Enhancing Satellite Remote Sensing Image Classification using Two Layer Convolutional Neural Network

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ABSTRACT
Due to the recent advancements in deep learning techniques, image classification based on Convolutional Neural Networks (CNN) has acquired an important place in various applications of remote sensing data. Tracking clouds for weather prediction, vegetation, wildlife, prior prediction of hurricanes, storms, and environment monitoring are a few of remote sensing applications in different domains. Still, all these applications require the identification and classification of images. Researchers have been implementing various strategies for classifying the images so that more accurate and appropriate techniques in hand for different applications. The experiment focuses on enhancing the existing accuracy by proposing a novel architecture for classification. In this paper, a novel CNN architecture for classifying 5631 images (Cloudy, Desert, Water, Green area) has been proposed. The proposed model has achieved an overall accuracy of 99.11%, which is better than any traditional approach.

Keywords
Machine Learning, Deep Learning, Classification, Remote Sensing, Convolutional Neural Networks.

1. INTRODUCTION
Remote Sensing is collecting information about an object from a certain distance without any physical contact with that object. Remote sensing is mostly associated with monitoring and collecting data about the Earth through aircraft and satellites. Different Sensors and radiations are used for the investigation and this technique has found its application in monitoring isolated and dangerous regions like dense Amazon forests, Glaciers, long-spread deserts, oceans, etc [1]. Different classification methods are presently available, Using the intensity of the pixel for interpretation is a traditional approach while classifying the images using semantic analysis is a modern method.

There are three broad categories of image classification: The Feature-Based method uses different properties of the image like colors, and shape to train the machine learning classifier. The unsupervised Feature Learning method focuses on basic functions like a bag of Words. The third is the Deep Learning Model which is a subfield of Machine learning. Deep learning is an emerging technology used nowadays for the classification of remote-sensing data [2].

The Deep Learning method further consists of Transfer learning techniques and Convolutional Neural Networks. CNN is a type of Neural Network which has a nonlinear function acting on each layer. The architecture of CNN is defined by several feature extraction layers one after another having a pooling layer in between to reduce the dimensions of the feature map. CNN is a feed-forward neural network. Transfer learning is a kind of state of art of Convolutional Neural Network. It is a technique where a pre-trained model is used to solve a new problem. Some Examples are SqueezeNet [3], AlexNet, GoogleNet [4], VGG-16 [5], ResNet [6], [7]. Digital image classification is considered one of the most used applications in the field of remote sensing because it serves the purpose of extracting distinct classes of landscape categories from data obtained as a result of remote sensing [8].

In this work, Deep Learning based Convolutional Neural Network that can classify different satellite images has been developed. The model can classify Cloudy, Desert, Water, and Green area images accurately and efficiently. The results obtained after the evaluation of the proposed model are highly encouraging to implement this model in different applications of Satellite Remote Sensing Image Recognition.

2. RELATED LITERATURE
Image classification using deep learning techniques has found its application [9] ranging from the medical health industry [10], [11], traffic control systems [12], satellite images [13], gaming applications, landscape categorization, etc. In recent years, during the pandemic, CNN was widely used for detecting Covid-19 using Radiological images [14]–[16]. Satellite Image Classification has been used since the beginning of AI when different algorithms were proposed that were based on Biogeography. In [17]

Biogeography image classification has been done to study the geographical distribution of different biological organisms. [17] added the functionality of clustering in the BBO algorithm that is not inherently present in such algorithms, as a result of which the Algorithm was able to extract highly accurate landcover features. The swarm data clustering method has been used for classifying satellite images. This swarm data clustering uses an artificial method of flower pollination by

