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COMPARATIVE ANALYSIS OF MACHINE LEARNING TECHNIQUES IN IDENTIFICATION AND MAPPING OF URBAN ROAD NETWORK WITH REMOTELY SENSED IMAGERY IN PARTS OF BENIN CITY, NIGERIA

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Abstract

Accurate mapping of urban road networks is fundamental for effective urban planning, transportation management, and infrastructure development, particularly in rapidly expanding cities. This study evaluates and compares the performance of three machine learning algorithms—Support Vector Machine (SVM), Convolutional Neural Network (CNN), and Random Forest (RF)—for automated extraction of urban road networks from high-resolution UAV imagery in Benin City, Nigeria. UAV data acquisition was conducted using a DJI Matrice 100 drone equipped with a Zen muse X5 camera, followed by extensive preprocessing including calibration, georeferencing, mosaicking, orthorectification, noise reduction, and feature extraction. The CNN model demonstrated superior performance, achieving an overall accuracy of 91.3%, precision of 0.89, recall of 0.85, F1-score of 0.87, and Intersection over Union (IoU) score of 0.834, outperforming both RF (88.7% accuracy) and SVM (87.3% accuracy). CNN's hierarchical feature extraction effectively addressed the complexity of urban morphology, varying road widths, and edge localization, though with increased computational demands. SVM exhibited high accuracy in primary road detection but struggled with narrower and shadow-obstructed roads, while RF demonstrated balanced performance but was sensitive to urban density and occlusions. Comparative analysis with conventional remote sensing methods, which achieved 76.8% accuracy, underscores the significant advantage of machine learning-based approaches in terms of accuracy, efficiency, and scalability. The findings highlight CNN as the most robust and reliable algorithm for urban road network mapping in complex urban environments. Future work should focus on developing hybrid models that integrate the strengths of CNN, RF, and SVM, as well as implementing advanced preprocessing techniques to mitigate challenges posed by shadows and occlusions.

Keywords: Urban road network; Machine learning; Remote sensing; UAV imagery; Support Vector Machine; Convolutional Neural Network; Random Forest.

1.0 INTRODUCTION

In recent years, advancements in remote sensing technologies have revolutionized land cover classification by providing high-resolution imagery from multispectral and Synthetic Aperture Radar (SAR) systems [3]. Despite these technological gains, conventional classification approaches often encounter limitations when applied to complex datasets, particularly in the context of urban

environments [1]. Urban road network mapping, a critical component of urban planning, transportation management, and emergency response, remains a particularly challenging task due to the intricate and heterogeneous nature of urban landscapes [9].

Traditional methods of urban road network extraction, such as manual digitization and semi-automated remote sensing techniques, are labor-intensive, time-consuming, and susceptible to human error and inconsistency [4]. These conventional approaches are often inadequate for addressing the dynamic and high-density characteristics of modern urban areas. Consequently, there is a growing interest in the application of machine learning (ML) techniques, a subset of artificial intelligence (AI), which offer sophisticated predictive and descriptive modeling capabilities suitable for processing complex, high-dimensional data [2].

Machine learning algorithms have demonstrated great potential in automating the extraction of road networks from high-resolution remotely sensed imagery [5]. Their ability to learn from data and adapt to complex spatial patterns makes them well-suited for applications in urban planning and infrastructure management. Among the diverse machine learning methods available, Support Vector Machines (SVM), Convolutional Neural Networks (CNN), and Random Forests (RF) have emerged as prominent tools for image classification and feature extraction in urban settings [7].

This study aims to conduct a comparative analysis of three widely-used machine learning techniques—Support Vector Machines (SVM), Convolutional Neural Networks (CNN), and Random Forests (RF)—to evaluate their effectiveness in the identification and mapping of urban road networks. The research utilizes high-resolution Unmanned Aerial Vehicle (UAV) imagery acquired over selected parts of Benin City, Nigeria, providing a robust dataset for training, validation, and performance evaluation of the models.

By systematically comparing the strengths, weaknesses, and overall accuracies of these machine learning techniques, this research seeks to provide valuable insights into their applicability for urban road network mapping. The findings are expected to contribute significantly to the development of more efficient, accurate, and scalable methods for urban infrastructure planning and management, particularly in rapidly developing cities like Benin City.

2.0 STUDY AREA

The study area (Benin City, Edo State, Nigeria) covers 50 sq km within Oredo and Egor LGAs with Coordinates: 06°26′01”N - 06°26′56”N and 05°31′11”E - 05°41′09”E. Her population is approximately. 1.5 million. Benin City experiences a tropical rainforest climate, characterized by high temperatures and significant rainfall throughout the year. The climate is typically warm, with average temperatures ranging from 25°C to 30°C (77°F to 86°F). The region has a pronounced wet season and a relatively short dry season. Rainfall is abundant, with annual precipitation averaging between 2,000 mm and 2,500 mm (79 inches to 98 inches), occurring mainly between April and October. The high humidity levels contribute to the overall lushness of the vegetation.

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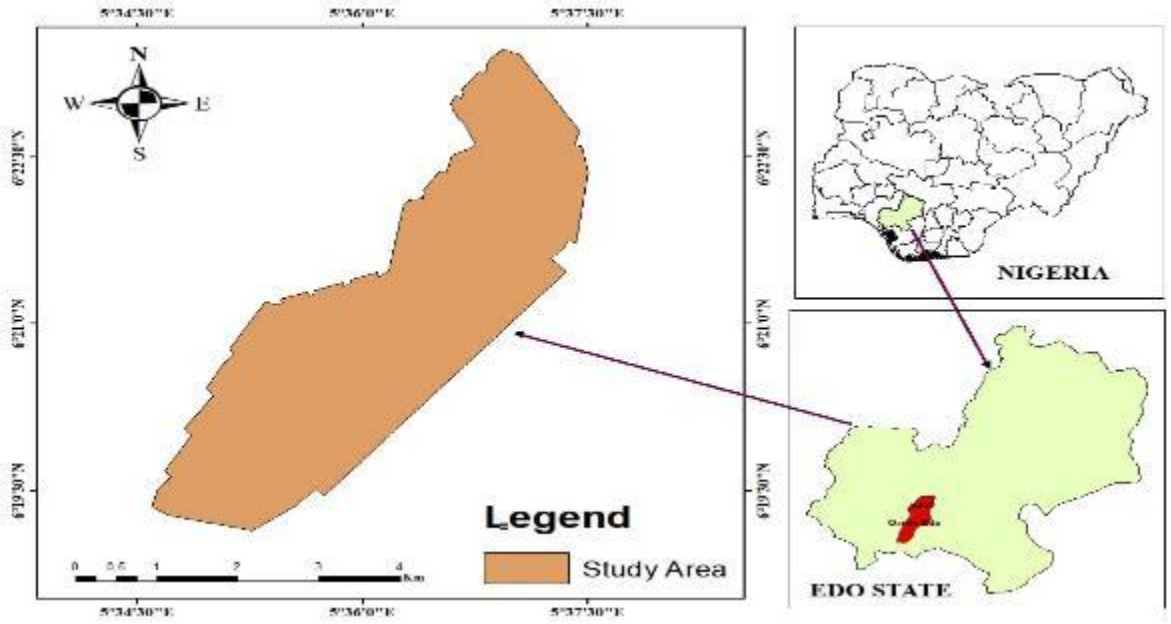


