Term project Final Report

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Title Land Use Land Cover Classification and Map Generation

1. Abstract

Satellite imaging has many uses, and it is present in all facets of daily life. In particular, landscape images have advanced over time to address numerous issues in various fields. Hyperspectral remote sensors are frequently employed in remote sensing to monitor the surface of the planet with a high spectral resolution which results in better image generation. Utilizing remote sensing technologies is a useful approach to keep an eye on Earth's developments. LULC images have been retrieved via satellite imagery on a large scale.

In recent years, the creation of LULC images has become more significant for studies pertaining to climate change, landscape ecology, and sustainable land management.
Furthermore, data scientists state that temporal variations in LULC provide information regarding the appropriate use and planning of natural resources as well as their management. Therefore, current and accurate LULC information is essential for maintaining a sustainable ecosystem. In addition, as uncontrolled and irregular urban expansion can alter the urban climate, it is crucial to periodically monitor changes in the local urban light-curriculum in rapidly expanding cities.

2. Problem Statement

Despite the increase in need for LULC classification models, many of the maps and digital databases that are currently in use were not created with the diverse needs of users in mind. Although it is typically overlooked, one of the primary causes is the kind of classification that is applied to fundamental data like land cover and land use. While there are numerous worldwide categorization schemes, there isn't a single internationally recognized system for classifying land use or cover. Here's why researchers are focused on preparing a more accurate LULC classification model-

1. Diverse User Requirements- Information on land cover and land use is needed by a variety of stakeholders, including researchers, legislators, urban planners, and environmentalists. Databases and maps that are currently in use might not always meet these various needs[2].
2. Classification and Legend Issues- The classification scheme and legend chosen to characterize land use and cover can have a big influence on how relevant and comparable geographical data are. Cross-regional or cross-project data comparison can be hampered by inconsistent classification schemes.
3. Project-Oriented Approaches- A large number of the land cover and land use classifications that are currently in use were created for particular projects or industries, which restricts their general application. This may result in a lack of uniformity and fragmentation in the representation of land cover and land use data.
4. Lack of International Standardization- There is no internationally recognized standard for classifying land use or cover, despite efforts to create a number of classification schemes across the globe. This lack of uniformity may make it more difficult for nations and regions to share data and interact with one another.[5]

3. Methodology

The primary aim for the project is to manipulate, analyze, and visualize geospatial data and to get a deeper understanding on how the LULC map is generated for an area of Interest. In order to achieve this, the project could be divided into two parts- Fine Tuning a Pre-trained model for Image classification and then using the pre-trained model to generate a LULC Map for a particular region.

The pre-trained model used is ResNet50. ResNet-50 is a convolutional neural network architecture that belongs to the family of ResNet (Residual Network) models. ResNet-50 is a specific variant of ResNet that consists of 50 layers, including convolutional layers, pooling layers, and fully connected layers. It was introduced in the paper titled "Deep Residual Learning for Image Recognition" in 2015[6]

Deep neural networks are difficult to train due to the problem of vanishing or exploding gradients (repeated multiplication making the gradient infinitely small). ResNet bypasses one or more levels in order to overcome this by creating shortcut connections, as seen below, that link activation from an earlier layer to a later one.[6].

