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Classification of Desert Areas Using Remote Sensing Images and Hybrid Machine Learning

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***Abstract* - In order to control desertification, it must first be discovered and classified, and then sustainable agriculture must be promoted to avoid it. It is identified using topographic features of desert areas that vary over time. Therefore, it is necessary to classify and identify desert areas with high accuracy using satellite remote sensing images (SRSI). In this paper, a hybridization was made between Exception transfer learning method, which was used to extract features, and state of art machine learning LightGBM method, which was used to classify (SRSI) dataset approved by Kaggle website. Several pre-processing was also performed on the dataset, such as image cropping to get the important features, as well as performing the data augmentation process to increase the amount of data and make it in different positions. After making a comparison with traditional and previous methods, such as Naive Bayes and K-Nearest Neighbors (KNN), the experiment results showed that LightGBM outperformed them and achieved a high accuracy of 99% and AUC of 100%.**

Keywords: LightGBM, desert, SRSI, Classification and Exception transfer learning.

I. INTRODUCTION

Only around 29% of the Earth's surface is made up of land continents and islands, while the majority of it is made up of water (71%), with roughly 2% of it frozen as ice and glaciers. The land is divided into agricultural grounds suited for habitation and barren lands unsuitable for either cultivation or habitation [1]. Desertification is a natural disaster that must be prevented or mitigated because it causes land degradation as a result of external factors such as wind and moving sand. To study desertification and reduce its effects, climatic and geographical factors must be studied such as rainfall rate, vegetation cover, temperature, latitude and longitude, etc. Manual classification of these areas using visual interpretation techniques[2] takes time and expertise in addition to data processing, hence automation is required.

In recent years, researchers have been able to monitor the Earth's climate and geographical landscape using remote sensing images. These images stand out for their correctness and sophisticated processing, as well as their processing speed[3]. Manual classification has become a significant burden for academics, as well as field professionals, due to the time and effort required. As a result, researchers have resorted to electronic classification methods that employ artificial intelligence and machine learning techniques[4].

Researchers have applied transfer learning techniques to classify arid or desert areas and achieved effective results, but some of them faced overfitting and underfitting problems[5]. To develop a machine learning algorithm and avoid previous problems, in this paper, a hybrid of the advanced machine learning approach (LGBM) with the pre-trained learning method Xception was used. Xception transfer learning was used to extract features which were passed to LGBM technique to be classified. The study used dataset satellite sensing images which taken from Kaggle website.

The rest of the study is organized as follows: Section 2 will discuss related works. Section 3 will include transfer and machine learning techniques. Section 4 will discuss the research methodology. Section 5 will provide results and discussions. Finally, section 6 will provide a conclusion.

II. RELATED WORK

Many academics have been interested in throwing light on drought prediction, and they have employed a variety of classic and sophisticated machine learning approaches to demonstrate their effectiveness.

Mohd Anul Haq *et al.* (2020) applied a deep learning-based supervised image classification system using images obtained by UAV to classify forest regions. The deep learning method stacking Auto-encoder has been shown to have enormous promise for image categorization and assessing forest covering area. The findings show that the accuracy of deep learning is superior to other machine learning algorithms. with an overall accuracy of about 93% [6].

Liguo Weng *et al.* (2021) remotely deployed two sets of desert environmental satellites (HJ-1A/1B) using the concept based multiscale residual network (MSRNet). The network used specific diffractions to extract key features from images

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before using multi-scale residual modules for feature map analysis Empirical analysis of data showed that the model achieved effective results in remote sensing images found at locations in the dry environment, with the original model scoring 0.94 and 0.95 kappa and OA, respectively, as obtained In the second model, the Kappa and OA metrics yielded results that increased by 0.96%, respectively accuracy 98.10% [7].

Humayra Ferdous *et al.* (2021) developed various artificial algorithms including K-nearest neighbor (KNN), Decision Tree (DT), and Neural Network to classify Statlog (Landsat Satellite) data set.KNN method is based on non-local neighborhood comparison and is compared. Neural network modeling follows the mental processes of the human brain while classifying the patterns primarily as a decision tree by visiting a few leaf nodes. Experimental results showed that the KNN model outperformed the other two methods was achieved with 90-92% accuracy due to the limited size of the dataset [8].

