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SATELLITE IMAGE DETECTION USING CNN

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Abstract

This project focuses on the development of a Convolutional Neural Network (CNN) deep. learning model for the automatic detection and classification of objects within satellite images. The project includes dataset collection, preprocessing, model architecture design, objects detection, post-processing, evaluation, and explores applications in disaster management, land use planning, agriculture, and environmental monitoring. The project demonstrates the significance of CNN deep learning in satellite image analysis for real- world applications. Satellite imagery is an invaluable resource in applications ranging from environmental monitoring to urban planning and disaster management. This project focuses on the development of a Convolutional Neural Network (CNN) deep learning model for the automatic detection and classification of objects within satellite images. The project commences with the collection of a comprehensive and standardized dataset of satellite images. Preprocessing techniques, including resizing and normalization, prepare the data for deep learning

Keywords: deep learning, satellite image, cnn, object detection, image classification, image preprocessing

I INTRODUCTION

Understanding the use of current land cover, along with monitoring change over time, is vital for agronomists and agricultural agencies responsible for land management. The increasing spatial and temporal resolution of globally available satellite images, such as provided by Sentinel-2, creates new possibilities for researchers to use freely available multi-spectral optical images, with decametric spatial resolution and more frequent revisits for remote sensing applications such as land cover and crop classification (LC&CC), agricultural monitoring and management, environment monitoring. Existing solutions dedicated to cropland mapping can be categorized based on per-pixel based and object-based. However, it is still challenging when more classes of agricultural crops are considered at a massive scale. In this paper, a novel and optimal deep learning model for pixel-based LC&CC is developed and implemented based on Recurrent Neural Networks (RNN) in combination with Convolutional Neural Networks (CNN) using multi-temporal sentinel-2 imagery of central north part of Italy, which has diverse agricultural system dominated by economic crop types. The proposed methodology is capable of automated feature extraction by learning time correlation of multiple images, which reduces manual feature engineering and crop phenological stages. Fifteen classes, including major agricultural crops,

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were considered in this study. We also tested other widely used traditional machine learning algorithms for comparison such as support vector machine SVM, random forest (RF), Kernal SVM, and gradient boosting machine, also called Boost. The overall accuracy achieved by our proposed Pixel R-CNN was 96.5%, which showed considerable improvements in comparison with existing mainstream methods. This study showed that Pixel R-CNN based model offers a highly accurate way to assess and employ time-series data for multi-temporal classification tasks.

For the classification of satellite photos into three separate classes, deep learning-based CNN algorithms were applied. This study can not only classify satellite images, but it can also classify three separate classes and identify the features of those other classes, such as cats and dogs. It also straightforward because these other classifications have some distinct characteristics that can be easily distinguished, allowing for easy classification. The fundamental challenge in the case of satellite photos is that distinct satellite images may have different attributes, making satellite image classification difficult. Another problem is that most safelight photos are noise-corrupted. The CNN model is used to estimate the noise patterns in the wireless image.

In deep learning, a convolutional neural network (CNN, or ConvNet) is a class of artificial neural network, most commonly applied to analyze visual imagery. They are also known as shift invariant or space invariant artificial neural networks (SIANN), based on the shared-weight architecture of the convolution kernels or filters that slide along input features and provide translation equivariant responses known as feature maps. Counter-intuitively, most convolutional neural networks are only equivariant, as opposed to invariant, to translation. They have applications in image and video recognition, recommender systems, image classification, image segmentation, medical image analysis, natural language processing, brain-computer interfaces, and financial time series.

