SATELLITE IMAGE CLASSIFICATION USING CONVOLUTIONAL NEURAL NETWORK

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Abstract- **For agronomists and agricultural organisations in charge of land management, it is essential to comprehend how the current land cover is used and to track changes over time. Researchers now have more opportunities to use publicly available multi-spectral optical images with decametric spatial resolution and more frequent revisits for remote sensing applications like land cover and crop classification (LC&CC), agricultural monitoring and management, and environment monitoring. This is due to the increasing spatial and temporal resolution of globally available satellite images, such as those provided by Sentinel-2. Cropland mapping systems now in use can be divided into two categories: object-based and per-pixel. When more agricultural crop classes are taken into account on a large basis, it is still difficult. This research develops an innovative and ideal Pixel-based LC&CC using a deep learning model. This work develops and applies a novel and optimal deep learning model for pixel-based LC&CC utilizing multi-temporal sentinel-2 data in the central north of Italy, which features a diverse agricultural system dominated by economic crop kinds. The model is built on a combination of convolutional and recurrent neural networks (RNN and CNN). By understanding the time correlation of several photos, the suggested methodology may extract features automatically, eliminating the need for manual crop phenology and feature engineering stage modelling. This study looked at fifteen classes, including important agricultural crops. For comparison, we also evaluated many other popular classical machinelearning techniques, including gradient boosting machine, or XGBoost, random forest (RF), kernel SVM, and support vector machine (SVM).**

Keywords: **Land Cover, Covolutional Neural Network, Crop classification, deep learning, Sentinel-2, Machine learning.**

I.INTRODUCTION

Technologies for remote sensing have advanced rapidly in recent years. This implies that it is now much easier to obtain a large collection of high-resolution remote sensing photos. Many remote sensing classification researchers has been switching from conventional methods to more modern strategies based on this idea. While newer techniques concentrate on the semantic understanding of the images, classic methods rely on the intensity of pixel-level interpretation. Semantic understanding attempts to classify into several groups and semantic categories based on the content of remote sensing images [1-3].Based on its features, the picture classification can be separated into three primary classes [1]. The "handcrafted feature-based method" emphasizes various attributes including hues and forms. The most popular encoding technique is known as quantization, this method uses a set of handcrafted qualities as the input and a group of learned features as the output, even though Fisher encoding is more efficient [5-7]. Lastly, "deep feature learning-based methods" (also known as Deep Learning, DL) [8–10]. Deep learning of features from images has demonstrated an amazing capacity for classification in recent years [1], by choosing the right features for the purpose of remote sensing image classification. Multiple learning layers provide the foundation of the "deep learning selection" subfield of machine learning. By increasing the number of layers in the hidden layer, the deep learning architecture builds upon the traditional Neural Network (NN). CNNs are a type of deep learning architecture used in artificial intelligence (AI). The CNN is widely used and has lately been used to handle a wide range of complex tasks, including image identification and classification, by using a number of feed-forward layers. The CNN is composed of neurons with learnable weights and biases, just like the conventional neural network. An artificial neural network that is feed-forward is created when a collection of inputs is processed nonlinearly by the neurons [11]. Convolutional network designs allow specific features to be embedded into the architecture by using images as inputs. The layers that typically comprise a CNN's structure include convolutional, pooling, and full connection layers. One may argue that it is a particular kind of neural network, with one or more convolutional layers that extract low-level features like edges, corners, and lines.

II.RELATED WORK

2.1 Title: Using Mask R-CNN for Agro-field Boundary Detection from Aerial and Satellite Images

Author :Temurbek Kuchkorov; Temur Ochilov; Elyor Gaybulloev; Nazokat Sobitova; Ortik Ruzibaev

Most nations in the world, especially emerging ones, depend on agriculture for both economic expansion and food security. Precise field boundary information is critical to precision farming and is very helpful to land management systems. This study introduces a deep learning approach for agricultural field border segmentation and detection that is based on the cutting-edge Mask Region Convolutional Neural Network (Mask R-CNN) instance segmentation algorithm. This model may identify each farming field in the satellite and aerial photos with precision. The outcomes of the experiment show that our automated method can identify agricultural fields with higher accuracy.

