APPLICATION OF ARTIFICIAL INTELLIGENCE ON DRONE-COLLECTED DATA FOR CUT-AND-FILL VOLUME ESTIMATION OF CHATOLOMA, KASUNGU-JENDA ROAD

MSc Thesis

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DECEMBER, 2025

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A THESIS SUBMITTED TO THE FACULTY OF ENVIRONMENTAL SCIENCES, DEPARTMENT OF BUILT ENVIRONMENT IN FULFILMENT OF THE REQUIREMENTS FOR THE AWARD OF A MASTER OF SCIENCE DEGREE IN GEOGRAPHICAL INFORMATION SYSTEMS

MZUZU UNIVERSITY

DECEMBER 2025

DECLARATION

I hereby declare that this thesis titled "Application of Artificial Intelligence on Drone-Collected Data for Cut-And-Fill Volume Estimation of Chatoloma, Kasungu-Jenda Road" has been written by me and is a record of my research work. All citations, references, and borrowed ideas have been duly acknowledged. This thesis is being submitted in fulfilment of the requirements for the award of the degree of Master of Science (MSc) in Geographic Information Systems at Mzuzu University. None of the present work has been submitted previously for any degree or examination at any other university.

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CERTIFICATE OF COMPLETION

The undersigned certify that this thesis is a result of the author's work and that, to the best of our knowledge, it has not been submitted for any other academic qualification within Mzuzu University or elsewhere. The thesis is acceptable in form and content, and that satisfactory knowledge of the field covered by the thesis was demonstrated by the candidate through an oral examination held on: ______________________________

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DEDICATION

This work is dedicated to my late Dad, Mr. Peterson Nyamwera, and my Mum, Mrs. Maggie Nyamwera, whose support, encouragement, and faith in my destiny made me complete this work. I further dedicate this work to Aimloce Greyfield for always pushing me beyond my capabilities.

ACKNOWLEDGEMENTS

I would like to express my deepest gratitude to God for giving me the strength to complete my thesis.

First and foremost, I am immensely grateful to my thesis supervisors, Associate Professor Mavuto Tembo, PhD, and Associate Professor Mtafu Manda, PhD, for their invaluable guidance, patience, and unwavering support throughout the entire research process. Their expertise, insightful feedback, and encouragement have been instrumental in shaping this work and pushing me to achieve my best.

I extend my sincere appreciation to the project Coordinator for Kasungu-Jenda Road, Eng Elias Sisya from the Roads Authority, Senior Engineer at Mota Engil, Eng. Kondwani Ng'oma and the entire Mota Engil staff, who generously dedicated their time and participated in this study. Their contribution and cooperation were vital in collecting the data needed for analysis and interpretation.

Lastly, I would like to express my profound gratitude to my friends and family members for their unwavering support, understanding, and encouragement throughout this challenging endeavour. Their belief in me and their continuous motivation has been a constant source of strength and inspiration.

ABSTRACT

Like many other engineering projects in developing countries, the Kasungu-Jenda Road has faced numerous challenges in data collection and analysis, including slowed surveying works, underestimations, and overestimations of cut and fill volumes. These challenges often lead to increased financial and time-related costs. This study examined the application of Artificial Intelligence processing techniques on drone-collected data for road surveying on the Kasungu-Jenda Road in Malawi. Specifically, it assessed the effectiveness of machine learning (ML) algorithms in object classification, evaluated their potential in predictive analytics for cut-and-fill volume estimation, and compared their volumetric accuracy with traditional computation methods. A quantitative experimental design was employed, utilising drone imagery, traditionally collected as-built data, and road design data. This data was processed and analysed through Convolutional Neural Networks (CNNs), Random Forest, XGBoost, and Support Vector Machine (SVM) algorithms. CNN models demonstrated high effectiveness in object classification, achieving 90.91% accuracy across multiple land cover types, including vegetation, bare land, and earthworks. For predictive analytics, XGBoost achieved the highest accuracy (MAE = 0.0052 m; $R^2 = 0.9847$), followed by Random Forest (MAE = 0.0106 m; $R^2 = 0.9451$) and SVM (MAE = 0.0150 m; $R^2 = 0.8908$), all indicating low error margins. On the other hand, a comparison of XGBoost with the Prismoidal Method in cut and fill volumetric estimations using 2-meter chainage drone elevations, and 20-meter traditional chainage elevations revealed statistically significant differences by a paired samples t-test ($p < 0.05$). The difference is attributed to XGBoost's ability to detect finer terrain variations from high-resolution data, which are not captured by traditional methods. The study concludes that while conventional approaches remain useful, ML-based models in combination with drone technology offer improved precision and spatial detail in engineering surveying. It therefore recommends incorporating these technologies to improve both the accuracy and reliability of survey work.

Key-words: *Artificial Intelligence, Machine Learning, Drone Imagery, Road Surveying, Cut-and-Fill Volume, Predictive Analytics*

ACRONYMS AND ABBREVIATIONS

AI	Artificial Intelligence
CAD	Computer-Aided Design
CNN	Convolutional Neural Network
DEM	Digital Elevation Model
GIS	Geographic Information Systems
GCP	Ground Control Point
GPS	Global Positioning System
IoU	Intersection over Union
KIA	Kamuzu International Airport
MAE	Mean Absolute Error
ML	Machine Learning
MSc	Master of Science
MZUNI	Mzuzu University
MZUNIREC	Mzuzu University Research Ethics Committee
QGIS	Quantum Geographic Information System
ReLU	Rectified Linear Unit
RMSE	Root Mean Squared Error
R^2	Coefficient of Determination
RBF	Radial Basis Function
SVM	Support Vector Machine
SPSS	Statistical Package for the Social Sciences
XGBoost	Extreme Gradient Boosting
UAV	Unmanned Aerial Vehicle (Drone)

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CHAPTER ONE: INTRODUCTION

1.1 Introduction

This Chapter provides an overview of how machine learning and drone data can transform data management in the field of engineering surveying, particularly in the estimation of cut and fill quantities. It also explores how the integration of drones and machine learning enhances the speed and accuracy of data when compared to ground-based surveying methods.

1.2 Study Background

Accurate cut-and-fill volume estimation is one of the most critical tasks in road construction. These measurements directly influence project planning, cost estimation, and scheduling, and any miscalculation can have a cascading effect on both budgets and timelines (Akinradewo et al., 2020). For decades, engineers have relied heavily on ground-based surveying techniques such as total stations, levels, and differential GPS to collect terrain data and compute earthwork quantities (Buba Aliyu & Dahiru, 2019; Matsimbe et al., 2022). While these methods are reliable, they become slow, labour-intensive, and costly when applied over long alignments (Kavitha et al., 2018). In large projects, the time required to traverse entire road sections often results in delays in data processing, leading to late decision-making, project slowdown, and increased operational costs (Dundas et al., 2021). The challenge is compounded in developing countries like Malawi, where resource constraints and logistical barriers make it even harder to collect and process data quickly while maintaining high accuracy standards (Chagunda, 2017).

Advances in surveying technology, particularly the introduction of unmanned aerial vehicles (UAVs), have transformed the way engineers can capture terrain data. Drones, equipped with high-resolution cameras and capable of automated flight paths, can rapidly collect overlapping imagery over large areas (Zhang & Zhu, 2023; Choi et al., 2024). When processed using photogrammetric techniques or LiDAR, this imagery produces detailed digital elevation models (DEMs) with centimetre-level resolution (Giordan et al., 2020). Such capabilities allow for faster and more comprehensive spatial data acquisition compared to conventional field methods (Zhang, 2025). Importantly, UAVs also improve safety by reducing the need for surveyors to access hazardous or hard-to-reach locations and minimise disruptions to ongoing construction activities (Askerbekov et al., 2024). Despite these benefits, the adoption of drone-based surveying in many infrastructure projects in Malawi remains limited, with most projects still following traditional workflows (Chagunda, 2017)

While drones have solved the challenge of rapid data capture, processing, and interpreting these large, high-density datasets present another challenge. This is where Artificial Intelligence (AI) and, more specifically, Machine Learning (ML) offer transformative potential. AI refers to the development of computer systems capable of performing tasks that typically require human intelligence, such as problem-solving, pattern recognition, and decision-making (Meshram & Reddy, 2022). ML, a subset of AI, uses statistical and computational algorithms to learn from data and improve its performance over time without being explicitly programmed (Raschka et al., 2020). When integrated with drone-collected datasets, ML models can automate the classification of terrain features, predict engineering quantities, and identify subtle variations that might be missed by traditional manual analysis (Su et al., 2023).

In engineering surveying, ML has shown strong potential in areas such as object classification and predictive analytics. For object classification, algorithms such as Convolutional Neural Networks (CNNs), Random Forests, and Support Vector Machines (SVMs) can be trained to recognise and categorise features like vegetation, bare ground, tarmac, or earthworks from high-resolution aerial images (Alzubaidi et al., 2021; Wang et al., 2021). CNNs, in particular, have demonstrated superior performance in capturing spatial patterns in imagery, making them especially suited for drone-based land cover mapping (Martinez-Castillo et al., 2020). This automated classification not only speeds up mapping tasks but also ensures consistency in feature identification across large datasets (Boston et al., 2022a).

Predictive analytics is another area where ML is proving vital. By utilising both historical and current datasets, such as as-built elevations, design profiles, and topographic models, ML algorithms can predict cut-and-fill volumes with remarkable accuracy (Rafsanjani & Nabizadeh, 2023). Traditional computation methods, like the prismoidal formula, often rely on cross-sections spaced at intervals (20-meter chainages), which can miss fine terrain variations between points (Babapour et al., 2018; Lee et al., 2024). In contrast, ML models trained on dense drone-derived elevations (for example, at 2-meter intervals) can detect subtle undulations, embankments, or depressions that significantly influence volume estimates. Algorithms such as XGBoost and Random Forest have been successfully adopted in other domains for high-precision regression tasks and are well-suited for this application (Imani et al., 2025; Yasasvi & Kumar, 2022).

Globally, AI and ML have revolutionized numerous sectors, from agriculture and environmental monitoring to mining and infrastructure management, by enabling faster, data-driven decision-making (Chen et al., 2023; Kayusi et al., 2024). In road construction, however, the combined use of drone imagery and ML for volumetric analysis remains relatively underexplored, especially in the context of African terrain and project environments. In Malawi, AI adoption in engineering has been slow, although some sectors, such as agriculture and healthcare, have begun integrating AI tools for diagnostics, monitoring, and analysis (Masina, 2023). The limited application of AI in surveying means that large volumes of valuable spatial data collected by drones may still be underutilised, processed with methods that do not fully exploit the available detail.

This gap is particularly significant for projects like the Kasungu–Jenda Road, an 85.5 km alignment which is undergoing rehabilitation and widening. The project involves extensive earthworks, where accurate and timely volume estimation is vital for resource planning, cost control, and maintaining construction schedules. The nature of the terrain, characterised by varying gradients, roadside drainage features, and cut-and-fill transitions, makes it an ideal case for testing whether ML models can outperform traditional methods in both speed and precision. By integrating object classification and predictive analytics into the workflow, survey teams can potentially generate more accurate, high-resolution volume estimates without sacrificing processing time. This research, therefore, aims to provide evidence for adopting AI-driven approaches in Malawi's road surveying practice, potentially setting a precedent for broader use of these technologies in infrastructure development across similar contexts

1.3 Problem Statement

Like many other engineering projects in developing countries, the Chatoloma, Kasungu-Jenda Road rehabilitation works have faced numerous data collection and analysis challenges. (Villanueva & Neza, 2023) . Due to the project's reliance on traditional ground-based surveying methods, as well as time-consuming manual computations, numerous challenges, such as slowed surveying works, underestimations, and overestimations of cut and fill volumes, are encountered (Matsimbe et al., 2022). According to Akinradewo et al. (2020), such inaccuracies increase costs, extend project timelines, and disrupt resource planning. Although Artificial Intelligence (AI) and Machine Learning (ML) have transformed data processing in other fields due to their speed, precision, and automation (Goel et al., 2022; Sarker, 2022), data processing in engineering surveying in Malawi still relies largely on traditional, time-consuming methods prone to accuracy loss. (Kamanga & Steyn, 2013). This has contributed to delays in several road projects central to the MW2063 development agenda (National Planning Commission, 2020; Chagunda, 2017).

On data collection related challenges, the integration of high-resolution drone imagery with ML algorithms offers a practical solution, which may enable fine-scale terrain analysis and faster, more precise volume estimation (Nabizadeh Rafsanjani & Nabizadeh, 2023; Zhang & Zhu, 2023). Yet, despite the maturity of these technologies internationally, their combined application to road projects in Malawi, particularly in complex terrains such as the Kasungu–Jenda stretch, remains largely unexplored. Without targeted research, the sector risks continuing to rely on outdated approaches, forfeiting gains in accuracy, efficiency, and cost-effectiveness (Chagunda, 2017). Therefore, this study explored the application of AI, ML, and drone images in processing volume data in engineering surveying.

1.4 Objective

The main objective of this study is to assess the application of artificial intelligence on drone-collected data for cut-and-fill volume estimation.

1.4.1 Specific objectives

1. To assess the effectiveness of machine learning algorithms in object classification for drone-collected data

2. To evaluate the potential of machine learning techniques for predictive analytics for cut-and-fill volume estimation

3. To compare the accuracy of machine learning derived output and traditionally computed output for cut-and-fill volume estimation

1.4.2 Hypothesis

1. Machine learning algorithms are effective for object detection and classification of drone data
2. Machine learning techniques have a significant potential for predictive analytics in estimating cut-and-fill volumes
3. There is a significant similarity in accuracy levels between machine learning derived volumes and traditionally computed volumes

1.5 Study Justification

As stipulated, engineering surveying suffers from numerous data processing challenges. This study, therefore, will contribute significantly to the improvement of accuracy, efficiency, and decision-making processes in engineering surveying, thereby positively impacting various industries reliant on precise surveying data. By adopting AI, ML, and drone images, this research will revolutionize engineering surveying practices and contribute to the broader field of geospatial data analysis by;

1. Improving terrain modelling for volume estimation, which, in a broader perspective, supports MW2063's digital transformation agenda and Transport Policy's adoption of modern data technologies for better infrastructure planning and decision-making.
2. Enabling timely planning and minimizing errors by aligning with pillar 3 (industrialisation) of the MW2063 agenda; cost-efficient development, which supports modern technologies.
3. Providing a practical guide to Malawi's Transport Policy, whose goal is to improve project efficiency through timely project delivery and efficient resource allocation.
4. Supporting MW2063's push for evidence-based innovation and the Transport policy's focus on data accuracy and safety in infrastructure development.

1.6 Conclusion

This chapter explored the challenges of data management in engineering surveying, highlighting how traditional methods struggle with processing large volumes of data efficiently. It discussed the technological advancements brought by drones and machine learning, emphasizing their potential to improve data processing and cut-and-fill volume estimation. Despite these advancements, the literature reveals a significant gap in the efficient handling and accurate analysis of drone-collected data within engineering surveying, which this study aims to address.

CHAPTER TWO: LITERATURE REVIEW

2.1 Introduction

In this chapter, relevant literature has been reviewed on the various data collection and processing methods in engineering surveying, including relevant data processing methods and challenges. It also reviews the applications of Artificial Intelligence in general engineering surveying tasks and in data processing tasks for other industries.

2.2 Data Acquisition in Engineering Surveying

Engineering surveying traces its roots back to ancient civilisations where rudimentary tools like chains and compasses were employed for land measurements and construction projects (Bowen, 2021). In modern days, engineering surveying relies heavily on advanced technologies, such as the Global Positioning System (GPS) devices, total stations, laser scanners, and, of very recent, drone-related tools (Ray, 2022; Yigit et al., 2023). GPS devices and total stations collect point data for a less detailed model of terrain. Total stations offer higher precision than GPS, which is faster with degraded accuracy, especially in between tall buildings and vegetated areas. (Buba Aliyu & Dahiru, 2019). Laser scanners, on the other hand, provide highly accurate surface data through dense point clouds. Drones capture large-area data from above using photogrammetry or LiDAR by allowing efficient and accurate volume estimation with more complex processing. (Zhang & Zhu, 2023). As a result, drones are becoming the most preferred method over traditional methods, which are time-consuming, costly, and require a lot of workforce. (Zhang, 2025).

Drones capture high-resolution images and generate accurate 3D models in a short period of time and are cost-effective (Choi et al., 2024). The coming in of drones makes work easier as their mode of data collection enhances workplace safety, swift data collection, and easy access to difficult locations, as they cover large areas without disrupting ongoing activities, unlike traditional survey methods (Askerbekov et al., 2024). Drones also minimize human error by using automated flight paths and advanced sensors for precise measurements (Zhao et al., 2024; Tavilla et al, 2024). Additionally, they provide real-time data allowing for quicker analysis and decision-making (Naranjo et al., 2023). This enhanced efficiency makes drones the preferred choice for modern data collection in various industries.

Object classification is a crucial step in analysing and interpreting drone-collected data for a project site (Taha & Shoufan, 2019). Modern models have dominated the traditional classification methods, as the traditional methods are heavily dependent on manual feature extraction (Rosca, 2023). Modern models use algorithms to identify and categorise objects based on features extracted from images and point cloud data (Manakitsa et al., 2024). Machine learning techniques automate the classification process, thus reducing the need for manual interpretation.

2.3 Effectiveness of machine learning algorithms in object classification for drone data

Machine learning algorithms have demonstrated high effectiveness in object classification, particularly when applied to drone-collected data in fields like surveying and remote sensing (Sargiotis, 2025). This is evidenced by the study by Mutale et al., (2024), which assessed the performance of SVM, RF, and ANN algorithms in detecting LULC changes in Lusaka and Colombo from 1995 to 2023 using Landsat data. The results showed that RF and ANN achieved the highest accuracies (up to 96%), outperforming SVM (77–94%), with RF yielding the best kappa values (0.92–0.97). Built-up areas increased significantly in both cities, demonstrating the effectiveness of ML algorithms for accurate land cover classification and prediction. Algorithms such as Support Vector Machines (SVM), Random Forests (RF), and Convolutional Neural Networks (CNNs) offer significant advantages such as high accuracy, scalability, and automation (Wang et al., 2021). These ML capabilities enable faster and more consistent classification of terrain features and other objects. Their adaptability to different environments and integration with GIS tools further enhances their practical application (Song et al., 2023).

Among these methods, CNNs have shown the highest accuracy in image-based classification tasks due to their ability to automatically learn spatial features directly from raw imagery (Alzubaidi et al., 2021). Unlike SVM and RF, which rely on manual feature selection, CNNs extract deep features directly from the data, making them more robust and effective, especially for high-resolution drone imagery (Martinez-Castillo et al., 2020a).