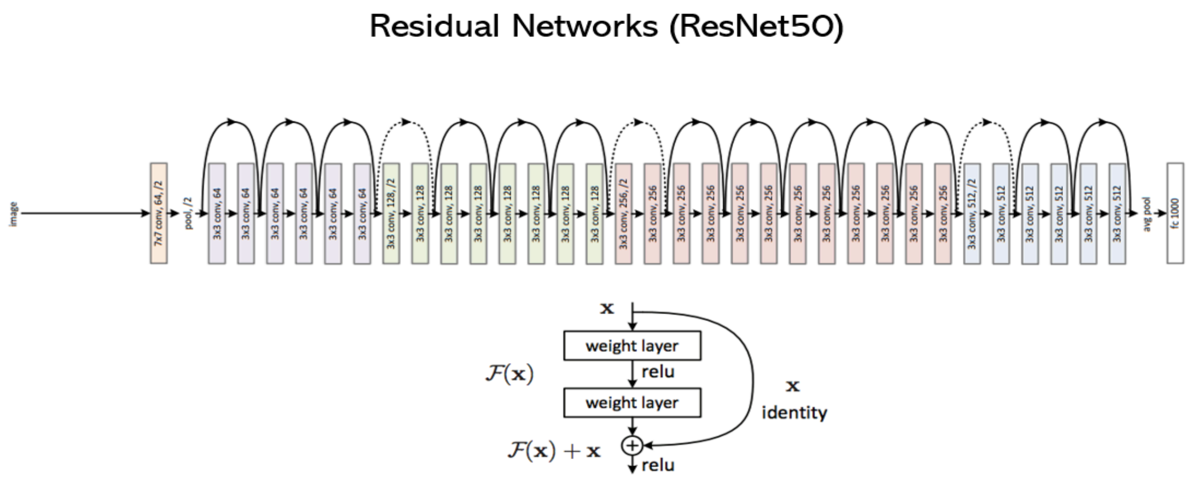


Image- [link]

1. <u>Fine-tuning the ResNet50 Model</u>
   Fine-tuning a pretrained model refers to the process of taking a neural network model that has been trained on a large dataset (typically a general dataset like ImageNet) and further training it on a new, smaller dataset specific to a particular task or domain. The goal of fine-tuning is to take advantage of the knowledge that the pretrained model (which was trained on a sizable dataset) has acquired and modify it so that it can function well on a new task or dataset. Below is the sequence of fine-tuning done for the ResNet50 model
   a. <u>Creating Custom dataset classes</u>- By Creating custom dataset classes In Pytorch the Dataset class allows you to define a custom class to load the input and target for a dataset. this capability is used to load the input in the form of RGB satellite images along with their labels and later apply any kind of transformations
   b. <u>Data Augmentation</u>- During model training, data augmentation involves randomly applying image changes, such as cropping, flips (horizontal and vertical), and other adjustments, to the input images. The neural network can more effectively generalize to the unknown test dataset thanks to these perturbations, which also lessen the network's overfitting to the training dataset.

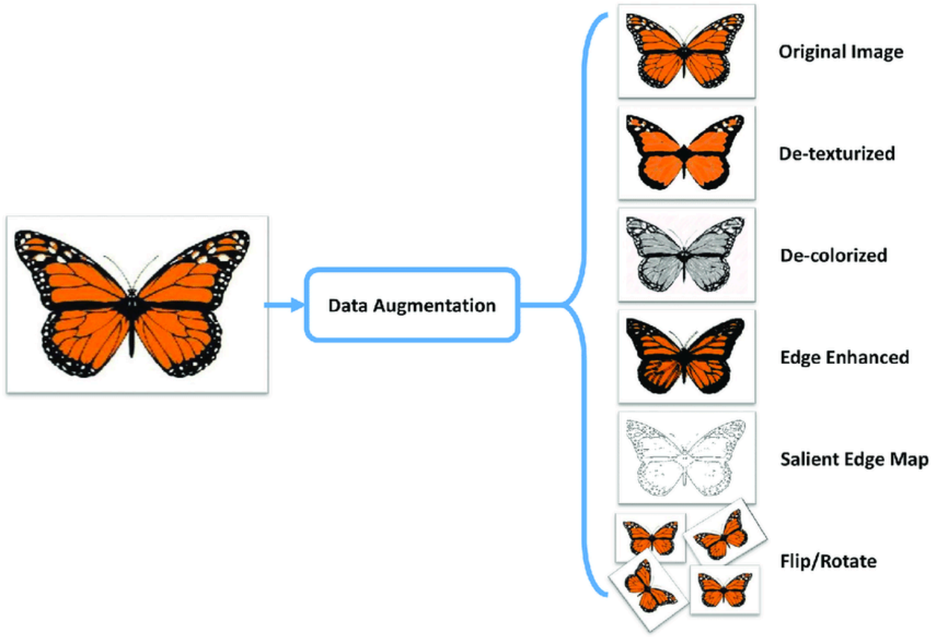


image-link

c. Image Normalization- Image normalization is a preprocessing method used to standardize an image's pixel values in computer vision and image processing. By ensuring that the input data (image pixels) have a constant scale and distribution, picture normalization aims to enhance the stability and performance of machine learning models.

