Forest Image Classification based on Deep Learning and XGBoost Algorithm

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Abstract. Deep learning and machine learning methods have been recently used in forest classification problems, and have shown significant improvement in terms of efficacy. However, as attributed from the literature, they have the challenge of having insufficient model variance and restricted generalization capabilities. The goal of this study is to improve the accuracy of forest image classification through the development of a hybrid model that incorporates both deep learning and machine learning techniques. This study has proposed an ensemble approach of the Deep Learning technique (ResNet50 in particular), and machine learning model (specifically XGBoost) to increase the prediction capability of classifying satellite forest images. The sole purpose of ResNet50 is to generate a set of features that will in turn be used by the XGBoost algorithm to perform the classification process. The XGBoost algorithm was compared against a fully connected ResNet50 model and other classifiers such as random forest (RF) and light gradient boost machine (LGBM). The best classification results were obtained from XGBoost(0.77), followed by RF(0.74), LGBM(0.73), and ResNet50(0.59).

Keywords: Machine learning, feature extraction, Convolutional Neural Networks, Image Processing

1 Introduction

Forests remain a key natural resource for both developing and developed countries as their wood and forestry products contribute significantly towards a country's Gross National Product (GDP). Both satellite and aerial images play a pivotal role when it comes to monitoring and evaluation of forests and other vegetation. Such images have made huge significant progress in solving remote sensing science classification problems. Data obtained from features such as spectral, radiometric, and spatial is usually used to perform the forest classification process [1]. Image classification refers to the process of labeling each image into its corresponding category or class [2]. Image segmentation is centered on pixel level classification, whereas image classification involves classifying the entire object into one of the given classes. In general, the majority of classification methods employ the technique of assessing and evaluating the image's content

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and then marshaling pixels into their respective categories. The new instance is classified based on an already trained data set whose classes are known. In general, an image is classified into only one of the predefined classes; however, in some cases, an image can be classified into multiple classes, which are referred to as multi-label classes [2]. In spite of the existence of many algorithms used in the classification of vegetation images, there are limited studies that have employed the ensemble machine learning approach in the classification of satellite forest images. Therefore, the purpose of this study is to report findings obtained from an ensemble approach of XGBoost algorithm and ResNet50 technique for the classification of satellite forest images. The new ensemble classifier approach's performance is evaluated against other classifiers such as Random Forest (RF) and Light Gradient Boost Machine (LGBM) in terms of classification accuracy. Different classes (bare-land, logged forest, shrubs, woodlands, and degraded forest) have been identified, and the ensemble learning approach for satellite forest image classification has been assessed by estimating image classification accuracy for different class labels. The rest of the paper is structured as follows. Section 2 deals with related work. Section 3 describes the flow of the proposed study. Section 4 describes the overview of the model architecture. Results and Discussion are presented in section 5. Section 6 concludes the paper.

2 Related studies

A study by [3] adopted the Random Forest (RF) algorithm to perform image classification on multi-spectral images obtained from Ikonos and QuickBoard data sets. The algorithm's performance was evaluated against results obtained from Gentle AdaBoost (GAB), Maximum Likelihood Classification (MLC), and Support Vector Machine (SVM) algorithms, and RF gave the best result compared to others. The major issue arising in their study was feature extraction. Features were generated using the Random Feature Selection technique. The main limitation of such a technique is giving equal or similar importance to correlated features. To solve this problem, the proposed study has adopted ResNet50 deep learning technique which excels at producing apt and specific features required to solve image classification problems.

[4] employed a deep learning supervised approach on Unmanned Aerial Vehicle (UAV) satellite images for forest area classification. The deep learning stacked Auto-encoder showed significant potential with regard to forest area classification accuracy. However, the major limitation of the deep learning model is that it requires high computational facilities as compared to machine learning algorithms. As a way of solving this challenge, this study is designed in such a way that the image classification process which is the major task that requires high computational capabilities is performed by the XGBoost machine learning algorithm, while the feature extraction part is performed by the ResNet50.

