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Satellite Image Classification Using CNN: Land Cover Analysis

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Abstract:

Satellite image classification categorizes different land cover types within satellite images, crucial for environmental monitoring, urban planning, agriculture, and disaster management. A Convolutional Neural Network (CNN) is trained to classify satellite images into ten categories, including AnnualCrop, Forest, and Residential, using a dataset with images resized to 150x150 pixels, converted from BGR to RGB, and normalized. The CNN architecture features Conv2D layers with ReLU activation, MaxPooling layers for spatial dimension reduction, Dropout layers to prevent overfitting, and final layers including Flatten, Dense with ReLU activation, and a softmax output for classification, achieving a test accuracy of 96.29% after training with the Adam optimizer and categorical cross-entropy loss over 200 epochs. The trained model is integrated into a Flask web application for real-time classification, making it accessible and practical for users, supported by visualizations of loss and accuracy plots showing the model's learning progress.

Keywords **—Satellite Image Classification, CNN,3D-CNN, Flask Web Application.**

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I. INTRODUCTION

Satellite image analysis holds significant importance in image processing, particularly within military, and environmental sciences [1]. The advancements in the technology of space have granted access to numerous high-resolution satellite images, presenting fresh challenges for their effective interpretation. Prior to the emergence of deep learning, traditional methods for satellite image segmentation relied on digital image processing, topology, and mathematics [2].

These methods mainly comprised Segmentation methods that rely on setting thresholds and methods that detect edges within an image to delineate different regions. The former, while straightforward and effective, solely considers pixel gray value features and often overlooks spatial features, rendering it susceptible to noise and lacking robustness [3]. On the other hand, edge detection-based segmentation offers precise edge localization and rapid processing. However, it struggles with maintaining edge continuity and closure, resulting in numerous fragmented edges in high-detail regions. Consequently, it faces difficulties in forming cohesive larger regions and isn't suitable for segmenting high-detail areas into smaller, more coherent fragments.

Lately, there has been rapid progress in deep learning, leading to the emergence of various highly effective algorithms for semantic segmentation in images. Common among these are FCN, Deconv-net, U-Net [4]. The FCN algorithm, while widely used, tends to yield less precise results as it disregards relationships of pixel-to-pixel and lacks consistency [5-6].

Vibration signals have been increasingly utilized in various engineering fields for analysis and monitoring purposes, including structural health monitoring, fault diagnosis and damage detection, where vibration signals can provide valuable information about the condition and integrity of structures. The proposed model addresses the challenges associated with structural vibration signals, which outperforms the prevailing algorithms for a wide range of noise levels, evaluated using PSNR, SNR, and WMAPE [7].

The CNN-based models explored include ResNet, DenseNet, EfficientNet, VGG and InceptionV3. The models were evaluated on three publicly available EuroSAT, UCMerced-LandUse and NWPU-RESISC45 datasets containing categories of images. The models achieve promising results in accuracy, recall, precision and F1-score.[8]

The papers focus on a variety of deep learning architectures, including Convolutional Neural Networks, Long Short-Term Memory networks, transformers, and hybrid CNN-recurrent neural network models, and incorporate techniques such as data augmentation, transfer learning, and multimodal fusion to improve model performance.[9] Fast Three-Dimensional Convolutional Neural Network-Based Spatiotemporal Fusion method using a spatial-temporal-spectral dataset.[10].

II. EXISTING SYSTEM

The existing system focuses on developing a 3D CNN model to analyse satellite imagery for detecting and monitoring land use changes. The existing system aims to overcome the challenges identified in the problem statement by leveraging state-of-the-art 3D CNN technology. Its primary goal is to provide a robust solution for detecting and monitoring changes in land use using satellite imagery, employing advanced techniques in deep learning to achieve accurate and efficient results.

Utilizing a 3D Convolutional Neural Network for satellite image classification represents an advanced strategy geared toward extracting both spatial and spectral details from Three-Dimensional satellite image datasets. This method harnesses deep learning's capabilities to autonomously discern features and structures, enabling precise classification of segments or volumes within satellite images into predefined categories and has an accuracy of 94.1%.

