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A Performance Comparison of Three Machine Learning Algorithms for Urban Land Cover Classification using High-Resolution Imagery

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Abstract:
Urban land cover classification using high-resolution imagery is important for many applications where detailed and precise urban land cover products are needed. Machine learning algorithms are currently some of the most commonly used methods for classifying high-resolution imagery due to their impressive capabilities. However, the reliability of the land cover products obtained from the classification of high-resolution urban imageries is dependent upon the accuracy of the Machine Learning (ML) classification algorithm used. The need for an appropriate selection of classifiers for urban land cover classification and their applicable settings necessitates the performance comparison of major ML algorithms used for classification. In this study, we compared the performance of three major Machine Learning (ML) classifier algorithms using a high-resolution image dataset of an urban area. The algorithms are Support Vector Machine (SVM), Naïve Bayes, and Ensemble classifiers. The performance of three model types of SVM classifiers namely Medium Gaussian, Linear, and Quadratic SVM, two model types of Naïve Bayes classifiers namely Gaussian and Kernel Naïve Bayes, and three model types of ensemble classifiers namely Bagged Trees, Subspace Discriminant, and RUSBoosted Trees were compared. Performance evaluation was carried out using Confusion Matrix (CM) and Receiver Operating Curves (ROC) plots. Results obtained from the comparison of the three ML classifier algorithms show that the Subspace Discriminant ensemble classifier had the highest accuracy at 85.1%, closely followed by the Medium Gaussian SVM classifier (84.5%) and Gaussian Naïve Bayes classifier (81.5%). This research provides insights into the selection of classifiers for future urban land cover classification and their applicable settings.

Keywords: Support Vector Machine, Naïve Bayes Classifiers, Ensemble Classifiers, High-resolution imagery, Urban land cover

1. Introduction

Land cover classification is an important and challenging remote sensing task that makes use of intelligent algorithms to interpret remotely sensed imagery and classify each pixel into a predefined land cover class [1, 2]. Urban land cover information is essential for various urban planning applications such as urban land resource management, urban environment monitoring, change detection, and nature conservation [3].

With improvements in remote sensing data acquisition technologies, a large amount of remotely sensed images with high spatial resolution are increasingly becoming widespread and available at little or no cost [4]. This opens new vistas and opportunities for urban land cover information classification at a very detailed level, therefore, allowing effective urban monitoring, planning, and management with a higher level of discrimination [5]. Urban land cover information obtained from the classification of high-resolution images is essential for many applications where the need for detailed and precise urban land cover maps is indispensable [3]. The accuracy of the classification algorithm used for the classification then becomes a matter of great importance as accurate land cover information is crucial for many remote sensing applications and of particular concern in urban land cover classification [6, 7, 8].
Machine learning-based classifier algorithms are currently some of the most commonly used methods for the classification of high-resolution imagery due to their impressive computational and spatial analysis capabilities [9].

As the number of machine learning algorithms increases, it is beneficial for the user community of these algorithms to gain a better knowledge of the performances of each algorithm as urban landscapes are extremely complex and spatially heterogeneous [10]. For ample quantification of the heterogeneity of urban land cover, high spatial-resolution images are needed. Due to the complex information brought by the increased spatial resolution of image acquisition, it is often challenging to find an efficient technique for achieving accurate land-cover classification with high-resolution and spatially heterogeneous images [11]. Thus, a more comprehensive comparison of major machine learning classifier algorithms' performance for classifying urban land cover using high-resolution imageries is essential as this will aid informed choice of appropriate landcover mapping methods.

Prior studies have been carried out to identify the performance of different classifiers for urban land cover classification [12, 13, 14]. It has also been shown that the use of different classifiers may lead to different classification results [15], thereby necessitating the need for a standardized comparison to gain a better knowledge of the performances of each classifier algorithm. Studies have also shown that various factors such as image segmentation, training sample selection, feature selection, model types, and parameter tuning options can significantly affect the classification accuracy of ML classifiers [15, 16, 17]. Most of these factors have been investigated but not many studies have been carried out to compare the performance of ML classifier model types and their tuning options using openly available standardized high-resolution imagery of an urban area.

