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EFFICIENT CLASSIFICATION ON REMOTE SENSING IMAGES USING TRANSFER LEARNING

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ABSTRACT

With a rapid advancement in aerial technology, applications of Remote Sensing Images (RSI) have become more diverse. Remote sensing image classification plays a crucial role in analyzing and interpreting Earth observation data for various applications, such as land cover mapping, environmental monitoring, and urban planning. However, accurately classifying remote sensing images poses significant challenges due to their complex spatial and spectral characteristics. In recent years, transfer learning has emerged as a promising technique to improve the classification accuracy by leveraging the knowledge learned from pre-trained models on large-scale datasets. The proposed model explores different transfer learning strategies employed in remote sensing image classification, including fine-tuning, feature extraction, and domain adaptation. It discusses popular pre-trained models, such as VGG16, VGG19, and Inceptionv3, and their applicability to remote sensing datasets. The advantages and limitations of each strategy are analyzed, providing insights into their suitability for various remote sensing applications. A comparative study is done on all these techniques to evaluate the performance measures like Accuracy and Loss. The benefits of the proposed system extend beyond accuracy alone. With the integration of transfer learning models, the system enables efficient processing of large datasets, thereby facilitating classifications on a larger scale.

I. INTRODUCTION

The process of detecting and monitoring the physical characteristics of an area by measuring its reflected and emitted radiation at a distance (typically from satellite or aircraft) is called Remote sensing. Special cameras collect remotely sensed images, which helps to sense things about the Earth. In LULC identification RS images are widely used to detect changes. The task of assigning classes described in a land cover and land use classification system, the schema to all the pixels in a remotely sensed image is called Remote sensing image classification. Transfer learning has been incorporated in the past times for remote sensing image classification. Initially, Random Forest has been employed; later Convolution Neural Network (CNN) has been used due to its feature extraction capability. In order to enhance the classification performance feature extraction strategy is used, which is a very important step for pattern identification and visualization.

It is an essential step that supports the model in identifying better accuracy. The methods that are used to remove noise and deal with complicated background images include: VGG16, VGG19 and Inceptionv3 with Adam optimizer used to train the models. The image classification methods such as VGG16, VGG19, and InceptionV3 have used for feature extraction process.

The project has proposed a novel approach for remote sensing image classification using transfer learning models. It uses the customized data for training the model using classification algorithms such as Visual Geometry Group16(VGG16), Visual Geometry Group 19(VGG19) and also InceptionV3. The system also classifies objects of different scale variations from aerial images using the above mentioned algorithms.

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II. LITERATURE REVIEW

Researchers have explored various techniques and methodologies to tackle the challenges posed by remote sensing data. Traditional deep learning algorithms, such as CNN algorithms have been widely used for image classification. These methods leverage handcrafted features like texture, shape, and spectral information to discriminate between different land cover classes. Several studies have shown the effectiveness of these approaches, especially when combined with feature selection and dimensionality reduction techniques.

Deep learning models, particularly Convolutional Neural Networks (CNN), have gained significant attention for remote sensing image classification. CNNs have demonstrated superior performance in capturing spatial and spectral features automatically from the images. This approach has shown promising results, especially when dealing with limited labeled remote sensing data

To address the challenges of semantic segmentation and class imbalance in remote sensing images, researchers have explored techniques like object-based classification, ensemble learning, and data augmentation. Object-based classification considers not only individual pixels but also spatial relationships among neighboring pixels, leading to more accurate and context-aware results. Ensemble learning methods, such as boosting and bagging, combine multiple classifiers to improve classification accuracy and robustness. Data augmentation, including rotation, flipping, and scaling of images, has been used to generate additional training samples and enhance the model's generalization capabilities.

S.NO	Title with Authors	Year	Methods, Techniques, Algorithms
1	Remote sensing image scene classification by transfer learning to augment the accuracy. S. Thirumaladevi, k. Veera Swamy, M. Sailaja	2022	Alex Net VGGNet
2	Ensemble of features for efficient classification of high-resolution remote sensing images Gladima Nisia T & Rajesh S	2022	Gabor Filter RLBP Features
3	An Efficient Multispectral Image classification and Optimization Using Remote Sensing Data. S. Janarthanan, T. Ganesh kumar, S. Janakiraman,Rajesh kumar Dhanaraj, and Mohd Asif Shah	2022	Inceptionv3 VGG16
4	Deep Learning Models Performance Evaluations for Remote Sensed Image Classification Abebaw Alem And Shailender kumar	2022	Convolutional Neural Network(CNN) Fine-Tuning on EfficientNet

III. METHODOLOGY

The methodology encompassed various stages, including data collection, data preprocessing, and feature extraction, deep learning model development, evaluation, and integration.

