Assessing the Performance of Machine Learning Algorithms for Urban Land Cover Classification using Multispectral Satellite Imagery*

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Abstract

Land use and land cover mapping is a critical process in effective land management, providing valuable insights into the spatial distribution and characteristics of different land uses and covers within a region. With the advancements in geospatial technology and the accessibility to high-resolution satellite imagery, various classification algorithms have emerged as powerful tools for mapping and analysing land cover patterns. The selection of a specific classification algorithm significantly influences the accuracy and reliability of the obtained results, thereby impacting the effectiveness of decision-making based on the classification outcomes. Aside the traditional classification techniques such as maximum likelihood, minimum distance and the parallelepiped classification algorithms, various machine learning methods have emerged for image classification. Machine learning techniques offer valuable advantages due to their capacity to learn from data, adapt to new datasets, and achieve good generalisation performance. This paper conducted a comparative study of four classification algorithms: Support Vector Machine (SVM), Random Forest (RF), K- Nearest Neighbour (KNN) and the Maximum Likelihood Classifier (MLC). A comprehensive dataset comprising of a high-resolution multispectral satellite imagery and ground truth data was employed. The study area is a representative of diverse land cover types including settlement, vegetation, forested, water and bare lands. The accuracy metrics obtained showed that the SVM obtained the best classification performance achieving a precision of 0.84, a recall of 0.82, an F1-Score of 0.83 and an overall accuracy of 0.8932.

Keywords: Multispectral, Machine Learning, Support Vector Machine, K-Nearest Neighbour, Random Forest, Image Classification

1 Introduction

Effective land management heavily relies on the knowledge of land use trend, providing crucial insights into the distribution and characteristics of different land types within a region. The advancement of geospatial technology and the accessibility of high-resolution satellite imagery have given rise to diverse classification algorithms that serve as potent tools for analysing and mapping land cover patterns. The choice of a suitable classification algorithm profoundly influences the accuracy and dependability of the outcomes, thereby influencing the effectiveness of decision-making based on the classification results (Rodriguez-Galiano *et al*., 2012; Noi *et al*., 2017).

In recent years, pixel-based image classification has gained popularity due to its inherent strength to exploit the wealth of spectral information contained within each pixel to assign the pixels to a specific land cover class. Pixel-based approaches offer a robust means of leveraging multispectral data to differentiate between the various land cover classes that comprise the urban landscape. The classification process of pixel-based methods typically involves data preprocessing, where multispectral satellite imagery is calibrated and radiometrically and atmospherically corrected to ensure data consistency and accuracy. Subsequently, feature extraction is performed to derive relevant spectral, textural, and contextual information from each pixel. Lastly, a classification algorithm is then applied to the extracted features to classify each pixel into predefined land cover classes (Tassi *et al*., 2021).

Conventional approaches utilised statistical techniques, such as ISO-cluster and Maximum Likelihood Classification (MLC), for the classification step. These techniques assume that pixel values' statistical properties differ among land cover classes and perform classification based on probability distributions. Regardless, while statistical approaches can offer insights into the distribution of land cover classes within an area of interest, these techniques lack adaptability and flexibility and rely on statistical parameters derived from the training data and the assumption that pixel values follow specific probability distributions (Rodriguez-Galiano *et al*., 2012). To overcome the limitations of the statistical approach, researchers have proposed using machine learning (ML) algorithms for the classification stage. In contrast to statistic approaches, machine learning algorithms can autonomously learn complex patterns from categorised training data and subsequently apply

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knowledge to classify new data, making them invaluable for urban land cover mapping.

Moreover, ML algorithms can effectively capture complex relationships between spectral signatures and land cover types, adapt to varying urban landscapes, and generalise well to diverse regions. Despite the strengths of machine learning algorithms, many machine learning algorithms exist, each having its strengths and limitations (Talukdar *et* al., 2020). For example, Support Vector Machine (SVM) is known for its ability to handle non-linear data and effectively separate classes in high-dimensional feature spaces. Random Forest (RF), an ensemble method, can handle large datasets and reduce overfitting. K-Nearest Neighbour (KNN), a non-parametric and lazy learning algorithm, is simple and robust for classification tasks. Given the abovementioned reason, it has become necessary to identify the most effective and accurate tools for land cover mapping.