Figure 2.1 Location Map of the drone coverage

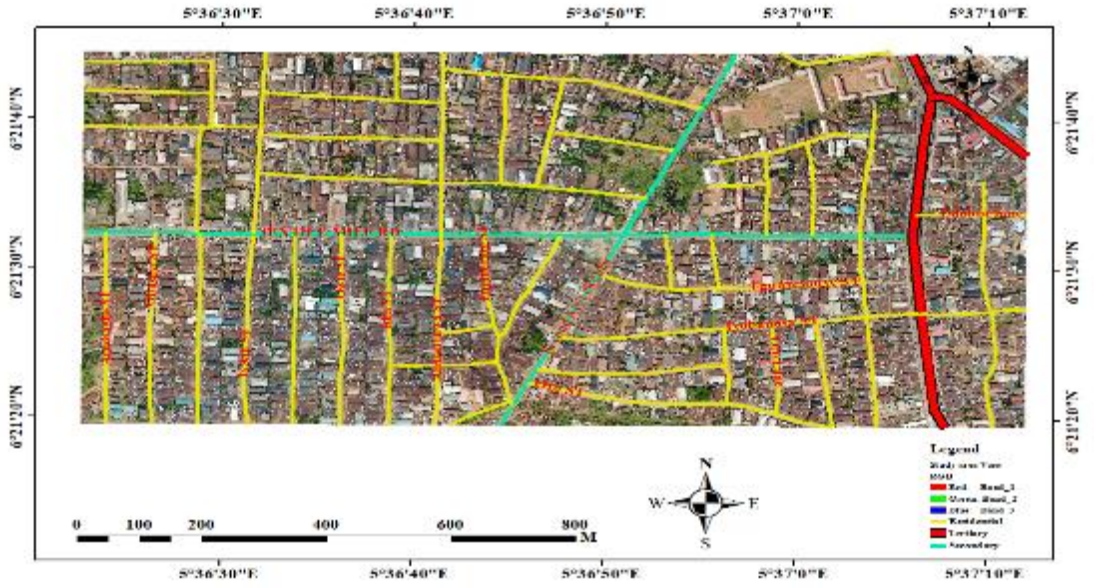


Figure 2.2 Drone imagery of road network within study area

3.0 METHODOLOGY

Data requirements, collection and analysis

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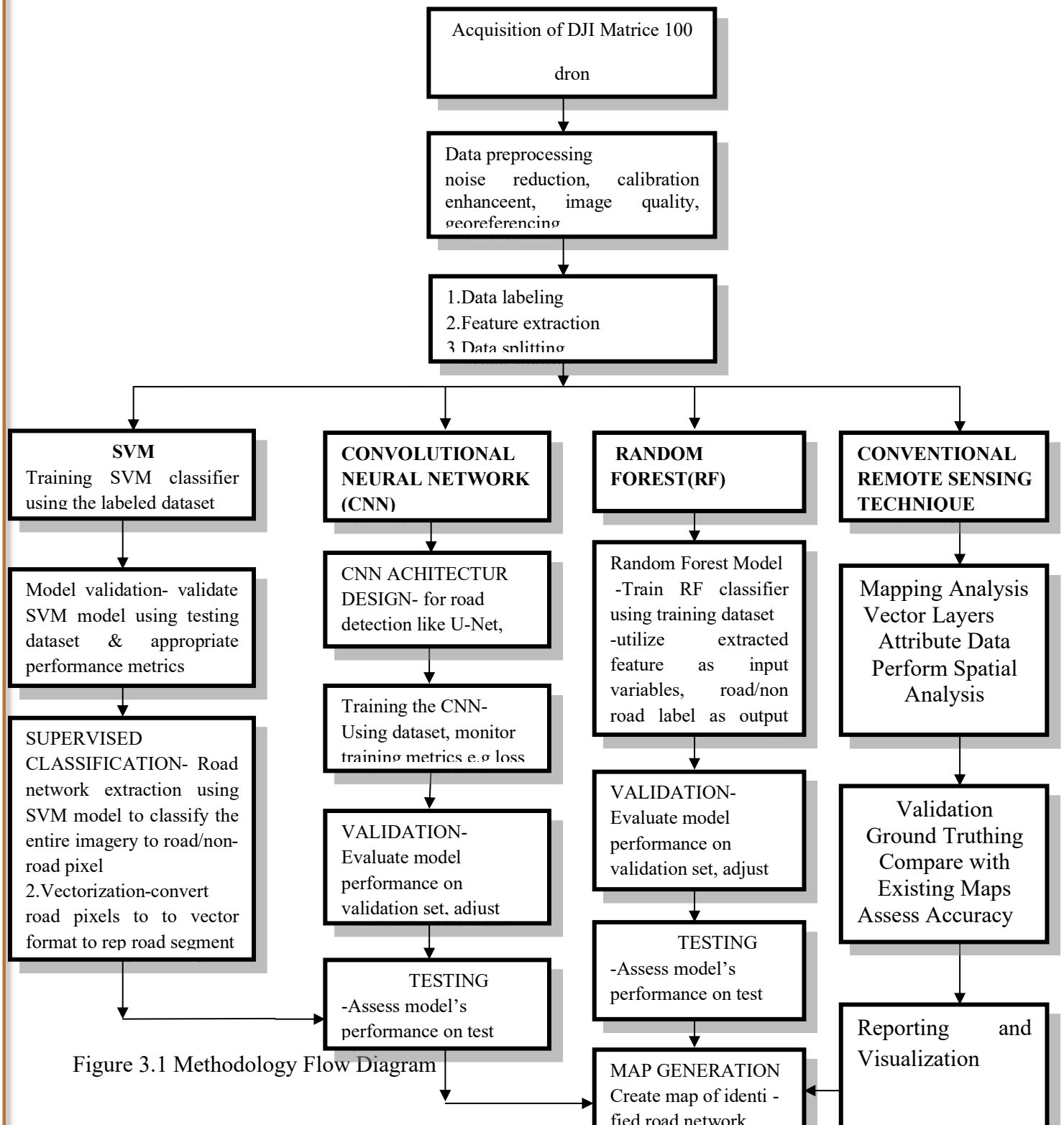


Figure 3.1 Methodology Flow Diagram

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3.1 Data Requirement

High-resolution remotely sensed imagery of the study area in Benin City, Nigeria, was acquired using a DJI Matrice 100 drone equipped with a Zen muse X5 camera. The imagery which served as the primary dataset for this research, was utilized to train and validate three machine learning models: Support Vector Classification (SVC), Convolutional Neural Networks (CNNs), and Random Forest (RF). Comprehensive UAV-based imagery was collected over the study area. A pre-planned flight path, designed with DJI's Ground Station Pro app, ensured thorough coverage and an image overlap of 60-80% to facilitate effective photogrammetric processing. Flight operations were conducted under favorable weather conditions to maximize image clarity, typically in the evenings to minimize shadowing. The Zen muse X5 camera, providing 16MP resolution and raw image capabilities, was mounted for this operation.