[5] developed a deep learning model for image classification of VHR (very high resolution) images obtained using UAV. The study was against the backdrop that UAV data sets have been found to be very useful for forest feature

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identification attributed to their high spatial resolution. Pre-processed data sets of forests of Nagli area were used for the study. The deep learning model incorporated a stacked Auto-encoder to perform image classification. Results showed that the deep learning technique outperformed other machine learning algorithms in terms of accuracy. Through Cross Validation the deep learning model achieved an accuracy 97%. The study's limitation was that it included all features for classification rather than only appropriate features, resulting in an overhead in terms of the model's time complexity. To address this problem, this study adopted the ResNet50 model to generate a set of features required for the forest image classification problem. The learning process of this model is such that the upper first layers are designed to learn general features and the last lower layers are designed to learn specific features. The final feature vector obtained from the ResNet50 model is specifically related to solving a specific classification problem.

When applied to image classification, traditional artificial neural networks, and machine learning approaches face difficulties in processing massive images for feature extraction, resulting in low efficiency and classification accuracy [6]. [6] proposed a deep learning model for image classification with the goal of providing support for classifying large image datasets. The study discussed various types of convolutional neural networks and their applications in image processing. The model was refined by adjusting parameters for feature extraction and by undergoing a process of noise reduction. This study optimized the proposed deep learning model in order to improve the model's classification efficiency and accuracy. The proposed model outperformed other models such as AleXNet and LeNet in terms of classification accuracy. Classification accuracy was also assessed before and after the optimization of the deep learning model. The results revealed that the optimized model significantly improved image classification accuracy. However, the model had challenges in classifying dynamic targets in a complex environment.

Convolutional neural networks adopted under transfer learning usually compress high-resolution input images [7]. A downsampling operation like this usually results in information loss, which affects image classification accuracy. [7] proposed a CNN model based on wavelets domain inputs to solve this problem. During the image pre-processing stage, the wave packet transform was used to extract information from input images. Some subband image channels were chosen as inputs for conventional CNNs with the first several convolutional layers removed, allowing the networks to learn directly in the wavelet domain. The model achieved a classification improvement of 2.15% and 10.26%, respectively on Caltech-256 dataset and Describable Textures Dataset. However, the model suffered huge problems in terms of training costs due to wavelet transform operations that were applied to each image generated through the augmentation process. To address this issue in the proposed study, output images were obtained from the third batch normalization layer of the ResNet50 architecture, where an image would not have been significantly compressed. [8] used an object-based random forest algorithm to identify eight forest types from freely available remote sensing images in Wuhan, China. The images were obtained using Sen-

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tinel -1A, Sentinel -2A, and Landsat 8 sensors. Results obtained indicated that a single sensor cannot obtain satisfactory results. Phenological and topographic information were used in the hierarchical classification to improve discrimination between different forest types. The final forest-type map was obtained using a hierarchical strategy and had an overall accuracy of 82.78%. However, the model encountered the issue of misclassification on types with similar spectral characteristics. This issue is attributed to the study's use of only the NDVI as the primary feature indicator for image classification. This challenge again is addressed in this study by adopting the ResNet50 model.

3 Proposed Model

The study proposes a hybrid machine learning technique for forest-type image classification that combines convolutional deep learning, specifically ResNet50, and traditional machine learning (XGBoost). Convolutional neural networks are widely used in generating features for solving specific classification problems [9]. Therefore in the same vein, the ResNet50 model was adopted in this study to generate a set of features for the XGBoost to perform the image classification task. The XGBoost algorithm was adopted only to perform the image classification process task. Traditional machine learning algorithms outperform deep learning techniques in terms of classification accuracy for a limited data set. Hence the study adopted the XGBoost (machine learning algorithm) to perform the classification task. Because the study uses limited forest images, the basic idea of the model is that CNN produces a feature vector, and then the XGBoost performs the image classification process. Traditional machine learning algorithms used in image classification include Support Vector Machines (SVM), decision trees (DT), extreme gradient boost (XGBoost), random forest (RF), and k-nearest neighbor (KNN). [10] conducted a study to compare the efficacy and effectiveness of LGBM and XGBoost in remote sensing image classification to RF, KNN, and SVM. Efficacy levels of XGBoost and LGBM were above 90%, while the other algorithms had efficacy levels below 90%. It is against this backdrop that the proposed model has advocated towards XGBoost. The ensemble model was used to perform multi-label image classification on forest images from the categories of logged forest, bare land, degraded forest, woodlands, shrubs, and grassland. The proposed algorithm is shown in figure 1. The proposed ensemble learning approach for multi-label image classification has the following key features.