2. Generating Land Use and Land Cover Map for an Area

Sentinel-2 satellite image for a region of interest is downloaded through Google Earth Engine and a trained CNN model(ResNet50) is applied on the image to generate a land use and land cover map.

a. Generating sentinel-2 Satellite images- Sentinel-2 is a Copernicus Program Earth observation project that produces global multispectral imagery at 10 m resolution every 10 days from 2015 to the present[1].A function is written to use the Python Earth Engine API to create a Sentinel-2 image from Google Earth. An aggregator is selected for a set of photographs taken over time rather than a single image on a specific date in order to reduce cloud cover.
b. Visualization of the Sentinel-2A Image- Once the API call is done and the image is received , a boundary is made to differentiate states(of U.S.A) and a portion of a state- California is selected as a region to generate the LULC map for. After the region is downloaded, it is visualized as a satellite raster image using the raster library. Pixels are arranged in a grid to form raster data. Digital elevation maps, maps of nocturnal

luminosity, and multispectral satellite photos are a few examples. For example, red, green, and blue values in satellite pictures; night light intensity in NTL maps; and height in elevation maps—each pixel denotes a value or class. GeoTIFFs (.tiff) are frequently used to store raster data.

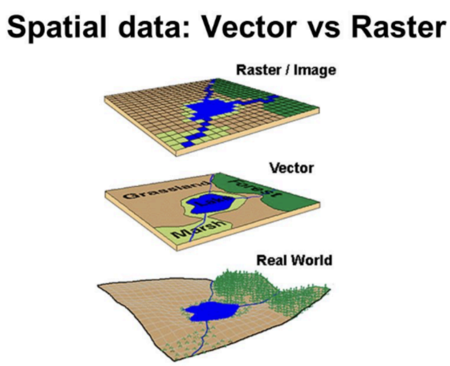


image- link

c. Generating & Visualizing 64x64 px GeoJSON Tiles- Since the deep learning model trained on RGB dataset was trained on 64*64 pixel Sentinel-2 image patches, the generated Sentinel-2 image from google earth engine need to be broken down as well into smaller 64*64 patch tiles. The is done by creating a function that generates a grid of 64*64 tiles using 'Rasterio Window Utilities'. Pixels are arranged in a grid to form raster data. The land use and land cover classification map is generated using the trained model. The RGB Dataset consists of 10 different LULC classes which will be explained further in the data section. Later, an interactive LULC map is generated using the Folium library after loading the resulting predictions made earlier.

By combining all the above steps, the finely-tuned ResNet-50 model is leveraged to create accurate and detailed LULC maps for various environmental and land management applications. The key is to adapt the deep learning model to the specific characteristics and requirements of the target area and land cover classification task.

3.1 Algorithms

Basic Algorithm structure Combining the above mentioned two parts

- Step1- Preparation of Data

Gather satellite imagery data that could be RGB or Multi-spetural captured by satellites like Sentinel-2 or Landsat and acquire ground truth data or labeled samples for training and validation.

- Step2- Load Pre-Trained ResNet-50 Model

Import the ResNet-50 model architecture along with pre-trained weights through Deep learning networks like pytorch

- Step3- Modify and Fine-Tune Model

Training the modified model using the RGB dataset and feeding the training images into the model for optimizing weights and minimizing the loss function (e.g., cross-entropy)

- Step4- Validation and Evaluation

Evaluate the fine-tuned model using a validation dataset to assess its performance in classifying LULC types

- Step5- Generate LULC Map

Generation of a pixel-wise LULC map based on the model's predictions where each pixel in the map represents a specific land cover or land use class

- Step6- Post-Processing and Visualization

Visualize the generated LULC map using mapping libraries (e.g., Folium) to visualize the distribution of different land cover and land use classes within the region of Interest.

LULC- A Big data problem

The complexity of LULC mapping from remotely sensed large data arises from the diversity and high dimensionality of remotely sensed data. Finding the appropriate datasets and combining them to create intricate large-scale LULC maps is difficult. Even though multi-source optical and microwave remotely sensed data enable us to get LULC information from many angles, they can occasionally make it difficult to determine which kind is best for a certain LULC mapping(**source**).

Furthermore, integrating diverse remotely sensed data from multiple sources with varied properties (such as spectral fingerprints in optical images and electromagnetic radiations in microwave imagery) is challenging due to the data representation difficulty. It is not possible to merge remotely sensed imagery with disparate sizes and/or formats using conventional pixel-level, feature-level, and decision-level fusion techniques. For LULC mapping, new methods must be created to combine remotely sensed imagery with other geospatial big data, like images from social media and crowdsourced spatial data.

