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Satellite images Classification using deep learning algorithms and interfacing with Django

Yepuri Karthikeya	Uddagiri Manoj	Katta N V D V Prasad	Dr. M. Neelaveni Ammal
Btech-ECE	Btech-ECE	Btech-ECE	Assistant Professor
SRM University	SRM University	SRM University	SRM University

Abstract:

Satellite imagery constitutes a pivotal component across diverse domains, spanning agriculture, urban planning, disaster management, and environmental monitoring. The efficient and accurate classification of satellite images serves as a linchpin for extracting valuable insights and facilitating informed decision-making processes. In this study, we advocate for the utilization of artificial intelligence (AI) techniques to propel satellite image classification to new heights.

Our methodology revolves around curating a comprehensive dataset comprising labelled satellite images that encapsulate various land cover types or objects of interest. This dataset undergoes meticulous pre-processing to bolster image quality, expunge noise, and normalize the data, thereby laying a robust foundation for subsequent analysis. To augment the dataset's richness and enhance the model's generalization prowess, we employ data augmentation techniques like rotation, scaling, and flipping.

In charting the course for future research endeavors, we envision delving into advanced deep learning architectures, such as Resnet, x-ception, densenet. These sophisticated models hold the promise of elevating classification performance to unprecedented levels, thereby unlocking new frontiers in satellite image analysis.

In summation, our study heralds a paradigm shift in satellite image classification, leveraging the transformative power of AI to unravel the intricate tapestry of our planet's surface. Through a judicious fusion of innovative methodologies and cutting-edge technologies, we stand poised to unravel new vistas of knowledge and usher in a future where satellite imagery becomes an indispensable tool for understanding and stewarding our planet.

Introduction:

Satellite imagery is instrumental in identifying various objects on Earth's surface, ranging from buildings, roads, plantations, rice fields, to ships at sea. For archipelagic nations surrounded by oceans, the detection and classification of images hold paramount importance. Such capabilities find utility in fisheries management, supervision of smuggling activities, ship traffic services, and maritime security.

The classification of satellite images is a pivotal tool utilized across diverse fields and industries for a multitude of purposes. Firstly, it aids in land cover and land use analysis by identifying and categorizing different types of terrain, such as forests, agriculture, water bodies, urban areas, and barren land. This information is indispensable for urban planning, agriculture, forestry management, environmental monitoring, and natural resource management endeavors.

High-resolution satellite images offer detailed information, albeit posing challenges in separating foreground objects from the background. This intricacy amplifies processing time and may lead to false alarms. To navigate the complexities of high-resolution imagery, two critical requisites emerge: reliable features for discerning objects from non-objects, and the method's accuracy.

Prior research by scholars has applied the Threshold method for background segmentation, particularly with ships, effectively distinguishing backgrounds based on threshold ratios and blue ribbons. The sea area typically exhibits a stationary gray distribution with minimal grayscale variations, contrasting with artificial objects manifesting through histograms with threshold segmentation.

In the realm of satellite image classification, leveraging AI techniques offers a promising avenue for advancement. AI algorithms can learn intricate patterns and features within satellite images, facilitating accurate classification across diverse landscapes and scenarios. By employing convolutional neural networks (CNNs) or other deep learning architectures, satellite images can be processed and classified with remarkable precision and efficiency.

DenseNet (Densely Connected Convolutional Networks):

Gao Huang et al. presented the DenseNet convolutional neural network (CNN) architecture in 2017. It introduces tight connectivity across layers, which sets it apart from conventional CNN architectures like VGG and ResNet. Every layer in DenseNet is feed-forward coupled to every other layer. Because of this extensive connection, gradient flow during training is improved and the vanishing gradient problem is lessened by promoting feature propagation throughout the network and facilitating feature reuse. Key features of DenseNet for satellite image classification include:

Dense connectivity: Each layer receives feature maps from all preceding layers, promoting feature reuse and enhancing model expressiveness.

Efficient parameter usage: Dense connectivity reduces the number of parameters compared to traditional architectures, making DenseNet models more parameter-efficient.

Feature fusion: Dense blocks facilitate feature fusion by concatenating feature maps from preceding layers, enabling the model to capture complex spatial dependencies in the data.

For satellite image classification tasks, DenseNet architectures can be fine-tuned using transfer learning techniques. Pre-trained DenseNet models trained on large-scale image datasets (e.g., ImageNet) can be fine-tuned on satellite image datasets to adapt the model's features to satellite-specific characteristics.

Xception:

"Extreme Inception," or "Xception," is the name of another CNN architecture intended for image classification applications. Xception is an extreme implementation of depth-wise separable convolutions, inspired by the Inception architecture and proposed by François Chollet, the inventor of the Keras library.

Depth-wise separable convolutions: Xception decomposes standard convolutions into depth-wise convolutions followed by point-wise convolutions. This separation of spatial and channel-wise information reduces the number of parameters and computational complexity.

Efficient feature extraction: By decoupling spatial and channel-wise information, Xception can capture spatial hierarchies and learn discriminative features efficiently.

Scalability: Xception can be scaled to different depths and widths, allowing for flexible trade-offs between model complexity and performance.

For satellite image classification, Xception's efficient feature extraction capabilities make it well-suited for extracting discriminative features from high-resolution satellite images. Like DenseNet, Xception models can be fine-tuned using transfer learning techniques to adapt the model's features to specific satellite image datasets.

ResNet:

The problem of vanishing gradients in very deep neural networks is the primary objective of the ResNet, abbreviation for Residual Network, a deep convolutional neural network architecture.

The residual units are the fundamental components of ResNet. Two convolutional layers with batch normalization and rectified linear unit (ReLU) activations make up each residual unit, which also has a skip connection. The skip connection bypasses the convolutional layers and directly adds the input to the output of these layers. Mathematically, if x is the input to a residual unit, the output y is computed as $y=F(x)+x$.

Firstly, we use ResNet, Densnert and Xception to train our dataset before applying Django to create a web application that offers high-quality research.