- ResNet50 is adopted under the transfer learning technique
- ResNet50 is used for feature extraction and XGBoost is used to perform the classification task.

3.1 Multi-label Image Classification

Multi-label classification is when a test forest image is assigned to a correct category from a set of categories. Fine-tuning done to the model to enable the

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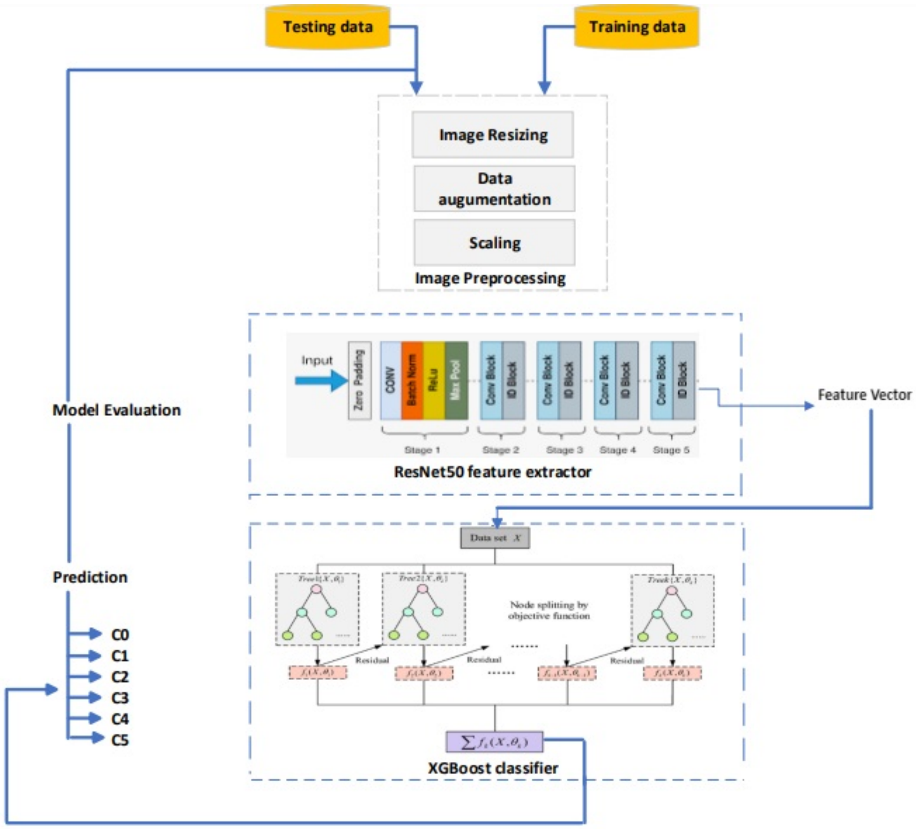

Fig. 1: Proposed ensemble hybrid algorithm for forest image classification.

classification processes involves converting class label strings to integer discrete values. Such conversion is made possible by applying the transform LabelEncoder function adopted from sklearn in Python on the class label vector set. The inverse transform function was invoked in the prediction phase for visualization purpose. Figure 2 shows a sample of forest-type image data set that was used in the study.

3.2 Pre-processing

Since there is no publicly available forest image data set [11], different types of forest images were obtained from the internet. All images were resized to 256 X 256 pixels since the images were of different sizes. Class labels were used as categorical data in this study, and the label encoder technique was used to convert non-numeric categorical data to numeric values. The class labels were transformed into a vector of values 0 through 5. Most machine learning algorithms require labels to numerical integer values. Table 1 represents the labeled

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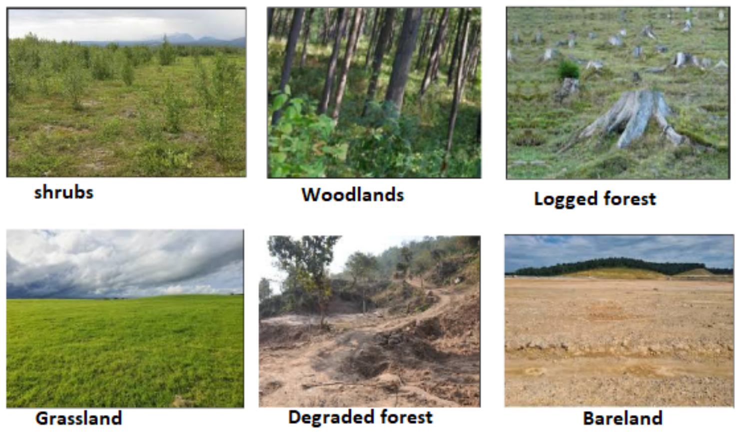