2.2 Title: Deep Learning-Based Small Object Detection of Satellite Images

Author : Ahmad Mansour; Wessam M Hussein; Ehab Said

Promising results are achieved when Deep Convolution Neural Network (CNN) is used for object detection of satellite photos, particularly for huge objects. However, the results of small item detection in photos with the same spatial resolution are not the same. When detecting a car, for example, in high-resolution satellite photos, the targeted object may have only occupied an area of 15 square pixels or less, which will not have a significant impact on deeper layers. Moreover, there is the background interference, noise, shadows cast by nearby objects, and variation in color of the vehicle. An analysis research is conducted in the suggested work to assess how altering the object size affects the detection outcomes. The input test photos are resized using a different resampling algorithm (keep in mind the integrated detection model resampling layer). This alters the object size and, as a result, increases the object impact in deeper levels. Using submeter satellite pictures and passenger cars as the target objects, the Fast R-CNN pre-trained object detection with Inception-V2 is trained by Transfer Learning. The experimental findings demonstrate how the size of the object affects detection accuracy.

2.3 Title: An enhanced single-stage target identification network-based model for satellite image target detection

Author : Runwu Liu; Tian Wang; Yi Zhou; Chuanyun Wang; Guangcun Shan; Hichem Snoussi

In order to address the issue of pinpoint identification in satellite imagery, this research suggests an enhanced approach that utilizes the YOLO V3 deep convolutional neural network. The target detection layer of the three scales was reset, and the network topology of the original YOLO V3 was changed. The test image is then recognized after being cut through the sliding window during the detection process because it is too big. The dataset was utilized to train and test the upgraded network in addition to the original YOLO V3 network during the project. According to the test findings, the enhanced network increases AP by 4.34%, detection accuracy by 1.79%, and recall rate by 4.55%.

2.4 Title: Deep Convolutional Neural Networks for the Identification of Military Targets from Satellite Images

Author : Harika Bandarupally; Harshitha Reddy Talusani; T Sridevi

The procedure of locating and separating the military targets is challenging, in the defence sector's photos because of their varied size, orientation, and backgrounds. In this field, several solutions have been put out, but far better and faultless results are still required. In this chapter, we elaborate on a two-level approach for target detection in satellite imagery: Edge Boxes and Convolutional Neural Networks (CNNs), which provide proper resolution of the image through the Dense-skip-connections. In the first level, Edge Boxes will be used to identify the military objects in the satellite image. The edge data of targets in satellite imagery includes clear and concise features.Large datasets are not well suited for the conventionally designed features like the Hough transform, Gabor feature, and Histogram of Oriented Gradients. But the Edge Boxes method creates contours around the objects that are the targets and removes everything else. The suggested targets proceed through picture super resolution in the second level, which receives the output from this level. The provided deep learning model has a propensity to automatically develop an end-to-end mapping between images of higher and lower resolutions. This level can be described as creating an output that is an unsampled high-resolution image inputted from a low-resolution image. This strategy seeks to optimize every layer simultaneously, in contrast to conventional methods (such as the bicubic method and the sparse coding-based method), which address each component independently. Moreover, Dense-skip-connections are used to alleviate the vanishing gradient issue that affects very deep networks. These allow shorter pathways to be built directly between layers. Despite its lightweight design, the suggested model displays cutting-edge repair quality.

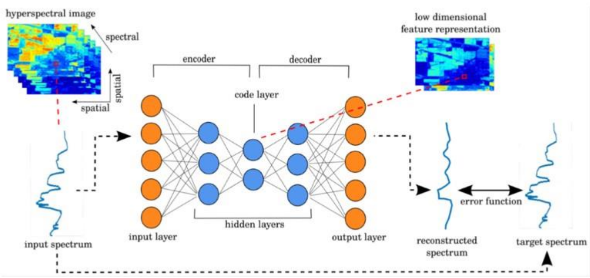


Fig 2.1 Architecture Diagram

III.EXISTING SYSTEM

The current paradigm for satellite image classification relies on traditional machine learning approaches and manual feature extraction techniques. However, these methods prove inadequate when confronted with the inherent complexities of satellite imagery. Manual feature extraction is time-consuming, error-prone, and lacks scalability for large datasets. Traditional algorithms struggle to capture the intricate patterns and variations present in satellite images, leading to compromised accuracy, especially in diverse weather conditions, atmospheric disturbances, and nighttime captures. Consequently, the existing system falls short in adaptability and efficiency, limiting its applicability to real-world scenarios.