This study aims to implement and assess the performance of three major machine learning classifiers, model types, and their optimum tuning options for urban land cover classification using a high-resolution image dataset of an urban area. The machine learning classifier algorithms are Support Vector Machine (SVM), Naïve Bayes, and Ensemble classifiers. The SVM classifier model types compared were Medium Gaussian SVM, Linear SVM, and Quadratic SVM. For Naïve Bayes classifiers the performance of Gaussian Naïve Bayes and Kernel Naïve Bayes model types was carried out. For ensemble classifiers, the model types evaluated are Bagged Trees, Subspace Discriminant, and RUSBoosted Trees. The results from this study would help provide valuable insights into classifier model type selection and tuning options parameter settings when carrying out urban land cover classification using high-resolution imageries.

The rest of the paper is organized as follows. Section 2 delves into the method used for carrying out the performance evaluation of the ML classifiers. Section 3 reports on the results obtained while section 4 discusses the results and performance comparison. Finally, section 5 concludes the study.

II METHODS

Methods used in carrying out the performance evaluation are highlighted here. The simulations were carried out using the MATLAB 2020a classification learner toolbox.

A. Data

In this study, classification performance comparison was carried out on an urban land cover dataset obtained from Johnson [18]. The dataset contains high-resolution (30 cm spatial resolution) aerial ortho-imagery of an urban area in Deerfield Beach, FL, USA. The image was approximately 1.4 km × 1.5 km (4630 × 4967 pixels) in size and contained 8-bit data for the near-infrared (NIR), red, and green spectral bands [18]. The dataset contains training and testing data for classifying a high-resolution aerial image into 9 types of urban land cover. The land cover classes are trees, grass, soil, concrete, asphalt, buildings, cars, pools, and shadows. These are features predominantly found in an urban area. There are a total of 147 features within the dataset and no missing values.

B. Machine Learning Algorithms.

A brief overview of the machine learning algorithms to be compared is outlined in this section.

1) Support Vector Machine.

Support Vector Machine (SVM) provides a collection of widely used and highly effective algorithms for image classification [19, 20]. The basic working principle of SVM algorithms is to create an optimal hyperplane or decision boundary that takes full benefit of the distance between the nearest samples (support vectors) to the plane and precisely separates classes [20]. The model aims to locate the ideal separating hyperplane between classes by focusing on the training cases that take place at the edge of the class distribution [20]. These confer a major advantage on the SVM algorithm by enabling it to handle high-dimensional data and achieve high accuracy even with very small training datasets [19]. The performance of three models of SVM classifiers (Medium Gaussian SVM, Linear SVM, and Quadratic SVM) with different kernel functions was compared in this study.

2) Naïve Bayes

Naive Bayes classifiers are a class of well-established probabilistic classifiers that make use of Bayes' theorem to assign events to classes. Their simplicity and accuracy place them among the class of highly efficient classification algorithms [21]. For the classification of an unknown event, Naïve Bayes classifiers work by computing the probability of occurrence of each class and then selecting the one with the highest probability. They are considered very effective supervised classifiers owing to their high level of accuracy and low computation time [22, 23]. The performance of Gaussian Naïve Bayes and Kernel Naïve Bayes classifier models were compared in this study.

3) Ensemble Classifier

Ensemble learning is a popular and effective machine learning approach for classification tasks due to its reliability and robust classification performance [24]. Ensemble classifiers work by combining a series of classifier models produced by several learners into an ensemble that will perform better than the original learners [25]. They generally achieve higher accuracy and better generalization compared to an individual classifier [26]. The ensemble classifier can consist of any type of base classifier algorithm such as Bagged trees or other sorts of base learner classification algorithms. In this study, the performance of Bagged Trees, Subspace Discriminant, and RUSBoosted Trees Ensemble classifiers models were compared.

C. Classifiers Performance Analysis

The performance analysis of the classifiers was carried out in two stages. In the first stage, the performance of Linear, Quadratic, and Gaussian kernel functions SVM classifier models were compared with each other. The same was done for Naïve Bayes (performance of Gaussian Naïve Bayes and Kernel Naïve Bayes classifiers models were compared) and

Ensemble classifier (performance of Bagged Trees, Subspace Discriminant, and RUSBoosted Trees Ensemble classifiers models were compared).
The second phase compared the performance of the best algorithms from the three ML classifiers considered (Support Vector Machine, Naïve Bayes, and Ensemble classifier).

D. Accuracy Assessment

Classification results are evaluated against a set of accuracy assessment parameters. The accuracy assessment parameters used in this study are receiver operating curves and confusion matrix.

1) Receiver Operating Curves (ROC) plot

The ROC curve graphically displayed the binary classification model's performance. To interpret the ROC curve, Area Under the Curve (AUC) values will be considered. An AUC of 1.0 suggests a perfect model fit [27].