According to Boston et al., (2022a), Segmentation test results for the best-performing U-Net CNN models achieved an overall accuracy of 79% and a weighted mean F1 score of 77% when using a 9-band input and 76% 6-band input for a simple nine-class land cover classification. In comparison, the best performing Random Forest model yielded 73% accuracy and a 68% F1 score with the same 6-band input. These results highlight CNN's potential in generating accurate land cover maps while preserving quality.

2.3.1 Accuracy and Efficiency of Different ML Algorithms in object recognition and classification

The effectiveness of ML algorithms in object classification depends on factors such as data quality, algorithm complexity, and computational power (Wang et al., 2012). Various models for machine learning algorithms are used for classification, but Convolutional Neural Networks (CNNs) exhibit a superior classification accuracy. CNNs typically offer the highest accuracy due to their ability to capture spatial relationships within images, but they require significant computational resources (Alzubaidi et al., 2021). Support Vector Machines and Random Forest classifiers, while computationally efficient, may struggle with complex image features (Patil et al., 2024). Studies by Bengani (2024) and Mohammed et al. (2022) have shown that hybrid models combining multiple ML techniques often achieve the best results, balancing accuracy and processing speed.

According to Martinez-Castillo et al., (2020), modern models, such as Random Forest, support vector machines, and convolutional neural networks, enhance accuracy. CNNs enhance accuracy by expanding training data and integrating knowledge from the already trained models (Wang et al., 2021). Random Forests enhances accuracy by mitigating overfitting issues through ensemble learning while combining the predictions of different decision trees. (Salman et al., 2024). SVM enhances accuracy by finding the best hyperplane that distinguishes image features with a few training data (Kranjčić et al., 2019). A Study by Boston et al., (2022) demonstrates that CNNs outperform traditional classification techniques by learning spatial patterns in topographic data. When a large dataset has been used, CNNs' classification accuracy is at 98% (Wang et al., 2021). Additionally, Random Forest and Decision Trees have been used to classify terrain features relevant to cut-and-fill estimation and other site operations (Zagajewski et al., 2021).

Although Random Forest uses decision trees to enhance accuracy, XGBoost often produces more accurate results (Imani et al., 2025). Both Random Forest and XGBoost rely on decision trees to make accurate predictions (Tarwidi et al., 2023). Random Forest builds multiple trees at the same time, while XGBoost builds one tree at a time while correcting errors of the previous tree (Salman et al., 2024).This makes Random Forest operations to be done faster than XGBoost since it requires a lot of time to correct the previous mistakes, thus producing more accurate results. A Study by Yasasvi & Kumar (2022), showed that XGBoost had a higher prediction accuracy of 87.97% outperforming Random Forest, which exhibited an accuracy of 82.86%.

2.4 Machine learning techniques for predictive analytics

Predictive analytics refers to the use of current and historical data to predict certain patterns using statistics and artificial intelligence with accuracy(Kumar, 2018). Predictive analytics have gained so much popularity due to their ability to provide solutions or warnings due to the use of current and historical data (Tashev et al., 2022; Alassafi et al., 2023). However, choosing the right machine learning algorithm and techniques to use for predictions is one of the factors that has to be considered to produce highly accurate data, which will have a high likelihood that an event will occur according to the predictions made (Aljohani, 2023). This was demonstrated by a study by Arif Ali et al., (2023) which used XGBoost along with weather and air pollution data to improve air quality predictions in Shanghai, rather than using the weather model alone, to reduce air pollution. According to Mutale et al., (2024), the chosen algorithms are also evaluated and analysed by comparative performance metrics such as training time, accuracy, sensitivity, specificity, accuracy, area under the curve, and error to ensure the reliability of the predictions.

2.4.1 Types of machine learning

Machine learning, as a subset of artificial intelligence, is categorised into three types, which enable it to achieve the desired outcomes, namely, supervised, unsupervised, and reinforced learning (Sarker, 2021). Supervised learning is done when the computer is given labelled data, which is the data with answers, and it learns to predict the correct answers when given new data (Nasteski, 2017). This approach is commonly used for classification and regression tasks. Classification is about finding a connection between specific inputs and specific outputs, known as categories or labels (Lindholm et al., n.d.). A classifier is created by studying training data. This classifier is then used to predict categories or labels for new data (Shadmani et al., 2023). Regression, on the other hand, is about predicting continuous values. It looks at the statistical features of inputs to figure out the relationship between two or more independent variables (Lindholm et al., n.d.).

Unsupervised learning involves training models on unlabeled data, where the system tries to identify patterns, structures, or relationships within the data without prior knowledge of outcomes (Naeem et al., 2023). Clustering similar items and anomaly detection are typical applications of unsupervised learning. Clustering involves grouping objects in a way that objects in the same group are as similar as possible, while objects in different groups are as different as possible (Yacizi et al., 2023). Dimensionality reduction aims to simplify large amounts of data by turning them into smaller, more manageable sets while keeping the important information intact (Nasteski, 2017).

Reinforced learning involves training models to make sequences of decisions through trial and error (Vaish et al., 2021). The model interacts with an environment, receives feedback through rewards or penalties, and gradually improves its decision-making strategy to maximize cumulative rewards (Naeem et al., 2020). Initially, the system does not know which actions are good or bad. Over time, the system gets better at choosing actions that lead to the best results, thus learning how to achieve its goal more efficiently (Terven, 2025).

2.4.2 Model training

Model training is the process of feeding data into a machine learning algorithm to help it learn the relationships between inputs and outputs (Taye, 2023). During training, the model adjusts its internal parameters like weights and biases through optimization techniques to minimize errors (Taherdoost, 2023). The process begins with data preparation, which involves cleaning, transforming, and splitting data into training, validation, and testing subsets (Tashev et al., 2022). After this, model selection is performed by choosing the appropriate model architecture and algorithm (Sarker, 2021). The training process itself involves feeding data through the model, calculating loss, and updating parameters iteratively using techniques such as gradient descent (Tufail et al., 2023). Finally, evaluation is conducted by monitoring the model's performance using metrics like accuracy, precision, recall, and F1-score (Manchala, 2020).

2.4.3 Model Prediction and Decision Making

Once a model is trained, it can be used to make predictions or decisions based on new, unseen data (Taherdoost, 2023). Prediction refers to generating outcomes based on learned patterns, while decision-making involves using these predictions to make informed choices (Pugliese et al., 2021). The process includes model inference, where the trained model is applied to new data to generate predictions (Bengani, n.d.). Decision-making algorithms are then used to select the most appropriate actions based on predictions, using rules, optimization, or reinforcement learning techniques (Taye, 2023). Performance monitoring is essential to continuously evaluate the model's accuracy and effectiveness in real-world scenarios.

2.4.4 Types of predictive analytics

Predictive analytics involves using historical data and statistical algorithms to make predictions about future events (Yadav et al., 2024). Common types of predictive analytics include classification, regression, and clustering models. Classification predicts categorical outcomes such as spam detection or medical diagnosis (Badmus et al., 2024). Regression estimates continuous values, like temperature predictions or stock prices. Time series analysis involves analyzing data collected over time to identify trends and make forecasts (Al-Hanash et al., 2023). Anomaly detection identifies unusual patterns that deviate from expected behavior, which is useful in fraud detection and equipment maintenance. Clustering groups similar data points together, commonly used in customer segmentation and image analysis (Naeem et al., 2023).

2.4.5 Predictive analytics of drone-collected data in different fields

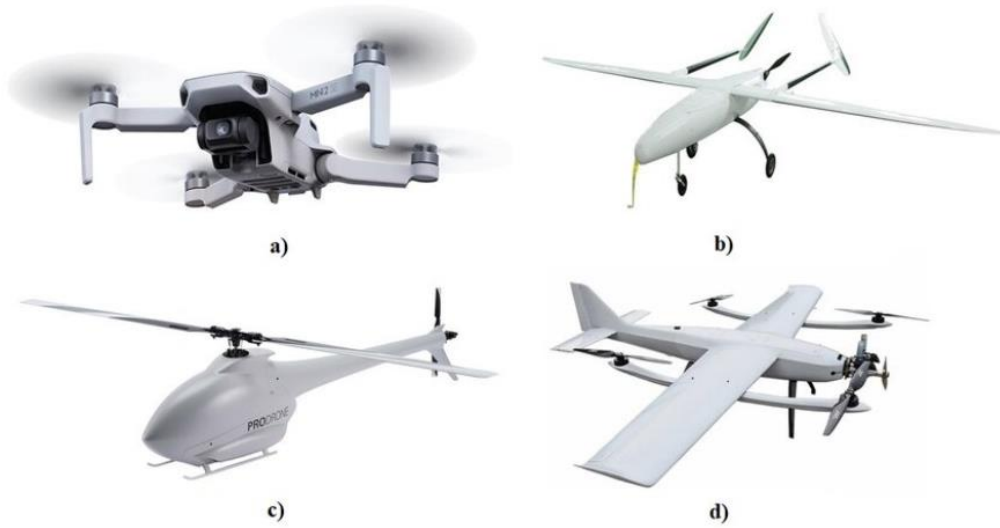
The application of predictive analytics on drone-collected data spans various fields, including agriculture, where it is used for crop monitoring, yield prediction, and disease detection using aerial imagery and environmental data (Ganeshkumar et al., 2023;Chin, Catal and Kassahun, 2023). In environmental monitoring, it helps predict pollution levels, wildlife patterns, and forest health based on aerial surveys (Olawade et al., 2024). Urban planning benefits from predictive analytics by analyzing land use, monitoring construction progress, and predicting traffic patterns (Durga et al., 2025). Disaster management also uses predictive analytics to identify areas at risk of floods, fires, or landslides using topographic and hydrological data (Adeoye Idowu Afolabi et al., 2023). In mining and resource management, it aids in predicting ore deposit locations, monitoring excavation progress, and assessing safety (Kayusi et al., 2024).

2.4.6 The potential of machine learning techniques for predictive analytics for cut-and-fill volume estimation

Over the past decade, Machine Learning has become a valuable tool for predicting cut-and-fill volumes, and it outperforms traditional methods because of its ability to process data with greater speed and accuracy (Nabizadeh Rafsanjani & Nabizadeh, 2023). Conventional approaches such as the use of Total Stations, levelling equipment, theodolites, and CAD-based cross-sectional methods have proven to be labour-intensive and time-consuming (Kavitha et al., 2018). In contrast, machine learning algorithms like Multiple Linear Regression, Decision Trees, and Random Forests can process spatial data more efficiently (Rodriguez-Galiano et al., 2015) . Advanced models such as Extreme Gradient Boosting (XGBoost) and deep neural networks outperform traditional techniques by handling complex, high-dimensional data and capturing nonlinear relationships (Lekan & Harry, 2025). These improvements make machine learning a powerful asset in modern surveying and cut-and-fill volume estimation.

2.3.5.1 Drone-based data collection methods

Due to their ability to capture high-resolution data, drones have seen their wide acceptance in engineering surveying for different purposes (Tambwe et al., 2023). Based on the engineering surveying need, the various types of drones that are used include the fixed-wing drones, multi-rotor, and hybrid drones (Lee et al., 2021). As noted by Raschka et al., (2020), fixed-wing drones, which resemble traditional airplanes, are commonly used for large-scale mapping and aerial surveys due to their being equipped with high-resolution cameras, which necessitate efficient wide area coverage. Conversely, multi-rotor drones such as Quadcopters and hexacopters are popular in project inspections and 3D modelling due to their close-range precision and flight flexibility (Lee et al., 2021).



a) Multi-Rotor Drones, b) Fixed-Wing Drones, c) Single-Rotor Drones, d) Fixed-Wing Hybrid VTOL [17]

Source: Anagnostis et al., 2024

In projects where data collection requires both the flexibility, close range, and wide area coverage, hybrid drones are used (Caillouet et al., 2019). Hybrid drones combine the features of fixed-wing drones and multi-rotor drones to achieve specific data collection objectives in engineering surveying which may not be achieved if only one type of drone is adopted (Shaik, 2023). However, many researchers have noted that, in engineering surveying, fixed-wing drones such as multispectral fixed-wing drones are preferred for their ability to capture data across different wavelengths, which provides detailed information for comprehensive analysis in engineering projects (Giordan et al, 2020; Kindervater, 2017; Mahajan, 2021; Postema, 2020).

2.4 Machine Learning Methods for Cut-and-Fill Volume Estimation

Machine learning methods refer to computational techniques that enable computers to learn from data and make predictions or decisions without being explicitly programmed (Carvalho et al., 2019). In the context of cut-and-fill volume estimation, machine learning models can analyze drone-collected data such as Digital Elevation Models (DEMs) to predict or classify terrain features and estimate volumes with high precision (Kamolov, 2024). Commonly used algorithms include Neural Networks, Support Vector Machines (SVMs), Random Forests, and Decision Trees. These techniques leverage large datasets, powerful computational resources, and complex mathematical models to enhance prediction accuracy (Sargiotis, 2025).

2.4.1 Traditional Computational Methods for Cut-and-Fill Volume Estimation

Traditional computational methods for cut-and-fill volume estimation involve manual or semi-automated calculations, typically performed using software like Excel or CAD-based programs (Lee et al., 2024). The cross-sectional area method is a prevalent technique, where cut-and-fill volumes are calculated by determining the area of cross-sections at intervals along a project alignment and multiplying by the distance between them (Babapour et al., 2018). These methods require detailed ground surveys, often conducted using total stations or differential GPS equipment (Matsimbe et al., 2022). Despite being straightforward and well-established procedures, these methods are increasingly being replaced by automated techniques due to their limitations in handling large datasets and the potential for human error (Babapour et al., 2018).

2.4.2 Data Processing Issues in Engineering Surveying

Primarily, the engineering surveying field relies on labor-intensive techniques (Sarkar et al., 2024). The advent of computers in the mid-20th century led to a more digital way of processing data thereby enabling efficient analysis (Kitchin & Fraser, 2020). In recent decades, the availability of GIS software has enhanced spatial data management (Breunig et al., 2020). Furthermore, the integration of drones and advanced engineering processing tools has transformed engineering surveying, resulting in high-resolution imagery for accurate mapping and analysis (Deliry & Avdan, 2021).

The adoption of drone-collected images in engineering surveying has, however, posed persistent challenges in data processing (Quamar et al., 2023). Despite advancements in other fields, engineering surveying struggles with time-consuming processes and accuracy deterioration during data processing, contributing to delays in decision-making (Ivanova et al., 2023). The ongoing need is to improve accuracy in engineering surveying data processing techniques by incorporating drone images and other advanced methods, such as AI, to address the existing challenges in the field (Zhang & Zhu, 2023).

Machine learning methods offer several advantages over traditional computational methods (Tufail et al., 2023). They provide high accuracy and efficient processing of large datasets, significantly reducing the time required for analysis (Sarker, 2021). Additionally, machine learning techniques minimize human error by automating the prediction process and can adapt to various terrain conditions by learning from the data (Taye, 2023). However, these methods also have limitations, such as the need for large training datasets, high computational resources, and complex implementation processes (L'Heureux et al., 2017). In contrast, traditional methods are simpler to implement and have lower computational requirements, but they are time-consuming and prone to inaccuracies, particularly when applied to large-scale projects (Akbar Firoozi & Asghar Firoozi, 2023).

2.4.3 Accuracy Determination in Machine Learning and Traditional Methods

The accuracy of machine learning-based methods is typically determined by evaluating the model's performance against a known dataset using metrics such as Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), or R^2 Score (Hodson, 2022). High accuracy is achieved through proper training and validation using appropriate algorithms and features (Maleki et al., 2020). For traditional methods, accuracy is generally determined through repeated measurements, averaging, and comparisons with known benchmarks (Koutsandreas et al., 2022). Factors influencing accuracy include survey precision, instrument quality, and interval selection in cross-sectional calculations (Contreras et al., n.d.). While traditional methods can be accurate within a limited scope, their precision diminishes when applied to complex or large-scale projects (Marle & Vidal, 2016).

2.4.4 The accuracy of machine learning derived output and traditionally computed output for cut-and-fill volume estimation

Traditional and ground-based methods, such as Total Station measurements, leveling, and CAD-based cross-sectional area calculations, rely on manual data collection and calculations, often introducing errors due to human factors, limited coverage, or complex terrain (Kaartinen et al., 2022). These methods typically capture data at specific points along a survey line or chainage interval, which can miss subtle variations in the terrain between those points, limiting the precision of volume calculations.

In contrast, drones equipped with LiDAR or photogrammetry technology can capture high-density point clouds, offering highly detailed 3D data over the entire survey area. Drones collect far more data within a particular chainage interval, capturing continuous surface information, which provides a more accurate and comprehensive representation of the terrain (Chonpatathip et al., 2023). Machine learning algorithms like Random Forests, XGBoost, and deep neural networks can then process these large datasets quickly, identifying complex patterns and making more precise predictions of cut-and-fill volumes (Liu et al., 2024). These algorithms can handle the rich, high-dimensional data from drone-captured point clouds, which include thousands or even millions of data points, improving the accuracy of volume estimates compared to traditional methods (Kamolov, 2024). As a result, the combination of drones and machine learning allows for more efficient and precise volume estimation especially in large-scale and challenging terrain.

2.4.4 Preference for Machine Learning Methods over Traditional Methods in Engineering Surveying

Machine learning methods are increasingly preferred for cut-and-fill volume estimation due to their ability to handle large datasets, improve prediction accuracy, and reduce human intervention (Husein et al., 2024). Their efficiency and precision make them a superior alternative for large-scale projects like road construction and other civil engineering applications (Kamolov, 2024). By making use of advanced computational techniques, machine learning approaches can produce reliable and accurate estimates more effectively than traditional methods (Sargiotis, 2025)

2.6 Application of AI in Image Data Processing

Artificial Intelligence algorithms play a significant role in image quality enhancement across various fields (Tian et al, 2023). In medical imaging, computer programs like CNNs and GANs help make X-rays and scans clearer and more accurate for better diagnosis and treatment planning (Shaik, 2023). The field of agriculture also relies on Random Forests for crop classification, Support Vector Machines for disease detection, and Neural Networks for yield prediction from drone images (Bassine et al., 2023a). Therefore, this simply shows how AI is increasingly becoming relevant in different fields for different image processing needs.

