Cycleway and Road Quality Analytics using IMU Sensor Data and Artificial Intelligence

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DECLARATION I, SHARAJ JAGADEESAN, hereby declare that this thesis, titled “Cycleway and Road Quality Analytics using IMU Sensor Data and Artificial Intelligence”, and the work presented in it are entirely my own except where explicitly stated otherwise in the text, and that this work has not been previously submitted, in part or whole, to any university or institution for any degree, diploma, or other qualification.

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Abstract

Cycleways are integral to modern urban transportation systems, offering a mode of commute that is not only economical and environmentally friendly but contributes to physical exercise. As cities continue to grow and urbanize, the importance of maintaining and improving the quality of these cycleways becomes increasingly critical. However, traditional methods of evaluating cycleway quality and the roughness of the road can be resource-intensive, often requiring expensive equipment and laborious manual inspections.

This thesis addresses these challenges by proposing a state of the art, innovative use of AI, including machine learning, neural networks and data analysis, to analyze IMU sensor data for real-time cycleway quality assessment, offering a low-cost and efficient alternative to traditional evaluation methods, inspired from [1] and [2]. The proposed system leverages accelerometer data obtained from an Inertial Measurement Unit (IMU) sensor embedded in a mobile phone through a mobile application - Sensor Logger, which is conveniently mounted on a bicycle during rides. As the cyclist travels along the cycleway, the IMU sensor present in the mobile phone, which contains accelerometer, gyroscope, GPS sensors, captures detailed data on the vibrations and movements experienced, which serve as indicators of the road surface quality.

This data is then fed into a multitude of Machine Learning algorithms and a Neural Networks like like Logistic Regression, Support Vector Machines (SVM), k-Nearest Neighbors (KNN), Random Forest, and Neural Networks which are then used to predict the quality of the cycleway for every second. This is later visualised in a map on the web application which helps in deeper analysis of the IMU data and cycleway roughness and road quality.

Keywords: Cycleway, Road Quality Index, Roughness, Machine Learning, Neural Networks, IMU sensor, Road Development

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Chapter 1

Introduction

Enhancing cycleway infrastructure requires comprehensive analysis of road conditions and the associated data specific to cycleways. A significant challenge in this area is the difficulty of efficiently collecting and analyzing such data, particularly in the absence of cost-effective tools. This gap in resources hinders the creation of effective systems that can continuously monitor and evaluate the quality of cycleways, which is essential for both public safety and infrastructure planning.

To address this challenge, the present project aims to develop a web-based system that leverages artificial intelligence [3] to process accelerometer data. Developing or using advanced sensors for this task is expensive and not feasible in the long run. Therefore, alternative approaches need to be explored where we can utilize less expensive and easily available methods to collect data. Hence, data is obtained from a low-cost Inertial Measurement Unit (IMU) sensor embedded in a mobile phone [4]. The system incorporates advanced AI models, such as YOLO for object detection, and employs machine learning algorithms, like Logistic Regression, Support Vector Machines (SVM), k-Nearest Neighbors (KNN), Random Forest, and Neural Networks, to classify and identify road segments that exhibit sub optimal conditions, potentially posing risks to cyclists.

By utilizing this AI-driven approach, the system will provide detailed insights into the condition of cycleway roads. These insights are expected to significantly improve cyclist safety by helping riders avoid hazardous areas and enabling more informed navigation decisions.

By providing thorough insights into road conditions, this project ultimately leads to safer and more accessible urban landscapes. The robust functionality and user-friendly interface of this solution offer a practical means of meeting the needs of road development authorities and cyclists, ensuring the continuous quality of cycleways and roads through proactive, predictive, and precise analytics.

This approach does have some limitations and restrictions, despite its benefits. The quality and consistency of the IMU sensor data from mobile phones—which can differ between devices also determines the system's accuracy and efficiency. Furthermore, the volume and variety of training data that is available affects how well the machine learning models perform, which may limit the system's capacity to generalize across various road conditions. Furthermore, even if the system is capable of detecting rough terrain, it might not be able to discriminate between various kinds of surface damage or challenges that could compromise the safety of cyclists.

In summary, by providing a low-cost artificial intelligence (AI) tool for real-time cycleway quality evaluation, the project aims to enhance the infrastructure of cycleways and analyse the ride quality based on the cycleway quality. By merging Artificial Intelligence with widely accessible mobile phone sensor technology, the system not only improves the safety and dependability of cycleways but also moves the goal closer to creating sustainable, bike-friendly urban environments.

Chapter 2

Background Work

This chapter covers the developments in artificial intelligence (AI) and machine learning that have been applied to the field of road condition monitoring. It also gives an overview of the current techniques and technology utilized in this field, with a special focus on cycleways.

2.0.1 Conventional Techniques for Monitoring Road Conditions

In the past, manual inspections and expensive equipment have been major components of road condition monitoring. Even though these techniques work well, they are labor-intensive and frequently impractical for ongoing surveillance over wide urban regions. Multiple studies focused on the use of cutting-edge sensors, like ground penetrating radar (GPR) and laser profilometers, to evaluate the state of the road surface. But its high costs have prevented them from being widely adopted, especially when it comes to cycleways, where financial limitations often prove more severe.