In this paper utilised a comprehensive dataset comprising high-resolution multispectral satellite imagery and ground truth data to compare the classification algorithms. The study area represents diverse land cover types: settlement, vegetation, forested areas, water bodies, and bare lands. This research aims to evaluate and compare the performance of SVM, RF, and KNN in urban land cover classification and highlight the strengths and weaknesses of each algorithm.

1.1 Review of Related Works

This section reviews relevant literature on multispectral satellite imagery that considers pixel-based image classification techniques. Land Use and Land Cover (LULC) monitoring is a crucial aspect of environmental analysis, and machine learning (ML) models have emerged as leading analytical techniques for this purpose. A search on Google Scholar and Science Direct webpages using keywords such as land cover and land cover classification using machine learning was used to gather works related to the study. To narrow the selection works utilising only machine learning approaches between 2011 and 2023 were considered.

The considered works revealed that various ML algorithms, such as K-Nearest Neighbour (KNN), Support Vector Machines (SVM), Artificial Neural Networks (ANN), and Random Forests (RF), have been applied to classify LULC types and satisfactory results were achieved. Nevertheless, it is noteworthy that the extensive application of these machine learning models in African tropical regions has been somewhat limited. This limitation primarily arises from methodological complexities associated with their implementation when working with coarse-resolution satellite imagery.

For instance, Rodrigues-Galiano et al. (2011) applied the RF model to classify land cover using Landsat-5 Thematic Mapper data. The results showed that the RF model was an efficient land cover classifications model, achieving an accuracy of 92% and a Kappa index of 0.92. RF demonstrated superiority to data reduction and noise, making it a reliable method for complex land cover areas.

Deilmei *et al.* (2014) in compared two different classifiers, the MLC and the SVM, for classifying land cover types in Malaysia based on multispectral data. The results obtained from the study revealed that the SVM classifier was more accurate, making it a suitable choice for land cover classification. The research focused on five land cover classes: forest, oil palm, urban area, water, and rubber.

In research by Noi and Kappas (2017), the performances of RF, KNN, and SVM classifiers for land use/cover classification were assessed using Sentinel-2 image data. Despite the few training dataset that was used, the SVM classifier achieved the highest overall accuracy showing less sensitivity to training sample sizes, surpassing both the RF and KNN. However, when the training sample size was large enough, all three classifiers exhibited high levels of accuracy in land use/cover classification tasks.

Alkaradaghi *et al.* (2019) analysed the land use and cover change in the Sulaimaniyah Governorate of Iraq from 2001 to 2017 using Landsat imagery. In order to ascertain the change, the authors exploited MLC and SVM in accurately extracting land cover information. The results indicated an immense shift in urban areas, with a massive growth in urban land and a decline in agricultural land.

An algorithm based on the RF classifier was applied by Amini *et al.* (2022) to analyse land use/cover changes using Landsat time-series data. The proposed method achieved high accuracy compared to the Copernicus Global Land Cover Layers (CGLCL) map for the study area, demonstrating its potential for LULC mapping.

Yuh *et al.* (2022) conducted research which compared four machine learning algorithms. The algorithms compared included KNN, SVM, ANN and RF. In their research, they employed Landsat 7 ETM+ and Landsat 8 OLI images. The results obtained showed that, the Random Forest achieved the highest accuracy. The results also quantified the amount of change that had occurred in the forested areas in a span of twenty (20) years

Research conducted by Atef *et al.* (2023) studied the spatio-temporal land use variations in El-Fayoum. Their research focused on investigating the performance of the MLC algorithm and two

machine learning classifiers (RF and SVM) for image classification. After their investigative study, the results indicated that the SVM technique produced the most accurate maps compared to MLC and RF.

Generally, machine learning classifiers, have shown promise for accurate land use and land cover mapping in various geographical regions, and their implementation can significantly aid decision-making processes for environmental management, urban planning, and conservation efforts. However, further research is needed to explore and optimize the application of these classifiers for different environmental contexts and data resolutions. While various studies have applied different machine learning algorithms for classification tasks, only a few research works have considered a comparative analysis of the performances of the most common classification algorithms. This paper will, therefore, consider three of these classifiers and assess their performance for pixel-based image classification tasks.

