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**7COM1039-0206-2024**

**Advanced Computer Science Masters Project**

**AI-Powered Pothole Detection Using Machine Learning**

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# 1. Background Research & Literature Review

## 1.1 Introduction

Potholes pose a significant challenge to road infrastructure, leading to vehicle damage, accidents, and increased maintenance costs. Traditional pothole detection methods rely on manual inspections and sensor-based technologies such as LiDAR and accelerometers, which are expensive and inefficient for large-scale implementation. To address these limitations, this research explores the application of AI-based image processing techniques for automating pothole detection and severity classification.

In order to identify the best strategy, this study examines three machine learning models: Random Forest classifiers, Support Vector Machines (SVMs), and Convolutional Neural Networks (CNNs). The project intends to create a scalable, economical, and precise pothole detecting system by utilizing publicly accessible road image datasets and deep learning algorithms. This study advances the field of road safety management and AI-based infrastructure monitoring.

## 1.2 Goals & Objectives

**Project Goal**

This study's main objective is to create and assess an AI-powered pothole detection system that uses machine learning and image processing techniques to automatically identify and classify potholes based on their severity.

**Objectives (Specific & Measurable)**

To achieve this goal, the project has the following objectives:

* Conduct a literature review on existing pothole detection methods using AI and image processing.
* Identify the challenges of traditional pothole detection approaches and assess how AI can overcome these limitations.
* Compare and evaluate machine learning models (CNN, SVM, Random Forest) for pothole detection accuracy.
* Analyze the role of AI in road safety and infrastructure monitoring, linking it to existing theoretical frameworks.
* Investigate real-world challenges in implementing AI-based pothole detection, particularly in data variability and model generalization.

These objectives ensure that the research aligns with both theoretical and practical advancements in pothole detection and contributes to AI-driven infrastructure maintenance solutions.

## 1.3 Research Problem & Research Questions

**Main Research Question:**

How can AI-based image processing techniques be leveraged to improve pothole detection and severity classification compared to traditional methods?

**Sub-Questions:**

* Can AI models accurately detect potholes in real-world road images?
* How does the performance of CNN compare to SVM and Random Forest in pothole detection?
* How can AI models be improved to generalize across different road conditions?

These questions guide the research in evaluating the effectiveness of AI-driven methods, particularly CNN-based deep learning, compared to conventional machine learning approaches.

## 1.4 Background Research & Theoretical Foundations

**Existing Pothole Detection Methods**

Pothole detection techniques can be categorized into three primary methods:

1. **Manual Inspection**: Requires human intervention, making it slow, costly, and inconsistent.
2. **Sensor-Based Detection**: Uses LiDAR, ultrasonic sensors, or accelerometers to detect road anomalies. While effective, these methods are expensive and require specialized hardware.
3. **AI-Based Image Processing**: Uses machine learning to analyze road surface images for pothole detection. This approach is scalable, cost-effective, and requires no additional hardware, making it an ideal solution.

**Machine Learning & Deep Learning for Pothole Detection**

The capacity of machine learning models, especially CNNs, to extract hierarchical characteristics from photos has led to their widespread use in image-based pothole identification. Other methods, such as SVM and Random Forest classifiers, rely on handcrafted features and are less effective in handling large-scale datasets. This study compares the accuracy, feature extraction, and resilience of CNNs as an end-to-end deep learning solution to more conventional methods.

## 1.5 Literature Review & Key Studies

Several studies have explored AI-based pothole detection:

* **Mohan & Poobal (2018)** analyzed crack detection using image processing, highlighting challenges in detecting road surface defects.
* **Maeda et al. (2018)** proposed a deep neural network approach using smartphone images for road damage detection.
* **Chowdhury et al. (2020)** developed a UAV-based pothole detection system using deep learning models.

**Key Findings & Gaps in Research:**

* Deep learning (CNNs) outperforms traditional computer vision methods in accuracy and robustness.
* Data preprocessing (image augmentation, edge detection) significantly improves model performance.
* High-resolution images enhance detection precision but pose computational challenges.
* Existing studies lack a standardized approach to severity classification, requiring further research.

This research builds upon these findings by integrating CNNs, SVM, and Random Forest for a comparative analysis, ensuring a data-driven approach to selecting the best model. Additionally, this study addresses gaps in existing research by evaluating model generalization across varying environmental conditions.

