Enhanced Satellite Image Classification through Deep Learning using CNN's

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ABSTRACT

Satellite image classification plays a crucial role in applications such as land cover mapping, urban planning, and environmental monitoring. This project focuses on the development of SpectrumNet, a custom Convolutional Neural Network (CNN) designed to classify satellite images from the EuroSAT dataset into ten distinct land-use categories. The primary goal is to improve the accuracy and efficiency of satellite image classification through the implementation of advanced preprocessing techniques, optimized training strategies, and multiple network configurations. By utilizing deep learning methodologies, SpectrumNet aims to provide reliable insights for real-world applications in remote sensing, geospatial analysis, and environmental studies. The project strives to enhance the ability to analyze and interpret large-scale satellite image data, offering valuable information for decision-making in various fields.

Key Words: Deep Learning, Convolutional Neural Networks, EuroSAT, SpectrumNet, Geospatial Analysis, Land Cover Mapping, Environmental Monitoring, Urban Planning.

I. INTRODUCTION

Satellite image classification is essential in several applications, including urban planning, agriculture, environmental monitoring, and disaster management. As the volume of satellite data continues to grow, manually processing and classifying these images has become increasingly difficult, especially when dealing with large datasets and varying image characteristics. The task of identifying and classifying objects within these images becomes complex due to differences in object sizes, orientations, and backgrounds, making traditional methods less efficient. This project aims to address these challenges by automating the classification process using deep learning techniques, specifically Convolutional Neural Networks(CNNs) to enhance both accuracy and efficiency.

Deep learning, particularly CNNs, has proven to be an effective tool for image classification tasks. Unlike conventional methods that require manual feature extraction, CNNs automatically learn relevant features directly from the image data. This characteristic makes CNNs particularly suitable for tasks such as satellite image classification, where the visual features of objects can be highly diverse. By training a CNN model on a large dataset of satellite images, it can learn to detect patterns and recognize objects across various land-use categories, such as urban areas, water bodies, forests, and agricultural fields.

The goal of this project is to develop a CNN-based model that can classify satellite images from the EuroSAT dataset into multiple land-use categories. The EuroSAT dataset offers high-resolution satellite images from different geographical regions, providing a diverse set of data that challenges the model to distinguish between different land types effectively. To improve the model's performance, advanced preprocessing techniques such as image normalization, data augmentation, and noise reduction are applied to ensure better accuracy and generalization across different types of images.

Through this approach, the project aims to improve the process of classifying satellite images, making it faster and more reliable. By automating the classification, this model will help reduce the time and effort traditionally spent on manual analysis, enabling quicker decision-making in fields such as environmental conservation, urban development, and resource management. Ultimately, this project seeks to showcase how deep learning can provide valuable insights from satellite imagery, supporting more informed decision-making and effective management of land and resources.

II. RELATED WORK

Satellite image classification has seen significant advancements with the evolution of deep learning and statistical algorithms. Various methods have been proposed to enhance accuracy and efficiency in classifying satellite imagery.

S. Abburu et al, [1] provided an extensive review of satellite image classification methods, categorizing them into supervised, unsupervised, and object-based techniques. They discussed the advantages of hybrid classification models, which integrate multiple approaches to improve classification accuracy.

R.Sowmya et al [2] conducted a comprehensive survey on remote sensing image processing techniques, emphasizing pre-processing, feature extraction, and classification models. Their study highlighted the effectiveness of spectral and spatial information fusion for improved accuracy in classifying land cover and vegetation types.

K.O.Murtaza et al[3] evaluated various statistical algorithms for satellite data classification and compared their performance. Their study demonstrated that while traditional statistical methods such as Maximum Likelihood Classification (MLC) and Support Vector Machines (SVM) are widely used, newer machine learning techniques show promise in handling large-scale datasets with complex patterns.

H.M.Valentin et al [4] explored land and crop classification using Landsat 8 satellite images. Their study utilized vegetation indices and supervised classification techniques, highlighting the importance of spectral bands in distinguishing different land cover types. This research provided insights into precision agriculture and land-use monitoring applications.

M.AI-Zuhairi et al, [5] introduced a spectral-spatial convolutional neural network (CNN) approach for high-resolution aerial image classification. Their model leveraged both spectral and spatial information to enhance classification accuracy. The study demonstrated that CNN-based methods outperform traditional classifiers by capturing intricate spatial patterns in remote sensing data.

