Clustering And Classification of Images obtained from Satellite

Rachana M Kanavi , Pavithra R , Nikhil B.M
Student , Dept of CSE , Sambhram Institute of Technology ,Bangalore.
Dept Of CSE

Abstract Presently a days unsupervised picture classification and division progressively prevalent. Existing data framework classification instruments utilized the same strategy for a long time. These fundamental classification strategies don't give palatable comes about when it connected on wide database of pictures. This paper depicts the execution of two calculations, to be specific Back Engendering Calculation of ANN and K-Means Calculation on wide database of pictures. It gives the instrument for division and classification of farther detecting pictures. This classified picture is given to K-Means Calculation and Back Proliferation Calculation of ANN to calculate the thickness tally. The thickness check is put away in database for future reference and for other applications. This device too has the capability to appear the comparison of the comes about of both the calculations. Tall determination fundamentally implies that an picture is duplicated with a tall level of detail. Ordinarily it is alluding to an picture that's of exceptionally tall quality, where there's a part of detail..

Index Terms - ***Keywords: CNN, Classification of Disciple Pictures, Information set, Python, Picture processing.***

I. Introduction

Satellite picture classification incorporates Division and Classification. Pictures may be developed by classes of picture sorts or characteristic scene itself may have assorted structures or surfaces. Division alludes to the method of dividing a advanced picture into numerous portions. The objective of division is to streamline and/or alter the representation of an picture into something that's more significant and simpler to analyze. Picture division is ordinarily utilized to find objects and boundaries (lines, bends, etc.) in pictures. More accurately, image segmentation is the method of relegating a name to each pixel in an picture such that pixels with the same name share certain visual characteristics. Classification is an imperative assignment for all farther detecting applications, which allotments the pictures into homogenous locales, each of which compares to a few specific landcover sort. The issue of pixel classification is frequently postured as clustering within the concentrated space. Clustering could be a well known unsupervised design classification method that segments a set of n objects into K bunches based on a few similarity/dissimilarity metric where the esteem of K may or may not be known a priori. Space Pictures gotten from obsequious have assorted structure or surfaces that are not legibleClustering of Pictures –Grouping of information into comparative kind. Collecting the unlabelled pictures with regard to conduct and attribute

II.

A. Classification of Images

Segment of pictures into homogenous districts based on likeness or disparity .Clustering and Classification is done for relegating a name to each pixel in an picture such that pixel with same name share certain visual characteristics Satellite pictures are one of the foremost effective and vital devices we have for checking the earth .A major inspiration for undertaking this venture was to discover application in military, farming, characteristic fiasco avoidance, normal assets distinguishing proof. We can keep a track on advancement and critical changes around the world.This extend plays critical part in meteorology field and keeps check on climate forecast.

II Literature survey

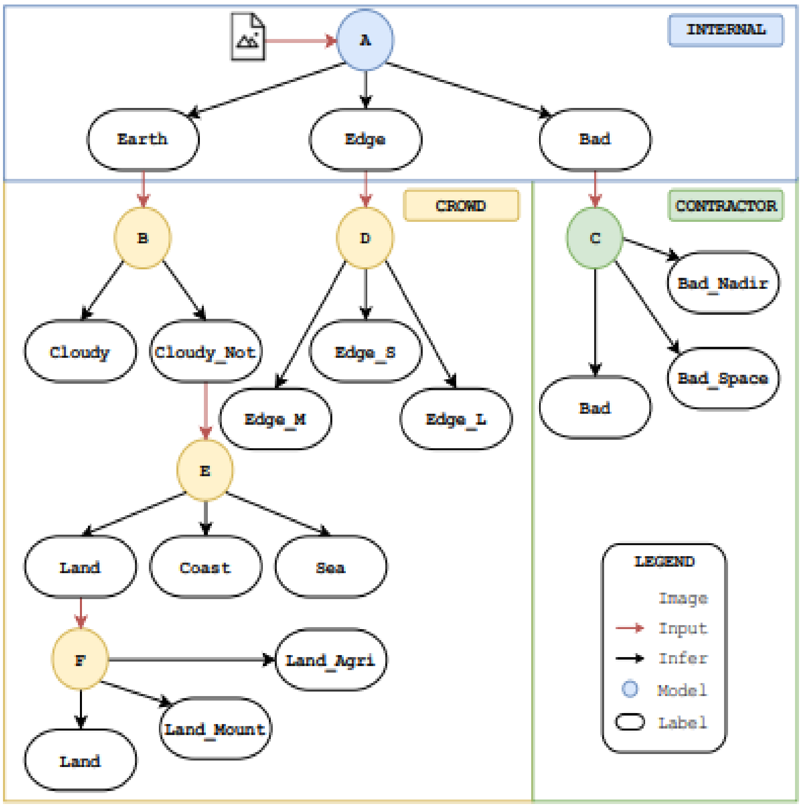
[1] Spry Advancement and Fast Prototyping in a Flying Mission with Open Source Computer program Reuse On-Board the OPS-SAT Shuttle Investigate paper