2 Resources and Methods Used

2.1 Dataset and Methods

The dataset adopted in this study was a 30-m LANDSAT multispectral image of path 196/row 054, depicted in Fig. 1, obtained from the USGS website (https://earthexplorer.usgs.gov). In the criteria used, images with less than 10% cloud cover were selected for the study. The dataset, initially in the raster tiff format, was converted into the array format for easy processing. The Support Vector Machine, Random Forest, K-Nearest Neighbour machine learning models, and the Maximum Likelihood Classification statistical model, used for comparative assessment, were developed and used to classify the dataset. Before developing the classification models, the dataset was pre-processed in the Python environment to render it in a format that could be easily implemented in the models. Various open-source Python libraries were used for this process. Five assessment metrics were used to evaluate the models' classification performance: Precision, Recall, F1-score, Kappa and Overall Accuracy. The methodology used in carrying out this study is summarised in Fig. 2.

Fig. 1 Footprints of the Satellite Image on Path 196 Row 054

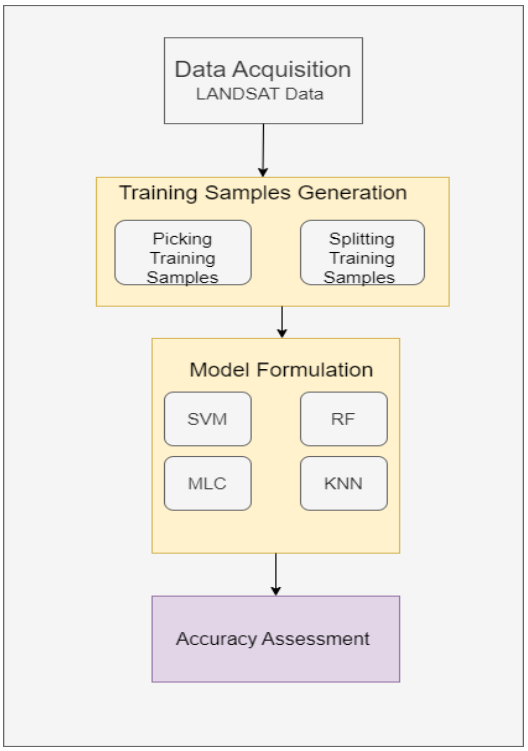

Fig 2 Flowchart of Methodology

2.2 Study Area

The Greater Accra Region, which houses Accra, the capital city of Gha Ghana, is one of Ghana's most rapidly urbanizing regions. The Region serves as the capital hub of the country and houses the country's most prominent seaport and international airport, making it an important international gateway. The region has attracted many investors, resulting in an influx of immigrants, primarily searching for greener pastures. This influx of immigrants has resulted in the need for space, mainly for settlement, thus resulting in the rapid change in the land cover and land use of the area. The land cover of the study area is a heterogeneous mix of natural and man-made features, including water bodies, vegetation, bare lands, and built-up areas. For the training and testing of the model, 2 440 ground truth points were randomly picked using the Google Earth Pro software. The sample points were split into training and test datasets in the 0.8: 0.2 ratio. Fig. 3 shows the map of the study area.

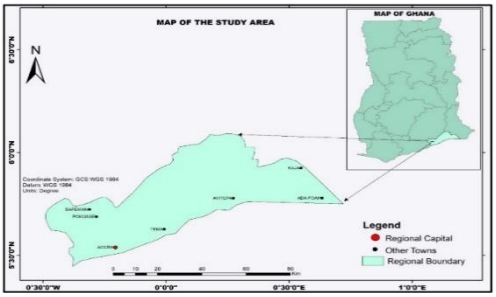

Fig. 3 Study Area

2.3 Methods

This section elaborates on the various methods employed in the study. The methods used included three machine learning classification algorithms: Support Vector Machine, Random Forest, and K-Nearest Neighbour.