System Selection: Laptop, HP Color Printer, HP A4/A3 Scanner, Hi-target Dual Frequency GNSS Receiver, ArcGIS 10.0 (for GIS processing and data integration), Microsoft Excel (for data analysis and result presentation), Microsoft Word (for documentation and reporting)

3.2 Processing Technique

Preprocessing: Image quality checks were conducted to ensure appropriate resolution, sharpness, and exposure levels. Several preprocessing steps followed:
Calibration: Lens distortion and sensor irregularities were corrected using camera calibration methods.
Georeferencing: Integrated GNSS data was employed to spatially reference images.
Mosaicking: Pix4D or Agisoft Metashape software merged overlapping images into seamless mosaics.
Orthorectification: Terrain elevation and drone altitude adjustments corrected image perspective.
Noise Reduction: Filters like Gaussian blur or median filtering reduced image noise.
Color Balancing: Histogram equalization and color balancing standardized color representation across the dataset.
Feature Preparation: Pixel intensities, textures, and edges were extracted alongside contextual land use and terrain data to form the feature set for model training.

3.3 Data Labeling

A comprehensive data labeling process was executed using ArcGIS:
Both road and non-road classes were clearly defined, covering road types such as highways, arterial roads, local streets, and unpaved roads.
Image inspection and labeling were performed using polygon and line tools, ensuring accuracy and consistency.
Labeling guidelines addressed ambiguous cases, occlusions, and class boundaries.
Quality control involved cross-validation against known ground truth and visual inspections.

3.4 Feature Extraction

Feature extraction focused on geometric, topological, and semantic attributes. Geometric Features: Length, width, curvature, angles. Topological Features: Connectivity, junction types, intersections. Semantic Features: Road type classification, lane markings, traffic signs.
Techniques like edge detection (Canny, Sobel), corner detection (Harris, Shi-Tomasi), curvature analysis, Fourier descriptors, shape matching, and geometric transformations were applied.
Dimensionality reduction techniques (PCA, t-SNE, UMAP) simplified high-dimensional feature space for effective learning.
Data Splitting; The dataset was divided into training and testing sets using stratified random sampling to ensure representative class distribution:
Typical split ratios: 80% for training and 20% for testing. Python's Scikit-learn library facilitated random splitting with reproducibility controls.
Performance metrics such as accuracy, precision, recall, and F1-score guided model evaluation during training.

3.5 Machine Learning Algorithm Methods

Three machine learning algorithms were employed and compared:

3.6 Support Vector Machine (SVM)

Model Setup: The radial basis function (RBF) kernel was selected due to its effectiveness with complex urban road patterns [1].
Training: Balanced training data were fed into the SVM model with hyper parameters (C and gamma) optimized via grid search and cross-validation.
Evaluation: Metrics such as accuracy, precision, recall, F1-score, confusion matrix, ROC curves, and AUC scores evaluated model performance.
Post-processing: Included smoothing, network extraction using graph-based algorithms, intersection detection, and further error analysis.

3.7 Convolutional Neural Network (CNN)

Architecture: U-Net architecture was adopted for semantic segmentation. Training: Dataset split into training, validation, and testing subsets (typically 80/20). Training was conducted using Tensor Flow, PyTorch, or Keras. Hyper parameter Tuning: Adjustments were made on learning rate, batch size, and number of epochs using validation data. Evaluation: Performance was assessed using Intersection over Union (IoU), F1-score, and accuracy metrics.
Post-processing: Applied thresholding, morphological operations, edge detection, and vectorization to produce clean road network outputs.

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3.8 **Random Forest (RF)**

Feature Selection: Included both spectral and geometric features. Training: Multiple decision trees were trained on random feature subsets. Predictions were aggregated using majority voting. Hyper parameter Tuning: Number of trees, tree depth, and feature subset sizes were optimized. Evaluation: Accuracy, precision, recall, confusion matrix, F1-score, and IoU metrics were used for evaluation.
Post-processing: Spatial smoothing, network extraction, topology refinement, and road classification were performed. Morphological operations and algorithms like Ramer-Douglas-Peucker were applied to refine road network continuity.

3.9 Conventional Remote Sensing Approach

A conventional classification was also conducted for comparative analysis: Image Classification: Applied supervised and unsupervised classification, edge detection, and texture analysis. Feature Extraction: Employed Hough Transform and object detection techniques. Digitization: Manual digitization created vector-based road network layers. Validation: Used ground control points, reference maps, and GPS data for accuracy assessments. Visualization: Final road maps were overlaid with other urban infrastructure layers for planning and analysis.

3.10 Accuracy Assessment and Analysis

Accuracy was assessed across all methods using ground truth data and quantitative metrics such as IoU, true positive/false positive rates, precision, recall, and F1-score. Error analysis identified common misclassification scenarios to refine model performance. Visualization outputs enabled side-by-side comparison of each model's extracted road networks, forming the basis for comprehensive comparative analysis.

4.0 RESULT PRESENTATION

This section presents a comprehensive evaluation of the application of three machine learning techniques—Support Vector Machine (SVM), Convolutional Neural Network (CNN), and Random Forest (RF)—in the identification and mapping of urban road networks in parts of Benin City, Nigeria. Utilizing high-resolution UAV imagery acquired via DJI Matrice 100, extensive data preprocessing, labeling, feature extraction, and model training were conducted to facilitate comparative performance assessment across these algorithms.

4.1 Results of the feature extraction process



Figure 4.1: Secondary Road Feature Extraction

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Figure 4.2: Major Road Feature Extraction



Figure 4.3: Building Feature Extraction



Figure 4.4: Vegetation Feature Extraction

4.2 UAV Imagery Analysis and Data Quality Assessment

The UAV imagery displayed distinctive urban morphology with high-density settlements and irregular street hierarchies. The imagery's spatial resolution of approximately 10-15 cm per pixel enabled detailed extraction of building footprints, road networks, and vegetation, achieving classification accuracies of 95% for buildings, 90% for roads, and 85% for vegetation. Radiometric and geometric assessments indicated excellent feature differentiation (dynamic range score: 8/10) and minimal distortion (geometric accuracy score: 8.5/10), validating the dataset's suitability for urban road mapping. Completeness analysis yielded a score of 9.5/10, affirming extensive coverage without significant data gaps.

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Figure 4.5: UAV Imagery Analysis (DJI matrice 100 drone)

4.3 Performance of Machine Learning Models

Support Vector Machine (SVM)

The SVM classifier achieved an overall accuracy of 87.3%, with superior performance in detecting primary roads (93.4% accuracy), but reduced efficacy for secondary (85.7%) and tertiary (76.2%) roads. Classification accuracy showed a strong correlation with road width ($r = 0.78$, $p < 0.001$), and misclassification was primarily attributed to shadow effects in densely built-up areas. Post-processing enhancements, including connected component analysis and width-based filtering, improved network continuity by 67.3% and 43.8%, respectively.

