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Efficient Classification on Remote Sensing Image Using Transfer Learning

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Abstract
With a rapid development 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.
Keywords: *Content Creation; Creative Literature; Ethical Consideration; Generative AI; Machine Learning.*

1. Introduction

Remote Deep learning and computer vision are used in various applications such as image classification, object detection in industrial production, medical image analysis, action recognition, and remote sensing. They have many applications which include hazard response, urban monitoring, traffic control and many more. Noise can be removed from grayscale and color photographs with a lot of techniques. Satellite images are considered the main source of acquiring geographic information, and there are many applications of satellite image analysis in the field of civil engineering such as design, construction, urban planning, and water resource management. [1] The data obtained from satellite sources are huge and are growing exponentially; to handle these large data, there is a need to have efficient techniques for data extraction purpose. Through image classification, these large number of satellite images can be arranged in semantic orders. The satellite image classification is a multilevel process that starts from extracting features from images to classifying them into categories. Image classification is a step-wise process that starts with designing scheme for classification of desired images.[3] After that, the images are preprocessed which include image clustering, image enhancement, scaling, and so on. At third step, the desired areas of those images are selected and initial clusters are generated. After that, the algorithm is applied on the images to get the desired classification, and corrective actions are made after that algorithm phase which is also called postprocessing.[4] The final phase is to assess the accuracy of this classification. The algorithms that have been effective in natural scene images are not adapted to aerial images taken in wide view. Convolutional Neural Networks are used based on their performance with the natural images. VGG16, VGG19 and Inceptionv3 works by dividing the image into several cells through a single network. To improve the classification accuracy and reduce computation time, the proposed methodology which consist of feature extraction models that gives a superior accuracy [6].

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2. Literature Survey

Machine Learning has been incorporated in the past times for remote sensing image classification. Any machine learning algorithm included feature extraction, selection and classification. Initially, Random Forest has been employed, later Convolution Neural Network (CNN) has been used due to its feature extraction capability [12]. In order to enhance the classification performance feature extraction strategy is used [13]. Feature extraction is the process of representing the data into numerical values, which is a very important step for pattern identification and visualization [8]. It is an essential step that supports the model in identifying better accuracy [5]. 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 [2]. The image classification methods such as VGG16, VGG19, and InceptionV3 have used for feature extraction process. InceptionV3 is a convolutional neural network for assisting in image analysis and image classification, and got its start as a module for GoogleNet. The algorithms VGG16 and VGG19 employ this strategy. [9]. Remote sensing image classification algorithms have been enhanced with context enhanced modules. Image Classifiers such as VGG16 and VGG19 uses feature extraction process [12]. The VGG16 feature extraction model has the capability of extracting a huge amount of data and results in good accuracy. It is one of the most popular techniques of image feature extraction, which performs better if any DL model is applied for classification tasks. Hence, the VGG16 model has been chosen for feature extraction in the proposed work. The VGG16 model is implemented on a collection of MRI scans. Various layers are utilized in the complete architecture of the proposed models' designs to extract features.

3. Methodology

The following step by step procedure implements the proposed model for detecting the objects in remote sensing images Show in Figure 1.

- **Data Collection:** Data was collected from aerial satellite images dataset.
- **Preprocessing:** Images have been preprocessed. Data augmentation is done to increase the data for custom object detection.
- **Feature Extraction:** The features from images are extracted using Residual Networks 101 and Zeiler and Fergus Net.

