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# A Comparison of Object-Based Classifiers for Land Cover Classification of Ankobra River Basin in Ghana

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***Abstract*: Remote sensing and GIS techniques on land cover classification using traditional pixel-based classification have been widely used. However, pixel-based classification uses only the spectral information during classification, which has some limitations. Object-based classification compensates for these limitations by merging the spectral and spatial information during the image segmentation phase. Using object-based approaches has allowed researchers to compare different machine-learning classifiers. Previous studies have shown that using different classifiers may lead to different classification accuracies. This has resulted in many studies investigating the effectiveness and efficiency of different classifiers. In this study, the performances of Naïve Bayes (NB), K-Nearest Neighbour (KNN), and Support Vector Machine (SVM) classifiers in object-based landcover classification using Landsat Imagery were explored. The Ankobra River Basin was used as the study area, with four land cover classes (Forest, Built-Up, Vegetation (grassland) and Water Bodies), based on 946 training datasets. A comparative assessment of the results showed that SVM and NB were superior to KNN. The SVM produced the highest overall accuracy (99.65%), followed by NB (95.65%) and lastly KNN (55.79%). A 95% confidence level statistical test was also carried out on the classifiers. SVM was identified as an effective and robust classification algorithm for performing object-based image analysis (OBIA) compared to NB and KNN. When implementing an Object-Based Image Analysis (OBIA) approach for land cover assessment, there is the need for appropriate tuning of parameters, and enough training samples since it affects the classification accuracy.***

***Keywords*— Object-Based Image Analysis, Support Vector Machine, K-Nearest Neighbor, Naïve Bayes**

## I. INTRODUCTION

Land Use/Land Cover (LULC) change has become an essential component in managing natural resources and monitoring environmental changes [1], [2], [3]. Monitoring of LULC change is essential for understanding change mechanisms on the environment and related ecosystems at different scales to help with environmental protection and relevant decision-making [4]. Remote Sensing data and Geographic Information System (GIS) techniques enable LU/LC change information to be extracted efficiently and analysed [5], [6]. Several Remote Sensing and GIS studies on land cover change have been undertaken, with most studies utilising the traditional pixel-based classification methods [3], [4], [5], [6]. The traditional pixel-based classification uses only the spectral information during classification, which has some limitations [3]. These limitations include problem of mixed pixels [7], and increased errors resulting from inadequately capturing small classes from high spectral resolution imagery. However, Object-Based Image Analysis (OBIA) uses spectral and spatial information for classification [8].

OBIA can, therefore, overcome the limitations of the pixel-based classification methods by merging both spectral and spatial information during the image segmentation phase. The OBIA process subdivides the image into homogeneous regions of identical pixels based on spectral and spatial characteristics, then hierarchically arranges them into image objects [8], [9].

The OBIA typically uses a rule-based procedure, statistical methods, or Machine Learning Algorithms (MLA) based on training samples during classification [10]. While rule-based procedures use expert knowledge for classification and often result in more interpretable models, they are less flexible when dealing with complex or large datasets. Statistical methods utilise parametric classifiers such as the Maximum Likelihood Classifier (MLC) and Bayes classifier and rely on mathematical models and assumptions about the underlying data distribution to perform classification. However, these approaches are often constrained by their assumptions about data distribution, their sensitivity to outliers, and the computational challenges they pose in high-dimensional spaces. On the other hand, MLAs automatically learn patterns from labelled training data, making them well-suited for supervised classifications, especially when dealing with high-dimensional data. These algorithms are non-parametric and include K-Nearest Neighbour (KNN), Decision Tree (DT) and Support Vector Machine (SVM), among others. Previous studies have shown that using different classifiers may produce different classification results. Many studies have been conducted to investigate the effectiveness and efficiency of the different classifiers. With object-based approaches, increasing interest has been in comparing different machine learning classifiers using object-based methods. The objective of this study is to evaluate the performances of the most frequently used MLA for OBIA land cover classification of a river basin in Ghana.