OPS-SAT may be a 3U European Space Office (ESA) CubeSat mission planned only to illustrate ground-breaking partisan and ground control computer program beneath genuine flight conditions. Conceived to break the "has never flown, will never fly" cycle, the shuttle has spearheaded many firsts, one of which could be a unused worldview to on-board computer program by presenting the concept of "apps" in space. These apps can be effectively created, repaired, tried, conveyed, and overhauled at any time without causing major issues to the shuttle. Apps run on an implanted 32-bit conveyance of Linux on best of the Adherent Exploratory Preparing Stage (SEPP); a capable processor with adequate on-board memory to carry out progressed computer program and equipment experiments.

[2] NanoSat Moment framework

Android gave the community an additional degree of flexibility by making their portable apps, convenient substances of program where the same app can run on the equipment of distinctive sellers as long as the gadgets have the same fundamental Android system. Comparatively, the NanoSat Moment System (NMF) based on CCSDS Mission Operations (Moment) administrations extreme to alter the current see on On-Board Computer program (OBSW) by turning it into adaptable “apps” that can be effortlessly created, repaired, tried, conveyed and overhauledat any time without causing any major issue to the shuttle. Besides, it'll be conceivable to utilize the same “app” on distinctive nanosatellite stages as long

III METHODOLOGY



All image thumbnails downloaded from the spacecraft are hosted on the OPS-SAT community platform [17]. Table 1 divides the 4,705 thumbnails used to train the model into the Training (60%), Validation (15%) and Testing (25%) sets labeled as either "Edge" (2.6%), "Earth" (12%), or "Bad" (85.4%). Inconsistent position control during the OPSSAT commissioning phase resulted in an unbalanced data set, with the onboard camera capturing a disproportionate number of "bad" images.
Methodology for Classification and segmentation of satellite image analysis typically involves several steps to preprocess, analyze, and interpret the data. Here is a general outline of the methodology:

Data Acquisition:
Obtain hyperspectral satellite imagery from reliable sources, ensuring that the data covers the desired spatial and spectral resolution.
Preprocessing:
Radiometric Calibration: Correct the image for sensor-specific variations and atmospheric effects.
Geometric Correction: Rectify the image to remove distortions caused by sensor position and Earth's curvature.
Atmospheric Correction: Adjust the image to account for atmospheric scattering and absorption effects.
Spectral Calibration: Align the spectral bands with reference spectral libraries or known spectral signatures.

Data Exploration and Visualization:
Explore the spectral bands and their corresponding wavelengths to understand the available information.
Conduct exploratory data analysis (EDA) to identify any anomalies, artifacts, or outliers in the data.
Generate visualizations such as false-color composites, band ratios, or spectral profiles to gain insights into the image.

Dimensionality Reduction:
Apply dimensionality reduction techniques (e.g., Principal Component Analysis (PCA), Independent Component Analysis (ICA), or Non-negative Matrix Factorization (NMF)) to reduce the high-dimensional data into a lower-dimensional representation.
Select a subset of transformed bands that retain the most relevant spectral information.

Feature Extraction:
Extract features from the reduced-dimensional data using techniques like spatial-spectral feature extraction (e.g., morphological operations, texture analysis) or spectral indices (e.g., Normalized Difference Vegetation Index (NDVI), Enhanced Vegetation Index (EVI), or Spectral Angle Mapper (SAM)).

Classification and Analysis:
Apply supervised or unsupervised classification algorithms to assign class labels to pixels or regions of interest.
Supervised Classification: Use training samples with known classes to train a classifier (e.g., Support Vector Machines (SVM), Random Forests, or Neural Networks) and classify the entire image.
Unsupervised Classification: Group pixels based on their spectral similarity without prior knowledge of class labels (e.g., K-means clustering or Gaussian Mixture Models).

Assess the accuracy of the classification results using ground truth data or validation samples.

