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Geographical Area Classification on Satellite Images Using CNN Architecture

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***Abstract*—This paper presents a novel approach for classifying geographical areas in satellite imagery using a modified Convolutional Neural Network (CNN) architecture.The architecture enhances feature extraction and classification accuracy by combining specialized layers like fully connected, pooling, and conventional layers. Our modified CNN performs better at accurately classifying a variety of geographic locations, according to our testing results. By efficiently capturing and analyzing complex spatial patterns, the use of customized layers enhances classification results in satellite-based geographical area classification.**

***Index Terms*—Geographical area classification, Convolutional Neural Network (CNN), Satellite imagery, Image classification, Fully connected layers, Pooling layers, Conventional layers**

I. Introduction

It is a major and complex task to comprehend and present land cover information through the classification of large amounts of satellite imagery. A wide variety of physical terrains, such as rivers, forests, farms, arid areas, and different kinds of vegetation, are included in the concept of land cover. Large-scale human societies ultimately benefit from the classification, strategic planning, monitoring, and development of sustainable resource management strategies that are made possible by this data.

Many different geospatial applications, including urban planning, agriculture, and environmental conservation, depend on timely and accurate land cover data. It provides a base upon which to map and analyze patterns of land use, pinpoint regions of ecological significance, and assess the effects of human activity on the environment. Governmental and non-governmental organizations

II. Related Work

G. Patowary et al [1] Convolutional Neural Network (CNN)architecture with depth-wise layers designed for efficient land classification on satellite images using dropout and batch normalization techniques which are employed for regularization and accelerated convergence during training. Also to reduce computational complexity, depthwise separable convolutional layers are used which separate spatial and depth-wise convolutions, significantly reducing the number of parameters. The model aims to classify satellite imagery into categories, including urban areas, vegetation, water bodies, barren land, and miscellaneous regions. Experimental results show that the proposed approach achieves competitive accuracy while significantly reducing computational resources and model size, making it well-suited for real-world applications with limited hardware capabilities.

A. Shukla et al [2] an approach to improve land cover classification in optical satellite images. It applies Convolutional Neural Networks (CNN) after noise removal to enhance accuracy and reliability. The study focuses on various land cover classes, including urban areas, agricultural fields, forests, water bodies and barren land. The research combines image preprocessing to remove noise and CNN for automatic feature learning. Training the CNN involves using labelled satellite images and validation sets to assess performance.

H. Ouchra et al [3] various methodologies for accurate and efficient satellite image classification are used. It explores Convolutional Neural Networks (CNNs), Support Vector Machines (SVM), Random Forest (RF) and other deep learning techniques like Recurrent Neural Networks (RNNs) and Long Short Term Memory (LSTM) networks. The study examines the effectiveness of CNNs, SVM, RF and deep learning techniques for extracting meaningful features from satellite images and classifying them into predefined categories such as forests, water bodies, urban areas and agricultural lands. The main focus is on land cover type classification, evaluating the performance of the mentioned methods in terms of accuracy,precision and computational efficiency.

S. Akshay et al [4] automation in detecting the unused land space and remote sensing earth images. The study includes converting image into grayscale image and segmentation is done to segregate into used and unused land. In further extraction process CNN applied i.e Convolutional Neural Networks (CNN) to enhance accuracy and reliability.

The feature extraction technique used her is LBP

C. Broni-Bediak et al [5] for remote sensing scene classification using two diverse datasets comprising images representing different land cover types, including urban areas, agricultural fields, forests, water bodies, and barren lands. The dataset "AID" contains single-label RGB aerial images captured from various sensors. Performance is measured using metrics like accuracy, precision, recall, and F1-score. The classification task involves categorizing the images into predefined land cover classes. The results highlight the strengths and weaknesses of each architecture, aiding in the identification of the most effective approach for remote sensing scene classification.

III. METHODOLOGY

A. Gathering and pre-processing data

A diverse set of data, including actual satellite images from a variety of datasets, constitutes an important first step towards the development of a robust system for classification of satellite imagery. A wide range of geographical areas, as well as satellite images, must be included in this dataset. Preprocessing is then performed on the collected satellite images.Normalization, augmentation, and feature extraction are examples of preprocessing techniques that improve the quality and usefulness of the gathered images for model training and assessment.