Object-Based Image Analysis (OBIA): Two image analysis methods are typically employed to classify remotely sensed data: pixel-based classification, which is the traditional approach, and object-based classification, which has become a frequently used tool for remote sensing image analysis [11]. OBIA has been defined by [12] as a sub-discipline of Geographic Information Science devoted to partitioning Remote Sensing (RS) imagery into meaningful image objects and assessing their characteristics through spatial, spectral and temporal scales. OBIA is one of the most recent innovations in image classification approaches compared with traditional pixel-based classification methods [9]. Pixel-based classification methods assume that individual pixels are independent and are treated in the classification algorithm without considering any spatial association with neighbouring pixels. The pixel-based classification results often show a "salt and pepper" effect, with individual pixels classified differently from their neighbours. OBIA is an alternative to a pixel-based method with basic analysis units as image objects instead of individual pixels. This method intends to bypass the problem of artificial square cells used in the per-pixel method by grouping several pixels into shapes with a meaningful representation of the objects [12]. OBIA typically merge both spectral and spatial information during the image segmentation phase. Several researchers have demonstrated that an object-based approach to image segmentation could improve the accuracy and efficiency of change detection [4], [9], [11], [12]. Object-based image analysis has the advantage of merging more object-related features than pixel-based classification, which decreases the "salt and pepper" effect and produces maps with higher accuracies [4], [9], [11], [12]. The primary purpose of OBIA is to provide a method for analysing high-spatial resolution imagery using spectral, spatial, textural, and topological characteristics. OBIA methods provide a relatively fast, automated method for identifying and extracting objects like rooftops or tree crowns, saving an analyst from digitising by hand [8].

Image Segmentation**:** Image segmentation is a method of dividing an image into homogeneous regions [13]. These regions represent land covers such as buildings, trees, water bodies and grasslands known as image objects. OBIA usually comprises two main phases: image segmentation and feature extraction, and classification. From an algorithmic perspective, image segmentation is generally divided into four categories: point-based, edge-based, region-based, and combined [14]. Irrespective of the method applied, segmentation provides the building blocks of object-based image analysis [14]. The first and most crucial stage in OBIA is the creation of image objects through the aggregation of pixels by image segmentation [13], [15]. The accuracy of object-based feature extraction and classification mostly depends on the quality of image segmentation [12].

## II. MATERIALS AND METHODS

### Study Area

The Ankobra River Basin (Fig. 1) is the study area and lies between latitudes 4° 50′ N and 6° 30′ N, and longitudes 1° 50' W and 2° 30′ W [16]. The Basin is surrounded to the East by the Pra Basin, North and West by the Tano Basin and the Southeast by the small Butre Basin. The drainage of the Ankobra River is part of the Western River System and covers an area of approximately 8 460 km$^2$. The river draws its source from the hills north of Basin Dare (near Bibiani) and flows mostly due south for about 260 km before joining the Gulf of Guinea at Asanta, just a few kilometres west of Axim [16]. The Ankobra Basin covers three subtypes of the high rainforest zone: the semi-deciduous moist, the evergreen moist and the evergreen wet forest. Most of the upstream northwest part of the Ankobra Basin lies in a subzone characterised by tall trees (up to 60 m). A total of 11 districts with four regions are represented within the Basin, which includes; Western North Region (Bibiani-Anhwiaso-Bekwai), Western Region (Wassa Amenfi West, Wassa Amenfi East, Tarkwa-Nsueam, Prestea-Huni Valley, Mpohor Wassa East, Nzema East, and Ahanta West), Central Region (Upper Denkyira, Twifo-Heman/Lower Denkyira) and Ashanti Region (Atwima Mponua). About 94% of the Ankobra River Basin area is located within the Western and Western North Regions, 5% is within the Central Region and 1% in the Ashanti Region around the northern fringe [16].