Prior work:

Recently, a number of annotated image datasets and detection and classification exercises have surfaced. The majority of deep learning techniques used with remotely sensed data have focused on classifying land cover or identifying buildings. For instance, the U.S. Geological Survey's 2100 aerial photos make up the UC Merced Land Use Dataset .The photos have a pixel resolution of 256x256 and a ground sample distance of 0.3 meters. The 21 classes include facility classes like storage tanks and tennis courts as well as land cover kinds like road, water, and farmland. Several researchers classified the UC Merced photos into land cover types using the VGG, ResNet, and Inception CNNs. One researcher obtained classification accuracies as high as 98.5%.

Literature Survey:

“Classification and Understanding of Cloud Structures via Satellite Images with EfficientUNet” by Ahmed, Tashin, and Noor Hossain Nuri Sabab:

This paper focuses on cloud structure classification using satellite imagery. They propose an approach based on the EfficientUNet architecture. The study aims to enhance our understanding of cloud formations in satellite images. The work provides insights into efficient cloud detection and classification techniques.

“Review of Deep Learning Methods for Remote Sensing Satellite Images Classification: Experimental Survey and Comparative Analysis” by Adegun, A.A., Viriri, S., and Tapamo, JR:

The authors review and analyze deep learning methods for classifying remote sensing satellite images. They explore models like ResNet, DenseNet, EfficientNet, VGG, and InceptionV3. The study evaluates these models on various datasets, demonstrating their effectiveness in handling complex features of high-resolution imagery.

“Ranking Ship Detection Methods on Machine Learning and Artificial Intelligence” by Muhammad Yasir, Abdoul Jelil Niang, Md Sakaouth Hossain, Qamar Ul Islam, Qian Yang, and Yuhang Yin:

This paper ranks ship detection methods using machine learning and artificial intelligence. It provides insights into effective techniques for detecting ships in satellite images.

“A Deep Framework for Hyperspectral Image Fusion between Different Satellites” by Guo, Anjing, Renwei Dian, and Shutao Li:

The authors propose a deep learning framework for fusing hyperspectral images from different satellites. Their approach aims to improve image quality and enhance information extraction from multispectral data.

“Satellite Image Classification Methods and Techniques” by Ouchra, Hafsa, and Abdessamad Belangour:

This paper discusses various methods and techniques for satellite image classification. It provides an overview of approaches used in the field, emphasizing the importance of accurate classification for applications like land cover mapping and environmental monitoring.

Scope of the work:

The scope of satellite image classification using AI techniques is broad and multifaceted, spanning applications in environmental monitoring, urban planning, agriculture, disaster management, security, healthcare, and beyond. Its scope encompasses tracking land cover changes, assessing infrastructure, aiding in resource management, and supporting decision-making across diverse sectors. AI-driven satellite image analysis facilitates timely responses to natural disasters, climate change mitigation, and sustainable development, offering valuable insights for policymakers, researchers, and industry professionals. As technology evolves and satellite data becomes more abundant, the scope of AI in satellite image classification continues to expand, addressing pressing global challenges and unlocking new opportunities for innovation and data-driven solutions.

Methodology:

The methodology follows figure as shown in the figure:

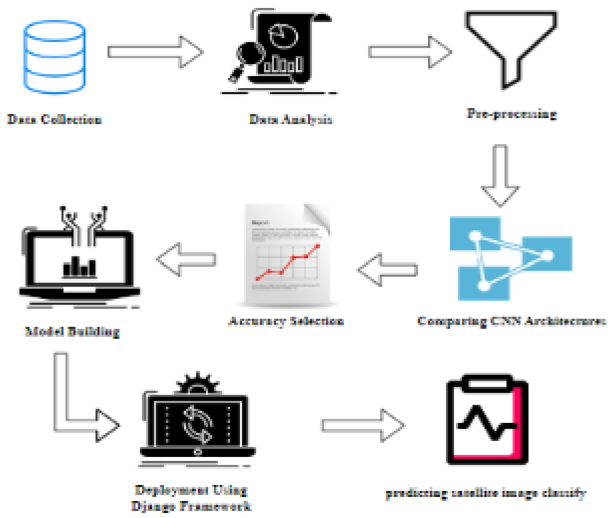


Fig 1 : Block diagram

Dataset:

This dataset contains test image records of features extracted, which were then classified into 6 classes.

- Source : Kaggle, Google
- Total images 1998 images
- Total Classes : Dividing it into 6
- Each Class having 333 images

Reply to this mail to get the dataset

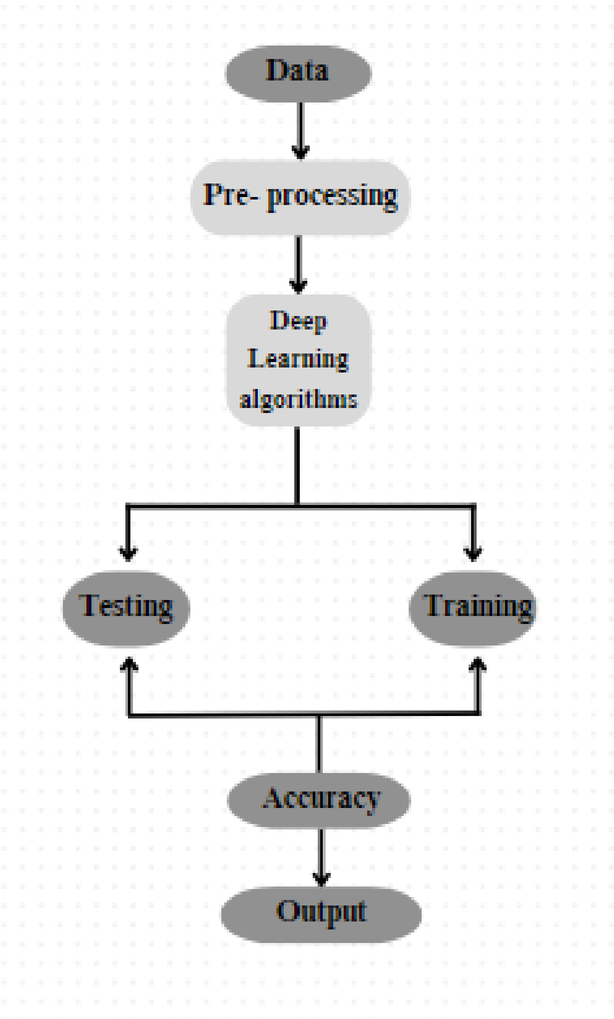


Fig : Block Diagram of ML applications

Preprocessing:

Preprocessing is essential to prepare the satellite photos for model training. This step may include tasks such as resizing images to a uniform size, normalization to standardize pixel values, and noise reduction techniques. Preprocessing aims to enhance the quality of the data and remove any noise or irrelevant information that could hinder model performance.

