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Satellite Image Classification by Using Artificial Intelligence Techniques

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ABSTRACT: A wide range of industries, including agriculture, urban planning, disaster relief, and environmental monitoring, rely heavily on satellite imaging. To extract useful information and make wise judgments, satellite picture categorization must be done quickly and precisely. In this paper, we suggest classifying satellite images using artificial intelligence methods. A large collection of captioned satellite photos is gathered, each one illustrating a distinct type of land cover or interesting object. To improve image quality, reduce noise, and standardize the data, the dataset is pre-processed. Techniques for augmentation data, like rotation, scaling, and flipping, are utilized to expand the dataset and enhance the model's capacity for generalization. To further enhance the classification performance, future research topics can examine sophisticated deep learning structures like graph neural networks or attention processes. Furthermore, temporal analysis and the integration of multi-sensor satellite data might improve the classification models' performance for applications involving change detection and dynamic monitoring.

KEYWORDS: Land cover classification, artificial intelligence, deep learning, transfer learning, convolutional neural networks, satellite imaging, and data augmentation.

I. INTRODUCTION

Satellite imagery has become an invaluable source of information for various applications, ranging from environmental monitoring and disaster management to urban planning and agricultural assessment. With the increasing availability of high-resolution satellite data and advancements in artificial intelligence (AI) techniques, the field of satellite image classification has witnessed significant progress. AI techniques, including deep learning, have demonstrated their effectiveness in automating the process of classifying objects and features within satellite images. Satellite image classification refers to the task of assigning predefined categories or labels to different regions or pixels within satellite images. Deep learning, a subset of machine learning, has gained substantial attention for its ability to automatically learn complex features through neural networks.

II. OBJECTIVE

The objectives of employing deep learning techniques for satellite image classification are focused on refining model architectures to effectively accommodate the distinctive characteristics of satellite imagery, including spatial intricacies, spectral variations, and textural nuances.

III. LITERATURE SURVEY

Weigang Bai, Hongming Yang, Jincheng Tong, Zhaotao Qin, Ruochen Lyu. Vector Segment Routing for Large-Scale Multilayer Satellite Network. Proposed vector segment routing improves efficiency in multi-layer satellite networks by establishing forwarding paths based on location and dynamic route maintenance.

LEO satellite networks adopt Orbital Edge Computing (OEC) deploying MEC servers, enhancing real-time applications. OEC-TA algorithm improves average delay and energy consumption.

BASSEL AL HOMSSI, CHIU C. CHAN1, KE WANG. Deep Learning Forecasting and Statistical Modelling for Q/V-Band LEO Satellite Channels. Paper proposes Q/V-band LEO satellite channel model using machine learning and statistical tools for radio channel forecasting.

Ziluan Liu, Yanru Wang. HGL: A hybrid global-local load balancing routing scheme for the Internet of Things through satellite networks. This article proposes a hybrid global-local load balancing routing scheme for Low Earth Orbit satellite networks to optimize Internet of Things data transmission, effectively managing varying traffic requirements.

IV. PROPOSED SYSTEM

We suggested utilizing a deep learning algorithm as a system to advance the endeavour. Artificial intelligence and deep learning have been key factors in the growth and development of several industries recently. Thus, in order to train our model using the data about the satellite image that had already been gathered, we attempted to design a deep learning algorithm. We train our model using the satellite photos, but in order to generate more accurate predictions, we must first pre-process the data. Following pre-processing, train our model and use metrics to assess its success. We can determine how well our model is trained using the input by looking at the accuracy score.

V. ENVIRONMENT REQUIREMENTS

Software Used

Operating System: Windows

Tool: Anaconda with Jupyter Notebook

Hardware requirements

Processor: Intel® Core™ i7 processor 14650HX (30MCache, up to 5.20 GHz)