2) Confusion Matrix.

The confusion matrix provides a performance summary of the classification model by comparing predicted and actual values. The matrix comprised rows and columns, with each row representing instances in a predicted class and each column representing instances in an actual class [27]. True Positive Rates (TPR) and False Negative Rates (FNR) will be used. The TPR is the proportion of correctly classified observations per true class while the FNR is the proportion of incorrectly classified observations per true class.

III RESULTS

The results obtained are presented in this section.

A. Support Vector Machine Classifier Models.

Results obtained from the comparison of the performance of Medium Gaussian, Linear, and Quadratic SVM classifier models are presented in Table 1. The tuning settings and options that gave the highest accuracy results are also shown in Table 1.

Table 1. Medium Gaussian, Linear and Quadratic SVM classifier performance comparison.

Preset	Kernel function	Kernel scale	Accuracy (%)	Misclassification cost
Medium Gaussian SVM	Gaussian	23	84.5	26
Linear SVM	Linear	Automatic	81	32
Quadratic SVM	Quadratic	22	81.5	31

B. Naïve Bayes Classifier Models.

Table 2 outlines the results obtained from the performance comparison of Gaussian and Kernel Naïve Bayes classifiers. Tuning settings and options with the highest accuracy rates are also shown in Table 2.

Table 2. Gaussian and Kernel Naïve Bayes performance comparison.

Preset	Numeric predictor	Kernel type	Accuracy (%)	Misclassification cost
Gaussian Naïve Bayes	Gaussian	Automatic	81.5	31
Kernel Naïve Bayes	Kernel	Gaussian	81	32

C. Ensemble Classifier Models.

A comparison of the performance of three ensemble classifier models is shown in Table 3. They are Bagged Trees, Subspace Discriminant, and RUSBoosted Trees ensemble classifiers. Tuning settings and options that gave the highest accuracy rates are also shown in Table 3.

Table 3. Bagged Trees, Subspace Discriminant, and RUSBoosted Trees Ensemble classifiers performance comparison.

Preset	Ensemble method	Learner type	No of splits	No of learners	Accuracy (%)	Misclassification cost
Bagged Trees	Bag	Decision tree	200	30	83.9	27
Subspace Discriminant	Subspace	Discriminant	Subspace dimension 15	50	85.1	25
RUSBoosted Trees	RUSBoost	Decision tree	200	30	81	32

D. SVM, Naïve Bayes, and Ensemble Classifiers Performance Comparison.

Results for model types with the highest accuracy from each of the three ML classifiers considered are presented in Table 4. AUC values for the various Land use classification classes are also presented in Table 4. Confusion matrix and ROC curves for the three best classifier models among the three ML algorithms (SVM, Naïve Bayes, and Ensemble classifiers) considered are shown in figures 1 to 6.

Table 4: SVM, Naïve Bayes and Ensemble classifiers performance comparison.

Classifier	Support Vector Machine	Naïve Bayes	Ensemble classifier
Model type	Medium Gaussian SVM	Gaussian Naïve Bayes	Subspace Discriminant
Accuracy	84.5	81.5	85.1
Misclassification cost	25	31	26
AUC for class 1 (Asphalt)	0.99	0.96	0.95
AUC for class 2 (Building)	0.97	0.91	0.98
AUC for class 3 (Car)	0.99	0.96	1

AUC for class 4 (Concrete)	0.97	0.94	0.96
AUC for class 5 (Grass)	0.99	0.92	0.98
AUC for class 6 (Pool)	1	0.99	1
AUC for class 7 (Shadow)	0.99	0.95	0.98
AUC for class 8 (Soil)	0.97	0.89	0.95
AUC for class 9 (Tree)	0.93	0.95	0.93