In this project the pre processing is happened in this way as shown in figure

Steps:

Reading the Image: Loading the image data into memory.

Resizing the Image: Adjusting the image dimensions to a consistent size.

Detection of which class: Detection refers to localizing the image belongs which class.

It involves segmenting the image and identifying the class.

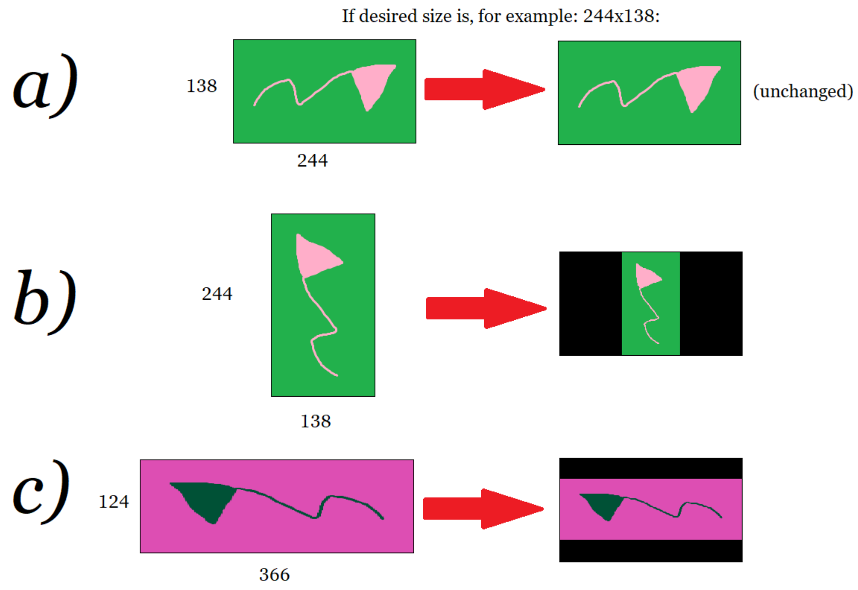


Fig 2 : Image resizing

CNN architectures:

Dense NET:

DenseNets are a kind of convolutional neural network (CNN) architecture, sometimes referred to as densely-connected convolutional networks. While they differ fundamentally from ResNet, they share several similarities. DenseNets use all of the previous outputs as input for a future layer, in contrast to ResNets, which employ an additive technique (using a prior output as input for a future layer). This dense connection pattern solves vanishing gradient problems in deep neural networks and improves accuracy.

DenseNets resolve this by connecting each layer directly to every other layer, creating a dense web of connections. For a network with L layers, there are approximately L(L+1)/2 direct connections.

Deeper into the network, the dense connectivity can no longer be maintained. For example, all nine layers before it would provide input to the tenth layer.DenseNets introduce dense blocks to handle this:There are a predetermined number of layers in each thick block.A dense block's output is supplied into a transition layer.To minimize feature map size, the transition layer usually consists of a max pooling step after a one-by-one convolution.DenseNets can efficiently train more than 100 layers thanks to this method.

In this denseNET they are different types:

Dense 121: This is the original DenseNet architecture with 121 layers. It consists of four dense blocks, each containing a set of densely connected layers, with transition layers in between.

Dense 169: DenseNet-169 is a variant with 169 layers. It is deeper than DenseNet-121 and provides increased representational power.

Dense 201: DenseNet-201 is an even deeper variant with 201 layers. It has a more complex architecture compared to DenseNet-121 and DenseNet-169, offering potentially improved performance, especially for more challenging datasets and tasks.

Dense 264: DenseNet-264 is the deepest variant among the commonly used DenseNet architectures.

Dense Bc: DenseNet-BC stands for DenseNet with bottleneck layers and compression. This variant introduces bottleneck layers, which reduce the number of feature maps before entering the densely connected layers, thus reducing computational cost.

In this project we have used Dense 121 architecture

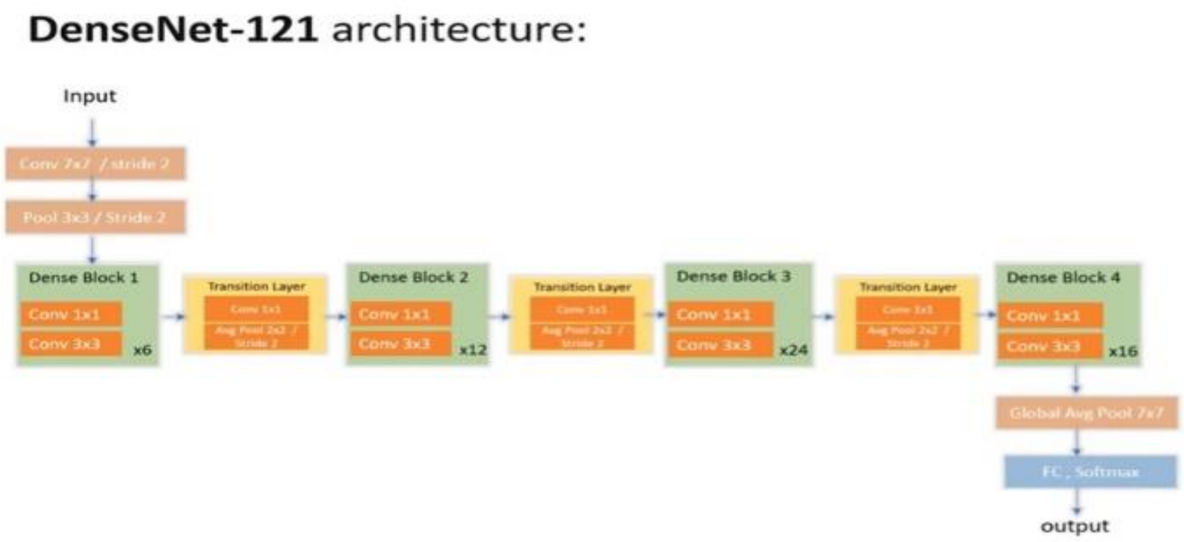


Fig 3 : Dense Net architecture

Xception Algorithm:

Xception, short for "Extreme Inception," is a convolutional neural network (CNN) architecture. It builds upon the principles of the Inception architecture but takes them to an extreme level.