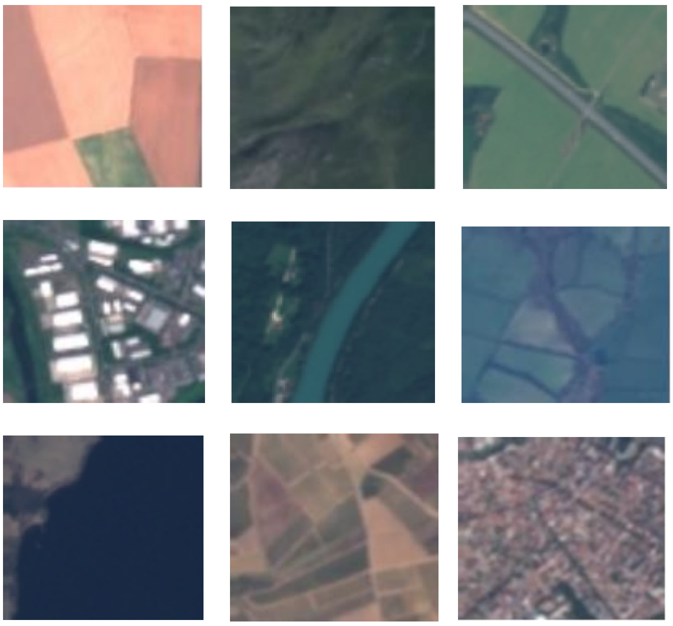
Ch.Pelletier et al, [6] proposed a temporal convolutional neural network (TCNN) for classifying satellite image time series. Their model effectively captured temporal variations in remote sensing data, making it suitable for monitoring environmental changes over time. The study emphasized the role of deep learning in extracting meaningful temporal features from satellite imagery.

These studies serve as the foundation for our research, guiding the development of a deep learning-based classification framework. By integrating CNN and Spectrum Net models, we aim to enhance classification accuracy while addressing challenges related to data diversity, computational efficiency, and real-time processing.

III. DATA SET

The EuroSAT dataset, used in this project, is a collection of high-resolution satellite images that cover a variety of land-use categories, making it ideal for training a model in satellite image classification. It contains approximately 27,000 labeled images, each representing one of ten different land-use classes such as urban areas, forests, agricultural fields, and water bodies. The images are captured from the Sentinel-2 satellite, which provides a spatial resolution of 10 meters per pixel. This allows the dataset to capture a detailed view of the Earth's surface, offering a diverse and representative sample of various geographical regions.

Each image in the EuroSAT dataset is a 64x64 pixel RGB image, making it suitable for deep learning models like Convolutional Neural Networks (CNNs), which require input images of consistent size. The dataset is divided into multiple classes, which include both natural and man-made features, providing a balanced and challenging classification task. By using this dataset, the model can learn to identify and classify different land-use types, making it applicable to various real-world applications such as environmental monitoring, urban planning, and resource management.



The EuroSAT dataset divides into three CSV files: train, test, and validation. These files contain the image paths along with their corresponding labels, dividing the dataset into different subsets for training, validation, and testing. The training CSV is used to train the model, the validation CSV is used to tune hyperparameters and monitor the model's performance during training, and the test CSV is used to evaluate the final model's accuracy.

1		Filename	Label	ClassName
2	2438	AnnualCrop	0	AnnualCrop
3	1018	Residential/	7	Residential
4	3	Pasture/Pas	5	Pasture
5	1011	Residential/	7	Residential
6	47	Pasture/Pas	5	Pasture
7	2512	PermanentC	6	PermanentCrop
8	197	Pasture/Pas	5	Pasture
9	1370	River/River_	8	River
10	1468	River/River_	8	River
11	647	Herbaceous	2	HerbaceousVegetation
12	1889	SeaLake/Se:	9	SeaLake
13	1180	Forest/Fore	1	Forest
14	1010	Residential/	7	Residential
15	2297	AnnualCrop	0	AnnualCrop
16	710	Herbaceous	2	HerbaceousVegetation
17	2357	AnnualCrop	0	AnnualCrop
18	2237	AnnualCrop	0	AnnualCrop
19	1357	River/River_	8	River
20	823	Residential/	7	Residential

