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Satellite Intelligence: Pioneering Machine Learning and Future Innovations in Land Cover Mapping

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A B S T R A C T

Satellite image classification plays a vital role in monitoring large geographic regions and tracking temporal changes with high-resolution precision. Monitoring vast, remote, or hard-to-reach areas is essential, especially when on-ground surveys are impractical. It provides a cost-effective alternative to ground surveys for environmental monitoring, urban planning, and disaster management. This study advances the field by evaluating a variety of machine learning algorithms on Landsat 8 imagery from different parts of the world, using Google Earth Engine. Expanding on previous work with algorithms such as Support Vector Machine (SVM), Minimum Distance (MD) and K-means, it also explores Random Forest (RF) and Gradient Tree Boosting (GTB) used in earlier studies. The findings show that Random Forest (RF) is the most accurate classifier, achieving superior performance. The Minimum Distance (MD) method also performed well when enhanced with indices like NDVI, NDBI, BSI, and MNDWI, while SVM showed lower accuracy. This research integrates Sentinel-2 imagery and examine multispectral and hyperspectral data to improve land cover differentiation. The study aim to develop hybrid models that combine deep learning techniques, including Convolutional Neural Networks (CNNs), with traditional algorithm Random Forest (RF) and analyse time series data to monitor land cover changes over time. This comprehensive approach seeks to identify the most effective classification techniques, providing valuable insights for urban and environmental decision-making

Keywords: Satellite Imagery, Land Cover Classification, Machine Learning, Google Earth Engine, Sentinel-2, Hybrid Model.

1. INTRODUCTION

Satellite image categorization is essential to environmental monitoring, urban planning, agriculture, and disaster management. It is a crucial instrument for monitoring changes over time and offering insightful information on the dynamics of land cover thanks to improvements in satellite technology and the availability of higher-resolution data. For applications in remote or inaccessible areas, satellite-based classification provides a scalable and affordable substitute for traditional on-ground surveys. Effective decision-making in the urban and environmental sectors is made possible by the precise identification and classification of different land cover types utilizing a mix of multispectral and hyperspectral data from satellites like Landsat 8 and Sentinel-**2.**

Because of growing availability of open-access satellite imagery, Google Earth Engine (GEE) has emerged as a powerful platform for large-scale geospatial analysis. Its cloud-based capabilities allow for real-time processing of satellite data, making it ideal for monitoring changes over time and across vast areas. The advancement of machine learning algorithms has significantly transformed the field of remote sensing, particularly in the classification of Land Use and Land Cover (LULC) using satellite imagery. Various machine learning techniques have been used to improve classification efficiency and accuracy in previous research using satellite images. Among the robust ensemble learning techniques, Random Forest (RF) is notable for its excellent accuracy and capacity to manage huge datasets. Another popular technique that has been hailed for its efficacy in both linear and non-linear classification problems is the Support Vector Machine (SVM), which performs well in high-dimensional domains. While Gradient Tree Boosting (GTB) increases prediction accuracy by creating models one after the other, Classification and Regression Trees (CART) use hierarchical structures to enable interpretable decision-making. The K-means Clustering complements supervised methods by providing an unsupervised way to divide data according to feature similarity. Researchers' toolkit is further enhanced by Artificial Neural Networks (ANN), which can capture intricate patterns, and Naive Bayes (NB), which is renowned for its simplicity. When combined, these algorithms tackle a number of LULC classification issues, advancing techniques and enhancing knowledge of various land cover categories.

This paper proposes a hybrid model that uses Random Forest (RF) for classification and Convolutional Neural Networks (CNNs) for feature extraction. By creating sophisticated hybrid models, this study seeks to advance the field of satellite picture classification.

2. Related work

Ouchra, H. A. F. S. A., Belangour, A., & Erraissi, A. L. L. A. E. (2023). This study used Landsat data from Morocco and GEE for satellite image classification. The Minimum Distance (MD) classifier achieved the highest overall accuracy of 93.85%, outperforming the Support Vector Machine (SVM) at 74%.But faced limitations due to GEE's restricted access to high-resolution data. The study did not thoroughly examine the unique limits of each algorithm [1].

Ouchra, H., Belangour, A., & Erraissi, A. (2023). This study evaluates the effectiveness of supervised and unsupervised learning methods for classifying satellite images, using a single Landsat 8 dataset processed through Google Earth Engine to enhance scalability and efficiency. The supervised Random Forest (RF) strategy produced the best accuracy at 95.42 highlighting the higher accuracy of supervised algorithms for categorizing satellite images in this scenario [2].

