LAND COVER CLASSIFICATION USING SATELLITE IMAGERY AND MACHINE LEARNING ALGORITHM

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ABSTRACT - Remote sensing has evidenced itself as a more efficient source of quantitative data than ground based surveys in terms of time and space. Remote sensing is crucial in the collection of data for many aspects of life or areas, such as political, economic, Urban Planning, Agriculture, Forestry, Barren, and even scientific. Land cover data is useful with regard to planning and decision making processes in urban areas and it has several solutions in terms of mapping and monitoring of the urban areas. A satellite image categorization based mainly on urban planning, land-use mapping, and environmental monitoring is used. Within this context, this study explores the possibility of bringing reinforcement learning in conjunction with pertinent point-matching techniques into the analysis of Landsat satellite picture classification via the Google Earth Engine (GEE). As opposed to the classic application of traditional supervised and unsupervised model in the process of satellite image classification, the RL presents a dynamic approach, strongly dependent on feedback for possible improvement over time in classification accuracy. This is further enhanced by key point matching, which makes it possible to identify important characteristics in many temporal pictures, recognize objects, and detect changes more robustly. In our discussion of a unique framework, we highlight the potential advantages of feature correspondence and adaptive categorization in complicated satellite data by integrating RL and key point matching with GEE's cloud based infrastructure. Results from experiments show how well this hybrid model works to increase classification accuracy.

Keywords: Satellite Image Classification, Google Earth Engine (GEE,) Landsat Satellite Data, Unsupervised Learning, Key Point Matching, Reinforcement Learning, Remote Sensing, Land-Use Mapping, Environmental Monitoring, Clustering Algorithm, Feature Extraction.

I. INTRODUCTION

Satellite images, such as those provided by the Landsat programme, significantly make it possible to monitor and study the earth's surface. Remote sensing technology has made large-scale long-term monitoring of the environments possible, thus providing insight into resource management, environmental changes, and land use. Satellites picture collections are on the need to extract valuable information that still is challenging because of this problem due to high dimensionality, temporal unpredictability, and noise in the form of clouds and shadows.Traditional categorization in satellite images is done using methods that involve learning from machines and their methodologies such as Random Forest Support Vector Machines SVM, and neural networks. Although these methods work wonderfully, they are essentially based on predefined attributes and static data sets, which greatly limit their applicability to time-varying conditions. This limitation will be obvious while dealing with large-scale multi-temporal data sets like the ones available from Landsat, which has been taking pictures since 1972. Framing picture categorization as a decision-making issue where an agent learns to improve the performance of the agent through input by the environment leads to reinforcement learning (RL) as an alternative. In that case, if the incentives associated with accurate or inaccurate predictions are dynamic, reinforcement learning (RL) may provide a pathway for eventual improvement in classification accuracy. More developed object and change detection in satellite data is achieved by the simultaneous identification and tracking of distinctive characteristics across images, via using key point matching techniques such as SIFT, ORB, and so on. This paper hereby puts forward a hybrid approach that integrates RL with key point matching for the classification of Landsat images on the GEE. GEE provides a very robust platform for the input and processing and analysis of satellite data in the cloud for large-scale geo spatial analysis. The paper is proposed with the aim of making the process of classifying satellite images more accurate with high precision because this integrates features of adaptability from RL combined with the accuracy associated with key point matching.

