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DEEP LEARNING FOR SATELLITE IMAGE LABELING

[1]Sreekar Sai Gudikandula, [2]Chaitanya Gowra, [3]Srushti Gandhe,
[4]Neha Domakuntla, [5]S. Priyanka

[1,2,3,4]Student, Department of CSE(AI&ML), CMR Engineering College, Hyderabad, Telangana

[5] Assistant Professor Department of CSE(AI&ML), CMR Engineering College, Hyderabad, Telangana

Abstract: Satellite photos are widely used in fields including emergency management, security, and environmental monitoring. These goals can't be achieved without the help of humans and the ability to properly identify objects. With so many possible search spaces and so few analysts on hand, automation is essential. However, owing to their focus on accuracy and precision, conventional techniques to identify items and categorization are constrained in their capacity to deliver a solution. Automating these steps using supervised neural class ML algorithms has shown some success. There is some evidence that convolutional neural networks, a kind of artificial neural network, may enhance both picture identification and understanding. In this case, we use them to learn how to identify artificial features in high-resolution, multispectral satellite imagery. We provide a deep learning approach to classifying features or architecture into 63 categories utilizing the IARPA Function World Map (fMoW) dataset.

Index Terms – Feature Classification, Deep Learning.

I. Introduction

Satellite image labeling is an essential step within the realm of remote sensing and geospatial analysis. This process involves the annotation of high-resolution satellite images to identify and categorize distinct features or objects present in the imagery. By assigning semantic labels to different regions or pixels in satellite images, this technique enables the extraction of valuable information about the Earth's surface. In recent years, the integration of deep learning techniques has revolutionized the field of satellite image analysis, particularly in the context of image labeling. Using many processing layers to represent input at varying levels of abstraction, deep learning is a kind of machine learning. By coupling massive neural network models, known as convolutional neural networks (CNNs), with potent graphics processing units (GPUs), it has achieved astounding success in object identification and categorization. During training, the network figures out which traits to look for and how to find them. In order to recognize handwritten zip codes, the first effective CNNs had less than 10 layers. Rapidly improving graphics processing units (GPUs) and open-source deep learning software frameworks like TensorFlow and Keras have fueled the field of deep learning

II. Objective

Disaster relief, police work, and environmental watch all benefit greatly from satellite photography. Objects and infrastructure in the images must be manually identified for these uses. Automation is necessary since there are large areas to search throughout and a limited number of analysts to execute these searches. However, the accuracy and dependability of existing object recognition and classification algorithms render them inadequate for the task. One class of predictive algorithms called "deep learning" has shown great potential for automating these kinds of jobs. Using convolutional neural networks, it has been able to successfully interpret images. In this study, we use them to address the issue of identifying structures and other objects in multispectral, high-resolution satellite images.

III. Literature Survey

Introduction to Satellite Imaging Technology and Creating Images Using Raw Data ICGTI, 2012 - S. Gupta, Vidhya Vihar

This paper aims at presenting various satellite imaging techniques and includes satellite sensors, their resolutions, the format in which they store data, the bands they use in their application in satellite imaging technology. Through this paper, they intend to present a logic for creating images using raw data obtained from Landsat satellite.

Multi-label Classification of Satellite Images Using Deep LearningStanford.edu, 2017 - Daniel Gardner, David Nichols

They implemented a CNN model to perform multi-label classification of Amazon satellite images. Their model identifies the weather conditions and natural terrain features in the images as well as man-made developments such as roads, farming, and logging.

Analysis of Various Optimizers on Deep Convolutional Neural Network Model in the Application of Hyperspectral Remote Sensing Image Classification International Journal of Remote Sensing, 2020 - Somenath Bera, Vimal K. Shrivastava

Hyperspectral image (HSI) classification is a challenging task in the hyperspectral remote sensing field due to the unique characteristics of HSI data. They presented a spatial feature extraction technique using deep CNN for HSI classification.

Monitoring Agriculture Areas with Satellite Images and Deep Learning Hanoi University of Science and Technology, 2020 - Tam Nguyen, Dat Thanh Hoang

This study focuses on addressing the challenges in monitoring agricultural land, particularly paddy areas, for effective food security control and support actions. The study proposes the development of an autonomous and intelligent system that utilizes imagery data from low-Earth orbiting satellites for cost-effective and timely mapping of paddy fields.

IV. Proposed System

The concept in the proposed system is to use deep learning for satellite image labeling, enhancing our ability to extract valuable information from satellite imagery. Enabling us to make informed decisions in various fields such as environmental monitoring, disaster management, urban planning, agriculture, defense, and more. Utilizing a CNN as the backbone for feature extraction, CNNs are well-suited for image data and can capture hierarchical features effectively. Since satellite images often contain spatial dependencies, integrating an RNN or Transformer component can capture contextual information across different regions of the image.to less accurate and relevant captions, which is not ideal for generating meaningful captions.

- Accuracy and Precision
- Flexibility and Adaptability
- Real-time Processing

V. Approach

Convolutional Neural Networks (CNNs):

CNNs are widely used for image analysis tasks, including satellite image labeling. It is a type of deep learning model designed for processing and analyzing structured grid data, such as images. They consist of convolutional layers that automatically learn hierarchical features from the input images. CNNs have proven to be highly effective in tasks related to computer vision, including image classification, object detection, and image segmentation.

Recurrent Neural Networks (RNNs):

RNN is a type of artificial neural network designed for sequential data processing and tasks where the order of data elements matters. RNNs can be employed for sequential data processing in satellite imagery, such as time-series data or sequences of images. They can capture temporal dependencies and patterns in satellite data over time. RNNs have connections that form a directed cycle, allowing them to maintain a hidden state that captures information about previous inputs in the sequence.