2.0.2 The Emergence of Sensing Technologies in Smartphones

The use of smartphones for monitoring road conditions has significantly increased as they have become available with a range of sensors, such as accelerometers and gyroscopes. Scholars have increasingly realized that smartphone-based systems have the potential to provide a cheap alternative to traditional methods. Research by Sattar et al. (2018) [4] and Douangphachanh and Oneyama (2014) [2] studied the use of smartphone accelerometers and gyroscopes to determine the roughness of road surfaces. These investigations showed that smartphones could efficiently record information about the state of the roads, opening the door for more widely available monitoring systems.

2.0.3 Denoising Techniques and the Use of Filters

The accuracy of sensor data in road condition monitoring is often compromised by noise, which can obscure meaningful signals and reduce the reliability of the analysis. Denoising techniques and filters are therefore critical in processing the raw data collected by smartphone sensors. Savitzky-Golay filters are frequently utilized in this situation because of their capacity to smooth data while maintaining significant characteristics like trends and peak values. According to Karaim et al. (2019) [5], these filters work well at denoising inexpensive IMU data, which is necessary for precise road condition monitoring. Furthermore, the use of different denoising approaches in mobile device-based road condition evaluation was covered by Sebestyen et al. (2015) [6]. The significance of selecting appropriate filters to strike a balance between noise reduction and the preservation of important data elements was brought to light by their work. Selecting the right filter can significantly affect the analysis that comes next, affecting how well AI and machine learning models work.

2.0.4 Artificial Intelligence's Use in Monitoring Road Conditions

Road condition monitoring has gained significantly from the use of AI, especially machine learning and deep learning methodologies, which have greatly enhanced data processing and analysis. In order to directly classify road conditions, Qureshi et al. (2023) [1] created a deep learning framework for intelligent pavement condition rating which made use of neural networks. Similar to this, Ranyal et al. (2022) [3] examined a number of artificial intelligence techniques to assess road surface data gathered from smart sensors, including Support Vector Machines (SVM) and Random Forest algorithms. These research proved AI's capacity to handle large amounts of data and derive insightful information, making it a useful tool for cycleway monitoring in real time.

2.0.5 YOLO and Object Detection in Road Monitoring

In recent years, object detection models—like YOLO (You Only Look Once)—have been extensively used for a variety of purposes, one of which is the detection of damage to road surfaces. The productivity of YOLO v5 in detecting road surface problems was evaluated by Pham and Nguyen (2023) [7], who further demonstrated how well it could recognize and categorize various pavement issues. YOLO models can be integrated into monitoring systems due to their flexibility in varying environmental circumstances and their real-time picture processing capabilities. This feature is especially important for bike lanes, where quick detection of potential hazards is crucial for ensuring the safety of cyclists.

2.0.6 Limitations and Challenges in Current Approaches

Despite the advancements in AI and sensing technologies, several limitations persist in the current approaches to road condition monitoring. One of the primary challenges is the variability in data quality and consistency across different smartphone models. Zang et al. (2018) [8] pointed out that the hardware and sensor calibration of the device being utilized can have an impact on how well smartphone-based monitoring systems work. This fluctuation may have an impact on the reliability of the AI models trained on the data, as well as the quality of the data collected.

Chapter 3

Data

Our project is analyse the surface quality of cycleway roads through the use of IMU sensor data and video data. For the data, we are utilising IMU data or Inertial Measurement Unit data which is collected through an IMU sensor. IMU sensor data offers several significant benefits, particularly in applications involving motion tracking, orientation, and environmental analysis. The data we use includes inputs from IMU sensors (Accelerometer, GPS) embedded in a smartphone through a smartphone application called - Sensor Logger [9], alongside video footage [8] obtained from the smartphone's camera. The smartphone, mounted on a bicycle, captures real-time data as the bicycle navigates various roads. The video will be recorded using the smartphone's rear camera. In adherence to the GDPR regulations, any private information will be blurred, including people's faces and license plates.

This data is appropriate for several reasons:

Relevance: The IMU sensors provide critical real-time data on the bicycle's movement and orientation, essential for assessing road quality and detecting surface anomalies.

Accessibility: Smartphones are widely available and come with high-precision sensors, making this an affordable and scalable solution.

Comprehensive Coverage: The combination of video footage with sensor data offers a detailed view of road conditions, capturing both visual and physical aspects of the road environment.

This approach ensures that the data accurately represents real-world cycling conditions, providing a solid foundation for analysis.

The collected sensor data and video inputs undergo pre-processing. During pre-processing, noise is effectively filtered out to ensure the accuracy of subsequent analyses.

IMU Data Explained:

IMU data refers to the information collected by an *Inertial Measurement Unit* (IMU), a device that measures motion and orientation. An IMU typically includes sensors such as accelerometers and gyroscopes.

- **Accelerometers** is a sensor that measures the specific force (the body mass normalizes the force). It provides the acceleration across the x, y, and z axes in its local frame [10]. For example, if you are riding a bike and hit a bump, the accelerometer detects the sudden movement caused by the bump and this can be observed visually as spikes or dips in a graph as shown here 5.1.