II. RELATED WORK

Currently, Google Earth Engine (GEE) is adding artificial intelligence in order to help with computational speed and to allow machine learning to be used on the images from the satellites and the massive amount of data they are pulling in. This is used especially for mapping and quantification of land cover and other related fields of remote sensing. By integrating machine learning methods and the GEE environment, the analysis offers sound solutions for monitoring environmental changes, managing resources, and identifying changes. HAFSA OUCHRA.[1] Machine learning has been applied in a rural and urban setting including detecting patterns of formations in satellite images in Random Forests, Support Vector Machines, and Classification and Regression Trees for ground coverage determination. But the same remains a concern in Morocco. Thanh Noi Phan[2] Technological advancement such as virtual reality, machine learning and space scanning can be used to solve problems which include land cover classification. Google Earth Engine is useful when working with enormous data. It's the versatility to propose any changes that makes a Random Forest such an excellent algorithm. Methods of picture compositions enhance the accuracy of classification, whereby the use of Landsat data, and vegetation indices record an accuracy of more than 85 percent. Septianto Aldiansyah[3]The goal of the study is to quantify the pattern of change in LULC for given periods based on modern RS technology. Urbanization's conversational consequences include deforestation, intense agriculture, and fragmentation of habitats. Thus, to achieve similar meteoric growth, Metropolitan Cities can be superimposed using ML Tools such as SVM, Random Forest and CART. The research also has sought to achieve the ability to define areas that should be conserved or degraded based on comparing past and current LULC maps. WON-KYUNG BAEK.[4] Convolutional neural networks (CNNs) can classify land cover from multi-spectral satellite images. Cascade-Poly and Dense-Coupled models, U-Net and DeepLabV3+ models are used. Combining U-Net architecture with attention modules improves accuracy for minority land cover classes. Challenges include transfer learning, synthetic data generation, and data augmentation. MOHAMMED ALJEBREEN.[5] Recent advances of DL models need to be applied to analyze LULCC based on remote sensing maps. The use of hybrid CNN-autoencoder models is also under consideration together with such hyper parameter tuning techniques as the evolutionary algorithm while challenges such as over-fitting and noise inferences are likely to prevail. Voelsen, Mirjana [6]The study also pays some light to the utilization of satellite image time series (SITS) for characterizing the land cover by using both spatial and temporal data. CNN and RNN structures are used and local spatial features are optimized by the Swin Transformer method for global temporal features. Attention-based and CNNs modules give better results but the differences could be due to specific application and data utilized. Sellami [7] This study hence involves applying MML in the mapping of LULC change using tools from the GEE platforms. Hence, GEE is very helpful when it comes to environmental monitoring especially when it comes to the management of land. Sentinel-2 footage and high spatial-resolution satellite photos are adopted to classify LULCs through algorithms such as SVM, RF plus CART. They may be utilized for activities concerning the use of territory, including comprehensive urban planning, and projects connected to the minimization of dangers.. Alabidi [8] In SAR and optical satellite images, machine learning and deep learning are prevalent to support studies of the environment, development, and disasters. Some of them include Unet, Swin Transformer, and auto encoders promote improved accuracy. There are procedures in remote sensing data analysis that are well automated by reinforcement learning. Md Golam Azam [9] Currently for the classification of land cover and agricultural monitoring there are two classes of methods: ObjectBased Image Analysis (OBIA) and Pixel-Based Image Analysis (PBIA). PBIA has many disadvantages, however, OBIA algorithm is more accurate and spatially coherent compared to PBIA and therefore is more appropriate for medical application. These technologies are useful to precision agriculture to monitor the health of crop.

III. PROPOSED METHODOLOGY

This proposed method utilized the Two- Layer Recurrent Learning (TLRL) architecture, replacing traditional MLPs for remote sensing (RS) scene classification tasks. By utilizing and comparing multiple pre-trained CNN and Vision Transformer (ViT)models, we identified the most suitable pairings for the TLRL Learning Architecture for Satellite and its required image classification system for the overall program can be given by the following figure that represents the two-layer occurrence,

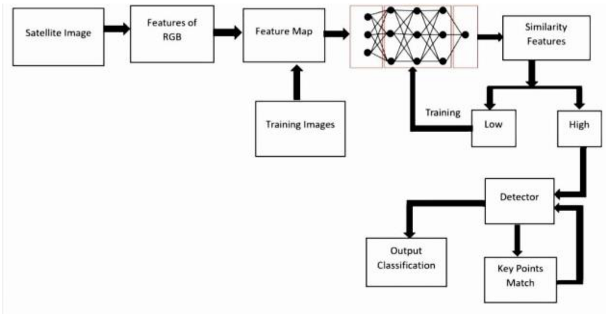

Figure 1. Two-Layer Occurreny

The above image depicts a guide for putting to use satellite images. The method to extract RGB features is to read them from the satellite photos and convert them into the feature map. Reinforcement learning type of neural network is used to train in order to obtain similarity features in a feature map. These qualities are described as "high" or "low" in similarity and then a detector to locate critical interfaces that correlate. Thus the above categorization result which categorizes objects based on how well the matched features estimate is the final output of the program.

