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CNN Architecture For Land Classification Using Satellite Images

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Abstract

Classifying land cover using satellite pictures is a crucial technique for researching terrestrial resources. Presently, several satellites, including Sentinel and Landsat 8, have captured enormous collections of high-resolution images that contain satellite-based data. Due to the vast quantity of data and variety of kinds, it is difficult to categorize the land cover in these images. Deep Neural Networks can categorize these massive volumes of data, which makes them quite helpful in this situation. Similar studies in the field, which need subject-matter expertise, relied on simpler models and a significant amount of manually constructed parameters. In this study, a deeper Convolutional Neural Network (CNN) model without any satellite imagespecific characteristics is proposed. On SAT4 and SAT6 pictures, our 10-layered network exhibits exceptional accuracy of up to 96 per cent. It is still referred to as a lightweight model because the majority of models in artificial intelligence (AI)-CNN are far bigger and deeper than ours [1]. Index Terms—sequential CNN, SAT4, SAT6, Convolutional Neural Networks, Remote Sensing, Satellite Image Classification.

Keywords: Sequential Cnn, Sat4, Sat6, Convolutional Neural Networks, Remote Sensing, Satellite Image Classification.

I. INTRODUCTION

The classification of large satellite images presents significant challenges in comprehending and representing information related to land cover. Land cover refers to the physical features that are present on the Earth's surface, including rivers, forests, crop fields, and barren lands. Accurate information about the land cover is crucial for categorizing, planning, monitoring, and making informed decisions regarding the use of earth's resources for the benefit of human mankind. Many geospatial applications, such as agriculture, environmental protection, and urban planning, heavily rely on this classification. Traditionally, field surveys have been conducted to gather information about land cover. However, these surveys are time-consuming, labour-intensive, and often result in outdated data. To overcome these limitations, satellite remote sensing images provide a practical solution for accurately determining land cover. Satellites offer a wide field of view and provide continuous coverage, enabling regular updates for planning purposes. However, raw satellite images cannot be directly processed due to the complex nature of the data. Satellite images consist of multiple spectral bands and vast amounts of information, making it challenging to distinguish between different land cover types. Additionally, the variability among various land cover classes further complicates the classification process. In summary, the classification of large satellite images for land cover analysis is crucial for government and other agencies involved in various applications. It provides accurate and current information for decision-making. Satellite remote sensing images offer a practical approach due to their wide coverage and regular updates. However, the complexity of the data and the variability among land cover classes pose significant challenges in accurately classifying and interpreting the images. The types of land cover are Agricultural, Baseball Diamond, Beach, Forest, Golf course, River and Runway. Two methods can be used to identify the land cover in these images, including Supervised learning and Unsupervised learning. When learning under supervision, data that has been labelled with the correct response is used for training. This prediction of unexpected data. Several methods used in satellite image processing fall under the category of supervised learning. These methods have the drawback of being difficult to scale to large amounts of data. Unsupervised learning algorithms are becoming more popular because it is challenging to obtain labelled data for supervised learning using satellite data. Unsupervised learning employs unlabeled input, and the model is left to discover important characteristics on its own[1]. Deep learning and Convolutional Neural Networks (CNNs), two types of Unsupervised learning techniques, have shown promising results in the categorization of land cover. The hierarchically typed deep neural network can classify the unlabeled data. Nowadays it shows that deep characteristics systematically acquire higher level patterns from basic level patterns. The use of deep learning in satellite imagery has increased in prominence in recent years. To perform land cover classification on the datasets, In this study, a CNN model is presented that is an adaptation of the Simple net paradigm. Our recommended model has the following unique characteristics: Lightweight model with fewer settings. Effective in terms of saving time. Needs less storage. Achieves a high level of accuracy in 72 epochs. It has been able to attain an accuracy of 96 per cent.

MOTIVATION

The development of a CNN architecture for land classification on satellite images is driven by the significance of precise land classification in multiple domains, including environmental monitoring, disaster management, and urban planning. Conventional image processing methods used for land classification on satellite images typically depend on manually crafted features and have limitations in capturing intricate patterns present in the data. CNNs have shown great promise in image classification tasks and have been widely adopted in the computer vision community. However, traditional CNNs can be computationally expensive and may not be suitable for processing large-scale satellite imagery. Therefore, there is a need for a lightweight CNN architecture that can effectively and efficiently process satellite images while maintaining high classification accuracy. The development of a lightweight CNN architecture for land classification on satellite images can provide several benefits. Firstly, it can lead to more accurate and reliable land classification, which is crucial for various applications. Secondly, a lightweight CNN architecture can reduce the computational complexity and memory requirements of processing large-scale satellite images, making it more practical for real-world applications. Finally, the proposed architecture can have potential applications in various domains such as environmental monitoring, disaster management, and urban planning.