3.2 Data and development

3.2.1 **About the Datasets**

There are 2 different types of Datasets used for generating the LULC Map for a region. One data set is used for fine tuning and adjusting the weights for the ResNet50 model and the other is an actual Raster image data on which the model is applied.

3.2.1.1 <u>EuroSat Data</u>- The Sentinel-2 satellite photos that span 13 spectral bands and comprise 10 classes with 27000 geo-referenced and annotated samples form the basis of the EuroSAT collection. The classification of land use in geospatial pictures is being done using this dataset. The ultimate objective of the classification process is to provide the user with the top two land uses in an image as output.

There are two available datasets: rgb, which is a JPEG image encoded with only the optical R, G, and B frequency bands. The Copernicus Earth observation program provides open and free access to Sentinel-2 satellite photos.

- Supervised keys- (image, label)
- Each image is 64x64 pixels with a Ground Sampling Distance of 10m
- Data set size- 2 GB
- Dataset Link- [Dataset]
- The dataset contains the following 10 labels-
    - AnnualCrop
    - Forest
    - Herbaceous Vegatation
    - Highway
    - Industrial
    - Pasture
    - PermanentCrop
    - Residential
    - River
    - SeaLake

3.2.1.2. A part of California Data image from Google Earth Engine

Google Earth Engine(GEE) is used as a data source for accessing Sentinel-2 RGB images as it offers several advantages and capabilities like access to a vast and continuously updated archive of petabytes of historical satellite imagery, including data from Sentinel-2, Landsat, MODIS, and other sensors.

GEE is a cloud-based platform that effectively processes and analyzes massive geographical datasets by utilizing Google's computational resources. With the help of this cloud-based method, users may carry out intricate studies without requiring a lot of local computer power. Apart from the cloud storage, Google has a python earth Engine API that provides a user-friendly interface for interacting with GEE, allowing developers and researchers to write code in Python to access, process, and visualize geospatial data.

GEE also supports advanced temporal and spatial analysis capabilities, such as time-series analysis, image compositing, and cloud masking, which are essential for tasks like monitoring land cover changes, studying environmental phenomena, and assessing natural resources.

Above all, GEE is publicly accessible. All the models and images extracted from GEE are directly stored in the respective drives and can easily be accessible by Google Python Engine thus by making it an All-in-one platform.

Access Link- Python API call Link

Data of the region used in the project- A region of california of **1.16GB** size '**.tif**' file

4. Evaluation and Results

4.1 Evaluation on ResNet50

- Preparing Test and Train Data-

  PyTorch is used to generate the Custom Dataset Class. A custom class can be defined to load the input and target for a dataset using the Dataset class. Using this capability, RGB satellite photos with the accompanying metadata are loaded into the system. In the subsequent segment of this dataset class, we will learn how to apply the appropriate picture transformations. The dataset has been divided into a train set and a test set. Eighty percent of the randomly chosen Eurosat dataset is used for training. The test set will consist of the last 20% of the dataset.

● Model Training and Evaluation-

After loading the pre-trained model, the evaluation and training of the model is done. Three main sections comprise this section:

a. Indicate the hyperparameters (such as n_epochs, learning rate, etc.), optimizer, and criteria.

b. By adjusting the weights of the model to minimize the loss function, train it on the training set.

c. Analyze the model using the test set to evaluate how it performs with fresh, untested data.

d. n_epochs times, repeat the second and third steps.

Loss is calculated by Cross-entropy loss and SGD

The model's performance is measured by cross entropy, and the model's output is a probability value between 0 and 1. When the anticipated probability deviates from the actual label, cross-entropy loss rises.

$$-\sum_{c=1}^{M} y_{o,c} log(p_{o,c})$$

where

- M - number of classes (dog, cat, fish)
- log - the natural log
- $y_{o,c}$ - binary indicator (0 or 1) if class label c is the classification for observation o
- $p_{o,c}$ - predicted probability observation o is of class c

Source- link

Also, SGD optimization algorithm is used to update the model parameters (weights) iteratively based on the gradient of the loss function and computes the slope (gradient) of the loss function at the current point and moves in the opposite direction of the slope towards the steepest descent.

