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Geospatial Land Classification Via Advanced Image Processing using CNN

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Abstract:- High resolution analysis of remote sensing images is pivotal for various classification including land use determination, environmental detection, environmental planning and geospatial object recognition. This paper introduces a robust method for categorizing satellite images into distinct groups, facilitating accurate classification for global geographical areas. It includes image compression, image preprocessing, image segmentation and feature extraction. This innovative approach enables precise identification and understanding of different areas, contributing to optimize resource allocation and improved land management practices in agriculture. CNN is the classifier that is employed in this experiment. The outcome demonstrates that our suggested strategy offers excellent accuracy, outperforming many recently published publications.

Keywords:- *CNN.*

I. INTRODUCTION

The paper focuses on the satellite images collected from UC merced land use dataset. The proposed system begins with the collection of images from UCMerced land use dataset consisting of 21 land use classes such as forests, deserts, highways, beaches, agriculture, and rivers. Each image measures 256x256 pixels. It captures high resolutions, multispectral imagery of the earth surface, allowing for detailed observations of landscapes, ecosystems and changes over time. Here the land is classified into four main categories such as agriculture, forest, water, buildings. One of the growing fields for image processing is agricultural image processing. Hence we are placing a greater emphasis on agricultural land. Here we access agricultural land and identify the specific crop cultivating in that area.

By offering a scalable and automated method for land classification and crop detection, the project aims to address issues with manual labour, inefficiency, and resource waste in agricultural monitoring and management. Using satellite or aerial imagery, a convolutional neural network (CNN) model that can precisely identify and classify various forms of land cover and crop detection on agricultural fields is being developed with an emphasis on agricultural land and crop detection. To help with agricultural management and monitoring, the process of identifying and categorizing different crops and land features will be automated.

II. RELATED WORKS

- This paper focuses on image processing within the XDB plant disease database to enhance the classification of 20 distinct diseases affecting 10 plant species. The processing involves two pre-processing steps—image selection and resizing—and employs modified VGG architectures (VGG16 and VGG19) with pre-trained weights from the ImageNet database. A comparative study based on classification metrics, including accuracy, precision, recall, and F1-score, reveals that, for this specific database, a pre-trained CNN with a depth equal to or smaller than VGG16 captures disease-sensitive features, enhancing the recognition of plant pathologies. This justifies the superior performance of VGG16 over VGG19 across training, validation, and test data.
- The dynamic landscape evolution has led to an increased utilization of previously untapped lands, providing opportunities for diverse purposes such as agriculture and urban infrastructure development. This paper introduces an automated approach to detect unused land spaces, utilizing satellite image processing techniques. The dataset comprises remote sensing Earth images, with preprocessing steps involving grayscale conversion, compression, and noise reduction.Segmentation distinguishes between used and unused land regions, and local binary feature extraction captures edges, flat areas, and corners.Various classification algorithms label and categorize remote sensing Earth images, including the utilization of a Convolutional Neural Network (CNN) for automatic classification and labeling. The application of Random Forest for segregating landscapes into used and unused land demonstrates superior accuracy compared to existing systems.
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- This paper focuses on agricultural remote sensing monitoring using HJ satellite imagery, presenting an efficient processing methodology. The workflow begins with image radiation correction, atmospheric correction, and the computation of over 10 vegetation indices using ENVI/IDL. Subsequently, the integration of ArcSDE with the Oracle Database facilitates rapid image storage. Finally, thematic agricultural remote sensing images are swiftly published on ArcGIS Server. This study offers a comprehensive solution for expediting the preprocessing, storage, and dissemination of remote sensing images for agricultural monitoring, ensuring timely and accurate data access.

III. PROPOSED METHODOLOGY

One of the hottest areas of research in computer vision is image classification. In other image application domains, image classification is the fundamental system that is broken down into three key components: classifier, picture preprocessing, and image feature extraction.

In this paper we have divided land into several groups including forests, agriculture and buildings. Since agriculture plays a big part in the field of image processing,we categorize agricultural land into several groups and determine which crop is being cultivated as well as the amount of land utilized for cultivation for future analysis.

