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Watermarking-Enabled VGG19 for Accurate Land Cover Classification in Satellite Imagery

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Abstract
Analysing land use and land cover images (LULC) plays a role in applications such as monitoring, managing natural resources and responding to disasters. This research investigates the effectiveness of using the VGG19 model and the Adam optimizer to classify satellite images into four habitat categories: cloudy, desert, green area, and water. By working with a dataset of 5631 photos from sensors and Google Maps snapshots transfer learning is employed to tailor the trained VGG19 model for this specific classification task. Through experimentation involving preparation, model training and evaluation an impressive accuracy score of 98.2% was achieved. Visual aids like graphs showing accuracy and loss trends, a confusion matrix, and performance parameter calculations were used to highlight the robustness and reliability of the model. This research contributes to enhancing automated processing of satellite images providing insights, for monitoring, urban planning, and disaster response efforts. Future studies could focus on improving classification accuracy and efficiency in satellite image analysis by exploring the scalability, adaptability, and integration of deep learning architectures.

Keywords— Land use and land cover, satellite image classification, VGG19, transfer learning

1. Introduction

Satellite image classification, essential to fields like agriculture and disaster relief, involves automatically interpreting and categorizing satellite imagery. This task has become more feasible and efficient as these images proliferate and deep learning techniques advance [1]. The extensive 5631-photo dataset, compiled from various sensors and Google Maps, guarantees a rich depiction of land cover and conditions. By using the deep, resilient VGG19 model to classify images into cloudy, desert, green area, and water categories, the forefront of digital image processing enables more fields to leverage satellite data efficiently [2]. By employing transfer learning, VGG19 architecture, initially trained on the ImageNet dataset, becomes a starting point for modifying feature extraction features pertinent to satellite imagery classification problem on hand [3]. This method not only has the effect of fastening the model training but also the improvement of its generalization [4], so that the optimization of classification can be carried out more accurately and validly.

The careful division of the dataset into training and testing sets at a ratio of 75:25 was carried out. It enables us to examine model's performance from different angles and reduces the likelihood of model overfitting [5] to the existing data. Such a process increases the quality of the training calibre while making the model capable of recognizing the multitude of variabilities that may characterize satellite images [6].

The Adam optimizer, a model-famous choice for its effect and the versatility, is used in the training stage to work out the categorical cross-entropy loss function with minimal value [7]. Introducing the procedure of adaptation of the model parameters therefore resulted in the acceleration of learning and the enhancement of overall performance through this optimization method. The change in accuracy and loss metrics during the learning process is monitored to spot possible prevention measures that might be employed in order to monitor the dynamics of the learning and the model convergence. Based on these visualizations, adjustments in strategies and hyperparameters can be made, which as a result lead to the model becoming better at discovering patterns and predicting features from satellite images. Thus, the confusion matrix [8] is subsequently utilized at the testing phase to examine the performance of the trained model thoroughly. This confusion matrix is a tabular form of data predictions in which the model efficacy across various classes is thoroughly evaluated by using important performance measures, such as accuracy, precision, and F1 score. It is possible to figure out whether the model is good or not in the case of satellite imagery and the identification of varied land covers, based on the outcome of these metrics. A succession of transfer learning, data augmentation and optimization methods were used. The results for the VGG19 model are summarized and demonstrated as having the potential to be precise and effective for classification tasks of satellite imagery. This study clearly emphasizes the profound impact of deep learning on image processing that is going on digitally and remote sensing as well as on an image analysis to be conducted automatically by satellites enabling the monitoring and decision making in a variety of fields [9].

2. Related Work

Recently, LULC categorization using ML and DL techniques has garnered a lot of attention from the remote sensing field. The topic of how to use machine learning models reliably and effectively for categorization has been the subject of numerous studies. This section provides an in-depth assessment of recent LULC classification research, illustrating significant approaches, findings, and breakthroughs in the field.

Talukdar et al. [10] undertook a comprehensive investigation to examine the outcomes of six machine learning algorithms for LULC classification. The study evaluated algorithms including RF, SVM, ANN, Fuzzy ARTMAP, SAM and MD. They used methods like Kappa coefficient, ROC analysis, index-based validation and RMSE to assess accuracy. While all models showed levels of accuracy, with variations RF performed the best with a score of 0.89 whereas MD had the lowest accuracy at 0.82. Moreover, the index-based land use/land cover (LULC) validation results indicated that RF outperformed models, in terms of accuracy.