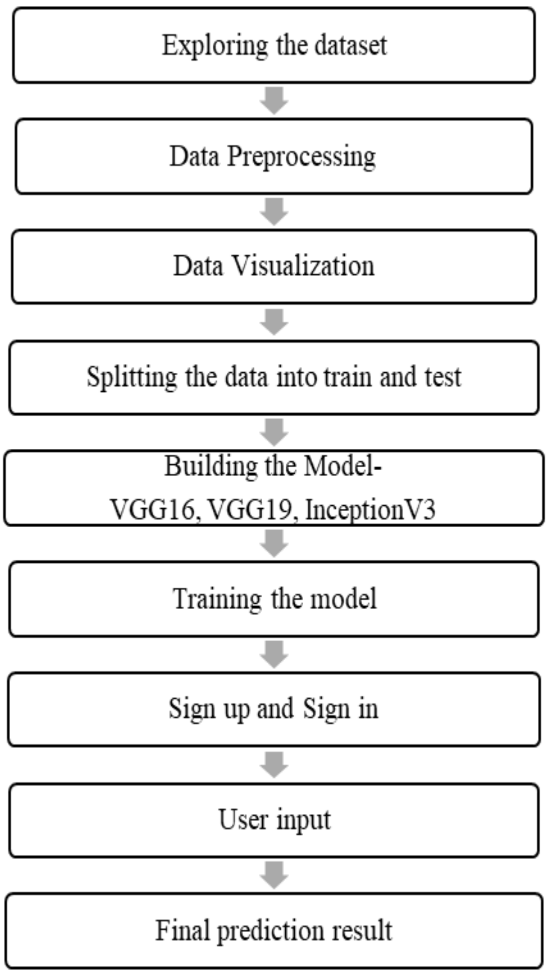

Figure 1 Flow of proposed system

- **Visual Geometry Group16:** VGG16 is a deep convolutional neural network at the University of Oxford. VGG16 has 16 weight layers,which include 13 convolutional layers 3 fully connected layers.
- **Visual Geometry Group19:** VGG19 widely used in computer vision tasks in image classification it has 19 weight layers,which include 16 convolutional layers and 3 fully connected layers.

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- **InceptionV3:** It is a convolutional neural network developed by Googles research team known as Google Brain Team for image classification and recognition tasks.

4. Implementation

4.1. A.Dataset

The RSSCN7 dataset [11] contains a total of 2,800 remote sensing images which are composed of seven scene classes: grass land, forest, farm land, parking lot, residential region, industrial region, and river/lake. For each class, there are 400 images collected from the Google Earth (Google Inc.) that are cropped on four different scales with 100 images per scale. Each image has a size of 400×400 pixels. The main challenge of this dataset comes from the scale variations of the images is Figure 2.

Figure 2 Data Annotation (a)Boundary Box (b)Data Labelling

4.2. B. Algorithms

INCEPTION V3: It is a convolutional neural network architecture that was developed as part of the Inception family of models, which was introduced by Google researchers in 2014. It represents a significant advancement in image recognition and classification tasks. Figure 5, It consists of multiple layers, including convolutional layers, pooling layers, and fully connected layers.[10] The architecture is based on the concept of inception modules, which allow the network to capture features at different scales and abstraction levels. Inception V3's unique architecture, computational efficiency, and strong performance have made it a popular choice for image recognition tasks. Its contributions have significantly influenced the field of deep learning and continue to inspire further research and development.

VGG16: VGG16 is characterized by its deep architecture, consisting of 16 layers. It follows a sequential structure with 13 convolutional layers, each followed by a max pooling layer, and ends with three fully connected layers. This depth allows the network to learn increasingly complex and abstract features from input images. Figure 3 is VGG16 is known for its extensive use of 3x3 convolutional filters throughout the architecture.[7] By using these small-sized filters, the model can capture local patterns and details efficiently while still preserving spatial information. The repeated use of 3x3 filters allows the network to learn hierarchical representations, enabling it to recognize features at different scales. VGG16 has been pretrained on large-scale image datasets such as ImageNet, which contains millions of labeled images. Pretraining involves training the model on a generic image classification task, which helps it learn meaningful and generalizable features. The pretrained weights of VGG16 can then be used as a starting point for transfer learning, where the model is fine-tuned on smaller, task-specific datasets. This approach enables faster convergence and better performance on specific visual recognition tasks, even with limited training data.

VGG19: VGG19 is an extension of the VGG16 architecture, featuring 19 layers. Figure 4 is It includes 16 convolutional layers, each followed by a max pooling layer, and ends with three fully connected layers. The additional layers in VGG19 allow for a deeper representation of features, which can capture more complex patterns and hierarchical structures in the input images.Similar to VGG16, VGG19 employs 3x3 convolutional filters throughout the network. These small-sized filters are used to convolve the input feature maps and capture local patterns and details effectively. The repeated use of 3x3 filters aids in learning multi-scale representations and enables the network to recognize features at various levels of abstraction. VGG19, like its predecessor, can be pretrained on large-scale image datasets such as ImageNet. The pretraining process involves training the model on a

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large collection of labeled images to learn general image representations. These pretrained weights can then be utilized for transfer learning, allowing the model to be fine-tuned on specific tasks or smaller datasets. By leveraging pretraining and transfer learning, VGG19 can benefit from the learned generic features and achieve better performance and convergence on domain-specific visual recognition tasks.