Post-classification Analysis:
Conduct accuracy assessment by comparing the classified image with reference data using error matrices or statistical metrics (e.g., overall accuracy, kappa coefficient).
Perform object-based analysis to group pixels into meaningful objects or regions.
Calculate various landscape metrics (e.g., patch size, fragmentation, or diversity indices) to characterize the spatial patterns.

Interpretation and Visualization:
Interpret the results of the analysis in the context of the study objectives.
Generate thematic maps and visualizations to communicate the findings effectively.
Incorporate ancillary data, such as topographic information or ground-based measurements, to enhance the interpretation.
Algorithm

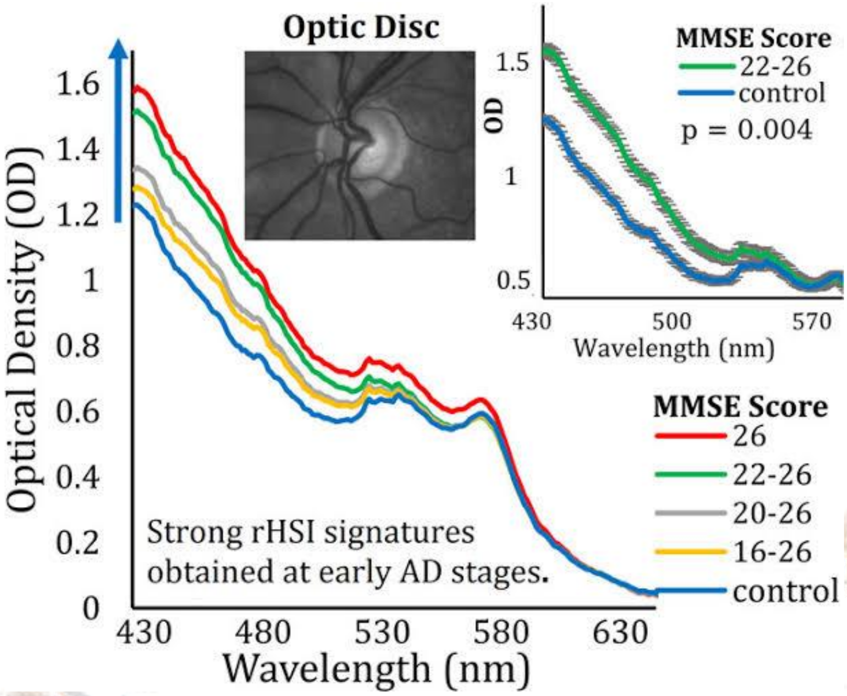
1. **Image classification with Convolutional Neural Network (CNN)** model inferences using TensorFlow Lite

    1: Download the dataset.
    2: Import the CIFAR dataset.
    3: Read the label names.
    4: Display the images using matplotlib.
    5: Use the helper function to handle data.
    6:Create the model.
    7: Apply the helper function.
    8: Create the layers for convolution and pooling.
    9: Create the flattened layer by reshaping the pooling layer.
    10: Create a fully connected layer.
    11: Set the output tp y_pred variable
    12: Apply the loss function.
    13: Create the optimizer.
    14: Create a variable to initialize all the global variables.
    15: Run the model by creating a graph session
2. Supervised learning to train **Fault Detection, Isolation, and Recovery (FDIR) model using online machine learning algorithms.** CNN inference with TensorFlow Lite running on-board the spacecraft showcases in-space application of an industry standard open-source solution originally developed for terrestrial edge and mobile computing
3. **Image clustering with unsupervised learning using k-means**
    1:Specify the number k of cluster to assign,
    2: Randomly initialize k centroids.
    3: repeat
    4: expectation: Assign each point to its closest centroid.
    5: maximization: Compute the new centroid (mean) of each cluster.
    6: until the centroid position do not change.

TESTING

Testing approach for the proposed satellite image analysis system:

Test Data Selection: The first step in testing the system is to select a representative set of satellite images that cover a wide range of land-cover types and features. This dataset should be representative of the real-world scenarios that the system is designed to handle.



Evaluate the performance of the CNN model:

Calculate the accuracy of the classification model by comparing the predicted labels with the ground truth labels.
Calculate the Intersection over Union (IoU) or Dice coefficient for each segmented image to evaluate the performance of the segmentation model.
Visualize the results:

Plot some of the test images along with their predicted labels or segmentation masks.
Analyze the results to understand the strengths and weaknesses of the CNN model for the task of interest.

CONCLUSION

In conclusion, the proposed approach for satellite image analysis using deep learning techniques has the potential to revolutionize the way we analyze and understand the Earth's surface. The use of deep learning models such as CNNs and modified U-Nets for land-cover classification and semantic segmentation of satellite images has shown promising results in accurately identifying and delineating land-cover features, including small and complex objects.