Xception Architecture:

The Xception architecture has 36 convolutional layers forming the feature extraction base of the network.

It follows a specific flow:

Entry Flow: Initial layers process the input data.

Middle Flow: Repeated eight times, this section further refines features.

Exit Flow: Final layers prepare the output.

Notably, all Convolution and Separable Convolution layers are followed by batch normalization (not shown in the diagram).

Depthwise separable convolutions are a key feature of Xception.

Depthwise Separable Convolutions: Instead of traditional convolutions, Xception uses depthwise separable convolutions:

Depthwise Convolution: Applies separate convolutions to each input channel. Creates new feature maps independently for each channel.

Pointwise Convolution (1x1 Convolution): Combines feature maps from the depthwise convolution. Produces the final set of feature maps. This approach reduces parameters while maintaining expressive power.

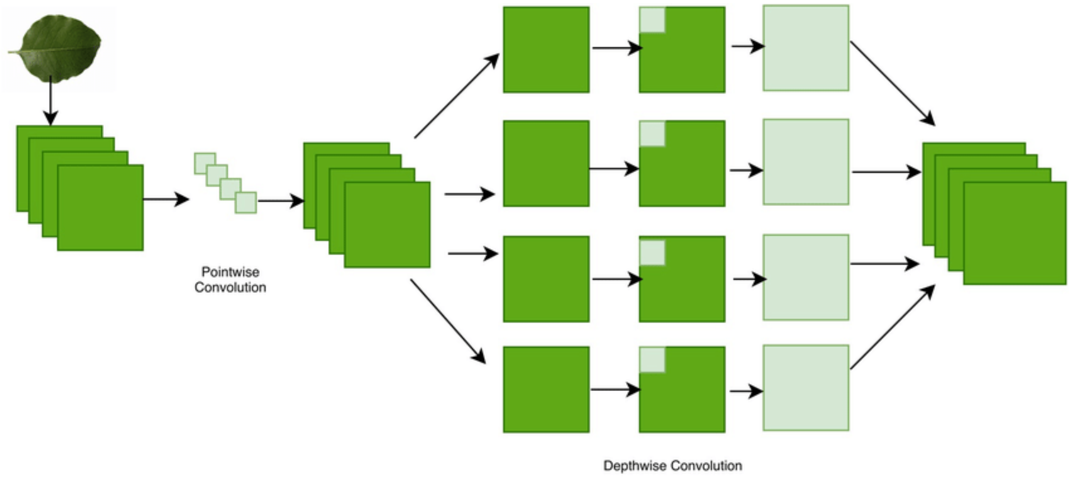


Fig 4 : Xception Architecture

RESNET:

The residual block, which adds shortcut connections—also referred to as skip connections or identity mappings—to get around one or more network layers, is the fundamental building piece of ResNet. By allowing the gradient to pass through the network more directly during training, these skip connections serve to address the issue of vanishing gradients and make it easier to train deeper networks.

The main elements and functionalities of ResNet are as follows:

Residual Block: Usually composed of two convolutional layers, batch normalization, and ReLU activation functions, the residual block is the fundamental building block of ResNet. The network learns residual mappings by appending the block's input to the convolutional layers' output. The output of a residual block is output in mathematics.

Skip Connections: ResNet's skip connections allow gradients to propagate through the network more efficiently by giving them shortcut routes. This facilitates the training of deeper architectures and keeps the gradients from getting too tiny during backpropagation, especially in deep networks.

Network Depth: ResNet topologies with hundreds or thousands of layers have the potential to be incredibly deep. Deeper networks can perform better on a variety of tasks, including segmentation, object detection, and picture classification, since they can learn more intricate features and representations from the input data.

Bottleneck Architectures: To lower computational complexity and boost efficiency, bottleneck architectures are employed in more advanced ResNet versions. In order to lower the number of parameters and computational cost, these architectures employ 1x1 convolutions to first reduce the dimensionality of the input feature maps before using traditional 3x3 convolutions.

Global Average Pooling and Fully Connected Layer: ResNet usually finishes with a fully connected layer and a softmax layer for classification, in order of decreasing depth. By condensing the feature maps generated by the convolutional layers into a vector of feature averages, global average pooling aids in the reduction of overfitting and the number of parameters in the network.

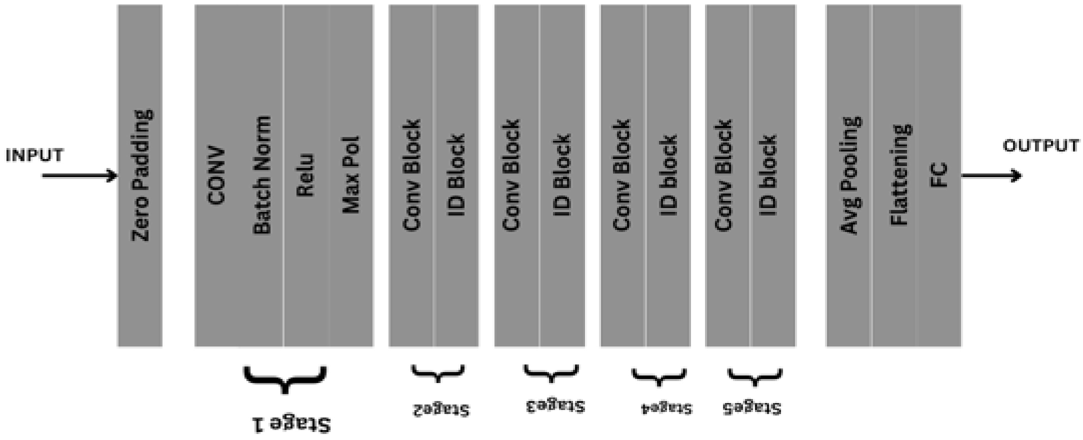


Fig : ResNet Architecture

Compare CNN architectures:

Algorithm	CNN	DENSE CNN	RESNET	Xception
Accuracy	61.2	82.3	87.4	94.7
Val_accuracy	0.63	0.56	0.53	0.47

Model Building:

Model development in Django provides a powerful and flexible way to define and manage your application's data, allowing you to focus on building robust web applications with clean, maintainable code.