5. Results

When the InceptionV3, VGG16, VGG19 algorithms are used in the process, the images are trained and tested, and the accuracies of the 3 algorithms have been compared show in Figure 6.

Performance Measures:

For analyzing the VGG16 Show in Table 1, VGG19 is Table 2 and Inception V3 Model is Table 3, accuracy, precision, recall and f1-score are looked over to figure out how well the model works.

- Accuracy=no. of correct predictions/Total no. of predictions =TP+TN/TP+TN+FP+FN
- Recall=no. Correct Actual Positives/ Tot. no. of Actual Positives=TP/TP+FN
- Precision= no. of Positive Predictions/Tot. no. of Positive Predicts =TP/TP+FP
- F1Score=2(Precision ∗ Recall)/ Precision + Recall
  =2((TPTP+FP)∗(TPTP+FN))/(TPTP+FP)+(TPTP+FN)
  = 2TP2TP+FP+FN

Table 1 Performance of VGG16

	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 2 Performance of VGG19

	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 3 Performance of Inception V3

	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	0.81	0.90	16
Accuracy			0.84	100
Macro avg	0.86	0.83	0.84	100
Weighted avg	0.86	0.84	0.84	100

The performance of deep learning models for remote sensing images have been analyzed. Three classification algorithms are trained which achieved an accuracy of 94% ,83% and 77% Show in Figure 7,8,9.

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5.1. Confusion Matrix of Three Algorithms