Hanon, W., & Salman, M. A. (2024). Evaluated six supervised machine learning methods for classifying land cover in Casablanca, Morocco. Accurate classification has particular challenges in Casablanca's unique urban terrain, which is marked by increasing urbanization and diversified land use patterns. The incorporation of spectral indices, such as NDVI and BSI, considerably improved classification accuracy.The Random Forest (RF) algorithm achieved the best overall accuracy while Support Vector Machine (SVM) had the lowest [3].

Loukika, K. N., Keesara, V. R., & Sridhar, V. (2021). Explored the application of non-parametric machine learning techniques for Land Use and Land Cover (LULC) classification using multitemporal Sentinel-2 and Landsat-8 data. Despite facing computational constraints and memory issues when processing large datasets in Google Earth Engine (GEE), the Random Forest (RF) classifier consistently demonstrated the highest accuracy [4].

Wang, Z., Gao, Y., Dang, X., & Han, Y. (2022). In orchestrate to address issues such as a lack of a standardized precision edge and inadequately planning tests, this paper proposed a novel mechanized methodology for Arrive Utilize and Arrive Cover (LULC) classification utilizing Self-assertive Forest (RF) and Classification and Backslide Trees (CART) classifiers on the Google Soil Engine (GEE) platform. The Sporadic Timberland classifier yielded prevalent centered on comes approximately than CART [5].

Ouchra, H., Belangour, A., & Erraissi, A. (2023). This work uses Landsat satellite data, Google Earth Engine (GEE), and unsupervised learning techniques to automatically classify land cover. Despite the significant benefits of automated classification using contemporary technology like GEE, the validation of unsupervised classification results still requires further development. Moderate accuracy was demonstrated when employing methods like K-means to distinguish between various forms of land cover [6].

Patil, A., & Panhalkar, S. (2023). Examined the performance of various machine learning techniques for classifying Land Use and Land Cover (LU/LC) using the Google Earth Engine (GEE) platform. These techniques include Gradient Tree Boosting (GTB), Support Vector Machine (SVM), Random Forest (RF), Classification and Regression Trees (CART), and Naive Bayes (NB). The study is limited in its applicability to other places by its concentration on the Kolhapur City Region [7].

Magaji, A., & Hassan, I. M. (2023). Evaluated the effectiveness of SVM, ANN, and Maximum Likelihood for Land Use and Land Cover (LULC) classification in the complex Yola-North landscape using multi-temporal Landsat images. Limited sampling and atmospheric variations posed challenges in time series classification. The use of Landsat 7 ETM+ and Landsat 8 OLI images from different years allowed for a robust analysis of land cover changes. The SVM algorithm achieved the highest overall accuracy [8].

Nguyen, H. T. T., Chau, Q. T. N., Pham, A. T., Phan, H. T., Tran, P. T. X., Cao, H. T., ... & Nguyen, D. T. H. (2020). The study maps Land Use and Land Cover Change (LULCC) in Dak Nong, Vietnam, using Landsat data and Random Forest classification. Although the integration of multitemporal Landsat 5 and Landsat 8 data allowed for a thorough analysis of changes in land cover over time, there were issues with differentiating between some groups, like industrial crops and semi evergreen woods [9].

Ahmadi, K. (2024). Three machine learning algorithms—Random Forest (RF), Support Vector Machine (SVM), and Classification and Regression Tree (CART)—on Google Earth Engine (GEE) were used to classify urban areas in Kabul City using satellite images from Landsat-8 and Sentinel-2 captured in 2023. Among the methods tested, RF performed the best, achieving 93.99% accuracy with Landsat-8 and 94.42% with Sentinel-2, while SVM and CART had lower accuracy scores. It suggested that RF is particularly well-suited for urban classification [10].

Zhao, Z., Islam, F., Waseem, L. A., Tariq, A., Nawaz, M., Islam, I. U., ... & Hatamleh, W. A. (2024). The study aims to compare the performance of three machine learning models—CART, SVM, and RF—for Land Use Land Cover (LULC) mapping using Sentinel-2 imagery on the Google Earth Engine (GEE) platform. CART is noted for its tendency to overfit and its sensitivity to changes in training datasets. RF performed the best, achieving an overall accuracy of 98.68%, surpassing both CART and SVM [11].