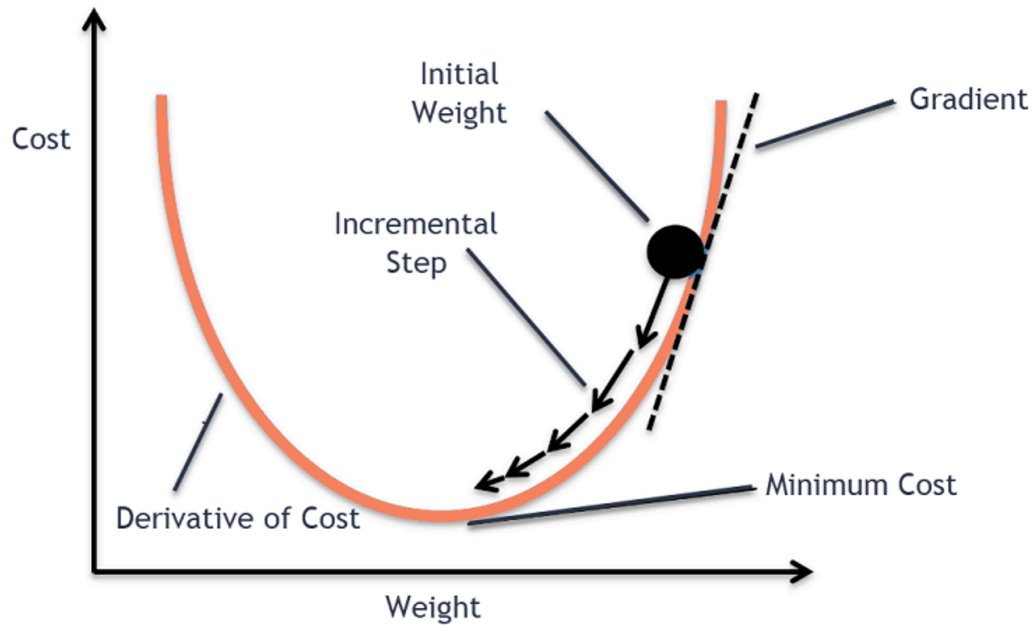


image- [link]()

After training the model using the training loader created using PyTorch data loader, ‘criterion’ is the loss function used to calculate the loss during training, and ‘optimizer’ is the optimization algorithm used to update the model parameters based on the loss function

```
Epoch 5
100% 1350/1350 [03:41<00:00,  6.13it/s]
Train Loss: 0.30; Accuracy: 90.41
100% 338/338 [00:20<00:00, 18.48it/s]
Test Loss: 0.09; Accuracy: 97.11
```

Reason for high accuracy

ResNet50 already has pre trained weights that were especially designed for RGB Band of Sentinel-2 dataset. The reasons are as follows-

1. Deep Learning Architecture- ResNet50 is a deep convolutional neural network (CNN) architecture that includes skip connections (or residual connections) and a feature of the deep learning architecture ResNet50, a convolutional neural network (CNN). Because of these connections, training very deep networks—up to 50 layers in ResNet50—is possible without running into problems with vanishing gradients. Accurate categorization of high-resolution satellite imagery, such as that seen in the EuroSAT dataset, depends on the model's ability to learn complex patterns and hierarchical features from the input data, which is made possible by its deep architecture.

2. Transfer Learning with Pre-trained Model- Transfer learning is the process of applying knowledge from one job—usually a big dataset like ImageNet—to another goal that is similar but different, such as classifying land use and cover. Because ResNet50 is so good at learning generic image features, it is frequently used as a pre-trained model for transfer learning. ResNet50 can be tuned to the unique properties of the satellite imagery by using the EuroSAT dataset, which gives the model access to pre-learned features.

3. Capacity to Capture Spatial Context- ResNet50's wide receptive field enables it to pick up dependencies and spatial context from satellite imagery. This is essential for comprehending the spatial relationships—which in high-resolution imagery like Sentinel-2 can be intricate and interconnected—between various land cover classes.

4. Efficient Management of Multispectral Information- The Sentinel-2 dataset includes multispectral information in many bands, such as red, green, blue, and near-infrared. Because ResNet50 can process multi-channel inputs and learn spectral patterns that represent various land cover types, it is ideally equipped to handle such data.

