# SATELLITE IMAGE CLASSIFICATION USING DEEP LEARNING APPROACH

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**ABSTRACT-**
Satellite image classification has become a pivotal aspect of remote sensing applications, leveraging the power of deep learning to achieve remarkable accuracy. This abstract explores the utilization of Convolutional Neural Networks (CNNs), ResNet50, and VGG16 architectures in the classification of satellite imagery. Because of its capacity to learn feature hierarchies automatically and adaptively via backpropagation, CNNs are ideal for picture analysis. The degradation issue in deep networks is addressed by Res Net's revolutionary residual learning framework, which enables the training of very deep structures via the facilitation of shortcut connections. VGG16, known for its simplicity and uniform architecture, employs 16 layers of convolutional and fully connected layers to extract intricate features from input images. This study demonstrates the comparative performance of these models on diverse satellite image datasets, highlighting the strengths and potential improvements in accuracy and efficiency. The results underscore the significance of deep learning techniques in advancing satellite image classification, paving the way for enhanced environmental monitoring, urban planning, and disaster management.

## I. INTRODUCTION

A crucial function of remote sensing is the classification of satellite images, which entails grouping pixels into four classes: vegetation, arid regions, bodies of water, and urban areas (buildings). This procedure is now much more accurate and efficient because to the development of deep learning.Deep learning, particularly Convolutional Neural Networks (CNNs), has transformed satellite image classification. CNNs are designed to automatically learn and extract features from raw pixel data, making them ideal for handling the complexity and variety of satellite images. Advanced CNN architectures like ResNet and VGG16 further refine this process, offering deeper and more efficient networks capable of handling large-scale image data.

## OBJECTIVE

Improving the pixel data accuracy, classification efficiency, and scalability from satellite pictures into meaningful classifications is the main goal of deep learning-based satellite image classification. This incorporates:

1. **Automated Feature Extraction**
2. **Enhanced Classification Accuracy**
3. **Scalability and Efficiency**
4. **Better Decision-Making**

## II. PROBLEM STATEMENT

Satellite imagery plays a crucial role in a wide range of applications, such as environmental monitoring, urban planning, and disaster management. However, the vast amount of data captured by satellites poses challenges in terms of efficient processing and accurate classification. Traditional image classification methods struggle with the complexity of high-resolution satellite images, which contain diverse land covers, varying textures, and different spectral signatures. To address these challenges, deep learning techniques offer promising solutions due to their ability to automatically extract and learn hierarchical features from large datasets.

## EXISTING SYSTEM

Although conventional and preliminary machine learning techniques for classifying satellite images have yielded insightful findings, they are often hampered by their dependence on human procedures, poor accuracy, scaling problems, and inconsistent outcomes. These shortcomings underline the need for more sophisticated methods, such as deep neural networks, which can overcome these restrictions by automating gathering features, increasing precision, and boosting scalability.

## DISADVANTAGES OF EXISTING SYSTEM:

Traditional procedures are sluggish and labor-intensive since they mostly depend on physical involvement. Classification accuracy is reduced when the complicated patterns and context-related data included in satellite photos are not fully captured by early or traditional machine learning algorithms. Massive-scale or time-sensitive activities cannot be effectively performed by most current systems because they are unable to analyze massive datasets or provide real-time analysis. Inconsistent classifications may arise due to human interpretation variability and some algorithms' susceptibility to noise and picture quality.

## PROPOSED SYSTEM

Proposals for a new system aim to remedy the problems with the existing ones. The proposed method employs deep learning techniques, such as transfer, to classify satellite images.

**ADVANTAGES OF PROPOSED SYSTEM:**

The suggested methodology extracts features from photos manually, saving time and improving accuracy compared to traditional methods that rely on human feature extraction. The proposed system uses CNN which gives high accuracy for image classification. The suggested solution is built to effectively handle massive volumes of data and provide quicker training. To lessen the issue of overfitting, the suggested method makes use of data enrichment and transfer learning. It can easily be utilized as a web application for environmental monitoring and catastrophe response since it has real-time categorization capabilities.