Balajee *et al.* (2021) introduced a deep convolutional neural community (DCNN) using the Landsat normalized difference water index (NDWI) to exactly forecast drought and fluctuations in water levels in the Chennai location. The version attains a root imply rectangular errors (RMSE) of beneath zero.03% without supplementary records, facilitating proactive water-saving initiatives. The dataset, spanning from 2000 to 2020, indicated a 50% discount in water ranges in 2020 relative to 2000. DCNN surpasses modern fuzzy SVM techniques, with an accuracy of ninety-four.02%, a consider of 98.25%, a precision of 97. Seventy-two%, and a blunders charge of 7.61%. Simulations of variables along with temperature and runoff from 2020 to 2080 forecast large will increase in water flow and stages throughout numerous timeframes, presenting insights into water management strategies. Satellite far flung sensing information are emphasized as critical for tracking land use changes and predicting water float and drought conditions inside the Chennai vicinity. Utilizing 67 years of each day time collection data (2013-2080) [9].

Huapeng Li *et al.* (2021) proposed an iterative machine learning algorithm for classifying agricultural objects using remotely sensed imagery. The researchers used an object-based convolutional neural network to classify low-level crops (LLC) and high-level crops (HLC). The analysis showed an overall accuracy of 88.4% for LLC and 91.2% for HLC [10].

Carolyn M. Gevaert and Mariana Belgium (2022) used conditional criteria to evaluate the similarity between training images and various unseen test images for insight construction The article examined the relationship between different context metrics in image a unknown and between training images From reference building designs With multiple scenario measures obtained, clustering and segmentation methods unsupervised, the classifier is significantly and weakly correlated with the F1 score The study obtained positive results [11].

Shilpa Chowdhury and Vandana Sardar (2023) proposed satellite image-based indices developed through deep learning into two categories of drought. The deep learning variants are assessed utilizing a satellite imagery database obtained from the Kolar region of Karnataka, India. The performance is compared to CNN variants like as AlexNet and VGG, in addition to the original CNN. The accuracy metrics for all indices in the original CNN surpass those of other CNN versions. CNN is 0.97, AlexNet is 0.67, VGGNet is 0.64, ENB0 is 0.91, ENB1 is 0.88, and both ENB2 and ENB3 are 0.94. Utilization of depth scaling [12].

Khalid En Nagre *et al.* (2024) employed various machine learning techniques to monitor drought conditions. The Standardized Precipitation Index (SPI) and Standardized Precipitation Evapotranspiration Index (SPEI) were assessed at many temporal scales (1, 3, 9, 12 months) for a Moroccan dataset spanning 1980 to 2019. The research indicated that drought distribution throughout the groundwater database is heterogeneous, with SPEI values exhibiting a clear declining tendency. The research revealed that the distribution of drought within the database is heterogeneous, characterized by a significant decline in SPEI values. The Random the Forest, Voting Regressor, and AdaBoost algorithms surpassed the K-Nearest Neighbors technique, exhibiting NSE values between 0.74 and 0.93. K-Nearest Neighbors yielded results between 0.44 and 0.84 [13].

III. MACHINE LEARNING METHODS

3.1 Xception Transfer Learning

The Xception model, created by François Chollet, augments the Inception architecture by employing depthwise separable convolutions, leading to enhanced performance on extensive datasets while preserving a comparable parameter count. This model is optimized for image classification and can be readily implemented using Keras or TensorFlow-Slim[14]. An enhanced iteration of the Xception model, tailored for the identification of counterfeit videos, alters the terminal layers by integrating Global Average Pooling (GAP), dropout, and logistic layers, resulting in a 5% increase in accuracy on the FaceForensics++ dataset. This model surpasses ResNet and Inception by 5.54% and 6.56%, respectively, highlighting its greater effectiveness [15]. The Xception architecture was favored over InceptionResNetV2 for its efficient parameter utilization, exceeding the processing

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efficiency of other CNNs such as ResNet50 while preserving excellent accuracy. Xception employs 36 convolutional layers and depthwise separable convolutions to diminish complexity and improve performance, particularly in a dual-Xception configuration utilized to evaluate the influence of image characteristics.[16]. Additionally, four pre-trained models, including Xception, were evaluated for fruit classification tasks, where Xception's accuracy improved from 84% to 99%.