In contrast, Vali et al. [11] provided a full overview of the use of deep learning algorithms in LULC classification, with a special emphasis on multispectral and hyperspectral data. The paper analysed accessible data sources and datasets exploited in empirical research, as well as providing readers with a framework for judging the present degree of deep learning in this context. The review presented insights into methodology, data, and difficulties observed in the sector, underlining the potential of deep learning techniques to change LULC categorization. DeFries et al. [12] looked at the performance of decision tree classifiers, that comprise a basic decision tree written in C5.0 and two techniques termed as "bagging" and "boosting." The study used these methods on two datasets: a worldwide land cover classification using 8 km AVHRR data and a Peruvian Landsat Thematic Mapper scene. The outcomes showed that the three kinds of decision tree algorithms had comparable accuracy, with boosting producing marginally improved accuracies. However, both bagging and boosting algorithms surpassed the usual decision tree in terms of stability and resilience to noise in the training data. The study underlined the significance of considering aspects other than usual accuracy measurements when picking on the ideal algorithm, highlighting the trade-offs between algorithm performance and processing resources. Qian et al. [13] investigated the effectiveness of four machine learning classifiers—SVM, NB, CART, and KNN—for categorizing very high-resolution photographs using an object-based classification technique. The study looked at the influence of tuning parameters and training samples on classification accuracy. The results suggested that SVM and NB topped CART and KNN, both obtaining remarkable accuracy for classification (>90%). Furthermore, the study indicated that altering parameters had a major impact on classification accuracy, specifically for the SVM classifier. Furthermore, the size of the training sample was found to have a major impact on classification performance, with bigger sample sizes providing higher accuracies for all four classifiers. Keshtkar et al. [14] assessed pixel-based random forest and decision tree classifiers to a support vector machine in land cover classification utilizing both pixel-based and object-based approaches. The study discovered that the object based SVM classifier had the highest overall accuracy of 93.54% and a kappa value of 0.88. The study also applied a post-classification change detection technique to explore spatiotemporal land cover changes throughout two decades. The study detected large changes in land cover dynamics over time, particularly in built-up locations, underlining the importance for continued monitoring.

McIver et al. [15] published a method for estimating the confidence in the classification of pixel-level land cover by utilizing nonparametric machine learning techniques. The method is founded upon recent theoretical advancements in the fields of statistics and machine learning, which elucidate the similarities between the boosting methodology and additive logistic regression. Pixels that achieved accurate classifications exhibited greater levels of confidence, according to the study, in contrast to pixels that tended to have lower levels of confidence despite incorrect classifications. The proposed approach generated valuable insights concerning the evaluation of classification uncertainty and accuracy. Additionally, it generated geographically explicit maps that depicted the quality of classification. Four non-parametric approaches were compared by Mohamed Abdi et al. [16] for LULC classification: SVM, RF, Xgboost, and DL. Sentinel-2 multi-temporal imagery representing a difficult mixed-use area in south-central Sweden was employed in the study. The results revealed that severe gradient boosting was closely followed by SVM, which had the highest overall accuracy. The study made evident how crucial it is to assess classifier performance by taking into consideration both overall accuracy and class-specific predictions. Scott et al. [17] researched into the categorization of land cover in high-resolution remote sensing data using deep convolutional neural networks (DCNN). Using the UC Merced dataset, the study used data augmentation and transfer learning methodologies to achieve significant classification accuracies. Findings indicated that multiple DCNN architectures could obtain classification accuracies of 97.6% to 98.5%, underlining the utility of deep learning algorithms for remote sensing image classification applications. For LULC classification over remote sensing data, Carranza-García et al.

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[18] presented a general CNN, which performed better than existing machine learning algorithms. The experiment proved that the CNN can acquire great accuracy on a variety of datasets, despite the changes in their properties. The outcomes demonstrated the deep learning techniques' capacity for remote sensing applications, especially in terms of precise and trustworthy land cover classification.