## 1.6 Theoretical Framework & AI in Road Safety

AI plays a crucial role in modern infrastructure maintenance and road safety by enabling automated monitoring systems. This research aligns with existing AI-driven frameworks for image classification, road defect detection, and intelligent transportation systems.

* **Image Classification Theory**: CNNs utilize hierarchical feature extraction, making them highly effective for visual anomaly detection.
* **AI in Road Safety**: Automated pothole detection contributes to proactive maintenance, reducing accidents and vehicle damage.
* **Challenges in AI Implementation**: Real-world AI deployment requires addressing issues such as domain adaptation, model drift, and edge-case handling.

Understanding these theoretical models allows this research to position itself within broader AI applications in civil engineering and intelligent transportation systems.

## 1.7 Project Deliverables

The following deliverables will be produced as part of this research:

• **AI Models**: Trained CNN, SVM, and Random Forest models

• **Dataset Preprocessing Scripts**: Scripts for image augmentation, edge detection, and feature extraction

• **Experimental Reports**: Performance evaluation of different models

• **Prototype Software**: A web-based application for real-time pothole detection

• **Documentation**: Research report, user guide, and implementation details

# 2. Progress to Date

## 2.1 Overview of Work Completed

Significant progress has been made in the research and development of the AI-powered pothole detection system. This includes completing the literature review, selecting and preprocessing the dataset, training multiple machine learning models, and evaluating their effectiveness. The following sections provide a detailed breakdown of the work accomplished so far, linking each milestone to the research objectives outlined in Section 1.

## 2.2 Literature Review & Research Alignment

A comprehensive literature review was conducted to explore existing pothole detection techniques, focusing on manual inspection, sensor-based detection, and AI-based image processing. Key studies were analyzed to identify gaps in research and validate the feasibility of machine learning-based approaches. This review informed the choice of Convolutional Neural Networks (CNNs) as the primary model for this project due to their superior performance in image classification tasks.

## 2.3 Dataset Selection & Preprocessing

**Dataset Justification**

* **Dataset Used**: **Normal-Pothole Dataset** (5,000 images, equally split between potholes and normal road images).
* **Dataset link**: <https://zenodo.org/records/13334878>
* **Selection Criteria**:
  + **Balanced Data**: Ensures unbiased training for pothole vs. non-pothole classification.
  + **Publicly Available & Reliable**: Hosted on Zenodo for reproducibility.
  + **Real-World Variability**: Captures diverse road conditions to enhance model generalization.

**Preprocessing Techniques Implemented**

1. **Image Augmentation** – Applied transformations (rotation, flipping, brightness adjustment) to improve robustness.
2. **Edge Detection (Canny Algorithm)** – Extracted key image features to assist in severity classification.
3. **Normalization** – Scaled pixel values between 0 and 1 to stabilize training and reduce overfitting.

## 2.4 Tools and Technologies Used

This project relies on a range of tools and libraries for data processing, model training, and deployment:

• **Programming Language**: Python 3.9

• **Deep Learning Framework**: TensorFlow/Keras for CNN training

• **Machine Learning Libraries**: Scikit-learn for SVM and Random Forest models

• **Image Processing Tools**: OpenCV for feature extraction, augmentation, and edge detection

• **Development Environment**: Visual Studio Code, Google Colab

• **Deployment Framework**: Streamlit for real-time prototype development

These tools and technologies enable efficient model training, evaluation, and real-time deployment for pothole detection.

## 2.5 Model Development & Evaluation

**Machine Learning Models Trained**

Three machine learning models were trained and tested for pothole detection:

1. **Convolutional Neural Networks (CNNs)** – Deep learning model for automatic feature extraction.
2. **Support Vector Machines (SVMs)** – Traditional machine learning model requiring manual feature engineering.
3. **Random Forest Classifier** – Ensemble learning model for structured data classification.

**Performance Evaluation**

Model performance was assessed using key metrics: Accuracy, Precision, Recall, and F1-score.