Hard disk: minimum 80 GB

RAM: minimum 4 GB

Algorithm Used

CNN Algorithm

VI. WORKING PRINCIPLE

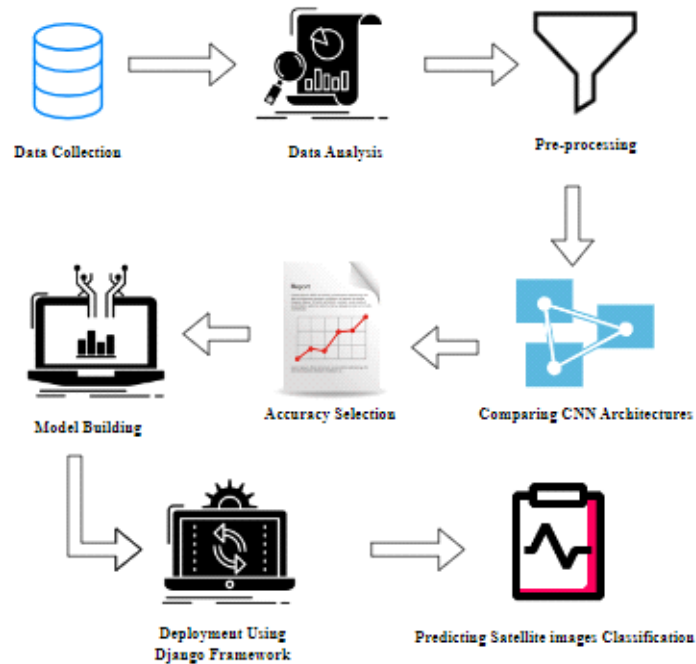
To begin delving into machine learning with Python, a logical starting point is to embark on a project. Not only does this necessitate the installation and initiation of the Python interpreter, but it also offers a comprehensive view of navigating through a small-scale project, fostering confidence for potential future endeavours. The process of executing a machine learning project may not adhere to a strictly linear path, yet it encompasses several well-defined stages: problem definition, data preparation, algorithm evaluation, result enhancement, and result presentation. Undertaking a machine learning project end-to-end, encompassing crucial steps such as data loading, summarization, algorithm evaluation, and prediction, is the optimal approach to grasp a new platform or tool thoroughly.

The following overview outlines the key components of our exploration:

- Installation of the Python Anaconda platform, serving as the foundation for our machine learning endeavours.
- Loading the dataset, a fundamental step in preparing our data for analysis and model training.
- Summarizing the dataset, wherein we extract insights and gain a comprehensive understanding of its structure and characteristics.
- Visualizing the dataset, employing graphical representations to uncover patterns and trends that may inform our modelling approach.
- Algorithm evaluation, a critical phase where we assess the performance of various machine learning algorithms to determine their suitability for our task.
- Making predictions, utilizing the chosen model to generate insights and forecasts based on the trained data.
- This structured approach will guide us through each stage of the machine learning project, facilitating a thorough understanding of the processes involved and enabling informed decision-making at every step.

Advantages: We've developed a framework-based application for deployment, leveraging deep learning for classification. Our development costs are minimized, but our process entails high time complexity.

VII. SYSTEM ARCHITECTURE



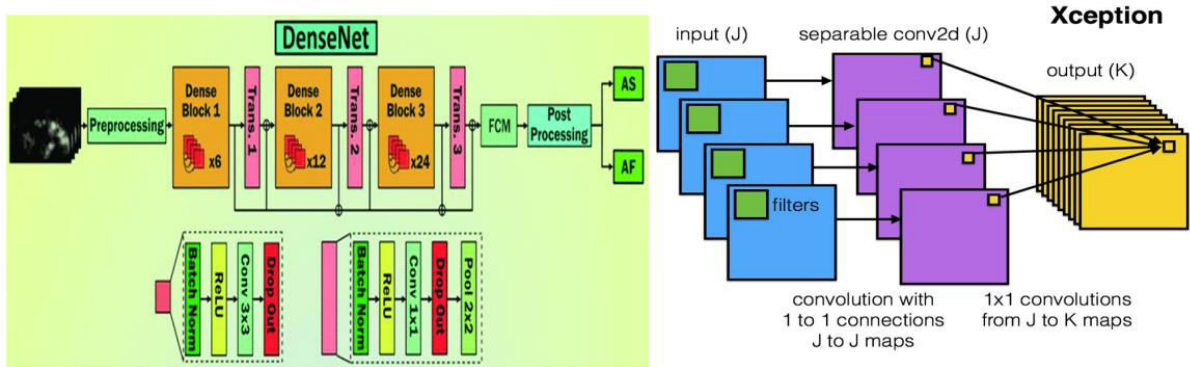
VIII. ARCHITECTURE

CONVOLUTION NEURAL NETWORK

This cornerstone of CNNs applies a convolution operation between the input image and a set of adaptable filters. Each filter discerns specific features within the input image. Following the convolution operation, an activation function such as ReLU (Rectified Linear Unit) is applied element-wise, introducing non-linearity. Pooling layers subsequently downsample the feature maps, reducing spatial dimensions and computational complexity, while preserving crucial information. After multiple convolutional and pooling layers, the final feature maps are flattened into a vector and linked to a conventional neural network for classification. In classification tasks, the softmax layer is utilized to generate probability distributions across classes, thereby determining the ultimate classification outcome.