3.2 Light Gradient Boosting Machine (LGBM)

It is a form of Gradient Boosting Machines (GBMs), which are ensemble learning methods that build an additive model from basic decision trees. These trees are not optimized individually but are combined to improve the loss function and achieve better performance. LGBM is characterized by the speed of training because it relies on histogram technique which divides continuous feature values into discrete bins, which accelerates the training process.

Although newer algorithms like LGBM have been developed, their adoption in research has been limited. Traditional algorithms such as Random Forest (RF) and Support Vector Machines (SVM) have been adequate for many projects. However, as the size of study sites increases, these methods become more time consuming and labor intensive. LGBM, offers great advantages with fast and accurate results, reaching accuracy rates up to 92.07% [17]. The efficiency of the LGBM algorithm is greatly affected by its hyperparameters, which are often manually set and refined through trial and error. Our method incorporates important methods for over-parameter optimization, including "num_leaves," which specifies the number of leaves per tree, "max_depth," which specifies the maximum depth of the tree, and "learning_rate" Furthermore, LightGBM uses the information acquisition (IG) technique for feature selection , which reduces the dimensionality of the training data by focusing on the most relevant features This technique is very effective with information such as credit card fraud detection, where it identifies the most important factors to distinguish between legitimate and fraudulent transactions [17].

LightGBM is very adept at handling imbalanced datasets because its GOSS method highlights highly error-prone models, especially underperforming classes This implementation, along with its ability to handle high-quality data by feature bundling on a separate surface makes LightGBM an effective tool for tasks such as sensitivity analysis, Where sparse data and imbalances are often problematic LightGBM converges faster than other gradient-enhancing algorithms, and provides less strategically short text so is the best choice for multi-class perceptual classification [18].

IV. RESEARCH METHODOLOGY

The investigation was conducted on Windows 10 utilizing a 2000 kHz CPU and 8 GB of RAM, and it was executed within the Spyder environment employing various Python libraries, including TensorFlow and Keras. The suggested technique begins with many pre-processing steps on the dataset, followed by feature extraction using Xception transfer learning, and finally classification using LGBM method. Figure (1) depicts a diagram of the proposed technique for this work.

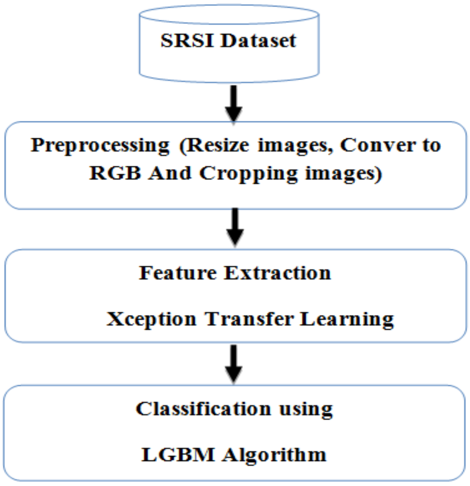

Figure 1: Diagram of the Proposed Technique

4.1 Dataset Description

The LGBM algorithm was applied to 4131 SRSI satellite remote sensing images obtained from the Kaggle website, which were sorted into only three categories (desert, water, and green areas). Figure 2 depicts examples of the data utilized in this study. The data was split among 80% training and 20% testing. Figure 3 depicts the data partition.

