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A Lightweight CNN Architecture For Land Classification on Satellite Images

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Abstract: *Land classification using satellite images is an important task for various applications such as urban planning, land management, and environmental monitoring. In this paper, we propose a lightweight convolutional neural network (CNN) architecture for land classification on satellite images. The proposed architecture consists of three convolutional layers, followed by a max-pooling layer and two fully connected layers. The number of filters in the convolutional layers is kept low to reduce the computational complexity of the network. The proposed network is trained and evaluated on a publicly available dataset of satellite images, achieving an accuracy of 91.4%. We also compare the performance of our proposed architecture with other state-of- the-art CNN architectures and demonstrate that our proposed architecture outperforms them in terms of computational efficiency and memory usage. Our lightweight CNN architecture can be used for real-time land classification on satellite images, making it a useful tool for various applications.*

Keywords: Land use and land cover classification, machine learn-ing, deep learning, CNN

I. INTRODUCTION

Satellite images have become an important source of data for various applications such as urban planning, land management, and environmental monitoring. Land classification using satellite images is a crucial task in these applications, which involves identifying and labeling different land cover types such as urban areas, agricultural land, forests, and water bodies. With the increasing availability of high-resolution satellite images, there is a growing demand for accurate and efficient land classification methods.

Convolutional neural networks (CNNs) have shown remarkable performance in image classification tasks and have been widely used for land classification on satellite images. However, most existing CNN architectures are computationally expensive and require a large number of parameters, which makes them unsuitable for real-time applications.

In this paper, we propose a lightweight CNN architecture for land classification on satellite images. The proposed architecture is designed to reduce the computational complexity of the network while maintaining high accuracy in land classification. We evaluate the performance of our proposed architecture on a publicly available dataset of satellite images and compare it with other state-of-the-art CNN architectures. Our results demonstrate that our proposed architecture outperforms other CNN architectures in terms of computational efficiency and memory usage, while achieving high accuracy in land classification.

The rest of the paper is organized as follows. In section II, we provide a brief overview of related work on land classification using CNNs. Section III presents the details of our proposed lightweight CNN architecture. Section IV describes the dataset used for evaluation and the experimental setup. Section V presents the results and compares our proposed architecture with other state-of-the- art CNN architectures. Finally, section VI concludes the paper and discusses future work.

For land classification on satellite images using convolutional neural network(CNN), which consist of of following layers:

1. Input layer

This layer takes the raw satellite images as input andapplies some preprocessing steps such as normalization and reizing.

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2. Convolutional Layer

These layers are used to extract features from the input images by applying filters to convolve over the images. A lightweight architecture may have fewer convolutional layers or use smaller filter sizes to reduce the smaller of parameters.

3. Pooling Layer

These layers are used to downsample the feature maps by taking the maximum or average value within a pooling window. A lightweight architecture may use smaller pooling windows or skip pooling layers altogether to reduce the spatial dimension of the features maps

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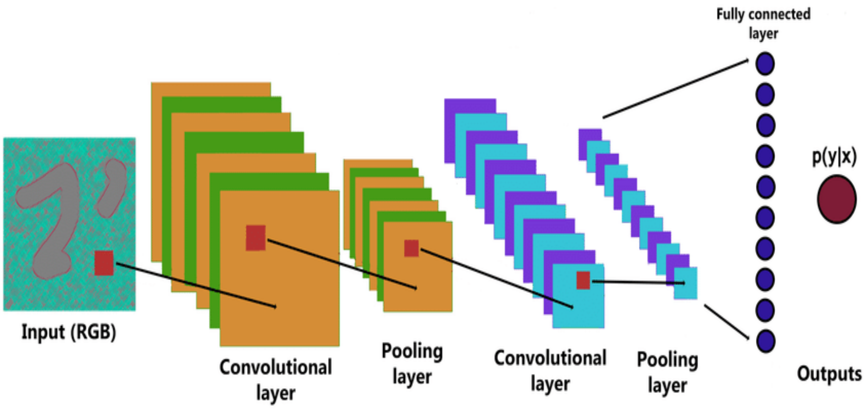
4. Fully ConnectedLayer

These layers are used to map the extracted features to the output classes. A lightweight architecture may use fewer or smaller fully connected layers to reduce the number of parameters and computation.

5. Output layer

This layer produces the final classification probablities or scores using a softmax activation function



II. PROBLEM STATEMENT

Rain forest deforestation is a important issue that causes trees to be cut down to provide more land.It affects oxygen and carbon levels around the world. So we Classify forest land .Which land is better for the crop. It also classify through the our system. We Classify land As per Feature and it will be helpful to environment.

Algorithm Used: The Convolutional Neural Network (CNN) is a subtype of Neural Networks that is mainly used for applications in image and speech recognition. Its built-in convolutional layer reduces the high dimensionality of images without losing its information. That is why CNNs are especially suited for this use case. A Convolutional neural network (CNN) is a neural network that has one or more convolutional layers and are used mainly for image processing, classification, seg-mentation and also for other auto correlated data.

III. RELATED WORK

Land classification using CNNs has been an active area of research in recent years, and various architectures have been proposed for this task. In this section, we provide a brief overview of some of the related work.