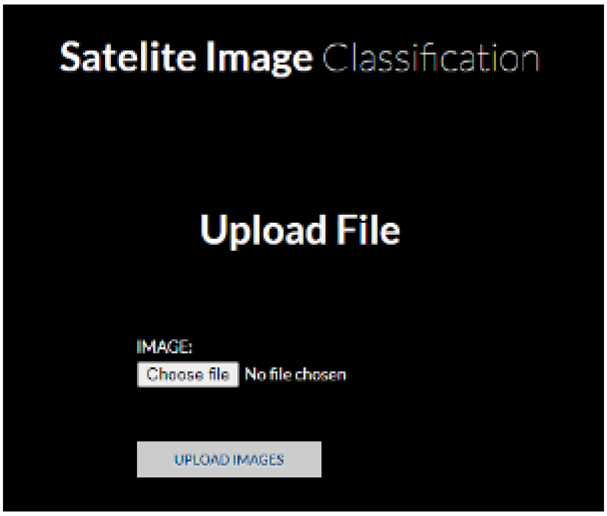


Fig 5 : Web application front page

Python and Django integrate seamlessly for web development. Python serves as the primary language, offering flexibility and simplicity. Django, a high-level web framework, extends Python's capabilities for rapid development. Through Django's django-admin utility, projects are initiated, following the Model-View-Template architecture. Python's role encompasses defining models, writing business logic within views, and managing various application functionalities. Django's built-in features, including ORM, URL routing, templating engine, form handling, authentication, and the admin interface, streamline development.

Python Interface:

Python is a programming language that supports various interfaces. In Python, an interface can refer to a description of how to interact with an object or a set of functionalities provided by a module, class, or library.

Python uses interfaces through class definitions, where methods and attributes define how objects of that class can be used.

Django Interface:

A high-level Python web framework called Django promotes efficient development and simple, straightforward design. In Django, the term "interface" usually refers to the way developers interact with Django's components, such as models, views, templates, and forms.

For example, the Model-View-Template (MVT) architecture in Django defines interfaces for developers to define database models, write view functions, and render HTML templates.

Admin Interface:

Django also provides an admin interface out of the box, which allows developers to manage site content without writing a lot of code. This admin interface is generated dynamically based on the models defined in your Django application.

Developers can customize the admin interface to some extent by configuring model admin classes, defining list displays, search fields, and other options.

FUTURE WORK:

The processes that follow can be used to further increase the accuracy and generalization of the network. Using the entire dataset for optimization is the initial step. Larger datasets are more suited for batch optimization. Analyzing each satellite image separately is an additional method. This may enable the detection of satellite photos that are more challenging to categorize..

Results :

Test data Extraction :

For each class of dataset:

the output (1, 14, 14, 448) indicates that the extracted features are organized in a tensor with a batch size of 1, spatial dimensions of 14x14, and 448 feature maps.

Classification

```
TRAINING DATA FOR CLOUDY:

======== Images in:  DATASET/TRAIN/cloudy
Images_count :   333
Min_width :      256
Max_width :      256
Min_height :     256
Max_height :     256
```

```
TRAINING DATA FOR GREENAREA:

======== Images in:  DATASET/TRAIN/green_area
Images_count :   333
Min_width :      64
Max_width :      64
Min_height :     64
Max_height :     64
```

```
TRAINING DATA FOR SHIPSNET:

======== Images in:  DATASET/TRAIN/shipsnet
Images_count :   331
Min_width :      80
Max_width :      80
Min_height :     80
Max_height :     80
```

```
TRAINING DATA FOR WILDFIRE:

======== Images in:  DATASET/TRAIN/wildfire
Images_count :   335
Min_width :      350
Max_width :      350
Min_height :     350
Max_height :     350
```

Fig 6 : Classification of images

The classifiers created in the study, using dense Net and xception has achieved strong results in classification of Satellite images. For densenet we achieved accuracy of 87.4% and for Xception achieved 94%.

For normal CNN achieved 63% accuracy and ResNet50 we achieved 84.7% from the research we have done it in .