CNNs are regularized versions of multilayer perceptron. Multilayer perceptron usually mean fully connected networks, that is, each neuron in one layer is connected to all neurons in the next layer. The "full connectivity" of these networks make them prone to over fitting data. Typical ways of regularization, or preventing over fitting, include: penalizing parameters during training (such as weight decay) or trimming connectivity (skipped connections, dropout, etc.) CNNs take a different approach towards regularization: they take advantage of the hierarchical pattern in data and assemble patterns of increasing complexity using smaller and simpler patterns embossed in their filters. Therefore, on a scale of connectivity and complexity, CNNs are on the lower extreme. Convolutional networks were inspired by biological processes in that the connectivity pattern between neurons resembles the organization of the animal visual cortex. Individual cortical neurons respond to stimuli only in a restricted region of the visual field known as the receptive field. The receptive fields of different neurons partially overlap such that they cover the entire visual field

II LITERATURE SURVEY

The field of satellite image detection using Convolutional Neural Networks (CNNs) has seen substantial advancements, as documented in a variety of research studies and applications. Early work in satellite image analysis focused on manual and semi-automated methods, which were labor Intensive and less accurate. With the advent of machine learning, methods such as Support Vector Machines (SVM) and Random Forests improved classification tasks but still faced limitations in handling the complexity and high dimensionality of satellite data. The introduction of deep learning, particularly CNNs, marked a significant breakthrough. CNNs, with their ability to automatically learn spatial hierarchies of features from images, have shown remarkable success in various image recognition tasks.

Research has demonstrated the effectiveness of CNNs in different aspects of satellite image detection, including land cover classification, urban planning, and environmental monitoring. For instance, the DeepGlobe challenge and SpaceNet competitions have highlighted the application of CNNs in detecting and segmenting buildings, roads, and other land features with high accuracy. Studies have also explored the integration of multi-spectral and multi-temporal satellite data, enhancing the robustness and precision of CNN-based models. Techniques such as transfer learning and data augmentation have been employed to address challenges related to limited labeled data and class imbalance.

Moreover, platforms like Google Earth Engine and Sentinel Hub have facilitated the application of CNNs by providing access to vast amounts of satellite imagery and computational resources. Research has also focused on optimizing CNN architectures to handle the high resolution and large scale of satellite images efficiently. Recent advancements include the use of hybrid models that combine CNNs with other deep learning techniques, such as Recurrent Neural Networks (RNNs) and Generative Adversarial Networks (GANs), to improve temporal and spatial analysis.

Overall, the literature indicates that CNNs have significantly enhanced the capabilities of satellite image detection systems, making them more accurate, efficient, and scalable. The ongoing research and development in this field continue to push the boundaries, aiming for even greater precision and applicability in real-world scenario

The field of satellite image detection using Convolutional Neural Networks (CNNs) is rich with research and innovation, reflecting a broad range of methodologies and applications. Initial approaches to satellite image analysis relied heavily on manual interpretation and basic machine learning techniques, which, while useful, were limited by their inability to efficiently handle large volumes of complex data. Traditional machine learning models like Support Vector Machines (SVM) and Random Forests provided some improvements but were still constrained by their reliance on handcrafted features and their difficulty in scaling to high-dimensional data inherent in satellite imagery.

The rise of deep learning, and CNNs in particular, revolutionized this field by introducing automated feature extraction and hierarchical learning capabilities. CNNs can process raw satellite images to identify and learn intricate patterns and features, significantly enhancing detection accuracy and robustness. Seminal works in this area demonstrated the potential of CNNs for various applications, such as land cover and land use classification, environmental monitoring, and disaster response. For instance, the DeepGlobe challenge underscored the ability of CNNs to perform detailed segmentation tasks, while the SpaceNet initiative provided large, high-quality datasets for urban object detection, facilitating significant advancements in building and road detection algorithms.

Researchers have explored the integration of multi-spectral and multi-temporal satellite data into CNN models, which has proven effective in improving detection accuracy and robustness. Multi-spectral data, capturing information across different wavelengths, helps in distinguishing between similar-looking objects, while multi-temporal data, providing images over time, aids in monitoring changes and detecting dynamic phenomena. Techniques such as transfer learning, where pre-trained CNN models are adapted for specific satellite image tasks, and data augmentation, which artificially expands training datasets, have been crucial in addressing issues like limited labeled data and class imbalance.