## III.RELATED WORK

Object-Based Image Analysis (OBIA) offers a more comprehensive approach by incorporating spectral, geographic, and contextual information to create meaningful image segments. Although more accurate, OBIA is computationally demanding and requires meticulous parameter tuning, making it less feasible for large-scale or real-time applications. Early machine learning models, such as Support Vector Machines (SVM) and Random Forests, provided another step forward by leveraging manually extracted features for classification. However, these models still face limitations due to the extensive feature engineering required and their reduced effectiveness in handling complex patterns compared to more modern deep learning approaches.

## IV.METHODOLOGY

Two aspects of the research are completed. Deep learning techniques are used to make predictions in the first phase. Transfer learning is used to conduct a thorough discussion of the suggested framework in the second part.

**MODULE NAMES:**

**DATA COLLECTION**

Some free publicly accessible data sets on the internet may also be used. Two of the most popular places to get machine learning model creation resources are the machine learning repository at UCI and Kaggle. Kaggle is a prominent platform for training deep learning algorithms.

**DATA PREPROCESSING**

Preparing unprocessed data so that it may be correctly and quickly evaluated is known as data pre-processing. Data fusion, data cleansing, data augmentation, data distribution, and data loading are just a few of the many discrete jobs that are included.

**MODEL SELECTION AND BUILDING**

Depending on the task's complexity and the available computing power, choose appropriate pre-trained models like VGG16, ResNet, MobileNet, which is Inception V3, or DenseNet.

**MODEL TRAINING**

Use the training dataset to train the model, and the validation dataset to validate it.
Make use of suitable optimization methods and loss functions.

**MODEL EVALUATION**

Evaluate the model performance using metrics such as accuracy, precision, recall, and F1-score. Analyze the confusion matrix to understand the classification errors.

**MODEL DEPLOYMENT**

Save the trained model in a format suitable for deployment (e.g., Tensor Flow Saved Model format, .h5). Deploy the model on a cloud platform (e.g., AWS, Google Cloud) or an edge device for real-time inference.

## V. ALGORITHMS USED IN PROJECT

**1. CONVOLUTIONAL NEURAL NETWORK ALGORITHM**

This kind of neural network that is often used to analyze visual images is the convolutional neural network. An picture may be fed into a Convolutional Neural Network, which is a machine learning technique that can distinguish between distinct objects and characteristics in the image by assigning each one a weight and bias that can be learned.

**2. VGG 16**

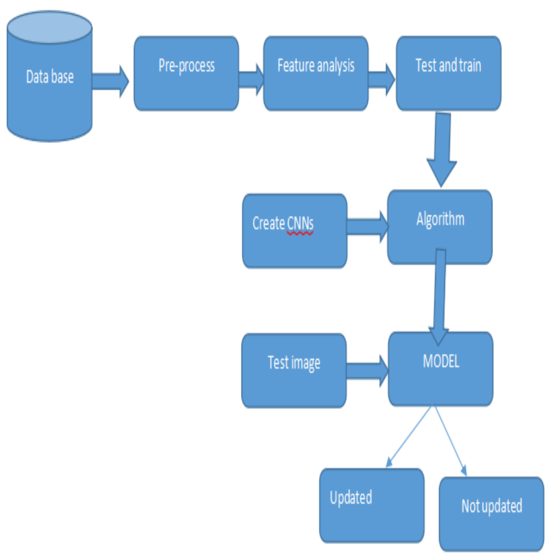
The Visual Figure Gang (VGG) at the College of Oxford unveiled VGG16, an advanced Convolutional Neural Networks, armature. With 16 weight layers—13 layers of convolution and 3 fully linked layers—it is renowned for its straightforwardness and depth. Through a number of complexity and pooling procedures, the armature is aimed to represent spatial scales in photographs.