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Model** | **Accuracy (%)** | **Precision** | **Recall** | **F1-score** |
| **CNN** | 95.10 | 0.97 | 0.93 | 0.95 |
| **SVM** | 77.30 | 0.88 | 0.62 | 0.73 |
| **Random Forest** | 89.60 | 0.86 | 0.94 | 0.90 |

**Selection of CNN as the Best Model**

* **Higher Accuracy**: CNN achieved 95.10%, outperforming SVM (77.30%) and Random Forest (89.60%).
* **Superior Feature Extraction**: CNN automatically learns hierarchical image features, eliminating the need for manual feature selection.
* **Better Generalization**: CNN maintains high precision and recall, reducing false positives and false negatives.
* **SVM & Random Forest Limitations**: SVM struggled with large-scale image classification, while Random Forest misclassified some non-pothole areas.

**More Reasons**:

* CNN automatically extracts spatial features, while SVM requires manual feature selection, making it less effective for large-scale image analysis.
* Random Forest performed well but misclassified small potholes due to reliance on pixel intensity variations rather than spatial patterns.

Based on these results, CNN was selected as the best model for pothole detection and severity classification.

## 2.6 Prototype Development & Initial Testing

The trained CNN model was integrated into a **web-based application** using **Streamlit** to allow real-time pothole detection. The system enables users to upload images and receive detection results, including severity classification.

**Prototype Features**

* **File Upload** – Users can upload **JPG, PNG, JPEG** images.
* **Real-Time Prediction** – The model detects potholes and classifies severity.
* **Confidence Score** – The detection confidence is displayed to users.

**Testing Results**

* A pothole detection **confidence of 100%** was recorded during prototype evaluation.
* Severity classification was validated using **contour-based area estimation**.

## 2.7 Challenges & Solutions Implemented

|  |  |  |
| --- | --- | --- |
| **Challenge** | **Issue Faced** | **Solution Implemented** |
| **Dataset Imbalance** | Variability in pothole size & lighting conditions affected detection. | Data Augmentation (rotation, brightness correction) improved robustness. |
| **Overfitting in CNN** | Model performed well in training, but generalization was poor. | Dropout layers (0.5 probability) and L2 Regularization were added. |
| **High Computational Cost** | CNN training took significant time on local hardware. | Google Colab GPU acceleration was used to speed up training. |
| **Edge Detection Complexity** | Small cracks were misclassified as potholes. | Canny Edge Detection parameters were fine-tuned. |
| **Prototype Deployment** | Image formats caused processing inconsistencies. | OpenCV-based preprocessing was integrated to handle different image types. |

## 2.8 Supporting Evidence & Deliverables

The materials provide documented proof of the progress made so far in **Appendix**

* **Preprocessed Dataset** samples.
* **Model Training Logs**: Showing **CNN improvement over multiple epoch**
* **Prototype Screenshots**: Confirming **working AI-based pothole detection**.
* **Test Results**: Model evaluation metrics validating CNN’s accuracy.

## 2.9 Summary & Next Steps

At this stage, the AI-powered pothole detection system is functional, with:

* A **95.1% accurate CNN model** trained on a balanced dataset.
* A **fully working prototype** allowing real-time pothole classification.
* A **robust preprocessing pipeline** ensuring optimized image analysis.

**Next Steps**

1. **Optimize CNN Model** further to improve training speed and stability.
2. **Enhance Severity Classification** to estimate the size and depth of potholes.
3. **Improve Model Deployment** for better scalability.

The remaining work will focus on refining the system and preparing for **final evaluation and project submission**.

# Section: 3. Ethical, Legal, and Social Considerations

The development of an AI-based pothole detection system raises several ethical, legal, professional, and social concerns that must be addressed to ensure responsible research practices. This section examines these considerations in the context of data usage, model fairness, compliance with legal frameworks, and the broader societal impact of the project.

## 3.1 Ethics Approval Requirement

This project **does not require formal ethics approval**, as it relies on a **publicly available dataset (Normal Pothole Dataset)** that contains **no personally identifiable information (PII)**. Since no private data is collected, issues related to **privacy, consent, or data security** are minimal.

However, if this system were to be deployed in a **real-time setting** using **dashcams, drones, or IoT-based surveillance**, ethics approval would become necessary due to:

* **Potential privacy concerns** related to capturing images of people or vehicles.
* **Legal compliance with data protection regulations** regarding real-world image collection.