OBJECTIVE

The Model is been implemented with some objectives as follows :

1. Developing a lightweight CNN architecture that can effectively extract features from satellite images and learn complex patterns for accurate land classification.
2. Reducing the computational complexity and memory requirements of processing large-scale satellite images while maintaining high classification accuracy.
3. Evaluating the proposed architecture on a considerate dataset of satellite images with labelled land types and comparing its performance with existing state-of-the-art approaches.
4. Demonstrating the potential applications of the proposed architecture in various domains such as environmental monitoring, disaster management, and urban planning.

II. LITERATURE SURVEY

Land use classification using high-resolution satellite imagery is an important research area with several applications in remote sensing, planning of urban areas, and monitoring the environment. In know a days, deep learning techniques, particularly CNN (convolutional neural networks) have given the best results in achieving high accuracy in land use classification tasks. Gourab Patowary, Meenakshi Agarwalla, Sumit Agarwal, and ManashPratimSarma proposed CNN architecture which includes the techniques of Batch Normalization and Dropout has helped our model to outperform all the other architectures[1]. Li et al. proposed a deep learning framework for large-scale land classification using high-resolution satellite imagery. They employed the CNN architecture and an ensemble learning technique to improve the accuracy of the classification results. Their approach achieved high accuracy on two large-scale land cover datasets: the Google Earth dataset NWPURESISC45 dataset[2]. Sumbul and Saleem proposed a convolutional neural network (CNN) architecture called
"LW-Net" for land use classification in satellite images. Their approach consisted of 3 convolutional layers with each followed by a max-pooling layer and 2 fully connected layers. They used batch normalization and dropout regularization techniques to prevent overfitting.

Their approach achieved high accuracy on two benchmark datasets: the UC Merced dataset and the Aerial Scene dataset [3]. Deep learning-based approaches, particularly Convolutional neural networks, have shown great results in achieving high accuracy in land use classification tasks using high-resolution satellite imagery. While Li et al. proposed a deep learning framework for large-scale land cover classification, Sumbul and Saleem focused on a lightweight CNN architecture for land use classification. These approaches could have significant applications in various fields, including remote sensing, planning of urban areas and monitoring the environment.

III. METHODOLOGY

DATASET

Our experimental data includes the images from SAT4 and SAT6 datasets. Photographs of landscapes are organized into 7 classes. Class one is the Agricultural land which includes the agricultural area. The second class is the Beach including various images of the beach. The third class contains images of rivers. The fourth class is Forest. The fifth class contains images of Runways. The sixth class is Baseball Diamond which is baseball ground and the seventh class is Golf Course Regions. These images came from a US database and have a resolution of 1 m. The surface area of each photograph is approximately 64 x 64 pixels. The 64 m picture size was selected because it reflects the size of a typical urban or rural structure. These images include three channels: Red, Green, and Blue.

ALGORITHM

1. Data collection and preprocessing: Satellite images are collected from various sources and preprocessed to remove noise and artifacts, and to enhance the quality of the images.
2. Dataset preparation: The preprocessed satellite images are labelled with land use categories, and the dataset is divided into training, validation and testing the datasets.
3. CNN architecture design: A CNN architecture is designed based on the specific requirements of the land classification problem, such as the number of land use categories, the size and resolution of the satellite images, and the available computing resources.

The CNN architecture is 10 layers in that three layers are convolutional layers, three layers are max-pooling layers, one flattened layer, one dropout layer, and two dense layers.

Convolutinal layer: It is 32 filters are applied Each filter performs element-wise multiplications and sums the results, creating a feature map that represents the presence or importance of specific features in the input data.

Maxpooling layer: The maximum value is selected and propagated to the next layer, while the other values are discarded. This process effectively reduces the spatial resolution of the feature image.