In recent years, engineering surveying has been significantly transformed by the integration of artificial intelligence and machine learning algorithms (Abioye et al., 2021). In detailed surveys, AI algorithms are commonly used to automatically identify and extract features from drone imagery, such as buildings, roads, or vegetation (Pérez et al., 2022). When performing topographic surveys, AI facilitates accurate terrain analysis for precise mapping (Xiong et al., 2022). These technologies offer advanced automation and data analysis capabilities by accelerating data interpretation, mapping, and reducing the reliance on manual labour (Saffre et al., 2022).

The various applications of AI and machine learning algorithms in image processing have transformed image processing. Sarker (2022) describes the potential of AI and Machine Learning algorithms for providing engineering data automation, adaptability, and scalability, compared to conventional methods. Mcneal (2014) also notes that utilizing these algorithms for processing drone-collected data in engineering surveying can enhance efficiency, accuracy, and the extraction of meaningful information from complex datasets. As technology progresses, therefore, the integration of machine learning consistently reshapes the potential and effectiveness of image processing across various domains, including engineering surveying (Raschka et al., 2020).

2.7 Conclusion

This chapter explored the various data collection and processing methods utilized in engineering surveying, highlighting the technological advancements and persistent challenges in the field. Despite the integration of sophisticated tools like drones and ML, the literature reveals a significant gap in the efficient processing and accurate analysis of drone-collected data, particularly in the context of engineering surveying.

CHAPTER THREE: METHODOLOGY

3.1 Introduction

In this chapter, the study area, materials, methods, and research design of this study are discussed in detail. The chapter explains data collection and analysis methods implemented to enhance the accuracy, validity, and reliability of the study results. The chapter also defines procedural steps of the research, including the timing and integration decisions of the study in line with considerations for ethical issues.

3.2 Study Area

The study used a case of "the Rehabilitation of the M1 Road from KIA turnoff to Mzimba Turnoff: section 2 Kasungu to Jenda M1 road at Chatoloma trading centre in Kasungu district, Malawi. The Kasungu-Jenda Road is approximately 85.5 kilometers long tarmac road lying in the central part of Malawi, which is currently under construction. The road connects the northern part of Malawi with the capital city, Lilongwe. The Project involves the rehabilitation, widening, and marginal alignment with no changes to the existing alignment. Kasungu-Jenda Road was chosen mainly because it has more earthwork activities occurring, as the study involved estimating earthwork volumes.

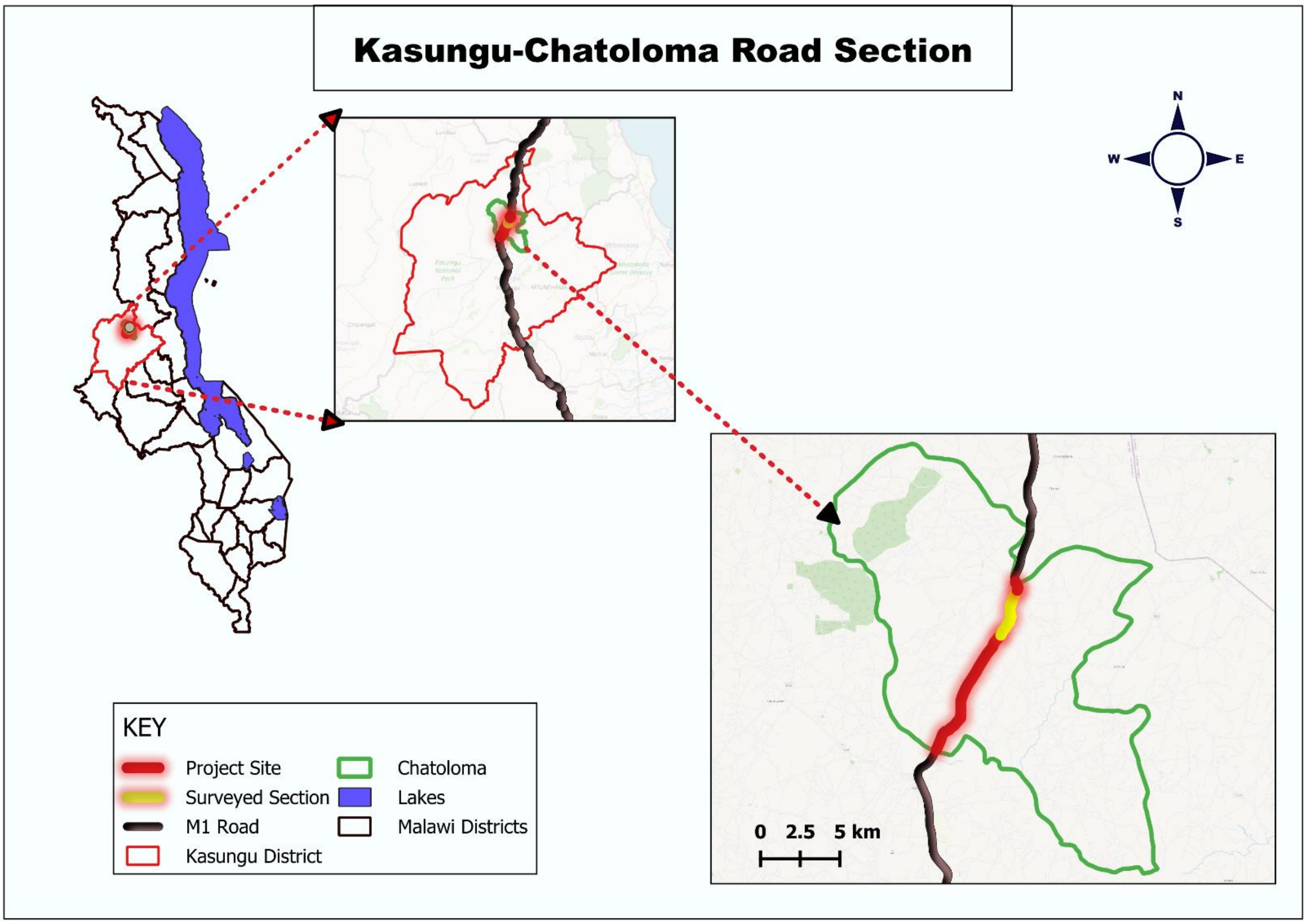


Figure 1: Map of Study Area

3.3 Study Design

An experimental quantitative research design was followed. A quantitative research design involved the examination of various variables while including numbers as well as statistics in a project to analyze its findings. An experimental research design refers to a systematic and controlled approach that involves the manipulation of an independent variable to observe its impact on dependent variables, to establish causal relationships (Boru, 2018). The experimental quantitative design allowed for a structured examination of the objectives, providing a foundation for understanding the causal connections between the application of machine learning and the observed outcomes in engineering surveying processes. The following flowchart summarizes the research design's inputs, processes, and outputs, guided by the research objectives.

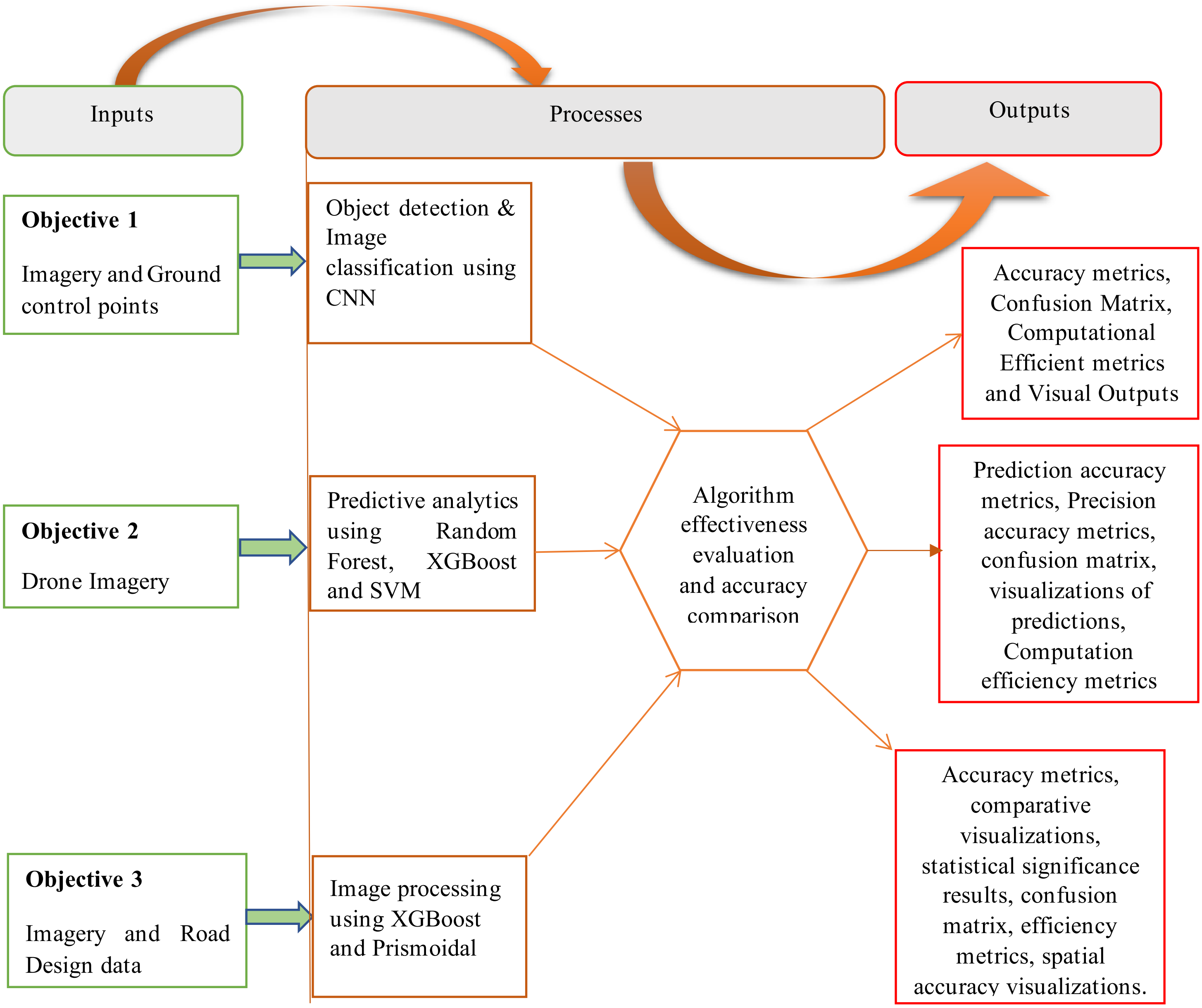


Figure 2: Study Workflow chart

3.4.1 Drone Data Collection

Drone collected aerial images data, captured various features of the engineering project, including vegetation, buildings, landmarks, road marks, topography, and many other features, for all objectives were collected using a DJI Mavic2 Pro drone from three different identified survey routes within the Kasungu-Jenda Road to represent different types of engineering survey scenarios. Additionally, the road design data was acquired from the client for the analysis.

Before a flight launch for data collection, the ground control points and checkpoints were fixed and checked using a differential GPS so that the image could be georeferenced. Table 1 below shows a list of the Control points used as ground control points and check points.

Table 1: List of control points

ID	EASTING (m)	NORTHING (m)	HEIGHT (m)
M5 152C NEW	552273.399	8593069.591	1139.670
M5 153C NEW	552746.108	8593903.393	1144.906
M5 153B NEW	552690.972	8593698.547	1147.461
M5 153A NEW	552514.831	8593493.904	1146.390
M5 153	552376.376	8593303.714	1140.811
M5 155A NEW	552980.024	8595231.771	1178.115
M5 155 NEW	552855.581	8595037.377	1172.474
M5 154C NEW	552779.092	8594859.092	1167.512
M5 154B NEW	552702.011	8594664.942	1160.656
M5 154A NEW	552706.534	8594406.611	1154.814
M5 154	552679.878	8594161.380	1147.456

3.5 Data analysis

Quantitative data analysis of the aerial images was done in Google Colab, Jupyter Notebook, and QGIS, in which model results and performance metrics were visualizations in graphs, tables, confusion matrices, and maps. The analysis was specifically performed as outlined in the following sections;

3.5.1 Effectiveness of machine learning algorithms in object detection and classification from drone-collected data

To assess the effectiveness of Machine Learning algorithms in detecting and classifying objects such as buildings, roads, vegetation, earthworks, bare land, and road markings of drone-collected data, the following steps were taken;

3.5.1.1 Data Pre-processing for Object Detection and Classification

Image stitching, noise removal, and gap filling were done in Agisoft Metashape Professional. Agisoft enables the creation of seamless orthomosaics from images and LiDAR point clouds. The break line and DEM editing tools in Metashape refine terrain details by closing voids in water areas and smoothing inconsistencies in roads and other linear features. This ensures the creation of high-quality orthomosaics and Digital Elevation Models (DEMs), thus enhancing mapping accuracy. Metashape can also generate vector data from the orthomosaics.

As a very important step, the pre-processing of the drone-collected data was done through annotations, formatting, and normalization using QGIS in readiness for object detection and classification.

3.5.1.2 Orthomosaics Processing

The orthomosaics processing, which involved stitching of 178 images, 215 images, and 259 images into route 1, 2, and 3 orthomosaic images, yielded a coverage of 539.01, 589.60, and 667.80 meters in length, as shown in Table 2. Having stitched the images in Agisoft Metashape Professional, the resultant orthomosaics revealed the presence of noise and motion blurs that resulted in coverage gaps, as shown in Figure 3.

Table 2 : Image Stitching

Route	**Number of Images**	**Orthomosaic Length (m)**
1	178	539.01
2	215	589.60
3	259	667.80
Total	652	1796.41

Figure 3: schematic view of unprocessed stitched images

To correct the observed noise, the Gradual Selection Tool in Agisoft Metashape Professional was utilized to refine the dataset by removing points with high reprojection errors and low confidence values, which are typically associated with misalignments in the image matching. After noise filtering, the gap filling was performed to achieve a continuous orthomosaic. An automatic interpolation of missing areas was done using neighbouring pixel values, which enhanced the continuity in the image. In regions where gaps persisted due to occlusions or insufficient image overlap, the Agisoft Metashape Professional's multi-view image selection was employed, which allowed for the reconstruction of missing areas by referencing additional images from different perspectives. The resultant orthomosaics yielded a very high resolution of 0.01 by 0.01 meters, as shown in Figures 4a, b, and c

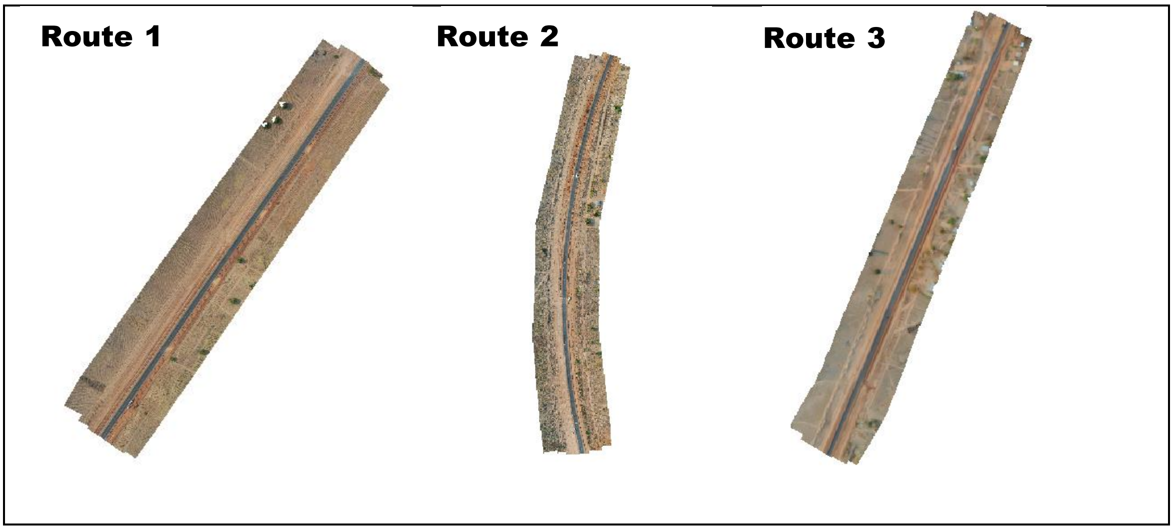


Figure 4: a, b, c: Route 1, 2, and 3 orthomosaics

3.5.1.2.1 Image Annotation, Formatting and Normalisation

Having stitched the images and processed the orthomosaics, image annotation was performed in QGIS by digitizing different sections of the orthomosaics into labeled images. Mainly, 6 classes, which included Tarmac Road, Road Marks, Vegetation, Earthworks, Built Area, and Bare Land, were annotated as shown in Table 3.

Table 3: Image Annotations by class

Object Class	Number of Annotations	Percentage
Built Area	100	13.25
Bare land	131	17.35
Vegetation	131	17.35
Tarmac Road	131	17.35
Earthworks	131	17.35
Road Marks	131	17.35
Total	755	100

As shown in Table 3, there were 755 annotated images from the orthomosaics. Due to a small number of built-up features, only 100 annotations were made as compared to the rest of the other groups, which have 131 average annotations. The number of annotations made depended so much on the available distinct features in the produced orthomosaics. After annotation, data formatting was performed to organize the dataset into a structured directory, ensuring that images and corresponding annotation files were easily accessible during training. Text files listing image paths and their respective annotation labels were generated for easy data loading into the Machine Learning pipeline. To make sure that the CNN model was able to handle the annotated images without errors, normalization techniques such as image resizing and coordinate normalization were used. All annotated images were resized to 32 by 32 pixels for uniformity and detailed analysis. The bounding box coordinates for the annotated images were then normalized by dividing the x and y values by the image width and height, respectively, ensuring that object positions remained proportional across different image sizes.

3.5.1.2.2 Algorithm Selection and Training

The Convolutional Neural Network, as indicated in Figure 4, fit for object detection and classification, was selected due to its prowess in general object detection and image classification (Baduge et al., 2022; Nahr et al., 2021). The classification classes included earthworks, vegetation, bareland, roadmarks, tarmac, and built-up area. CNNs are a class of deep neural networks designed to automatically learn hierarchical features from grid-like data, which makes them particularly adept at processing visual information such as images (Ciaburro & Venkateswaran, 2017). The network architecture comprises convolutional layers that apply filters to extract local patterns, pooling layers for down-sampling and feature reduction, as well as fully connected layers for high-level reasoning. This algorithm was first trained in which iterative processes, such as hyperparameter tuning and optimizations, were performed to enhance its performance in identifying and categorizing objects within the drone-collected aerial images.