Nguyen, H. T. T., Doan, T. M., Tomppo, E., & McRoberts, R. E. (2020). This study used both parametric and non-parametric classifiers, such as Logistic Regression (MLR), Improved k-Nearest Neighbors (K-NN), Support Vector Machine (SVM), and Random Forest (RF), to classify land use and land cover (LULC) in Dak Nong province, Vietnam, using multi-temporal Sentinel-2 imagery. The importance of variables such seasonal data, classifier selection, and image quality on classification accuracy was emphasized in the study [12].

Basheer, S., Wang, X., Farooque, A. A., Nawaz, R. A., Liu, K., Adekanmbi, T., & Liu, S. (2022). Examined various machine learning classifiers for the classification of land use and land cover (LULC) using high-resolution satellite imagery, paying particular attention to Charlottetown. The classifier performance of Google Earth Engine and ArcGIS Pro was thoroughly compared. Notable for its superior performance is the support vector machine (SVM) classifier [13].

Zhang, T., Su, J., Xu, Z., Luo, Y., & Li, J. (2021). This study seeks to improve land cover classification by automatically fine-tuning the random forest (RF) classifier using Bayesian optimization and Sentinel-2A/B satellite images. The issues addressed include the occurrence of mixed pixels at class boundaries, which causes inaccuracy, and the limits of a short training dataset, which impacts model robustness. Both the traditional support vector machine (SVM) and RF with default parameters are outperformed by the optimized RF classifier [14].

Rahman, A., Abdullah, H. M., Tanzir, M. T., Hossain, M. J., Khan, B. M., Miah, M. G., & Islam, I. (2020). Assessed the performance of machine learning algorithms—Random Forest (RF), Support Vector Machine (SVM), and stacked models—on satellite image classification in rural (Bhola) and urban (Dhaka) settings. The challenge of mixed pixels in lower-resolution images like Landsat-8 hampers accurate land cover identification. SVM on Sentinel-2 imagery achieved the best accuracy, with 96.9% in Bhola and 98.3% in Dhaka. However, the study lacks a detailed temporal analysis [15].

Sellami, E. M., & Rhinane, H. A. S. S. A. N. (2023). This study used machine learning algorithms on Sentinel-2 L2 images to present a novel method for mapping land use and land cover (LULC) in Tetouan, Morocco. The aggregation functions median, mean, max, min, and mode were used to produce five datasets, and the accuracy of three machine learning classifiers—Support Vector Machine (SVM), Random Forest (RF), and Classification and Regression Trees (CART) was evaluated. Among all models, the mean composite dataset yielded the best results for LULC mapping. But the mode composite did not perform well, especially when it came to differentiating between grassland and bare ground [16].

Nininahazwe, F., Théau, J., Marc Antoine, G., & Varin, M. (2023). Demonstrated the effectiveness of remote sensing techniques, OBIA, multi-date classification, and feature selection in mapping invasive alien plant species, crucial for biodiversity management. Despite achieving 91% accuracy using Random Forest (RF), faced addressing gaps like seasonal variability, spatial resolution concerns, error analysis, and limited generalizability to other regions [17].

Avcı, C., Budak, M., Yağmur, N., & Balçık, F. (2023). The paper compared Random Forest and Support Vector Machine algorithms for LULC classification using Sentinel-2 imagery, achieving 92.5% accuracy. It highlighted gaps such as limited exploration of algorithms, insufficient data quality analysis, lack of detailed error analysis, geographical focus on specific areas, brief temporal dynamics, and challenges with mixed pixels [18].

Huong, N. T. T., Hang, P. T., Hoai, C. T., & Bao, H. D. (2024, August). The study emphasized integrating Landsat 9 with Random Forest, achieving 84.75% accuracy in forest cover classification for effective tropical biodiversity management. It excelled in accuracy, multi-source data use, and advanced algorithms, supporting forest conservation. This study identified gaps including difficulties in classifying complex land cover types, limited seasonal data analysis, generalizability concerns, and the need for specialized approaches and additional data sources [19].

Musleh, A. A., & Jaber, H. S. (2021). The study compared pixel-based and feature extraction classification techniques, finding feature extraction superior in accuracy for high-resolution imagery, particularly in urban settings like Baghdad, aiding urban planning. It achieved high accuracy (SVM=95%, MLC=92%) and demonstrated advanced algorithms and detailed categories [20].