Fig. 2: Sample of forest type image dataset.

classes. Scaling features in machine learning is one of the most critical steps in

Table 1: Labels of forest type images

Value	Class
0	bareland
1	degraded forest
2	grassland
3	woodlands
4	logged forest
5	shrubs

pre-processing of data as most models are sensitive to the magnitude of features. Scaling refers to bringing all values to a uniform scale. All images were scaled by dividing image pixel values by 255 since the images were 8-bit images such that the scaling was in the range between 0 and 1. Data augmentation is a process of generating more image data sets from already existing images. 30 images for each category were downloaded from the internet and 90 more images respectively were generated through the data augmentation process with settings prescribed in table 2. The forest image data set was split in a way that 80% was reserved for training and 20% for testing.

4 Overview of the Model Architecture

This section provides a description of algorithms that were harmonized together to form the proposed hybrid model.

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Table 2: Data Augmentation Properties

Property	Value
rotation_ range	45
width_shift_range	0.2
height_shift_range	0.2
zoom_range	0.2
horizontal_flip	True
fill_mode	reflect

4.1 The XGBOOST algorithm

XGBoost has become predominant in the fraternity of machine learning. It is highly preferred as an alternative to Light Gradient Boost Machines (LGBMs) due to its high execution speed and performance. During the CPU's running time, the XGBoost algorithm employs a parallel computing technique for subsequent tree construction. It uses the 'maxdepth' criteria, instead of the traditional stopping criterion first, and the tree pruning process is initiated from a backward direction. Such a technique significantly improves the computational speed of XGBoost over other LGBM frameworks. Another strength of XGBoost is that it uses the training loss function to automatically learn the best missing values, hence it has the ability to handle different sparsity patterns in the data provided as input efficiently. The XGBoost algorithm uses the following equations for classification:

$$x(t) \approx x(s) + x'(s)(t-a) + \frac{1}{2}x^n(s)(t-s)^2, \tag{1}$$

$$\zeta \simeq \sum_{i=1}^{n}[l(q_i, q^{t-1}) + r_i x_t(t_i) + \frac{1}{2}s_i x_t^2(m_i)] + \omega(x_t + C), \tag{2}$$

Where C is constant, m_i is the input, Ω(x) is the complexity of the tree. r_i and s_i are defined as follows:

$$r_i = \delta \hat{z}_i^{(b-1)}. \int (z_i \hat{z}_i^{n(b-1)}, \tag{3}$$

$$s_i = \delta \hat{z}_i^{(b-1)}. \int (z_i \hat{z}_i^{n(b-1)}, \tag{4}$$

Where z_i represents the real value obtained from the training data set. [12] conducted a comparative performance assessment of the XGBoost algorithm, random forest, logistic regression, and standard gradient boosting, and the XGBoost algorithm was found to be most efficient against all other algorithms. It is against this backdrop that the study has settled for the XGBoost technique.

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4.2 ResNet50 Network Architecture

A CNN composed of 50 layers is referred to as ResNet-50. Such a deep network with so many layers suffer from network degradation problem. The network is made up of stalked residual blocks. It performs its function with identity shortcut connections that jump one or more layers during the training phase using the residual connections. Intermediate layers have the learning ability to self-adjust their weights to values closer to zero such that the residual block becomes an identity function. The residual skip connections in the ResNet50 architecture helps solves the problem of vanishing gradient experienced in deep neural networks. It is against this backdrop that the study has adopted the ResNet50 model in the framework. Due to the limited labeled training data set, the study sped up the learning process by adopting the ResNet50 under the transfer learning technique pre-trained on the ImageNet database. ResNet50 architecture is widely known for producing good features for solving classification problems. Features are produced in a way that the upper learns lower-level features and lower layers learn specific features.