While ethics approval is not currently needed, **future iterations of this project** must ensure compliance with institutional and legal requirements if real-world data collection is introduced.

## 3.2 Legal Compliance & GDPR

The principles of the **General Data Protection Regulation (GDPR)** should be considered even though this project does not handle personal data, especially if the system is later expanded. Important things to think about are:

* **Transparency:** Users must be informed if real-time data collection is introduced.
* **Data Minimization:** The system should only collect essential image data necessary for pothole detection.
* **Storage Limitation:** Any collected data should only be stored temporarily and used for immediate processing.

Currently, **compliance is ensured by utilizing publicly available datasets** with open-access licensing. Future applications that involve **real-world image collection** would require strict adherence to GDPR and other data protection laws.

## 3.3 Bias, Fairness, and Model Generalization

AI systems can be prone to bias if trained on **non-representative datasets**, potentially affecting model fairness and real-world reliability. This project mitigates these risks through the following strategies:

* **Dataset Augmentation:** Techniques such as brightness adjustment and rotation enhance the model’s ability to generalize across different conditions.
* **Performance Evaluation Across Varied Road Conditions:** The dataset includes images from **different lighting conditions, weather scenarios, and road types** to reduce bias.
* **Alignment with AI Ethics Guidelines:** The project follows best practices outlined by the **IEEE and ACM** to promote fairness and responsible AI development.

By integrating these measures, the model is designed to **minimize biases and ensure equitable performance across different environments**.

## 3.4 Social & Professional Impact

The deployment of AI-based pothole detection systems has significant **societal and professional implications**. This research contributes to **road safety, cost efficiency, and sustainability** in the following ways:

* **Road Safety:** Automated pothole detection enables **early intervention**, reducing **accidents and vehicle damage** caused by road defects.
* **Cost Efficiency:** Municipalities and road maintenance teams can use AI-driven detection to **optimize repair schedules and reduce unnecessary costs**.
* **Sustainability:** Proactive pothole detection leads to **better road maintenance planning**, reducing material wastage and **lowering the carbon footprint** from emergency repairs.

From a **professional standpoint**, this research aligns with the **UK Engineering Council’s ethical guidelines**, emphasizing **accuracy, transparency, and responsible AI deployment**.

## 3.5 Future Considerations for Deployment

While this research establishes a strong foundation for AI-driven pothole detection, additional challenges must be considered if the system is deployed at scale:

* **Data Ownership:** If municipalities or private organizations deploy this system, **who owns the collected road data**?
* **Privacy Risks:** Could real-time monitoring **infringe on personal privacy**, particularly if camera systems capture unintended elements?
* **Liability Issues:** If the AI model misclassifies potholes or fails to detect road hazards, **who is responsible for incorrect repairs or accidents**?

To ensure ethical deployment, collaboration with **transportation authorities, regulatory bodies, and AI governance organizations** would be necessary to develop policies that address these concerns.

## 3.6 Conclusion

This project adheres to best **ethical, legal, and social responsibility practices**, ensuring compliance with existing regulations and AI governance principles.

* **Ethics approval is not required**, but future real-world implementations would need regulatory oversight.
* **Legal compliance** is maintained through GDPR-aligned practices, ensuring responsible data use.
* **Bias and fairness concerns** are addressed through dataset augmentation and model evaluation techniques.
* **The societal impact is positive**, improving **road safety, reducing maintenance costs, and supporting sustainable infrastructure management**.

While this system is currently in an **experimental phase**, future deployments must incorporate legal safeguards, **data protection mechanisms, and accountability frameworks** to ensure ethical and responsible use.

# Section: 4. Project Plan

The project has successfully progressed through **data collection, model training, and prototype development**. The next phase will focus on **model optimization, improving the user interface, and final preparations for the viva and report submission**.

## 4.1 Project Management Approach

The project follows an adaptive **milestone-based approach** with flexibility to refine models and enhance the UI. Key principles include:

* **Scope Management:** Remaining work is focused on **refining model accuracy, improving UI usability, and preparing final documentation**.
* **Time & Resource Allocation:** Dedicated periods for **UI enhancement, model optimization, testing, and report writing** ensure efficient time utilization.
* **Risk Management:** Key risks include **limited improvement in model accuracy** and **UI complexity**, mitigated through continuous testing and feedback.
* **Quality Control:** The model’s final selection will be validated through **benchmarking, real-world testing, and feedback** from users and supervisors.