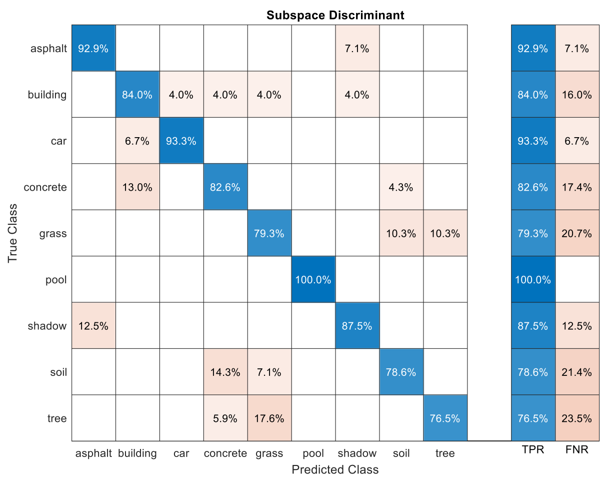

Figure 1: Confusion matrix for Subspace Discriminant Ensemble classifier

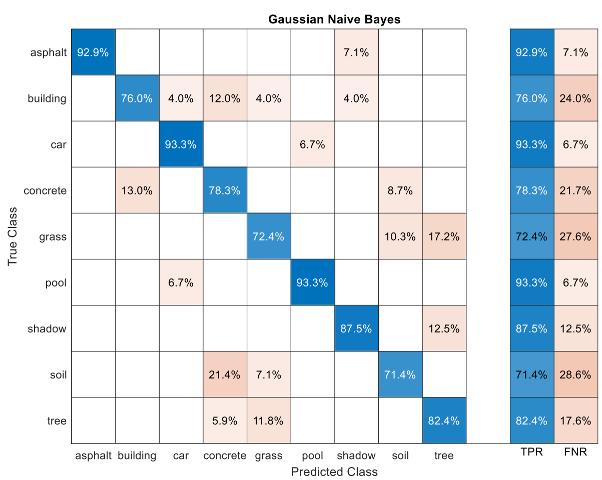

Figure 2: Confusion matrix for Gaussian Naïve Bayes classifier

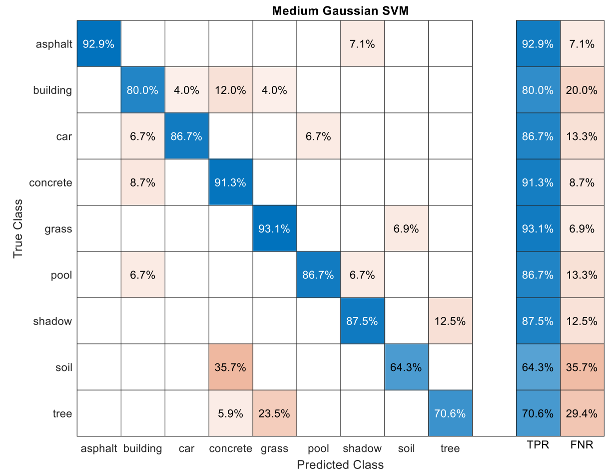

Figure 3: Confusion matrix for Medium Gaussian SVM classifier

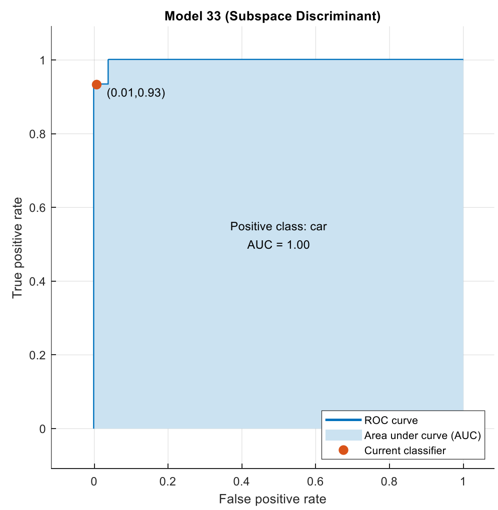

Figure 4: ROC plot for Subspace Discriminant Ensemble classifier

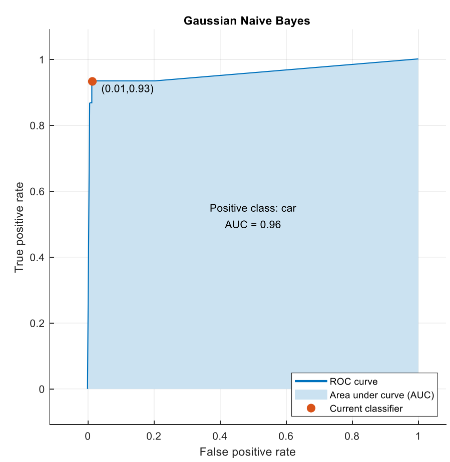

Figure 5: ROC plot for Gaussian Naïve Bayes classifier

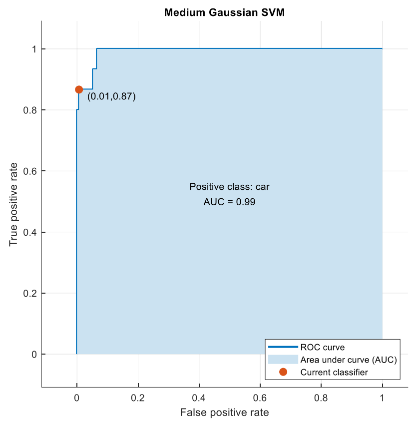

Figure 6: ROC plot for Medium Gaussian SVM classifier

IV. DISCUSSION

A. Performance Comparison of the Support Vector Machine Classifiers Models.

The tuning parameters that give the highest classification rates for each model are shown in Table 1. After multiple trials, a tuning setting of twenty three (23) for the kernel scale gave the highest accuracy for the Medium Gaussian SVM model. Similar kernel settings of automatic and twenty two (22) gave the highest accuracy rate for Linear and Quadratic SVM models. From Table 1, the performance comparison of the SVM models show that the Medium Gaussian SVM model with an accuracy rate of 84.5% outperforms Linear SVM model at 81% and Quadratic SVM model at 81.5% .

B. Performance Comparison of Naïve Bayes Classifiers Models.

Tuning the settings of the kernel types to default and Gaussian gave the highest accuracy rate for Gaussian and Kernel Naïve Bayes Classifier models respectively. Performance comparison of both models as shown in Table 2 reveals that the Gaussian Naïve Bayes Classifier model with an accuracy rate of 81.5% out performs the Kernel Naïve Bayes Classifier model with an accuracy rate of 81%.

C. Performance Comparison of Ensemble Classifiers Models.

Tuning settings for Bagged Trees, Subspace Discriminant and RUSBoosted Trees Ensemble classifier models that gave the highest accuracy rates are shown in Table 3. Performance comparison of the three ensemble classifier models shows that Subspace Discriminant model with an accuracy rate of 85.1% outperforms Bagged Trees and RUSBoosted Trees Ensemble classifier models with accuracy rates of 83.9% and 81% respectively.

D. Performance Comparison of SVM, Naïve Bayes and Ensemble classifiers.

Table 4 compares the performance of the best models from each of the three ML classifiers evaluated in this study. The models are Medium Gaussian SVM, Gaussian Naïve Bayes and Subspace Discriminant Ensemble classifier. The Subspace Discriminant Ensemble classifier had the highest accuracy at 85.1%, closely followed by the Medium Gaussian SVM classifier (84.5%) and Gaussian Naïve Bayes classifier (81.5%). The Misclassification cost and AUC values for each landcover class in the dataset are also shown for the three ML classifiers.