artificial bees so, as to make clusters of satellite image pixels, this clustering method was followed by biogeography-based optimization [18].
The main problem with satellite images is to search for objects, facilities, and events of interest because of the diversity of the data. Different traditional algorithms failed or proved to be unreliable in classifying huge datasets into a set of classes. Deep learning with its unlimited capabilities is the only solution. [19] is one of the attempts to solve the problem of object identification and event classification, [19] proposed an ensemble of convolutional neural networks along with an additional neural network to classify the satellite images into 63 different classes, where 83% accuracy was achieved. Remote sensing data along with the application of deep learning can also help in a natural disaster. Different remote sensing sensors are deployed on different platforms to map the damage in the building caused by natural disasters [20]–[22]. A convolutional neural network using several convolutions and residual connections has been trained with multiresolution satellite and airborne image samples. Using both types of images helped to improve overall accuracy than those CNN which is trained only on satellite images. The proposed model is capable of classifying images of damaged buildings after natural calamities [23].
The overall aim of remote sensing is to develop an intelligent earth observation system that allows one to automatically recognize, identify, and recommend the scene of interest, classification of land use and land cover scene is another important aspect [24]. Different applications have been made such as natural hazard detection [25]–[27], geospatial object detection, LULC determination [28], [29] , environment monitoring, weather prediction, vegetation mapping [30], construction monitoring, etc. A supervised workflow based on Object-oriented image analysis and machine learning algorithm to map landslides [26]. The proposed [26] work has achieved an accuracy of up to 87%. [25] has proposed multiscale classification to detect landslides using object-based image analysis. It can detect five different types of landslides with an accuracy of 76.9%.

3. MATERIALS AND METHODS

3.1 Dataset Description

The dataset consists of four classes of images namely Cloudy, Desert, Green Area, and Water. A total of 5631 images have been used where 1500 are cloud images, 1131 Desert images, 1500 are Green Area images, and 1500 are water images. The dataset was taken from the Kaggle repository https://www.kaggle.com/datasets/mahmoudreda55/satellite-image-classification.

3.2 Research Methodology

This section discusses in detail the overall workflow of the experiment, the steps involved in the experiment, and also the architecture of the proposed Neural Network. As discussed earlier, there are many existing methods for the classification of Remote sensing satellite images. There are several steps involved in the whole experiment, Beginning with the collection of the dataset followed by pre-processing of the data i.e. resizing images into 128x128, and all images were then converted into RGB Channel. After data preprocessing, the preprocessed data is split into 80% and 20% for training and testing respectively. In the next step training data is fed to the proposed model for training and after running 200 epochs, the trained model was deployed on testing data for evaluation of the model. The model is evaluated on different parameters that are given in the table. The whole procedure is represented in the form of a flowchart given in Figure 1. We employed a dataset of diverse satellite pictures from several sources for this study, each labeled with various categories of green landcover, such as forests, clouds, aquatic bodies, and dessert regions. The photos were normalized and standardized to 128 by 128 pixels. Data augmentation methods including random rotations, flips, and zooms is used to increase the variety of the training set and decrease overfitting. An input layer, two convolutional layers with ReLU activation and max-pooling, a flatten layer, a fully connected layer with 127 neurons, and a final output layer with softmax activation for classification comprises the Convolutional Neural Network (CNN) architecture created for this task. Accuracy, precision, recall, F1-score, and confusion matrix metrics were used to assess performance. On an NVIDIA GPU, experiments were performed with Python and packages like as TensorFlow and Keras. The robust and precise classification of satellite photos was assured by this methodical technique.