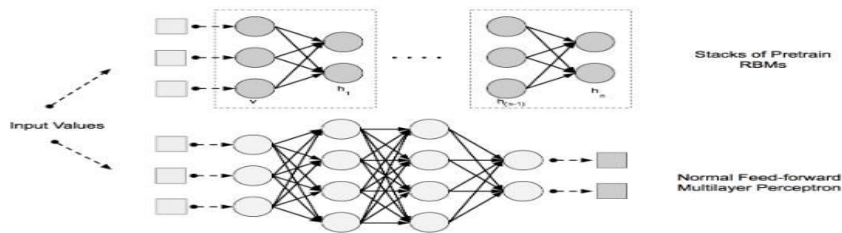
XCEPTION AND DENSENET

Xception and DenseNet represent groundbreaking advancements in Convolutional Neural Network (CNN) architectures. Xception, derived from "Extreme Inception," enhances the traditional Inception model by employing depthwise separable convolutions. This strategy, by separating spatial and channel-wise convolutions, significantly reduces computational complexity while preserving performance standards. Conversely, DenseNet, or Dense Convolutional Network, introduces dense connectivity patterns among layers. In DenseNet, each layer receives direct input from all preceding layers and shares its feature maps with all subsequent layers. This design fosters extensive feature reuse, promotes gradient flow, and effectively addresses the vanishing-gradient problem. Consequently, DenseNet achieves superior performance and parameter efficiency. Both Xception and DenseNet have demonstrated exceptional performance across various computer vision tasks, providing unique advantages in computational efficiency and feature utilization.

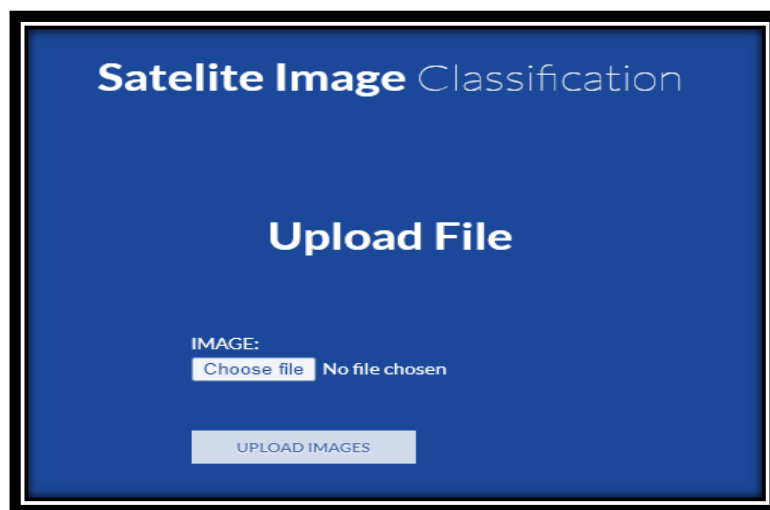


ARTIFICIAL NEURAL NETWORK

Artificial Neural Networks (ANNs) are computational frameworks inspired by the structure and functions of biological neural networks in the human brain. Consisting of interconnected nodes, or neurons, ANNs possess the capability to discern intricate patterns and correlations within datasets, rendering them versatile tools for diverse machine learning endeavours.