## 4.2 Key Tasks & Timeline

|  |  |  |  |
| --- | --- | --- | --- |
| **Task** | **Description** | **Deliverables** | **Target Completion** |
| **Data Collection & Preprocessing** | Dataset selection and augmentation to improve generalization. | Preprocessed dataset, augmentation logs. | **Completed** |
| **Model Training & Evaluation** | Trained CNN, SVM, and Random Forest models, selecting the best-performing model. | Model training logs, evaluation reports. | **Completed** |
| **Prototype Development (Streamlit UI)** | Created a web-based interface for real-time pothole detection. | Initial Streamlit-based AI detection system. | **Completed** |
| **Model Optimization & Accuracy Improvement** | Improving the accuracy and efficiency of the best-selected model. | Optimized AI model, performance comparison report. | March 25, 2025 |
| **User Interface Enhancement** | Enhancing UI for better usability, interactivity, and streamlined user experience. | Updated Streamlit UI with improved design and accessibility. | April 5, 2025 |
| **Performance Testing & Validation** | Conducting multiple tests to evaluate the AI model’s reliability across different conditions. | Test reports, model benchmarking. | April 15, 2025 |
| **Final Report Writing & Submission** | Structuring and finalizing the research report. | Completed MSc Project Report. | April 25, 2025 |
| **Presentation & Viva Preparation** | Preparing for the project defense, creating slides, and finalizing results. | Presentation slides, live demo setup. | April 26 – May 5, 2025 |

## 4.3 Quality Assurance & Evaluation

The project will be evaluated using the following methods:

**Model Performance Improvement**

* The AI model’s accuracy, precision, recall, and F1-score will be analyzed.
* Additional **testing of alternative models** may be explored if time permits, though not guaranteed.

**UI Usability & Testing**

* The **Streamlit-based UI** will be enhanced for **better user experience**.
* Testing with different **users** will provide feedback on usability.

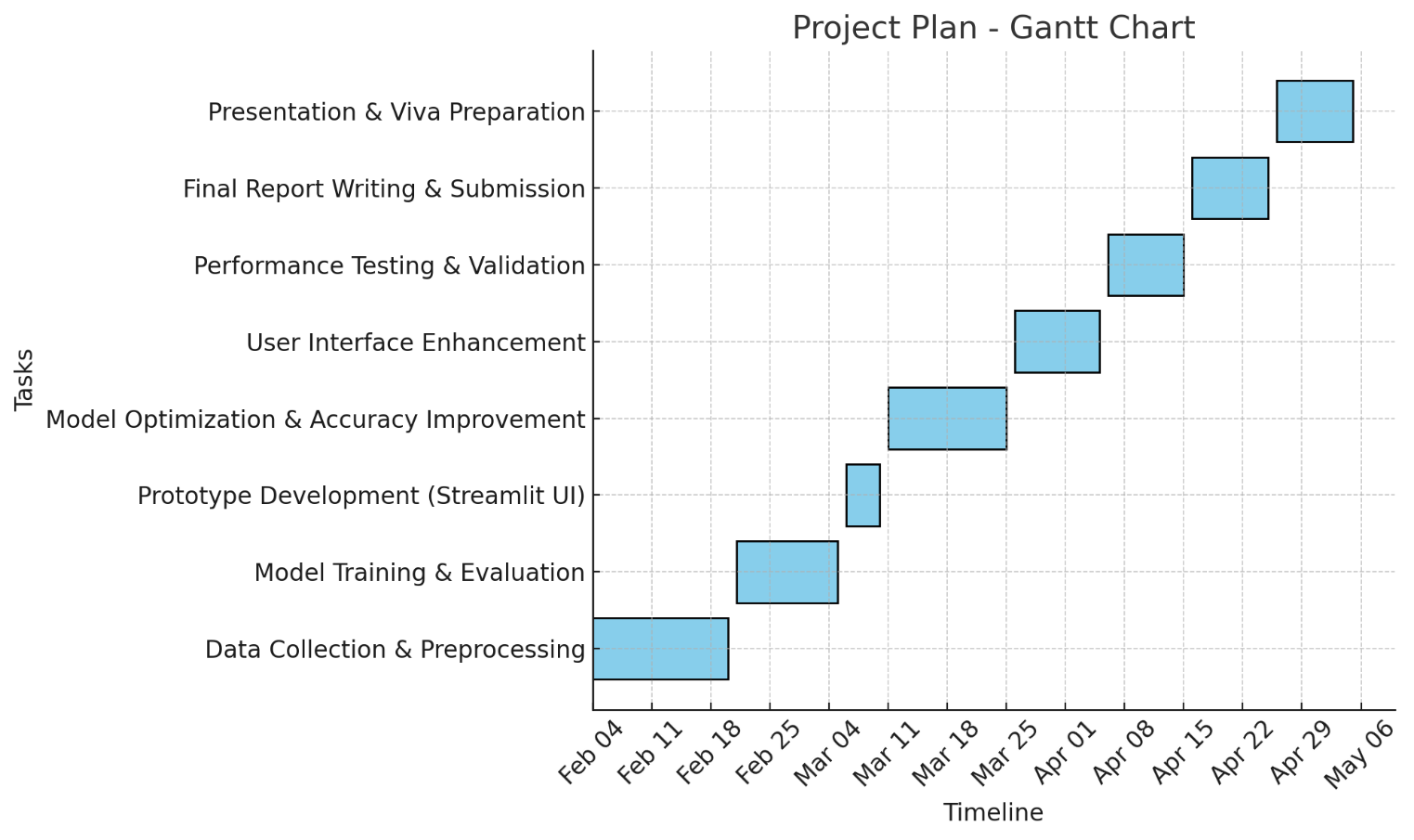
**Comparative Benchmarking & Validation**