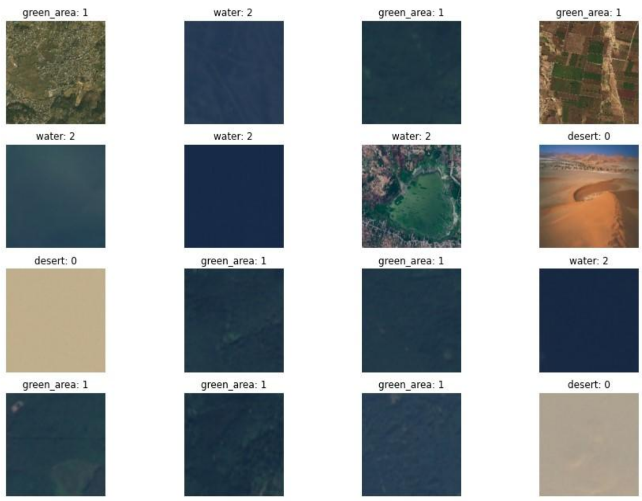

Figure 2: Examples of (SRSI) Dataset

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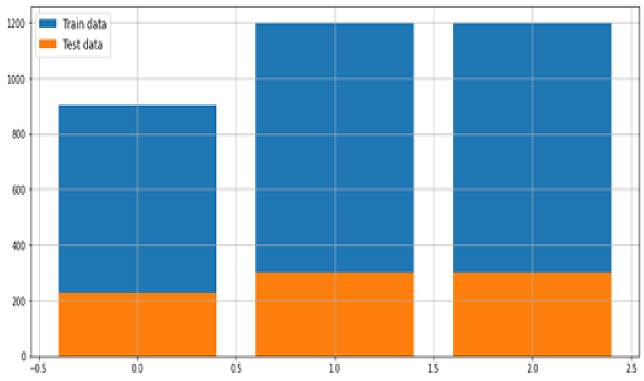

Figure 3: Splitting (SRSI) Dataset into training and testing

4.2 Preprocessing of Images

Data preparation is an essential step in obtaining crucial and relevant characteristics. The study involved scaling the image to 224 × 224, unifying its size, and decreasing it to lessen the amount of processing necessary, and then converting the image from GBR to RGB using the OpenCV library to clarify the image. After that, the image was cropped to remove the white and unnecessary portions.

4.3 Feature Extraction

The pre-trained Xception learning model was used to extract key characteristics from the SRSI dataset. The Xception model employs pointwise and depthwise convolution to decrease computing processes. It also includes a few convolutional layers with two-dimensional matrices. In this study, weights were frozen and the output layer was deleted.

4.4 Classification Process

In this study, one of the states of art machine learning methods (LGBM) was used to classify SRSI images. LGBM is non-parametric, which means that it adjusts to vast amounts of data rather than using a fixed model. It also employs a collection of categorization and numerical data. Important hyperparameters, such as the number of levels = 30, the number of estimators = 100, and the max depth = 7, were improved using the Grid Search algorithm, which is characterized by the cross-validation feature that divides the data into K-folds for training and another for evaluation. This study employed a K-fold of 10.

4.5 Performance Evaluation

The performance of the LGBM algorithm was evaluated using various metrics such as AUC-ROC, Accuracy, Precision, Recall and F1score. The AUC-ROC uses a threshold to distinguish between classes. When its value is 0.5, it means that it does not show any discrimination, but if its value is one, it is perfect discrimination. The accuracy metric is also calculated by measuring the number of by measuring the number of properly evaluated occurrence across all data samples recall is an effective quantity for spotting model mistakes. whereas the precision is a quality metric that describes the percentage of positive event that are accurately detected. F1 score is a static that attempted to create a balance between recall and precision. The metrices are stated as follows in equation 1,2,3 and 4.

$$\text{Precision} = \frac{TP}{TP+FP} \qquad (1)$$

$$\text{Recall} = \frac{TP}{TP+FP} \qquad (2)$$

$$\text{F1 score} = \frac{2*\text{Precision} \ *\text{Recall}}{\text{Precision} \ +\text{Recall}} \qquad (3)$$

$$\text{Accuracy} = \frac{\text{TN} + \text{TP}}{\text{TN} + \text{TP} + \text{FN} + \text{FP}} \qquad (4)$$

V. RESULTS AND DISCUSSIONS

In this section, the performance of the LGBM algorithm for classifying satellite remote sensing images was evaluated after improving it by hybridizing it with one of the transfer learning methods.