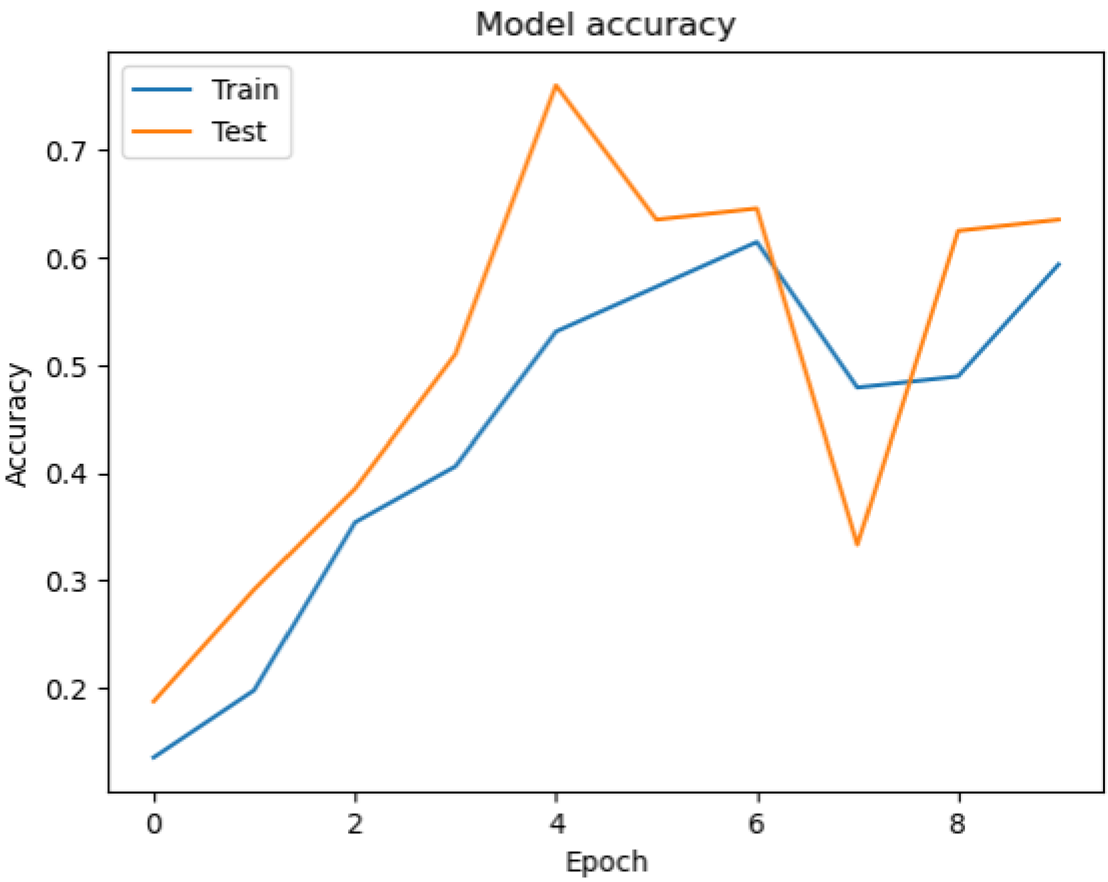


Fig 7 : Model Gain

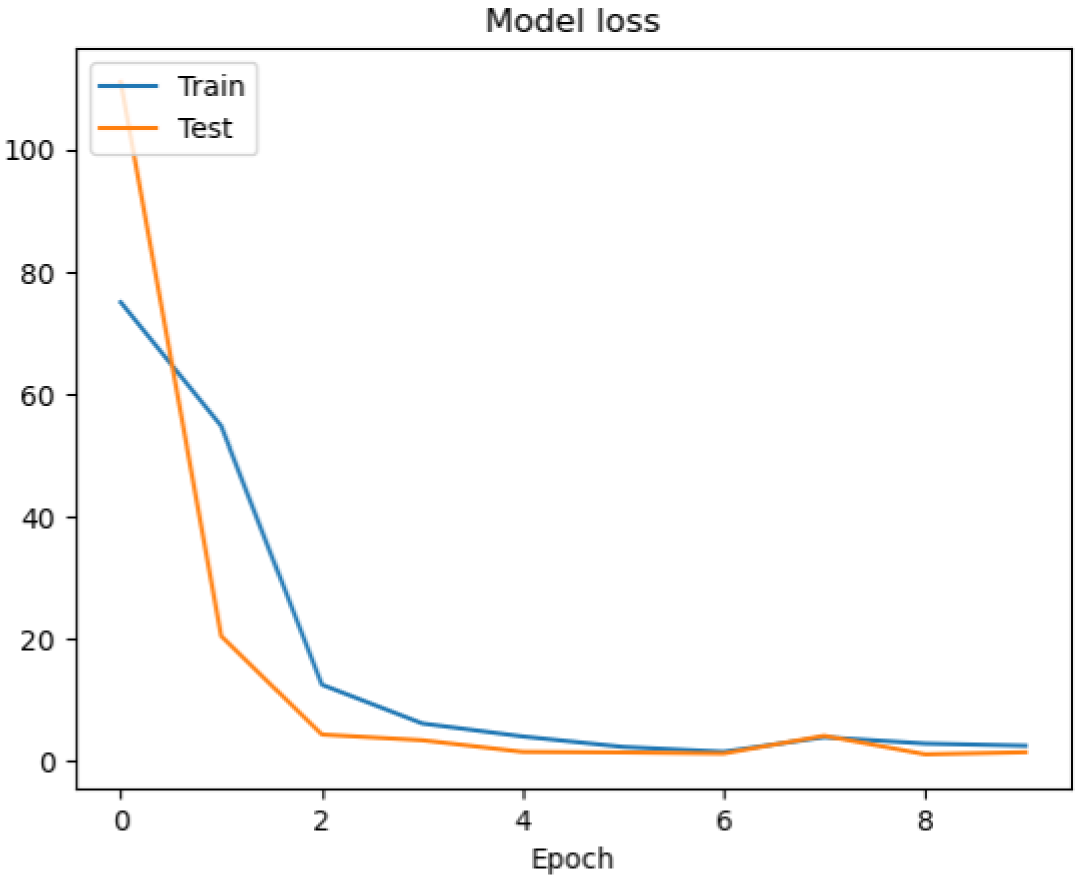
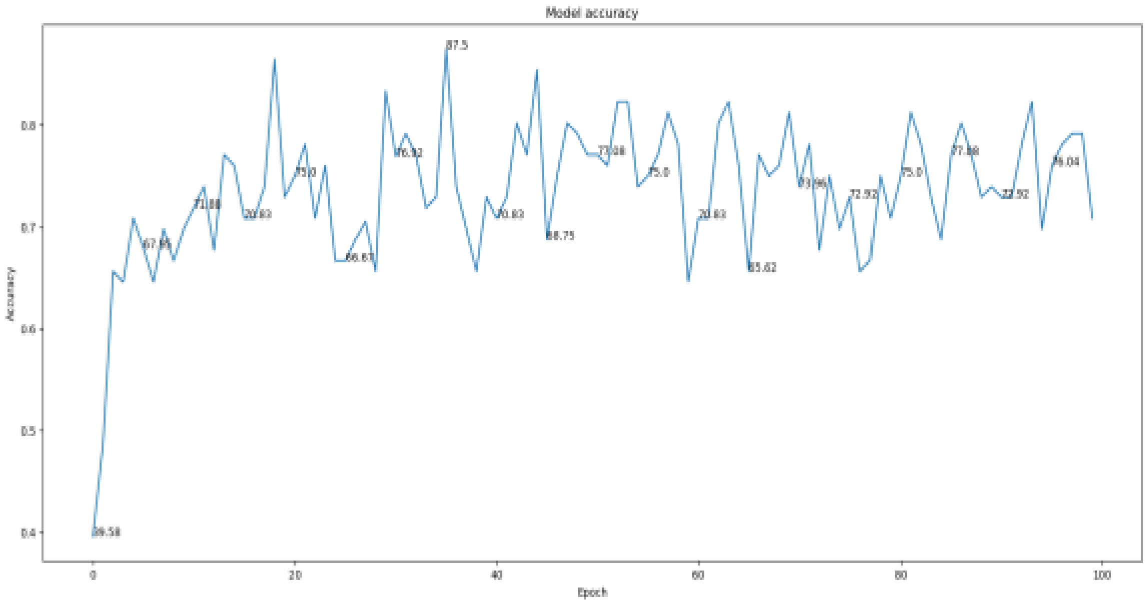