The application provides an easy to use interface to capture accelerometer, location and video data. The smartphone is mounted on a bicycle at a fixed position and the data is captured along a 30 minutes ride. The collected data is then pre-processed to remove any noise [4] and processed for further analysis.

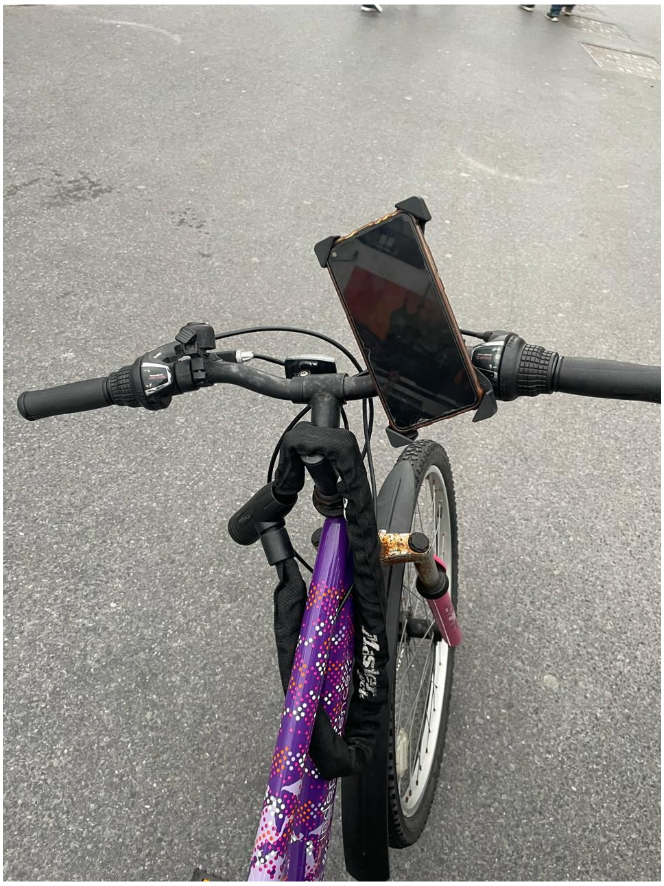

Figure 3.1: Smartphone mounted on the bicycle for data collection

Utilising low pass filters or high pass filters are some of the common methods used [6] to de-noise the data and remove any outliers. The data which we obtain from different locations is then merged and the numbers of seconds elapsed is used as an index. This merged data is then used for training purposes.

Chapter 4

Methodology

Our project uses video and IMU sensor data to analyze the surface quality of cycleway roads. We use the video captured from the smartphone's camera in addition to inputs from IMU sensors (GPS, accelerometer) included in the device. Mounted on a bicycle, the smartphone records data in real time while the bike travels across different types of roadways.

The collected sensor data and video inputs undergo pre-processing. During pre-processing, noise is effectively filtered out to ensure the accuracy of subsequent analyses. The clean data is then fed into machine learning algorithms and neural networks, where we implement YOLO (You Only Look Once) for object detection [7] on the video footage. This step identifies and labels various road assets and conditions.

Pre-processing: Python libraries such as Pandas and PIL are used for data cleaning and Scipy is used for noise filtering, which are essential for accurate data analysis.

Object Detection: YOLO is employed for its speed and accuracy in real-time video processing, allowing efficient identification and labeling of road assets and conditions [11].

Statistical Analysis: The cleaned data is analyzed using Pandas to generate comprehensive statistical insights.

Python Libraries: Pandas and PIL are extensively used for data manipulation and image processing, respectively. Libraries like Plotly, Seaborn and Matplotlib are used for visualization. Libraries like Keras and Tensorflow are used for Deep Learning. Flask is used for creating a web application and Folium is used to visualise the map. These libraries are well-suited for managing large datasets and conducting detailed analyses. These tools and algorithms were selected based on their effectiveness in handling the specific requirements of our project, such as real-time processing and high accuracy in detection and analysis.