Machine learning techniques and algorithms, from deep learning approaches like DCNNs to more conventional classifiers like RF and SVM, have developed substantially in recent LULC classification research. These studies have proved how crucial it is to take into account a variety of elements when determining the ideal classifier for a certain job, including tuning parameters, training sample sizes, and algorithm stability. Furthermore, the utilization of high-resolution, multi-temporal imaging in conjunction with unique methods like data augmentation and transfer learning has increased classification accuracy and dependability in remote sensing applications.

3. METHODOLOGY

Nowadays in real-life remote sensing projects there is a major problem of classification of satellite images which requires following a strategy that would include, model selection, dataset preparation, and optimization techniques for ultimate success. The presented approach involves categorizing satellite images based on the VGG19 model and Adam optimizer. This is done to make sure that the dataset which is generated to be the one that is robust enough to be representative, will make use of the features of the VGG19 model hence and the parameters of our model will also be adjusted using the Adam optimizer. The final aim is to construct a method to classify satellite images, for the accurate classification of various land cover types.

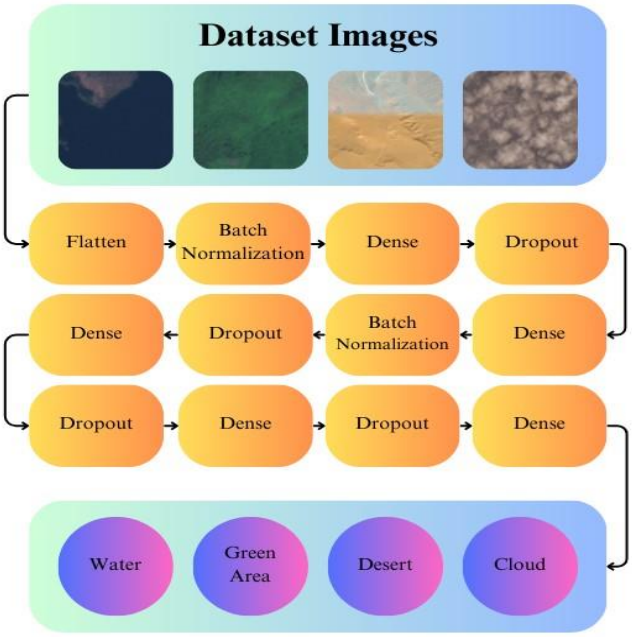

Fig. 1 Methodology Flow

A. Dataset Description

This research examines 5631 satellite images with the aim of producing a sample of the wide diversity of land cover types and environmental conditions that reflect the peculiar natural features of the environment. The multitude of images were shot by using a variety of sensors as well as Google Maps snapshots in order to provide a clear representation of landscape and regions from different places. The collection is divided into four distinct groups: cloudy, desert, green vegetation, and landscape with water. Within these localities are relatively homogenous settlements suited to the primary land cover types that are characteristic of observable satellite imagery analysis.

Through the application of data augmentation approaches, for instance, rotation, flipping and zooming, to the dataset a great deal of diversity was achieved which had a positive influence on the model's ability to extrapolate to the new dataset. To make sure that every class was not only evenly represented in the dataset as a whole but also in both the train and test sets, the dataset is stratified in a split ratio of 75:25. The 75% of the dataset has been used for training of the VGG19 model, while the remaining 25% has been left out to evaluate the performance of the model. The partitioning solution is critical to reduce the chances for overfitting, then the model will be able to perform well and also respond to unknown data effectively, which leads to an enhanced model evaluation. That is precisely what is done by giving multiple types of data to create a machine and test that machine. An example of the used images of the input dataset is given in Figure 2.