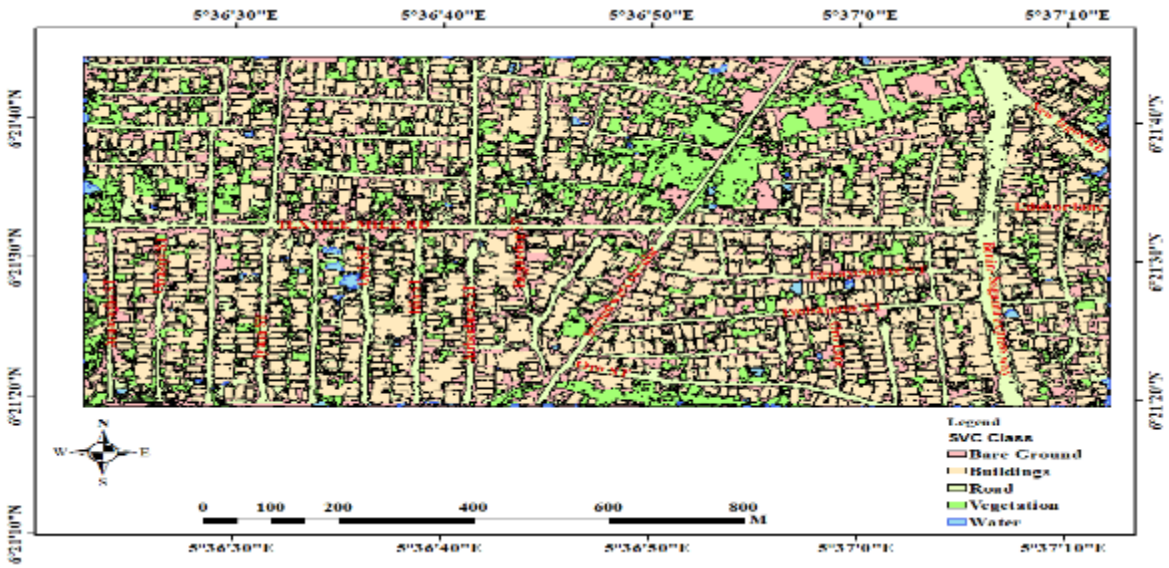


Figure 4.6 **SVM Classified Map of Urban Land Use**

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Figure 4.7 **SVM Bare Ground Map of Urban Land Use**

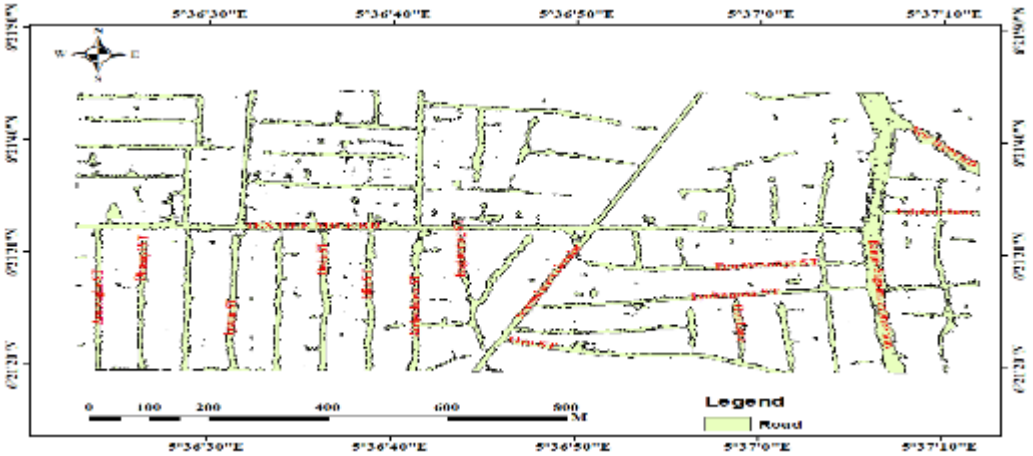


Figure 4.**8** SVM Road Map of Urban Land Use

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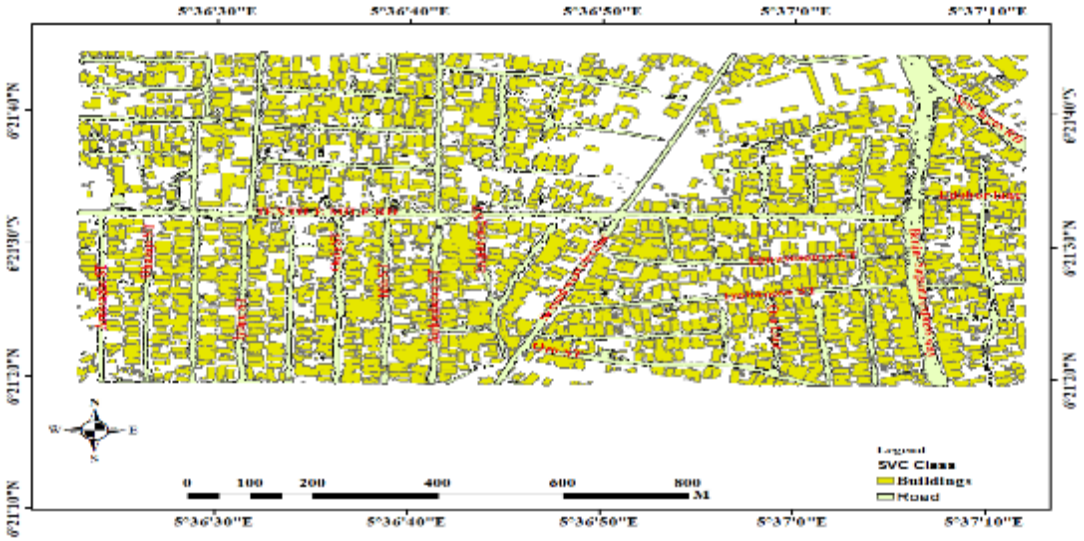