2.3.1 Support Vector Machine

The Support Vector Machine (SVM) is a machine learning model that is suitable for both classification and regression problems. Developed by Vapnik *et al.* in the 1990s, it was used to solve binary classification problems. However, the basic idea behind the SVM is to construct a line, also known as a hyperplane, that perfectly separates the various classes of data in a dataset. In the SVM algorithm, the data points that are nearest to the decision boundary are known as the support vectors, and the distance from the support vectors to the decision boundary is referred to as the margin. The main objective of the SVM, is to find the optimal hyperplane with the maximum margin. The concept of the hyperplane is indicated in Fig. 4. The hyperplane can be defined as shown in Equation (1):

$$f(x) = \omega^T \Phi(x) + b \quad (1)$$

where ω is the weight vector dimensional space, b is the bias term, and $\Phi(x)$ is a function that maps the input space into a high-dimensional space. In order to find the optimal hyperplane, the SVM becomes a convex quadratic programming problem, as indicated in Equation (2).

$$\min_{\omega} \left\{ \begin{array}{c} \frac{1}{2}\|\omega\|^2 \\ y_i\left(w_{x_i}^T + b\right) \geq 1 \end{array} \right\} \quad (2)$$

However, the data may not be perfectly separable in real-world applications, resulting in misclassifications. To allow for a certain degree of misclassification, SVM introduces a slack variable 'ξ_i' for each data point, representing the classification error. The optimization problem in (2), therefore, becomes:

$$min \frac{1}{2}\|\omega\|^2 + c\sum_{i=1}^{n} \tau_i \quad (3)$$

s.t $y_i(\omega^T x_i + b) \geq 1 - \tau_i \;\; i = 1,2,\ldots., n, \; \tau_i \geq 0$

where c is the regularisation parameter and τ_i is the slack variable. When the slack variables are introduced, the SVM becomes a soft margin classifier; the model can misclassify a few data points. The regularisation parameter, c, determines how much misclassification is allowed in the SVM problem. As the value of c is varied, the number of misclassifications also varies. A lower C value allows for more misclassification, while a higher value of C implies a lower misclassification. Although SVM is a linear classifier, real-world data often exhibits non-linearity, which poses a challenge for direct application. To address this issue, SVM employs the "kernel trick." This technique maps the data from its original linear space to a higher-dimensional feature space. The dataset becomes linearly separable through this transformation, allowing the algorithm to fit a decision boundary effectively. Kernel functions are used for this transformation, and the most commonly utilized ones include linear, sigmoid, polynomial, and radial basis functions. SVM can handle non-linear data and achieve accurate classification results by employing the kernel trick and suitable kernel functions. In this research, the radial basis function kernel was adopted.

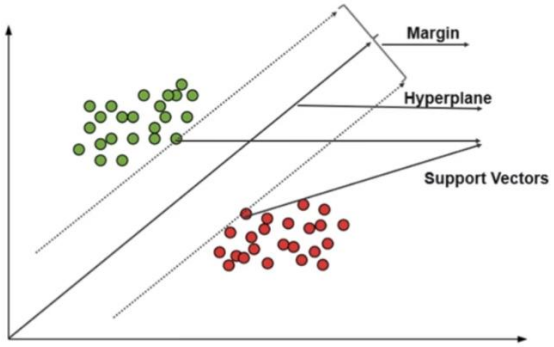

Fig. 4 Support Vector Machine showing the Hyperplane (Source: Analytics Vidhya, 2021)

2.3.2 Random Forest

The Random Forest (RF) classifier is a machine learning technique introduced by Leo Breiman in 2001. It is an ensemble learning method that leverages the power of multiple decision trees to improve the accuracy and robustness of classification tasks. Instead of relying on a single decision tree, which can be prone to overfitting or instability, Random Forest combines the predictions from multiple trees to make more reliable classifications. This ensemble approach helps reduce the risk of errors and enhances the overall performance of the classifier, making it a popular choice in various applications, including remote sensing image classification. It has gained popularity in various fields, including remote sensing, due to its efficiency, ability to handle large datasets with numerous input variables for the classification process (Dietterich, 2000). The RF algorithm creates a collection of decision trees through bagging, which generates subsets of the training data by resampling with replacement. Each tree is grown with a random subset of input features, making them diverse and less correlated. During the