1. **Exploring the Dataset:** The RSSCN7 dataset contains satellite images acquired from Google Earth, which is originally collected for remote sensing scene classification. It has seven classes: grassland, farmland, industrial and commercial regions, river and lake, forest field, residential region, and parking lot. Each class has 400 images, so there are total 2,800 images in the RSSCN7 dataset.
2. **Data preprocessing:** Data preprocessing is a crucial step in remote sensing image classification. It involves preparing the raw remote sensing data before feeding it into the image classification algorithms. The main goal of data preprocessing is to enhance the quality of the data and extract meaningful features that will improve the accuracy of the classification model
3. **Training the Model:** Training deep learning models like VGG16, VGG19, and Inceptionv3 for image classification in remote sensing follows a similar process to training them for general image classification tasks.
4. **Classification Using VGG16, VGG19 and InceptionV3:**VGG-16 is a convolutional neural network that is 16 layers deep. A pre-trained version of the network trained on more than a million images from the ImageNet database. VGG19 is a convolutional neural network that is 19 layers deep and pre-trained version of the

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network trained on more than a million images from the ImageNet database Inceptionv3 is deep convolutional neural network architecture for image classification, and it is one of the variants in the Inception family of models.

5. **Evaluation of Results:** Evaluation of results is a critical step in remote sensing image classification to assess the performance and accuracy of the classification model. It helps in understanding how well the model is generalizing to new, unseen data and how reliable the predictions are for different land cover or land use classes. Several evaluation metrics are commonly used to quantify the performance of a remote sensing image classification model.

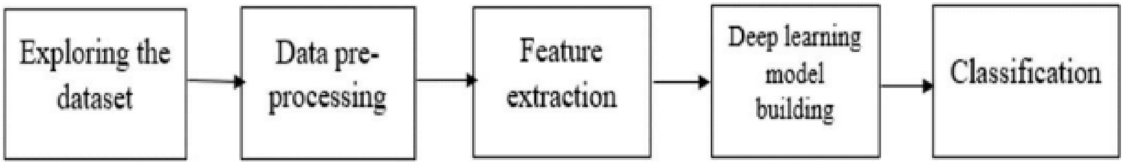

Fig 1: Methodology

IV. EXISTING SYSTEM

In the field of image classification, several existing systems and approaches have been developed. This existing system contains two main models. They are CNN (Convolutional neural networks), and FT (fine tuning). When using CNN models and fine-tuning for image classification, there are several drawbacks that can arise. Here are some drawbacks of CNN model and fine-tuning:1. Limited transferability, 2. Loss of generalization, 3. Need for large labeled datasets,4. Sensitivity to hyper parameters, 5. Computational Demands, 6. Difficulty in interpreting results, 7. Risk of catastrophic forgetting. CNN models and fine-tuning require labeled training data. Acquiring a large, high-quality labeled dataset can be time-consuming, costly, or even unfeasible in certain scenarios. Limited labeled data may result in reduced model performance and generalization.

V. PROPOSED SYSTEM

Key components and methodology of the proposed system: Focus on Remote Sensing Images: Acknowledging the diverse features in remote sensing images, the proposed system tailors solutions for classification, recognizing the unique challenges presented by this imagery. Spatial-Level Analysis: Beginning with a spatial-level analysis, the system examines features at the pixel level, allowing for a detailed understanding of the visual components within the remote sensing images. Spectral Analysis: Integral to the analysis is scrutinizing spectral characteristics, studying electromagnetic radiation intensity and frequency in different bands to discern patterns and anomalies in remote sensing images. Feature Extraction: The system employs feature extraction to identify critical elements like edges, corners, and textures, enhancing understanding of content and context in remote sensing images. Deep Learning Classification: The system utilizes Inception V3, VGG16, and VGG19 deep learning models to classify remote sensing images into predefined categories, capitalizing on their capacity to learn hierarchical features for accurate classification.