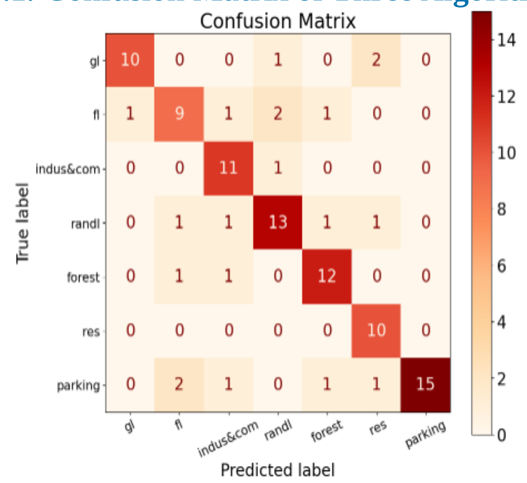

Figure 3 VGG 16

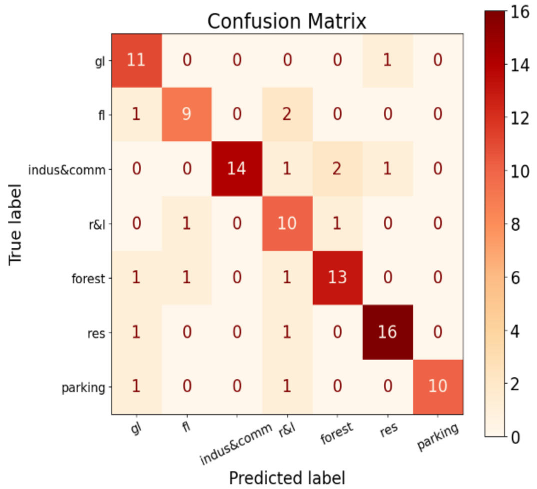

Figure 4 VGG19

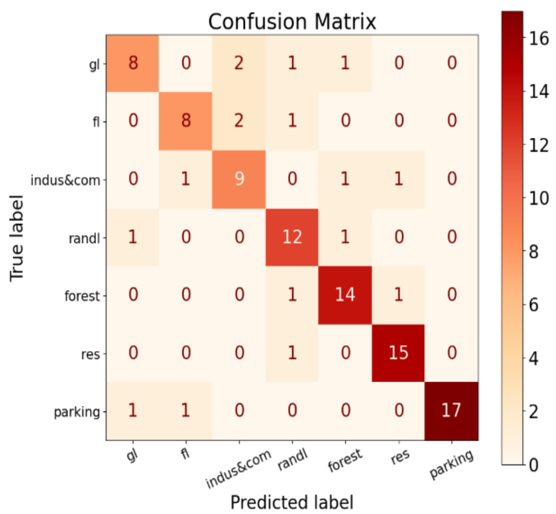

Figure 5 Inception V3

5.2. Epoch Result of Three Algorithms

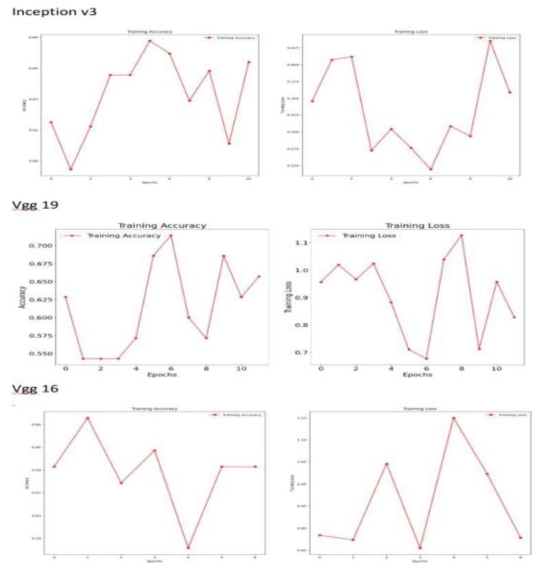

Figure 6 Epoch Result of Three Algorithms

1.1. Histograms of Three Algorithms

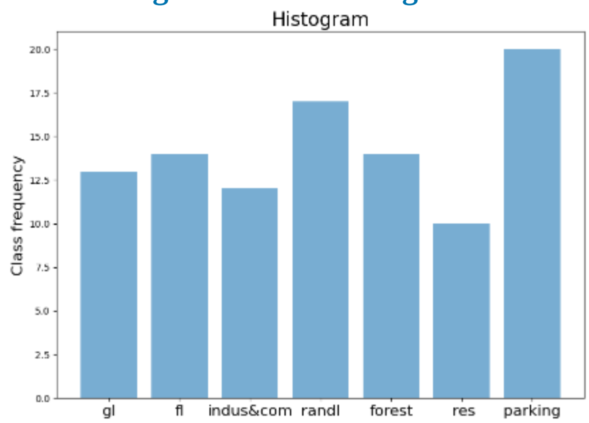

Figure 7 VGG 16

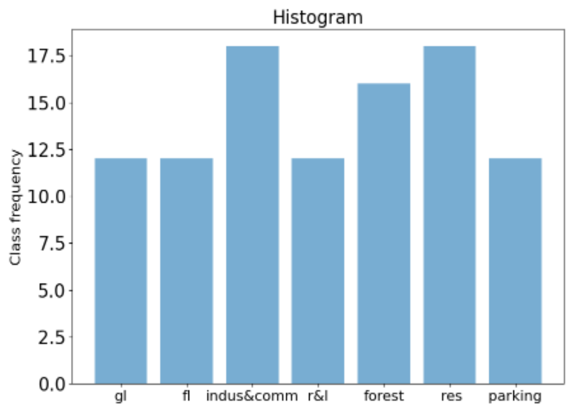

Figure 8 VGG 19

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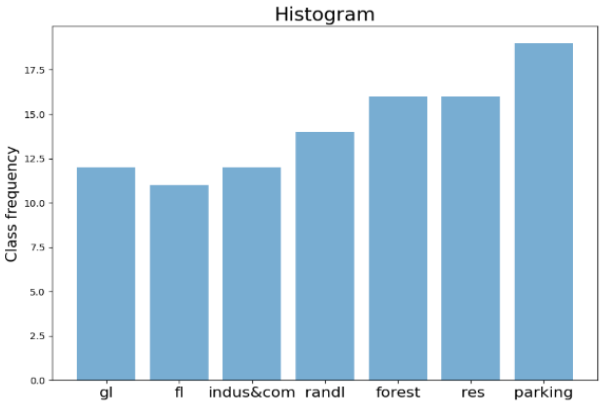

Figure 9 **Inception V3**

Conclusion

The proposed system uses the customized data for training the model using classification algorithms such as Visual Geometry Group 16(VGG16), Visual Geometry Group 19(VGG19) and also Inception V3. The system also classifies objects of different scale variations from aerial images using the above-mentioned algorithms. The accuracy obtained by VGG16 is 77%, VGG19 is 83% and for Inception V3 is 94%. Inception V3 has given better results when compared to VGG16 and VGG19. The future enhancement of the project would be the incorporation of detecting the small objects effectively and transfer learning for the algorithms.

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