A. Two-Layer Occurrent Learning

Two-layer recurrent Learning Recurrence is the process of a two-layer neuronal network where a feature is transformed by a set of spline-based functions to aggregate intermediate results used in the computation of a given layer. The use of only one PathTracktenth function does not result in a decrease in error rate. TheTwo-Layer Recurrent Layer (TLRLs), which are a bysh01-online.com/lpoff/ethcrackfree download link of Kolmogorov-Arnold representation, implements the transformation of each edge by a learnable path function on the edge instead of the fixed vertex activation of neurons in Multi-Layer Perceptron (MLPs). These learnable path functions are case-sensitive by the set of parameters B-splines, which are the piecewise polynomial functions declared by control points and the subset. To illustrate, each feature of the molecular compound ys is taken by spline- polynomials ϕr,s, with some being used by adding them together into an intermediate result for each q to move through the acting categories Φr. The final result s(y) is obtained by the sum of these values, which makes it possible to compress high amounts of data in very flexible and efficient ways. The sum of a basis function and a spline (or other component) with a basis function being the Sigmoid Linear Unit (SiLU) is typical for TLRL activation functions.. The inclusion of the spline equation in the machine (spline(y) = Pi AiDi(y)) uses B-spline basis functions Bi(y) and coefficients Ci which are changed while the model learns. These coefficients express the optimal form of td(2/2) for the activation functions, eliminating the need for linear transformation parameters W and b in MLPs. The formula for the TLRL is as follows:

$$S(Y) = \sum_{r=1}^{2m+1} \emptyset\, r(\sum_{s=1}^{m} \varphi r_1 s(y_S))$$

In a TLRL, the function f(y) is defined using spline functions φr,s(ys) and transformation Φr .

$$\phi(y) = w(T(y) + spline(y))$$

Here, φ(y) represents the activation function, w denotes a weight, t(x) is the basis function, and spline(y) refer to the spline function.

$$T(Y) = silu(Y) = \frac{y}{1 + e^{-y}}$$

The basis function t(x) is implemented as silu(x), which stands for the (Sigmoid Linear Unit).

$$spline(Y) = \Sigma_j A_i D_i(Y)$$

B. Feature Extraction Network

The proposed algorithm introduces TLRL-based enhancement into the ConvNeXt architecture to enhance the learning capabilities of a pre-trained model ConvNeXt. First, the ConvNeXt model is pre-trained, and all the layers are frozen and kept intact preserving the features learned at the pre-training stageThe model uses two TLRL linear layers instead of the conventional MLP classifier. One difference between the TLRL layers compared to conventional models with fixed activation function on nodes is that they include learnable activation functions on the edges. In particular, we use a B-spline activation function to enhance the stability and flexibility. The TLRL Linear layer, which uses spline functions instead of linear weights in place as a more flexible modification to input data. We used multiple strategies to evaluate the TLRL's performance for RS classification tasks in remote sensing. The Two layers of the proposed RL is depicted in the below that is given Fig:

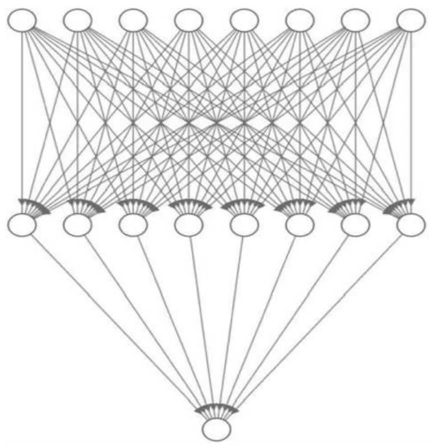

Figure 2 . Two-Layer Recurrent Layer

In the case of recurrent operations, there's a window size denoted as m, n as well as a and b which depict strides.feature map of artificial neural network is a rectilinear unit model used for the activation of feature sets.We first determined nine major divisions of interest by looking at our collection of similar features: natural, agriculture, cloud formation, desert, mountainous, river, sea ice formation, snow, and water. These are different geological formations or geographical formations as the case may be distinguished by immediately discernible variations in colour and texture, and which are therefore classified. Similar correlation feature. Once we label our classes with patterns or other visual properties, if our skilled laborers have tools of the river to define classes, the flow, or the whiteness of snow, then we can. It also shows that no georeferencing had been done when the pictures were taken. Specifically, we did not include mountains, rivers, or signals of human habitation in desert sands to define rural and undisturbed natural matches. Similarly distinguishable to nature there were characteristics we used (crop presence or absence) to distinguish those. If more than 50% of the area showed snowy mountain resemblance characteristics, labelers were told to look for snowy mountain characteristics.However, the similarity features without significant differences are described with artifacts or increased noise on the In the image prepossessing step, still, it remained a confusing term for many. For example,similarity features were unusual without coastal areas; they looked more or2 less like desert similarity features,especially The observed colors looked considerably shifted." This difficulty, however, could be prevented by anchoring the similarity feature. We have to include the feature image as a whole image to allow the label-er to pull the additional information from the other similarity features in the surrounding. To ensure right labeling, only full resolution but feature-rich satellite map images were provided to the labelers.

