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CATEGORIZATION OF SATELLITE IMAGES EFFICIENTLY CREATING SCALABLE DEEP LEARNING TECHNIQUES PROCESSING LARGE DATASETS

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Abstract:
Applications such as environmental monitoring, law enforcement, and disaster response depend heavily on satellite imagery. These jobs frequently call for the manual identification of structures and objects in the pictures. But there's a growing need for automation because of the wide geographic regions involved and the scarcity of available analysts. To address this challenge, traditional object detection and classification methods are proving to be insufficient and unreliable. This is where a group of machine learning techniques called deep learning come into play; they have the ability to successfully automate these tasks. Convolutional neural networks (CNNs), a subset of deep learning, in particular, have demonstrated remarkably promising results in image comprehension. This work focuses on using CNNs to handle the challenging task of multispectral, high-resolution satellite image recognition of different objects and facilities. In order to accurately categorize the dataset, the research presents a deep learning system that makes use of both satellite metadata and image features. Python is used in the system's implementation, and the Keras and TensorFlow libraries are utilized. A comparative study with current systems shows that this method offers a notable improvement in overall accuracy.

Keywords —**Satellite Image Classification, Tensorflow, Deep Learning, Python, Keras and CNN**

I. INTRODUCTION

A subset of machine learning known as "deep learning" uses many processing layers to represent data at different levels of abstraction [1]. Its remarkable successes in tasks such as object detection and classification are mainly due to the combination of strong graphical processing units (GPUs) and convolutional neural networks (CNNs).

A CNN is made up of several processing layers, each of which has a collection of convolution filters that are used to recognize features in images[2]. These feature detectors in the first layers are similar to color blob filters and Gabor-like filters. Then, more complex feature detectors are constructed by subsequent layers. With fully connected "dense" layers, the CNN combines detector outputs as the sequence goes on, finally generating predicted probabilities for every class.

Unlike previous methods such as SIFT and HOG, CNNs do not require the algorithm designer to perform manual feature engineering. Rather, during training, the network learns on its own what features to look for and how to look for them. Less than ten layers made up the first effective CNNs, which were mainly intended to recognize handwritten zip codes. Notable examples include the five-layer LeNet and the eight-layer AlexNet [1, 3]. But since then, the general trend has changed to more complex network architectures.

Fig. 1Example of classifying a satellite image

The value of satellite imagery is found in its capacity to offer insightful geographic information. These images provide easily accessible and high-quality data through remote sensing, which eliminates the need for extensive fieldwork and saves valuable research time[2, 3]. However, over time, the classification methods used in Geographic Information Systems (GIS) have become antiquated, producing less than ideal results. As a result, it is imperative to improve this domain in order to stay up with technological advancements. Satellites are used in remote sensing to gather data about different objects from far-off locations[2]. Satellite images obtained through remote sensing are essential for a number of industries, such as transportation, defense, agriculture, and medicine. These pictures fill in information gaps about things that may be poorly understood in remote areas.

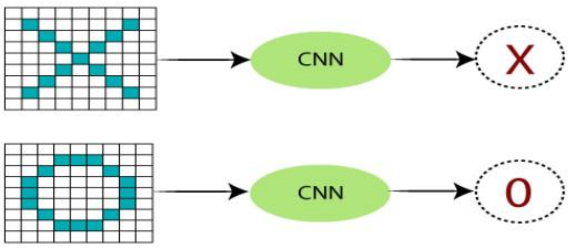

Fig. 2Example of how CNN works

Sorting these photos into categories makes it possible to identify and retrieve specific data pertaining to a given object[4]. Our goal in this scenario is to classify satellite images into areas that are used and areas that are not, then further subcategorize the results using a Convolutional Neural Network (CNN).

This research is structured as follows: The literature review is presented in Section 2. The problem statement and the suggested solution are presented in Section 3. The hardware and software requirements needed to implement this system are listed in Section 4. In Section 5, the flow diagram is presented. A thorough description of the suggested solution's functionality is provided in Section 6. Practical implementation examples and corresponding code are presented in Section 7, and the final product is shown in Section 8. The paper's conclusion is provided by Section 9's summary of the findings.