Object-Based Machine Learning Algorithms (OBMLAs): Object-Based Machine Learning Algorithms (OBMLAs) are statistical models that computer systems use to perform a specific task by relying on patterns and inference [17]. OBMLAs build mathematical models based on sample data, known as "training data", in order to make predictions [17]. Some advantages of OBMLAs include reviewing large volumes of data and discovering specific trends and patterns that would not be apparent to humans. OBMLAs gain experience based on predictions, which improves efficiency. They are good at handling multi-dimensional and multi-variety data and can do this in dynamic or uncertain environments [13], [17]. There are three types of OBMLAs. They are supervised, unsupervised, and reinforced learning algorithms. Many different kinds of OBMLAs have been applied for supervised classifications, and these algorithms are commonly categorised as parametric and non-parametric classifiers [10]. The two widely used types of parametric algorithms are the Maximum Likelihood Classifier (MLC) and Bayes classifiers. However, in recent years, the use of non-parametric classifiers, including Support Vector Machines (SVM), Decision Trees (DT), K-Nearest Neighbour (KNN), and ensemble learning-based algorithms (e.g., boosting, bagging and Random Forest (RF)) in object-based classifications have been used in remote sensing [15]. This study focuses on Naïve-Bayes, Support Vector Machine (SVM) and K-Nearest Neighbors (KNN).

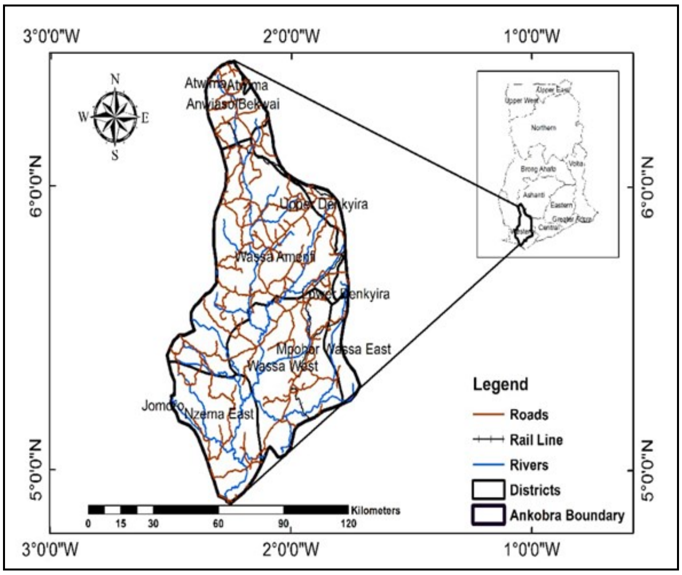


Fig. 1. Location of Ankobra River Basin in Ghana

## Materials

Data Used: Cloud-free Landsat 7 ETM+ datasets were downloaded from the United States Geological Surveys (USGS) website using the Earth Explorer (http://earthexplorer.usgs.gov. Accessed: 05th October 2023) and acquired in Level 1 Terrain (L1T) format. The acquisition dates were 10th January 1991 and 20th September 2023, with a pixel size of 30 m spectral bands. These data were selected based on availability and the dataset's quality for the study area. The paths/rows of 194/56 and 194/57 were merged into new multispectral images using ArcMap 10.4 software to cover the entire study area. Four land cover classes were identified for the study area: Forest, Built-Up, Vegetation (grassland), Water Bodies and Built-Up.

Software Used: ArcMap 10.4 software was used to convert Landsat images from digital numbers to radiance and reflectance and to create composite bands. eCognition Developer 64 software was also used to create image segmentation, and then RStudio software was used to script.

## Methods Used

Pre-processing: remote sensing imagery has some degree of geometric distortion; these distortions are due to the curvature of the Earth, terrain changes, and inaccuracies caused by the motion of the (sensor/scanner). Geometric and Radiometric correction procedures were used to check and convert these imageries of the study area to absolute spectral radiance (units of energy) and then to top-of-atmosphere spectral reflectance.