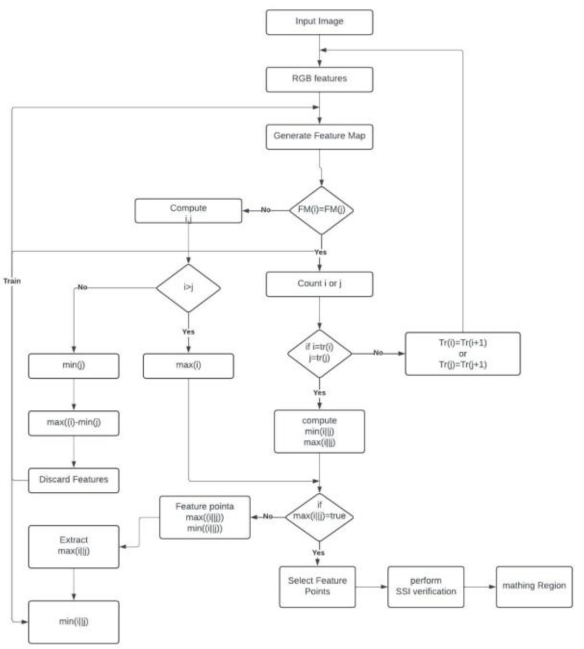

Figure 3. Flowchart

A flowchart illustrating a feature extraction and matching procedure from an input image is presented as follows. To begin with, RGB features are first used in producing a feature map. Following this, two sets of feature points are compared, and maximum and minimum candidates are identified for analysis. The algorithm is able to choose important feature points while removing the features that do not bear the capability to be used for training. The final step in the-procedure to verify is called the Scale-Space Invariant (SSI) verification which matches areas in the image.

C. Training for Low/High Similarity

To reduce such distortions that could lead to an underestimation of the classification error, we partitioned the data by image type. This means that the characteristics from the same image have never been split between the training set and the test set at all: they were either all assigned to the training set or all to the test. For the construction of the training data, ten labeled features for each class were selected To ,the features selected were the most consistent ones from the labeling of the various labels. Moreover, pictures from satellites were delivered to rivals so they could purchase the data without labels. Therefore, as our competition design had advanced to this level, we had agreed to apply a one-layer RL model for machine learning. Apart from a demonstration that the data divides apply to this set of data in this paper, we used this RL model to train it on many data splits so as to ensure we selected the finest data split. The figure below illustrates the architecture of the 1-layer network model that was employed to perform the categorization.

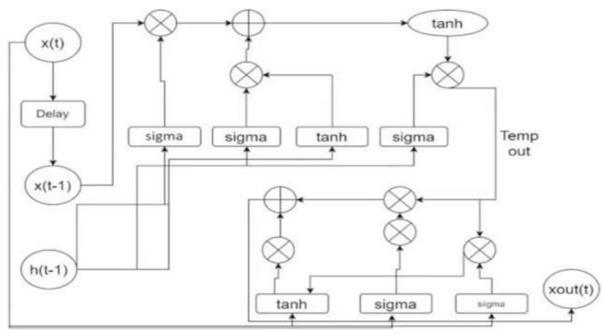

Figure 4. Long Short-Term Memory

Initially, the proposed model extracts many various sets of features from each image. These feature sets are derived using a newly proposed high-low hybrid approach.The prime simple model first derives initialization (i), temporal output feature (t), and temporal output features by the following equations farther below as follows

$$j = var(yin * V^j + g_s - 1 * U^j)$$
$$b = var(yin * V^b + g_s - 1 * U^b)$$
$$r = var(yin * V^r z + g_s - 1 * U^r)$$