training process, Random Forest (RF) generates an out-of-bag (OOB) subset, which consists of data points that were not utilised for training each individual tree within the ensemble. Subsequently, each tree in the RF classifier applies its classification to these OOB elements. The OOB error, calculated based on these OOB classifications, serves as an estimate of the classifier's generalisation error. This helps to assess the classifier's ability to make accurate predictions on unseen data without overfitting (Amini *et al.*, 2022). The selection of the best split at each node is based on the Gini Index, which measures the impurity of elements concerning the class distribution (Rodriguez-Galiano *et al.*, 2012). The RF does not prune the trees, making them computationally lighter and allowing them to grow to their maximum depth.
The RF algorithm also calculates the Variable Importance (VI) to know how each input variable can affect the overall prediction accuracy. The lower the accuracy, the less critical the variable is for the classification (Amini *et al.*, 2022).

2.3.3 K- Nearest Neighbour

The K-nearest neighbour (KNN) is a supervised classification algorithm that categorizes a data point based on the classes of its neighbouring data points. The performance of KNN is highly influenced by factors like the distance measure, weighting function, and the number of nearest neighbours (K) used in the analysis. The algorithm computes the Euclidean distance between the new data point and its neighbours, which can be mathematically expressed as:

$$d(p,q) = d(q,p)$$

$$= \sqrt{(q_1 - {p_1}^2) + (q_2 - {p_2}^2) + \cdots + (q_n - {q_n}^2)}$$

where $d(q,p)$ is the distance between data point q and p.

The choice of K is crucial and has significant impact on the model's accuracy. A low K value may introduce lot of noise, while a high K value might lead to underfitting. To determine the appropriate K, the algorithm calculates the similarity measure between the features of the test dataset and the training dataset features. Then, it ranks the class labels based on the frequency of their occurrence in the K nearest training samples, with the most frequent label assigned as the class label for the test sample.

2.3.4 Maximum Likelihood Classification

The Maximum Likelihood Classification (MLC), is a supervised method of classification method that is usually employed in remote sensing and image processing. This classification method is based on the idea that the statistical properties of each class within each spectral band exhibit a normal distribution. This method computes the probability of a given pixel belonging to a particular class. It does so for all pixels in the image, providing classifications for each one. In this process, every pixel is assigned to the class for which it has the highest probability, representing the maximum likelihood outcome (Medina and Atehortua, 2019). It is derived from the Bayes Theorem which describes the likelihood of a given feature belonging to a particular class using prior information. This theorem is represented mathematically as shown in equation 5.

$$P(A|B) = \frac{P(B|A)\cdot(P|A)}{P(B)} \quad (5)$$

where $P(A|B)$ is the probability of event A occurring given that event B has occurred, $P(B|A)$ is the conditional probability of event B occurring given that event A has occurred. $(P|A)$ is the prior probability of event A occurring. $P(B)$ is the independent probability of event B occurring (Bayes, 1764).

2.3.5 Accuracy Assessment

To evaluate the performance of the developed models, five key metrics were employed: recall, precision, F1-score, Kappa and Overall accuracy. Recall measures how well a model can distinguish between all of the real positive examples. It is determined using Equation 6 which is the ratio of true positives to all positive events. High recall values show that the model successfully detects positive cases, reducing the number of positive occurrences that are missed (false negatives). Precision, on the other hand, evaluates the accuracy of the model's positive predictions. It is determined by the ratio of true positives to the total number of instances predicted as positive (Equation 7). High precision values signify that when the model predicts a positive case, it is more likely to be correct, and false positives are minimized.
The F1 score, represented by Equation 8, serves as a balanced measure by considering both false positives and false negatives. It is the harmonic mean of recall and precision and provides an overall assessment of the model's accuracy in predicting positive class instances. The F1 score reaches its optimal value at 1, indicating perfect precision and recall, and descends to 0 as performance deteriorates. Kappa is the ratio of the observed agreement (the proportion of agreement between the two raters beyond what would be expected by chance) to the maximum possible agreement.

When kappa is 1, there is complete agreement.
Kappa numbers closer to 0 reflect agreement that is

no better than what would be predicted by chance, and values less than 1 indicate less than perfect agr eement.

If kappa is negative, it implies that there is systema tic disagreement and less agreement than would be predicted by chance. Lastly, Overall accuracy is a metric employed to gauge the classification model's performance. It signifies the proportion of correctly classified samples (pixels or instances) relative to the total number of samples. Essentially, it measures the model's ability to accurately predict the correct class labels.

