Enhancing Road Infrastructure Management through Computer Vision: Deep Learning for Road Condition Classification

PROJECT REPORT

Date: May 3rd, 2024

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Business Understanding

Business Overview

The Kenya Roads Board (KRB) manages an extensive network of roads totaling approximately 162,055 km, as reported in the Strategic Plan 2023-2027. These road assets are crucial for the nation's economic development and mobility. Currently, the Road Inventory and Condition Survey (RICS) is conducted through manual processes that demand considerable time and human resources. This approach frequently results in delayed maintenance and variable data quality due to the subjective nature of human assessments. To illustrate the substantial scope of the survey, this interactive dashboard showcases Kenya’s extensive road network as managed by various Road Agencies i.e. KeNHA, KeRRA, KURA, and County Governments.

Business Objectives

This project aims to transform the RICS by incorporating a deep learning-based model to automate and enhance the accuracy of road condition assessments. Specific objectives include:

- Automating the classification of road conditions to reduce dependency on manual, labor-intensive methods.
- Improving the accuracy and consistency of data collected during surveys.
- Enabling real-time data processing and faster decision-making for road maintenance and repairs.

Success Criteria

The project will be considered successful if it achieves:

- At least a 50% reduction in the time required to report and process road conditions.
- Demonstrable improvement in the accuracy of road condition data as reflected by reduced discrepancies in subsequent maintenance validations.
- Positive feedback from end-users and key stakeholders, indicating ease of use and satisfaction with the system functionalities.

Data Understanding

Overview

The use of a comprehensive and diverse dataset is crucial for training an effective deep-learning model capable of recognizing various road conditions across different environments.

Data Description

The dataset includes 1,729 images collected from different geographical regions, representing a range of road conditions. Each image is labeled with one of five road conditions, ensuring a supervised learning approach can be effectively applied. The distribution is as follows:

- **Good (655 images):** Roads with no or minimal defects.
- **Fair (269 images):** Roads with minor surface damage such as small cracks.
- **Poor (228 images):** Roads suffering from major defects, including large potholes.
- **Flooded (258 images):** Roads that are temporarily impassable due to water accumulation.
- **Unpaved (319 images):** Dirt or gravel roads without pavement/ blacktop.