VI. TECHNOLOGY USED

Python: Python is a versatile and readable programming language with a large ecosystem of libraries for various domains, including web development, data science, and machine learning, making it popular among developers for its simplicity and flexibility.

Pandas: Pandas is a Python library for data manipulation and analysis, offering easy-to-use data structures and tools for tasks like loading data, cleaning, transforming, and analyzing structured data, making it essential for data scientists and analysts.

Scikit-learn: Scikit-learn is a machine learning library built on Python's foundation, providing a wide range of supervised and unsupervised learning algorithms, along with tools for model selection, evaluation, and preprocessing.

Seaborn: Seaborn is a Python visualization library based on Matplotlib, providing a high-level interface for creating attractive statistical graphics, with built-in themes and color palettes, making it popular among data scientists and analysts for insightful visualizations.

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Keras: There are many libraries that support deep learning, such as Theano, TensorFlow, Caffe, MxNet, and others. It is one of the most powerful and user-friendly Python libraries, and it is built on top of well-known deep learning libraries like TensorFlow, Theano, etc.

Streamlit: Streamlit is a free and open-source framework to rapidly build and share beautiful machine learning and data science web apps. It is a Python-based library specifically designed for machine learning engineers.

VII. ALGORITHMS

Various classifiers that are used to remove noise and deal with complicated background images include: VGG16, VGG19 and Inceptionv3 with Adam optimizer used to train the models. The image classification methods such as VGG16, VGG19, and InceptionV3 have used for feature extraction process.

	precision	recall	F1-score	Support
0	0.91	0.77	0.83	13
1	0.69	0.64	0.67	14
2	0.73	0.92	0.81	12
3	0.76	0.76	0.76	17
4	0.80	0.86	0.83	14
5	0.71	1.00	0.83	14
6	1.00	0.75	0.86	20
Accuracy			0.80	100
Macro avg	0.80	0.81	0.80	100
Weighted avg	0.82	0.80	0.80	100

TABLE 1.1: Performance of VGG16

	Precision	recall	F1-score	Support
0	0.73	0.92	0.81	12
1	0.82	0.75	0.78	12
2	1.00	0.78	0.88	18
3	0.62	0.83	0.71	12
4	0.81	0.81	0.81	16
5	0.89	0.89	0.89	18
6	1.00	0.83	0.91	12
Accuracy			0.83	100
Macro avg	0.84	0.83	0.83	100
Weighted avg	0.85	0.83	0.83	100

TABLE 1.2: Performance of VGG19

	precision	recall	F1-score	Support
0	1.00	0.70	0.82	10
1	0.85	0.85	0.85	20
2	0.60	0.82	0.69	11
3	0.81	0.87	0.84	15
4	0.87	0.93	0.90	14
5	0.86	0.86	0.86	14
6	1.00	0.91	0.90	16
Accuracy			0.92	100
Macro avg	0.92	0.92	0.92	100
Weighted avg	0.93	0.91	0.91	100

TABLE 1.3: Performance of Inception V3

Fig 2: Performance of models

VGG16: The classification layer is fully connected; batch normalized, and uses ReLU activation. The Xavier weight initialization approach is used to initialize the fully connected layer's weights

VGG19: VGG19 is a variant of VGG model which in short consists of 19 layers (16 convolution layers, 3 fully connected layers, 5 MaxPool layers and 1 SoftMax layer). There are other variants of VGG like VGG11, VGG16 and others. VGG19 has 19.6 billion FLOPs.

Inception V3: The inception v3 model was released in the year 2015, it has a total of 42 layers and a lower error rate than its predecessors. Inception-v3 is a convolutional neural network architecture from the Inception family that makes several improvements including using Label Smoothing, Factorized 7 x 7 convolutions as shown in Figure 2.3, and the use of an auxiliary classifer to propagate label information lower down the network