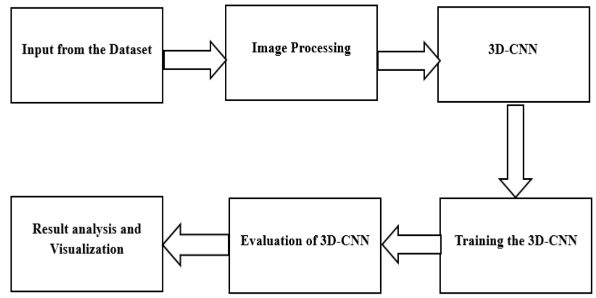

Fig. 1Architecture of the Image classification using 3D-CNN.

III. PROPOSEDSYSTEM

Satellite imagery is essential for observing and comprehending Earth's surface, providing valuable data for environmental monitoring, urban planning, agriculture, and disaster management. These images capture extensive information, revealing intricate details about various land cover types. To effectively analyse and categorize the data, Convolutional Neural Networks are employed due to their exceptional capability to automatically learn and identify complex patterns and features from raw pixel data.

The proposed system utilizes CNNs to classify satellite images into distinct land cover categories. CNNs consist of multiple layers that extract features at different levels of abstraction, enabling them to recognize and distinguish between various land cover types such as forests, water bodies, urban areas, and agricultural fields. This hierarchical feature extraction is particularly advantageous for processing high-dimensional satellite images, making CNNs a powerful tool for land cover classification and has an accuracy of 96.29%.

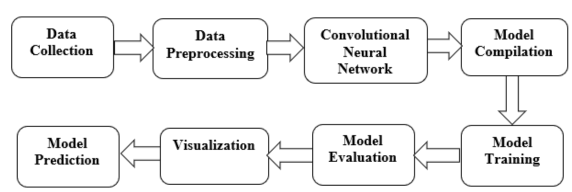

Fig. 2Architecture diagram of Satellite Image Classification using CNN.

The initial phase of data collection involves gathering satellite images from various sources and organizing them into directories based on their respective classes (e.g., AnnualCrop, Forest, HerbaceousVegetation). This structured approach facilitates efficient data handling and labeling. In the data preprocessing phase, collected images undergo several steps to ensure they are suitable for training the CNN, including resizing, normalizing, and converting color formats if necessary. The preprocessed data is then split into training and testing sets.

The core of the architecture, the CNN model, is constructed by stacking multiple layers such as convolutional layers, pooling layers, dropout layers, and dense layers. During the training phase, the preprocessed training data is fed into the compiled CNN model, which learns to classify images by adjusting its weights based on the input data and labels, iterating over multiple epochs to optimize performance.

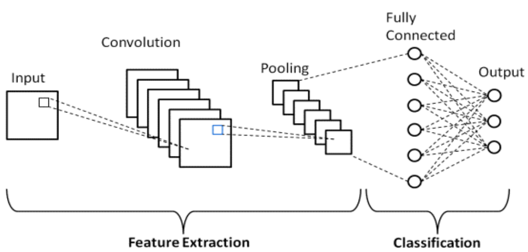

Fig. 3Structure Diagram of CNN

To build a CNN for processing satellite images, start with an input layer with 150x150 pixel images with three color channels. Add multiple 2D convolutional layers with specified filters and ReLU activation to extract spatial features, followed by 2D pooling layers to downsample feature maps and dropout layers for regularization. Finally, flatten the output, add dense layers for classification, and use a softmax-activated output layer to classify the images into 10 land cover categories.

Visualization tools track the model's training progress, with loss and accuracy graphs plotted to monitor the learning curve and sample predictions displayed for visual assessment. Finally, the trained model is used to make predictions on new, unseen data, mapping predictions to class labels.