3. MATERIAL AND METHODS

3.1 Dataset: -

The Sentinel-2 satellite imaging dataset, which includes 500 photos per class, has a total of 2500 images. Different land cover types, including River, Forest, Barren, Industrial, Sea Lake, and Residential are included in this dataset, which is intended for land cover classification tasks. Google Earth Engine (GEE) is used to obtain the photos, providing effective access to enormous geographic datasets and robust cloud-based processing capabilities. With pixel resolutions of 10 meters per pixel for certain bands and 20-60 meters per pixel for others, the Sentinel-2 satellite offers high-resolution multispectral photographs. For machine learning models, these photos have been scaled to 224x224 pixels. With an equal amount of photos for each class, the dataset is balanced, reducing class imbalance and guaranteeing that the model does not favour any one class over another during training. The pictures are prepared for deep learning models such as Convolutional Neural Networks (CNNs) by normalizing pixel values to a range of 0 to 1. To enhance the model's capacity for generalization, data augmentation methods like rotation, shifting, and zooming are also used to artificially expand the training data. Agricultural land classification, urbanization studies, environmental monitoring, and tracking changes in land cover over time are just a few of the applications for this dataset, which offers useful information for decision-making in fields like climate change, urban planning, and natural resource management

4. METHODOLOGY

The flowchart portrays a crossover strategy for classifying disciple pictures. Sentinel-2 symbolism is obtained by means of Google Soil Motor, taken after by information preprocessing with fix extraction and changes. The dataset is part into 70% for preparing and 30% for testing. RegNet50, a pretrained CNN demonstrate that has as of now been prepared employments convolutional, pooling, and smooth layers to extricate highlight vectors. These highlights are bolstered into a Irregular Timberland (RF) classifier, which is prepared on the preparing set and utilized to classify the test information. At long last, a disarray framework assesses the classification accuracy.

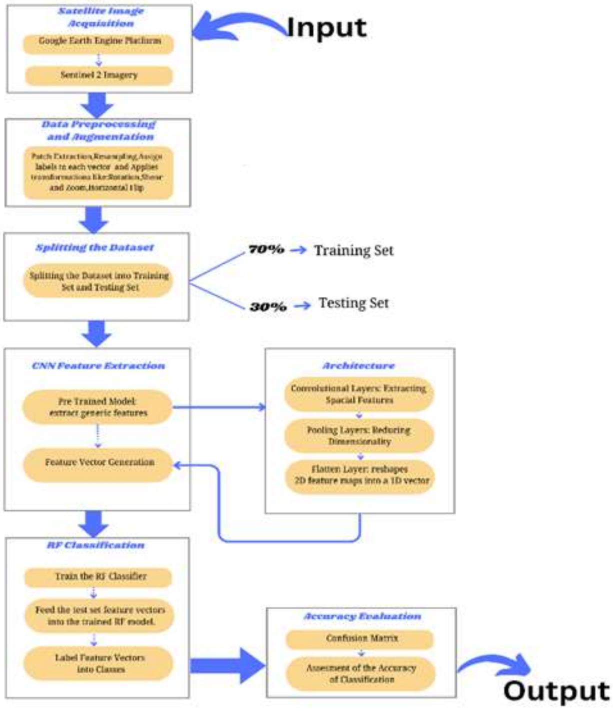

Figure 1. Flowchart of Hybrid Model Proposed in this study.

4.1. Satellite Image Acquisition

The initial stage is using the Google Earth Engine (GEE) platform to obtain satellite pictures, specifically Sentinel-2 data. Sentinel-2 is a high-resolution multispectral imaging satellite that is very useful for environmental monitoring and land cover classification since it can produce detailed images with a spatial resolution of up to 10 meters. These datasets are easily accessible using GEE, a cloud-based geospatial platform that offers strong capabilities for processing satellite pictures without the need for local hardware. This stage guarantees that pertinent information is obtained from trustworthy sources, which will form the basis for additional investigation. By using Sentinel-2 pictures, the method makes use of the satellite's wide spectral range, which includes bands sensitive to urban surfaces, water, and vegetation, making it easier to classify land cover accurately.

4.2. Data Preprocessing and Augmentation

This step involves preprocessing the unprocessed satellite photos so that the machine learning pipeline can use them. Patch extraction is the technique of dividing the data into smaller image patches or tiles in order to streamline the convolutional neural networks (CNN) input and enhance learning. Since satellite photos frequently have different resolutions, resampling is done to make sure that every patch has a constant spatial resolution, which could compromise the accuracy of the model. After that, each patch is given a term that corresponds to its actual class, such as Forest, River, Industrial, Residential, etc. In order to prevent the model from overfitting to particular patterns during training, data augmentation techniques such as rotation, zoom, shear, and horizontal flipping are used to guarantee that the classifier performs effectively when exposed to unseen data.

TABLE 1. Land cover classes defined for the study.