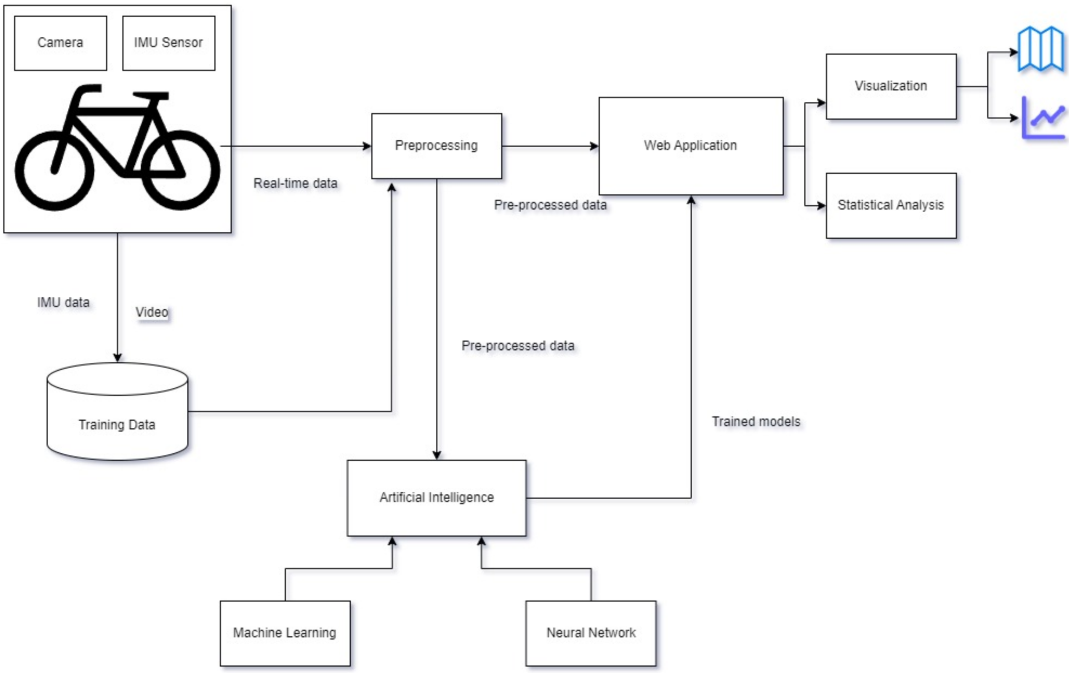

Figure 4.1: Software diagram of the proposed solution

As shown in 4.1, the proposed system will store the IMU data and the video data in a database or a cloud instance and will use it to train the Machine Learning and Deep Learning models on the backend. These trained models will then in turn power the Web Application to provide accurate real-time analytics of the road conditions based on the IMU data inputted.

Several machine learning models were implemented and trained using the pre-processed data:

1. **Random Forest Classifier**: A robust ensemble model that uses multiple decision trees to improve classification accuracy.
2. **Support Vector Machine (SVM)**: A model that maximizes the margin between data points of different classes, with a radial

basis function (RBF) kernel.

3. **K-Nearest Neighbors (KNN)**: A non-parametric model that classifies data points based on the majority vote of their nearest neighbors.

4. **Logistic Regression**: A statistical model that estimates the probability of a binary outcome.

5. **Neural Network**: A deep learning model with multiple layers, designed to capture complex patterns in the data. The network architecture included three dense layers with ReLU activation functions and a final softmax layer for classification.

Similarly, a Neural Network [3] was trained on the preprocessed accelerometer data to predict the quality of the surface of the cycleway as either “good quality” or “bad quality”.

The parameters of the Artificial Intelligence models were determined through trial and errors and rigorous testing on different sets of data. Using a novel approach, an algorithm was developed to label the quality of the cycleway based on the x, y, and z accelerometer data. The algorithm used is as follows:

Calculating the Average Values

The average values of the smoothed accelerometer data in the x, y, and z directions are calculated as:

$$\text{accelerometer\_y\_avg} = \frac{1}{n}\sum_{i=1}^{n} \text{accelerometer\_y\_smooth}_i$$
$$\text{accelerometer\_x\_avg} = \frac{1}{n}\sum_{i=1}^{n} \text{accelerometer\_x\_smooth}_i$$
$$\text{accelerometer\_z\_avg} = \frac{1}{n}\sum_{i=1}^{n} \text{accelerometer\_z\_smooth}_i$$

Subtracting the Average from Each Data Point

The data is then adjusted by subtracting the average value:

$$\text{accelerometer\_y\_data}_i = \text{accelerometer\_y\_smooth}_i - \text{accelerometer\_y\_avg}$$
$$\text{accelerometer\_x\_data}_i = \text{accelerometer\_x\_smooth}_i - \text{accelerometer\_x\_avg}$$
$$\text{accelerometer\_z\_data}_i = \text{accelerometer\_z\_smooth}_i - \text{accelerometer\_z\_avg}$$

Labeling the Data

The labeling is done by evaluating the difference between consecutive adjusted data points. The label is assigned as:

$$\text{label}_i = \begin{cases} 0 & \text{if } \Delta\text{accelerometer\_y\_data}_i > 0.2 \\ & \quad \text{or } \Delta\text{accelerometer\_x\_data}_i > 0.2 \\ & \quad \text{or } \Delta\text{accelerometer\_z\_data}_i > 0.3 \\ 1 & \text{otherwise} \end{cases}$$

Here, $\Delta\text{accelerometer\_y\_data}_i$, $\Delta\text{accelerometer\_x\_data}_i$, and $\Delta\text{accelerometer\_z\_data}_i$

represent the first difference of the adjusted accelerometer data at point i.

The above algorithm provides an index for defining the quality of the cycleway road roughness which can in-turn be used to analyse the road quality and provide further analysis on the ride quality.

Chapter 5

Experiments

5.1 Experiment Description

The objective of this experiment was to develop and evaluate a machine learning-based system for detecting cycleway road surface quality using IMU sensor data collected from a smartphone mounted on a bicycle and develop a web application to visualize the quality of the cycleway using statistical methods. The experiment involved the preprocessing of sensor data, the application of multiple machine learning models, and the creation of a web application for visualization and analysis. The following sections provide a comprehensive overview of the experimental approach, including data pre-processing, model training, and deployment.