The confusion matrix plots in Figures 1 to 3 show the classifiers' performance in each landcover classes. It can be seen that the Subspace Discriminant Ensemble classifier had the highest average values for TPR and lowest average values of FNR for the nine classes followed by that of Medium Gaussian SVM and Gaussian Naïve Bayes classifiers respectively. Figures 4 to 6 show the ROC plot for one of the urban landcover classes (Car). It can be seen that the Subspace Discriminant ensemble classifier had a perfect AUC value of 1 compared with 0.99 and 0.96 for the Medium Gaussian SVM classifier and Gaussian Naïve Bayes classifier respectively.

In related works by Feng et al. [28] and Han et al. [29], it was shown that the use of an ensemble learning approach achieved higher classification accuracy compared with individual machine learning algorithms. This is in agreement with the results obtained from this study as the Subspace Discriminant Ensemble classifier outperformed the SVM and Naïve Bayes classifiers.

V. Conclusions and Recommendations.

In this paper, a performance comparison of three major Machine Learning (ML) classifier algorithms using a high-resolution image dataset of an urban area was carried out. The ML classifiers are Support Vector Machine (SVM), Naïve Bayes, and Ensemble classifiers. Confusion matrix and Receiver Operating Curves (ROC) plots were used for performance comparison. Results obtained from the three major classifiers compared show that the Subspace Discriminant ensemble classifier had the highest accuracy at 85.1%, closely followed by the Medium Gaussian SVM classifier at 84.5% and Gaussian Naïve Bayes classifier at 81.5%. The results were obtained after several rounds of simulation to obtain tuning settings that will produce the highest accuracy rates. This results will aid the selection of appropriate ML classifier models and applicable tuning for future urban land cover classification. This will provide more reliable urban landcover classification products.

Further research would be directed towards comparison with deep learning neural network classifiers models and developing techniques to automatically find the best tuning parameters for ML classifier models.

Conflicts of interest

The authors declare no conflicts of interest.

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