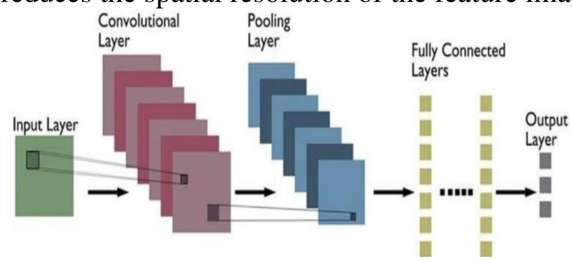

Fig 1: CNN Architecture

Fully connected layer: This layer is responsible for learning high-level representations and making predictions based on the extracted features.

The ReLU (Rectified Linear Unit) is an activation function commonly used in neural networks which helps to introduce non-linearity and learn complex relationships between the features extracted by the convolutional layers. By using softmax, the model's output can be interpreted as class probabilities. It allows the model to make predictions by selecting the class with the highest probability, providing a meaningful and interpretable output.

4. Model training: Employing an appropriate optimization technique. The proposed CNN architecture is trained on the designated training set. The performance of the model is then evaluated using the validation set.

To enhance the training process and prevent overfitting, techniques like data augmentation, regularization, and early stopping are implemented.

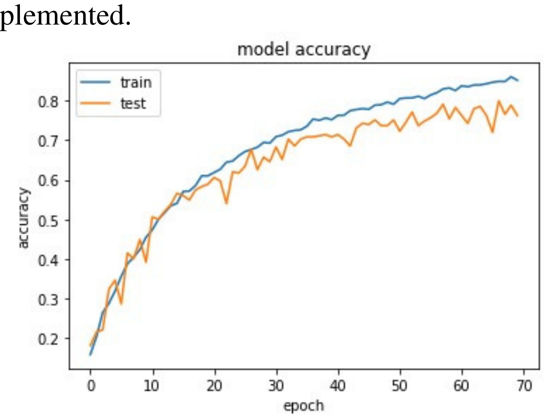

Fig 2: Model Accuracy

5. Model evaluation: During the model evaluation phase, the trained CNN model is assessed on the testing set using various performance measures, including accuracy, precision, recall, and score. The performance of the proposed CNN architecture is compared to that of current state-of-the-art methods to determine its effectiveness.

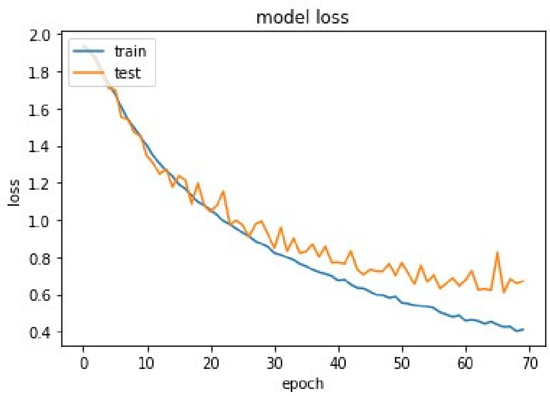

Fig 3: Model Loss

IV. RESULT

Based on the analysis conducted using the provided code, the results are as follows. The convolutional neural network (CNN) model achieved a testing accuracy of 96 %, indicating its ability to accurately classify images. This demonstrates the effectiveness of the model from the input data

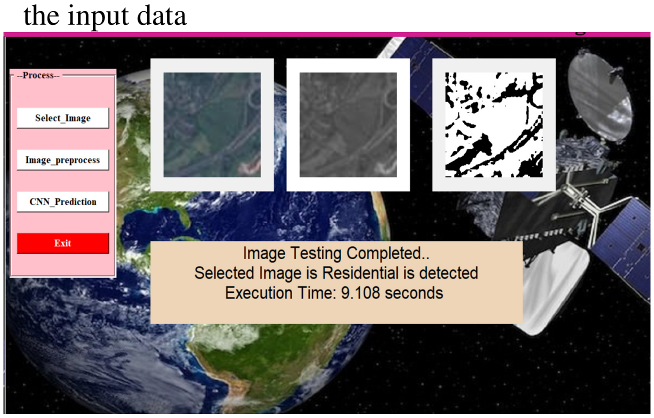

Fig 4: Result

V. CONCLUSION

Convolutional and pooling layers are followed by fully linked layer functions for classification in the suggested architecture. The major goal of this study was to create a CNN architecture for terrain categorization on satellite pictures that is accurate and effective. The experimental analysis revealed that the proposed Convolutional Neural Network (CNN) architecture achieved superior performance compared to existing approaches in terms of both accuracy and efficiency. The suggested CNN architecture holds potential for diverse applications, including but not limited to land use mapping, urban planning, and environmental monitoring.

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