Testing Techniques:

A. Unit Testing:

Ensures that each individual component of the program operates correctly. Verifies that inputs yield valid outputs for each isolated unit, such as functions, classes, or methods.

B. Integration Testing:

Evaluates how well the combined components of the software work together. Confirms that the integrated components interact and function as a unified system.

C. Functional Testing:

Checks that specific features perform according to business and technical requirements. Validates that the system's functionalities operate as specified.

D. System Testing:

Assures that the entire software system meets its design and performance requirements. Tests the complete system configuration to ensure consistent and expected outcomes.

E. Acceptance Testing:

Determines if the software satisfies the business requirements and is ready for deployment. Verifies that the final product aligns with all business criteria and meets end-user needs.

F. Usability Testing:

Assesses the ease of use and user-friendliness of the application. Examines the user experience and interface design to ensure they meet usability standards.

The dataset is taken from Kaggle with the memory size of about 1.8GB that is 70,000 trained and tested data.

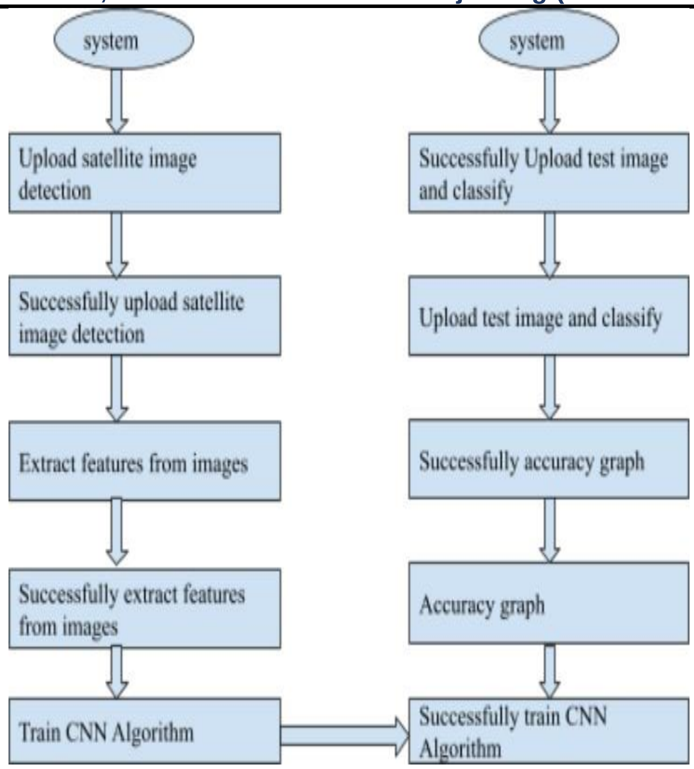


Fig. 5.1 Data Flow Diagram

VI. OUTPUT

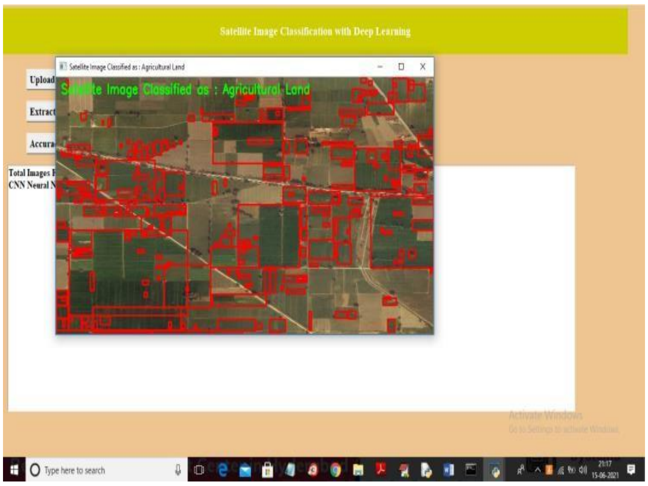
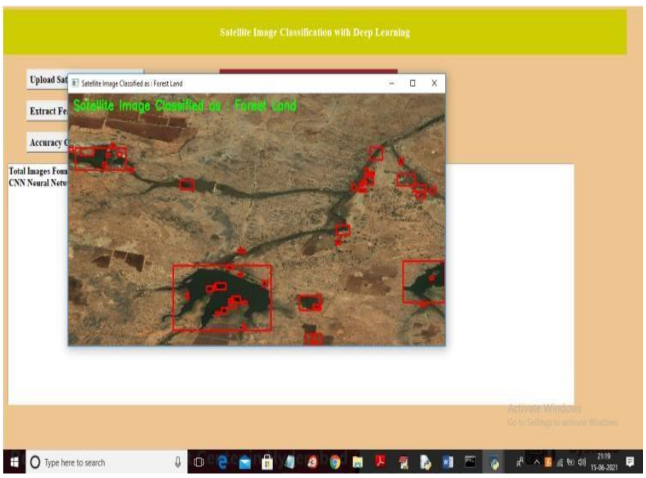


Fig. 6.1



Fg. 6.2

VII. CONCLUSION

Using high-resolution multispectral satellite data, we have demonstrated a deep learning system that can accurately categorize items and infrastructure. An ensemble of CNNs and neural networks used for post-processing integrate the predictions of the CNN algorithms with satellite information. The system achieves a reliability of 0.83 and a first-order score of 0.797 on the IARPA fMoW dataset, which contains one million photos divided into 63 classes. It outperforms the Johns Hopkins University APL engine in the fMoW Top Coder competition by 4.3%. The system can sift through massive volumes of satellite images in search of specific items or infrastructure. This might be the answer to issues raised at the beginning of this article. With access to a database of satellite images, authorities could crack down on illegal mining and fishing operations, rescue workers could better map mudslides and hurricane damage, and investors could keep tabs on crop development and oil well progress.

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