**3. RESNET50**

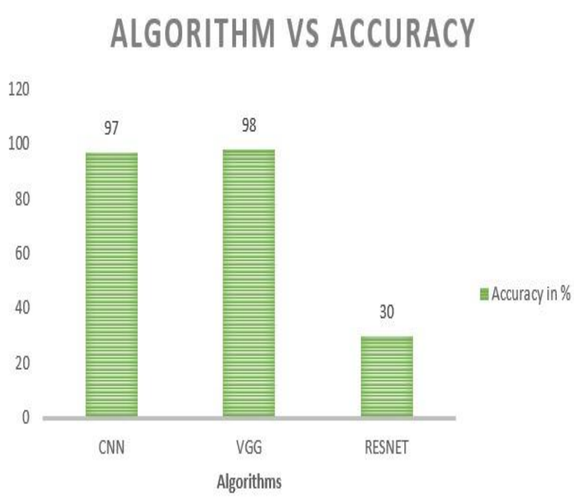
A sophisticated convolutional neural network framework called ResNet50—short for Residual Network with 50 layers—was created by Microsoft Research. It belongs to the family of ResNet, which developed residual literacy as a means of addressing the issue of slant evaporation in really deep networks.

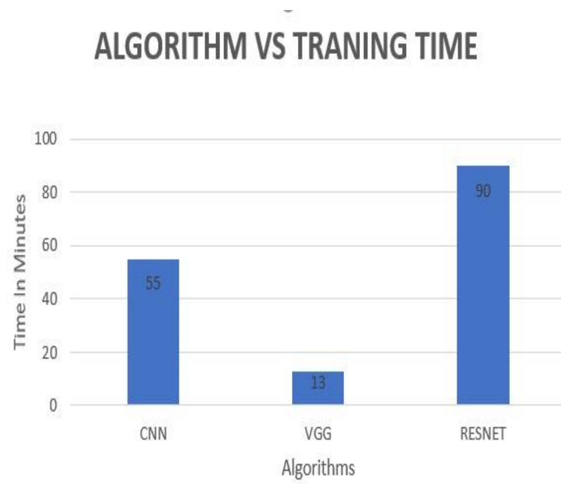
Due of its ability to retain high delicacy at a reasonably efficient computational cost, ResNet50 is widely utilized. The Essential Elements of ResNet50, which Residual Blocks ResNet50 use residual blocks to train significant deeper networks without experiencing vanishing slants and to help the network acquire identity mappings. Backbone Layers. Tailback layers are used by the armature to lower the amount of parameters without sacrificing performance. Three layers of convolution with 1the variables x1, 3x3, or 1x1 kernel typically make up a tailback block. Don't bother about connections. In order to provide more fluid data flow during backpropagation, the network has skip links that omit one or more tiers.