4.2 Evaluation on LULC map generation from Sentinel-2 satellite image

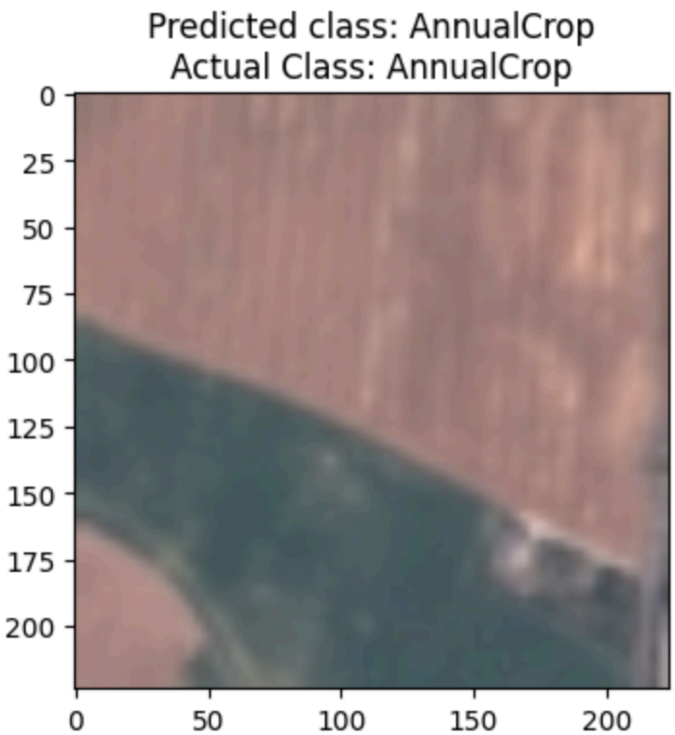
For Map Generation, 2 functions are created-

1. One to Crop the source image using the 64x64 tile geometry and iterate over every 64x64 px tile to generate model predictions for the corresponding cropped image
2. The other that Generates a prediction for the cropped image using the trained model and outputs the final map including the predictions made by the pre trained model

- Data processing- Import and prepare the image data from Sentinel-2.
- Image Cropping- To extract tiles from the original image, use the image cropping feature.
- Prediction Generation- To provide predictions for the cropped image tiles, use the pre-trained model.
- Map Generation- Create a final representation of the LULC map by combining the forecasts.

Note- Given that the predicted LULC map is generated independently, it offers a unique perspective without the need for direct comparison against a base map, highlighting its standalone value and applicability in contexts where traditional metric-based comparisons are not required.

Model Prediction-



5. Analysis and Discussion

5.1 Results

Aim- To apply LULc classification on a Google Earth Engine, obtain a Sentinel-2 satellite image for a region of interest, then use a trained CNN model to create a map of land cover and use.

Output- As expected the model was able to generate LULC classification labels for a Sentinel-2 image generated by Google Earth Engine for a given time frame and region.

Final output of the project-

	id	index_right	shapeName	shapeISO	shapeID	shapeGroup	shapeType	pred	geometry	color
0	california-135568	16	California	US-CA	66186276B43071933723331	USA	ADM1	AnnualCrop	POLYGON ((-117.59684 37.28368, -117.59684 37.2...	#90ee90
1	california-136160	16	California	US-CA	66186276B43071933723331	USA	ADM1	PermanentCrop	POLYGON ((-117.59684 37.27793, -117.59684 37.2...	#7fff00
2	california-136161	16	California	US-CA	66186276B43071933723331	USA	ADM1	AnnualCrop	POLYGON ((-117.59109 37.27793, -117.59109 37.2...	#90ee90
3	california-136752	16	California	US-CA	66186276B43071933723331	USA	ADM1	AnnualCrop	POLYGON ((-117.59684 37.27218, -117.59684 37.2...	#90ee90
4	california-136753	16	California	US-CA	66186276B43071933723331	USA	ADM1	AnnualCrop	POLYGON ((-117.59109 37.27218, -117.59109 37.2...	#90ee90
5	california-136754	16	California	US-CA	66186276B43071933723331	USA	ADM1	AnnualCrop	POLYGON ((-117.58534 37.27218, -117.58534 37.2...	#90ee90
6	california-137344	16	California	US-CA	66186276B43071933723331	USA	ADM1	AnnualCrop	POLYGON ((-117.59684 37.26643, -117.59684 37.2...	#90ee90
7	california-137345	16	California	US-CA	66186276B43071933723331	USA	ADM1	AnnualCrop	POLYGON ((-117.59109 37.26643, -117.59109 37.2...	#90ee90
8	california-137346	16	California	US-CA	66186276B43071933723331	USA	ADM1	AnnualCrop	POLYGON ((-117.58534 37.26643, -117.58534 37.2...	#90ee90
9	california-137347	16	California	US-CA	66186276B43071933723331	USA	ADM1	AnnualCrop	POLYGON ((-117.57959 37.26643, -117.57959 37.2...	#90ee90