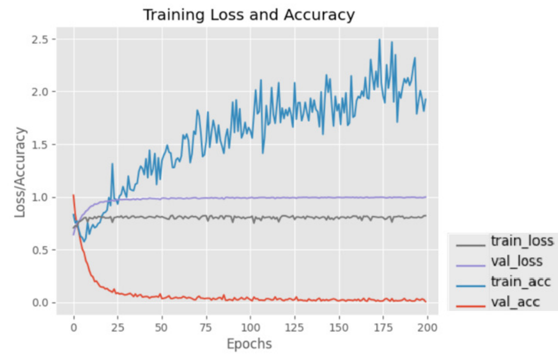

Fig. 4Training Loss and Accuracy Over Epochs

After training, the model is tested on new, unseen data to evaluate its generalization ability. The proposed system uses Flask, a lightweight Python web framework, to create a user-friendly web application that interfaces with the trained CNN model for land cover classification. Users can upload satellite images through the application's homepage, which are then processed by the CNN model for real-time classification, demonstrating the model's practical utility in real-world scenarios.

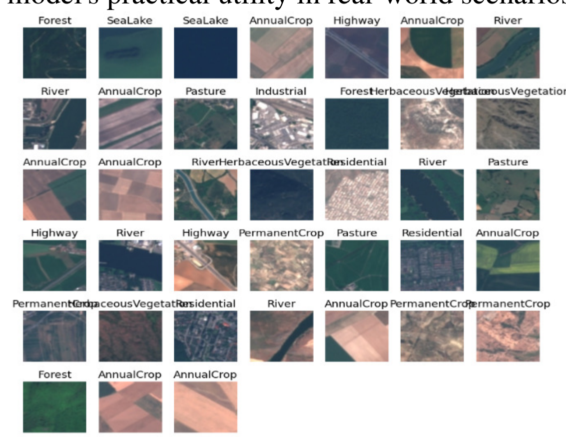

Fig. 5Images from Dataset

IV. RESULT

The proposed system adeptly achieves the objectives of land cover classification from satellite imagery through Convolutional Neural Networks. By leveraging advanced deep learning models, the system ensures high accuracy in identifying diverse land cover types across varying environmental conditions and resolutions. Rigorous data preprocessing standardizes satellite images to uniform dimensions (150x150 pixels), RGB color format, and ensures dataset uniformity. Exploratory analysis of dataset characteristics, such as class distribution and image variability, informs effective model training. Furthermore, the system expands its dataset size with additional labeled images, enhancing model robustness and generalization capabilities. This approach not only improves classification accuracy but also mitigates risks associated with dataset dependency and computational intensity. By prioritizing CNNs over more complex alternatives like PCA and 3D CNNs, the system maintains efficiency and interpretability while overcoming potential information loss and computational overhead. The proposed system achieves an accuracy of 96.29%. These strategies collectively ensure that the proposed system achieves reliable land cover classification results while addressing inherent challenges in satellite image analysis.

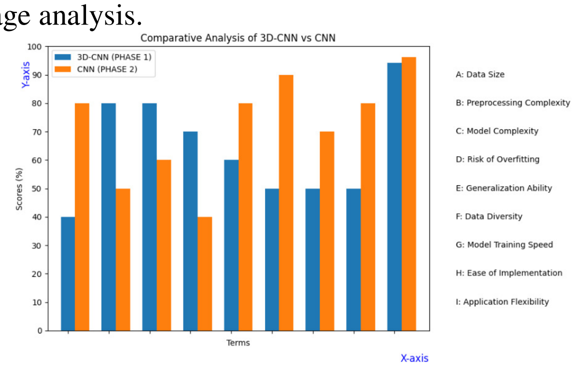

Fig. 6Comparison Analysis

The above figure represents the bar chart that visually compares the performance metrics between Phase 1, employing a 3D Convolutional Neural Network (3D-CNN) and Phase 2, utilizing a Convolutional Neural Network (CNN) for satellite image classification. The chart illustrates key metrics such as accuracy, Dataset size, and possibly other relevant measures specific to each model type.