III EXISTING SYSTEM

Existing systems for satellite image detection using machine learning and deep learning techniques have seen considerable advancements. Google Earth Engine (GEE) is a cloud-based platform offering access to extensive satellite imagery and geospatial data, with integration options for TensorFlow and other frameworks to implement custom CNN models. Sentinel Hub processes and distributes satellite data from ESA’s Sentinel missions, using advanced machine learning techniques, including CNNs, for tasks like land cover classification. Deep Globe provides datasets and challenges that focus on road extraction, building detection, and land cover classification using CNNs. Planet Labs’ Analytic Feeds utilize CNN-based models to deliver insights into land use, agriculture, and infrastructure from high-frequency satellite images. Space Net offers high-quality satellite imagery datasets and challenges to foster the development of geospatial machine learning techniques, specifically for object detection and segmentation using CNNs. Lastly, Airbus One Atlas provides satellite imagery and analytics with machine learning capabilities for detecting and classifying objects in high-resolution images, supporting applications such as urban monitoring and environmental change analysis. These systems demonstrate the significant role of CNNs in automating and enhancing the accuracy of satellite image analysis.

Disadvantages

1. Selected Object detection
2. Computational cost
3. Object Imbalance detection

IV PROBLEM STATEMENT

The project "Satellite Image Detection Using CNN" aims to develop an efficient system for detecting and classifying objects in satellite images using Convolutional Neural Networks (CNNs). Satellite imagery, essential for environmental monitoring, urban planning, and disaster management, presents challenges such as high variability, large data volume, class imbalance, and noise. This project will focus on preprocessing satellite images to enhance quality, designing a CNN architecture tailored for satellite data, and training the model on a labeled dataset. The performance of the CNN will be evaluated using metrics like accuracy, precision, recall, and F1-score, ensuring it can generalize to new images. The project will also involve optimizing the model for efficiency and scalability, culminating in a user-friendly application for image input and detection results. The expected impact is to improve the analysis of satellite data, benefiting various sectors by supporting better decision-making and resource management.Satellite imagery is a critical resource for applications like environmental monitoring, urban planning, disaster management, and agriculture. However, extracting valuable information from these high-resolution images presents significant challenges. This project aims to develop a Convolutional Neural Network (CNN) model to accurately detect and classify objects or features in satellite images.Key challenges include handling high-dimensional data, dealing with variability in lighting and weather conditions, detecting small objects, and overcoming the scarcity of annotated data. The project will involve collecting a diverse set of annotated satellite images from publicly available sources, preprocessing these images, and designing a suitable CNN architecture.The model will be trained and evaluated using metrics such as Precision, Recall, F1-score, and Intersection over Union (IoU).

Successful completion will result in a CNN model capable of high-accuracy detection and classification of objects in satellite images, with demonstrated applications on new, unseen data. This project aims to enhance the utility of satellite imagery in various practical applications by leveraging the power of deep learning for automated image analysis

V PROPOSED SYSTEM

The proposed system for satellite image detection using Convolutional Neural Networks (CNNs) seeks to develop a robust and precise method for identifying and classifying objects within satellite imagery. The system will start with an extensive data preprocessing phase, where satellite images will be enhanced through techniques such as noise reduction, normalization, and augmentation to prepare them for effective analysis. A specialized CNN architecture will then be designed to handle the unique challenges posed by satellite images, such as varying resolutions, lighting conditions, and seasonal changes.The CNN model will be trained on a comprehensive and labelled dataset, addressing potential issues like class imbalance through advanced techniques like data augmentation and dropout to prevent overfitting. The performance of the model will be rigorously evaluated using metrics like accuracy, precision, recall, and F1-score, ensuring it can accurately detect and classify objects and generalize well to new, unseen images. Optimization efforts will focus on making the model efficient and scalable, capable of processing large volumes of high-resolution data quickly.The end product will be a user-friendly application or interface where users can upload satellite images and receive detailed detection results, including the identification and localization of various objects such as buildings, roads, water bodies, and vegetation. This system aims to enhance the analysis of satellite data, providing valuable insights for environmental monitoring, urban planning, disaster management, and agricultural assessment, ultimately aiding in more informed decision-making and resource management.