5.1.1 Data Collection

The data used in this experiment were collected from various locations and the speed was assumed to be constant throughout the collection process. The data was processed as a CSV file along with video input from the camera.

5.1.2 Data Pre-processing

The pre-processing phase included several key steps to prepare the data for machine learning models:

1. **Smoothing Sensor Data**: Raw accelerometer data were smoothed using the Savitzky-Golay filter to reduce noise as shown in 5.1 and highlight significant changes in road surface conditions. Savitzky-Golay filter gives faster and more accurate results than traditional denoising methods [5].

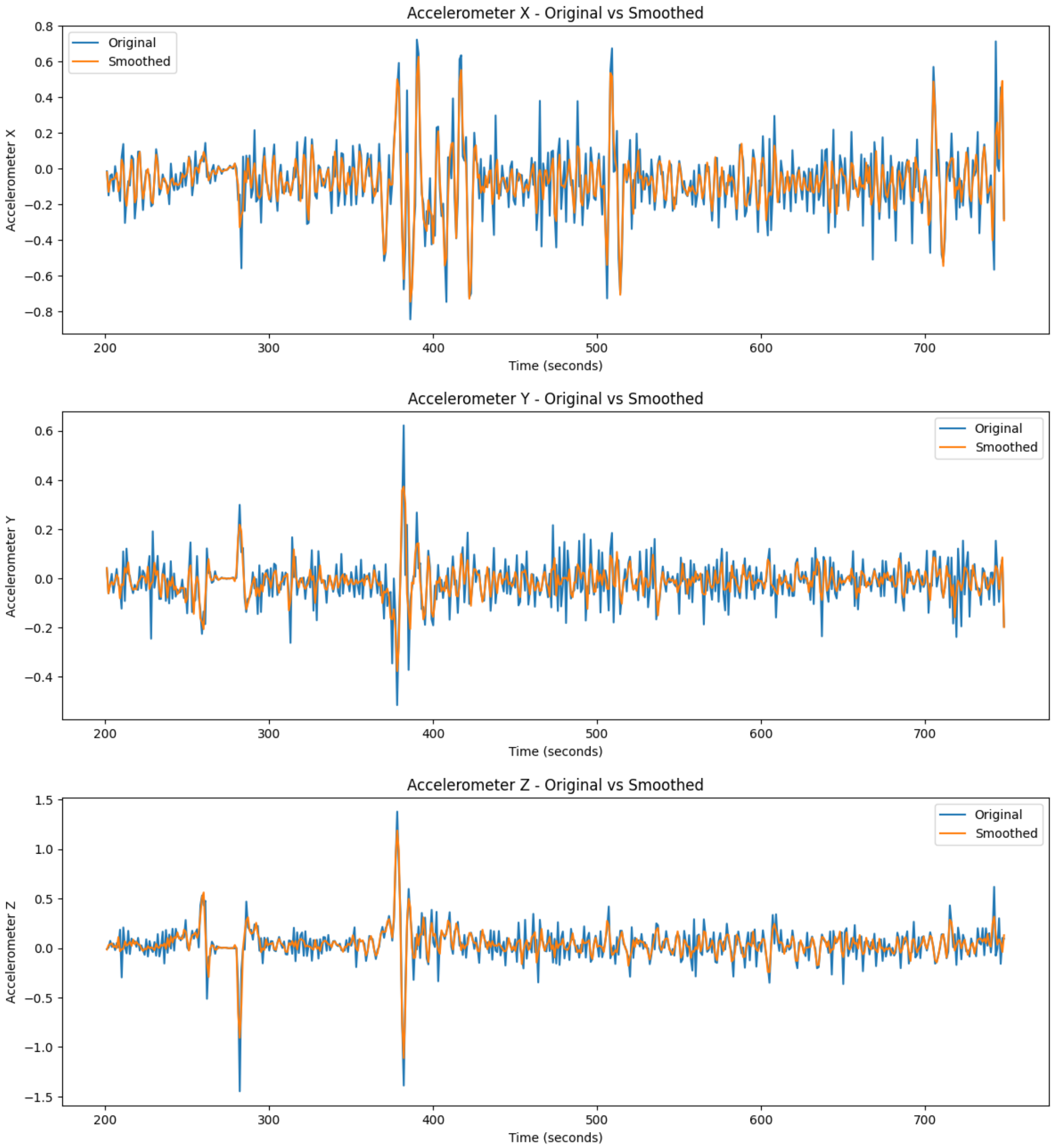

Figure 5.1: Graph showing smoothened data vs raw data over time.

2. **Feature Selection**: The data were reduced to a set of relevant features, including smoothed accelerometer data (`accelerometer_x_smooth`, `accelerometer_y_smooth`, `accelerometer_z_smooth`) and raw sensor readings (`accelerometer_x`, `accelerometer_y`, `accelerometer_z`).