B. Feature Extraction

The essential part of this process is to extract relevant features from satellite imagery that have already been processed. These characteristics capture the distinctive features of each image, such as its shape, size, as well as additional relevant elements.

C. Image representation

The choice of data format depends on the specific machine learning tasks and algorithms used, ensuring compatibility and efficient processing during model training and evaluation. The transformed features undergo normalization, scaling, or encoding as necessary, further enhancing their suitability for machine learning models.

D. Dataset Splitting

Two subsets of the data are then added: a larger training set and a smaller test setting. The training set is used to train a machine learning model, and the test sets are used for evaluation of its performance. In order to ensure that the model can be efficiently generalised, it is necessary to carefully allocate data for those subsets.

E. Machine Learning Model Training and Tuning

Using an appropriate optimization algorithm, the modified CNN architecture is trained on a preprocessed dataset. The training phase involves exposing a model to the t model, techniques such as crossvalidation and grid search are commonly used to ensure that the model is accurate in distinguishing between genuine and forged signatures.

IV. SYSTEM ARCHITECTURE

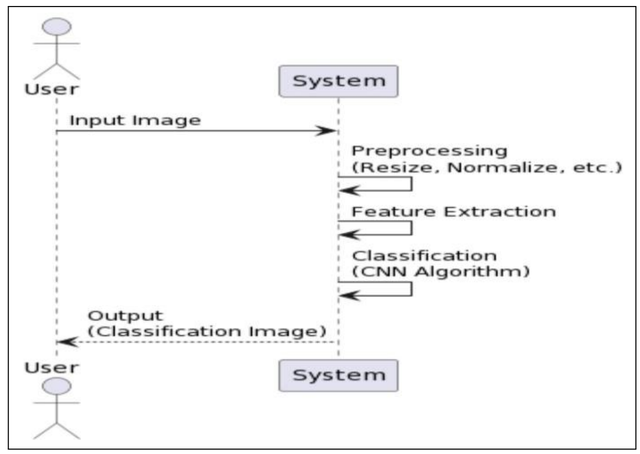

Fig. 1. System Architecture

V. MATHEMATICAL MODEL

The provided code implements a Convolutional Neural Network (CNN) for satellite land classification using the Keras library in Python.The CNN model consists of multiple layers, including convolutional layers, pooling layers, and fully connected layers. Here's a mathematical model representing the architecture and operations of the CNN:

Let's define some notations:

- N : Number of training samples - nh: Height of the input image (in pixels) - nw: Width of the input image (in pixels) - nc: Number of channels in the input image (e.g., 3 for RGB) - K: Number of convolutional filters - F : Size of the convolutional filters (in pixels) - S: Stride of the convolutional filters - P : Padding size - MP : Size of the max-pooling filters - D: Dropout rate - $H1$: Number of neurons in the first fully connected layer - $H2$: Number of neurons in the second fully connected layer - C: Number of classes (7 in this case)

With these notations, the mathematical model of the CNN can be represented as follows:

1. Input Layer: $nh \times nw \times nc$ matrix representing the input image.

2. Convolutional Layer 1: - Input: $nh \times nw \times nc$ - Output: $(nh - F + 2P)/S + 1 \times (nw - F + 2P)/S + 1 \times K$ (after applying K filters) - Activation: ReLU

3. Max Pooling Layer 1: - Input: Output of Convolutional Layer 1 - Output: $(nh-MP)/MP+1 \times (nw-MP)/MP+1 \times K$

4. Convolutional Layer 2: - Input: Output of Max Pooling Layer 1 - Output: $((nh-MP)/MP-F+2P)/S+1\times((nw-MP)/MP-F+2P)/S+1\times K$ (after applying K filters) - Activation: ReLU

5. Max Pooling Layer 2: - Input: Output of Convolutional Layer 2 - Output: $((nh-MP)/MP-MP)/MP+1\times((nw-MP)/MP-MP)/MP+1\times K$