Test.csv

1		Filename	Label	ClassName
2	16257	AnnualCrop	0	AnnualCrop
3	3297	Herbaceous	2	HerbaceousVegetation
4	17881	PermanentC	6	PermanentCrop
5	2223	Industrial/Ir	4	Industrial
6	4887	Herbaceous	2	HerbaceousVegetation
7	761	Pasture/Pas	5	Pasture
8	4584	Herbaceous	2	HerbaceousVegetation
9	1746	Industrial/Ir	4	Industrial
10	11598	Highway/Hi	3	Highway
11	2635	Industrial/Ir	4	Industrial
12	15402	AnnualCrop	0	AnnualCrop
13	11301	Highway/Hi	3	Highway
14	4557	Herbaceous	2	HerbaceousVegetation
15	7290	Residential/	7	Residential
16	7171	Residential/	7	Residential
17	12622	Highway/Hi	3	Highway
18	15928	AnnualCrop	0	AnnualCrop
19	4992	Herbaceous	2	HerbaceousVegetation
20	17217	PermanentC	6	PermanentCrop

Train.csv

1		Filename	Label	ClassName
2	258	Pasture/Pas	5	Pasture
3	2134	Forest/Fore	1	Forest
4	3518	Highway/Hi	3	Highway
5	3048	River/River_	8	River
6	3996	SeaLake/Se	9	SeaLake
7	4870	AnnualCrop	0	AnnualCrop
8	4965	PermanentC	6	PermanentCrop
9	3490	Highway/Hi	3	Highway
10	5360	PermanentC	6	PermanentCrop
11	2601	Forest/Fore	1	Forest
12	4313	AnnualCrop	0	AnnualCrop
13	1780	Residential/	7	Residential
14	5284	PermanentC	6	PermanentCrop
15	3116	River/River_	8	River
16	1786	Residential/	7	Residential
17	4367	AnnualCrop	0	AnnualCrop
18	2189	Forest/Fore	1	Forest
19	2872	River/River_	8	River
20	4463	AnnualCrop	0	AnnualCrop

Validation.csv

IV. METHODS AND METHODOLOGY

Data Preprocessing

To ensure the model learns effectively and generalizes well to unseen data, various preprocessing techniques are applied to the dataset. These include normalization, tensor conversion, one-hot encoding, dataset splitting, and data augmentation. Each step plays a crucial role in improving model performance, reducing noise, and ensuring consistency in data representation.

Normalization:

Normalization is applied to scale pixel values to the range [0,1], ensuring uniformity across all images. Since raw images contain pixel intensity values ranging from 0 to 255, scaling them helps improve model convergence and prevents numerical instability. This transformation also aids in faster learning and reduces computation time.

Tensor Conversion:

Deep learning models require inputs to be in tensor format for efficient processing. Images are converted into tensors, which are multi-dimensional numerical representations. This conversion allows operations like batch processing and parallel computation, enabling the model to handle large datasets more effectively.

One-Hot Encoding:

Since labels in classification tasks are categorical, they are transformed using one-hot encoding. Each class is represented as a binary vector where only the correct class is marked with 1 while others remain 0. This encoding ensures that the model does not mistakenly interpret categorical labels as numerical values, improving classification accuracy.

Dataset Splitting:

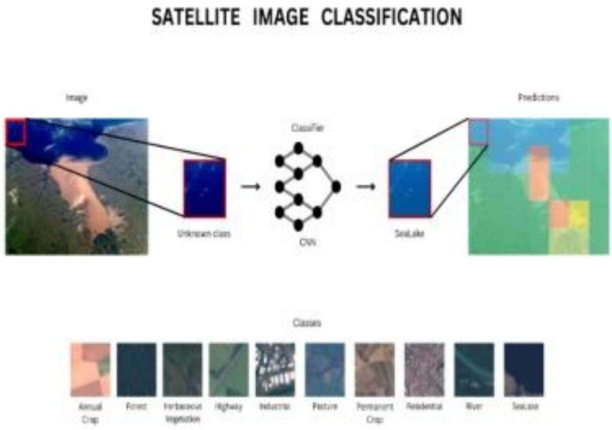
To evaluate the model's performance, the dataset is divided into three parts: training, validation, and test sets. The training set is used to train the model, the validation set is used to fine-tune hyperparameters and detect overfitting, and the test set assesses final model performance. A balanced split ensures fair evaluation across all classes.