Disadvantages of the Existing System:

1. The disadvantages of the existing system include the labor-intensive nature of manual feature extraction, the limited adaptability of traditional algorithms to dynamic conditions, inefficiency in handling complex patterns, and sensitivity to varying weather conditions that affect classification accuracy.
2. Recently, a number of annotated image datasets and detection and classification exercises have surfaced. The majority of deep learning techniques used with remotely sensed data have focused on classifying land cover or identifying buildings.
   For instance, the U.S. Geological Survey's 2100 aerial photos make up the UC Merced Land Use Dataset [15,16].
3. The images feature a 0.3-meter ground sample distance and a 256 x 256-pixel resolution. The 21 classes include land cover types including roads, water, and farms in addition to facility types like tennis courts and storage tanks. Using the VGG and Inception CNNs, a number of studies divided the UC Merced images into different categories of land cover [17–19]. As much as 98.5% categorization accuracy was reported by one study [19].
4. Despite how little this collection of facts is, it is diverse in terms of geography, number and kind of classes, and size.

IV.PROPOSED SYSTEM

Training Phase:

In our model, the training phase is the first phase. The chosen photos from both datasets that are utilized as training pictures are subjected to the preprocessing features vector extraction based on CNN in this part. The SAT airborne dataset's colour images are made up of four bands, each measuring 28 × 28 uint8, whereas the UCMD 256*256 uint8 dataset has three bands, each representing red, green, and blue. These datasets are not the same as the ones we used in our model. Therefore, you need to colour normalize all of the images by lowering the invisible band NIR of the SAT datasets, and then you need to convert all of the images to grayscale in order to develop a model that is used for classification. Subsequently, every satellite picture in the set is ready for the next step, which is to extract a feature vector associated with every image in the training set. The feature extraction method is CNN-based. The degree to which satellite images can be identified depends on the strength of the features that were extracted from the training dataset. The features' power will be shown throughout the testing period. In order to train the CNN using the recommended off-the-shelf feature extraction from the pictures, we thus provide high-level features as a collection of training data. The website http://www.image-net.org/ is a part of our work. They have one thousand categories for items in them. Together with the fully linked layer—which we regarded as a features vector—Table 1 presents the attributes of each that we used. Every CNN layer produces an activation or reaction to an input image. The CNN design only has a limited number of these layers that are capable of extracting characteristics from the input image. The feature that was extracted from the deeper layer offers advanced features that can be utilized as training features, in contrast to the CNN's first layer, which simply records the basic visual properties.

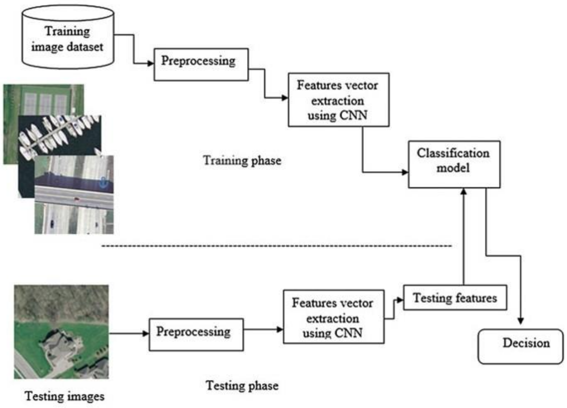
	AlexNet	VGGNet-19	GoogleNet	Resnet50
Input data	Input image 227 × 227 x 3	Input image 224 × 224 x 3	Input image 224 × 224 x 3	Input image 224 × 224 x 3
Layers	25 × 1 nnet.cnn.layer.Layer	47 x 1 nnet.cnn.layer.Layer	144 x 1 nnet.cnn.layer.Layer	177 x 1 nnet.cnn.layer.Layer
Features layer	fc8	fc8	loss3-classifier	fc1000