Class	Number of Images	Description
Forest	500	Represents regions that are heavily covered in vegetation.
Industrial	500	Regions, including factories, power plants, and major manufacturing complexes.
Residential	500	Represents areas with human-made structures like cities, towns, buildings.
River	500	Terrain regions that contain rivers or other bodies of flowing water.
SeaLake	500	Refers to large bodies of water, including seas and large lakes.

4.3. Splitting the Dataset

Following preprocessing and labelling, the data is separated into two subsets: a testing set and a training set. The CNN and Random Forest (RF) models are typically trained using 70% of the data in the training set, with the remaining 30% designated as the testing set to assess the model's performance. With enough unseen samples remaining for an objective assessment of performance, this split guarantees that the model learns from a sizable enough amount of the data.

4.4. CNN Feature Extraction

In this step, a pre-trained Convolutional Neural Network (CNN) is used to extract feature vectors from the satellite image patches. Pre-trained model ResNet50 is often employed, as it has already learned to recognize patterns from large datasets, saving time and computational resources. The CNN's convolutional layers scan the input images to detect spatial patterns and features such as edges, textures, and shapes that are relevant for classification. By applying pooling layers, the dimensionality of the feature maps is decreased, improving computation efficiency. The 2D feature maps are then transformed into a 1D vector by the flatten layer, which provides the input for the RF classifier that follows.

4.5. RF Classification

Once the feature vectors have been generated by the CNN, they are fed into a Random Forest (RF) classifier for classification. In order to increase classification accuracy and lower the possibility of overfitting, the RF ensemble learning algorithm constructs several decision trees during training and aggregates their outputs. The feature vectors from the training set are used to train the RF classifier in this stage. The model gains the ability to recognize patterns that are associated with several classes, such as "Sea Lake" "Forest," and "Residential". Following training, the learned RF model is used to predict the labels of the testing set feature vectors. The RF classifier assigns a class to each feature vector, effectively labelling the satellite image patches.

4.6. Accuracy Evaluation

The final step evaluates the performance of the model using a confusion matrix, which provides a detailed breakdown of the predictions. The confusion matrix displays the proportion of accurate and inaccurate predictions for each class by comparing the RF classifier's predicted labels with the test set's actual labels. A number of performance indicators, including accuracy, precision, recall, and F1-score, are obtained from the confusion matrix to provide a thorough evaluation of the model's efficacy. Accuracy measures the overall correctness of the predictions, while precision and recall indicate how well the model distinguishes between different classes.

5.ARCHITECTURAL DESIGN

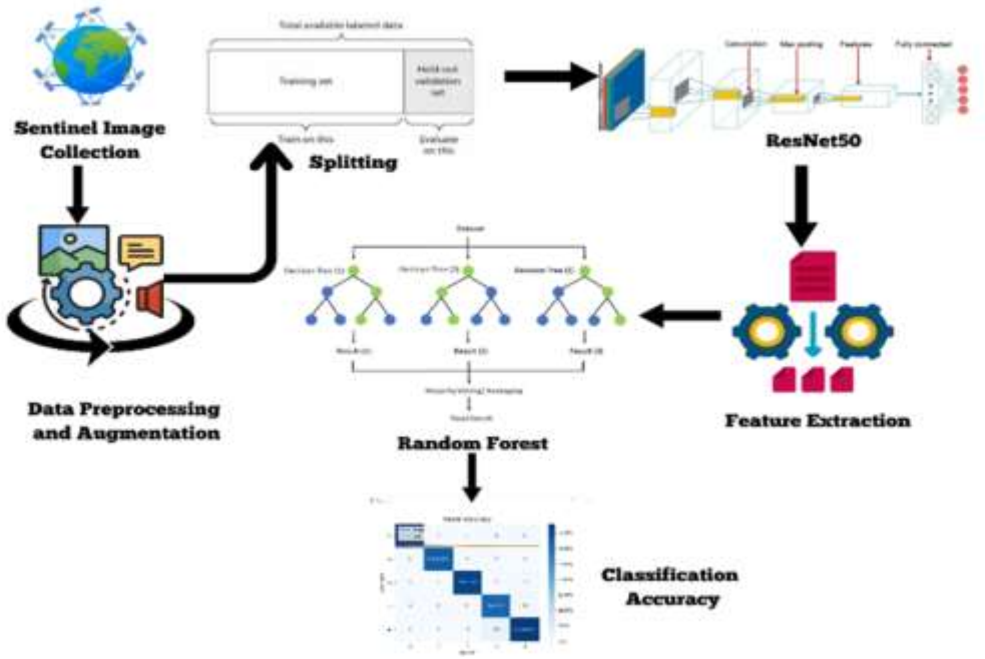

Figure 2. Architecture of Hybrid Model Proposed in this study.