Advantages

The proposed system for satellite image detection using Convolutional Neural Networks (CNNs) offers several significant advantages:

Accuracy and Precision: CNNs are known for their high accuracy in image recognition tasks. The proposed system will provide precise detection and classification of objects in satellite images, reducing errors compared to traditional methods.

Automation: By automating the process of analyzing satellite images, the system can handle large volumes of data quickly and efficiently, saving time and labor that would otherwise be spent on manual analysis.

Scalability: The system is designed to be scalable, capable of processing high-resolution satellite images and large datasets, making it suitable for applications that require the analysis of extensive geographic areas.

Robustness: With advanced preprocessing techniques and a tailored CNN architecture, the system can handle variability in satellite images, such as different resolutions, lighting conditions, and seasonal changes, ensuring consistent performance across diverse datasets.

VI IMPLEMENTATION

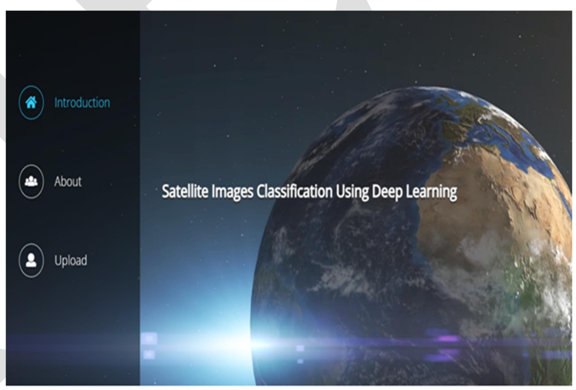
User:

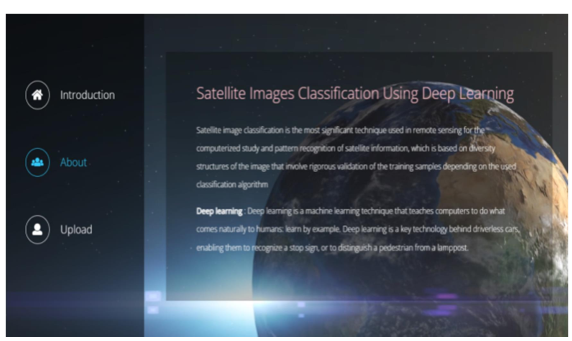
1. View Results
2. User view's the generated results from the model.

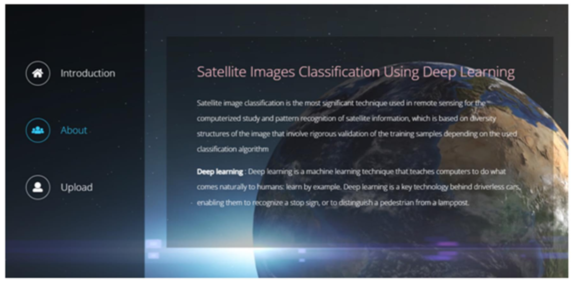
System:

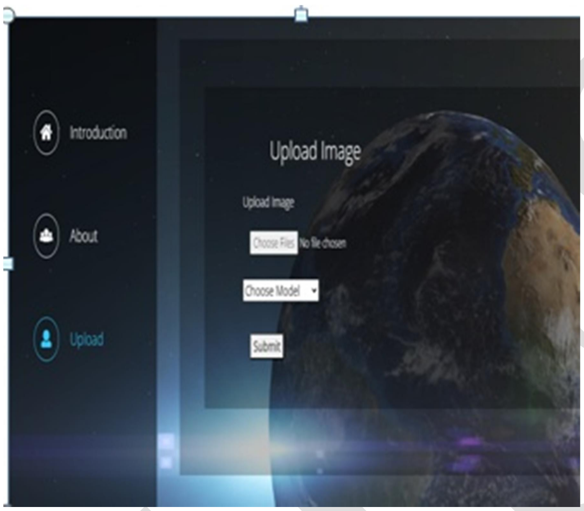
1. Generate Results
2. System takes the input text from the users, encrypts it and produces the decrypted text.