3. **Labeling**: Labels were generated based on the difference between consecutive smoothed accelerometer readings. If the difference exceeded certain thresholds, the segment was labeled as "bad quality" (0), otherwise as "good quality" (1).
4. **Training and Testing Split**: The pre-processed data were split into training and testing sets using an 80/20 ratio, ensuring that the model could be evaluated on unseen data.

Since neural networks are so good at identifying intricate patterns and relationships in data that may be too complex for conventional machine learning algorithms, I decided to train one neural network model. Because of their layered architecture, which enables them to automatically learn and extract significant features, neural networks are especially effective at handling large datasets with numerous features. Furthermore, they are very successful at tasks involving non-linear decision boundaries due to their capacity to generalize from training data, offering a reliable and adaptable method of simulating real-world events.

To address the class imbalance, the Synthetic Minority Over-sampling Technique (SMOTE) was applied to the training data. This technique generates synthetic samples to balance the class distribution, ensuring that the models were trained on a more representative dataset.

5.1.3 Web Application Development

A web application was developed using Flask to allow users to upload new sensor data, process it using the trained models, and visualize the results. The application provided the following functionalities:

Data Upload: Users could upload CSV files containing new sensor data for analysis.

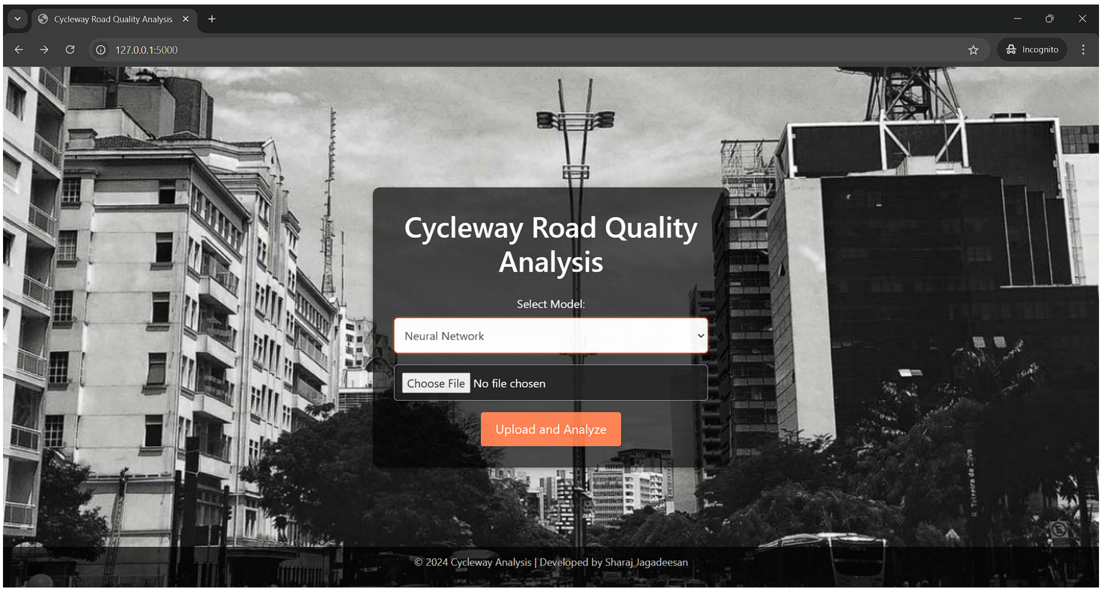

Figure 5.2: Web application interface for uploading CSV files for analysis.

Model Selection: The application allowed users to select from the trained models (Random Forest, SVM, KNN, Logistic Regression, Neural Network) for road quality prediction.

Visualization: The application generated maps with GPS coordinates, marking road segments predicted as "bad quality" and displaying corresponding images as shown in Figure 5.3. Additionally, graphs were created to visualize the smoothed accelerometer data, correlations between axes, and label distributions, as shown in Figure 5.4.