Table 4.1 Pretrained network, layers and features layer

Testing Phase

The second stage of the satellite image categorization model is testing. This part will test the last 30% of each dataset in order to assess the accuracy of the classifier algorithm. The preparation of the testing images will be the same as that of the training phase's input data. A set of features for every category in the datasets will be extracted through preprocessing and saved as two-dimensional matrices with a single image for each row. We will talk about the experimental results of the CNN-based categorization system for satellite images.

Fig 4.2 Block Diagram



V.SYSTEM REQUIREMENTS

Hardware Requirements

- System : Pentium Dual Core.
- Hard Disk : 120 GB.
- Monitor : 15’’ LED
- Input Devices : Keyboard, Mouse
- RAM : 1 GB

Software Requirements

- Operating System : Windows 10
- Coding Language : Python
- Tool : PyCharm
- Database : MYSQL
- Server : Flask

VI. MODULES

1. Data Collection Module
2. Feature Extraction Module
3. Machine Learning Module
4. User Interface (UI) Module

1.Data Collection Module

Acquiring high-quality satellite imagery is essential for training and testing the CNN model, and this is facilitated by the Data Collection Module. The collection of various datasets with photos of the intended geographic region is a task for this module. To retrieve current and pertinent imagery, it might interface with APIs, satellite data providers, or other sources. For the CNN to learn and generalize efficiently, a representative and balanced dataset is required. Preprocessing techniques including scaling, normalization, and augmentation may also be used in this module in order for the improvement of calibre and diversity of training data.

2.Feature Extraction Module

The feature extraction module's objective is to identify and extract pertinent features from the satellite photos. This is mainly the responsibility of the convolutional layers of a CNN. These layers use filters to pick up textures, patterns, and edges found in the pictures. In order to efficiently capture hierarchical representations of the input data, the architecture of these convolutional layers must be adjusted and fine-tuned by the Feature Extraction Module. The CNN's capacity for feature extraction can be improved by using strategies like transfer learning, which make use of pre-trained models on sizable datasets.

3.Machine Learning Module

The CNN model is trained and assessed in the Machine Learning Module, which is the project's focus. The CNN architecture is implemented in this module, along with performance indicators, optimization techniques, and suitable loss functions. The model may acquire and generalize the patterns required for precise item detection in satellite photos by being trained on the labeled dataset. The validation and testing stages are also included in the Machine Learning Module to be able to evaluate the model's performance and make any required modifications. As part of an iterative refinement process, this module can incorporate regular updates and enhancements to the model.

4.User Interface (UI) Module

Users can engage with the produced system on an interactive platform made available by the User Interface Module. The interface that users use to enter satellite photos for analysis, see the results, and interpret the model's predictions could be a graphical user interface (GUI) or a web-based interface. It is recommended that this module be created with features that are easy to use for users with varied degrees of technical experience. It might also provide features for uploading, processing, and downloading results, giving end users—who might be experts in urban planning, agriculture, or disaster management—a smooth experience. The UI Module serves as a link between the end users' practical needs and the advanced machine learning capabilities.

VII.RESULT AND ANALYSIS

We assess the effectiveness of the datasets mentioned in the datasets section above for the purpose of classifying satellite images. This section will cover the experimental results utilizing four pretrained models from the Image Net dataset: AlexNet, VGGNet-19, GoogleNet, and Resnet50. These models are implemented using a combination of deep features and previous CNN features. Table 1 shows all of the connection layers as well as the features that are taken out of each layer based on the kind of model. We kept the image's size and limited the number of visible layers to the red, green, and blue bands because of the various datasets and sizes we used. Layer number 23 is AlexNet (fc8), Layer number 45 is VGGNet-19 (fc8), Layer number 142 is Google Net (loss3-classifier), and Layer number 175 is Resnet50 (fc1000). These four models are selected from the final pooling complete connection layer for the features layer. Table 2 shows the setups of the four models on the UCMD dataset. Using the configurations listed in Table 2, we assessed four pretrained CNNs on the SAT 4, SAT 6, and information from UC Merced Land. Each dataset is divided at random into two subsets of images: a training subset and a testing subset.