The procedure for classifying satellite images using a hybrid model is shown in this diagram:

1. Sentinel Image Collection: The Sentinel dataset is used to collect satellite photos.

2. Data Preprocessing and Augmentation: The photos are cleaned, transformed, and enhanced to improve model performance.

3. Splitting: To assess the model, the dataset is separated into training and validation sets.

4. ResNet50: Using several convolutional layers, this deep learning network collects pertinent visual features.

5. Feature Extraction: The extracted characteristics are collected for further analysis.

6. Random Forest: These characteristics are fed into a Random Forest model, which generates predictions by average or majority voting over several decision trees.

7. Classification Accuracy: Metrics, such as the confusion matrix, are used to evaluate the model's performance.

6.RESULTS

6.1. LAND COVER CLASSIFICATION

In this study, Sentinel-2 satellite imagery was used for land cover mapping of the study area. These images have a spatial resolution of 10 meters for visible and near-infrared bands. By processing the data through the Google Earth Engine (GEE) cloud platform, we were able to overcome issues with data availability, storage, and processing without requiring a significant amount of local computing power. Given that Sentinel-2 offers various spectral bands, which are crucial for capturing a variety of land cover types within the research region, GEE made it easier to preprocess the data and compute the complicated feature space needed for this mission. The study area includes multiple land cover classes (e.g., Forest, Water, Residential, Industrial, and Sea Lake), requiring significant computational effort. The land cover map produced is evaluated using various accuracy metrics, including Overall accuracy, Precision, Recall and F1 score all derived from the confusion matrix. The diagonal elements of the matrix represent the areas that were correctly classified.

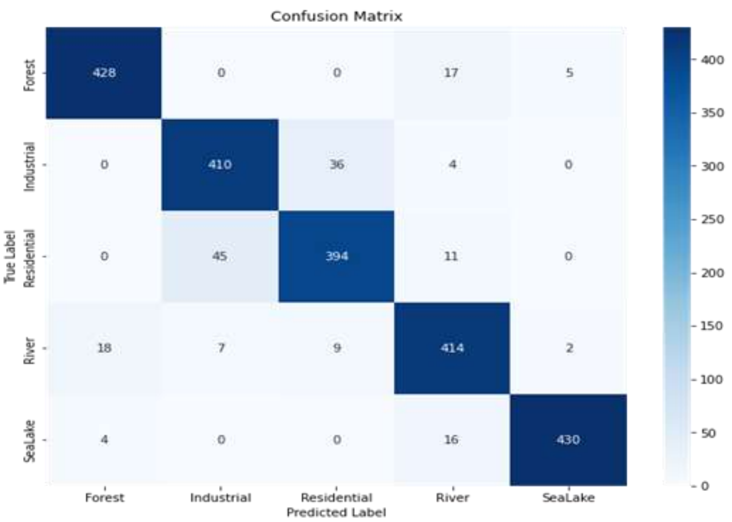

Figure 3. Land cover confusion matrix or error matrix of Hybrid Model

The inclining components of the lattice speak to the regions that were accurately classified. Figure 3.Land cover disarray framework or mistake network of Cross breed Demonstrate The by and large precision (OA) basically tells us, among all the reference locales, what extent was mapped accurately and is more often than not communicated as a rate. It is calculated by including the number of accurately classified destinations and giving it to the add up to number of reference locales (see Formula 1).

$$OA = \frac{\text{Number of correctly classified samples}}{\text{Number of samples}} \quad (1)$$

Number of accurately classified tests OA = (1) Number of tests The exactness metric shows the extent of positive recognizable pieces of proof that were really adjust for a specific course. By concentrating on the illustrations that the demonstrate recognized as having a place to each lesson, it surveys how precise the forecasts are for each course. By separating the add up to number of tests anticipated to be positive for that course by the number of genuine positive tests, accuracy is computed (see Formula 2).

$$Precision = \frac{\text{True Positive}}{\text{True Positive + False Positive}} \quad (2)$$

The ability of a classification model to detect every true positive case in the dataset is measured by its recall, which is often referred to as sensitivity or true positive rate. A high recall value indicates that the model is adept at spotting favourable examples (see Formula 3).

$$\text{Recall} = \frac{\text{True Positive}}{\text{True Positive} + \text{False Negative}} \tag{3}$$