3.5.1.3 CNN Model Training and Performance Evaluation

3.5.1.3.1 Model Architecture

To perform the object detection and classification, the model structure, as shown in Figure 5, was used.

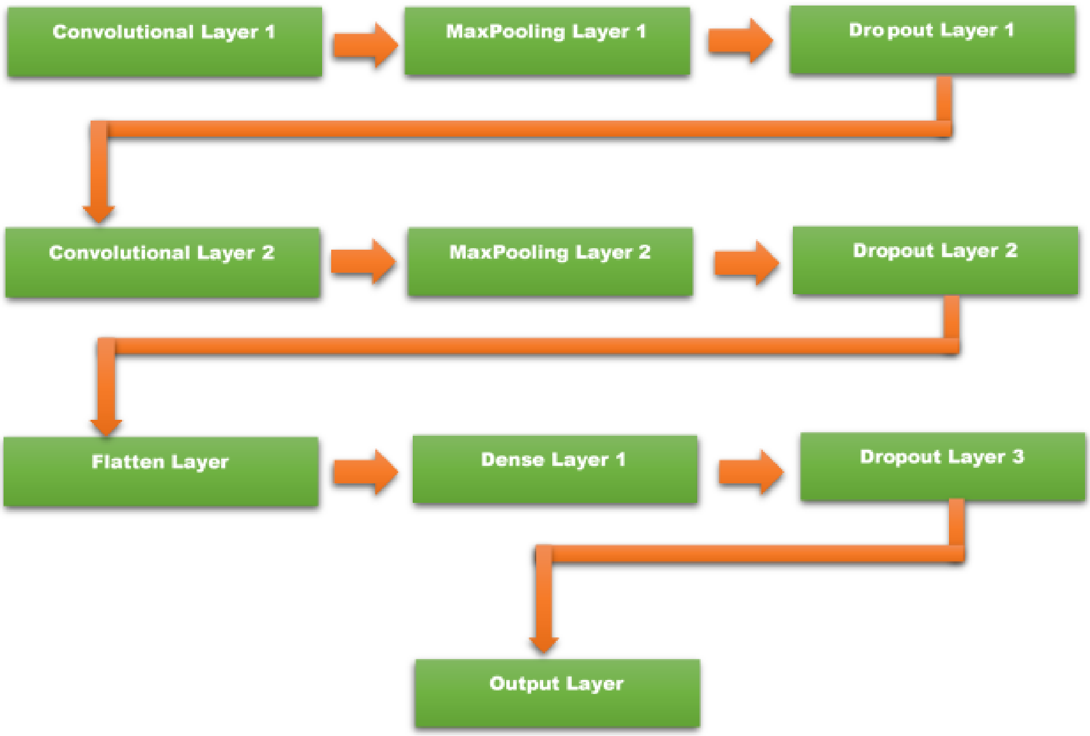


Figure 5: CNN Model Structure Workflow

As Figure 5 shows, the Convolutional Neural Network (CNN) model developed for object classification followed a structured sequence of layers designed to extract spatial features and classify objects effectively. The model architecture consisted of multiple convolutional layers with Linear Rectified Unit (ReLU) activation functions, followed by max pooling layers to reduce spatial dimensions while preserving important image features, and dropout layers to mitigate model overfitting. Specifically, the model comprised firstly the 2D Convolutional (Conv2D) layer that had 32 filters of size 3×3 pixels, which was applied to extract low-level spatial features. This was followed by a 2D MaxPooling (MaxPooling2D) layer to downsample the feature maps and a Dropout (0.2) layer to prevent overfitting. The second block in the model structure comprised a deeper Conv2D layer with 64 filters, which was applied to extract more complex features, followed by MaxPooling2D and Dropout (0.3) for further regularization. The third layer of the model structure had Flattening and Fully Connected (Dense) Layers. The extracted features from the previous blocks were flattened and passed through a fully connected layer with 128 neurons. These neurons were activated by ReLU, which was then followed by Dropout (0.4) to ensure robust generalization. Finally, the classification layer consisted of softmax activation, which output probabilities for each class. This model structure was selected due to its ability to efficiently learn spatial hierarchies while minimizing the risk of model overfitting to produce good results.

3.5.1.3.2 Object Detection Performance Metrics

Performance measurement metrics for the selected algorithms in object detection and training used include precision, recall, and F1-score. As defined by Francies et al., (2022) Precision refers to the ratio of true positives to the sum of true positives and false positives, as shown in equation 1, whereas recall refers to the ratio of true positives to the sum of true positives and false negatives (equation 2). F1-score refers to the harmonic mean of precision and recall (equation 3). In model assessments using precision, recall, and F1-score, 0 indicates poor performance, while 1 indicates perfect performance for each respective metric (Yacouby & Axman, 2020). These metrics helped to provide insights into the accuracy of the selected algorithm in identifying objects while minimizing false positives and negatives.

$$\text{Precision} = \frac{\text{True Positives}}{\text{True Positives} + \text{False Positives}} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (1)$$

$$\text{Recall} = \frac{\text{True Positives}}{\text{True Positives} + \text{False Negatives}} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (2)$$

$$\text{F1} - \text{Score} = 2 * \frac{\text{Precision} * \text{Recall}}{\text{Precision} + \text{Recall}} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (3)$$

3.5.1.3.3 Object Classification Accuracy

The accuracy metrics and confusion matrices were used to gauge the precision of the selected algorithm in correctly categorizing detected objects. This research utilized the confusion matrices due to their ability to provide an understanding of misclassifications and errors in the classification process (Bithas et al., 2019). Thereafter, visual outputs, such as sample images displaying detected objects and their respective classifications, were used to visually represent the performance of the CNN. These outputs aided in the provision of a qualitative comparative evaluation of the algorithms' effectiveness and facilitated a more intuitive understanding of the results.

3.5.2 The potential of machine learning techniques for predictive analytics in engineering surveying

In this objective, the road design data for different sections was used along with the drone-collected as-built data to predict cut and fill volume, or if at the as-built data conforms to the design data (Nahr et al., 2021). The variables of interest were design elevation, as-built elevation obtained from ground survey methods, as-built elevation in the form of point clouds extracted from drone-collected images (as independent variables), and cut and fill or design conformity (dependent variable). The collected data will undergo the cleaning, normalization, and transformation procedures to ensure uniformity and readiness for predictive analytics.

3.5.2.1 Elevation Data Processing and Extraction

Aerial images were aligned with GPS Ground Control Points (GCPs) using Agisoft Metashape Professional. This was done to generate tie points and dense point clouds. The georeferenced point clouds were compared to the as-built data obtained using ground-based survey methods through coordinate matching in Python using the cKDTree algorithm. This was done so that each observed ground-based elevation had a corresponding drone-derived elevation value.

The extraction of elevation data from the drone-collected images was conducted using Agisoft Metashape Professional. To achieve the elevation extraction, a total of 652 geo-tagged aerial images, captured during systematic drone surveys across the three designated road routes, were processed into orthomosaics. Following the generation of these orthomosaics, Digital Elevation Models (DEMs) were processed from which the elevation data would be extracted.

3.5.2.1.2 Tie Point and Dense Point Cloud Generation

The first step in the generation of sparse elevation points (Tie Points) and dense elevation points (Dense Point Cloud) involved the alignment of the input images for each route. Using the embedded GPS metadata and the provided coordinates on the used Ground Control Points (GCPs), Metashape aligned the overlapping images through feature matching and triangulation. This process generated 95575, 123152, and 124821 sparse point cloud elevation points for routes 1, 2, and 3, respectively, which represented the initial 3D structure of the terrain based on shared key points among multiple stitched images, as shown in Table 4

Table 3: Tie and Dense Point Cloud

Route	Tie Points	Dense Cloud Points
1	95,575	27,502,342
2	123,152	37,128,071
3	124,821	37,035,576

Having achieved successful alignment and creation of a sparse point cloud, a dense point cloud was generated using the software's depth-map reconstruction algorithm. This step involved reconstructing 3D geometry by estimating the depth of each pixel across the image set, using the camera positions calculated during image alignment. The dense cloud was built using the 'High' quality and 'Mild' depth filtering settings to preserve surface detail while minimizing noise. This produced a dense 3D dataset (27502342, 37128071, and 37035576 dense point clouds for routes 1, 2, and 3, respectively), as shown in Table 4, capturing fine terrain features, such as slight slope changes, roadside depressions, and fill areas. As the analysis targeted the earthworks sections where vegetation was already cleared, the dense point clouds were not converted to a continuous surface model to be used in filtering out non-ground points. All points within the earthwork's sections represented the elevations of the bare earth surface. The georeferenced dense point cloud data was then exported for further analysis.

3.5.2.2 Algorithm Selection and Model Building

To achieve this objective, Random Forest, XGBoost, and Support Vector Machine algorithms were evaluated. Random Forest is an ensemble learning technique, constructs an ensemble of decision trees during training, offering a robust approach for classification and regression tasks (Bithas et al., 2019). In contrast to the other algorithms, Bithas *et al.* (2019) explain that Support Vector Machines (SVMs) stand out as a supervised learning algorithm that effectively classifies data points by identifying an optimal hyperplane for maximizing the margin between classes. As stipulated by Bassine *et al.* (2023b), SVMs offer strong functionalities in anomaly detection in geospatial datasets. Aside from the SVM and Random Forest, XGBoost is an optimized gradient boosting framework that builds decision trees sequentially and corrects errors while avoiding overfitting. These algorithms were chosen due to their wide usage in other industries such as finance, robotics, water resources management, and many others, for predictive purposes (Baduge et al., 2022; Ciaburro & Venkateswaran, 2017; OECD, 2021). Just as in the first objective, these models (SVM, RF, and XGBoost) were trained and adjusted by fine-tuning hyperparameters and optimizing model architectures to fit the characteristics of the collected data. To ensure the robustness of the models, the pre-processed data was partitioned into training and validation sets in a process called cross-validation. The model performance was evaluated on the validation sets to guide the iterative model refinements, which helped to prevent overfitting and maximize predictive accuracy.

3.5.2.2.1 Performance Evaluation Metrics

Performance measurement metrics such as Mean Absolute Error and R-squared were used in model assessment. These were performed together with other precision accuracy metrics such as F1-score and recall, visualizations of predictions, and computation efficiency metrics. These performance measurement tools were employed to assess the accuracy of the selected models in predicting cut-and-fill volume outcomes, accounting for spatial trends, variations, and complexities within the provided dataset.

3.5.2.2.2 Model Assessment and Selection

The identified models, Random Forest, XGBoost, and Support Vector Machine, were assessed for their predictive capabilities, scrutinizing their performance on the test set to measure generalizability and reliability in forecasting cut and fill trends. A comparative analysis of the selected machine learning models was then conducted based on their performances in predictive analytics to identify and select the model with robust and accurate predictive power for volume estimates. For comparison, the as-built elevation data's coordinates were used to extract elevation data from the exported dense point cloud data through coordinate matching. The coordinate matching was done using the cKDTree Python library to map the dense point cloud elevation data with the georeferenced as-built data.

3.5.2.2.3 Model Validation

A comparative analysis was conducted between the right-hand side (RHS) and the left-hand side (LHS) field-observed as-built elevation values to validate the reliability of the drone-based elevation extracted for cut-and-fill predictions. To further compare the elevation data collected by the two methods, descriptive statistics were calculated to measure the central tendency and dispersion of the data. To assess the significance of the differences between drone-derived elevations and elevations obtained using ground-based survey methods, a paired sample t-test was conducted to evaluate whether the elevations obtained using these two methods differ significantly.

3.5.2.3 Cut and Fill Prediction

To perform predictive analytics for cut-and-fill volume estimations using the validated drone-collected images-based elevations, the Support Vector Machine, Random Forest, and Extreme Gradient Boosting (XGBoost) models were compared.

3.5.2.3.1 Model Training and Performance Evaluation

The modelling process was conducted in two phases. The first phase established baseline models using conventional configurations and a training dataset comprising 70 percent of the data. The predictor variables used included the combined LHS and RHS Drone as Built Elevation, Crossfalls, and Offsets, with Observed Cut and Fill levels as the response variable. The second phase involved systematic hyperparameter tuning and an increase in the training data proportion to 80 percent. The models' performances were evaluated using MAE and R^2 metrics. The following sections provide the detailed adjustments to the model structures and architectures for the three models.

3.5.2.3.2 Random Forest Architecture and Optimization

To predict the cut and fill values using the Random Forest Model, the initial model configuration comprised 100 decision trees, in which each tree was allowed a maximum training depth of 10. In this configuration, all available model predictor variables were considered at each decision split. To regulate overfitting and improve model generalization, the minimum number of observations required to split a node was set at 10, while the minimum number of observations required at a leaf node was 2.

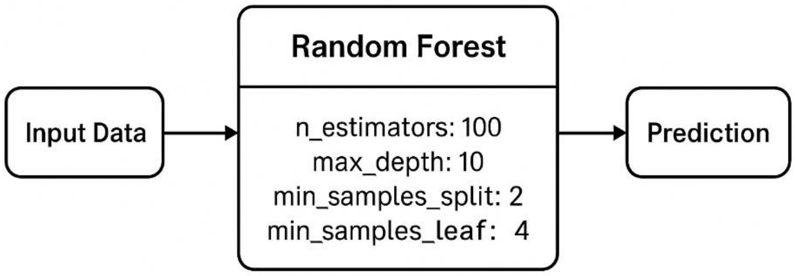


Figure 6: Optimized Random Forest model architecture

The hyperparameter tuning process employed a randomized search cross-validation. This process involved generating 50 random combinations from a defined hyperparameter space (estimators, maximum tree depth and unrestricted depth, and minimum leaf node sampl es) and evaluating each configuration using five-fold cross-validation. The ranges for the selected parameters included several estimators ranging from 100 to 400, maximum tree depths of 10, 20, 30, and unrestricted depth, as well as minimum samples for splitting set at either 2 or 5. The minimum number of samples required at a leaf node was set to 1, 2, or 4. Additionally, the number of features (training data points) considered for each split was constrained to either the square root or the logarithm base two of the total number of features.

Finally, the optimal configuration identified through this process, as shown in Figure 6, consisted of 100 decision trees, a maximum depth of 10, a requirement of at least 2 samples to perform a split, and a minimum of 4 samples at each leaf node. Furthermore, the model selected the square root of the total number of predictors to be considered at each split. These refinements improved the model’s capacity to capture the underlying data structure while controlling variance.

3.5.2.3.3 Support Vector Machine Architecture and Optimization

Similar to the Random Forest Model, modelling with Support Vector Machine (SVM) was also done in two phases: the unoptimized and the optimized. The initial SVM model employed a Radial Basis Function (RBF) as the kernel to handle non-linear relationships between the predictors and the target variable. In its initial implementation, the model used default regularization, loss function, and gamma parameter values and provided a moderate level of predictive accuracy. However, just as with the first model (Random Forest), to improve the SVM's performance, a comprehensive grid search was conducted using five-fold cross-validation on the scaled training dataset.

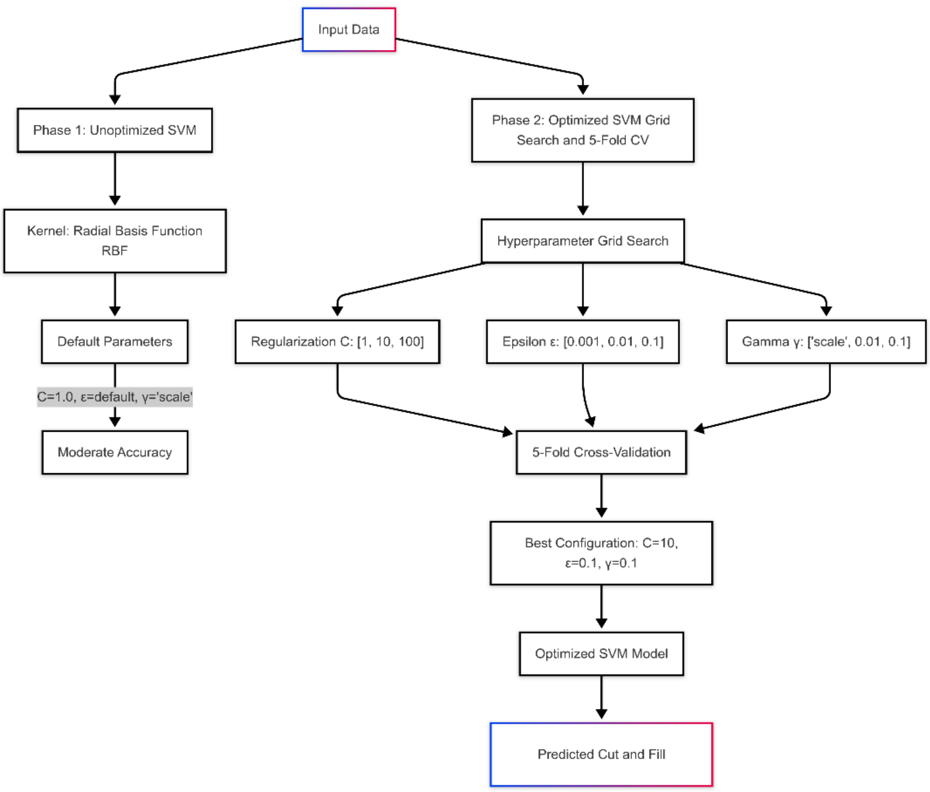
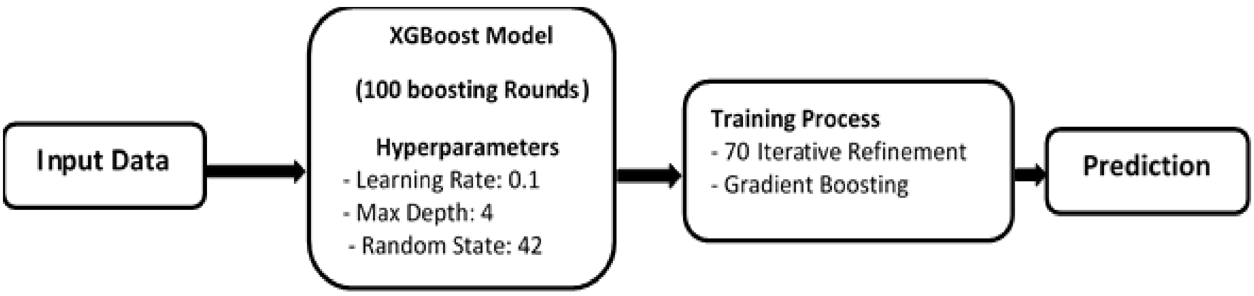


Figure 7: Support Vector Machine model architecture

To optimise the model, the regularization parameter was tested at values of 1, 10, and 100, representing varying degrees of penalty for model complexity, as shown in Figure 7. The epsilon values tested included 0.001, 0.01, and 0.1, which controlled the margin within which no penalty was given in the training loss function. Finally, the gamma parameter, which influences the reach of a single training point, was evaluated using 'scale' (based on inverse feature count), 0.01, and 0.1. The best performing configuration, selected based on the lowest mean squared error across the validation folds, included a regularization parameter value of 10, an epsilon margin of 10, and a 0.1 gamma value. This combination of optimal regularization strength, epsilon margin, and the gamma values allowed the model to balance flexibility with generalization, which in turn reduced both underfitting and overfitting tendencies.