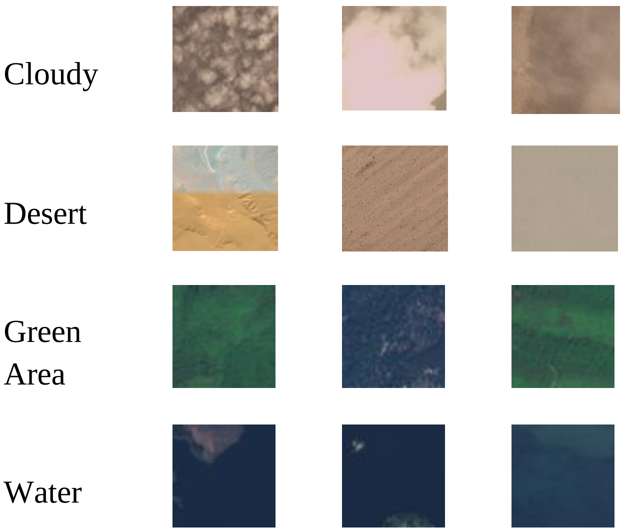

Fig. 2 Dataset Images

B. VGG19

The VGG19 network is the main architecture on which the satellite images were being classified. Being both simple and deep, it is also very well-known and prominent. The architecture can find that special detailing of the satellites' scale and views, which are in satellite images. Transfer learning is used to optimize the VGG19 model that is already established for use in the classification job. At the beginning, the model is trained on the ImageNet dataset, which is a large collection of images having a million of annotated images and thousands of categories. The main aim is using VGG19's architecture to have it as a basis model for satellite image recognition, obtaining the skills applied from general images classes for special satellite scenes. The word transfer learning demonstrates the fact that, while training the convolutional layers of the VGG19 model, its parameters are not allowed to be changed. At this stage, this model serves as the feature extractor. This makes possible the selection of features that are appropriate for objects and landscape representing them in plans.

C. Adam Optimizer

Another apparently significant emphasis in the research is the application of the Adam optimizer to diminish the value of the categorical cross-entropy function. The optimizer that is highly efficient known as Adaptive Moment Estimation (Adam) which inherits the best features from adaptive feature of AdaGrad and RMSProp holds momentum. Adam runs equivalent over the multi-dimensional parameter space by selectively varying the learning rate for each of the parameter, and that a balance is achieved by which the rate of training is greatly increased but convergence is also accelerated. This involves model choice, data cleaning, and the examining of various optimization methods, all of which are critical tools of research.

4. RESULT

The evaluation of the proposed transfer learning approach by using the VGG19 model with fine-tuning layers for the classification of satellite images was done through the use of various techniques including accuracy plot, loss plot, and confusion matrix. Furthermore, certain quantitative performance measures were derived for the verification of the performance of the model.

D. Accuracy Plot

The accuracy plot demonstrates how model performance measured in terms of classification accuracy shifts throughout the training session. Model accuracy is increased consistently over the intermission of epochs, representing the generalization the model acquires to memorize, process, and absorb unique features of training set through increasing completion of epochs. The exponential increase in the accuracy plot implies how well model's parameters converge in the end analytically speaking, which as a result, achieves an extremely high accuracy.

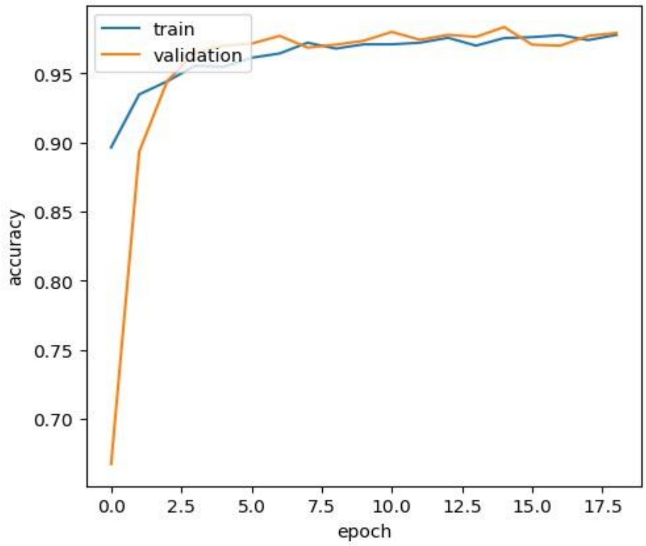

Fig. 3 Accuracy Plot

E. Loss Plot

The Loss plot tracks the learning curve of the model through variation of loss function during successive epochs while learning. The rate of errors declines impressively during the training, so it is obvious that the period is more appropriate for making lesser mistakes and delivering accurate forecasts. The line graph is constantly reducing, and this signifies that, in essence, the model is increasingly successful at the convergence and extraction processes as it brings to the fore the most important features present in the satellite photos.