Image Segmentation: The first and most important stage in object-based image analysis is the creation of image objects or segments, called image segmentation. Using eCognition Developer 9 software, the basic processing unit of object-based classification was generated through the bottom-up region-merging technique referred to as the Multi-Resolution Segmentation (MRS) algorithm. Segmentation scale, shape, and compactness are the three main parameters that control the size and shape of segments. However, the scale parameter is considered the most important as it controls the relative size of the image objects, which directly impacts the classification steps [15]. After an extensive iterative trial and error process and analysis of the segmentation results (Fig. 2), the optimal scale parameter was chosen as 5, and the other parameters (*i.e.*, shape and compactness) were set to 0.2.

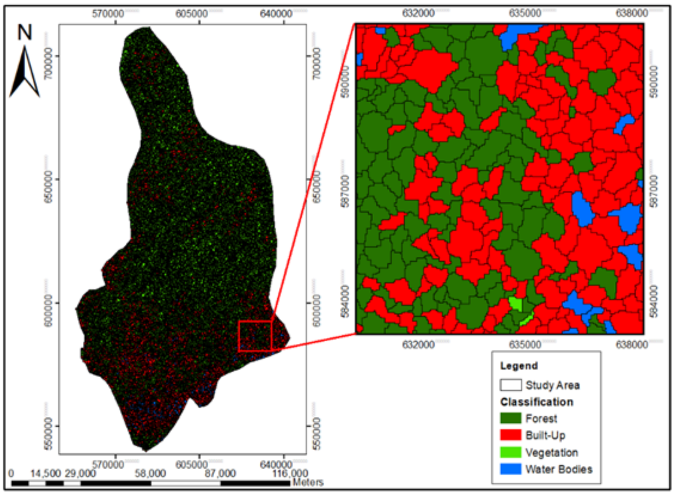


Fig. 2. Segmentation with Scale (5), Shape (0.2) and Compactness (0.2) (2023 Image)

Training and Testing Sample Datasets: After image segmentation in eCognition Developer 9, classes were sent to ArcMap. Point shapefiles were generated in ArcMap from the segmented images based on colour composites. Thus, sample points were selected for each landover and were saved as a shapefile. The points selected for each class were then converted to raster so that the frequency of the classified image and the raster point could be computed (Fig. 2). A table was then created and saved as a dBase file for further analysis. The file contains the class name, grid code, and class identity. A total of 946 datasets were generated, 661 objects were selected as training samples, and 285 objects were used as testing samples.

Classification Algorithms and Tuning Parameters: Tuning is the process of maximising a model's performance without overfitting or creating too high of variance [18]. Tuned parameters are essential in producing high-accuracy results when using MLA algorithms. Each classifier has different tuning steps and tuned parameters. For each classifier, a series of values for the tuning process were tested, with the optimal parameters determined based on the highest overall classification accuracy. In this study, the classified results under the optimal parameters of each classifier were used to compare the performance of classifiers.

Support Vector Machine (SVM): The goal of SVMs is to find a hyperplane that can separate the input dataset into a discrete predefined number of classes consistent with the training samples [10], [19]. With the SVM algorithm, a hyperplane is first built based on the maximum gap of the given training sample sets, and then the segmented objects are classified into identified land cover classes (in this study, four classes). An

SVM training algorithm is a non-probabilistic, binary, linear classifier. However, methods such as Platt scaling exist to use SVM in a probabilistic classification setting; in addition to performing linear classification, SVMs can efficiently perform a non-linear classification using what is called the kernel trick, implicitly mapping their inputs into high-dimensional feature spaces (Anon., 2020b). The most frequently used and superior to other kernels (Radial Basis Function (RBF)) [21] was used in this study. The RBF kernel has two important tuning parameters, Cost (C) and Gamma (γ), which affect the overall classification accuracy [22], [23]. The C parameter decides the size of misclassification allowed for non-separable training data, making adjusting the rigidity of training data possible. The γ affects the smoothing of the shape of the class-dividing the hyperplane. To examine how these two key parameters, affect the performance of SVM within the object-based approach, ten (10) values for Cost (C) and gamma were systematically tested. Specifically, five (5) values of C ($2^{-1}$, $2^0$, $2^1$, $2^2$ $2^3$) and five (5) values of gamma ($5^3$, $5^4$, $5^5$, $5^6$, $5^7$) were tested.