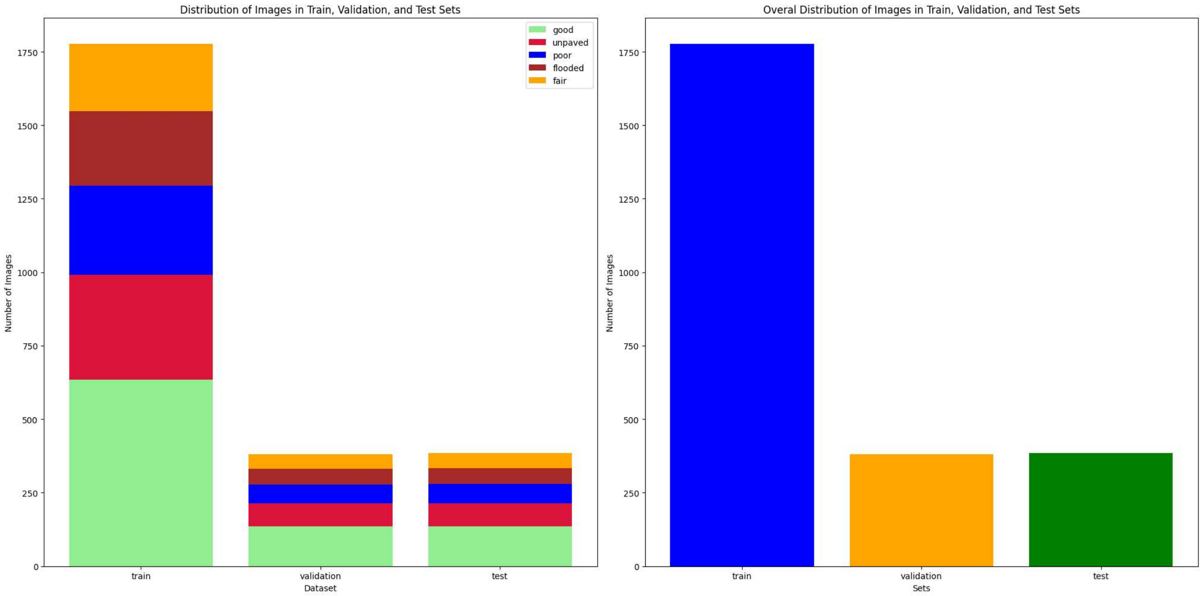

Figure 1.1: Distribution of Images in Train, Validation & Test Sets

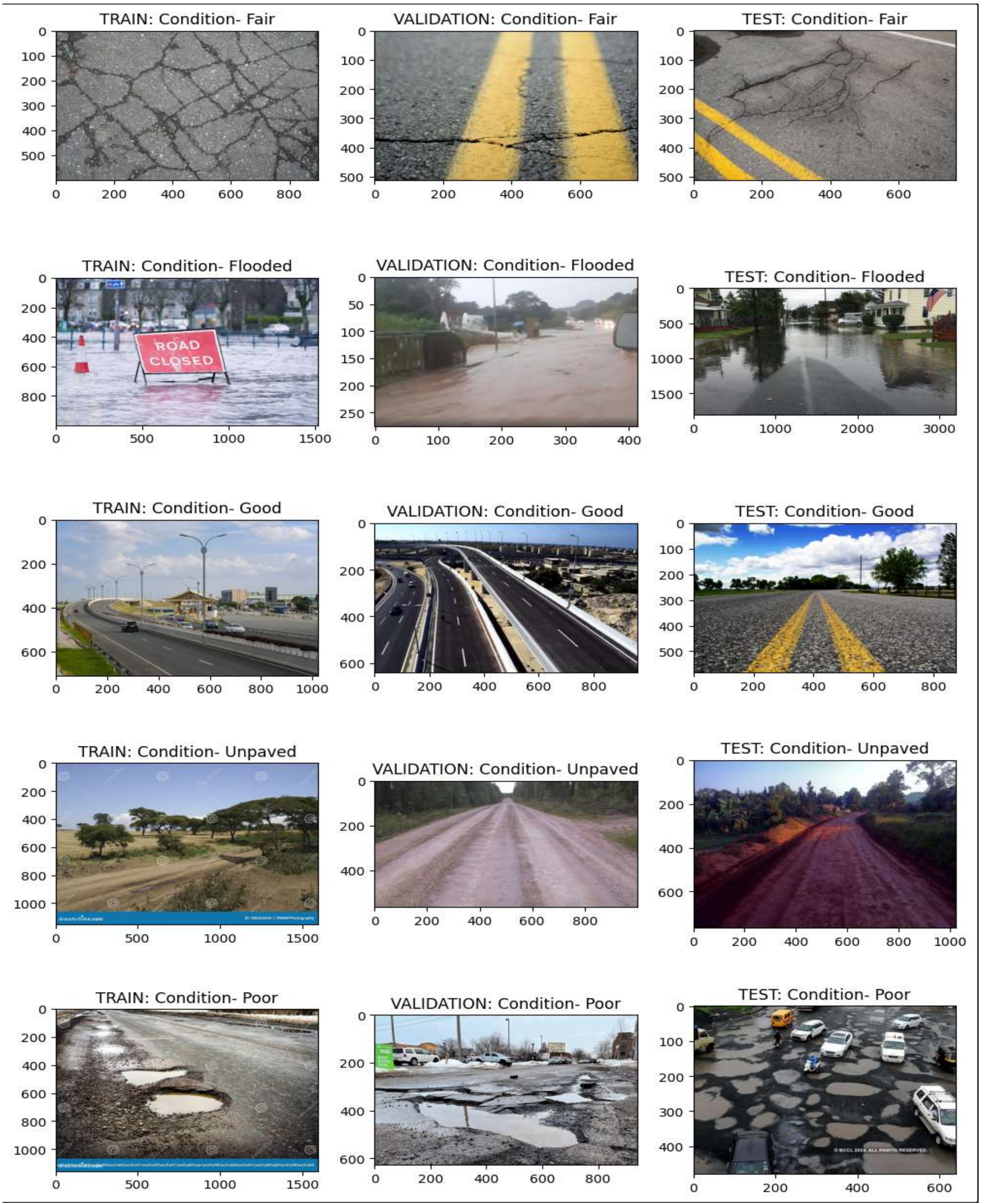

Figure 1.2: Sample of Road Images for Each Label Across the Train, Validation, and Test Sets

Verifying Data Quality

Data quality is assured by:

- Conducting a thorough initial review to ensure accurate labeling and categorization of all images.
- Implementing automated scripts to detect and remove any corrupted files.
- Regular audits to reassess the dataset and incorporate additional images to address any discovered imbalances or biases.