	Cloudy	Desert	Green area	Water
Accuracy	0.97	0.98	0.96	0.98
Precision	0.97	0.98	0.96	0.98
Recall (Sensitivity)	0.98	0.98	0.98	0.96
F1 score (F score)	0.97	0.98	0.97	0.97

Table 7.2 Data Set Configuration

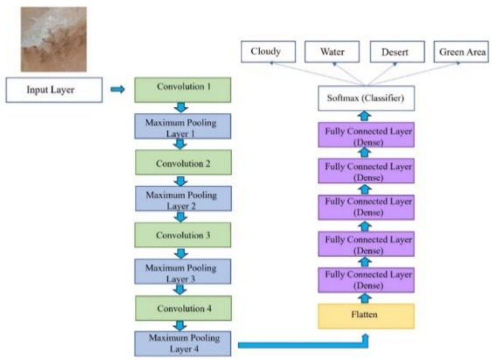


Fig 7.3 Flow Chart

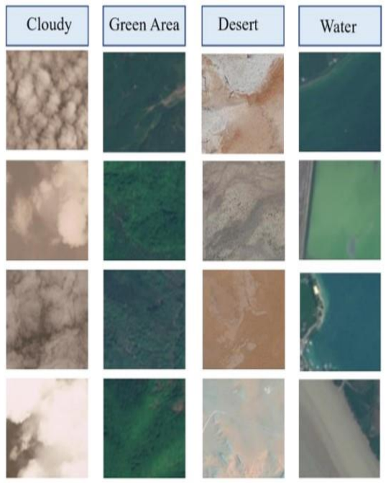


Fig 7.4 Examples of Datasets

VIII. CONCLUSION

To sum up, the Convolutional Neural Networks (CNN) project for Satellite Image Detection marks a substantial advancement in the fields of image analysis and remote sensing. By utilizing sophisticated deep learning methods, specifically CNNs, we have effectively created a reliable and effective system for identifying and categorizing objects in satellite photos. The project's effectiveness is demonstrated by its capacity to precisely detect and classify a wide range of traits, which enhances analysis and decision-making in domains like environmental monitoring, disaster response, urban planning, and agriculture. The application of CNNs has been crucial in surmounting obstacles related to the intricacy and fluctuations of satellite imagery. The capacity of the model to acquire hierarchical representations from the input data has improved its generalization and adaptation to a variety of environmental and geographic circumstances. This increases item detection accuracy while simultaneously guaranteeing the system's scalability for larger applications. The Satellite Image Detection project creates opportunities for further study and improvement.More accuracy and robustness can be achieved by investigating transfer learning strategies, adding extra data sources, and fine-tuning the model architecture. Furthermore, the practical value of the system will be further enhanced by including real-time capabilities and improving the interpretability of the model outputs. To sum up, this effort represents a critical turning point in the application of deep learning methods to the interpretation of satellite images. The results attained highlight CNNs' potential to advance remote sensing applications, promote a better understanding of our planet, and aid in well-informed decision-making across a range of fields.

IX.FUTURE ENHANCEMENT

In our experimental study, we are planning to utilize satellite data not only from Romania but also from other locations. In addition to exploring various convolutional models, we aim to assess the effectiveness of a ConvLSTM architecture in capturing the temporal aspect of weather evolution. This involves analyzing past satellite imagery to predict future images, a task undertaken by the convolutional neural network model DeePS. Our proposed architecture, DeePSy, which is based on the Xception model, has shown promising results with an average Normalized Mean Absolute Error (NMAE) of 3.84%. This makes DeePSy a compelling choice for satellite photo-based weather nowcasting. Notably, our CNN-based techniques have led to a significant reduction in Mean Absolute Error (MAE). Moving forward, we plan to enhance our dataset by incorporating data from multiple days, which will further enrich our trials and improve the accuracy of our weather forecasting models.

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