VIII. RESULT AND ANALYSIS

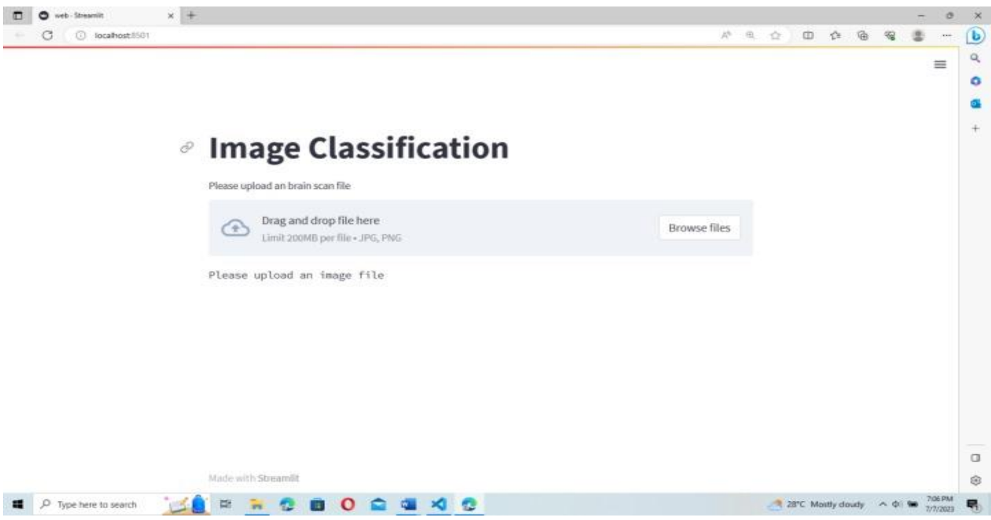

Fig 3: User interface

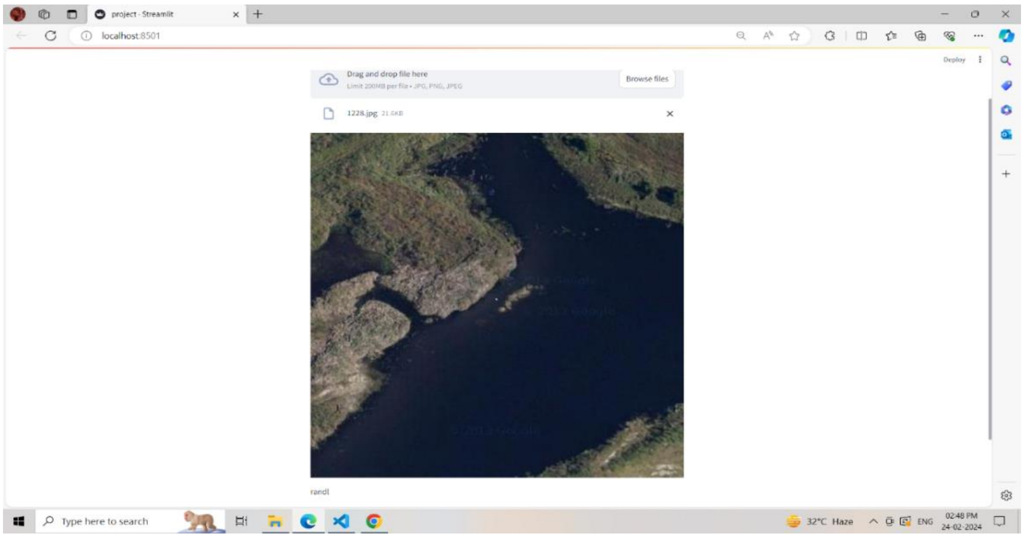

Fig 4: Classification of aerial image

IX. CONCLUSION

In conclusion, project focused on the remote sensing image classification using machine learning models. Collecting remote sensing data and performed data preprocessing to clean and prepare the dataset for analysis. Feature extraction was then conducted to identify relevant features for image classification. Employed four machine learning algorithms, namely Visual Geometry Group (VGG16), Visual Geometry Group (VGG19), and Inceptionv3. The accuracy of these models using different training and testing ratios, including 80%-20%, 70%-30%, and 60%-40%. Among these ratios, the inceptionv3 model with 70% training and 30% testing ratio yielded the highest accuracy of 93%.Furthermore, explored the impact of unused images from the dataset. After this preprocessing step, we observed slight improvements in the accuracy of the VGG16, VGG19, and Inceptionv3. The inceptionv3 model remained the most accurate than other models.Overall, it contributes to the field of remote sensing image classification by demonstrating the effectiveness of CNN models. The accuracy achieved by the inceptionv3 is more accurate than other models which are trained.

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