* The **optimized AI model will be compared against initial models** and traditional pothole detection approaches.
* Testing will focus on **performance across different road conditions** to ensure real-world applicability.

**Final Report & Viva Preparation**

* The MSc report will undergo multiple reviews to ensure clarity and completeness.
* The **viva presentation will be rehearsed** to demonstrate both technical and practical project insights.

## 4.4 Gantt Chart Representation

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# Section: 5. Level of the Project

This section critically reflects on the **depth, complexity, and rigor** of this MSc project, demonstrating its suitability for an advanced academic undertaking. It assesses the **problems being solved, research methodologies, experimentation, testing, and the artefact developed**, aligning with MSc-level expectations.

## 5.1 Problem Statement & Relevance

Pothole detection remains a significant **infrastructure challenge**, contributing to **road accidents, vehicle damage, and costly repairs**. Traditional pothole detection methods, such as **manual inspections and sensor-based solutions (LiDAR, accelerometers)**, are either **time-consuming, expensive, or inefficient for large-scale deployment**.

This project seeks to address these limitations by developing an **AI-powered pothole detection system** capable of:

* **Automatically identifying potholes** from images.
* **Classifying their severity** based on visual characteristics.
* **Providing a scalable, cost-effective alternative** to traditional detection methods.

This project aligns with my **career aspirations in AI, computer vision, and machine learning** by allowing me to explore **deep learning for real-world infrastructure challenges**.

## 5.2 Artefact Developed

The artefact is a **fully functional AI-powered pothole detection system**, consisting of:

* **A trained deep learning model (CNN)** that identifies potholes with high accuracy.
* **A web-based interface (Streamlit UI)** for user interaction and real-time detection.
* **A classification system** to assess pothole severity.

The **innovation lies in the combination of AI-driven detection and user accessibility** through a real-time interactive interface.

## 5.3 Demonstrating Complexity & Rigor

This project involves a **rigorous experimental approach**, including:

* **Comparative Model Evaluation:**
  + Trained and tested **three different models (CNN, SVM, Random Forest)**.
  + Selected the **best-performing model (CNN)** based on accuracy, precision, recall, and F1-score.
* **Advanced Model Optimization:**
  + Implemented **hyperparameter tuning** to improve accuracy.
  + Experimenting with **different architectures** to enhance performance.
  + Testing additional models (**if time allows**) for further improvement.
* **Addressing AI Bias & Generalization Challenges:**
  + Applied **data augmentation techniques** (rotation, brightness adjustment) to improve generalization.
  + Evaluated model performance on **diverse road conditions** (urban, rural, low-light environments).
* **Ethical & Legal Considerations:**
  + Ensured compliance with **GDPR** by using a **publicly available dataset**.
  + Considered **bias and fairness** in AI model training.