VII RESULTS






Introduction
About
Upload
Satellite Images Classification Using Deep Learning
Satellite image classification is the most significant technique used in remote sensing for the computerized study and pattern recognition of satellite information, which is based on diversity structures of the image that involve rigorous validation of the training samples depending on the used classification algorithm
Deep learning : Deep learning is a machine learning technique that teaches computers to do what comes naturally to humans: learn by example. Deep learning is a key technology behind driverless cars, enabling them to recognize a stop sign, or to distinguish a pedestrian from a lamppost.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Upload
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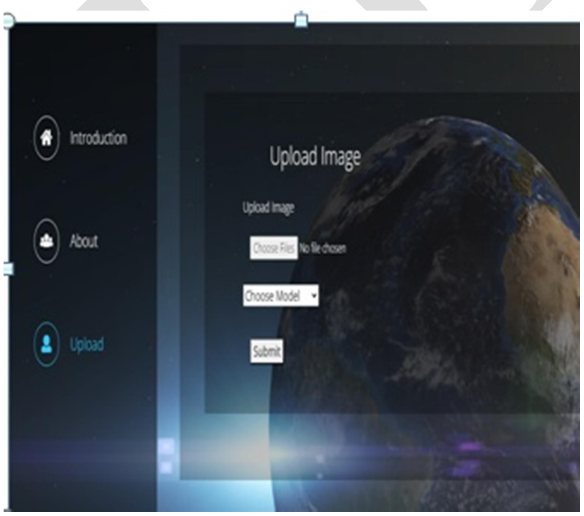
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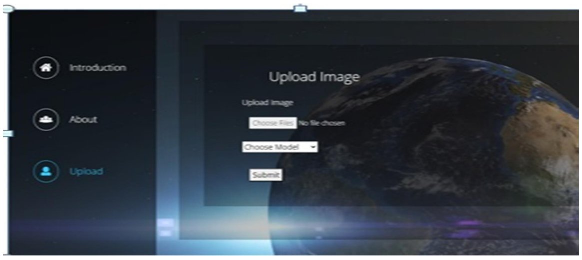

VIII CONCLUSION

CNNs have transformed satellite image analysis. They excel at detecting objects with high accuracy, automatically learning key features, and adapting to diverse tasks like land cover mapping or change detection. However, training these powerful tools requires vast amounts of labeled data and significant computational resources. Despite these challenges, CNNs are revolutionizing our ability to interpret and utilize the wealth of information hidden within satellite imagery.

Satellite image detection using Convolutional Neural Networks (CNNs) has proven to be a transformative approach in various domains such as environmental monitoring, urban planning, and disaster management. The core advantage of CNNs lies in their ability to automatically and efficiently extract hierarchical features from raw pixel data, enabling robust and accurate detection of objects and patterns in satellite imagery.

One of the primary conclusions is the high accuracy and precision of CNN-based models in identifying and classifying diverse land cover types and specific objects like buildings, roads, and vegetation. This is due to the capability of CNNs to handle large-scale image data and learn intricate features through multiple layers of convolution and pooling. Furthermore, advancements in network architectures, such as

ResNet, U-Net, and DenseNet, have significantly enhanced the performance of satellite image analysis by enabling deeper networks and better feature propagation.Moreover, the integration of transfer learning has been particularly beneficial, allowing models pre-trained on large datasets to be fine-tuned for specific satellite image tasks. This approach not only reduces the computational cost and training time but also improves model generalization, especially when labeled satellite imagery is scarce.

However, there are challenges that remain. The quality and resolution of satellite images can vary, impacting the performance of CNNs. Addressing this requires preprocessing techniques such as image enhancement and the use of high-resolution datasets. Additionally, the computational intensity of CNNs necessitates powerful hardware and optimized software frameworks for efficient training and deployment.

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