It is represented as shown in Equation (10).

$$\text{Recall} = \frac{TP}{TP+FN} \quad (6)$$

$$\text{Precision} = \frac{TP}{TP+FP} \quad (7)$$

$$\text{F1-score} = \frac{2*Precision*Recall}{Precision+Recall} \quad (8)$$

$$\text{Kappa} = (P_{obs} - P_{exp}) / (1 - P_{exp}) \quad (9)$$

$$\text{Overall Accuracy} = \frac{Number\ of\ Correctly\ Classified}{Total\ Number\ of\ Samples} * 100 \quad (10)$$

where TP is the True Positives, TN is the True Negative, FP are the false positives, and FN are the false negatives. P_{obs} represents the observed proportion of agreement and P_{exp} represents Expected Proportion of Agreement

3 Results and Discussion

3.1 Data Processing

The training samples generated from Google Earth were subsequently transformed into shapefiles. In total, a set of 2,440 points was carefully selected, as depicted in Figs 5 and 6. Using the extract values to point tool in QGIS, the pixel values corresponding to various spectral bands were extracted to the training sample for analysis. A sample of the extracted band information is depicted in Fig. 7.

Fig. 5 Training Samples Generated in Google Earth

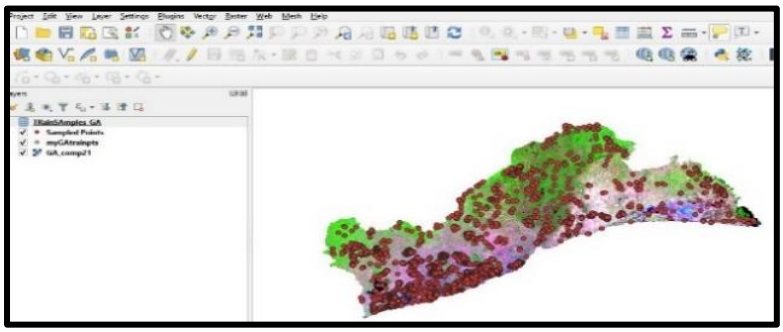

Fig.6 Training Samples Converted to Shapefiles

	fid	Name	id	rvalue_1	rvalue_2	rvalue_3	rvalue_4	rvalue_5	rvalue_6
1	1283	s	4	15347	14246	12166	11397	9807	8911
2	1284	s	4	14500	14006	11565	10884	9538	8915
3	1285	s	4	15702	14732	12092	11399	9903	9090
4	1286	s	4	16228	14719	12059	11379	9833	9145
5	1287	s	4	14782	14036	11898	11168	9791	9142
6	1528	v	3	12513	17839	10612	10497	8951	8173
7	1529	v	3	11977	17367	10380	10390	8773	7923
8	1530	v	3	12873	16290	10758	10498	8817	8083
9	1531	v	3	11363	16267	10101	10171	8353	7534
10	1532	v	3	10033	18454	9247	9566	7965	7222
11	1533	v	3	10013	17477	9425	9736	8126	7369
12	1534	v	3	9755	19100	9212	9590	8062	7365
13	1535	v	3	10777	17484	9643	9979	8382	7691
14	1520	v	3	10729	20494	9980	10493	8445	7499
15	1521	v	3	10799	19400	10009	10465	8492	7524
16	1522	v	3	9952	12548	10212	10208	8541	7571
17	1523	v	3	13684	16169	10792	10581	8930	7977
18	1524	v	3	11792	17186	10317	10442	8578	7580
19	1525	v	3	11945	17267	10457	10493	8715	7786
20	1526	v	3	12268	18696	10389	10594	8711	7807
21	1527	v	3	11643	16723	10134	10263	8486	7575

Fig. 7 A Section of the Sampled Raster Values of the Training Samples

3.2 Model Formulation

The implementation of the models was carried out using the Python programming language. The

models were trained, fitted, and tested. The significant libraries used included the GDAL, Numpy, Matplotlib, and Scikit-learn libraries, among others. The hyperparameters for each model were also defined.