The F1-score is a statistical measure used to evaluate the performance of a classification model. It is the harmonic mean of precision and recall, providing a balanced score that takes both false positives and false negatives into account. The F1-score is especially useful when the class distribution is imbalanced, as it doesn't let a model's performance on the majority class dominate the overall score (see Formula 4).

$$\text{F1} = \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \tag{4}$$

The classification model performed well in differentiating between the five classes—forest, industrial, residential, river, and sea lake—achieving a remarkable overall accuracy of 92.27%. The model successfully strikes a compromise between recall and precision across all classes, as evidenced by its weighted F1-score of 0.92. Notably, the Forest class exhibited a precision and recall of 0.95, resulting in a high F1-score of 0.95, indicating excellent identification of forested areas. Additionally, the Sea Lake class showed remarkable performance, with very few misclassifications with a precision of 0.98 and a recall of 0.96. The Industrial class performed well but showed some potential for improvement with a precision of 0.89 and a recall of 0.91. With a precision of 0.90 and a recall of 0.88 for the Residential class and a precision of 0.90 and a recall of 0.92 for the River class, both classes demonstrated dependable identification with very slight misclassifications. Overall, its robust performance highlights the effectiveness of this hybrid approach in handling complex classification tasks.

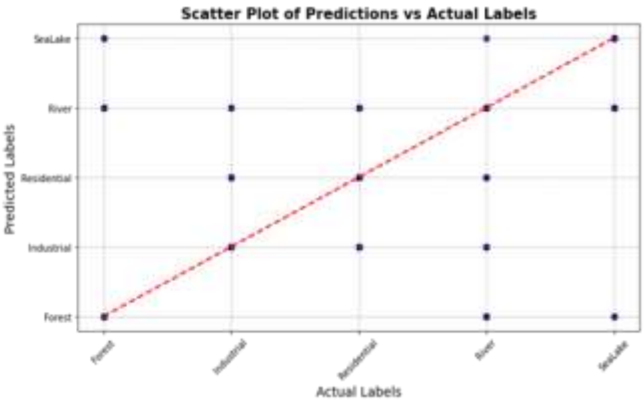

Figure 4 Scatter plot of Predictions vs Actual Labels of this Hybrid Model.

The scatter plot provides information about the hybrid model's classification performance by graphically illustrating the relationship between the actual labels and the model's predictions. With the x-axis showing the actual labels and the y-axis showing the anticipated labels, each point on the plot represents a distinct instance. Perfect predictions, in which the expected and actual labels coincide, are indicated by the existence of a dotted line at a 45-degree angle. The graph shows that the majority of predictions closely match the actual values, indicating the general efficacy of the model.

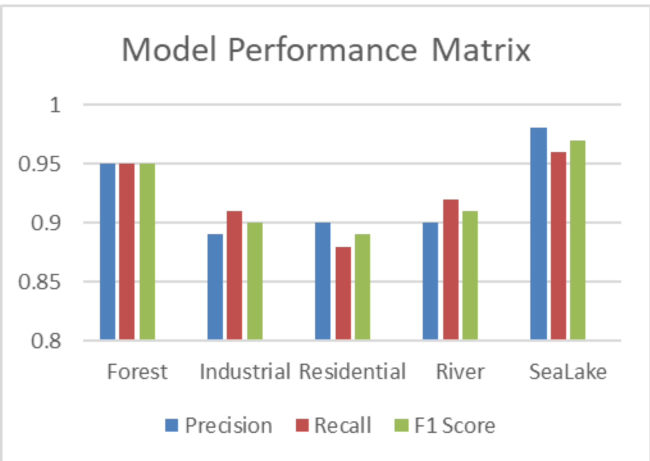

Figure 5. Model Performance Matrix of this Hybrid Model

6.CONCLUSION

The classification model performs admirably when it comes to correctly differentiating between the five land cover classes: residential, industrial, river, sea lake, and forest. A weighted F1-score of 0.92 and an overall accuracy of 92.27% show that the model takes a well-balanced approach to recall and precision. High precision and recall ratings for the Forest and Sea Lake classes highlight the model's exceptional performance in identifying these crucial regions. Despite their strong performance, the Industrial and Residential classes might yet do more, especially in terms of lowering misclassifications. Overall, this hybrid model successfully uses cutting-edge methods to handle the challenges of classifying land cover, which makes it an invaluable instrument for resource management and environmental monitoring. Future studies could look into further optimizing the current algorithms, such as adjusting hyperparameters and investigating different ensemble approaches

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] Ouchra, H., Belangour, A., & Erraissi, A. (2023). Comparison of Machine Learning Methods for Satellite Image Classification: A Case Study of Casablanca Using Landsat Imagery and Google Earth Engine. Journal of Environmental & Earth Sciences, 5(2), 118-134.