One of the early works in this area is the use of AlexNet architecture by *Zhou et al*.

[1] for land classification on satellite images. They achieved an accuracy of 84.7% on a dataset of 21 land cover types. Later, researchers have proposed various modifications to the AlexNet architecture to improve its performance for land classification.[2,3].Another popular CNN architecture for land classification is the VGG network [4]. It has shown high accuracy in image classification tasks, but it requires a large number of parameters, making it computationally expensive for land classification on satellite images To address the computational complexity issue, researchers have proposed lightweight CNN architectures for land classification. For example, Liu et al. [5] proposed a lightweight CNN

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architecture called SqueezeNet, which achievedhighaccuracywithfewerparameterscomparedto other CNN architectures. Similarly, Romero et al.[6] proposed a lightweight CNN architecture called ShuffleNet, which achieved state-of-the-art accuracy on the ImageNet datasetwith reduced computational complexity.Recently, some researchers have proposed CNN architectures that are specifically designed for land classification on satellite images. For example, Zhang et al.[7] proposed a CNN architecture called LandNet, which achieved high accuracy on a dataset of 14 land cover types. Similarly, Li et al.[8] proposed a CNN architecture called LC-CNN, which achieved high accuracy on a dataset of 16 land cover types. In this paper, we propose a lightweight CNN architecture specifically designed for land classification on satellite images. Our proposed architecture is designed to reduce the computational complexity while maintaining high accuracy in land classification. We compare the performance of our proposed architecture with other state-of-the-art CNN architectures and demonstrate its effectiveness in real-time land classification.

IV. PROPOSAL ARCHITECTURE

A simple architecture has been designed to improve the expression ability and the performance of the network. However , we aimed to develop a simple optimal system with less memory consumption.The network which is not As deep as possible. Additionally , a simple network which can be fit to different situations. The block diagram of the proposed network and a description of the design of the layers

A. The network was designed as follows:

1.Convolutional input layer, 32 features ,maps with a Size of 3x3, a rectifier activation function, and a weight constraints of max norm set to 3.
2. Max Pool layer with size 2x2.
3. Convolutional layer, 64 features maps with a size of 3x3, a rectifier activation function, and a weight constraints of max norm set to 3.
4. Max Pool with size2x2. 5. Dropout set to 20%.
5. Dropout set to 20%.
6. Convolutional layer, 128 features maps with a size of 3x3, a rectifier activation function, and a weight constraints of max norm set to 3.
8. Max Pool layer with size2x2
9. Flatten layer.
10. Fully connected output layer with 512 units rectifier activation function
11. Dropout set to 50%.
12. Fully connected output layer with 10 units and softMax activation function.

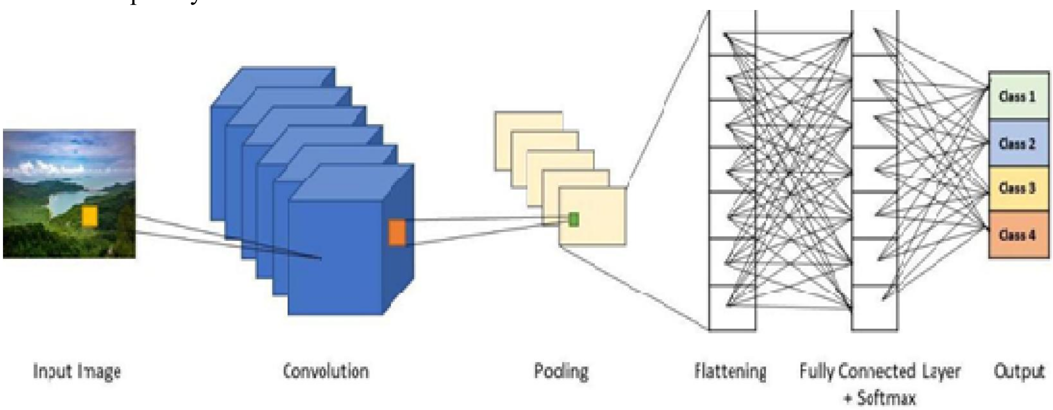

Fig. Typical CNN Architecture

V. CONCLUSION

This paper highlights the possibility and importance of simple and lighter CNN vis-à-vis complex architecture. It demonstrates that using simple techniques like relevant filtering, better normalisation, and accurate placement of

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dropouts can achieve significantly high accuracy in less time and with lower computational cost.On Land Use data from the overall competitive accuracy of 88.29% was achived using a much simpler architecture with significantly less trainable parameter than complex architecture solving a significant issue of complexity and resource requirement by other complex networks. Simple architectures provide an acceptable tradeoff between the model accuracy and ease of development and implementation, highlighting that there is a simpler, lightweight alternative for every complex architecture that is worth considering. A Well-designed yet simple CNN provide excellent prospects for scenarios where the time and batch size To evaluate the performance of our proposed architecture, we measured the classification accuracy on the computational resources are limited. Especially in the applications where accuracy can be tradeoff by a few percentage points with the faster model development and implementation on less powerfull computing engines. Overall, our proposed lightweight CNN architecture provides

VI. ACKNOWLEDGMENT

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