3.5.2.3.4 Extreme Gradient Boosting (XGBoost) Architecture and Optimization

The final model used was the XGBoost, which is an implementation of gradient boosted decision trees. The initial architecture comprised 50 estimators, a learning rate of 0.001, and a maximum depth of 4 for each tree. This initial setup prioritized stability and control over model complexity during the preliminary assessment phase. Although the model yielded good results, its performance was still optimised to produce the desired output, which would reduce the difference between the predicted values and the actual Cut and fill values.



The final and optimised XGBoost model architecture consisted of 100 boosting rounds from 50 to allow for more iterative refinement of the model. The learning rate was raised to 0.1 to accelerate convergence during training, while the maximum depth of each tree remained fixed at 4 to limit overfitting. The model was also assigned a fixed random state value of 42 to ensure reproducibility across experiments. The optimised architecture enabled the XGBoost model to learn complex relationships in the training data more efficiently while benefiting from the algorithm's built-in regularization mechanisms, such as shrinkage and column subsampling, which are aimed at reducing the risk of overfitting.

3.5.3 Comparison of the accuracy standards of machine learning derived output and traditionally computed output in road surveying

To analyze this objective, Prismoidal Method and XGBoost were used as traditional and selected Machine Learning algorithms, respectively. As a last objective, the study endeavoured to compare the accuracy of machine-derived output to the traditionally computed output.

3.5.3.1 Traditional Computation with Prismoidal Method of Volume Calculation

The data was collected using an automatic level at 20m intervals and later adjusted using the control points along the project site. The volumes were later computed using the Prismoidal method.

3.5.3.1.1 Machine Learning (XGBoost) Output Processing

To achieve this objective, the highest performing and validated Machine Learning model (XGBoost) from the second objective was subjected to dense elevation data produced from the drone imagery. The dense point clouds, which are drone-collected elevations, were used to predict cut and fill volumes at 2-meter chainage intervals, whose results were later compounded at the traditional 20-meter chainage interval. The assessment between the traditionally computed output and the Machine Learning based outputs was therefore assessed at 20-meter chainage intervals to evaluate the method that picked the finest details of variations from the design conformity. In total, the traditional surveying method had 167 chainages, as shown in Table 7, whereas the chainages from the drone collected levels were 1670.

Table 7: Traditional and Drone Collected Elevations Based Chainages

Method	Cut and Fill Calculation Chainage Interval (m)	Total Number of Chainages
Machine Learning (XGBoost)	2	1670
Traditional	20	167

3.5.3.1.2 Model Architecture and Performance Measurement

To predict the cut and fill values, the already trained and validated model was used. The model was not reassessed and validated for its performance, as this was already done in objective 2 as well. To achieve the results of the current objective, the predictor variables were Offset, Crossfall, and Drone Collected 2 Meter Interval elevations, whereas the response variable was the predicted cut and fill volumes.

3.5.3.1.3 Accuracy Assessment

The accuracy of the XGBoost-derived output was evaluated by comparing it with ground truth data or a reference dataset, emphasizing both spatial and correlation considerations(Bassine et al., 2023b). Statistical analysis tools, specifically SPSS's paired sample t-test and correlation tests, were utilized to assess significance in volume differences and trend similarity between the two volume calculation methods.

3.5.3.1.4 Comparative Analysis

A comprehensive comparative analysis was undertaken to assess the accuracy standards of the XGBoost-derived output and Prismoidal method results. To further compare the accuracy levels between the cut and fill volumes computed from traditional methods and those computed using Machine Learning algorithms, a Paired Samples T-test was calculated. A visual examination of graphs and elevation differences, emphasizing spatial characteristics, was also conducted(Elamin & El-Rabbany, 2022; Mota-Delfin et al., 2022). Just as used by Elamin & El-Rabbany (2022), SPSS was used for the visualization of outputs from both the XGBoost and Prismoidal method to show the overestimations and underestimations within the surveyed route.

3.6 Ethical Considerations

As defined by Creswell (2009), ethics are norms or standards of behaviour that guide moral choices about our behaviour as well as our relationship with others. Research ethics provides guidelines for the responsible conduct of research. The researcher made sure to satisfy the ethical concerns through the following: obtaining an ethical clearance from the Mzuzu University Research Ethics Committee with reference number MZUNI/DOR/24/151 and introducing herself to the relevant authorities before the commencement of the study. When collecting data, participants' rights and dignity were respected to collect accurate information. In areas where drones flew, factors that were taken into consideration included seeking consent from local authorities as well as maintaining the confidentiality of the data collected. However, the study area was shifted from the Chitipa-Ilomba road to the Kasungu-Jenda because construction activities at the original site had been inactive for some time. Furthermore, to the side of a researcher, the following ethical issues: bias, provision or deprivation of a treatment, using inappropriate research methodology, incorrect reporting, and inappropriate use of the information were avoided.

3.7 Conclusion

This chapter has presented the study design, data collection techniques, methods of data analysis, ethical considerations, reliability and validity of research, and limitations, which will guide the processes of this study. The next chapter presents the results of the study.

CHAPTER FOUR: RESULTS

4.1 Introduction

This chapter presents the results of the study, which was conducted in the three sections of Lot 2 along the Kasungu-Jenda M1 road at Chatoloma trading centre in Kasungu District. The first section presents the results of the effectiveness of machine learning algorithms in object detection and classification from drone-collected data. While the second and third sections present the evaluation results of the potential of machine learning techniques for predictive analytics for cut-and-fill volume estimation, as well as the comparative results of the accuracy levels of machine learning derived output and traditionally computed output in engineering surveying.

4.2 The effectiveness of machine learning algorithms in object detection and classification from drone-collected data

4.2.1 Model Performance

The Convolutional Neural Network (CNN) model was trained for image classification on 70 % of the total annotated images (combined annotated images for all routes 1, 2, and 3), with performance primarily being evaluated based on training loss, validation loss, and accuracy over multiple epochs. The initial training was conducted using a learning rate (the rate at which the model adjusts its connection weights during training in response to the error it encounters) of 0.5 and 30 epochs. As Figure 11 shows, the initial parameter settings produced a poor model with a higher training loss of 0.09 and validation loss of 0.68. Consequently, the model yielded training and validation accuracy of 97 % and 77 % respectively (Figure 12). The observed huge gap between both training and validation losses (0.09 and 0.68), respectively, as well as training and validation accuracy (97 % and 77 %), respectively, indicated that the model was overfitting. It meant that the model was able to learn the pixel patterns too well from the training data, including noise and specific details. However, when tested on unseen validation data, it failed to generalize, which resulted in high validation loss and low validation accuracy. Therefore, hyperparameter tuning was performed to optimize model performance by reducing the learning rate to 0.0003 and increasing the number of epochs to 60.

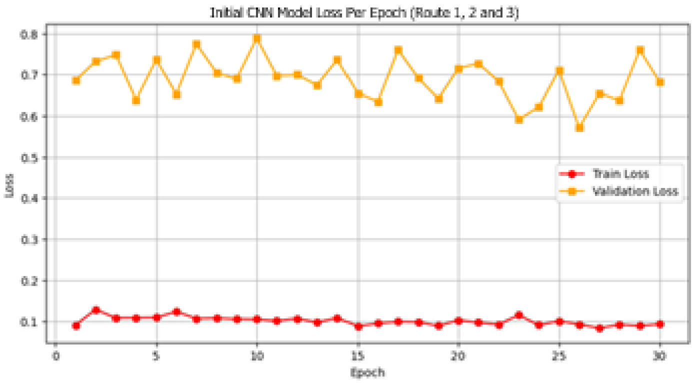


Figure 8: Initial Training and Validation Losses

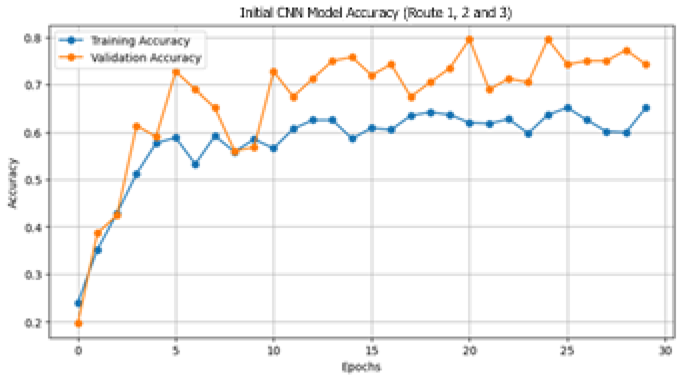


Figure 12: Initial Training and Validation Accuracy

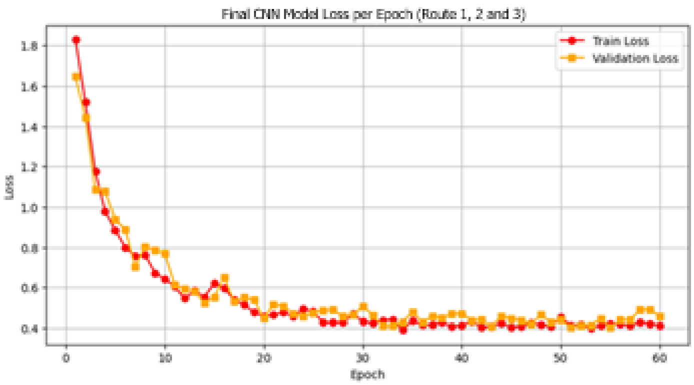


Figure 13: Post-Hyperparameter Tuning Training and Validation Losses

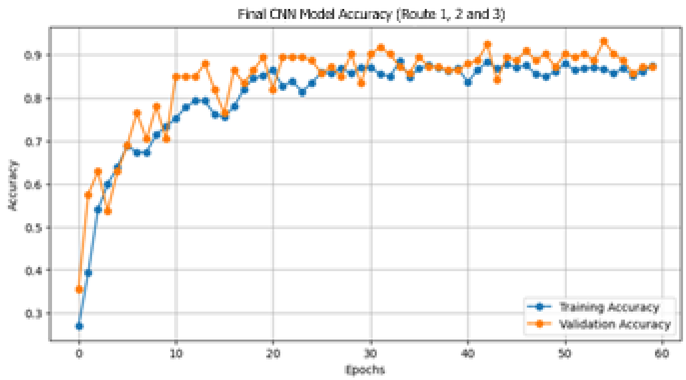


Figure 14: Post-Hyperparameter Tuning Training and Validation Accuracy

As shown in Figures 13 and 14, the final training process, incorporating the mentioned optimized hyperparameters, demonstrated significant improvements in the performance. The training loss decreased progressively, stabilizing at 0.015 by epoch 60, as the validation loss followed a similar declining trend, reaching 0.022 at the final epoch. Finally, the accuracy of the model improved steadily throughout training, with the final training accuracy recorded at 98.7% and validation accuracy at 97.9%.

4.2.1.1 Object Classification Performance Metrics

Using performance metrics such as accuracy, precision, recall, and F1-score, the overall model's performance in object classification on all orthomosaics was assessed, and the results are shown in Figures 13 and 14

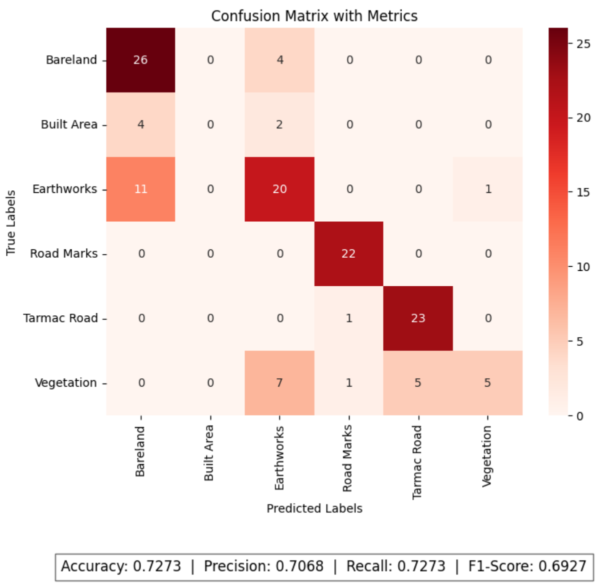


Figure 15: Model accuracy before hyperparameter tuning

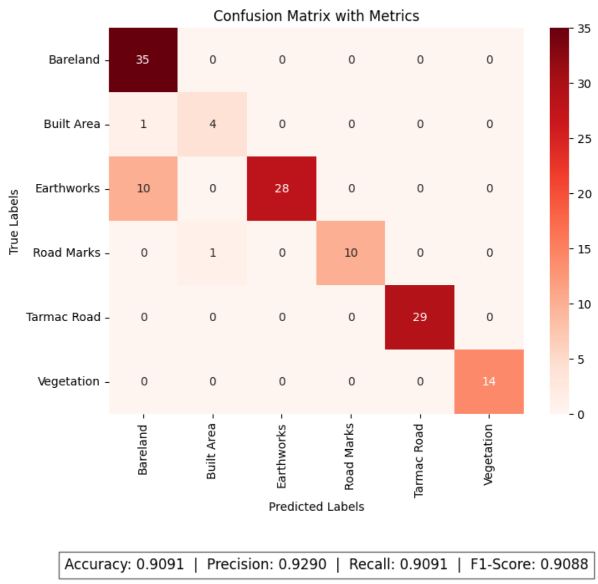


Figure 16: Model accuracy after hyperparameter tuning

As indicated in Figure 15, the initial model achieved an overall accuracy of 72.73 %, followed by 70.68 %,72.73 % and 69.27 % respectively, for Precision, Recall, and F1-Score, respectively. These results suggested that while the model demonstrated moderate classification performance, there was an imbalance between precision and recall, indicating misclassification of certain classes. This result was confirmed by the confusion matrix in Figure 15 which indicated that during validation, 4 samples belonging to Bareland were misclassified into Earthworks, all Built Area samples were misclassified into Earthworks (2) and Bareland (4), 11 samples for Earthworks were misclassified as Bareland and 1 sample for the same class was misclassified into Vegetation, 1 sample belonging to the Tarmac Road class was misclassified into Road Marks class, and 7, 1, and 5 samples belonging to Vegetation were misclassified into Earthworks, Road Marks and Tarmac Road, respectively. These results, therefore, warranted further optimization such as hyperparameter tuning and regularization as indicated in section 4.2.1.

After the hyperparameter tuning and regularization, the model improved in its overall performance on unseen data, as evidenced by the 90.91% accuracy reported in Figure 16. The model adjustments also increased both Precision, Recall, and F1-Score to 92.90%, 90.91%, and 90.88%, respectively. These improvements now meant that the model exhibited a significantly enhanced ability to correctly classify instances and reduced both false positives and false negatives. The increase in precision indicated that the model made fewer incorrect positive predictions, as evidenced by the confusion matrix, which indicates few misclassifications on Built Area (1 sample misclassified into Bareland) and Road Marks (1 sample misclassified into Built Area). The improved recall, on the other hand, indicated a higher rate of correctly identifying all relevant instances, while the balanced enhancement in the F1-score further confirmed that the model effectively maintains a trade-off between precision and recall, leading to overall better generalization to unseen data.

4.2.2.4 Classification Results

Having achieved a good model, orthomosaics for all routes were now classified, and the results are as shown in the following Figures 17, 18, and 19

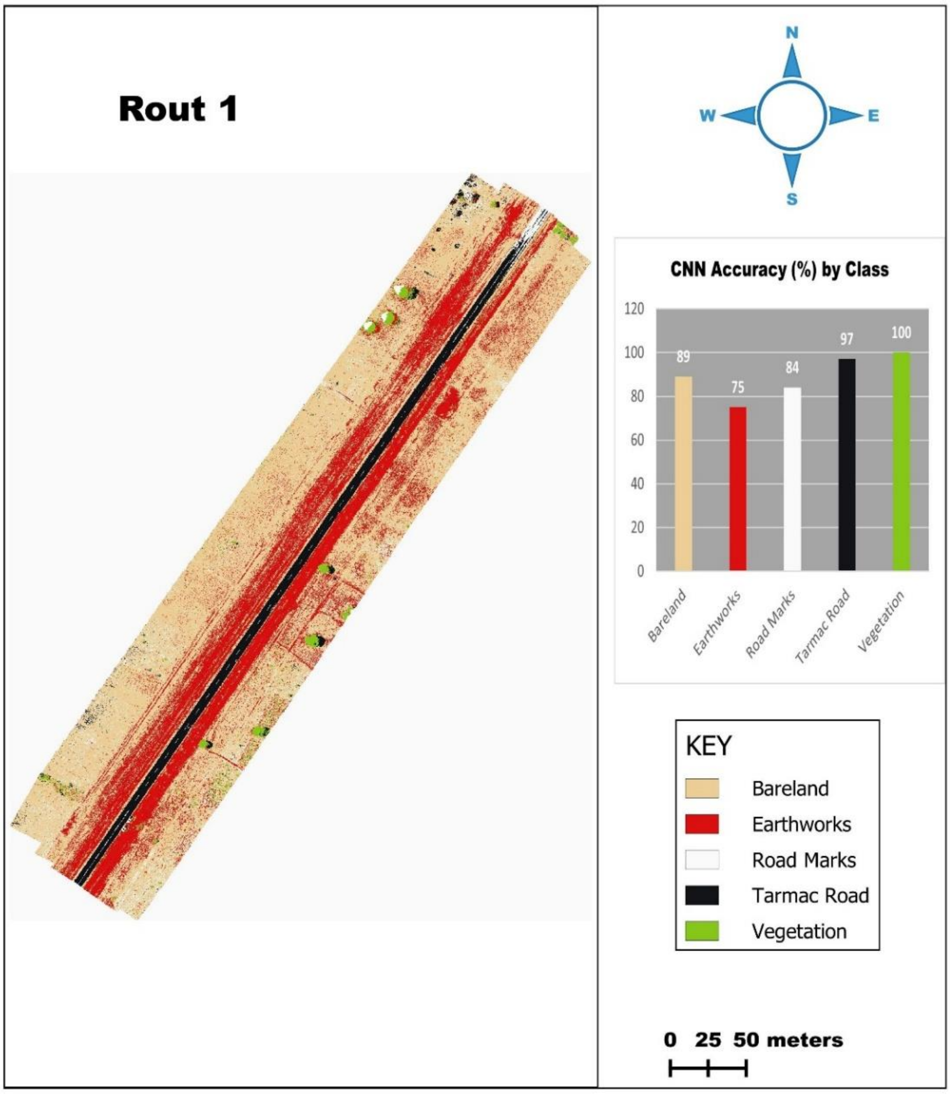


Figure 17: Classified Route 1

The classification results show that the model was effective and performed well in all drone routes. In Route 1, the CNN model showed 89%, 75%, 84%, 97% and 100% accuracy for Bareland, Earthworks, Road Marks, Tarmac Road, and Vegetation, respectively.