Naïve Bayes (NB): Naïve Bayes (NB) is a probabilistic classifier based on Bayes' theorem (from Bayesian statistics) [24]. The NB classifier assumes that feature vectors from each land cover type are normally distributed but not necessarily independently distributed. With the NB classifier, the data distribution function is assumed to be a Gaussian mixture [25]. Using the training samples, the algorithm first estimates the mean vectors and covariance matrices of the selected features for each class and then uses them for classification. One advantage of the NB classifier is that, there is no need to set any tuning parameter (s), which could be subjective and tedious [10].

K- Nearest Neighbor (KNN): The KNN approach is a non-parametric method used in statistical applications in the early 1970s [26]. The basic theory behind KNN is that a group of k samples nearest to unknown samples (*e.g.*, based on distance functions) is found in the calibration dataset. From these k samples, the class of unknown samples is determined by calculating the average of the response variables (*i.e.*, the class attributes of the k nearest neighbour) [10]. As a result, for this classifier, the k value plays an essential role in the performance of the KNN, *i.e.*, it is the key tuning parameter of the KNN. In this study, we examined k values from 1 to 5 to identify the optimal k value for all training sample sets.

Accuracy Assessment and Comparisons: In order to assess and compare the performance of the classifiers, overall accuracies (OA) were used as the criterion. The Overall Accuracy (OA) was calculated for each of the classifiers, and a 95% confidence level of the probability estimate for every OA was calculated.

## III. RESULTS AND DISCUSSION

### Results

The KNN Classifier: To classify an object with the KNN classifier, the algorithm is based on the class of attributes of its k nearest neighbours. Therefore, the k value plays a vital role in the performance of KNN and is the key tuning parameter of the KNN algorithm. In this study, a range of (1 to 5) k values were tested. Tables 1 and 2 show the results of the KNN classifier when applied to different Tuning parameter (W) values.

**Table 1 Summary of K-Nearest Neighbour (KNN) Classifier for 1991 Image**

| TUNING PARAMETERS (W) | OVERALL ACCURACY (OA) | 95% CONFIDENCE INTERVAL | |
|---|---|---|---|
| 1 | 0.5579 | 0.4981 | 0.6164 |
| 2 | 0.4703 | 0.4111 | 0.5299 |
| 3 | 0.4389 | 0.3801 | 0.4983 |
| 4 | 0.4863 | 0.3801 | 0.4983 |
| 5 | 0.4317 | 0.3733 | 0.4913 |

**Table 2 Summary of K-Nearest Neighbour (KNN) Classifier for 2023 Image**

| TUNING PARAMETERS (W) | OVERALL ACCURACY (OA) | 95% CONFIDENCE INTERVAL | |
|---|---|---|---|
| 1 | 0.5568 | 0.4981 | 0.6164 |
| 2 | 0.4700 | 0.4110 | 0.5290 |
| 3 | 0.4387 | 0.3802 | 0.4982 |
| 4 | 0.4861 | 0.3803 | 0.4982 |
| 5 | 0.4315 | 0.3731 | 0.4912 |

When W increased from 1 to 5, the overall accuracy and confidence interval (CI) also decreased. The optimal W for the KNN classifier was then chosen as W = 1 since it gave the highest Overall Accuracy (OA) and Confidence Interval (CI) compared with the other W values. Therefore, the overall accuracy when W = 1 are respectively 55.79% and 53.09% for 1991 image and 55.68% and 53.01% for 2023.

The SVM Classifier: The Cost (C) and Gamma (γ) values play important roles in the performance of SVM and are the key tuning parameters of the SVM algorithm. In this study, a range of 10 values for C and γ were tested. In order to find the optimal values for the SVM model, several values were examined for C and γ: C ($2^{-1}$, $2^0$, $2^1$, $2^2$, $2^3$), γ ($5^3$, $5^4$, $5^5$, $5^6$, $5^7$). Tables 3 and 4 show the results of the SVM classifier when applied to different C and γ values for both 1991 and 2023 images.