II. RELATED WORK

The following literature is the basis for this section's discussion of various approaches and strategies for categorizing satellite photos.

In their thorough analysis of image classification techniques, Lu and Weng (2007) looked into ways to improve remote sensing classification performance. They covered a wide range of methods, including SVMs, artificial neural networks, and decision trees, and they shed light on the advantages and disadvantages of each. Researchers and practitioners of remote sensing classification can benefit greatly from their work[5]. In 2017, Altaei and Mhaimeed presented a novel method for classifying satellite images that combines artificial neural networks (ANN) with image encoding. Through encoding, their approach extracted informative features, which were subsequently fed into an ANN classifier for classification[6]. They sought to improve classification accuracy by combining encoding and ANN, showing promise for expanding remote sensing applications.

In order to classify satellite data, Murtaza and Romshoo (2014) evaluated and compared several statistical algorithms[7]. Their research evaluated the suitability and precision of different methods, offering valuable perspectives on the effectiveness of statistical algorithms in the classification of satellite images.

A case study on the categorization of land and crops using Landsat 8 satellite images was provided by Hrebei and Sala (2016). Their study illustrated the usefulness of satellite imagery for crop classification and land use analysis, highlighting its applicability to environmental and agricultural research[8].

An innovative technique for classifying satellite images was presented by Nayak, Rao, and Prabhu (2014). It combined color-based thresholding with the K-Means clustering algorithm. Their strategy attempted to address complexity in image data and improve classification accuracy by utilizing color information and clustering techniques[9].

A fuzzy rule-based system for classifying extremely high-resolution satellite images was proposed by Jabari and Zhang (2013)[10]. They offered a framework able to handle the uncertainties present in picture classification tasks by introducing fuzzy logic, which produced more complex and reliable classification results.

A framework based on ontology was presented by Jesus, Almendros-Jiménez, Domene, and Piedra-Fernández (2013) for the classification of ocean satellite images. Their method increased classification accuracy by incorporating ontological knowledge and included domain-specific semantic data, which is especially pertinent to oceanographic research[11].

An unsupervised method for segmenting satellite images was presented by Ahmed et al. (2009), and it was based on the initialization of the K-Means clustering algorithm and the Pearson system[12]. Their approach improved segmentation by making use of the features of the Pearson system, which improved unsupervised segmentation methods for data from remote sensing.

A temporal convolutional neural network (CNN) designed specifically for classifying satellite image time series was presented by Pelletier, Webb, and Petitjean (2019)[13]. Their model provided a solid framework for context-aware classification in dynamic environments by identifying temporal patterns in satellite image sequences. The potential of deep learning methods, in particular deep neural networks, for satellite image classification was investigated by Pritt and Chern (2017)[14]. They looked into how deep neural networks might be able to learn features from data on their own, which could revolutionize classification accuracy.

Using spectral-spatial convolutional neural networks, Sameen, Pradhan, and Aziz (2018) classified extremely high-resolution aerial photos. Their method improved classification accuracy by utilizing both spatial and spectral data, proving the usefulness of deep learning for remote sensing applications[15]. Al-Najjar et al. (2019) presented a land cover classification technique that combined convolutional neural networks (CNNs) with digital surface models (DSM) and UAV images. Accurate land cover classification was improved by this combination of data sources, especially in complex landscapes and intricate terrains[16].

In their 2017 study, Sowmya, Deepa, and Venugopal provided an extensive overview of remote sensing satellite image processing methods for image classification. Their work, which covered a wide range of approaches, strategies, and applications, provided insights into the rapidly changing field of remote sensing image classification research[17]. Pandya and Priya (2015) focused on employing image processing techniques to accurately classify vegetation areas in satellite images[18]. By addressing the difficulty of identifying and classifying different vegetation types, their work aided in ecological and environmental evaluations.

A method for object recognition in satellite photos using data mining techniques was presented by Muhammad et al. (2012). Their approach demonstrated the possibility for automated image analysis by combining data mining algorithms to locate and categorize objects of interest in satellite imagery[19].