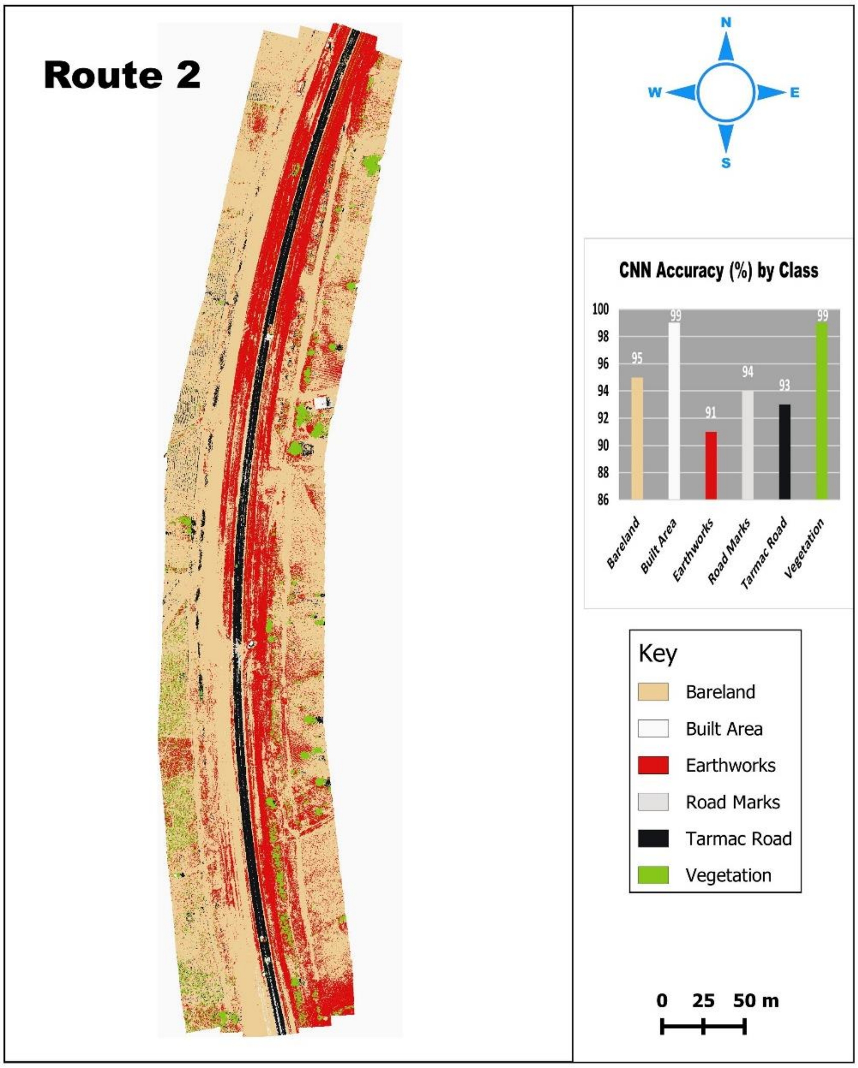


Figure 18: Classified Route 2

Unlike in Route 1, the model performance on orthomosaics of images collected in Routes 2 and 3 showed very high accuracy levels for all land use classes. In Route 2, the model was able to correctly predict 95%, 99%, 91%, 94%, 93% and 99% of the Bareland, Built Area, Earthworks, Road Marks, Tarmac Road, and Vegetation, respectively.

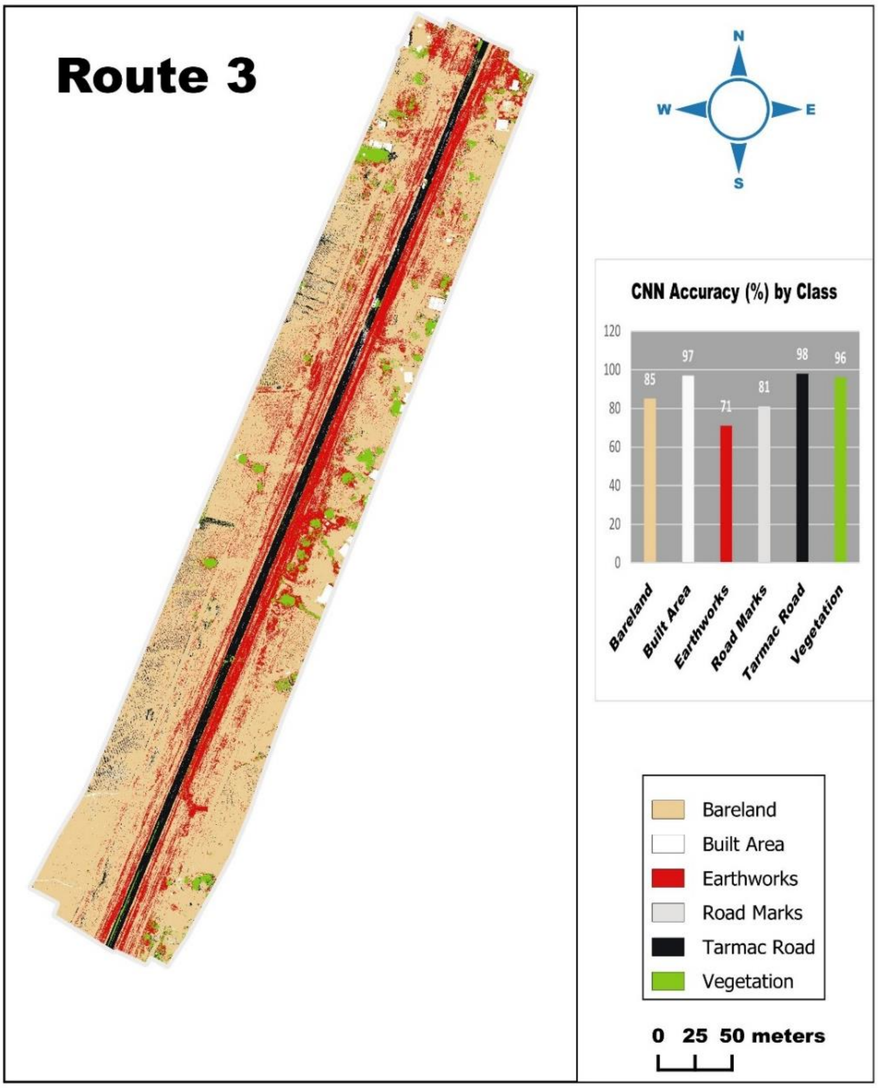


Figure 19: Classified Route 3

In Route 3, whose images were collected between 3:00 and 3:30 PM, the validated model also performed well, with the overall accuracy of 85%, 97%, 71%, 81%, 98% and 96% on Bareland, Built Area, Earthworks, Road Marks, Tarmac Road, and Vegetation, respectively.

4.3 The potential of machine learning techniques for predictive analytics for cut-and-fill volume estimation.

To evaluate the potential of Machine Learning techniques for cut-and-fill volume estimation, elevations processed from drone-collected data were used. The following section illustrates elevation data processing from the drone-collected images. For comparison, the as-built elevation data's coordinates were used to extract elevation data from the exported dense point cloud data through coordinate matching. The coordinate matching was done to map the dense point cloud elevation data with the georeferenced as-built data, and the comparative results are shown in Figure 20 and Table 4.

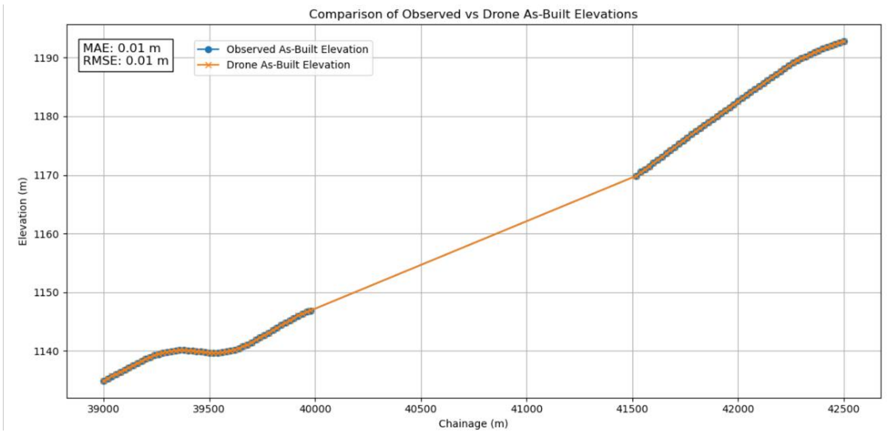


Figure 20: Comparison of observed and Drone As-built elevations (Left Hand Side)

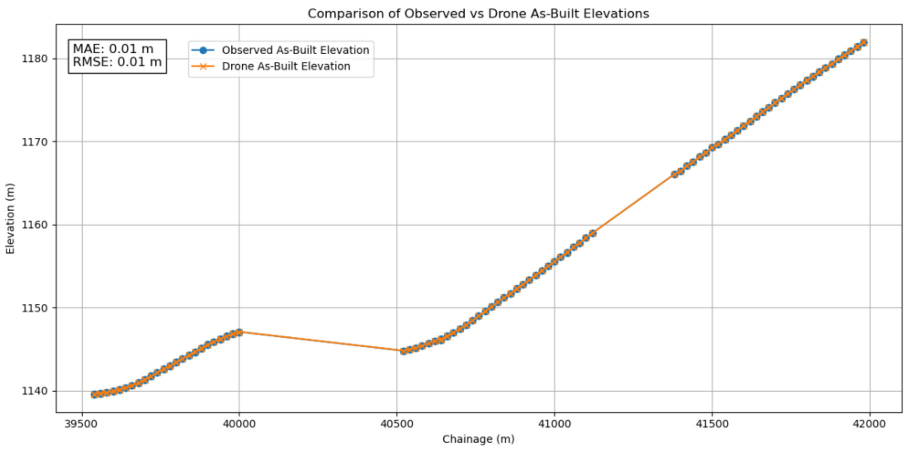


Figure 21: Comparison of observed and Drone As-built elevations (Right Hand Side)

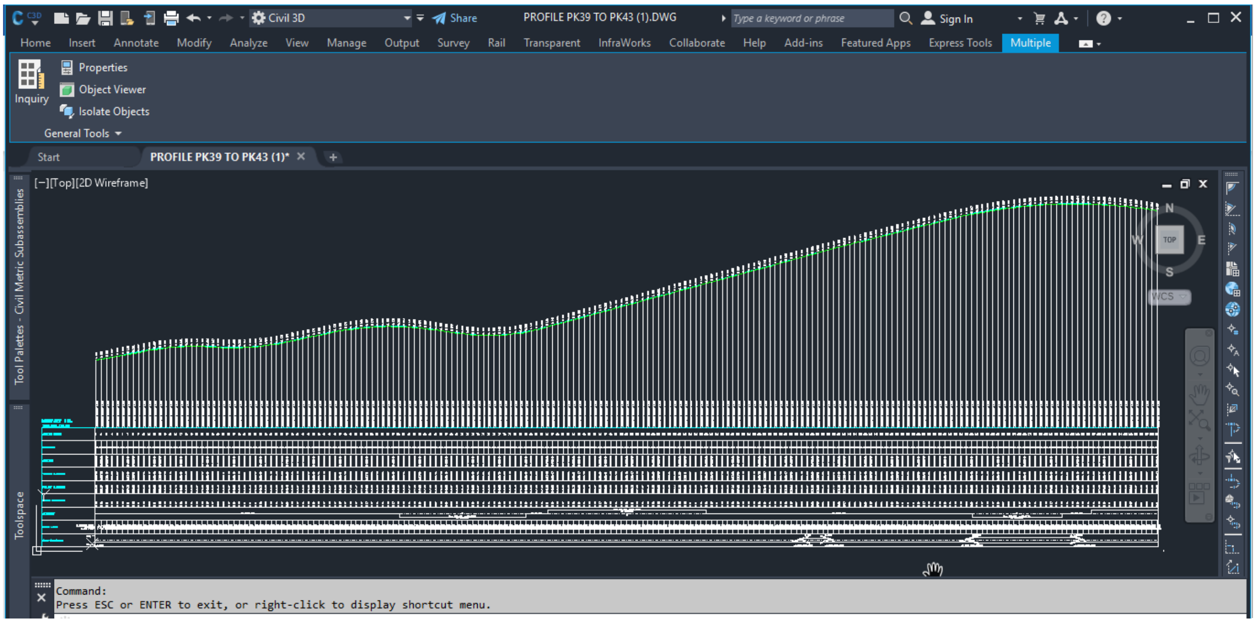


Figure 22: Road Section Profiles

Table 8a: Drone Collected As-built elevations and Observed As-built elevations descriptive statistics for LHS

Descriptive Statistics

	Minimum	Maximum	Mean	Std. Deviation	Variance
LHS Observed As-built Elevation	1139.534	1181.997	1159.10468	16.979056	288.288
LHS Drone As-Built Elevation	1162.761	1186.463	1169.61205	7.964982	63.441

Table 8b: Drone Collected As-built elevations and Observed As-built elevations descriptive statistics for RHS

Descriptive Statistics

	Minimum	Maximum	Mean	Std. Deviation	Variance
RHS Observed As-built Elevation	1139.575	1181.963	1157.06290	13.816339	190.891
RHS Drone As-built Elevation	1139.561	1181.977	1161.06272	13.816230	190.888

A comparative analysis was conducted between the right-hand side (RHS) and the left-hand side (LHS) field-observed as-built elevation values to validate the reliability of the drone-based elevation extracted for cut-and-fill predictions. As Figures 20 and 21 inset show, the Mean Absolute Error (MAE) between the two datasets was both found to be 0.01 meters, indicating a very high level of agreement between the drone-derived and the observed as-built elevation values. This small margin of error indicated the precision of the photogrammetric process and affirmed its suitability for engineering-grade elevation modelling and predictive analytics in road surveying. The elevation shapes of the linear graphs (Figures 20 and 21) were also found to conform to the sampled road section profile as shown in Figure 22, indicating the conformity of the extracted elevations to the road design.

To further compare the elevation data collected by the two methods, descriptive statistics were calculated to measure the central tendency and dispersion of the data. The LHS observed elevations displayed a broader range, spanning from 1139.534 m to 1181.997 m, with a higher standard deviation of 16.98 m, indicating greater variability in field measurements. In contrast, the drone-derived elevations were slightly more clustered, ranging from 1162.761m to 1186.463m, and showed a lower standard deviation of 7.96m, suggesting more consistent elevation estimates. While the drone data appeared slightly elevated on average (1169.61m**)** compared to the field observations (mean = 1159.10m), the low error metrics and tight clustering of values suggested this deviation is systematic and potentially attributable to equipment or datum differences during ground data collection.

Similar to the descriptive statistics of the LHS observations, the RHS mean values between the observed and drone-derived elevations were slightly different (RHS Drone As-built Elevation = 1161.06m, RHS Observed As-built Elevation =1157.06 m). Both datasets exhibited near-identical variability as well, with standard deviations of approximately 13.82m. Therefore, this strong alignment provided further evidence of the drone system's accuracy when elevation extraction is conducted carefully within a well-controlled photogrammetric workflow. In conclusion, the results validated the accuracy and consistency of drone-based elevation data for cut and fill predictions and volume estimations.

4.3.2.2 Model Performance

To assess the performance of the three models (SVM, Random Forest, and XGBoost), two performance metrics, namely Mean Absolute Error and the Coefficient of Determination (R^2), were used. As Table 9 shows, the initially developed models showed relatively fair performance.

