing	5 days?
22	ITERATION 2	22 days?
23	Initial Wep application Developemet	7 days
24	Initial Maping Tool Development	6 days?
25	Intergation Of Mapping Tool And Web Applicati	5 days?
26	Testing	4 days?
27	ITERATION 3	16 days?
28	Implementation	10 days?
29	Experiments	4 days
30	Evaluation+WriteUp	2 days
31	SYSTEM TESTING	9 days?
32	Componet Testing	2 days?
33	Integration Testing	2 days?
34	User Acceptance Testing	5 days?
35	ITERATION 4	13 days?
36	Project Source Code Submission	0 days
37	Project Demonstration	1 day?
38	Draft of Project Report	10 days?
39	Project Report	0 days
40	Preesntation of Final Project	0 days?