3.3 Model Performance Evaluation

The performance of the models was evaluated using the accuracy metrics. Table 1 presents the performance metrics of four different classifiers, namely Support Vector Machine (SVM), Random Forest (RF), K-Nearest Neighbours (KNN), and Maximum Likelihood Classifier (MLC), for pixel-based image classification. Based on the table, it is evident that SVM and RF have the highest precision values of 0.84, indicating that they make accurate positive predictions for the respective classes. In terms of recall. SVM obtained the highest value of 0.82, indicating that it can efficiently classify more positive instances than the other classifiers. The F1-score, the harmonic mean of precision and recall, provides a balanced measure of the classifier's performance. It is also seen that SVM has the highest F1-score of 0.83, indicating a well-balanced performance in terms of precision and recall, followed by RF with a value of 0.79, MLC with a value of 0.75, and KNN obtaining the lowest value of 0.74. The SVM achieved the highest overall accuracy of 0.8932 for the overall accuracy obtained. This result indicates the superiority of the SVM in correctly classifying pixels based on their land cover classes in the pixel-based image classification task.

Table 1: Performance Metrics of ML Models

Classifier	Precision	Recall	F1-score	Kappa	O/A
SVM	0.84	0.82	0.83	0.85	0.8932
RF	0.84	0.77	0.79	0.81	0.8710
KNN	0.78	0.79	0.74	0.82	0.8543
MLC	0.76	0.73	0.75	0.74	0.7322

3.4 Visual Interpretation

Graphical representations of the accuracies were plotted, as shown in Figs. 8, 9, and 10, to illustrate how the classified had performed in classifying the land cover classes.

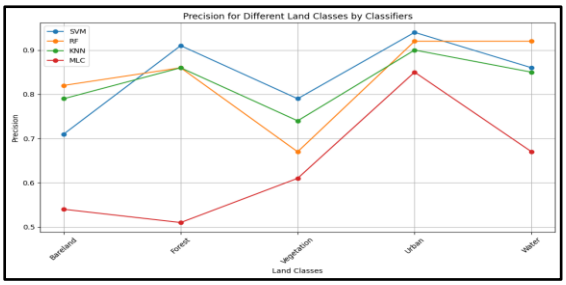

Fig. 8 Graphical Plot of Precisions Achieved per Class

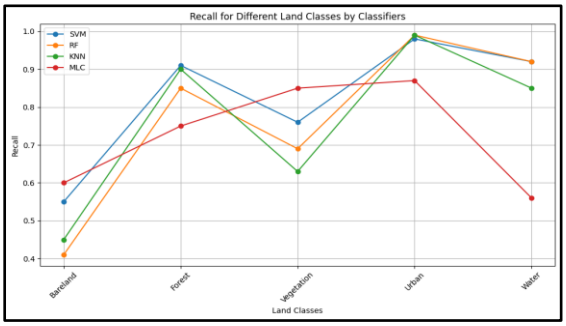

Fig 9 Graphical Plot of Recall Achieved per Class

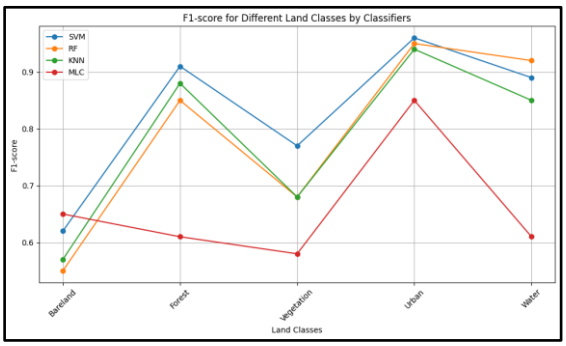

Fig. 10 Plot of F1-Score Achieved per Class

3.4.1 Land Use Land Cover Maps

Land Use Land Cover Maps were generated using SVM, RF, KNN, and MLC. It could be observed from the images that the three machine learning classifiers gave out almost similar results. The MLC, however, could not classify bareland, hence misclassified bareland as settlement. This performance can be seen from the graphical plots (Figs 8 and 9), where the MLC had a higher recall (ability to identify positive instances) but recorded the lowest precision (ability to predict positive instances). The various LULC images are shown in Figs. 11 to 14.