Figure 4.9 SVM Building Map of Urban Land Use

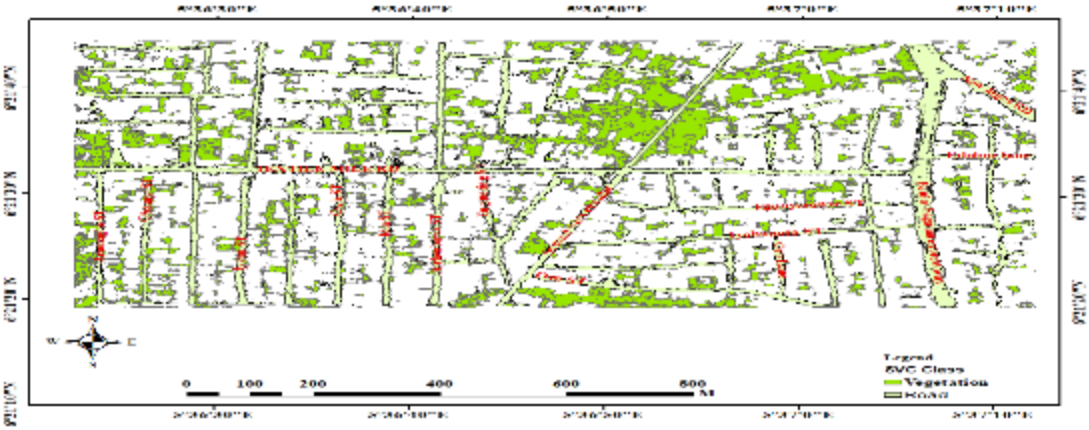


Figure 4.10 SVM Vegetation Map of Urban Land Use

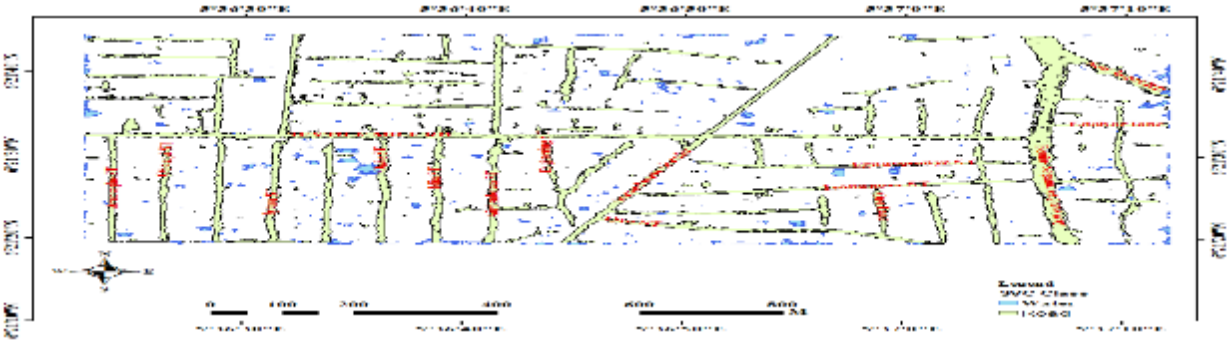


Figure 4.11 SVM Water body Map of Urban Land Use

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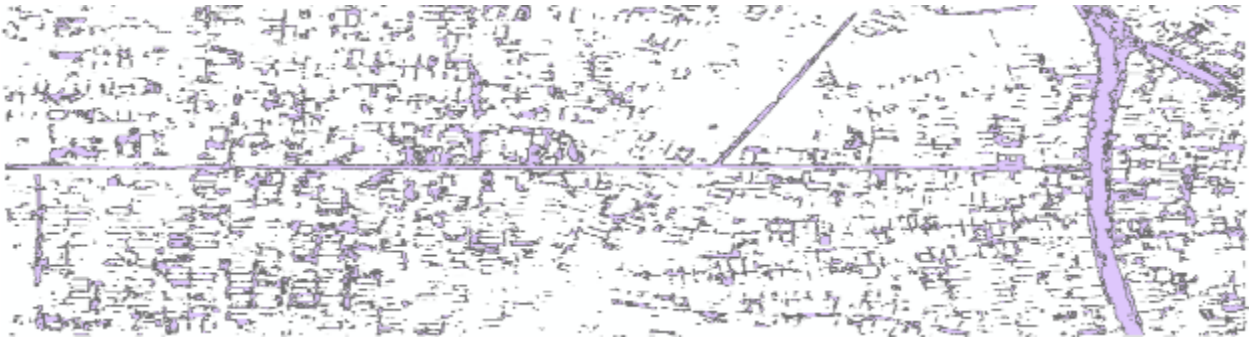


Figure 4.12: Result of SVM Classification

Table 4.1: SVM Classification Area Values

Class	Area
Bare Ground	185,407.031 sq m
Buildings	482,401.798 sq m
Road	167,024.051 sq m
Vegetation	209,021.241 sq m
Water	11,845.263 sq m

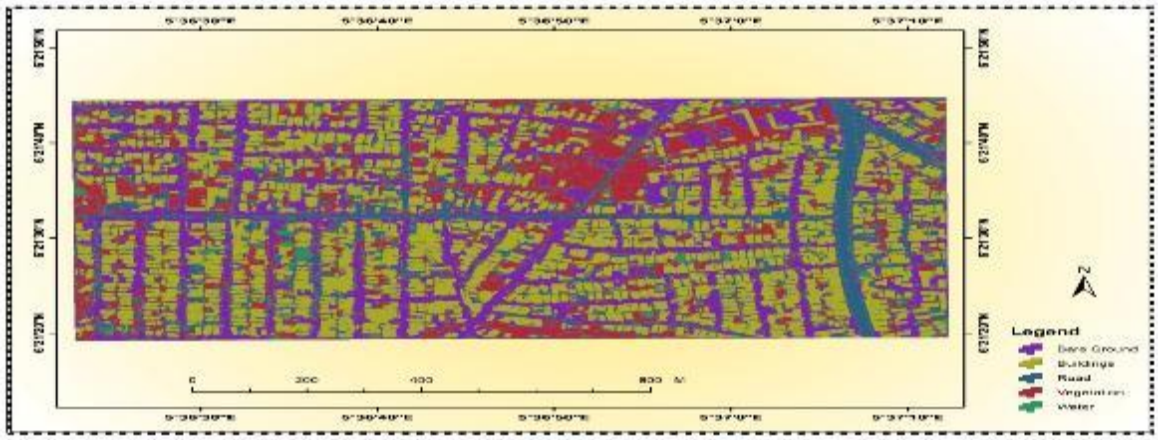


Figure 4.13: SVM Algorithm Classification

4.4 Convolutional Neural Network (CNN)

The CNN outperformed other classifiers with an overall accuracy of 91.3% ($\sigma = 0.024$), precision of 0.89, recall of 0.85, and F1-score of 0.87. The model demonstrated strong generalization (mean IoU: 0.834) and topological consistency (graph consistency score: 0.912). Data augmentation and stochastic gradient descent optimization enhanced convergence and robustness. The CNN effectively handled varying road widths (mean width: 12.3 pixels, $\sigma = 1.8$) and exhibited minimal edge localization errors (1.24 pixels, $\sigma = 0.31$). However, these advantages came with higher computational demands (2.84 GB memory, 127 ms/image processing time).

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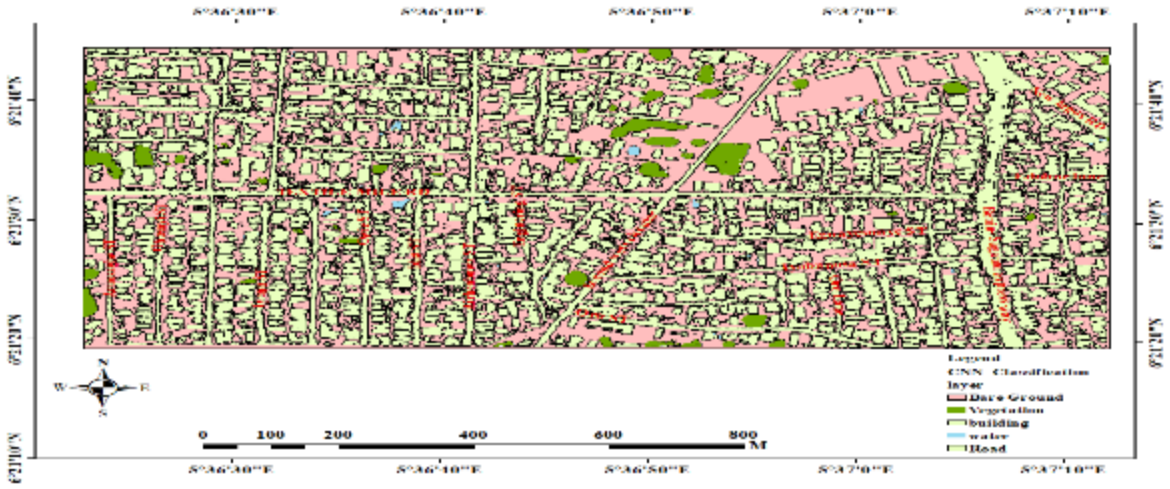