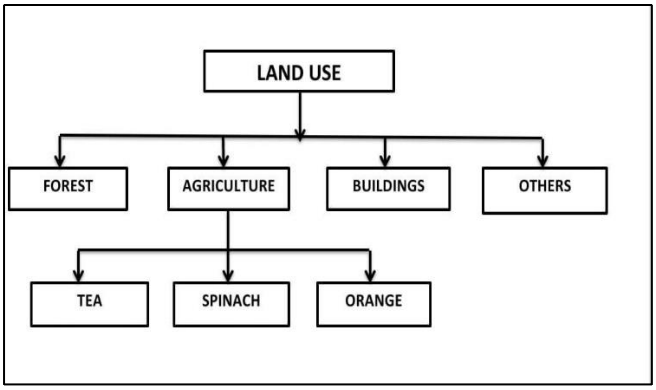

Fig 1: Classification Scheme of Land Use

The UCmerced landscape data set is used to capture satellite imagery. There are twenty-one classes of land use, including agriculture, buildings, and forests. Pixel size for each image is 256x256. From the training data set, 21 images—referred to astest images—were chosen. The photos are trained using CNN as the machine learning model. Images are downsized to lower computational demands and memory complexity because they are usually huge, which results in longer processing times and more memory consumption.Preprocessing module input consists of scaled photos from the previous phase. Preprocessing of the supplied photos is done to improve final results. Converting the image to RGB and grayscale representations is part of this preprocessing.Next, in an effort to improve representation and ease analysis, digital images are segmented, which entails dividing them into discrete portions. Here, region-based segmentation is used, especially with thresholding segmentation to recognise borders and objects based on color or grayscale discontinuities.After extracting pertinent elements from the photos, the model is used to train and images are classified.

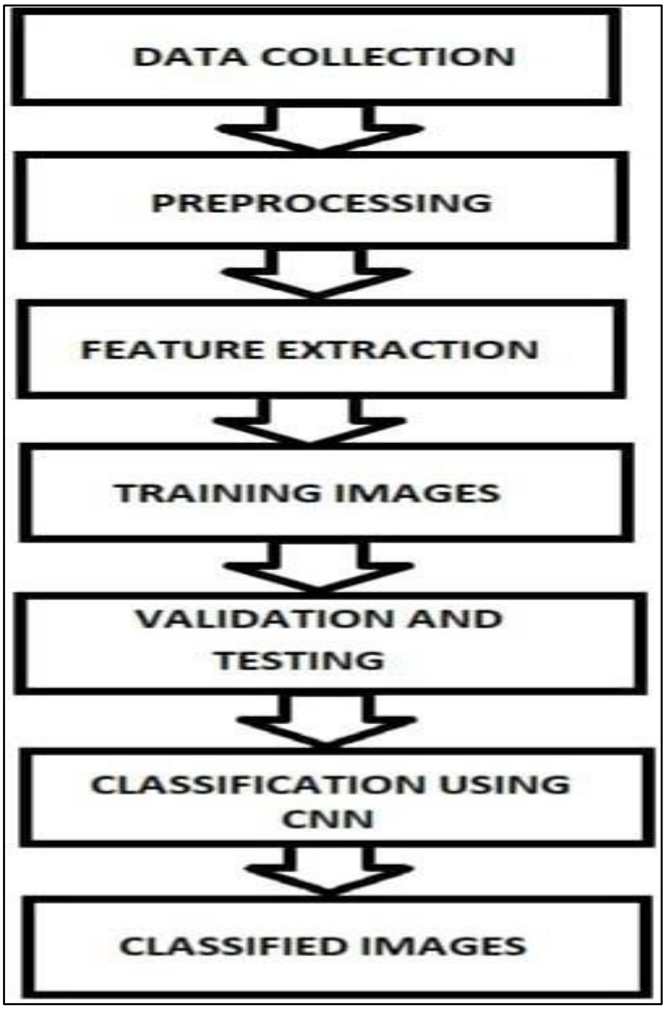

Fig 2: Proposed Framework

A. CNN Classifier

CNN stands for Convolutional Neural Network. It is a kind of neural network that is frequently applied to problems involving computer vision and image processing. An input picture filter that expands the input volume to its greatest size is taken into consideration by CNN. The dot product is found between the filter and a portion of an image because of a spatial position. The filter computes the dot product at each pixel and is directed and complex at each pixel. The process isrepeated with more filters, each of which looks through the input for a distinct set of template forms. A series of convolution layers with activation functions strewn in between make up a convolutional neural network. It makes use of a RELU activation function. Each layer's output serves as the subsequent layer's input. There are numerous filters in each layer, and they all result in various activation functions.

High-level and middle-level filters examine high-level features like corners and edges, while the filters at the earlier layer typically reflect low-level features.Thus, it progresses from basic to more intricate aspects.

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➢ *Advantages of CNN*

- Reduced overfitting due to fewer characteristics requiring adjustment than with a typical CNN
- Computationally cheaper due to fewer calculations, makingit more suitable for mobile applications.
- Preserves the spatial structure of the image.
- Enables the identification of both low-level and high-level features by using a variety of filters to search the input for various template forms.