Results

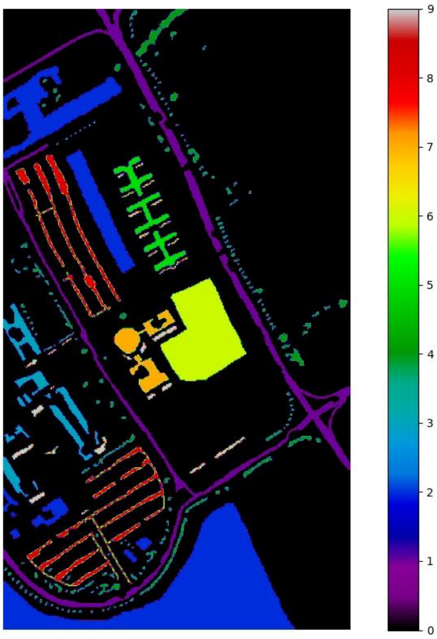
	precision	recall	f1-score	support
1.Brocoli_green_weeds_1	0.99	1.00	1.00	599
2.Brocoli_green_weeds_2	1.00	1.00	1.00	1121
3.Fallow	1.00	1.00	1.00	593
4.Fallow_rough_plow	1.00	0.99	0.99	423
5.Fallow_smooth	0.99	1.00	0.99	802
6.Stubble	1.00	1.00	1.00	1187
7.Celery	1.00	1.00	1.00	1070
8.Grapes_untrained	0.91	0.79	0.85	3854
9.Soil_vinyard_develop	1.00	0.99	0.99	1875
10.Corn_senesced_green_weeds	0.95	0.96	0.96	971
11.Lettuce_romaine_4wk	0.99	0.98	0.99	325
12.Lettuce_romaine_5wk	1.00	0.98	0.99	588
13.Lettuce_romaine_6wk	0.99	0.95	0.97	286
14.Lettuce_romaine_7wk	0.93	0.99	0.96	303
15.Vinyard_untrained	0.64	0.82	0.72	1700
16.Vinyard_vertical_trellis	0.99	0.99	0.99	542
accuracy			0.93	16239
macro avg	0.96	0.97	0.96	16239
weighted avg	0.93	0.93	0.93	16239

RGB Composite Image

```
mdata = np.moveaxis(data, -1, 0)

ep.plot_rgb(mdata, (29, 19, 9), figsize=(15, 15))

plt.show()
```



FUTURE ENHANCEMENT

There are several potential avenues for future enhancements and improvements to the proposed satellite image analysis system. Some possible areas for future research and development include:

- Integration of Multi-sensor Data: The use of multi-sensor data, such as optical and radar data, can improve the accuracy of land-cover classification and semantic segmentation by providing complementary information on land-cover features.

REFERENCES

1. Chen, C., et al. (2017). Deep Learning-Based Classification of Hyperspectral Data. IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, 10(1), 54-65.
2. Chen, L. C., et al. (2018). DeepLab: Semantic Image Segmentation with Deep Convolutional Nets, Atrous Convolution, and Fully Connected CRFs. IEEE Transactions on Pattern Analysis and Machine Intelligence, 40(4), 834-848.
3. Goodfellow, I., et al. (2016). Deep Learning. MIT Press.
4. He, K., et al. (2016). Deep Residual Learning for Image Recognition. IEEE Conference on Computer Vision and Pattern Recognition, 770-778.
5. Huang, G., et al. (2017). Densely Connected Convolutional Networks. IEEE Conference on Computer Vision and Pattern Recognition, 2261-2269.
6. Krizhevsky, A., et al. (2012). ImageNet Classification with Deep Convolutional Neural Networks. Advances in Neural Information Processing Systems, 1097-1105.
7. Li, X., et al. (2020). A Review of Deep Learning for Satellite Data Processing. Remote Sensing, 12(11), 1-30.
8. Ronneberger, O., et al. (2015). U-Net: Convolutional Networks for Biomedical Image Segmentation. International Conference on Medical Image Computing and Computer-Assisted Intervention, 234-241.
9. Russakovsky, O., et al. (2015). ImageNet Large Scale Visual Recognition Challenge. International Journal of Computer Vision, 115(3), 211-252.
10. Sherrah, J., et al. (2019). Deep Learning for Land Cover Classification and Semantic Segmentation of Aerial Imagery. Remote Sensing, 11(19), 1-22.