Table 9: Initial Models' Performance

	Performance Metrics	
Algorithms	MAE	R^2
Random Forest	0.0232	0.7538
Support Vector Machine	0.0232	0.7170
XGBoost	0.005	0.8334

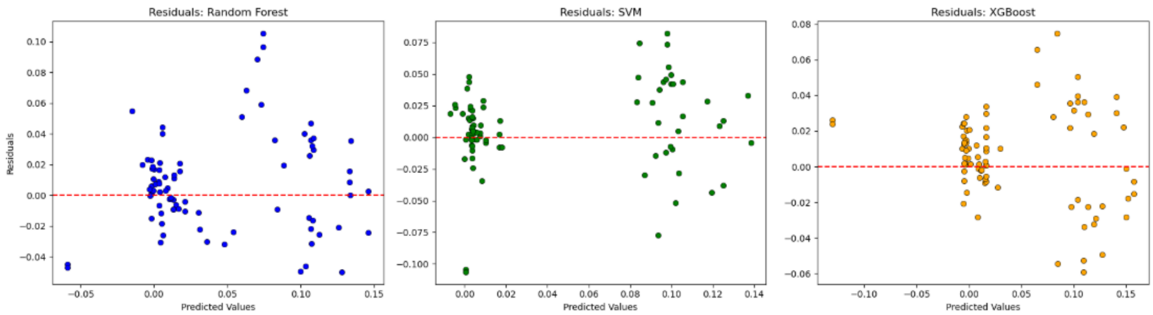


Figure 23a, b, c: Residual Plots for initial RF, SVM, and XGBoost Models

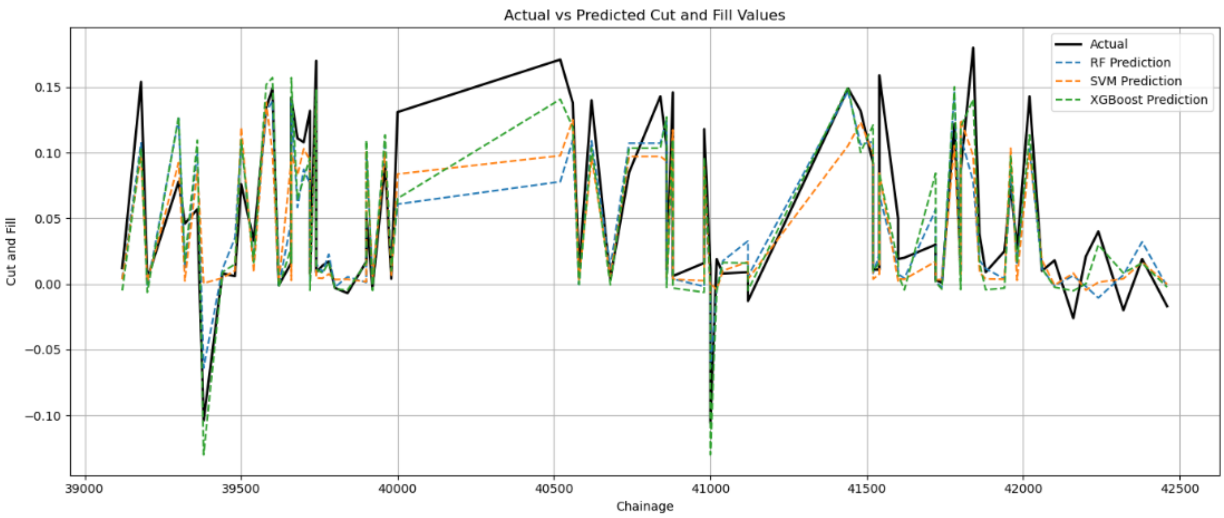


Figure 24: Initial Predicted vs Actual Cut and Fill

Overall Random Forest model was able to explain 75.38% (R^2 =0.7538) of the variations in the predicted Cut and Fill values, whereas the Support Vector Machine and XGBoost models explained 71.70% and 83.34%, respectively. Both models also showed lower differences between the predicted and actual Cut and Fill values as revealed by the MAE. The XGBoost's MAE values, however, showed that although the model performed relatively well, the predictions by both Random Forest (RF) and Support Vector Machine (SVM) were found to deviate from the actual observations by less than 3 cm (RF: MAE=0.0232 and SVM: MAE=0.0232). Therefore, despite the models displaying relatively high coefficients of determination, the differences between the predicted and observed values were higher for road engineering purposes; as such, they warranted further model optimization to improve their predictive abilities.

The residual representation of initial models' results also concurred with the calculated performance metrics. As shown in Figure 23a, the Random Forest model exhibited some clustering near zero but with increasing variance for higher predicted values. This indicated that the model was slightly underpredicting, especially on higher targets. The Support Vector Machine model, on the other hand (Figure 23b), showed residuals that were more widely spread, especially at the lower and higher ends of predicted values. The observed heteroscedasticity made the SVM model struggle more with predictions across the entire range. Finally, the XGBoost model showed relatively tighter clustering compared to the others (Figure 23c). The residuals were observed to be more negative for higher predicted values, indicating that the model was slightly overestimating high values and underestimating low ones. Overall, the initial models, therefore, did not predict well the observed cut and fill values in the initial phase, as shown in Figure 24. All models failed to follow the actual Cut-and-Fill trend line in almost all chainage sections.

Table 10: Improved Model's Performance

Performance Metrics (Improved)		
Algorithms	MAE	R^2
Random Forest	0.0106	0.9451
Support Vector Machine	0.0150	0.8908
XGBoost	0.0052	0.9847

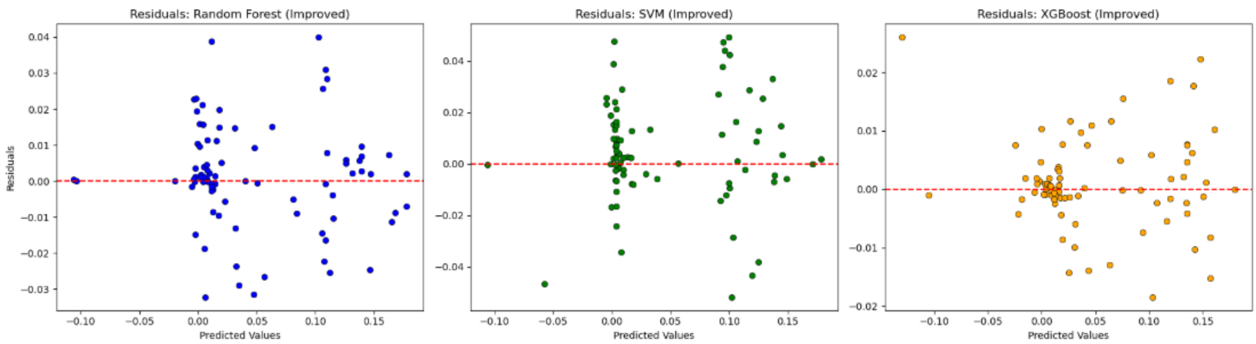


Figure 25a, b, and c: Residual Plots for Final RF, SVM, and XGBoost Models

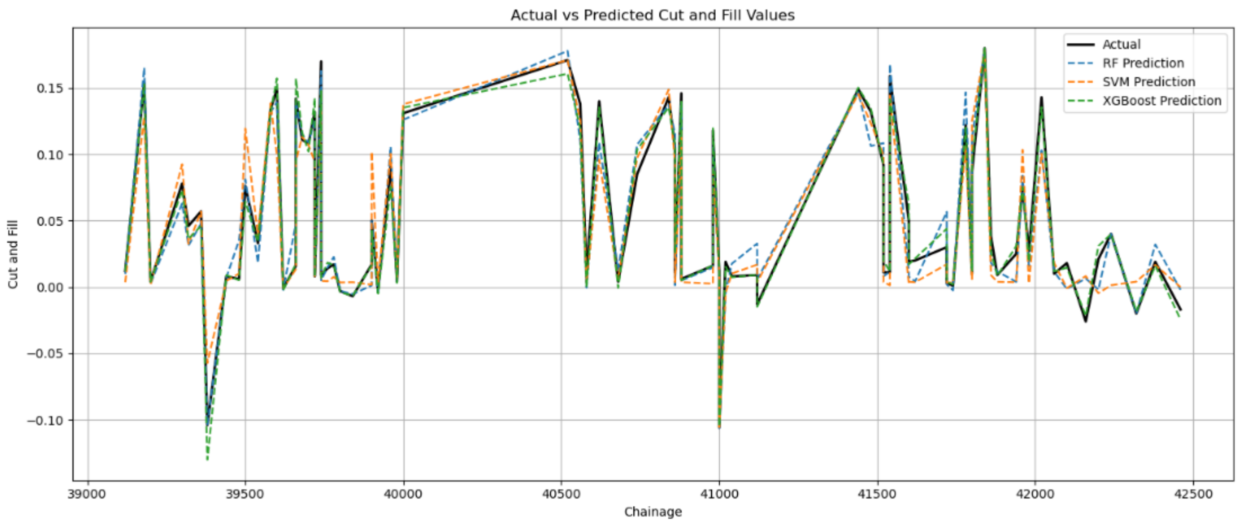


Figure 26:Final Predicted vs Actual Cut and Fill.

Having optimized the models through a series of hyperparameter tuning, an improvement was seen in all models as evidenced by their improved performance metrics, as shown in Table 10. Just like in the initial phase, the final model phase showed that XGBoost had a better predictive power as compared to the rest of other models. The XGBoost model was finally able to explain

98.47% of the variations in the target variable (Cut and Fill), followed by Random Forest, which explained 94.51% of the variations, while Support Vector Machine trailed behind in explanation power (R^2= 0.8908). While the hyperparameter tuning reduced the gap between the predicted and actual Cut and Fill value to less than 2 cm for all models, XGBoost exhibited a remarkable reduction in differences between the predicted and actual values. The XGBoost's MAE values of 0.0052 meant that the calculated difference between the predicted and actual Cut and Fill values was less than 6 mm.

Further prediction evaluation on the three models using residual plots (Figures 25a, b, and c) also confirmed that XGBoost stands out among the other two models. Figure 25c shows that the model's residuals are tightly clustered around the zero line and display minimal spread. This indicated a well-calibrated model with consistently low error across all predicted values. Although the residuals across all models are generally centered around zero, which indicates that the predictions do not systematically overestimate or underestimate the target values, the Random Forest model demonstrates a moderate dispersion of residuals, with a slightly wider spread observed at higher predicted values (Figure 25a). This suggested that although an improvement was seen in the model, it still exhibited variability in performance across the prediction range. The SVM model, on the other hand, as shown in Figure 25b, exhibits a less uniform pattern, with more pronounced residuals at the upper end of the prediction spectrum, which implies potential heteroscedasticity and a slight decline in accuracy for larger predictions. Collectively, therefore, these results revealed that the XGBoost model is superior, followed closely by Random Forest, in predicting Cut and Fill values from the elevation data extracted from drone-collected images.

As Figure 24 also shows, the XGBoost predictions closely matched the actual Cut and Fill values as compared to the rest of the other models. Although the predictions by the XGBoost model deviated from the actual Cut and Fill line in a few instances, such as between chainage

41500 and 52000 meters, as well as between 42000 and 42500 meters, in general, the model followed the actual Cut and Fill trendline. Based on these results, therefore, the cut and fill volume estimations were done using the best-performing XGBoost model's predicted values and compared to the actual volume, as shown in Table 11.

4.3.3 Cut and Fill Volumes

Using the predicted values by the XGBoost model, cut and fill volumes were calculated using the prismoidal method of calculating cut and fill volumes. The results were compared with the calculated cut and fill volumes from the ground data, as shown in Table 11. Based on the results, the predicted cut and fill volumes from the drone collected elevation (cut =21.249 m^3 and fill=1.094 m^3), as predicted by the XGBoost model, were seen to be very similar to the actual ground cut and fill volumes (cut 21.252 m^3 and fill 1.164m^3).

Table 11: Cut and Fill Volume Comparison

Type	Cut Volume (m^3)	Fill Volume (m^3)
Actual	21.252	1.164
Predicted	21.249	1.094

Paired Samples Statistics

		Mean	Std. Deviation	Std. Error Mean
Pair 1	Actual Cut Volume	.3251	.3459	.0382
	Predicted Cut Volume	.3205	.3393	.0374
Pair 2	Actual Fill Volume	.0219	.1001	.0110
	Predicted Fill Volume	.0218	.0992	.0109

The Paired Samples Statistics, as indicated in Table 11, also revealed that the mean difference between actual and predicted volumes is minimal for both cut (Actual: 0.3251 and Predicted: 0.3205) and fill volumes (Actual: 0.0219 and Predicted: 0.0218). Similarly, the standard deviations and standard errors are also low, which reflects consistent prediction performance.

Further analysis using the Paired Samples Correlation Test showed extremely strong positive relationships between the actual and predicted values, with a correlation coefficient of 0.997 for cut volumes and 0.999 for fill volumes, both statistically significant at $p < 0.001$. These values, therefore, suggest that the predictions made by the XGBoost model, using the elevation data from drone-collected images, were almost perfectly aligned with the actual values, which further supports the model's high level of accuracy.

Table 12: Paired Samples Correlations

Paired Samples Correlations

		Correlation	Sig.
Pair 1	Actual Cut Volume & Predicted Cut Volume	.997	.000
Pair 2	Actual Fill Volume & Predicted Fill Volume	.999	.000

Table 13: Paired Samples T-Test

Paired Samples Test

		Paired Differences							Sig. (2-tailed)
					95% Confidence Interval of the Difference				
		Mean	Std. Deviation	Std. Error Mean	Lower	Upper	t	df	
Pair 1	Actual Cut Volume – Predicted Cut Volume	.0045	.0266	.0029	-.0012	.0104	1.553	81	.124
Pair 2	Actual Fill Volume – Predicted Fill Volume	.0001	.0038	.0004	-.0007	.0001	.147	81	.883

Finally, to test the alternate hypothesis that Machine learning techniques have a significant potential for predictive analytics in estimating cut-and-fill volumes, a Paired Samples T-test was calculated for the predicted and actual cut-and-fill measurement volumes, and the results are presented in Table 13. The results indicate that there is no statistically significant difference between the actual and predicted cut volumes ($t = 1.553, p = 0.124$). Similarly, for fill volumes, no significant difference was observed between the actual and predicted values ($t = 0.147, p =$

0.883). In both cases, the p-values also exceeded the confidence interval of 0.05, which indicated that the differences between the actual measurements and predicted values are statistically negligible. The lack of significant difference between actual and predicted values, coupled with the high correlation, therefore confirms that the XGBoost model (Machine Learning) is capable of predicting accurate and reliable estimates of cut-and-fill volumes. These findings reveal the effectiveness of machine learning techniques and drone technology in supporting data-driven decision-making in road engineering contexts such as earthwork estimation.

4.4 The accuracy levels of machine learning derived output and traditionally computed output in road surveying.

4.4.1 Traditional and Machine Learning Based Cut and Fill Volumes.

Having subjected the XGBoost model to the 2-meter interval drone collected elevations, the results were compared to cut and fill values calculated from the traditionally surveyed elevations at 20m intervals, and the results are shown in Table 14 and Figure 21.

Table 14: Traditional and Machine Learning Based Cut and Fill

Type	Cut Volume (m^3)	Fill Volume (m^3)
Traditional	21.252	1.164
Predicted	26.0420	0.55
Difference	4.79	0.614

As results in Table 14 show, the computation of cut and fill volumes using traditionally surveyed elevations at 20-meter intervals underestimated the cut volume by 4.79 m^3 of Cut volume, while overestimating the Fill volume by 0.614 m^3. The Machine Learning based computations using the 2-meter interval drone collected elevations provided a detailed scan of the ground levels as compared to the 20-meter traditional assessments, which overlooked some deviations from the design elevations. As indicated in Figure 25, the visible discrepancies between the computed cut and fill volumes from the traditional methods and the ML methods revealed that, in some instances, the traditional method strongly underestimated or overestimated the cut and/or fill volumes. For instance, at chainage 39380, the traditional method overestimated the fill volume to -0.624 m^3 as compared to the fill computed from the dense drone collected elevations (-0.161 m^3). The visible overestimations of cut volumes across the surveyed routes also include the chainages between 40000 m and 40500 m, as well as at chainages 41840 m and 42020 m (Figure 27). The compounded results of these overestimations and underestimations, therefore, resulted in the observed difference as indicated in Table 14

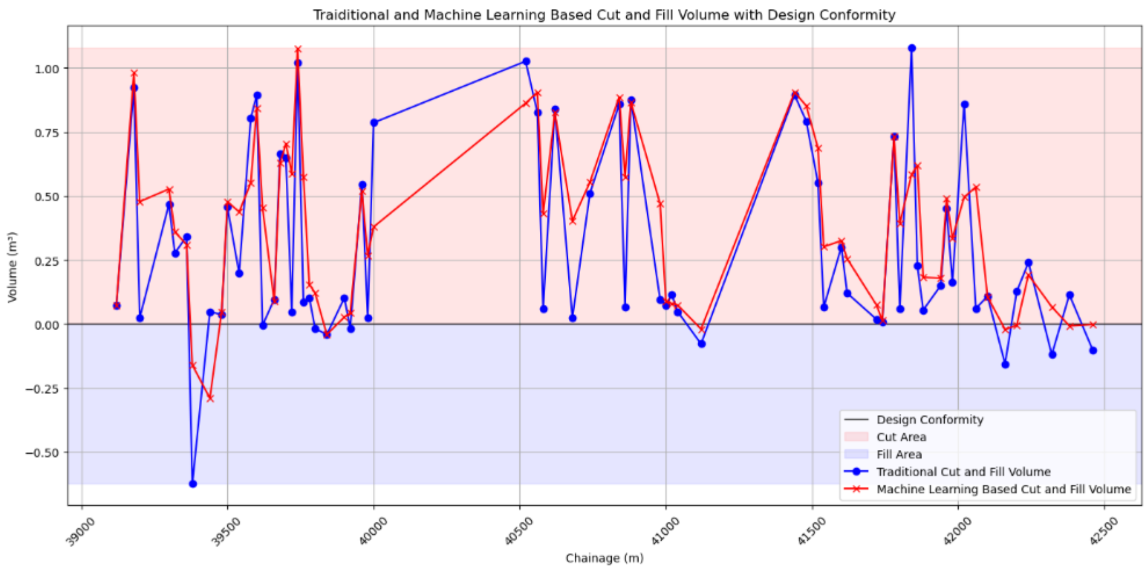


Figure 27: Traditional and Machine Learning Based Cut and Fill Volumes against Design Conformity

4.4.2.1 Computed Cut and Fill Volume Comparisons

To further compare the accuracy levels between the cut and fill volumes computed from traditional methods and those computed using Machine Learning algorithms, a Paired Samples t-test was calculated. The results of this statistical test also helped to test the alternative hypothesis that there is a significant similarity in accuracy levels between machine learning derived volume and traditionally computed volumes, and the results are shown in the following section.

Table 15: Paired Samples Statistics for Traditional and Machine Learning Based Cut and Fill Volumes

Paired Samples Statistics

		Mean	Std. Deviation	Std. Error Mean
Pair 1	Traditional Cut Volume	.3251	.3459	.0382
	Predicted Cut Volume	.3886	.3059	.0373
Pair 2	Traditional Fill Volume	.0219	.1001	.0110
	Predicted Fill Volume	.0082	.0405	.0049

Table 16: Paired Samples Correlation for Traditional and Machine Learning Based Cut and Fill Volumes

Paired Samples Correlations

		Correlation	Sig.
Pair 1	Traditional Cut Volume & Predicted Cut Volume	.812	.000
Pair 2	Traditional Fill Volume & Predicted Fill Volume	.455	.000

Table 17: Paired Samples T-Test for Traditional and Machine Learning Based Cut and Fill Volumes.

Paired Samples Test

		Paired Differences							
					95% Confidence Interval of the Difference				
		Mean	Std. Deviation	Std. Error Mean	Lower	Upper	t	df	Sig. (2-tailed)
Pair 1	Traditional Cut Volume – Predicted Cut Volume	-.0714	.2048	.0250	-.1214	-.0215	-2.856	81	.006
Pair 2	Traditional Fill Volume – Predicted Fill Volume	.0092	.0717	.0087	-.0083	.0266	1.045	81	.300

As observed in Table 15, the traditional method consistently reported lower cut volumes (mean = 0.3251 m³) than the machine learning predictions (mean = 0.3886 m³), while slightly overestimating the fill volumes (traditional =0.0219 m^3, Machine Learning based= 0.0082 m^3). These differences mirror the volume differences reported earlier and indicate a recurring pattern of underestimation and overestimation in the traditional method. While mean differences were observed in both cut and fill between the outputs of the two methods, some relationships between them were also observed. In Table 16, the cut volumes showed a strong positive relationship between the two methods ($r = 0.812$, $p < .001$), which suggested that while the magnitudes differed, the general trends were quite similar. In contrast to the cut volumes, the correlation for fill volumes was notably lower ($r = 0.455$, $p < .001$), a phenomenon which revealed that the traditional and machine learning outputs did not always shift in tandem, especially where smaller variations were involved.