5 Metrics for the study

The multi-class classification evaluation metrics used are accuracy, precision, recall, F1-score, mean average error, root mean square, and confusion matrix. Mean Absolute Error is a measure of the difference between the predicted value and the actual value. It gives an error associated with a predicted image

The root mean square error (RMSE) and the mean absolute error (MAE)are two widely standard metrics used to assess the performance of a model. MEA gives an error associated with a predicted image while RMSE as the name suggests gives the mean square of all errors. Considering a set of m observations $x(x_i, i = 1, 2, 3...m)$ and the corresponding model predictions $\hat{x}$ the MAE and RMSE are

$$MAE = \frac{1}{m}\sum_{i=1}^{m}|x_i - \hat{x}_i| \tag{5}$$

$$RMSE = \frac{1}{m}\sqrt{\sum_{i=1}^{m}(x_i - \hat{x_i})^2} \tag{6}$$

Precision being closely related to the measure of quality and recall to the measure of quantity, these two metrics are expressed as follows:

$$precision = \frac{TP}{TP + FP} \tag{7}$$

$$recall = \frac{TP}{TP + FN} \tag{8}$$

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Where TP is true positives, FP denotes false positives and FP denotes false negatives. F1-Score calculates the harmonic average between recall and precision rates and is expressed as follows:

$$F1 - Score = 2 * \frac{precision * recall}{precision + recall} \tag{9}$$

Accuracy is the overall measure of the model performance and it is expressed as:

$$accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{10}$$

6 Results and Discussion

Discussion and results obtained by the study are presented in this section. Table

Table 3: Metrics for Random Forest

Label	Precision	Recall	F1-Score
0	0.88	0.54	0.67
1	0.50	0.55	0.52
2	0.67	0.80	0.73
3	0.78	0.70	0.74
4	0.71	0.85	0.77
5	0.83	1.00	0.88

3 shows that the RF algorithm returns the highest precision for category 0 and subsequently followed by category 5, 3, and 4 respectively, and performed poorly for category 1. Precision is also referred to as the measure of quality. Most of the images in Category 1 were misclassified into Category 0 and this is most likely due to image ambiguity between bare land and degraded forests. However, for recall, category 5 received the most relevant images followed by categories 4, 2, and 3 respectively. Recall is also referred to as the measure of quantity. F1-score provides a balance between precision and recall in relation to positive classes. RF achieved the highest F1-Score for category 5, followed by categories 4, 3, 2, and 1 respectively. Table 4 shows that XGBoost obtained high precision for category 0 with 0.86, i.e slightly lower than RF. Categories 2, 3, and 4 obtained good quality results in terms of precision as all the scores are above 0.7. Similar to the RF algorithm, the XGBoost algorithm obtained poor results for category 1, and the same reason attributed to poor results in category 1 in RF is also attributed here. The general performance of XGBoost in terms of recall and F1-score is generally the same as with RF. Table 5 shows that LGBM performed poorly for category 1 in terms of precision, recall, and F1- score. That is, the algorithms failed to distinguish clearly between bare land and degraded forests. For the remaining categories, the algorithm obtained good promising results because on

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Table 4: Metrics for XGBoost

Label	Precision	Recall	F1-Score
0	0.86	0.69	0.77
1	0.50	0.64	0.56
2	0.82	0.70	0.76
3	0.82	0.70	0.76
4	0.75	0.90	0.82
5	0.79	0.95	0.86

Table 5: Metrics for LGBM

Label	Precision	Recall	F1-Score
0	0.75	0.69	0.72
1	0.33	0.18	0.24
2	0.78	0.70	0.74
3	0.82	0.70	0.76
4	0.63	0.85	0.72
5	0.80	1.00	0.89

average the values obtained were above 70% for all the metrics. The performance of a fully linked ResNet50 was subpar in comparison to that of other classifiers. As presented in Table 6, the model performed the poorest in Category 1 as it registered a zero for all the metrics.

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Table 6: Metrics for ResNet50

Label	Precision	Recall	F1-Score
0	0.37	0.38	0.38
1	0.00	0.00	0.00
2	0.44	0.60	0.51
3	0.75	0.75	0.75
4	0.76	0.65	0.70
5	0.76	0.95	0.84

Table 7: Metrics for Classifiers

Classifier	MAE	RMSE	Accuracy
Random Forest	0.63	1.86	0.74
XGBoost	0.56	1.30	0.77
LGBM	0.67	0.40	0.73
ResNet50	0.97	1.68	0.59