Data Augmentation:

To improve model robustness, various augmentation techniques such as random flips, brightness adjustments, rotations, and cropping are applied. These modifications create diverse versions of the same image, helping the model learn better representations. Augmentation prevents overfitting and enhances the model's ability to recognize objects under different conditions.

B)Convolutional Neural Networks (CNN's)

Convolutional Neural Networks (CNNs) play a crucial role in analyzing and classifying satellite images. The primary function of the CNN is to automatically extract important features from the images, such as edges, textures, and patterns that are significant for identifying different land-use categories. By using convolutional layers, the model detects low-level features like shapes and structures, which gradually combine into more complex and abstract patterns as the network deepens. This hierarchical learning approach helps the CNN capture essential details from satellite images, which is key to accurate classification.



Once the CNN has learned to extract these features, pooling layers reduce the image's dimensionality, retaining only the most vital information. This process helps the model focus on important patterns while reducing computational complexity. Finally, fully connected layers process the extracted features and make a final classification decision, determining the land-use category for each satellite image. The CNN is trained using a large set of labeled satellite images, allowing it to fine-tune its filters and improve its accuracy through backpropagation. This enables the model to classify satellite images with high precision and reliability.

Model: "SpectrumNet"

Layer (type)	Output Shape	Param #	Connected to
input (InputLayer)	[(None, 64, 64, 3)]	0	[]
conv1 (Conv2D)	(None, 32, 32, 96)	384	['input[0][0]']
squeeze_2_brancha (Conv2D)	(None, 32, 32, 16)	1552	['conv1[0][0]']
squeeze_2_branchb (Conv2D)	(None, 32, 32, 96)	1632	['squeeze_2_brancha[0][0]']
squeeze_2_branchc (Conv2D)	(None, 32, 32, 32)	4640	['squeeze_2_brancha[0][0]']
concatenate_2 (Concatenate)	(None, 32, 32, 128)	0	['squeeze_2_branchb[0][0]', 'squeeze_2_branchc[0][0]']
bn_2_branch (BatchNormalization)	(None, 32, 32, 128)	512	['concatenate_2[0][0]']
spectral2 (Activation)	(None, 32, 32, 128)	0	['bn_2_branch[0][0]']
squeeze_3_brancha (Conv2D)	(None, 32, 32, 16)	2064	['spectral2[0][0]']
squeeze_3_branchb (Conv2D)	(None, 32, 32, 96)	1632	['squeeze_3_brancha[0][0]']
squeeze_3_branchc (Conv2D)	(None, 32, 32, 32)	4640	['squeeze_3_brancha[0][0]']
concatenate_3 (Concatenate)	(None, 32, 32, 128)	0	['squeeze_3_branchb[0][0]', 'squeeze_3_branchc[0][0]']
bn_3_branch (BatchNormalization)	(None, 32, 32, 128)	512	['concatenate_3[0][0]']
spectral3 (Activation)	(None, 32, 32, 128)	0	['bn_3_branch[0][0]']
squeeze_4_brancha (Conv2D)	(None, 32, 32, 32)	4128	['spectral3[0][0]']

C)Spectrum Net Architecture

Spectrum Net is a custom Convolutional Neural Network (CNN) designed to classify satellite images into distinct land-use categories.

Here's a breakdown of the Spectrum Net architecture:

a)Input Layer:

The model receives satellite images, which are pre-processed to ensure they are resized to a consistent dimension and normalized for input.

b)Feature-Extraction:
The convolutional layers automatically detect low-level features like edges and textures, progressively learning more complex patterns as the image moves through deeper layers.

c)Pooling Layers:

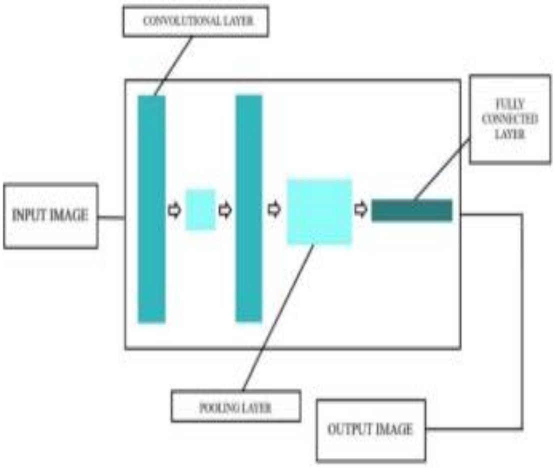
Max pooling layers reduce the spatial dimensions of the feature maps, helping retain important features while reducing computational load.