They argued that U and W are variance constants for high and low similarity processes while g is a kernel matrix that turns these features on. These features are then compiled into the temporal recurrent feature set C that can articulate input images in multi-modal sets.

$$c_s^{'} = tang(yin * V^x + g_s - 1 * U)$$

The effectiveness of this type of feature extraction needs to be confirmed for real augmentation. Finally, using all the possible solutions, the best fitness value is chosen for satellite image classification. This classification is done using a Temporal Learning Recurrent Layer (TLRL), which comprises recurrent, max pooling, as well as dropout layers in order to find a number of augmented feature sets. The reinforcement learning (RL) model .

IV. RESULTS AND DISCUSSIONS

In satellite image classification,the proposed Two-Level Representation Learning (2LRL) technique yields significant performance gains in F1 scores, and sensitivity as well as accuracy and precision. Due to the ambiguous boundary of shape and color for two similar or overlapping objects in the satellite pictures, 2LRL uses a two-step learning process.

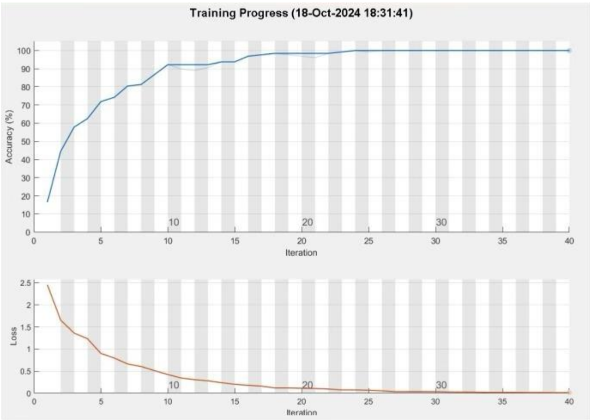

Figure 5. Model Training Progress: Accuracy and Loss over Iterations

To accomplish better division, it employs feature maps which are designed for separating certain attributes only. After classification, these feature maps are reconstructed where improvements are made in every iteration while these maintain and increase the level of accuracy and precision in the data set. Also, with the help of this reconstruction, the 2LRL can easily change its classification over the period with the overall gains of comparable measurements of performances.

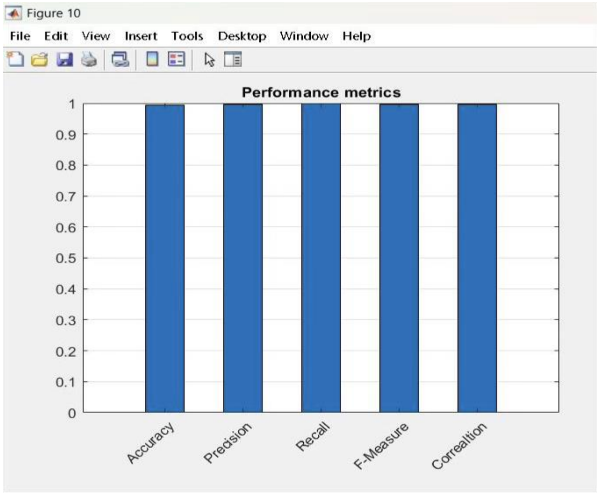

Figure 6. Performance Metrics Comparison of Classification Model

Additionally, concerning the findings of classification, the number of iterations is also adjusted where necessary to meet the demand for either more learning or improvement depending on performance at a certain time. Therefore, 2LRL enhances the learning process to pick up fine distinctions when the classification rates are low in 2LRL by having higher iterative training. On the other hand, with the high classification rates the model prioritizes the detection-based training to enhance accuracy regardless of the slight decrease in F1 score. This deliberate emphasis on precision over quantity ensures that the model can remain viable in difficult and high-risk environments because precise feature detection is critical in these environments thereby making 2LRL a highly useful and effective methodology for categorizing satellite images.