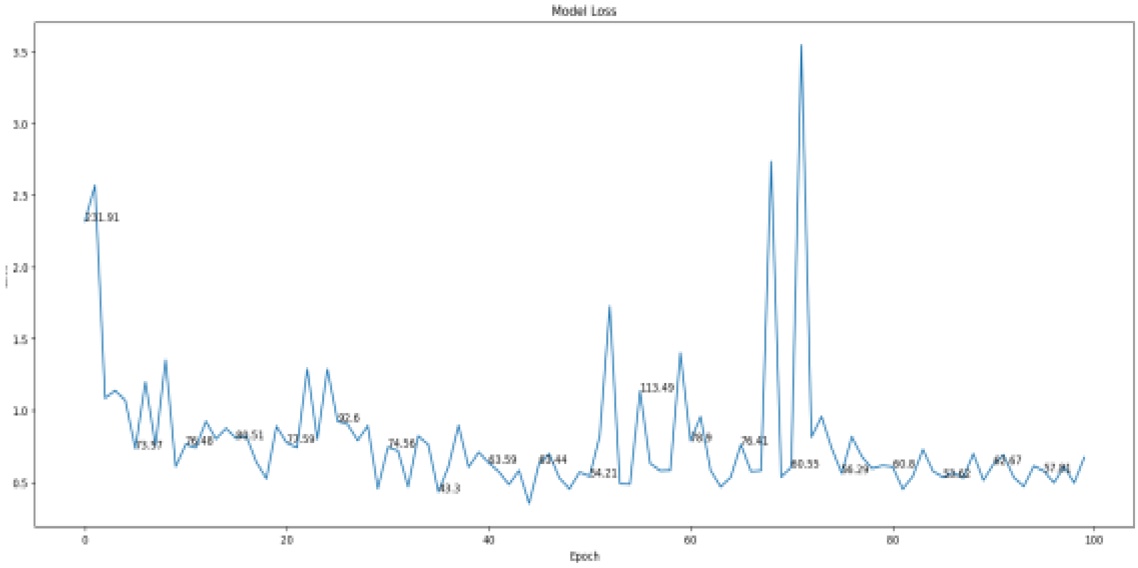
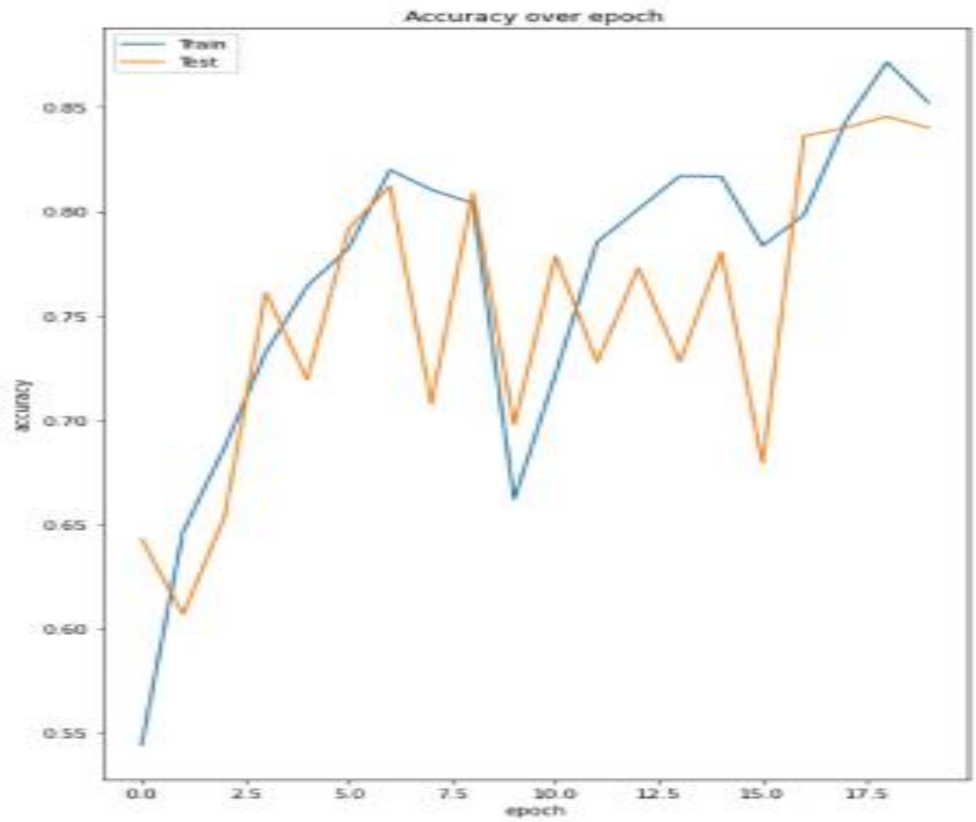
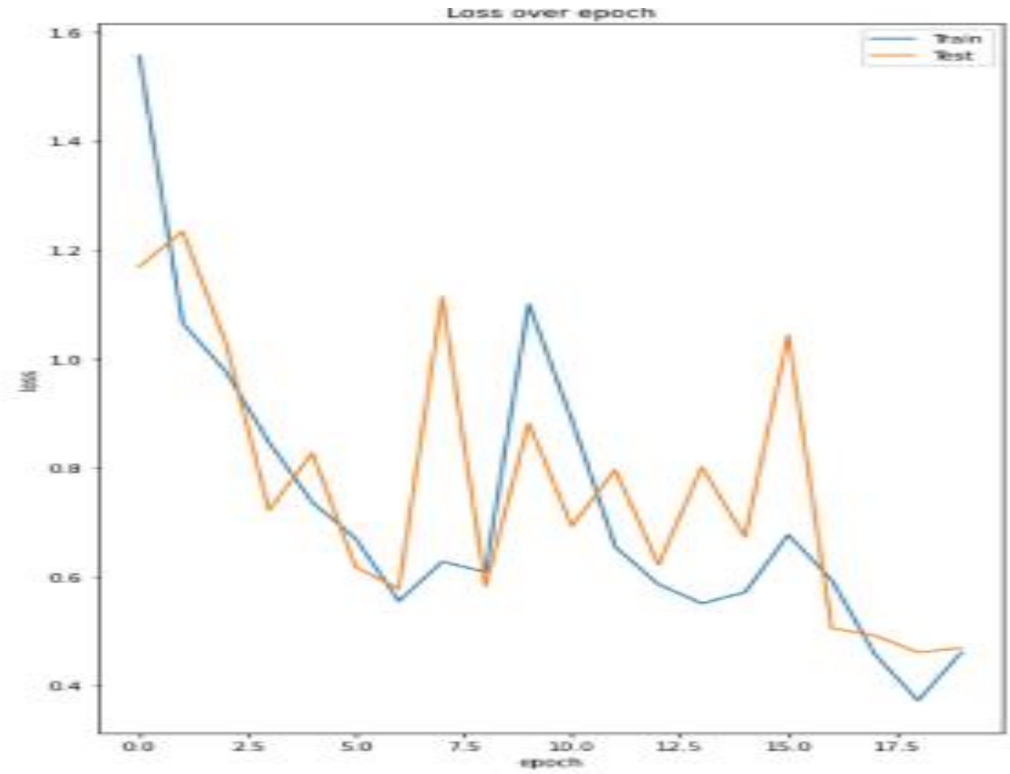