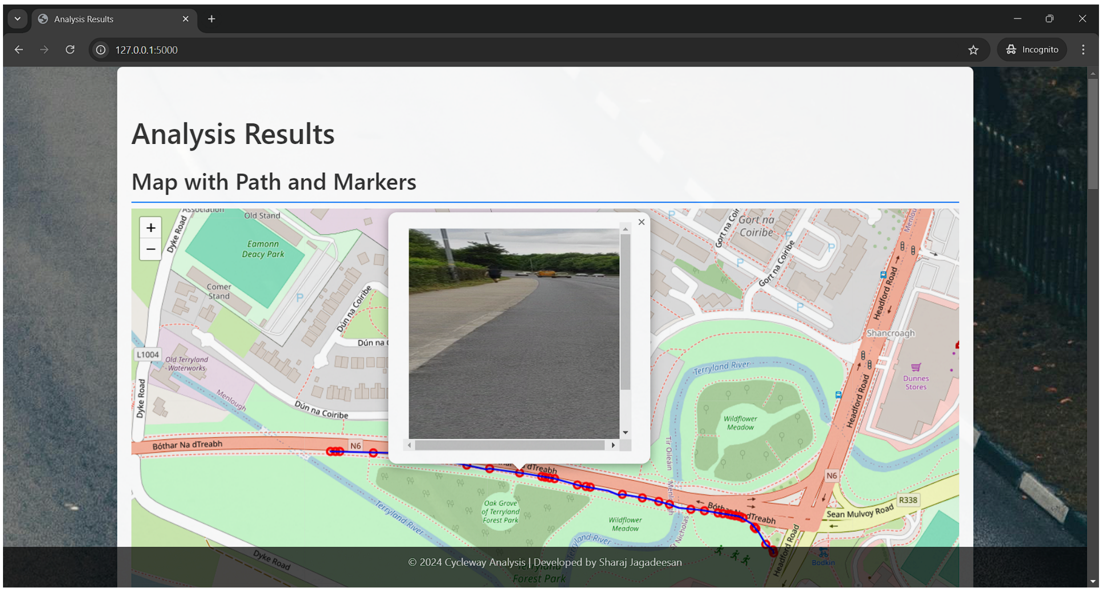

Figure 5.3: Map showing the road segments.

Figure 5.4: Graph displaying the accelerometer data over time.

Prediction Results: The application presented the prediction counts and percentages for "good" and "bad" road quality, providing an overview of the road conditions based on the uploaded data, as shown in Figure 5.5.

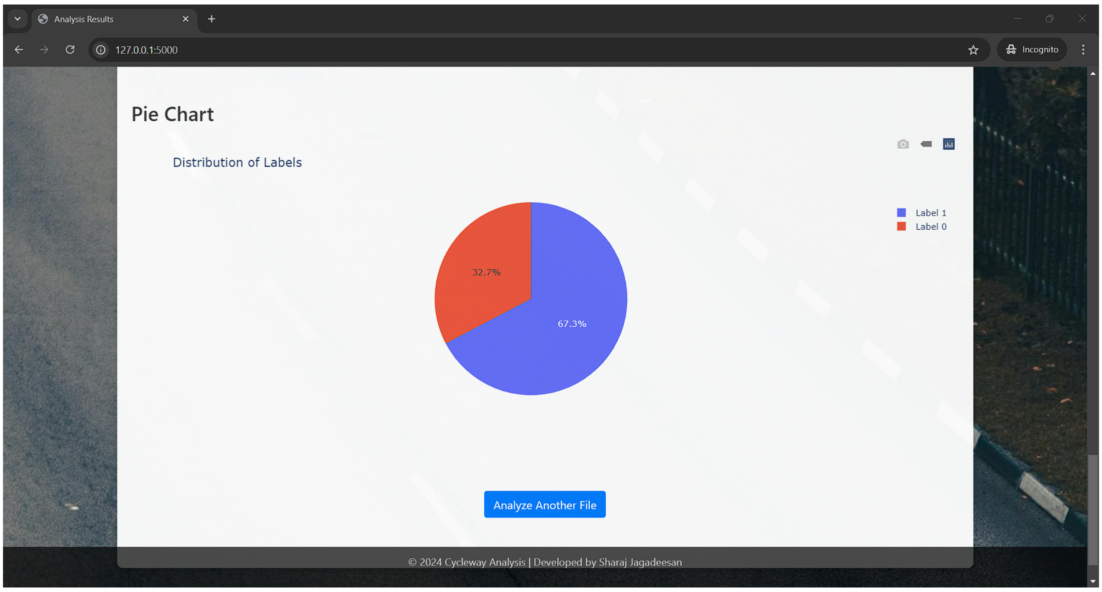

Figure 5.5: Pie chart showing the label counts.

The web application served as a practical tool for deploying the models and making the system accessible to end-users, facilitating real-time cycleway road quality assessment using mobile devices.

Chapter 6

Results

The models were evaluated using K-Fold Cross Validation, a technique that splits the data into multiple folds, ensuring that each fold serves as a validation set once. The average accuracy across folds was recorded for each model. Additionally, confusion matrices and classification reports were generated to assess the precision, recall, and F1-score of each model.

The neural network model was trained separately, using a 60-epoch training process with a validation split of 20%. The performance of the neural network was evaluated on the test set, and predictions were compared with those from traditional machine learning models.

Below are the evaluation matrices of the models for the classes.

Model	Accuracy	Precision (Class 0)	Recall (Class 0)	F1-Score (Class 0)
Random Forest	0.915448	0.901442	0.932836	0.916870
Support Vector Machine	0.776188	0.796791	0.741294	0.768041
K-Nearest Neighbors	0.866759	0.801636	0.975124	0.879910
Logistic Regression	0.702654	0.709512	0.686567	0.697851
Neural Network	0.936364	0.500000	0.142857	0.222222

Table 6.1: Evaluation Metrics for Label 0

Model	Accuracy	Precision (Class 1)	Recall (Class 1)	F1-Score (Class 1)
Random Forest	0.915448	0.930412	0.898010	0.913924
Support Vector Machine	0.776188	0.758140	0.810945	0.783654
K-Nearest Neighbors	0.866759	0.968254	0.758706	0.850767
Logistic Regression	0.702654	0.696386	0.718905	0.707466
Neural Network	0.936364	0.944444	0.990291	0.966825

Table 6.2: Evaluation Metrics for Label 1

The machine learning models were evaluated based on their accuracy in classifying road surface quality using the test dataset. The following table summarizes the accuracy of each model:

Model	Accuracy (%)
Logistic Regression	70.27
K-Nearest Neighbours	86.68
Support Vector Machine	77.62
Random Forest	91.54
Neural Network	94.55

Table 6.3: Accuracy of different machine learning models in detecting road surface quality.