III. PROPOSED SYSTEM AND DEFINITION OF PROBLEM

When classifying satellite images, robust validation of training samples is performed and the image's diverse structure is analyzed using computer learning algorithms. This method is essential for identifying satellite data in remote sensing. This system uses deep learning and image processing techniques to detect and identify objects in high-resolution multispectral satellite images.

IV. FLOW CHART

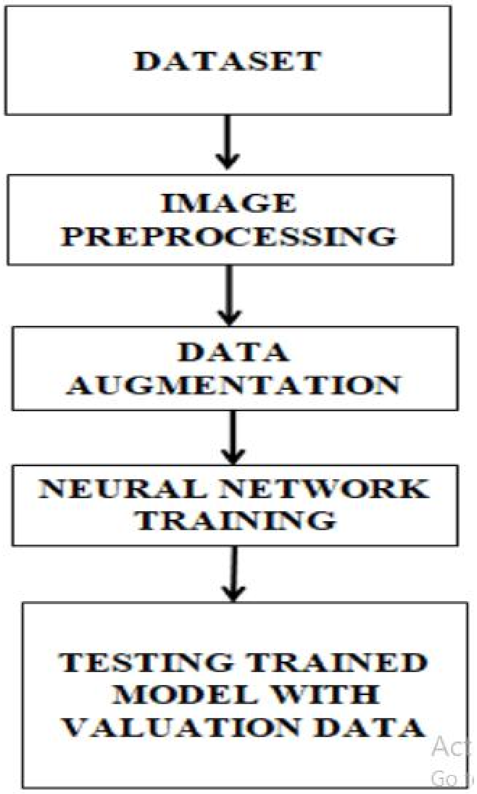

Fig. 3Flow chart for the suggested system

V. WORKING

A. Assembling of the Dataset

An easy way to comply with the conference paper formatting requirements is to use this document as a template and simply type your text into it.

B. Preprocessing Images and Labeling them

The quality, resolution, and formats of the downloaded images varied. The images that were going to be used in the deep neural network classifier were preprocessed in order to guarantee consistent feature extraction. The area of interest was highlighted by hand cropping in this process.

C. Process of Augmentation

In order to reduce overfitting during training, augmentation was used to enlarge the dataset and add minute distortions to the photos. Augmenting image data involves creating modified versions of the images in the dataset, which essentially creates an artificially larger training dataset.

D. Neural Network Training

Learning the distinctive characteristics of each class is the main goal of neural network training. The likelihood that the network will pick up the necessary features is increased when augmented images are used.

E. Applying Validation Data to Trained Model Testing

Lastly, input images from the validation dataset are processed by the trained network to identify classes, and the outcomes are examined.

VI. CODE IMPLEMENTATION

Python is used as the programming language for implementing the code. First, the command is used to download the required dependencies, which include TensorFlow, Matplotlib, and other prerequisites.

```
$pip install tensorflow tensorflow_addons
tensorflow_datasets numpy matplotlib sklearn seaborn
```

During model training, the TensorFlow Addons library is needed to compute the F1 score.

The code then downloads, loads, and imports the required libraries. The dataset is split, with 20% set aside for validation and 60% designated for training. Figure 4 shows the distribution of each sample.

After the training and validation sets have been processed, the model is constructed and fine-tuning is applied. Next, the following syntax is used to create the confusion matrix:

```
tf.math.confusion_matrix(labels, predictions).numpy()
```

The given code is used to obtain the prediction. Next, the following code is used to display the image's accuracy and F1 score:

```
predictions=m.predict(images)
accuracy=tf.keras.metrics.Accuracy()
f1=f1_score(labels,predictions,average=”macro”)
```