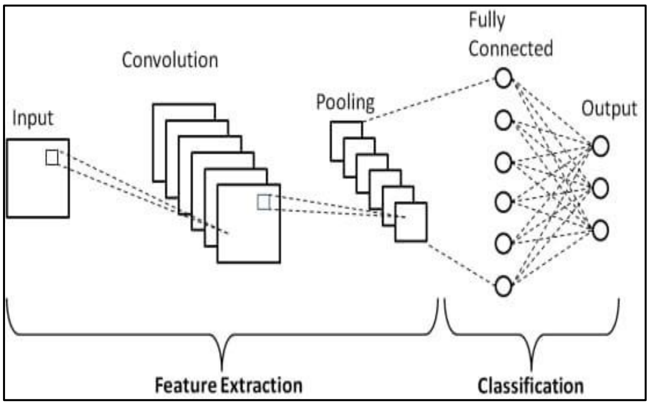

Fig 3: Basic CNN Architecture

Each convolutional layer in the chain that processes the input image applies a different set of filters to the image in order to extract features. A non-linear filter known as a RELU is applied to the output following each convolutional layer in order to add non-linearity to the model. After passing through a pooling layer, the output of the RELU layer shrinks the feature maps' size by down sampling them. A fully connected layer receives the pooling layer's output after it has been flattened into a 1D vector. After being flattened, the output is sent to a fully linked layer, which applies logic to determine the type of image it is.