Data Preparation

Preprocessing

The preprocessing of data involves several key steps designed to prepare the images for effective model training:

- Image Resizing: Standardizing all images to a uniform size (224x224 pixels) to ensure consistency in model input.
- Normalization: Scaling pixel values to a [0,1] range to facilitate model training and convergence.
- Data Augmentation: Employing techniques such as rotation, flipping, and zooming to artificially expand the training dataset, enhancing the model's ability to generalize from the training data to unseen real-world data.

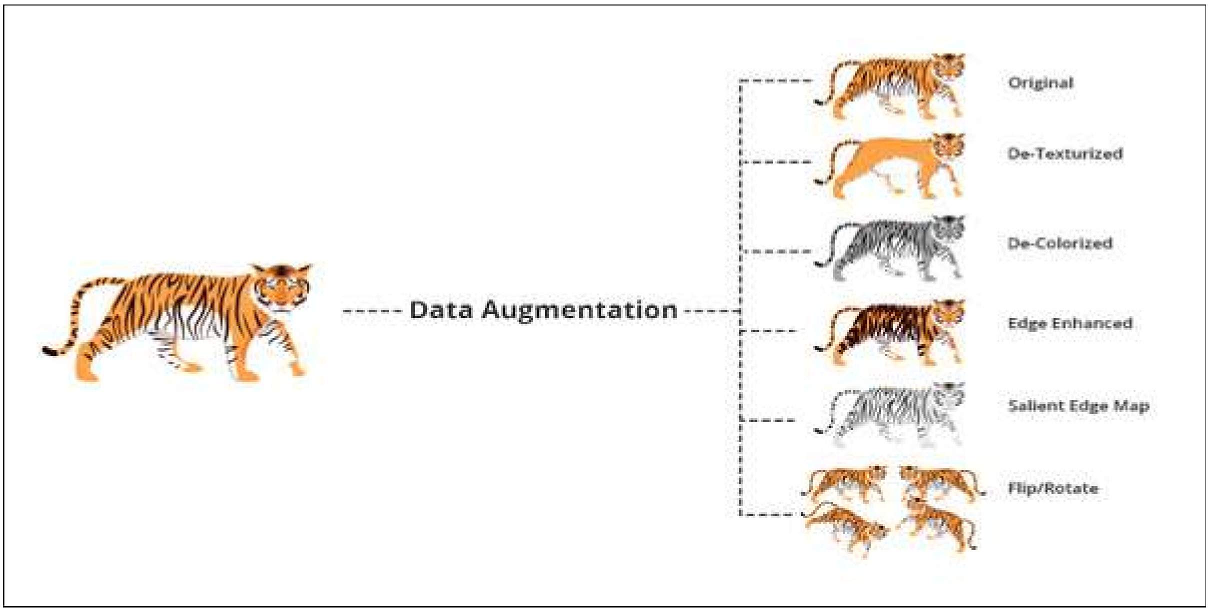

Figure 1.3: Illustration of Data Augmentation in Deep Learning

Modeling

Modeling Approach

The project explores several modeling approaches:

- **Baseline Model:** Establishing a simple CNN architecture as a baseline to gauge initial performance.
- **Advanced Models:** Evaluating several pre-trained models (DenseNet, EfficientNet, VGG16, ResNet, and NasNet) to leverage transfer learning, which can significantly improve the model's ability to classify complex images.
- **Model Selection:** Choosing the best-performing model based on a comprehensive evaluation of its accuracy, speed, and robustness across diverse road conditions.

Evaluation

Evaluation Metrics

Comprehensive metrics are employed to assess each model:

- **Accuracy:** Measures the proportion of total correct predictions.
- **Precision and Recall:** Important in scenarios where imbalances in class distribution exist.