Table 3 Summary of Support Vector Machine (SVM) Classifier for 1991 Image

| GAMMA (γ) | COST (C) | OVERALL ACCURACY (OA) |
|---|---|---|
| $5^3$ | $2^{-1}$ | 0.9965 |
| $5^4$ | $2^0$ | 0.9860 |
| $5^5$ | $2^1$ | 0.8912 |
| $5^6$ | $2^2$ | 0.7930 |
| $5^7$ | $2^3$ | 0.5930 |

Table 4 Summary of Support Vector Machine (SVM) Classifier for 2023 Image

| GAMMA (γ) | COST (C) | OVERALL ACCURACY (OA) |
|---|---|---|
| $5^3$ | $2^{-1}$ | 0.9955 |
| $5^4$ | $2^0$ | 0.9850 |
| $5^5$ | $2^1$ | 0.8910 |
| $5^6$ | $2^2$ | 0.7935 |
| $5^7$ | $2^3$ | 0.5934 |

When C and $\gamma$ values increased from $2^{-1}$ to $2^3$ and $5^3$ to $5^7$, respectively, the overall accuracies and confidence intervals (CI) also decreased. The optimal C and $\gamma$ values for the SVM classifier were then chosen as C= $2^{-1}$ and $\gamma = 5^3$ since it gave the highest Overall Accuracies (OA) and Confidence Intervals (CI). Therefore, the overall accuracies when C= $2^{-1}$ and $\gamma = 5^3$ were 99.65% for 1991 image and 99.55% for 2023 image, respectively.

The NB Classifier: The NB classifier assumes that feature vectors from each land cover type are normally distributed but not necessarily independently distributed. The data distribution function is assumed to be a Gaussian mixture with the NB classifier, one component per class. Using the training samples, the algorithm first estimates the mean vectors and covariance matrices of the selected features for each class and then uses them for classification.
Unlike SVM and KNN, which rely on tuning parameters to determine the optimal results for classification, NB relies on the training dataset to get the optimal results. Previous studies show that the lower the training sample dataset, the lower the accuracy, but the higher the training sample dataset, the higher the accuracy.
To get a precise and consistent accuracy, nine (9) cross-validations were taken, and the average was then finalised. Therefore, the overall accuracies when the 946-sample dataset were used yielded 95.65% for 1991 image and 95.60% for 2023 image respectively.

The Object-Based Classifiers: Tables 5 and 6 summarise the classification results with the highest overall accuracies for each classifier. Fig. 3 also shows a sample classification map of the Ankobra Basin from the object-based classifiers. The classes generated from the Basin include forest, built-up, vegetation (grassland), and water bodies. The overall accuracies of SVM were 99.65% for 1991 image and 99.55% for 2023 that of NB were 95.65% for 1991 image and 95.60% for 2023 and finally KNN were 55.79% for 1991 image and 55.55% respectively. SVM performed the best among the three classifiers. SVM was the most sensitive to the setting of tuning parameters, but KNN was relatively insensitive to the tuning parameters. Furthermore, SVM produced significantly better results than NB and KNN at 95% confidence level out of the three classifiers.

Table 5 Summary of the Object-Based Classifiers for 1991 image

| OBJECT-BASED CLASSIFIERS | OA | 95% CI | |
|---|---|---|---|
| SVM | 0.9965 | 0.9806 | 0.9990 |
| NB | 0.9565 | 0.9756 | 0.9839 |
| KNN | 0.5579 | 0.4981 | 0.6164 |

Table 6 Summary of the Object-Based Classifiers for 2020 image

| OBJECT-BASED CLASSIFIERS | OA | 95% CI | |
|---|---|---|---|
| SVM | 0.9965 | 0.9806 | 0.9994 |
| NB | 0.9565 | 0.9756 | 0.9849 |
| KNN | 0.5579 | 0.4981 | 0.6166 |