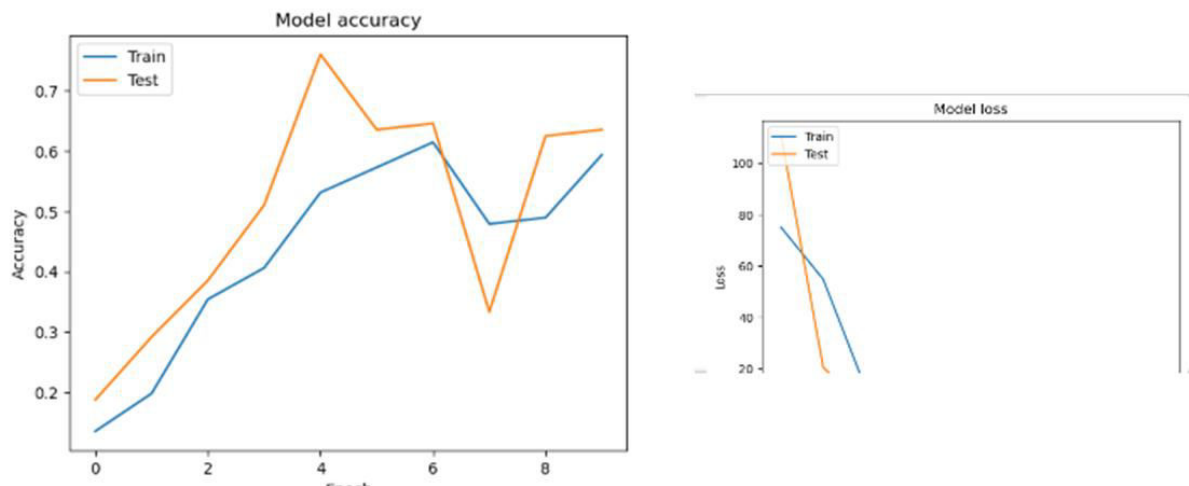


Each neuron within a layer establishes connections with every neuron in the subsequent layer, with each connection endowed with a weight reflecting its significance. During the training phase, ANNs refine these weights via backpropagation, where the network learns from the disparity between its predicted outcomes and actual target results. This iterative adjustment process minimizes the network's errors, enhancing its predictive accuracy over time. ANNs find application across a broad spectrum of tasks encompassing classification, regression, pattern recognition, and even creative endeavours like image and text generation. Their adeptness at learning from extensive datasets and generalizing to novel data renders ANNs indispensable in contemporary artificial intelligence systems.



IX. OUTPUT

In satellite image classification, both ANN and CNN models assign class labels to image segments. ANNs provide probabilities for each class, whereas CNNs offer probability distributions. Performance metrics such as overall accuracy, precision, recall, and F1-score evaluate model accuracy. The choice between ANN and CNN depends on factors like data complexity, availability of labeled data, computational resources, and desired accuracy levels.



X. CONCLUSION

The use of artificial intelligence approaches for satellite classification of images represents an enormous advance in remote sensing and data analysis. This project has shown promise in transforming our understanding of and ability to use satellite imagery through the investigation of various machine learning and deep learning techniques. We have effectively obtained more precise and effective land cover classifications by modifying and creating architectures that capture complex spatial, spectral, and texture patterns within satellite pictures.

REFERENCES

1. Q. Tong, Y. Xue, and L. Zhang, "Progress in hyperspectral remote sensing science and technology in china over the past three decades," *IEEE J. Sel. Top. Appl. Earth Observ. Remote Sens.*, vol. 7, no. 1, pp.70–91, Jan. 2014.
2. J. M. Bioucas-Dias, A. Plaza, G. Camps-Valls, P. Scheunders, N.Nasrabadi, and J. Chanussot, "Hyperspectral remote sensing data analysis and future challenges," *IEEE Geosci. Remote Sens. Mag.*, vol. 1, no. 2, pp. 6–36, Jun. 2013.
3. P. S. Thenkabail and J. G. Lyon, *Hyperspectral Remote Sensing of Vegetation*, Boca Raton, FL, USA: CRC, 2016.
4. A. F. Goetz, "Three decades of hyperspectral remote sensing of the earth: A personal view," *Remote Sens. Environ.*, vol. 113, pp. 5–16, 2009.
5. V. E. Brando and A. G. Dekker, "Satellite hyperspectral remote sensing for estimating estuarine and coastal water quality," *IEEE Trans. Geosci. Remote Sens.*, vol. 41, no. 6, pp. 1378–1387, Jun. 2003.
6. Y. Fu, T. Zhang, Y. Zheng, D. Zhang, and H. Huang, "Joint camera spectral response selection and hyperspectral image recovery," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 44, no. 1, pp. 256–272, Jan. 2022.
7. F. Melgani and L. Bruzzone, "Classification of hyperspectral remote sensing images with support vector machines," *IEEE Trans. Geosci. Remote Sens.*, vol. 42, no. 8, pp. 1778–1790, Aug. 2004.
8. J. L. Fang, S. Li, W. Duan, J. Ren, and J. A. Benediktsson, "Classification of hyperspectral images by exploiting spectral–spatial information of superpixel via multiple kernels," *IEEE Trans. Geosci. Remote Sens.*, vol. 53, no. 12, pp. 6663–6674, Dec. 2015.
9. W. Song, S. Li, L. Fang, and T. Lu, "Hyperspectral image classification with deep feature fusion network," *IEEE Trans. Geosci. Remote Sens.*, vol. 56, no. 6, pp. 3173–3184, Jun. 2018.



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