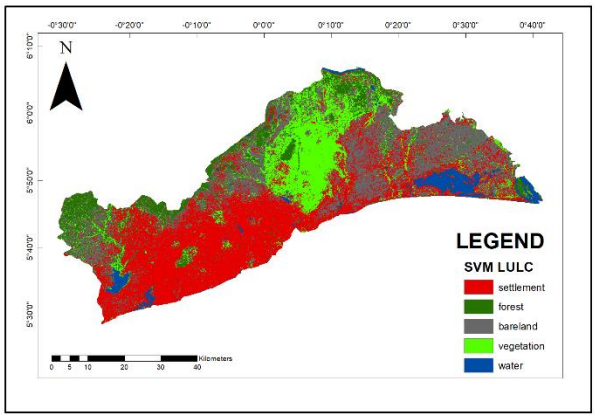

Fig. 11 SVM-LULC

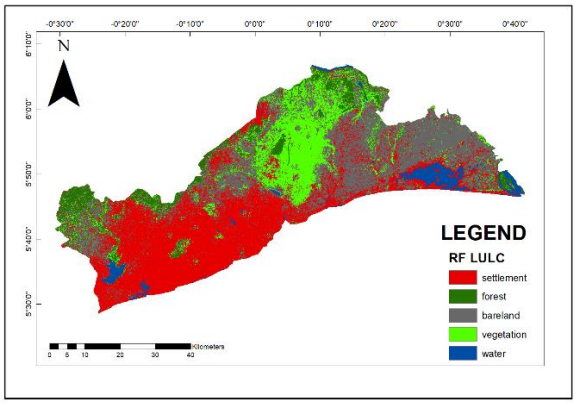

Fig. 12 RF-LULC

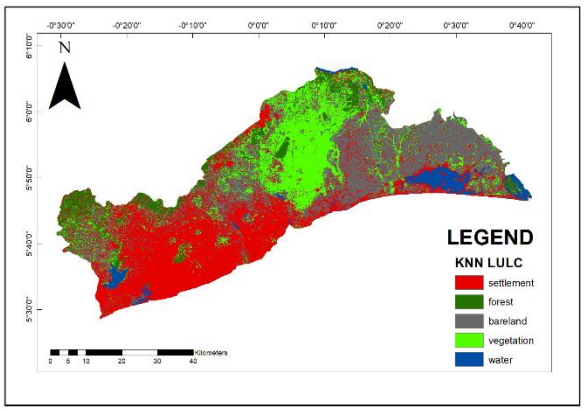

Fig. 13 KNN- LULC

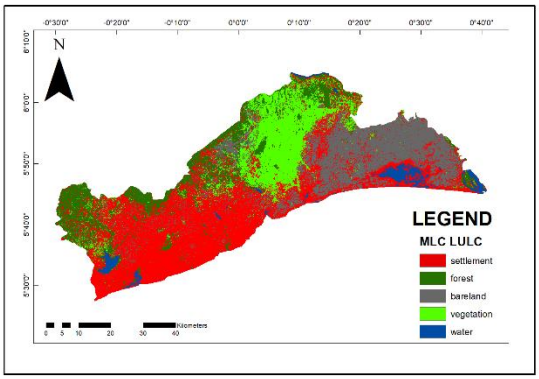

Fig. 14 MLC-LULC

4 Conclusions and Recommendations

This paper assessed the performance of three Machine Learning Algorithms and one classical algorithm (SVM, RF, KNN, and MLC, respectively) for pixel-based image classification. The algorithms were trained and developed to classify a 2021 multispectral Landsat dataset. Five accuracy metrics were employed to ascertain the accuracies of the classifiers. The accuracy metrics were Precision, Recall, F1-score, Kappa, and Overall Accuracy.

The results showed that the SVM consistently showed more robustness in terms of its accuracies, thus outperforming the other classifiers. Despite achieving competitive results, the implementation of the model encountered certain limitations, notably prolonged processing times and the need for manual hyperparameter selection. As a direction for future research, it is recommended that emphasis be placed on optimizing the model's performance. In this regard, the exploration of metaheuristic algorithms should be undertaken to automate the process of hyperparameter selection, aiming to yield more optimal and efficient results. These efforts will contribute to advancing image classification techniques and enhancing their applicability in various real-world scenarios.

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