d)Fully Connected Layers:

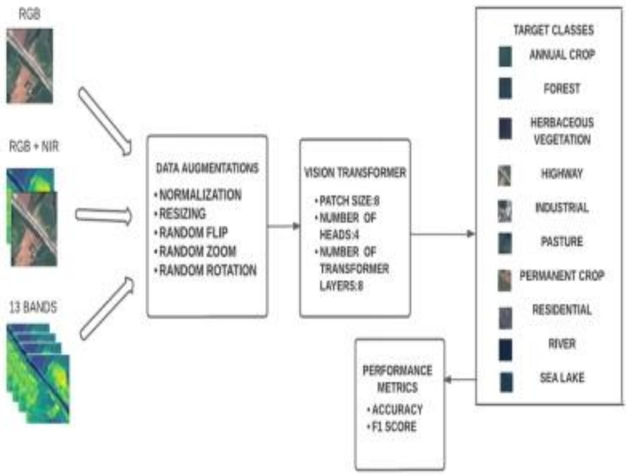
These layers combine the extracted features and use them to classify the image into one of the land-use categories.

e)Output Layer:

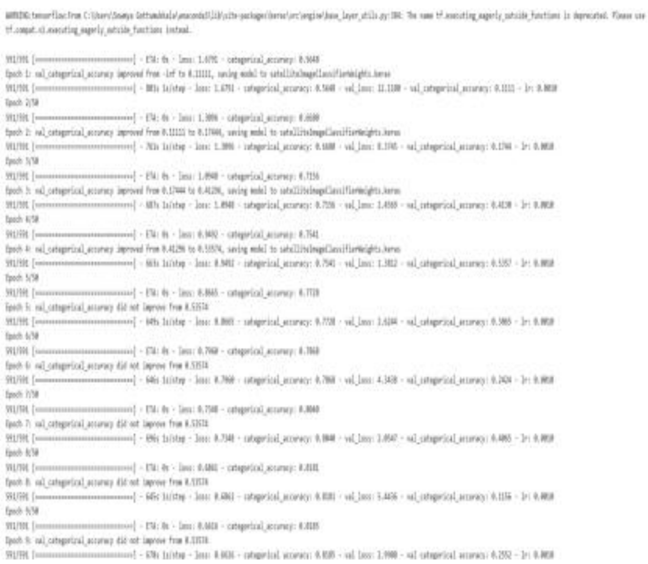
The output layer uses a softmax function to assign a probability to each category, selecting the one with the highest probability as the final prediction.



Spectrum Net's architecture enables accurate satellite image classification by extracting relevant features and efficiently processing them for land-use prediction.



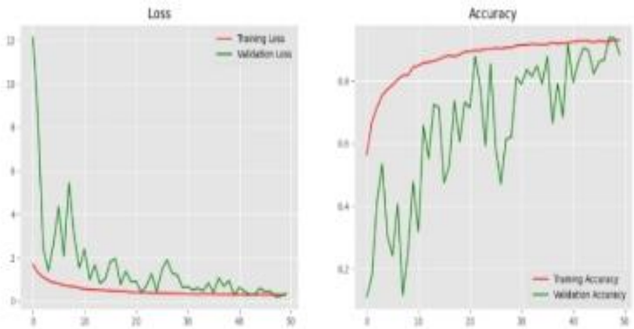
V. RESULTS AND DISCUSSIONS



Accuracy of the model

Test-Loss-and-Test-Accuracy:

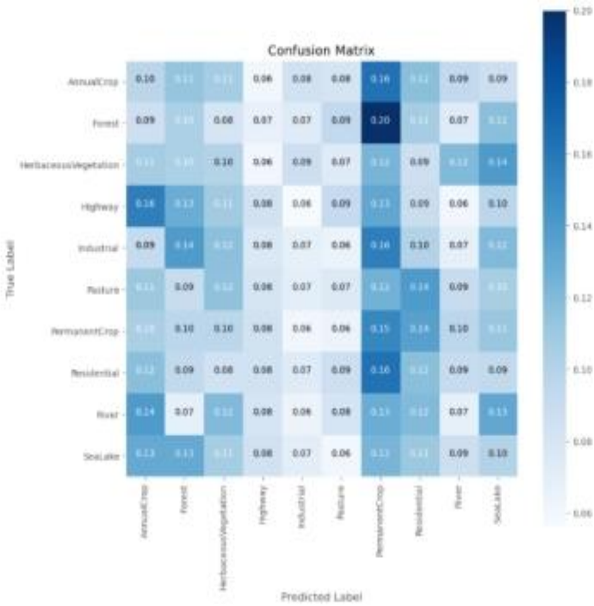
The test loss and accuracy evaluate the model's performance on unseen data. A lower test loss and higher accuracy indicate better generalization and reliability in satellite image classification.



Test Loss: **10.62%** Test Accuracy: **96.93%**

Confusion Matrix:

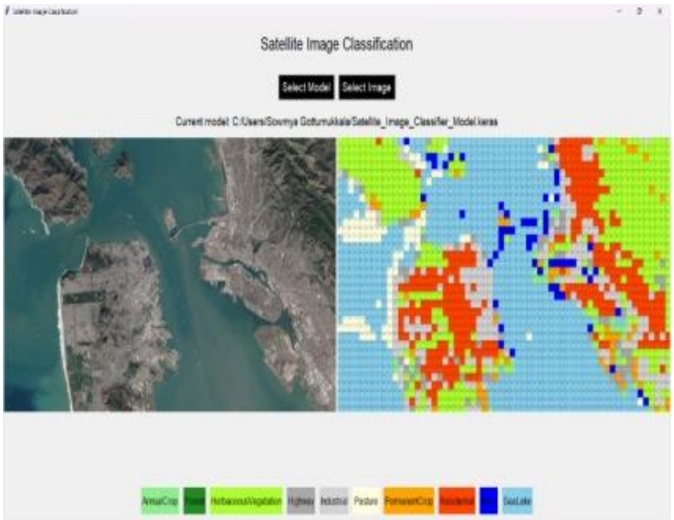
The confusion matrix provides a detailed evaluation of classification performance by showing correct and incorrect predictions across all categories, helping to assess model accuracy and misclassification patterns.



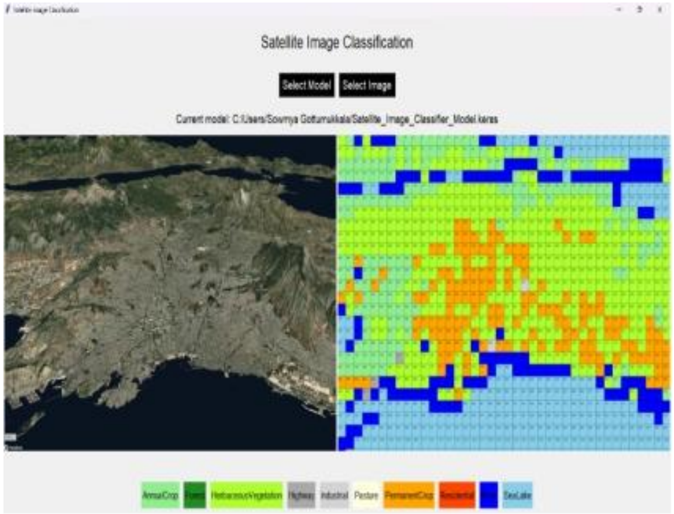
This is the User Interface which can be the first page when the user runs the code *app.py*

User Interface

Whenever the user selects the pre-trained model file with the .keras extension. The user can select the input image by clicking Select Image we can Drag and Browse files. The supported extensions are .jpg,.jpeg,.png.



They can also upload a pre-trained model file with the .keras extension. Once the inputs are provided, the model processes the image, and the predicted land-use category is displayed as the output, providing a seamless experience for the user.



VI. CONCLUSION

Satellite image classification is essential for many applications, but traditional methods can be slow and less accurate. This project improves classification using SpectrumNet, a custom CNN model, for faster and more precise results. By automating land-use classification, it aids in environmental monitoring, urban planning, and disaster management, making satellite image analysis more efficient and reliable.

VII. REFERENCES

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