Among the models tested, the **Neural Network** achieved the highest accuracy at **94.55%**, followed closely by the **Random Forest** model with an accuracy of **91.54%**. The **K-Nearest Neighbours (KNN)** model also performed well, achieving an accuracy of **86.68%**. The **Support Vector Machine (SVM)** and **Logistic Regression** models achieved accuracies of **77.62%** and **70.27%**, respectively.

The results indicate that the Neural Network model is the most effective for the given task, likely due to its ability to capture complex patterns in the data through its deep learning architecture. The Random Forest model also demonstrated strong performance, benefiting from its ensemble approach to decision trees. In contrast, the Logistic Regression model, which is simpler and assumes a linear relationship between features, performed less effectively in this context.

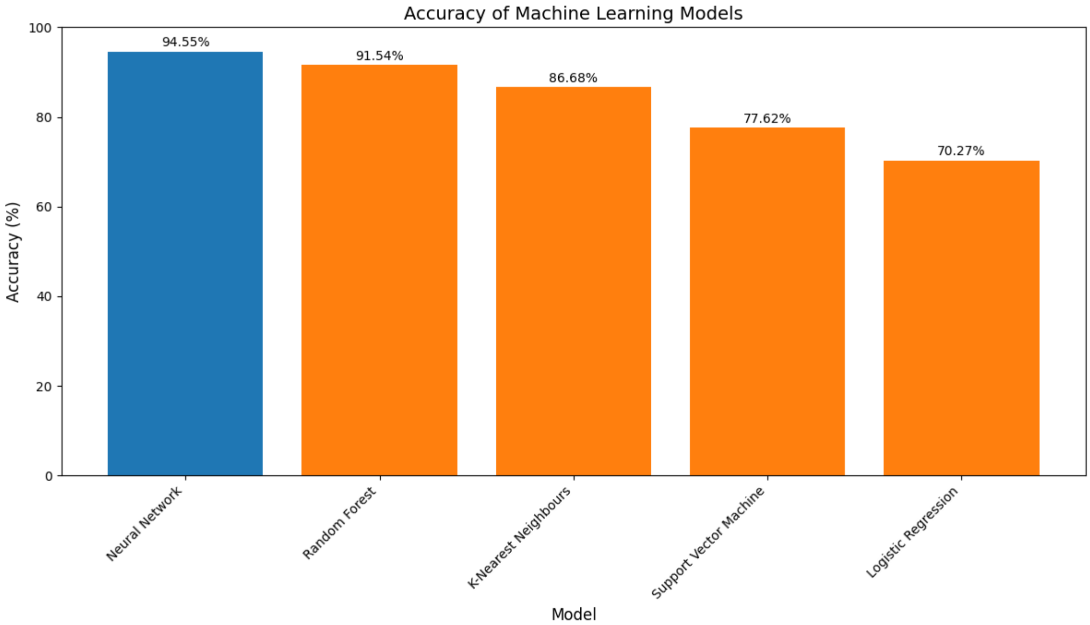

Figure 6.1: Comparison of model accuracies for road surface quality detection.

Figure 6.1 provides a visual comparison of the accuracies achieved by each model. This further highlights the superior performance of the Neural Network and Random Forest models in classifying road surface quality based on sensor data.

Chapter 7

Conclusion

This thesis presents a significant contribution to the field of cycleway infrastructure management by developing an innovative, cost-effective web application designed to assess and enhance cycleway quality. By leveraging widely available smartphone sensors, such as the IMU sensor, and integrating them with advanced machine learning algorithms—including Random Forest, SVM, KNN, Logistic Regression, and Neural Networks—this work addresses the critical need for more accessible and efficient tools in evaluating road conditions.

The main contributions of this research include the development of an index for measuring cycleway quality, the creation of a user-friendly web application for real-time data analysis, and the successful implementation of machine learning models to predict and visualize road conditions. These achievements bridge the gap identified in current methodologies, which often overlook the specific requirements of cycleway infrastructure management.

However, there are certain limitations. The accuracy of the machine learning models is tied to the quality and diversity of the training data, which may limit the web application's applicability to scenarios outside the data's scope. Additionally, the dependency on smoothened accelerometer data could obscure critical details needed for precise classification, and the static model selection process may not always yield the optimal model for varying datasets. Future improvements could include expanding the dataset to cover a wider range of road conditions, integrating additional sensors like gyroscopes for more accurate data, and implementing a more dynamic model selection process, potentially involving ensemble methods.

In conclusion, while there are areas for future enhancement, this thesis lays a strong foundation for further research and development. The web application developed here has the potential to make a significant impact on cycleway infrastructure by providing a practical, data-driven approach to improving cyclist safety and optimizing maintenance strategies in urban environments.

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Appendix A

Appendix

GitHub link for the code and other resources: https://github.com/Sharaj17/Thesis-Project/