[3] Hanon, W., & Salman, M. A. (2024). Supervised Machine Learning Algorithms for Land Cover Classification in Casablanca, Morocco. Ingénierie des Systèmes d'Information, 29(1).

[4] Choudhary, T., Mhapankar, S., Bhddha, R., Kharuk, A., & Dr. Rohini Patil. (2023). A Machine Learning Approach for Phishing Attack Detection. Journal of Artificial Intelligence and Technology, 3(3), 108–113. https://doi.org/10.37965/jait.2023.0197

[5] Loukika, K. N., Keesara, V. R., & Sridhar, V. (2021). Analysis of land use and land cover using machine learning algorithms on google earth engine for Munneru River Basin, India. Sustainability, 13(24), 13758.

[6] Pan, X., Wang, Z., Gao, Y., Dang, X., & Han, Y. (2022). Detailed and automated classification of land use/land cover using machine learning algorithms in Google Earth Engine. Geocarto International, 37(18), 5415-5432.

[7] Ouchra, H., Belangour, A., & Erraissi, A. (2023). Comparing Unsupervised Land Use Classification of Landsat 8 OLI Data Using K-means and LVQ Algorithms in Google Earth Engine: A Case Study of Casablanca. International Journal of Geoinformatics, 19(12).

[8] Patil, A., & Panhalkar, S. (2023). A comparative analysis of machine learning algorithms for land use and land cover classification using google earth engine platform. Journal of Geomatics, 17(2), 226-233.

[9] Magaji, A., & Hassan, I. M. (2023). Evaluating the Performance of Machine Learning Algorithms and Maximum Likelihood Classifier for Land-Use and Land-Cover Change Detection in Yola, Nigeria

[10] Nguyen, H. T. T., Chau, Q. T. N., Pham, A. T., Phan, H. T., Tran, P. T. X., Cao, H. T., ... & Nguyen, D. T. H. (2020). Land use/land cover changes using multi-temporal satellite. ISPRS Annals of the Photogrammetry, Remote Sensing and Spatial Information Sciences, 6, 83-90.

[11] Ahmadi, K. (2024). Assessment of the Accuracy of Various Machine Learning Algorithms for Classifying Urban Areas through Google Earth Engine: A Case Study of Kabul City, Afghanistan. European Journal of Artificial Intelligence and Machine Learning, 3(3), 1-8

[12] Nguyen, H. T. T., Doan, T. M., Tomppo, E., & McRoberts, R. E. (2020). Land Use/land cover mapping using multitemporal Sentinel-2 imagery and four classification methods—A case study from Dak Nong, Vietnam. Remote Sensing, 12(9), 1367.

[13] 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.

[14] Zhang, T., Su, J., Xu, Z., Luo, Y., & Li, J. (2021). Sentinel-2 satellite imagery for urban land cover classification by optimized random forest classifier. Applied Sciences, 11(2), 543.

[15] Rahman, A., Abdullah, H. M., Tanzir, M. T., Hossain, M. J., Khan, B. M., Miah, M. G., & Islam, I. (2020). Performance of different machine learning algorithms on satellite image classification in rural and urban setup. Remote Sensing Applications: Society and Environment, 20, 100410.

[16] Sellami, E. M., & Rhinane, 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

[17] Nininahazwe, F., Théau, J., Marc Antoine, G., & Varin, M. (2023). Mapping invasive alien plant species with very high spatial resolution and multi-date satellite imagery using object-based and machine learning techniques: A comparative study. GIScience & Remote Sensing, 60(1), 2190203

[18] Avcı, C., Budak, M., Yağmur, N., & Balçık, F. (2023). Comparison between random forest and support vector machine algorithms for LULC classification. International Journal of Engineering and Geosciences, 8(1), 1-10.

[19] Huong, N. T. T., Hang, P. T., Hoai, C. T., & Bao, H. D. (2024, August). Classification of forest cover of Ta Dung National Park, Vietnam using optical satellite images. In IOP Conference Series: Earth and Environmental Science (Vol. 1391, No. 1, p. 012018). IOP Publishing.

[20] Musleh, A. A., & Jaber, H. S. (2021). Comparative analysis of feature extraction and pixel-based classification of high-resolution satellite images using geospatial techniques. In E3S Web of Conferences (Vol. 318, p. 04007). EDP Sciences