Figure (4) shows that LGBM algorithm`s Roc-AUC metric has the greatest percentage, which is 100% since it uses parallel learning on a huge dataset to accelerate the data training process and reduces the cost of loss by dividing the three and two leaves.

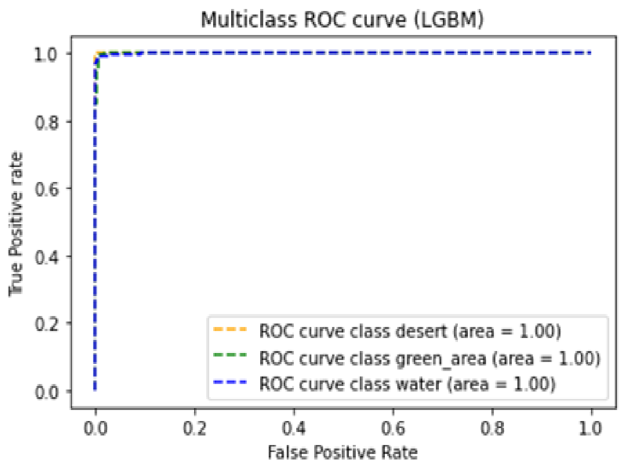

Figure 4: AUC-ROC Curve of LGBM

Figure (5) depicts the confusion matrix for distinguishing (SRSI) images, as well as the difficulty in selecting the LGBM method among the three classes. The confusion matrix is a numerical table that identifies areas of confusion in the classifier and relates predictions to the original data classes.

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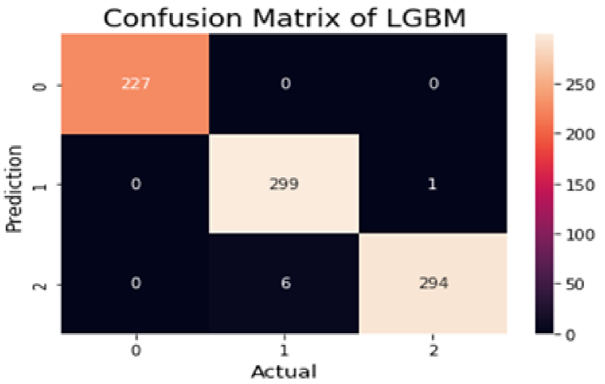

Figure 5: Confusion Matrix of LGBM

The LGBM model correctly predicted high values (diagonal values), as seen in the figure (5). It was also discovered that there were some non-diagonal values, indicating that the LGBM model was successful in avoiding mixing up the class samples.

In Table 1, it is observed that the LGBM model achieved the best results in the metrics of accuracy, precision, recall and F1 score compared to other traditional methods such as KNN and Naive Byes, which means that the LGBM succeeds in predicting more positive samples of SRSI images.

Table 1: Evaluation Metrics of ML Models

Evaluation Metrics	LGBM	KNN	NB
Precision	0.99	0.96	0.57
Recall	0.99	0.95	0.50
F1-score	0.99	0.96	0.48
Accuracy	0.99	0.95	0.50

Finally, the results were compared to a prior study [12] that employed the same dataset (SRSI). Table 2 demonstrated that the hybrid model suggested in this work outperformed the prior study.

Table 2: Comparison with previous study

paper	Total Accuracy	F1 score
M. Pritt and G. Chern[19]	0.83	0.797
Proposed Method hybrid transfer learning+LGBM	0.99	0.99

VI. CONCLUSION

Discrimination of desert places is critical; many developed countries promote sustainable agriculture. In this work, the LGBM algorithm was enhanced by hybridizing it with pre-training approaches to produce a high-level model. Xception transfer learning was used to extract features, which were then sent to the LGBM algorithm for discriminating. The grid search technique was used to optimize the most essential hyperparameters. The suggested model was assessed using remote sensing satellite images (SRSI) obtained from the Kaggle website. The findings indicated that the LGBM technique performed best, with 99% accuracy, precision, recall, and F1 score, as well as 100% AUC-ROC.

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