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Article

# Deep Convolutional neural network model for Land Classification using Satellite Images

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**Abstract:** The significance of land image classification extends across diverse fields and disciplines, playing a crucial role in offering valuable insights into the Earth's surface. This intricate process entails the categorization of land cover types, including forests, urban areas, water bodies, and agricultural land, utilizing satellite or aerial imagery. Its relevance is evident in its applications spanning environmental monitoring, urban planning, agriculture, forestry, and disaster management. The ability of machine learning models to adapt and improve over time enhances the precision and reliability of land cover classifications, making them invaluable tools for decision-makers. This integration not only expedites the classification process but also opens up possibilities for real-time monitoring and adaptive management strategies, contributing to more effective and sustainable resource utilization. In this work, a Convolution neural network is used for land classification using satellite images.

**Keywords:** Land classification, Convolution neural network, Satellite image analysis, Machine Learning, Deep Learning

## I. Introduction

Land classification is a systematic process [1] of categorizing and organizing land areas based on various characteristics such as topography, soil composition, climate, land use, and vegetation cover. This classification is essential for effective land management, urban planning, agricultural development, and environmental conservation. By understanding the diverse features of different land types, authorities can make informed decisions about land use planning, zoning regulations, and sustainable resource management. Land classification helps identify areas suitable for specific purposes, such as agriculture, residential development, or conservation, thereby optimizing land utilization and minimizing potential environmental impacts. Additionally, it plays a crucial role in assessing the vulnerability of land to natural hazards, guiding disaster preparedness, and promoting resilient communities. Through the application of advanced technologies like remote sensing and Geographic Information Systems (GIS), accurate and up-to-date land classification maps can be created, aiding policymakers, planners, and researchers in making informed decisions for the sustainable development of landscapes. Land classification involves several approaches that consider different aspects of the land, providing valuable insights for effective management and planning. One common approach is the physiographic or geomorphological method [2] , which classifies land based on its physical features such as elevation, slope, and landforms. This approach helps identify areas prone to erosion, landslides, or flooding, guiding land-use decisions and infrastructure development. Another approach involves the use of remote sensing and GIS technologies [3]. Remote sensing enables the collection of data from a distance, often through satellite imagery, to assess land characteristics like vegetation cover, land use patterns, and soil composition. GIS, on the other hand, facilitates the analysis and interpretation of spatial data, allowing for detailed mapping and classification of different land types. Ecological approaches focus on the biodiversity and ecosystems of an area [4]. This method considers factors like climate, vegetation types, and the presence of unique species. It aids in the identification of ecologically sensitive areas and supports conservation efforts to protect diverse habitats. These various approaches to land classification offer a comprehensive understanding of the diverse aspects of the land, enabling informed decision-making in areas such as urban planning, agriculture, conservation, and environmental management. Integrating multiple approaches often leads to a holistic perspective that considers both natural and human-induced factors for sustainable land use and development

Machine learning plays a pivotal role in modern land classification processes [5] by leveraging advanced algorithms to analyze vast amounts of data and extract valuable insights for accurate land categorization. Through the utilization of machine learning techniques, such as supervised and unsupervised learning, classification models can be trained on diverse datasets, incorporating features like satellite imagery, topographic data, and soil information. Supervised learning algorithms, for example, can be trained on labeled data to recognize patterns and relationships between different land characteristics, enabling them to classify unseen data into specific land categories. Unsupervised learning techniques, on the other hand, allow the system to identify inherent patterns and groupings within the data, aiding in the discovery of natural land classes. The integration of machine learning in land classification not only enhances the efficiency of the process but also enables the adaptation of models to changing environmental conditions. This adaptability is particularly valuable for monitoring dynamic landscapes and responding to shifts in land use patterns or climate variations. Moreover, machine learning facilitates the identification of subtle and complex relationships among multiple variables, contributing to more accurate and nuanced land classifications. As technology continues to evolve, machine learning is expected to play an increasingly crucial role in land classification, providing valuable tools for sustainable land management, environmental conservation, and informed decision-making in various fields such as agriculture, urban planning, and natural resource management. Convolutional neural network [6] stands out as highly effective tools for image processing, surpassing other models in the machine learning and shallow learning domains. Their efficiency stems from the ability to autonomously learn hierarchical features from input images. Unlike conventional machine learning models dependent on handcrafted features, CNNs utilize convolutional layers to automatically extract features of various complexities, concurrently capturing local patterns and global structures. While shallow learning models may struggle with intricate spatial dependencies in images, CNNs thrive in managing the nuanced details and complex structures inherent in visual data. The architectural layout of CNNs, incorporating convolutional layers succeeded by fully connected layers, streamlines the extraction and integration of high-level features, establishing them as a cornerstone in the field of image processing. In this work, a deep learning model, Deep CNN, has been used for land classification using satellite images.