6. Convolutional Layer 3: - Input: Output of Max Pooling Layer 2 - Output: $(((nh-MP)/MP-MP)/MP-F+2P)/S+1\times(((nw-MP)/MP-MP)/MP-F+2P)/S+1\times 64$ (after applying 64 filters) - Activation: ReLU

7. Flattening Layer: - Input: Output of Convolutional Layer 3 - Output: $1\times$ Number of neurons

8. Fully Connected Layer 1: - Input: Output of Flattening Layer - Output: $1\times H1$ (with ReLU activation) - Regularization: Dropout with rate D

9. Fully Connected Layer 2: - Input: Output of Fully Connected Layer 1 - Output: $1\times H2$ (with ReLU activation) - Regularization: Dropout with rate D

10. Output Layer: - Input: Output of Fully Connected Layer 2 - Output: $1\times C$ (where C is the number of classes) - Activation: Softmax

The loss function used is categorical cross-entropy, and the optimization algorithm is Stochastic Gradient Descent (SGD) with a learning rate of 0.01.

VI. Algorithm

Step 1: Prepare each frame by scaling it down and turning it into RGB. Step 2: Determine pose landmarks by applying the pose estimation model.
Step 3: Find the pertinent landmarks for the particular yoga pose or exercise.
Step 4: Use these landmarks to calculate angles. Map angles to a percentage scale in step five. Step 6: Keep an eye on angle variations to count repetitions.
Step 7: Establish standards for determining the beginning and end of repetition.
Step 8: Using these criteria, update the repetition count.
Step 9: For visual feedback, draw pose landmarks on the frame.
Step 10: On the video frame, show the number of repetitions.
Step 11: Give the user the option to close the program (by hitting 'q,' for example).
Step 12: When finished, release the video capture and shut the OpenCV windows.

VII. Result

The project resulted with a training accuracy of 94% and a testing accuracy of 93%. The Output is generated accurately and the area is classified accordingly. Both text and audio output are generated based on the input image classified.

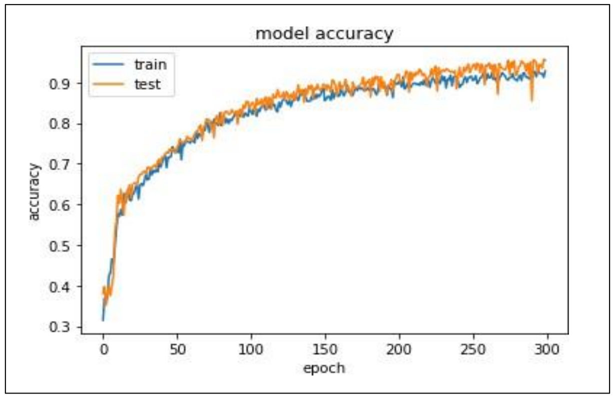

Fig. 2. Accuracy Graph

VIII. Conclusion

In conclusion, employing a modified Convolutional Neural Network (CNN) architecture to classify geographic areas from satellite photos offers a viable and effective approach. Through the integration of different layers, including fully connected, pooling, and conventional layers, the model is able to extract more complex spatial features and patterns from the input data. While pooling layers help create spatial hierarchies and simplify features, fully connected layers are essential for capturing overarching relationships within the dataset. Conventional layers are essential for understanding spatial correlations and extracting local features because they use convolution and activation functions. With the help of these layers, the model is able to accurately and robustly classify locations by capturing the complex structures present in satellite photos.As a result, the adapted CNN architecture highlights its potential for wider applications in domains like remote sensing, environmental monitoring, and land cover assessment by showcasing its proficiency in handling the intricacies of spatial data.

IX. Future Scope

The majority, if not all, of the comprehensive plan's components—natural resources, economic development, housing, and transportation—should be incorporated into the future land classification map.By using pre-trained convolutional neural network (CNN) models from large datasets like ImageNet and refining them on satellite image datasets, transfer learning techniques are employed.When handling massive satellite image datasets, scalability and efficiency must be guaranteed through CNN architecture optimization.Evaluating model reliability and making informed decisions depend heavily on the estimation of uncertainty in geographical area classification predictions.Using different regularization strategies and training approaches can strengthen the model's resistance to intentional disruptions.

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