- **F1 Score:** Combines precision and recall into a single metric, providing a balanced view of model performance.
- **Loss Metrics:** Track how well the model is performing during training, helping identify convergence and overfitting issues.

Step 5 | Model Comparison

This table summarizes the performance of various deep learning models used in this road condition classification project.

SN.NO	Model Name	Test Loss	Test Accuracy	Test F1 Score	Test Precision	Test Recall	Training Time	Notes
1	Baseline Model	1.0663	59.01%	55.55%	63.36%	59.01%	28.42 mins	Baseline configuration
2	CNN with Different Architecture	1.3793	47.26%	36.71%	30.90%	47.26%	27.47 mins	Added more layers to baseline CNN, may overfit
3	VGG16 Model	0.5673	77.28%	77.02%	77.87%	77.28%	33:29 mins	Good generalization capabilities
4	Densenet Model	0.2688	91.12%	91.03%	91.24%	91.12%	30:54 mins	Small size and accurate, excellent efficiency
5	Tuned Densenet Model	0.3269	90.08%	90.02%	90.40%	90.08%	39:54 mins	Fine-tuned with Early Stopping, optimized parameters
6	EfficientnetB0	1.5391	35.25%	18.37%	12.42%	35.25%	38:26 mins	Struggled with complex road conditions
7	EfficientnetB5	1.5378	35.25%	18.37%	12.42%	35.25%	38:27 mins	Similar issues as B0, no improvement
8	Resnet50	1.3915	35.51%	18.92%	25.51%	35.51%	35:52 mins	Underperformed in precision and recall
9	NasnetLarge Model	0.2679	89.03%	88.97%	89.05%	89.03%	25:11 mins	Shortest training time, highly efficient

Figure 1.4: Comparative Analysis of Models Across Key Performance Metrics

Deployment

Deployment Strategy

Deployment involves:

- **Streamlit Web Application:** Developing an intuitive web application that allows end-users to upload road images and receive instant condition classifications.
- **Ongoing Model Updates:** Implementing a feedback loop where the model is continually refined and updated based on new data and user feedback.