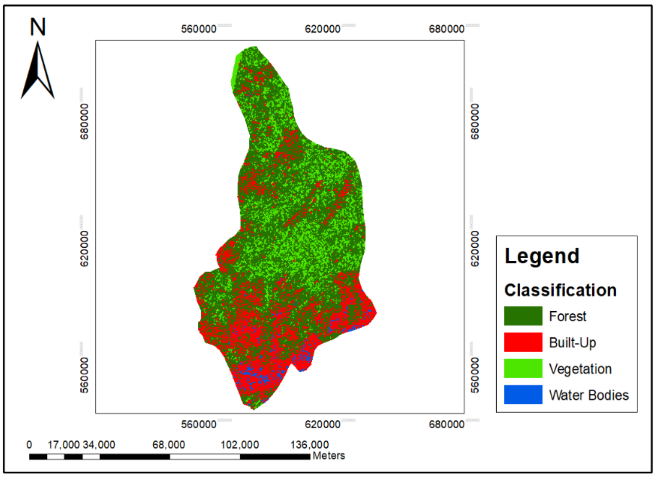


Fig. 3 Object-Based Classified Map of Ankobra River Basin (2023 Image)

## DISCUSSIONS

The performances of the Object-Based Classifiers (SVM, NB, and KNN) were compared and analysed using 946 training sample datasets from the Ankobra Basin. SVM, NB, and KNN classification models with optimum parameter configurations were applied to the segmented image objects. The optimised parameter settings for the KNN (K), SVM (gamma (γ) and cost parameter (C)), and NB algorithms were set as listed in Tables 3 and 4. For SVM, 10 values were selected, 5 for each, to obtain the optimal setting for gamma (γ) and cost parameter (C) using the data set. For KNN, 5 values were chosen to get the optimal setting for K using the data set. Some critical observations can be drawn from the accuracy results presented in Tables 5 and 6. Firstly, it was clearly seen that the highest classification accuracies were estimated by the SVM algorithm, 99.65% and 99.55%, followed by NB with 95.65% and 95.60%, while KNN gave the lowest accuracies with 55.79% and 55.55%. These results clearly indicated that the SVM and NB outperformed the KNN algorithm for object-based classification.

It should be noted that both statistical tests were two-tailed, and results were interpreted at 95% confidence levels. Within these confidence levels, if the calculated statistic is smaller than the critical value, it was concluded that there is no statistical significance between the two classification results at a 95% confidence level. In other words, the SVM and NB classifier produced a statistically similar classification result. All remaining statistical test results indicated that the SVM algorithm performed better than the other classifiers with respect to the dataset. In addition, the NB algorithm produced better classification results than KNN algorithms for the datasets. In summary, statistical test results verified that the SVM and NB algorithms, in all cases, outperformed the KNN algorithm.

## IV. CONCLUSIONS AND RECOMMENDATIONS

This paper evaluated the performance of three Object-Based classifiers, namely SVM, NB, and KNN, using an object-based classification procedure on the River Ankobra Basin in Ghana. Four different classes were determined, i.e., Forest, Vegetation (grassland), Water Bodies and Built-Up with training sample sizes of about 946 pixels/class. The results showed that SVM and NB were superior to KNN. Both SVM and NB achieved very high classification accuracies, with appropriate settings of the tuning parameters and/or enough training samples. The tuning parameters of the classifier had a significant impact on the classification accuracy. SVM was the most sensitive to the setting of tuning parameters, but KNN was relatively insensitive to the tuning parameters.

Furthermore, out of the three classifiers, SVM produced significantly the best results at a 95% confidence level. The results showed that SVM was an effective and robust classification algorithm for performing object-based image analysis, especially compared with NB and KNN when the data set in this study was considered. These findings provide insights into the selection of classifiers, the size of training samples, and tuning parameters when implementing an object-based approach for land cover classification.

Based on the accuracy and performance of the object-based classifiers obtained from this paper, it is recommended that SVM be implemented when performing classification using object-based image analysis (OBIA) classification. When implementing an object-based approach for land cover classification, the appropriate setting of the tuning parameters and enough training samples should be considered since they affect classification accuracies.

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