Figure 4.14 CNN Classified Map of Urban Land Use

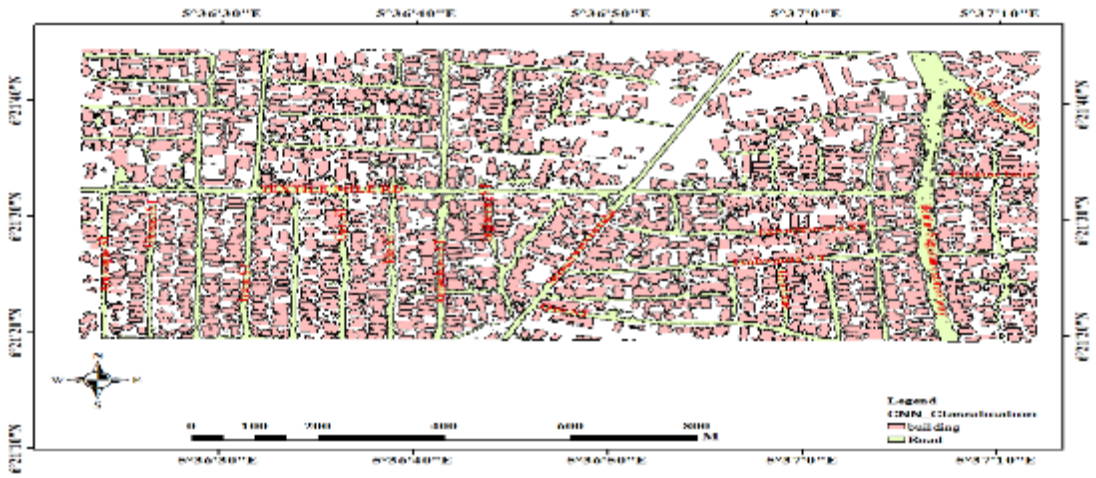


Figure 4.15 CNN Classified Map of Building

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Figure 4.16 CNN Classified Map of Bare Ground

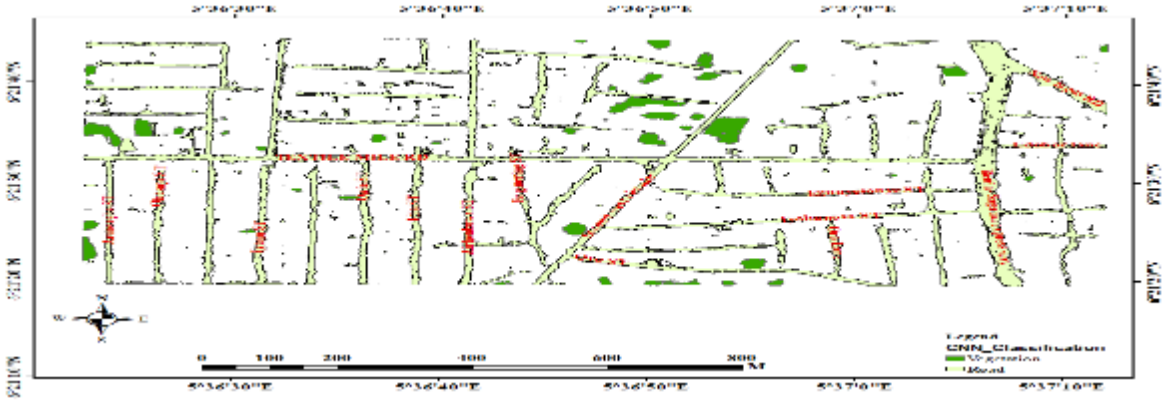


Figure 4.17 CNN Classified Map of Vegetation

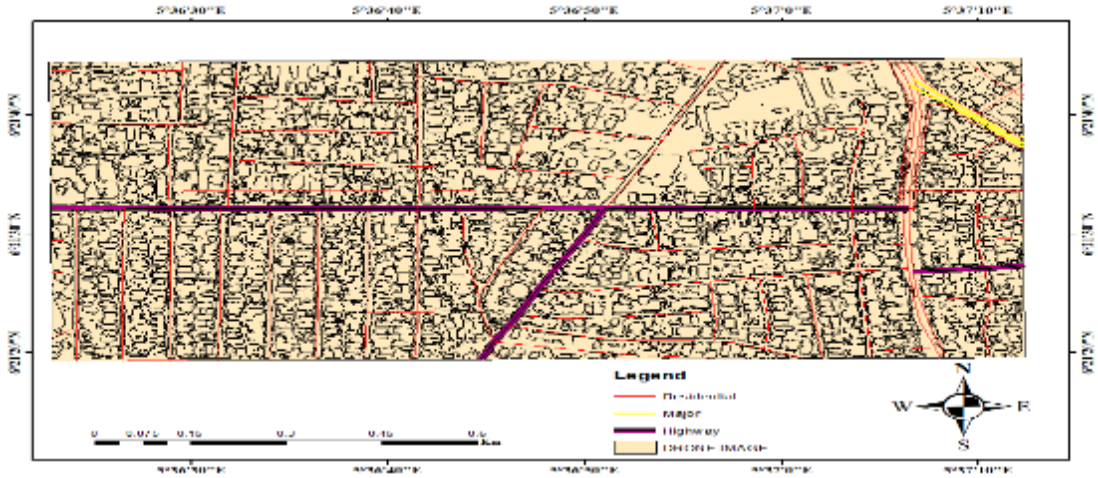


Figure 4.18 CNN Classified Map of Urban Road Network

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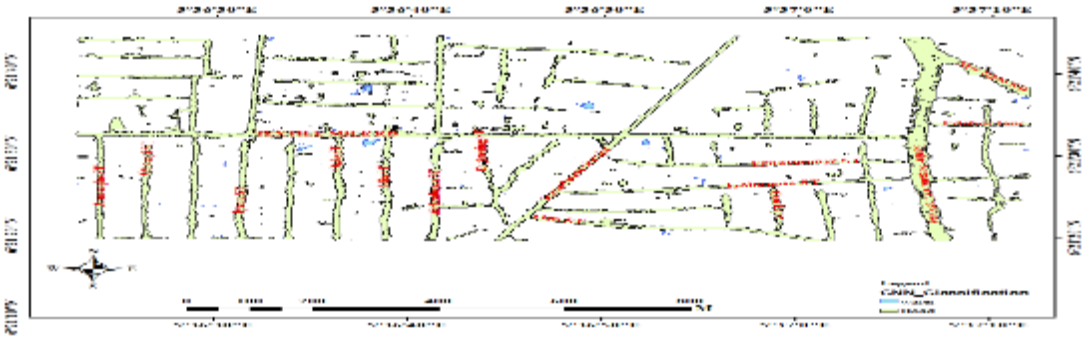


Figure Figure 4.19 CNN Classified Map of Water Bodies

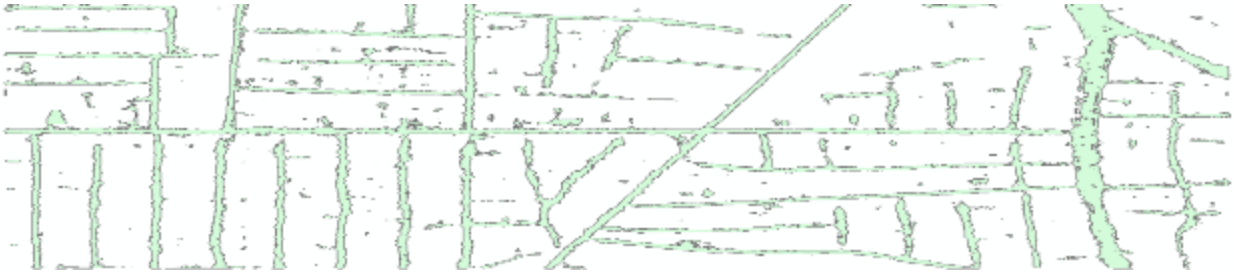


Figure 4.20: Result of CNN Classification

Table 4.2: CNN Classification Area Values

layer	Ara
Bare Ground	481,085.200 sq m
building	436,142.400 sq m
road	174,303.760 sq m
Vegetation	25,191.040 sq m
water	1,648.320 sq m