VII. OUTPUTS AND DISCUSSION

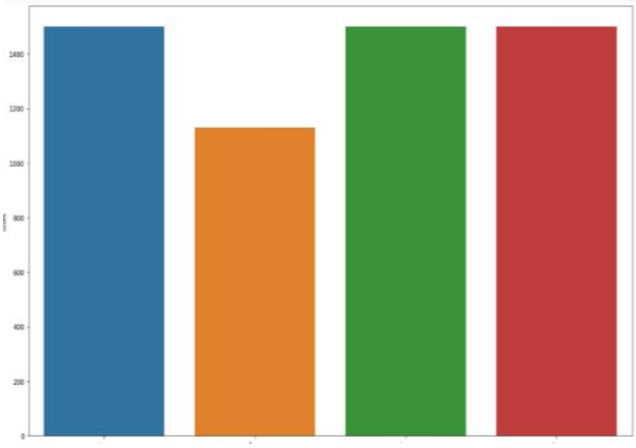

Fig. 4The maximum number of Images

```
Epoch 10/15
132/132 [==============================] - 239s 2s/step - loss: 0.0726 - accuracy: 0.9735 - val_loss: 0.0598 - val_accuracy: 0.
9808
Epoch 11/15
132/132 [==============================] - 237s 2s/step - loss: 0.0668 - accuracy: 0.9770 - val_loss: 0.0566 - val_accuracy: 0.
9844
Epoch 12/15
132/132 [==============================] - 237s 2s/step - loss: 0.0699 - accuracy: 0.9761 - val_loss: 0.0559 - val_accuracy: 0.
9822
Epoch 13/15
132/132 [==============================] - 236s 2s/step - loss: 0.0666 - accuracy: 0.9756 - val_loss: 0.0583 - val_accuracy: 0.
9765
Epoch 14/15
132/132 [==============================] - 236s 2s/step - loss: 0.0550 - accuracy: 0.9785 - val_loss: 0.0509 - val_accuracy: 0.
9801
Epoch 15/15
132/132 [==============================] - 238s 2s/step - loss: 0.0670 - accuracy: 0.9799 - val_loss: 0.0731 - val_accuracy: 0.
9765
```

Fig. 5Accuracy

The output obtained after the code is run through thousands of images is shown in figures 4 and 5. In addition to these pictures, our algorithm was used to train the model, which yielded a train accuracy of about 97.99% and a validation accuracy of about 97.65%.

Fig. 6Outcomes of Prediction

The suggested algorithm's prediction results are displayed in Fig. 6. The model is given the input images, and it makes predictions about them using the features it has learned.

VIII. CONCLUSION

The suggested deep learning system reliably classifies categories within high-resolution satellite photos with an amazing accuracy rate of 90% or higher. Its abilities, however, go far beyond simple accuracy. By incorporating an advanced detection component, the suggested system becomes capable of navigating through large amounts of satellite imagery and effectively identifying important objects and facilities. The synergy that results could have a revolutionary effect. Still, this system's potential goes beyond what it can do now; by acting as a continuous satellite imagery surveillance tool, it can reach even higher levels of potential. This dynamic role has the potential to significantly impact law enforcement efforts by promptly detecting illegal mining activities or the presence of fishing vessels. The system provides authorities with the ability to respond quickly and efficiently to environmental and regulatory challenges by providing real-time alerts and insights.

The system's lightning-fast image analysis capabilities are its main advantage when it comes to responding to natural disasters. Its capacity to carry out jobs like mudslide mapping and hurricane damage assessment could change the scope and pace of disaster response initiatives. This possibility might result in the implementation of life-saving techniques, the effective use of resources, and the reduction of the effects of disasters.

The implications of the system go beyond these crucial industries and into the commercial sphere. With this powerful tool, investors can now keep a close eye on agricultural landscapes. After selecting datasets with particular goals in mind and training the system, it becomes an invaluable tool for assessing crop health and growth. This ability has the potential to guide well-informed choices regarding the distribution of resources and management tactics. Likewise, the system shows promise in the field of resource extraction, e.g., oil well development. It can closely monitor the dynamics of the environment and the evolution of infrastructure, offering insights that support responsible decision-making and regulatory compliance.

To put it simply, adding a detection component propels the deep learning system into a realm of extensive utility. Its exceptional accuracy in classifying images establishes the foundation, and its ability to search and examine large datasets reveals a plethora of uses. With applications in resource management, agriculture, law enforcement, and disaster relief, the suggested system offers a comprehensive approach that has the potential to transform communication and the extraction of priceless insights from satellite imagery.

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