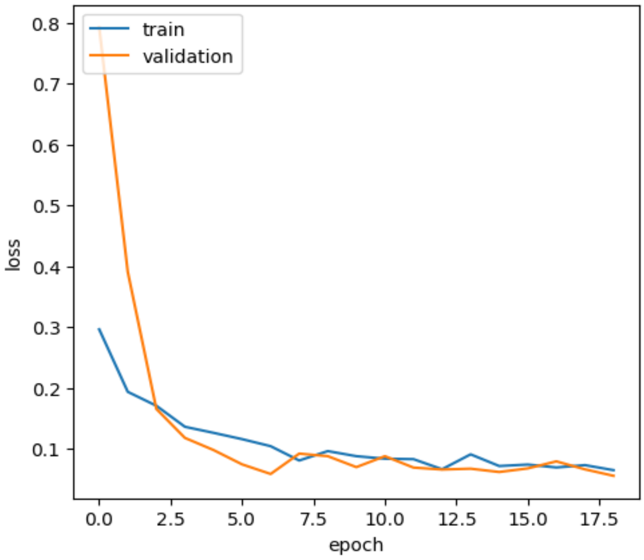

Fig. 4 Loss Plot

F. Confusion Matrix

The Confusion Matrix assesses the model performance across the period from the multivariate data and land cover classification. The horizontal rows display the real class labels, while all the columns had, display the predicted class labels. Through the confusion matrix we can gain an insight into how good the model is in its capacity to classify between classes and identify possible future misclassification hotspots. By exploring changes in the off-diagonal components of the matrix, when matrices are compared, we can see how misclassifications have been minimized and where cases have been accurately labelled. One of the valuable practices noted for the reliability of the model and catching bad performance is the confusion matrix.

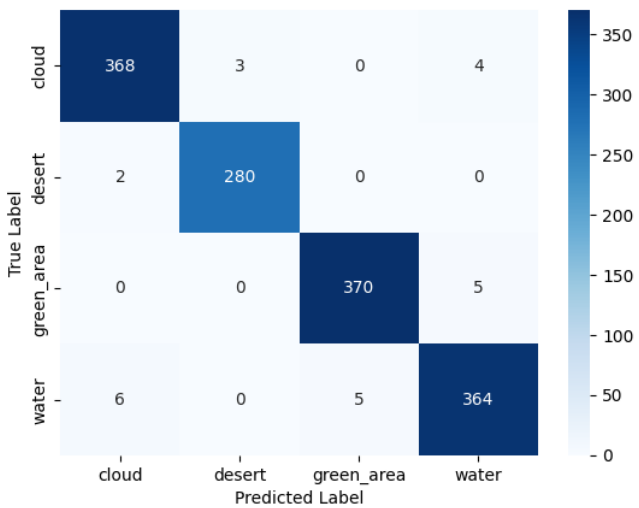

Fig. 5 Confusion Matrix

G. Performance Parameters

Crucial performance metrics, like recall, accuracy and F1 score appear from the confusion matrix concerning the classes. Though accuracy denotes the percentage of accurately predicted samples out of all included observation examples that are predicted to belong to a particular class, recall calculates the number of correctly categorized samples among all instances that belong to a specific class. F1 score, the primary measure of accuracy that averages precision and recall gives a comprehensive overview of the model's performance. Table 1 presents the performance parameters of the VGG19 model with fine-tuning layers.

TABLE I. PERFORMANCE PARAMETERS

Classes	Precision	Recall	F1 Score	Accuracy
Cloudy	0.98	0.98	0.98	0.982
Desert	0.99	0.99	0.99	
Green_Area	0.98	0.98	0.98	
Water	0.97	0.97	0.97	

5. CONCLUSION

Conclusively, the research shows that the VGG19 model having the Adam optimizer applied to, is appropriate for identifying satellite images with a remarkable 98.2% accuracy. The satellite images were studied in detail by conducting massive dataset processing, model building, and assessment. Therefore, the study presents a strong type of architecture that enables the researchers to divide the images into simple zones of different landscape applications. The metrics and figures illustrating classifications' accuracy, loss plots, confusion matrix and the model performance parameters show its reliability and usefulness in environmental monitoring, urban planning and response to disasters.

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