## 2. Methodology

### *2.1. Convolutional Neural Network*

CNNs are a special kind of deep neural networks crafted for handling visual data. They excel at tasks like recognizing and classifying images. The main elements of CNNs are convolutional layers, using operations to find patterns and features in the input data. These networks also include pooling layers, which reduce dimensions and parameters, making computations more efficient. The layers in a CNN, connected together and including fully connected layers, create a powerful structure that can understand complex visual data by identifying detailed hierarchies of features. CNNs have transformed image analysis, object detection, and various other tasks, displaying their versatility across a range of applications. As a crucial component of contemporary deep learning, CNNs continue to push forward advancements in artificial intelligence, empowering machines to grasp and interpret visual information with exceptional accuracy. The working of CNN can be realized by following basic steps:

Step - 1: Input data is received, typically in the form of images.

Step - 2: Convolutional operations are applied to the input data using filters (kernels). This involves sliding a filter over the input data, computing the dot product at each step, resulting in a feature map highlighting spatial hierarchies of patterns.

Step - 3: An activation function, often ReLU (Rectified Linear Unit), is applied to introduce non-linearity and capture complex relationships in the data.

Step - 4: Spatial dimensions of the feature map are downsampled to reduce computational complexity and retain important information. Common pooling operations include max pooling or average pooling.

Step - 5: The 2D or 3D feature map is flattened into a 1D vector, preparing the data for input into a fully connected layer.

Step - 6: Neurons in one layer are connected to every neuron in the next layer, allowing the network to learn global features and relationships in high-level representations.

Step - 7: The final output is produced based on the learned features, often using a softmax activation function for classification problems to generate probability scores for each class.

Step - 8: A loss function is defined to measure the difference between the predicted output and the actual target, with categorical cross-entropy being common for classification problems.

Step - 9: An optimization algorithm, such as Stochastic Gradient Descent, is used to minimize the loss by adjusting the network's weights and biases. Backpropagation is employed to calculate gradients and update parameters.

Step - 10: The dataset is iterated through multiple times (epochs), adjusting weights and biases during each iteration. Performance is monitored on a validation set to avoid overfitting.

Step - 11: The trained model is evaluated on a separate test set to assess its generalization performance, using metrics like accuracy, precision, recall, and F1 score for classification tasks.

## 3. Proposed Method

In this study, the task of land use and land cover classification is performed using a satellite image dataset [7]. The dataset employed comprises 27,000 images with labels, featuring 10 distinct classes for land cover and land use. These images are georeferenced and derived from openly accessible Earth observation data, facilitating a diverse array of applications. This dataset is accessible to the public at [8]. Extracted patches are utilized to discern the specific class depicted in the images. The accompanying visualization (Fig.1) emphasizes the classes of annual crop, highway, river, residential buildings, and industrial buildings.