IV. EXPERIMENTATION RESULTS

➢ *The Depiction of Complete Experiment is as Follows:*

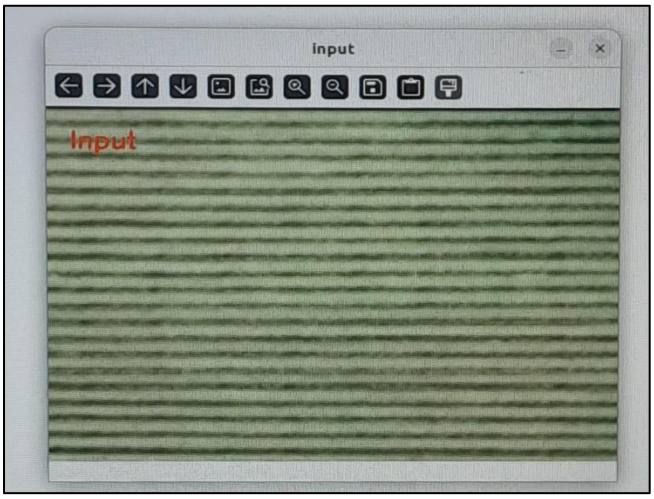

Fig 4: Input Image

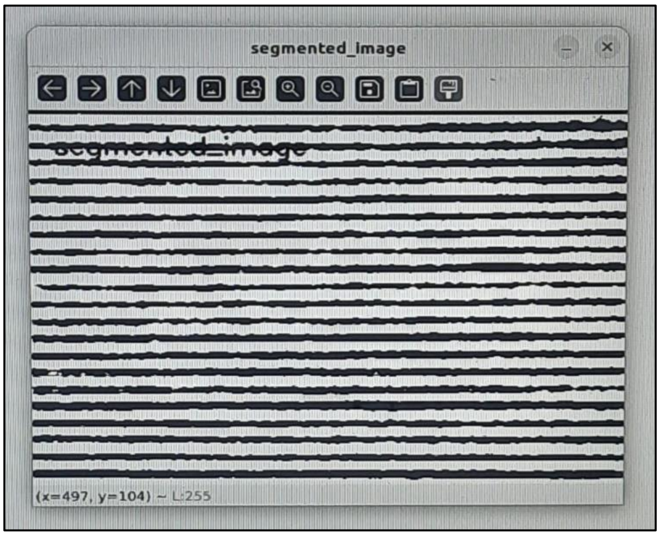

Fig 5: Segmented Image

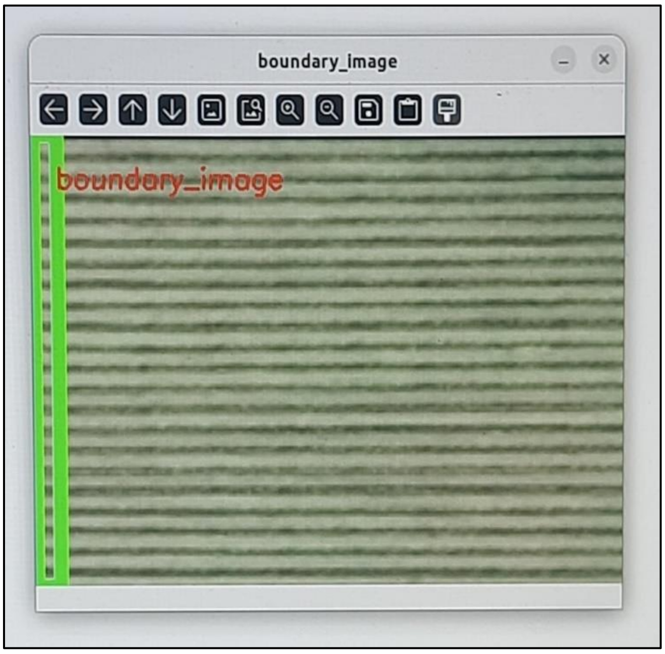

Fig 6: Boundary Image

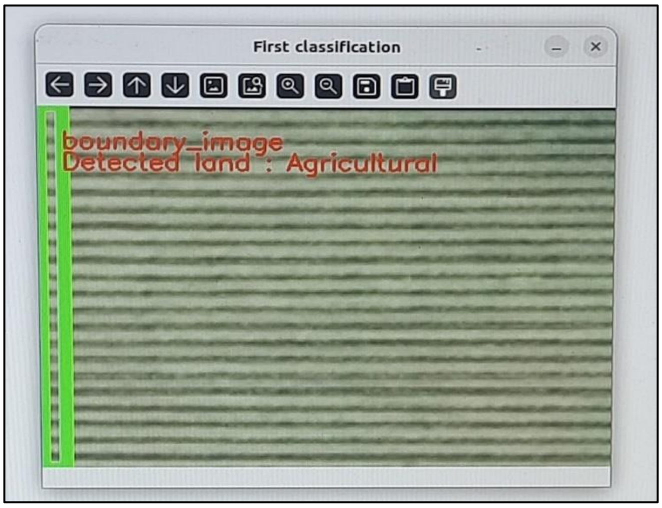

Fig 7: Detected Land Image

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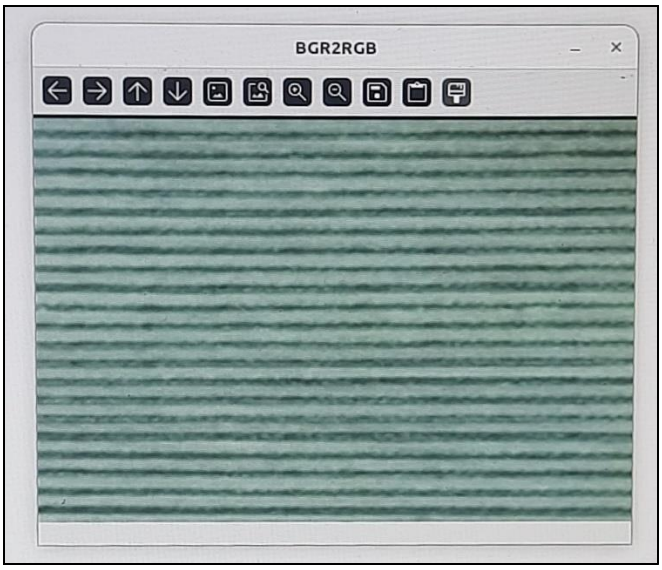

Fig 8: BGR to RGB Conversion

Fig 9: Cultivated Area and Crop Type

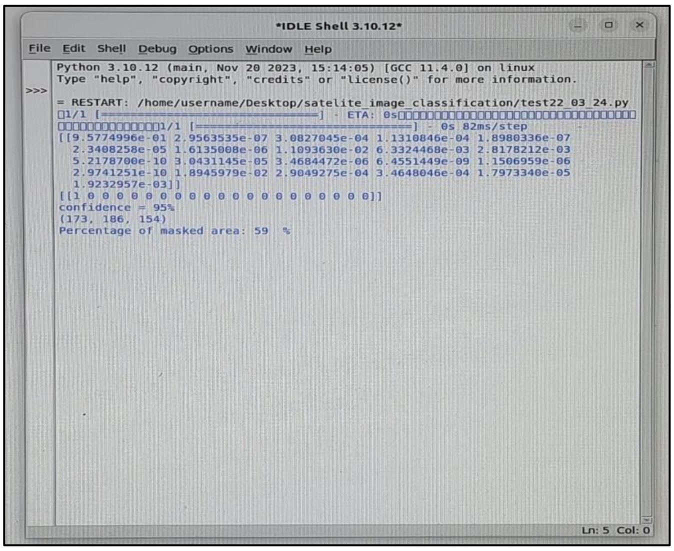

Fig 10: Accuracy

V. CONCLUSION

Requiring a robust approach to categorize the enormous dataset of high-resolution photos, the performance of deep learning-based remote sensing classification has shown their feasibility in solving real-world problems and assists in various statistical surveys. A thorough and comprehensive definition of land recognition and classification is provided in this study. The study has investigated agricultural image processing and related application areas, and it has established a more comprehensive model for efficient picture recognition. CNN, the classifier which yields the highest accuracy results is used in this experiment.

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