IV. CONCLUSION

In conclusion, the developed system for land cover classification using Convolutional Neural Networks (CNNs) demonstrates robust performance in accurately identifying and categorizing diverse land cover types from satellite images. By employing advanced deep learning techniques and rigorous data preprocessing, the system achieves high accuracy and efficiency, crucial for applications in environmental monitoring, urban planning, and agriculture. The expansion of the dataset size through additional labeled images enriches model training and enhances its ability to generalize across different environmental conditions. Furthermore, the utilization of regularization mitigates risks associated with overfitting, ensuring reliable classification results. The system's capability to standardize image sizes, colors, and formats enhances dataset uniformity, facilitating effective model training and validation. Overall, this system not only meets the objectives of accurate land cover classification but also making it a valuable tool for decision-making processes requiring detailed land cover information.

Looking ahead, several avenues for enhancing the proposed land cover classification system could be explored. Firstly, integrating more advanced CNN architectures such as ResNet or DenseNet could potentially further improve classification accuracy by capturing more intricate spatial and spectral features from satellite images. Additionally, exploring transfer learning techniques by pretraining CNNs on large-scale datasets like ImageNet and fine-tuning them for specific land cover classification tasks could expedite model convergence and enhance performance. Moreover, incorporating ensemble learning methods that combine predictions from multiple CNN models could increase robustness and reliability, particularly in challenging environmental contexts. By pursuing these enhancements, the proposed system can evolve into a more versatile and powerful tool for accurate and efficient land cover classification in diverse real-world scenarios.

REFERENCES

[1] Liang, Youzhi& Liang, Wen & Jia, Jianguo. "Structural Vibration Signal Denoising Using Stacking Ensemble of Hybrid CNN-RNN". Advances in Artificial Intelligence and Machine Learning. Vol 03. Pg 1110-1122,2023.

[2] Meshkini, Khatereh &Bovolo, Francesca & Bruzzone, Lorenzo. "A 3D CNN Approach For Change Detection In HR Satellite Image Time Series Based On A Pretrained 2D CNN." The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences. Vol XLIII-B3-2022. Pg 143-150 ,2022.

[3] Liu, J.; Zhang, K.; Wu, S.; Shi, H.; Zhao, Y.; Sun, Y.; Zhuang, H.;. "An Investigation of a Multidimensional CNN Combined with an Attention Mechanism Model to Resolve Small-Sample Problems in

Hyperspectral Image Classification." Remote Sensing, Vol 14, Pg 785, 2022.

[4] Ji, Min & Liu, Lanfa& Du, Runlin&Buchroithner, Manfred. "A Comparative Study of Texture and Convolutional Neural Network Features for Detecting Collapsed Buildings After Earthquakes Using Pre- and Post-Event Satellite Imagery". Remote Sensing, Vol 11, Pg 1202,2019.

[5] Varela Quintela, Sebastian & Pederson, Taylor & Leakey, Andrew. "Implementing Spatio-Temporal 3D-Convolution Neural Networks and UAV Time Series Imagery to Better Predict Lodging Damage in Sorghum." Remote Sensing. Vol 14, 733, 2022.

[6] Liu, Ziqian& Wang, Wenbing& Ma, Qing & Liu, Xianming& Jiang, Junjun."Rethinking 3D-CNN in Hyperspectral Image Super-Resolution." Remote Sensing. Vol 15. Pg 2574, 2023.

[7] Ilesanmi, A.E., & Ilesanmi, T." Methods for image denoising using convolutional neural network: a review." Complex & Intelligent Systems, Vol 7, Pg 2179 - 2198, 2021.

[8] Adegun, Adekanmi&Viriri, Serestina&Tapamo, Jules-Raymond. "Review of deep learning methods for remote sensing satellite images classification: experimental survey and comparative analysis". Journal of Big Data. Vol 10. Pg 93, 2023.

[9] Teixeira I, Morais R, Sousa JJ, Cunha A. "Deep Learning Models for the Classification of Crops in Aerial Imagery: A Review." Agriculture. Vol 13(5), Pg 965,2023.

[10] Tim Yngesjö, Gustav Hager," 3D reconstruction from satellite imagery using deep learning", IJERT ,Pg.371 ,Vol.10,2021.