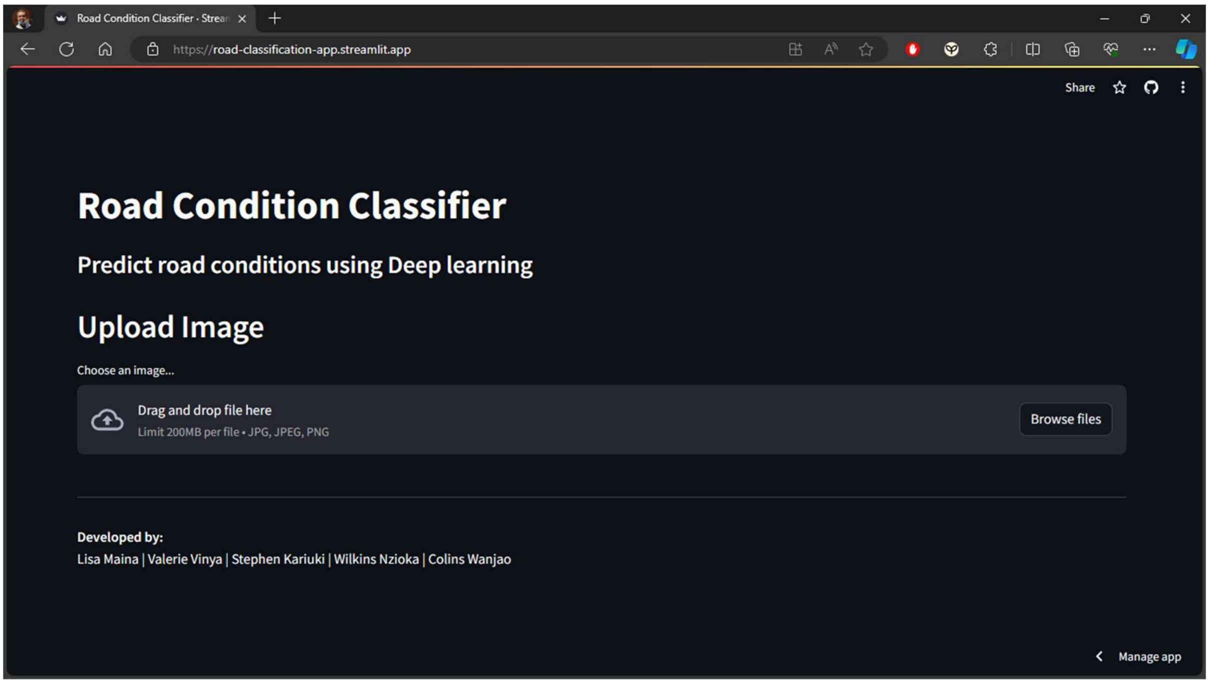

Figure 1.5: User Interface of the Streamlit Web Application for the Road Condition Classification Tool

Conclusion

Integrating deep learning into the Road Inventory and Condition Survey (RICS) process is poised to yield significant enhancements in the efficiency, accuracy, and reliability of road condition assessments. This project forms a foundational step towards broader innovations in infrastructure management, establishing a precedent for the incorporation of artificial intelligence (AI) into public service delivery mechanisms. The adoption of deep learning technologies in this context is expected to revolutionize how road data is processed and interpreted, leading to substantial improvements across various facets of road maintenance and policy formulation.

The anticipated benefits of this integration are manifold. Firstly, by automating the analysis of road conditions, deep learning can significantly reduce the time and labour traditionally required, translating into considerable cost savings for government Road Agencies (RA). Moreover, the increased accuracy and objectivity offered by AI-driven assessments can lead to more effective identification of critical repair needs, thereby enhancing road safety for users. Furthermore, the ability to analyze large volumes of data rapidly enables more agile and responsive infrastructure policies. Decision-makers will be equipped with timely and precise information, allowing for quicker responses to emerging issues and a more strategic allocation of resources.

In sum, the integration of deep learning into the RICS process not only promises to enhance the operational aspects of road assessment but also sets the stage for a more data-driven and proactive approach to infrastructure management. This initiative is expected to serve as a model for future applications of AI in enhancing public service delivery, marking a significant leap forward in the use of technology to improve the quality of life and safety of the public.

Recommendations

1. **Integration of Geographic Information Systems (GIS)**

   We recommend the incorporation of our road condition classification model into Geographic Information Systems (GIS). This combination would facilitate the accurate mapping and monitoring of road conditions, offering capabilities for real-time visualization and detailed analytics. Utilizing geotagged images, the classified data can be precisely located on a map, granting the Kenya Roads Board detailed spatial information about areas of road deterioration and critical spots for degradation, which is crucial for optimizing maintenance efforts and quick intervention strategies.

2. **Creation of a Crowdsourced Data Collection Platform**

   By introducing a simple training module along with rewards, the Kenya Roads Board can effectively utilize crowdsourcing within the Road Inventory and Condition Survey (RICS) to collect images depicting road conditions. This method would allow the public to contribute to data gathering, enabling engineers to allocate their skills toward the more specialized, analytical parts of road maintenance planning.

3. **Policy Formulation Using Predictive Analytics**

   Employ the sophisticated analytics derived from road condition data to support and push for policy formation. Through the analysis of existing conditions and forecasting of future road scenarios, the Kenya Roads Board can improve the planning of maintenance intervals, budgeting, and infrastructural enhancements. Predictive analytics represents a crucial instrument in advocating for the essential support and legislation needed to uphold and improve road infrastructure.

4. **Advancement of Training and Capacity Enhancement**

   Organize educational workshops for personnel from the Kenya Roads Board and other pertinent parties to boost their proficiency with new technological integrations in the RICS framework. This training should include handling the GIS platform, interpreting data processed by the model, and utilizing the crowdsourcing tool efficiently, ensuring comprehensive skill in exploiting these technologies to their maximum potential.

5. **Collaboration with Technology Firms and Academic Entities**

Establish strategic partnerships with technology vendors and academic bodies to sustain ongoing enhancement and support for the technologies implemented. These collaborations can provide access to the most recent developments in GIS, machine learning, and crowdsourcing technologies and present opportunities for joint research and innovation in monitoring road conditions.

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