V. CONCLUSION

In this work, a novel two-layer recurrent learning method for the purpose of satellite images classification focusing on the aspects of landscape categories is proposed. The suggested approach works using input photos and forms a collection of feature maps that are then used for the evaluation of matching patterns for classification of the parts of a landscape. High or low similarity factors are analysed depending on the presence of particular elements in the produced maps to a greater extent. The approach known as 2LRL is organized in two stages. The first layer handles iterations with relatively low classification score and focuses on refining the first feature extraction so as to enhance the precision of detection. This layer also ensures accuracy is enhanced and is able to enhance the model in complex situations through the strengthening of pattern recognition in small details. Building on this foundation, the second layer enhances the ability to probe for a balanced classification of the input image and to enable a class-differentiated classification of a variety of landscape elements by training the high classification examples under one set of features and the low classification examples under another set. As proved through the experiments, this layering methodology improves precision, accuracy, and the F1 measure in classification substantially to demonstrate the efficiency of the method for managing intricate satellite images.

VI. REFERENCES

[1]Ouchra, H. A. F. S. A., Belangour, A., & Erraissi, A. L. L. A. E. (2023). Machine learning algorithms for satellite image classification using Google Earth Engine and Landsat satellite data: Morocco case study. *IEEE Access*.

[2]Phan, T. N., Kuch, V., & Lehnert, L. W. (2020). Land cover classification using Google Earth Engine and random forest classifier—The role of image composition. Remote Sensing, 12(15), 2411.

[3].Aldiansyah, Septianto, and Randi Adrian Saputra. Comparison of machine learning algorithms for land use and land cover analysis using Google Earth engine (Case study: Wanggu watershed). International Journal of Remote Sensing and Earth Sciences (IJReSES) 19.2 (2023): 197-210.

[4]Baek, W. K., Lee, M. J., & Jung, H. S. (2024). Land Cover Classification From RGB and NIR Satellite Images Using Modified U-Net Model. IEEE Access.

[5]Aljebreen, M., Mengash, H. A., Alamgeer, M., Alotaibi, S. S., Salama, A. S., & Hamza, M. A. (2024). Land Use and Land Cover Classification Using River Formation Dynamics Algorithm With Deep Learning on Remote Sensing Images. IEEE Access.

[6]Voelsen, M., Rottensteiner, F., & Heipke, C. (2024). Transformer models for Land Cover Classification with Satellite Image Time Series. PFG–Journal of Photogrammetry, Remote Sensing and Geoinformation Science, 92(5), 547-568.

[7]Sellami, E. M., & Rhianne, H. A. S. S. A. N. (2023). A new approach for mapping land use/land cover using google earth engine: a comparison of composition images. The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences, 48, 343-349.

[8]Alabidi, S. A., & Al-Zubaidi, E. A. (2024). Satellite Image Classification Using Unsupervised Machine Learning. Al-Furat Journal of Innovations in Electronics and Computer Engineering, 276-298.

[9]Mollick, T., Azam, M. G., & Karim, S. (2023). Geospatial-based machine learning techniques for land use and land cover mapping using a high-resolution unmanned aerial vehicle image. Remote Sensing Applications: Society and Environment, 29, 100859.

[10]Basheer, S., Wang, X., Farooque, A. A., Nawaz, R. A., Liu, K., Adekanmbi, T., & Liu, S. (2022). Comparison of land use land cover classifiers using different satellite imagery and machine learning techniques. Remote Sensing, 14(19), 4978.Remote Sensing
14.19 (2022): 4978.

[11]Singh, R. K., Singh, P., Drews, M., Kumar, P., Singh, H., Gupta, A. K., ... & Kumar, M. (2021). A machine learning-based classification of LANDSAT images to map land use and land cover of India. Remote Sensing Applications: Society and Environment, 24, 100624.

[12]Saralioglu, E., & Gungor, O. (2022). Semantic segmentation of land cover from high resolution multispectral satellite images by spectral-spatial convolutional neural network. Geocarto International, 37(2), 657-677.

[13]Yadav, D., Kapoor, K., Yadav, A. K., Kumar, M., Jain, A., & Morato, J. (2024). Satellite image classification using deep learning approach. Earth Science Informatics, 17(3), 2495-2508.

[14]Zhao, Z., Islam, F., Waseem, L. A., Tariq, A., Nawaz, M., Islam, I. U., ... & Hatamleh, W. A. (2024). Comparison of three machine learning algorithms using google earth engine for land use land cover classification. Rangeland ecology & management, 92, 129-137.

[15]Aziz, G., Minallah, N., Saeed, A., Frnda, J., & Khan, W. (2024). Remote sensing based forest cover classification using machine learning. Scientific Reports, 14(1), 69.