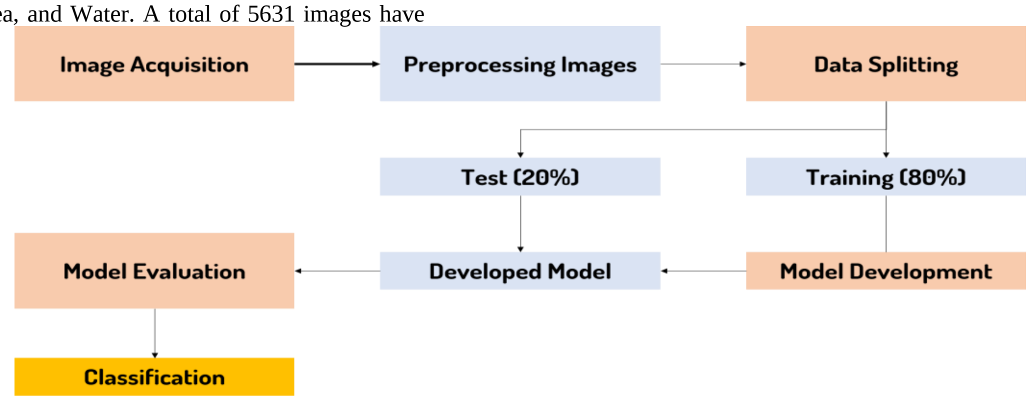

Figure 1: Work Flow Diagram of Experiment

3.2.1 Parameter Tunning

The images in the datasets are not of the same resolution. So, images were scaled to a fixed size of 128 x 128 pixels. The dataset used was randomly split into 80% and 20% for training and testing. To train the model 200 epochs were conducted to avoid the overfitting problem with a batch size of 25. Adamax optimizer has been used to enhance the learning rate of the model. The above-given parameters have been fixed for each convolutional layer. After successful training of the model, it can classify the image into four classes.

3.2.2 Model Description

The whole description of the model is given in Table 1. The shape of the convolutional layer, Kernel is given in the table while the parameter extracted by each layer is also given. The total number of parameters that are used for model training is more than 5 million and 1344 unused parameters are not used for the training.

4 EXPERIMENT EVALUATION AND RESULTS

Different parameters are available on which the proposed deep learning model can evaluate. For classification using a convolutional neural network, different researchers used different parameters for evaluation. The accuracy of any model is calculated by identifying the correctly predicted samples by the model to the total number of samples. The specificity of the model defines the model's capability to predict True negative for all available classes. The sensitivity of the Model defines the ability of a model to detect a positive sample. Precession is sometimes referred to as a measure of quality while Recall is referred to as a measure of quantity.

The proposed model is evaluated using metrics such as Precession, Recall, Specificity, F1-Score, and overall accuracy. The detailed performance using each parameter is given in Table 2. The model has correctly classified cloudy and dessert images with 100% precision, 100% Recall rate, 100% Specificity, and 100% F1-Score each. The model has achieved 97% precision, 100% Recall, 100% Specificity, and 98% F1-Score for Green areas. Alon with other classifications Model was able to achieve 100% Precision, 97% Recall, 100% Specificity, and 98% F1-score for water images. Overall 99.11% accuracy has been achieved by the model. All the parameters are calculated using the confusion matrix.

All the performance measuring parameters given in Table 2 are calculated using the Confusion matrix generated during the experiment. The confusion matrix used for the evaluation of the model is given in Figure 2.

Table 2: Performance Table

Label	Precision (in %)	Recall (in %)	Specificity (in %)	F1-Score (in %)	Overall Accuracy
Cloudy	100	100	100	100	**99.11%**
Desert	100	100	100	100	
Green Area	97	100	100	98	
Water	100	97	100	98	

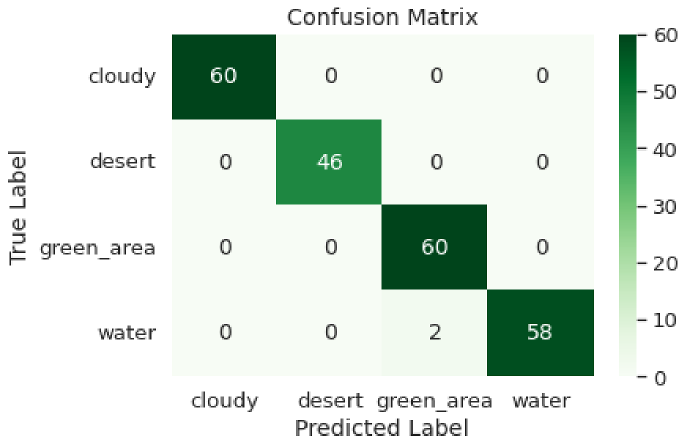

Figure 2: Confusion Matrix

The experiment was conducted to categorize Satellite Remote Sensing images into four different classes(Cloudy, Desert, Water, and Green Area). Performance Parameters have been used to check the effectiveness of the Model. The model's accuracy curve and Loss curve are given in Figure 3.