## 5.4 Testing & Validation

The project is structured around a **robust validation process**, ensuring reliability across multiple conditions:

**Planned Testing Approaches:**

* **Performance Testing:** Model evaluated on test data with key metrics (Accuracy, Precision, Recall, F1-score).
* **Edge Case Testing:** Assessing performance under **low-light, occluded potholes, and extreme weather conditions**.
* **User Testing:** Gathering feedback on UI usability and efficiency.
* **Comparative Analysis:** Evaluating AI against **traditional pothole detection methods** to justify real-world viability.

These validation steps ensure that the system is **not only technically sound but also practical for real-world use**.

## 5.5 Justification of Methods & Tools

This project was designed using **state-of-the-art tools and methodologies**, selected based on their effectiveness for image classification tasks:

|  |  |
| --- | --- |
| Method/Tool | Justification |
| CNN (Deep Learning) | Automatically extracts high-level image features, outperforming traditional ML models. |
| Streamlit (UI Framework) | Provides an easy-to-use web-based interface for real-time image processing. |
| TensorFlow/Keras | Industry-standard deep learning framework for training and deploying AI models. |
| OpenCV | Used for preprocessing, edge detection, and image enhancements. |
| Scikit-learn (SVM, Random Forest) | Provided comparative analysis for benchmarking CNN performance. |

These tools enable a **comprehensive testing and experimentation environment**, ensuring **high-quality, repeatable, and scalable results**.

## 5.6 Conclusion

This project meets MSc-level expectations by demonstrating:

* **A significant real-world challenge** with AI-driven innovation.
* **Advanced research, model experimentation, and comparative evaluation.**
* **A rigorous testing and validation strategy ensuring reliability.**
* **Practical applicability through a functional UI and real-time model deployment.**

Through **deep learning, rigorous validation, and a user-friendly interface**, this project contributes to **intelligent infrastructure monitoring**, aligning with industry advancements in AI-driven road maintenance.

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# Appendices

## Appendix 1: Code Snippets

* 1. **Model Training Code (Python)**

import os

import cv2

import numpy as np

import matplotlib.pyplot as plt

from sklearn.model\_selection import train\_test\_split

from sklearn.metrics import accuracy\_score, precision\_score, recall\_score, f1\_score

from sklearn.svm import SVC

from sklearn.ensemble import RandomForestClassifier

from tensorflow.keras.utils import to\_categorical

from tensorflow.keras.models import Sequential

from tensorflow.keras.layers import Conv2D, MaxPooling2D, Flatten, Dense, Dropout

import joblib

dataset\_root = r"C:\Users\theon\OneDrive\Desktop\pothole detection\Normal pothole dataset\Neha Pothole and normal dataset"

normal\_path = os.path.join(dataset\_root, "Normal")

pothole\_path = os.path.join(dataset\_root, "Pothole")

if not os.path.exists(normal\_path) or not os.path.exists(pothole\_path):

raise FileNotFoundError(f"Dataset folders not found:\n{normal\_path}\n{pothole\_path}")

def load\_images(folder, label, img\_size=(128, 128)):

images, labels = [], []

for filename in os.listdir(folder):

img\_path = os.path.join(folder, filename)

img = cv2.imread(img\_path)

if img is not None:

img = cv2.resize(img, img\_size)

img = img / 255.0

images.append(img)

labels.append(label)

return images, labels

normal\_images, normal\_labels = load\_images(normal\_path, label=0)

pothole\_images, pothole\_labels = load\_images(pothole\_path, label=1)

X = np.array(normal\_images + pothole\_images)

y = np.array(normal\_labels + pothole\_labels)

X\_train, X\_test, y\_train, y\_test = train\_test\_split(X, y, test\_size=0.2, random\_state=42)

y\_train\_cnn = to\_categorical(y\_train, num\_classes=2)

y\_test\_cnn = to\_categorical(y\_test, num\_classes=2)

cnn\_model = Sequential([

Conv2D(32, (3,3), activation='relu', input\_shape=(128, 128, 3)),

MaxPooling2D(2,2),

Conv2D(64, (3,3), activation='relu'),

MaxPooling2D(2,2),

Flatten(),

Dense(128, activation='relu'),

Dropout(0.5),

Dense(2, activation='softmax')