The above tables will finally act as a layer on the present google map, creating an LULC map over the specified region

5.2 Discussion

A trained CNN model for LULC classification and Google Earth Engine's capabilities for satellite image retrieval and preprocessing can be combined to provide maps and insights that are useful for environmental monitoring, land management, and urban planning applications. This integrated strategy makes use of machine learning techniques and remote sensing data to extract useful information about the features of Earth's surface at scale.

5.2.1 Land Use and Land Cover (LULC) classification’s importance- LULChelps us comprehend resource management, environmental changes, and the dynamics of the Earth's surface. We may learn a great deal about urban growth, agricultural trends, forest cover, and other topics by classifying land according to its use and cover.
The utilization of satellite images, particularly from Sentinel-2 platforms, offers an abundance of information for the classification of land use and land cover (LULC). The multispectral and temporal information provided by these photos makes it possible to identify and map different forms of land cover.

5.2 Thoughts on resNet50 used in the project- Through the model used in the project, it allowed to dive deep into the challenges encountered, such as class imbalance, dataset quality, and computational constraints. It goes over how these elements affected the LULC map quality that was produced as well as the model's performance. The study sheds light on how transfer learning, data augmentation, and hyperparameter adjustment affect model performance.

5.3 RestNet50 on different satellite Imagery Dataset- The project's thorough testing and assessment successfully highlights the significance of the end products. The study highlights the importance of deep learning in remote sensing applications by using the ResNet50 model for LULC classification and map production.The study assesses how several elements, including training methods, model design, and input data quality, affect the performance of the model. It emphasizes how important preprocessing techniques like class balance, data augmentation, and picture normalization are to improving the robustness and accuracy of the model.The study illustrates how the created LULC map can be used for land management, urban planning, and environmental monitoring through comparison analysis and visualizations. The significance of thorough assessment in remote sensing applications is highlighted by the discussion of evaluation measures and their ramifications.

6. Contributions

All contributions are of the single member or the team

The websites used for acquiring satellite data

- Google Earth Engine- A public data archive with petabytes of historical satellite pictures and geospatial datasets is Google Earth Engine. Keep in mind that you must register at https://code.earthengine.google.com/ to have access to Google Earth Engine.
- GeoPandas - Expands the capabilities of pandas to include geospatial analysis and support for geographical data.
- Rasterio- The GeoTIFF format is frequently used to store raster data, such as satellite photos. These formats can be read and written in Rasterio, and advanced geospatial operations can be carried out on these datasets.
- Folium- Geospatial data can be seen on an interactive leaflet map with Folium.

7. Areas Struggled

7.1 Processing and Accessing Satellite Data

Data Access- Because of their size and format, huge satellite datasets can be difficult to acquire and manage. Data manipulation skills are necessary to ensure effective access to the data, whether via direct downloads or APIs like Google Earth Engine.

Data preprocessing- This includes geometric correction, band selection, cloud masking, normalizing, and geometric correction before satellite imagery is ready for analysis. Accurately carrying out these preprocessing processes can be challenging.

7.2 Integration of Earth Observation and Machine Learning

Data Integration- Remote sensing and data science expertise must be bridged in order to combine satellite data with machine learning operations. Gaining an understanding of both domains can be somewhat difficult.

Algorithm Complexity- Handling high-dimensional data and memory limitations may be a part of implementing sophisticated algorithms (such as CNNs) for geographic applications.

8. Future Work

- The first priority as the future work for the project would be to generate an interactive map using the output table and color code each pixel of a region on Interest as a specific class of LULC
- Advanced Data Analysis from Satellites
    - Include Additional Data Sources- For multi-modal analysis and feature extraction, include datasets from additional remote sensing technologies (such as SAR and LiDAR).
    - Temporal Analysis: To capture seasonal variations and changes over time, extend the analysis to include temporal information from satellite time series data. Analyze spatial variability at various scales by investigating multi-resolution analytic method

9. References

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