Finally, the t-test results in Table 17 provided further insight into whether the observed differences were statistically meaningful. The observed gap in cut volumes was found to be significant ($t = -2.856$, $p = .006$), affirming that traditional measurements tend to underrepresent cuts compared to the machine learning-based outputs. The difference in fill volumes, however, was not statistically significant ($t = 1.045$, $p = .300$). This, therefore, meant that variations between the two methods in the case of estimating low lands that needed to be filled could have occurred by chance and do not imply a consistent bias.

4.5 Conclusion

This chapter has presented the study results based on the collected and analysed data along the Kasungu-Jenda M1 road. The data has shown that drones, combined with artificial intelligence ability to classify and estimate cut-and-fill volumes. The results have further demonstrated noticeable differences in accuracy between traditional and machine learning outputs. These results confirm that when paired with photogrammetrically processed drone data, machine learning can serve as a reliable tool for earthwork volume estimation, offering an efficient data-driven alternative to traditional data processing methods in road engineering and design.

CHAPTER FIVE: DISCUSSION

5.0 Introduction

This chapter discusses the findings of research as presented in the previous chapter. With reference to the extant literature, the chapter starts with the discussion on the effectiveness of machine learning algorithms in object classification of drone-collected data, followed by the potential of machine learning techniques for predictive analytics for cut-and-fill volume estimation, and the accuracy levels of machine learning derived output and traditionally computed output in road surveying.

5.1 Effectiveness of machine learning algorithms in object classification of drone-collected data

This study has provided compelling evidence that machine learning algorithms, such as the Convolutional Neural Networks (CNNs), can effectively address the essential classification-related data processing challenges in road surveying applications. The demonstrated capabilities of the CNN model in classifying objects from drone-collected imagery directly respond to the identified gaps in current surveying practices, where traditional methods struggle with both processing speed and accuracy maintenance, especially during topographic surveying activities (Guimarães et al., 2020). The success of the implemented CNN architecture in achieving 90.91% overall classification accuracy supports the existing literature that advocates for the integration of Artificial Intelligence in geospatial analysis (Song et al., 2023). As Dritsas and Trigka (2025) consider the time constraints inherent in road engineering projects, the application of Artificial Intelligence algorithms with the ability to process and classify extensive orthomosaic datasets within minutes presents a substantial improvement over manual and traditional interpretation methods, which typically take days or weeks to complete.

5.1.1 Data Processing Variations

While the present study shows the potential of reducing classification data processing challenges in road surveying, the variation in classification accuracy across different land cover classes also offers valuable lessons on the AI models' operational characteristics. (Sim et al., 2024). As noted, depending on the classes being defined, as well as the time of the day during which images were taken, the accuracy levels differed. There was a reduction in accuracy for Route 1 (collected at noon) compared to Routes 2 and 3 (afternoon collections), which provides evidence supporting the importance of flight planning in AI-assisted surveying. As Corcione et al., (2021) stipulated in spectral-related analyses, the direction of lighting bears consequences on the resultant spectral signature of an object being classified. Laborte et al., (2010) also reveals that in spatial analysis, when spectral signatures are very much related, as was observed between bare land and earthworks (which are all soils, just differing slightly in hue), classification accuracy becomes compromised. Therefore, the consistent high performance on vegetation and tarmac road classification (reaching 100% accuracy in some instances) confirmed that when well-defined features with distinct spectral signatures are classified using AI-based algorithms, the data processing errors are avoided (Sekrecka & Karwowska, 2025). The observed confusion between earthworks and bare land classes (with accuracy dropping to 71% in Route 3) also indicated an important limitation that warrants consideration, especially in flight planning to reduce the lighting and shadow-related errors.

5.1.2 Operational Economics of AI Integration

Beyond technical performance, this study's outcomes also reveal important facts about the operational economics of AI in surveying. While off-the-shelf AI tools might lack the generalizability to custom operations like road surveying, the hyperparameter tuning process of custom models reveals the hidden costs of implementation. As Murumkar et al. (2023) indicated, to fully integrate custom AI tools in different domains like land surveying, there is always a need for specialized expertise to achieve optimal results (evidenced by the improvement from 77% to 97.9% validation accuracy). These results agree with the findings of Innocenti & Golin (2022), who concluded that companies and organizations ought to weigh the benefits of automation against the required investments in human capital. The initial investment in automation is relatively high due to the need for high-quality drones, laptops, and personnel training to effectively manage the project. However, it becomes more cost-efficient over time, especially for large-scale projects. Furthermore, the route-specific variations in accuracy imply that the return on investment for AI classification may be project task-specific. For applications where vegetation and paved surfaces are primary concerns, such as in topographic surveying, which determines the topographic features before the actual construction works begin, the mapping and classification of ground objects using AI technology becomes very much viable.

In conclusion, the examination of CNN performance in drone-based classification in this study moves beyond simple accuracy metrics to reveal the considerations for practical implementation. The study has proved that the technology's strengths in processing speed and excellent classification abilities in certain tasks. It has also been revealed that the AI algorithms' application limitations help in creating defined boundaries for effective application. The study ultimately reframes the discussion from whether AI can be used in road surveying to how it should be used. By identifying the precise conditions under which the technology excels and where it requires supplementation, this research provides a roadmap for thoughtful integration that addresses the field's data processing challenges while respecting its precision requirements.

5.2 The potential of machine learning techniques for predictive analytics for cut-and-fill volume estimation.

The results of this objective demonstrate the potential of machine learning (ML) techniques, specifically the XGBoost, in enhancing the accuracy and efficiency of cut-and-fill volume estimation for road engineering projects. This aligns with broader trends in geospatial analytics, where Machine Learning models are increasingly being adopted to overcome the limitations of traditional surveying methods (Murumkar et al., 2023). The success of XGBoost in this study can be attributed to its inherent advantages in handling non-linear relationships and high-dimensional data, which are common challenges in terrain modeling (Chen & Guestrin, 2016). The model's ability to achieve a higher Coefficient of Determination confirmed its robustness, a finding consistent with prior research that indicates the superiority of ensemble methods in regression tasks (Sarker, 2021).

5.2.1 Reliability of Drone-Collected Elevation Data

The photogrammetric workflow employed in this study, which also yielded elevation data with high precision, addresses a critical trade-off between data collection speed and accuracy in surveying and road engineering. This is particularly relevant in the context of large-scale infrastructure projects, where traditional methods often struggle with scalability (Huang et al., 2022). The low MAE values observed in this study further validate the reliability of drone-based data, which reinforces the findings from recent studies that advocate for UAS as a viable alternative to ground surveys (Huang et al., 2022;Perera and Nalani, 2022)

5.2.2 Models' Performance

The performance differences among the tested ML models (XGBoost, Random Forest, and SVM) in this study also warrant further discussion. While XGBoost excelled, the comparatively lower performance of SVM may be linked to its sensitivity to hyperparameter tuning and kernel selection, which can limit its effectiveness in high-variability datasets like surface elevations (Hastie et al., 2017). Random Forest, though less accurate than XGBoost, demonstrated resilience against overfitting, a trait that makes it suitable for applications where interpretability is prioritized over peak performance (Breiman, 2001). These observations therefore suggest that model selection should be guided by project-specific requirements, balancing accuracy, computational efficiency, and interpretability.

The statistical validation of the results, on the other hand, particularly the paired samples t-test and high correlation coefficients, provides strong evidence for the reliability of ML-based predictions. The absence of significant differences between predicted and actual volumes mirrors findings in other studies where Machine Learning models have been successfully applied to geospatial problems (Murumkar et al., 2023). The study shows the potential for Machine Learning algorithms and drone technology to streamline decision-making in road earthworks. By reducing reliance on manual data processing, these tools can mitigate delays and high costs, which are noted by (Kamanga & Steyn, 2013) as prevalent issues in road engineering. However, the computational demands of advanced ML models like XGBoost may necessitate infrastructure upgrades for widespread adoption, particularly in resource-constrained settings.

In conclusion, this study provides evidence that supports the use of ML in engineering surveying. The success of XGBoost in predicting cut-and-fill volumes with high precision underlines the value of integrating modern data-driven approaches with traditional practices. The results, as discussed in this objective, therefore, have shown that Machine learning techniques have a significant potential for predictive analytics in estimating cut-and-fill volumes.

5.3 The accuracy levels of machine learning derived output and traditionally computed output in road surveying.

The results for this objective have revealed that a significant difference exists between the accuracy levels of Machine Learning derived outputs and the outputs from the traditional methods, rejecting the alternative hypothesis that posited the opposite. It has been observed that the key advantage of the ML-based approach lies in its ability to process dense elevation data collected at 2-meter intervals in minutes, which could otherwise take weeks to be achieved through traditional methods. The higher spatial resolution enabled the XGBoost model to detect the smallest deviations in terrain, which translated into more accurate volume calculations. This result, therefore, agrees with broader trends in geospatial analytics, where ML and remote sensing are increasingly recognized for their ability to capture fine-grained terrain variations that traditional methods may overlook (Huang et al., 2022; Murumkar et al., 2023). The evident significant mean differences for cut volumes were also found to be consistent with studies that emphasize the limitations of sparse sampling in conventional surveys on the calculation of cut and fill volume. (Papa et al., 2023).

In contrast to the observed differences in the cut volume estimations, the weaker correlation for fill volumes and the lack of statistical significance in their difference reflected the inherently smaller magnitudes of fill activities. The main reason for this observation was because of the surveyed area was a formation layer, an initial layer upon which other layers are built. As such, in this layer, there are more areas to be cut than to be filled. Therefore, based on the graphical presentation in the previous section, the sparsely 20-meter surveyed elevations through the traditional methods resulted in overestimation of fill in most cases. The detailed 2-meter surveying, on the other hand, provided a detailed analysis of the terrain changes, hence reflecting the ideal fill values. These discrepancies in the long run resulted in a weak correlation between the Machine Learning derived outputs and the traditionally computed outputs.

Based on the findings of this study, therefore, the ML approach offers tangible benefits for road surveying, where accurate cut-and-fill estimations are crucial for cost control and project planning. The traditional method's tendency to underestimate cut volumes, for instance, could lead to budgetary shortfalls or material shortages during construction. Conversely, the overestimation of fill volumes might result in unnecessary material transport and handling costs. These findings align with industry reports that emphasize the financial implications of inaccurate earthwork calculations emanating from traditional techniques. (Kamanga & Steyn, 2013).

Overall, this objective refutes the hypothesis of equivalence between traditional and ML-based volume computations. The statistical and practical superiority of the XGBoost model, coupled with the density of drone-collected elevation data, positions ML as a transformative tool for earthwork estimation. While traditional surveying methods remain valuable for broad-scale assessments, the adoption of drone and Machine Learning technology offers a window for reduced operational costs. By scaling these methods to more complex environments and integrating them with real-time monitoring systems, surveyors and engineers can therefore enhance their (MLs) utility in road surveying and engineering practice.

5.4 Conclusion

This chapter has discussed the results as presented in Chapter 4 with respect to the existing literature. Arguments have been made that have shown the agreement as well as disagreements of the findings of this study with other studies worldwide.

CHAPTER SIX: CONCLUSIONS AND RECOMMENDATIONS

6.1 Introduction

Through the designed objectives of this study, key findings on the application of Artificial Intelligence on drone-collected data in road surveying have been presented. This chapter, therefore, concludes the research findings and provides recommendations.

6.2 Conclusion

6.2.1 Effectiveness of Machine Learning Algorithms in Object Classification for Drone Data

The study demonstrated that machine learning algorithms, particularly Convolutional Neural Networks (CNNs), are highly effective in object classification from drone-collected images. The CNN model, after tuning, achieved a high validation accuracy of 97.9% and an overall classification accuracy of 90.91%. The model was particularly effective in distinguishing among road features such as vegetation, bare land, road marks, and built areas, although minor misclassifications occurred in compressed earthworks zones due to spectral similarities with bare land.

6.2.2 Potential of Machine Learning Techniques for Predictive Analytics in Cut-and-Fill Volume Estimation

The use of machine learning techniques for predictive analytics also yielded promising results. Algorithms such as XGBoost, Random Forest, and Support Vector Machine (SVM) successfully predicted cut-and-fill volumes using drone-derived elevation data. Among them, XGBoost demonstrated the highest predictive accuracy with a coefficient of determination (R^2) of 0.9847. The Mean Absolute Error (MAE) values were low, confirming the potential of these algorithms in modelling terrain features and predicting volumetric outcomes with high precision.

6.2.3 Comparison of Accuracy Between Machine Learning Derived Output and Traditionally Computed Output

A comparative analysis between machine learning derived outputs and traditionally computed cut-and-fill volumes using the Prismoidal Method showed significant differences, as the p-value was less than 0.05. XGBoost outperformed traditional methods in capturing detailed terrain variations due to its ability to process dense drone-derived elevation data at finer spatial resolutions. The Paired Samples T-test of $P>0.05$ also revealed no significant similarities between the two outputs, more especially the cut volumes, thereby validating the use of machine learning as a reliable alternative to conventional methods in road surveying.

6.3 Study Recommendations

6.3.1 Use of Machine Learning Algorithms for Object Classification

- Land Surveyors should adopt Convolutional Neural Networks (CNNs) in engineering survey projects where classification of features from drone imagery is required due to their high accuracy and generalization capabilities.
- Drone pilots should utilize image acquisition under consistent lighting conditions to reduce misclassification caused by shadows and low spectral contrast.

6.3.2 Use of Machine Learning for Predictive Analytics in Cut-and-Fill Estimation

- Integrate machine learning algorithms such as XGBoost and Random Forest in earthwork volume prediction processes to improve accuracy and reduce manual computation time.
- Ensure adequate training datasets and appropriate model tuning to maximize predictive accuracy and avoid overfitting.
- Invest in training surveyors and engineers in the implementation of drone and AI-based data processing techniques to enable effective adoption of the technology

6.3.3 On Accuracy Comparison with Traditional Methods

- Consider replacing or complementing traditional volume estimation methods with drone and machine learning-based approaches in complex and large-scale projects to benefit from increased precision.
- Invest in training surveyors and engineers in machine learning techniques to enable effective adoption and integration into standard workflows.

6.4 Areas of Further Study

- Conduct longitudinal studies to evaluate the robustness of machine learning models across different project sites and seasons.
- Develop a standardized framework for assessing and comparing the computational efficiency of different machine learning models used in road engineering surveying.

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Annex 1: Consent to fly a drone

Mzuzu University Research Ethics Committee (MZUNIREC)

Informed Consent Form for Research on

Application of Artificial Intelligence on Drone-collected Data for Cut-and-Fill Volume Estimation: Kasungu-Jenda Road

Introduction

I am Rosemary Nyamwera from the Department of Built Environment, Mzuzu University. We are doing research on the Application of Artificial Intelligence on Drone-collected data for cut-and-fill volume estimation: Chatoloma, Kasungu-Jenda Road.

This consent form may contain words that you do not understand. Please ask me to stop as we go through the information, and I will take time to explain. If you have questions later, you can ask them to another researcher or me.

Purpose of the research

The main purpose of this research is to assess the application of artificial Intelligence on drone-collected data for cut-and-fill volume estimation on the Kasungu-Jenda Road.

Type of Research Intervention

This research will involve flying the drone over the study area to capture data.

Participant Selection

You are being invited to participate because the drone will fly over your area, and we need your permission.

Voluntary Participation

Your participation in this research is entirely voluntary. You can choose to participate or not, and can withdraw at any time.

Duration

The drone flights will occur for a period of 2 days.

Risks

There are minimal risks. All safety and privacy precautions will be taken.

Reimbursements

There is no payment for participating in this research.

Sharing the Results

The results will be shared with you and relevant stakeholders before public release.

Who to Contact

If you have any questions, contact Miss Rosemary Nyamwera. (Mzuzu University, Department of Built Environment; +265883523877 /997514180, rosenyamwera35@gmail.com).

This proposal has been reviewed and approved by Mzuzu University Research Ethics Committee (MZUNIREC), which is a committee whose task is to make sure that research participants are protected from harm. If you wish to find out more about the Committee, contact the ethics committee on mzunirec@mzuni.ac.mw

Annex 2: Research Ethics Approval

MZUZU UNIVERSITY

DIRECTORATE OF RESEARCH

Mzuzu University
Private Bag 201
Luwinga
Mzuzu 2
MALAWI
TEL: 01 320 722
FAX: 01 320 648

MZUZU UNIVERSITY RESEARCH ETHICS COMMITTEE (MZUNIREC)

Ref No: MZUNIREC/DOR/24/151 **27/03/2025**

Rosemary Nyamwera,
Mzuzu University,
P/Bag 201,
Luwinga,
Mzuzu 2.

Email: rosenyamwera35@gmail.com

Dear Rosemary,

RESEARCH ETHICS AND REGULATORY APPROVAL AND PERMIT FOR PROTOCOL REF NO. MZUNIREC/DOR/24/151 : APPLICATION OF ARTIFICIAL INTELLIGENCE ON DRONE-COLLECTED DATA FOR CUT-AND-FILL VOLUME ESTIMATION IN CHITIPA-ILOMBA ROAD, MALAWI.

Having satisfied all the relevant ethical and regulatory requirements, I am pleased to inform you that the above referred research protocol has officially been approved. You are now permitted to proceed with its implementation. Should there be any amendments to the approved protocol in the course of implementing it, you shall be required to seek approval of such amendments before implementation of the same.

This approval is valid for one year from the date of issuance of this approval. If the study goes beyond one year, an annual approval for continuation shall be required to be sought from the Mzuzu University Research Ethics Committee (MZUNIREC) in a format that is available at the Secretariat. Once the study is finalised, you are required to furnish the Committee with a final report of the study.

1

The Committee reserves the right to carry out compliance inspection of this approved protocol at any time as may be deemed by it. As such, you are expected to properly maintain all study documents including consent forms.

Wishing you a successful implementation of your study.

Yours Sincerely,

Faith Mwangonde
Ethics Administrator
FOR:MZUNIREC CHAIRPERSON

MZUZU UNIVERSITY
RESEARCH ETHICS COMMITTEE
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