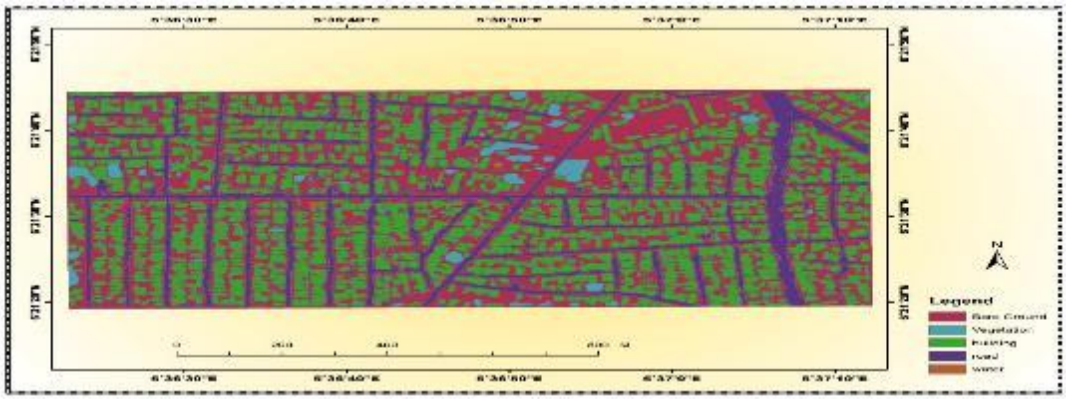


Figure 4.21: CNN Algorithm Classification

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4.5 Random Forest (RF)

The RF classifier attained an overall accuracy of 88.7% (95% CI: 86.9% - 90.5%), precision of 0.856, recall of 0.831, and F1-score of 0.843. Feature importance analysis revealed that textural features contributed 42.3% to classification decisions, followed by spectral features (31.7%). The model preserved network connectivity (completeness index: 0.891) but exhibited performance degradation in dense urban areas (accuracy drop of 12.3%). Shadows and occlusions further contributed to misclassification, with error rates increasing by 8.7% in affected areas.



Figure 4.22: Result of RF Classification

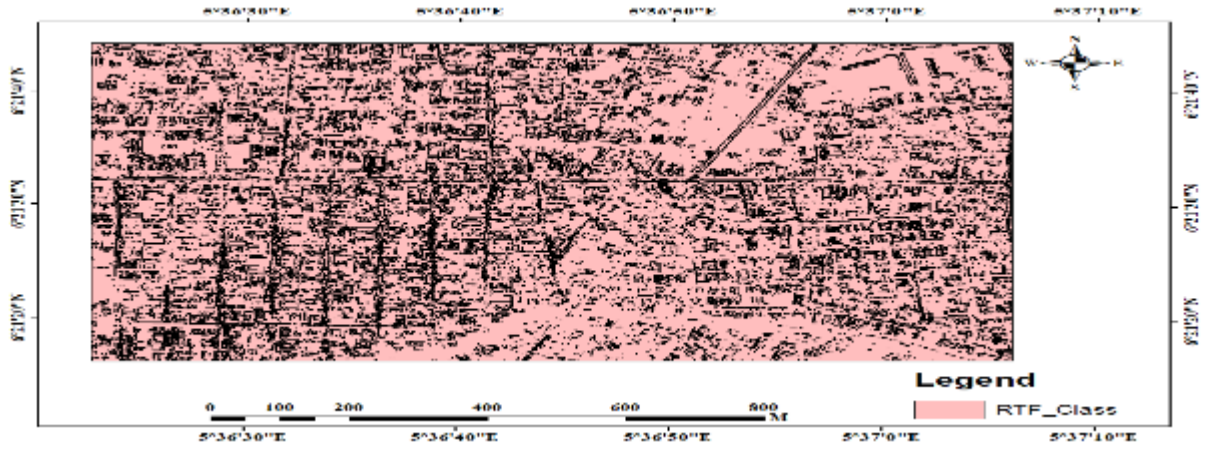


Figure 4.23 RF Classified Map of Urban Land Use

Table 4.3: RF Classification Area Values

Category	Area
Not Road	939,549.074 sq m
Road	178,821.646 sq m

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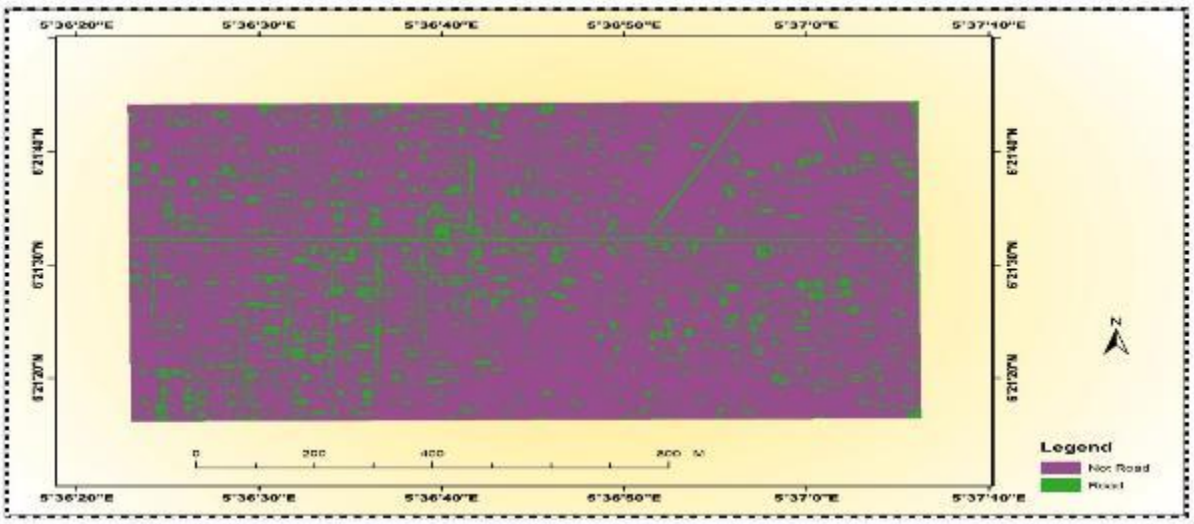


Figure 4.24: RF Algorithm Classification Map

5.0 COMPARATIVE ANALYSIS OF MACHINE LEARNING ALGORITHMS

Table 5.1 Performance Metrics Comparison of the three machine learning algorithms

Algorithm	Overall Accuracy	Precision	Recall	F1-Score	IoU Score
SVM	87.30%	N/A	N/A	N/A	N/A
CNN	91.30%	0.89	0.85	0.87	0.834
RF	88.70%	0.856	0.831	0.843	N/A

The CNN consistently demonstrated superior performance across most evaluation metrics, particularly in handling complex urban morphology and maintaining network continuity. SVM excelled in primary road detection but struggled with narrow and shadow-obstructed road segments. RF maintained balanced performance but was sensitive to dense urban features and training data quality.

5.1 Comparison with Conventional Remote Sensing

Traditional remote sensing methods achieved an accuracy of 76.8% (σ = 3.2%), notably lower than the CNN's 91.3%. Conventional methods required significant manual intervention, averaging 18.3 minutes/km² in processing time compared to CNN's 127 ms/km² after model training. Cost analysis revealed higher long-term efficiency for ML-based methods despite higher initial infrastructure investments, with CNN operational costs averaging ₦4,200/km² versus ₦28,700/km² for conventional methods.