])

cnn\_model.compile(optimizer='adam', loss='categorical\_crossentropy', metrics=['accuracy'])

cnn\_model.fit(X\_train, y\_train\_cnn, epochs=10, batch\_size=32, validation\_data=(X\_test, y\_test\_cnn))

**1.2 Streamlit Web Application Code**

import streamlit as st

import cv2

import numpy as np

import tensorflow as tf

import tempfile

import os

MODEL\_PATH = r"C:\Users\theon\OneDrive\Desktop\pothole detection\best\_model.h5"

if not os.path.exists(MODEL\_PATH):

st.error(f"Model file not found at: {MODEL\_PATH}")

st.stop()

model = tf.keras.models.load\_model(MODEL\_PATH)

def preprocess\_image(image):

image = cv2.cvtColor(image, cv2.COLOR\_BGR2RGB)

image = cv2.resize(image, (128, 128))

image = image / 255.0

return np.expand\_dims(image, axis=0)

def predict\_pothole(image):

processed\_image = preprocess\_image(image)

prediction = model.predict(processed\_image)

class\_label = "Pothole" if np.argmax(prediction) == 1 else "Normal Road"

confidence = np.max(prediction) \* 100

return class\_label, confidence

st.title("AI-Powered Pothole Detection System")

st.write("This AI model detects potholes in road images and estimates their severity.")

uploaded\_file = st.file\_uploader("Choose an image...", type=["jpg", "png", "jpeg"])

if uploaded\_file is not None:

with tempfile.NamedTemporaryFile(delete=False) as temp\_file:

temp\_file.write(uploaded\_file.getbuffer())

image\_path = temp\_file.name

image = cv2.imread(image\_path)

st.image(image, caption="Uploaded Image", use\_column\_width=True)

if st.button("Detect Pothole"):

prediction, confidence = predict\_pothole(image)

st.write(f"Road Condition: {prediction}")

st.write(f"Confidence Level: {confidence:.2f}%")

## Appendix 2: Dataset Sample images

1. **Normal Road Images**

**A road with a few cars on it

AI-generated content may be incorrect.**

Figure 1 Normal Road Images

****

Figure 2 Normal Road Images

1. **Pothole Images**

****

Figure 3 Pothole Image

****

Figure 4 Pothole Image

## Appendix 3: Model Training Epochs

This section includes **training logs** showing the model's performance across **10 epochs**.

* Accuracy: **95.10%**
* Precision: **0.97**
* Recall: **0.93**
* F1-score: **0.95**

A screenshot of a computer screen

AI-generated content may be incorrect.

Figure 5: CNN epoch training

## Appendix 4: Prototype Screenshots

The prototype includes a **Streamlit-based web interface** for real-time pothole detection.

* **Screenshot 1:** User Interface with Image Upload Feature

A screenshot of a computer

AI-generated content may be incorrect.

Figure 6: User Interface:

* **Screenshot 2:** Detection Output with Confidence Score

A screenshot of a computer

AI-generated content may be incorrect.

Figure 7: Results

## Appendix 5: Supervisor Feedback

**Supervisor:** Dr. Muawya Eldaw  
**Date:** February 21, 2025

**Feedback Received:**

* More details need to be provided about the dataset used.
* The completion plan should include a **Gantt chart**, which was missing from the initial submission.
* Required updates must be made before the next meeting.

**Actions Taken:**

* The dataset section has been expanded.
* The **Gantt chart** was created and included.

## Appendix 6: Supervisor Meeting Notes

**Meeting Date:** February 13, 2025  
**Summary:**

* Discussed project scope and expectations.
* Clarified that the supervisor's role is to provide guidance, but the project must be completed independently.
* Agreed on submitting **weekly summaries via email**.
* The required project document includes:
  + Introduction
  + Problem Definition
  + Aim and Objectives
  + Scope
  + Literature Review
  + Completion Plan with Gantt Chart
* Deadline for document submission: **February 19, 2025**.
* If feedback is positive, proceed with development; otherwise, another meeting is scheduled.