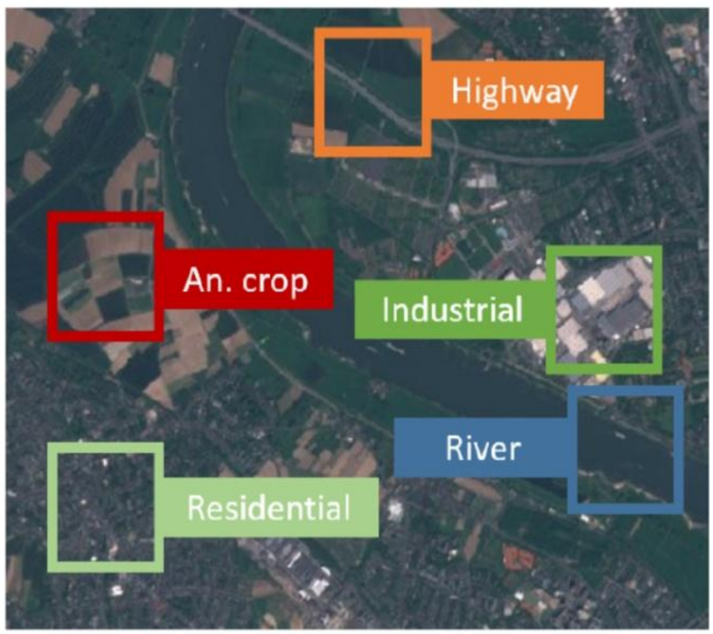


**Fig 1. Satellite (Sentinel-2) images for Land cover and land use classification (Source: [7])**

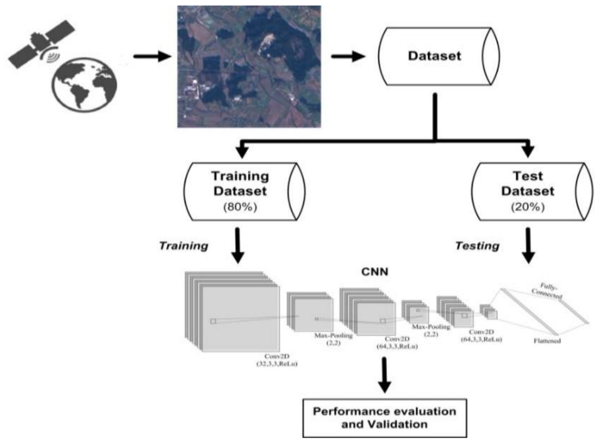


**Fig 2. Proposed method for land cover and land use classification using satellite images**

The images in this dataset have dimensions ranging from 64 x 64 pixels. To optimize the training process, we employ augmentation techniques such as vertical clipping, horizontal clipping, and shifting. Due to limited computational resources, the initial dataset comprising 27,000 images is downsized to a sample of 10,000 using stratified sampling. Subsequently, 80% of this stratified sample is utilized for training the proposed CNN architecture (refer to Figure 2), while the remaining 20% serves as a validation test.

## 4. Result Analysis

The outcome of land classification is depicted through training and validation curves, measured in terms of accuracy (Eq.1). The training curve is derived from the training dataset, reflecting the proficiency of the prototype in learning. Meanwhile, the validation curve, obtained from the hold-out validation dataset, illustrates the model's ability to generalize effectively. Figure 3 displays the training and validation curves of the proposed model.

**Table 1. Investigating the performance of proposed CNN architecture with different number of epochs**

| Proposed CNN architecture | |
|---|---|
| **No. of Epochs** | **Accuracy** |
| 100 | 70.32% |
| 150 | 75.46% |
| 200 | 78.50% |

$$Accuracy = \frac{TP + TN}{All} \quad (1)$$

In Equation 1, '$TP$', '$TN$', '$All$' are True Positive, True Negative, and Total data samples respectively.

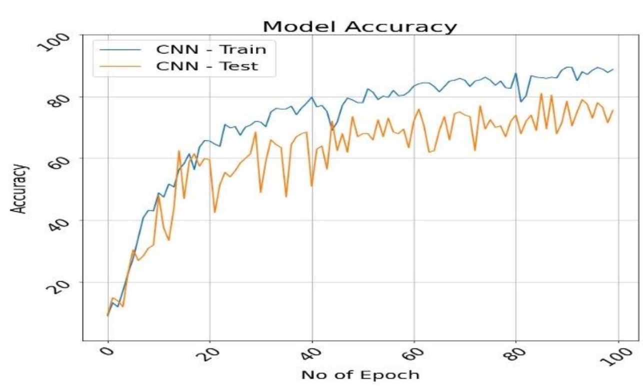


**Fig 3. Performance of proposed CNN architecture with 100 Epochs**

Table 1 outlines a comprehensive comparative analysis of the proposed CNN architecture, considering different numbers of training epochs for land classification based on classification accuracy. The data in Table 1 reveals that the proposed CNN architecture achieves superior accuracy performance when trained with 200 epochs. It is to be noticed that the increasing number of epochs may lead to further better performance with a cost of high computational burden.

## 5. Conclusion

In this work, a deep CNN based model has been used for land classification using satellite images. This proposed method has been implemented and tested, and found as one of the efficient approach. Land classification using satellite images is a valuable tool for understanding and managing Earth's surface. However, it comes with its set of challenges. One significant hurdle is the diversity of land cover types, including forests, urban areas, water bodies, and agricultural fields. The intricate and dynamic nature of these landscapes makes accurate classification a complex task. Additionally, satellite images may be affected by atmospheric conditions, leading to distortions and inaccuracies in the classification process. The spatial and spectral resolution of the images can also pose challenges, especially when dealing with small or homogeneous land features. Furthermore, seasonal changes and variations in environmental conditions can impact the consistency of land classification results over time. As technology evolves, addressing these challenges becomes crucial to enhance the reliability and precision of land classification using satellite imagery, contributing to effective land management and environmental monitoring. This proposed work makes use of a specific CNN architecture has been used for land classification, which is trained from the satellite images. This approach has been tested and found to acceptable in terms of performance metric. However, applying Deep CNN for land classification using satellite images introduces both promise and challenges to the field. One of the significant challenges lies in the need for vast amounts of labeled training data. Creating a comprehensive dataset for the diverse land cover types found globally is a resource-intensive task. Additionally, the computational demands of training deep networks, especially on high-resolution satellite imagery, require substantial computing power. CNNs are sensitive to variations in image quality and may struggle with inconsistencies caused by atmospheric conditions, sensor differences, and varying acquisition times

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