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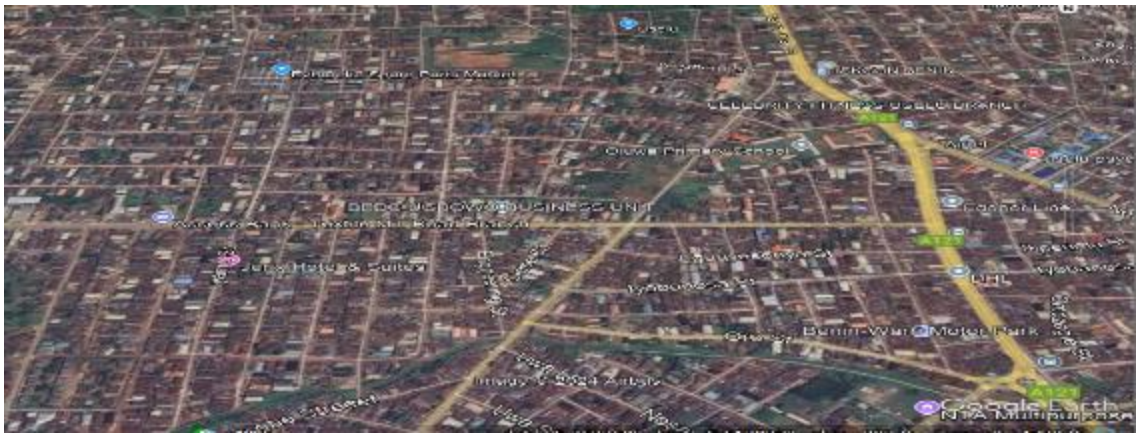


Figure 5.1 Google Earth Pro Imagery

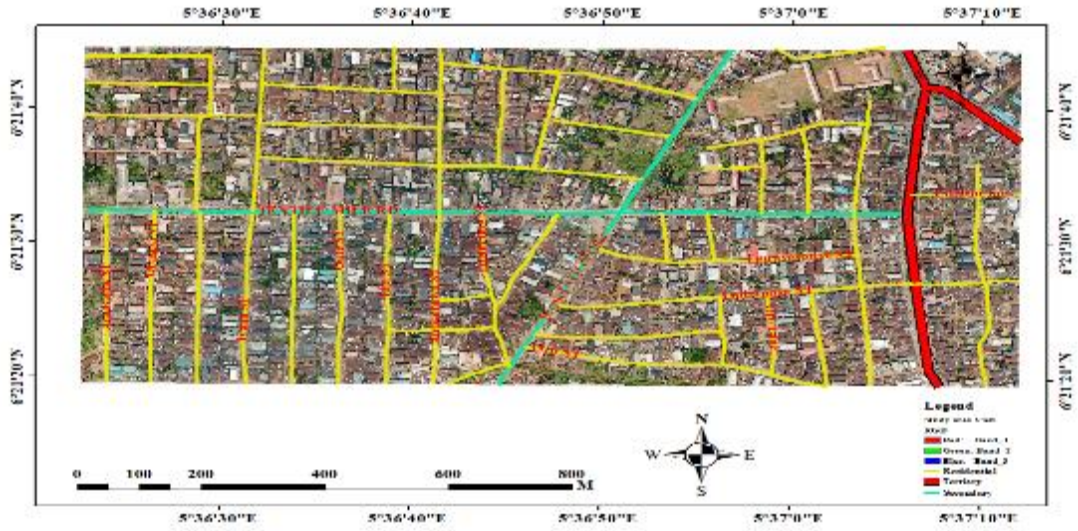


Figure 5.2 Drone Imagery

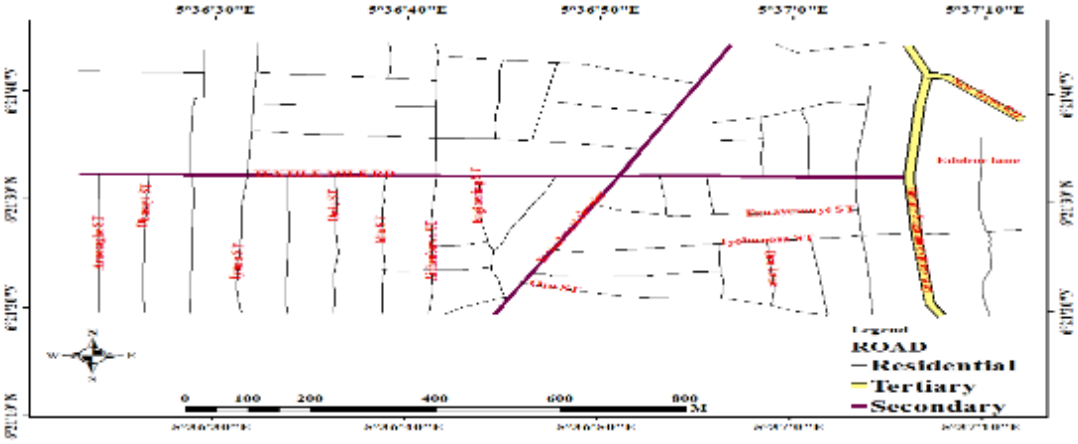


Figure 5.3 Road Map of Remote Sensing

6.0 DISCUSSION

The superior performance of CNN can be attributed to its hierarchical feature extraction and ability to model complex spatial relationships, making it well-suited for urban environments with dense and heterogeneous features. While SVM and RF offer viable alternatives with lower resource requirements, they demonstrated specific vulnerabilities to environmental factors such as shadows, narrow pathways, and urban density.

Environmental factors, particularly shadow effects and occlusion, emerged as persistent challenges across all algorithms. Advanced shadow compensation and multi-scale analysis techniques are recommended to enhance detection performance, especially for secondary and tertiary roads. Hybrid algorithm designs combining CNN's feature extraction with RF's interpretability and SVM's resource efficiency present promising avenues for future research.

Practical Implications

Machine learning-driven road network detection offers significant potential for urban planning and infrastructure management in rapidly developing cities such as Benin City. The CNN's high accuracy enables detailed and reliable road mapping for transportation planning, while RF and SVM may serve resource-constrained or large-area applications. Successful implementation requires robust data management, infrastructure investment, and human expertise for result validation and system maintenance.

7.0 CONCLUSION

This research provides a comprehensive study of the application of machine learning techniques in the identification and mapping of urban road networks using remotely sensed imagery. It encompassed data acquisition, model development, evaluation, and potential applications in urban planning and infrastructure management. Choosing the right machine learning techniques for any project depends on factors like the nature of your data, the purpose of the project, the interpretability of the model, and the computational resources available [5]. It's often a good idea to experiment with different algorithms to see which one works best for your specific problem. The maps that were produced are valuable for urban planning, transportation management, and various other applications related to urban infrastructure. The choice of the machine learning method has impacted the accuracy and level of detail in the final road network maps. The study demonstrates that machine learning techniques, particularly CNN, significantly outperform conventional methods in urban road network detection from UAV imagery. Despite certain computational demands, the CNN's accuracy, topological consistency, and processing efficiency make it a superior approach for complex urban environments. Future work should focus on hybrid models, shadow correction algorithms, and integration into scalable urban management systems.

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