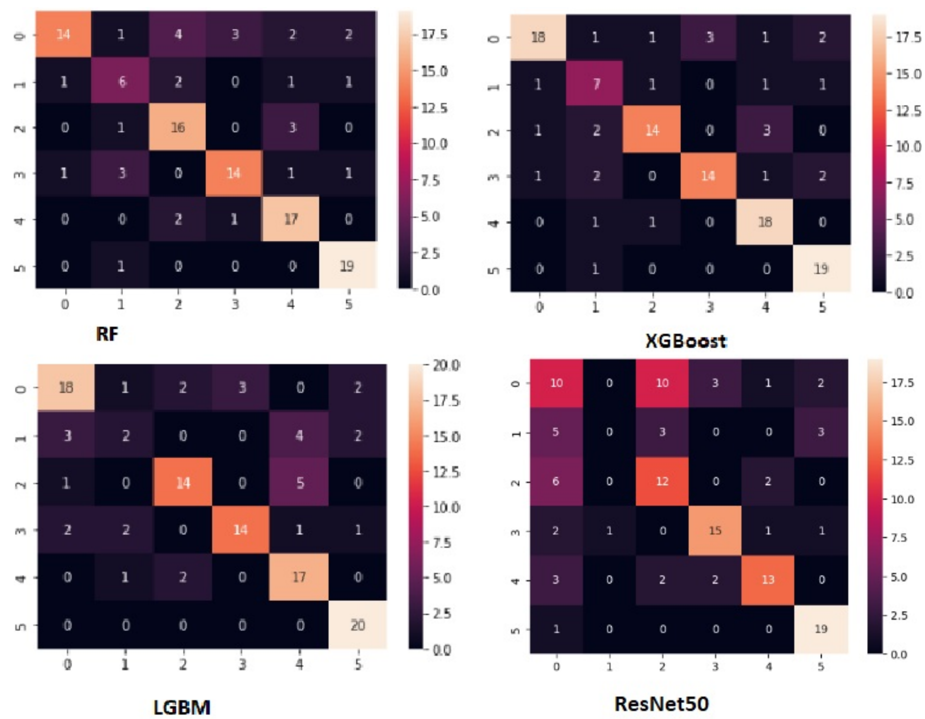

Fig. 3: Confusion Matrix results obtained from RF, XGBoost, LGBM, and ResNet50.

Accuracy, MAE, and RSME are the most commonly used metrics to evaluate the performance of the model. The hybrid model with XGBoost outperformed

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the other algorithms in terms of Accuracy, MAE, and RMSE, which obtained values of 0.77, 0.56, and 1.30, respectively. Our proposed model's accuracy outperformed the model proposed by [13]. The model used CNN and Multitemporal High-Resolution Remote Sensing Images to classify individual Tree Species and it obtained an overall accuracy of 75.1% for seven tree species using only the WorldView-3 image data set. The classification accuracy of our proposed model also performed better compared to the results obtained by [14]. Their study achieved a classification accuracy of 68% for classifying multispectral images using Support Vector Machine (SVM). However, the ResNet50 deep learning model proposed by [15] for classifying forest image data set outperformed our model as it achieved an accuracy of 92% for classifying forest images belonging to 3 categories. Such high accuracy could be attributed to the fact that the model was applied on only 3 categories whilst our model was applied to 6 different categories. The performance of a classification algorithm is reflected in a two-dimensional table called the confusion matrix. It is important for summarizing and visualizing a classification algorithm's results. The confusion matrix results as presented in Figure 3 show that there was high misclassification for category 1 by all the algorithms, with the worst performance by ResNet50. Apart from Category 1, the performance of LGBM and XGBoost in the other categories is generally the same.

7 Conclusion

An ensemble learning approach of ResNet50 and XGBoost was developed to classify forest images into their respective categories. ReNet50 adopted under the transfer learning technique was used as a feature generator, while the XGBoost algorithm was used to perform the forest image classification process. The model was evaluated against a fully connected ResNet50 and other baseline classifiers such as LGBM and Random Forest. The proposed ensemble learning technique achieved a classification accuracy of 77%. Therefore the proposed model in this study can be used to classify forest images since it recorded high classification accuracy and low RMSE and MAE values as compared to other classifiers. For future studies, it is recommended to incorporate an ensemble stack of CNNs for generating plausible features for subsequent image classification. This approach would significantly increase the scope of features required to perform the image classification process.

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