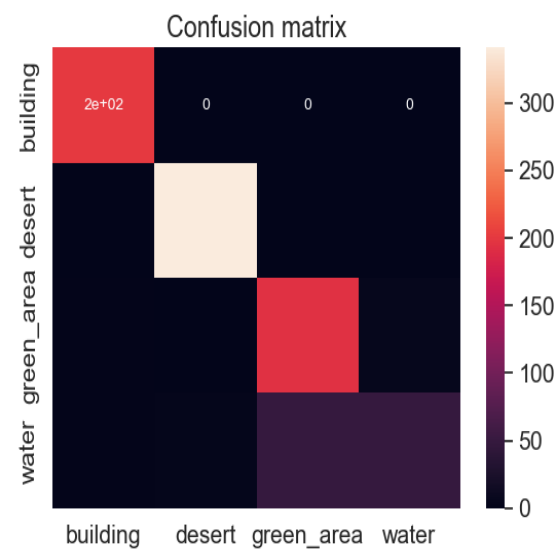
## VI.SYSTEM ARCHITECTURE

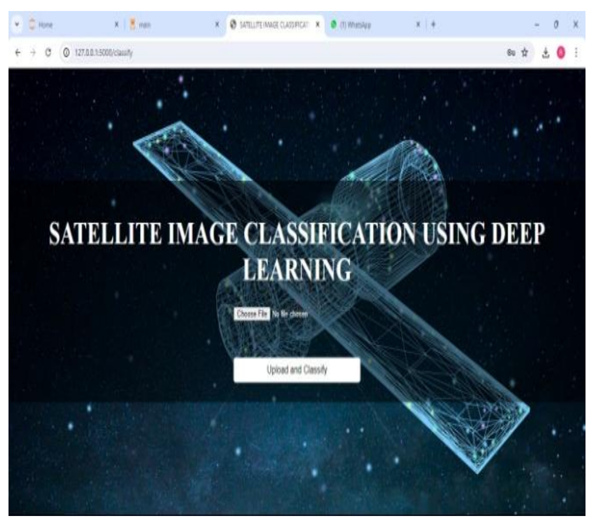


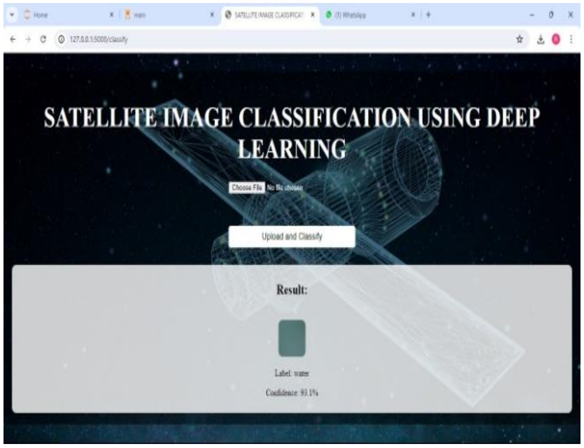

## VII. RESULT AND DISCUSSION






## VIII. FUTURE ENHANCEMENT

Enforcing sophisticated data addition methods, such as generative adversarial networks (GANs), may further improve the conceptualization and resilience of the model, especially in situations when the training data is scarce. Similarly, sphere adaptation and transfe literacy techniques may assist acclimate pre-trained models to certain satellite image collections and applications, improving performance with a minimal amount of labeled data. Transparency and interpretability of brackets findings will be provided by integrating resolvable AI (XAI) methods, enhancing confidence and acceptability in crucial processes. Working with Geographical Information Systems (GIS) might potentially improve decision-making and provide a geographical context for activities like ecological tracking and civic planning.

## IX.REFERENCES

1. AdekanmiAdeyinkaAdegun, SerestinaViriri and Jules-Raymond Tapamo, Review of deep learning methods for remote sensing satellite images classification: experimental survey and comparative analysis, 2023.
2. HafsaOuchra, AbdessamadBelangour, AllaeErraissi, Machine learning for satellite image classification: A comprehensive review.
3. Jaya H. Dewan, Rik Das, Sudeep D. Thepade, Harsh Jadhav, NishantNarsale, AjinkyaMhasawade, SinuNambiar, Image Classification by Transfer Learning using Pre-Trained CNN Models ,2023.
4. Li, Y., et al. "Deep Learning for Hyperspectral Image Classiication: Recent Advances and Future Trends." IEEE Geoscience and Remote Sensing Magazine, vol. 9, no. 2, 2021, pp. 33-54. DOI: 10.1109/MGRS.2021.3065725.
5. Ma, L., et al. "Deep Learning in Remote Sensing: Advances and Comprehensive Review." IEEE Geoscience and Remote Sensing Magazine, vol. 9, no. 2, 2021, pp. 39-67. DOI: 10.1109/MGRS.2021.3067437.
6. Shafaey, M.A., Salem, M.A.M., Ebied, H.M., Al-Berry, M.N., & Tolba, M.F. (2023). Classification of Satellite Images Using an Ensembling Approach Based on Deep Learning. Journal of Applied Remote Sensing.
7. Zhang, Y., Xu, Z., & Zhang, Y. (2022). Attention-Based Pyramid Network for Remote Sensing Image Classification. Remote Sensing.
8. Masouleh, M., Asl, A.H., & Motlagh, M. (2023). Deep Learning for UAV-Based Thermal Infrared Imagery Classification**.** Journal of Sensors and Sensor Systems.
9. Radovic, D., & Milicevic, M. (2023). Integration of Attention Mechanisms in Deep Learning for Satellite Image Classification**.** Applied Soft Computing.
10. Alhichri, H., Alghamdi, A., Boukerche, A., & Alkaabi, S. (2023). Review of Deep Learning Methods for Remote Sensing Satellite Images Classification: Experimental Survey and Comparative Analysis. Journal of Big Data.