Fig 8 : Model Loss

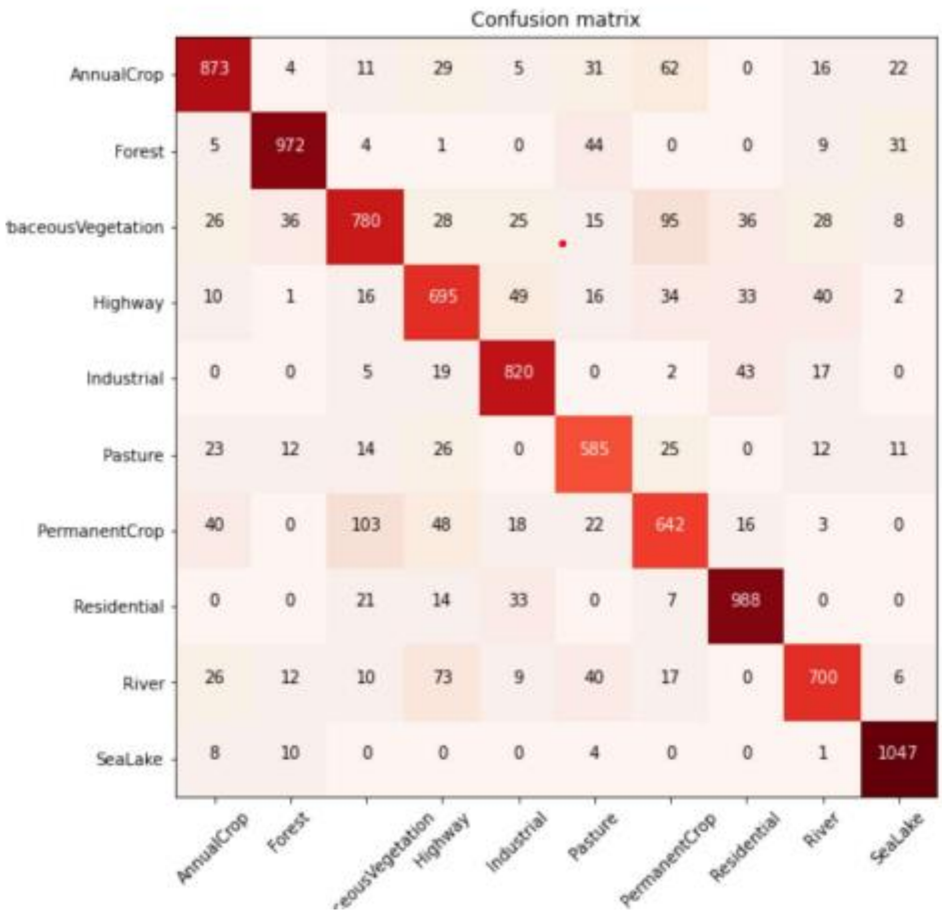



Model Loss
3.5
3.0
2.5
2.0
1.5
1.0
0.5
0
20
40
60
80
100
Epoch
113.49
92.6
77.59
74.58
63.59
54.21
76.41
80.55
60.8


Accuracy over epoch
Train
Test
0.85
0.80
0.75
0.70
0.65
0.60
0.55
accuracy
0.0
2.5
5.0
7.5
10.0
12.5
15.0
17.5
epoch



Confusion Matrix:



Conclusion:

The classification of satellite images using DenseNet and Xception models offers promising avenues for accurate and efficient analysis of Earth observation data. Through the utilization of deep learning architectures like DenseNet and Xception, we've witnessed significant advancements in the ability to classify satellite images with high precision and robustness.

DenseNet's dense connectivity patterns and Xception's depthwise separable convolutions contribute to their effectiveness in capturing intricate patterns and features within satellite images, enabling the models to learn rich representations of spatial and spectral information.

The classification of satellite images using DenseNet and Xception represents a powerful paradigm shift in remote sensing and geospatial analysis, offering unprecedented opportunities to extract valuable insights from Earth observation data and support informed decision-making for a wide range of societal and environmental challenges.

This project conducted a study to use deep learning techniques for satellite picture classification. This is a challenging issue that has already been tackled multiple times using various methods. Although feature engineering has yielded good results, this study concentrated on feature learning, one of the promises of deep learning. Although it's not required, image pre-processing improves categorization

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