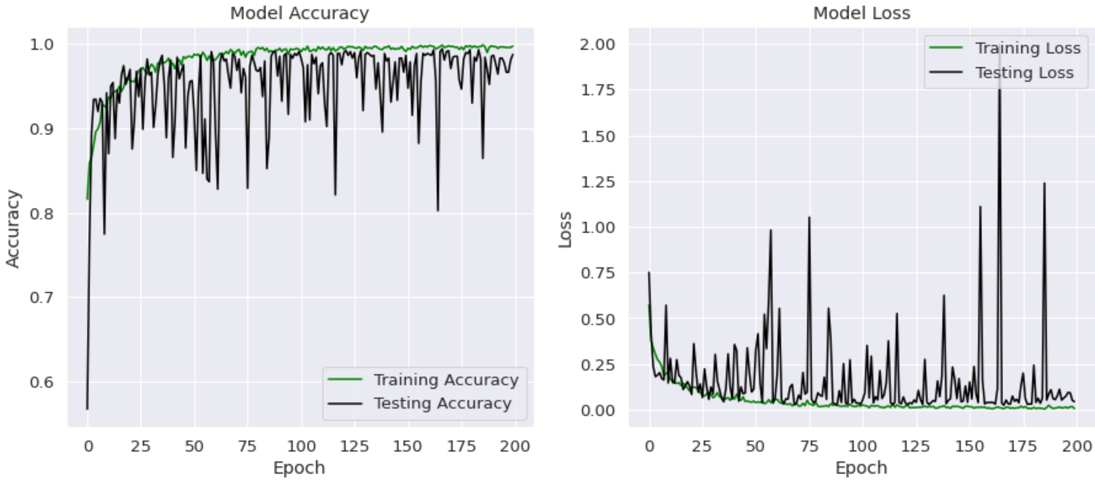

Figure 3: Accuracy and Loss curve

Table 1: Model Descriptions

Layer (type)	Output Shape	Param #
conv2d_10 (Conv2D)	(None, 127, 127, 32)	416
batch_normalization_15	(None, 127, 127, 32)	128
leaky_re_lu_22 (LeakyReLU)	(None, 127, 127, 32)	0
max_pooling2d_10 (MaxPoolin	(None, 63, 63, 32	0
conv2d_11 (Conv2D)	(None, 61, 61, 128)	36992
batch_normalization_16	(None, 61, 61, 128)	512
leaky_re_lu_23	(None, 61, 61, 128)	0
max_pooling2d_11	(None, 30, 30, 128)	0
flatten_5 (Flatten)	(None, 115200)	0
dense_17 (Dense)	(None, 512)	58982912
leaky_re_lu_24 (LeakyReLU	(None, 512)	0
dropout_14 (Dropout)	(None, 512)	0
batch_normalization_17	(None, 512)	2048
dropout_15 (Dropout)	(None, 512)	0
dense_18 (Dense)	(None, 4)	2052

5 DISCUSSION

The significant development in the field of machine learning technologies has made it possible to classify large numbers of images and automatically labeling of the data. However, there is a lack of publically available remote sensing data which limits AI in the field of remote sensing. Few available datasets have made it possible to progress in satellite image scene classification. The proposed method is one of the attempts to contribute to the field of Satellite image scene classification.

6 CONCLUSION AND FUTURE WORK

In this paper, a novel deep-learning architecture that classifies satellite images into Cloudy, Water, Green Areas, and Desert has been presented. On the dataset of 5631 images, the proposed model has achieved an overall accuracy of 99.11%. The model is trained on more than 5 million parameters. 100% Specificity has been achieved for each class of Satellite images. The Proposed architecture outperforms all available models for the classification of remote sensing data. Also, the proposed model has few parameters that make use of minimal computational resources to process high-resolution satellite data. The proposed method can be used for different applications of Remote sensing data. It can also be used for the development of automation systems.

Present work can be extended by adding a larger dataset of different classes so that the model can classify images into other classes as well. This work can be incorporated with automated tools for classification and object detection.

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