Machine Learning Models for the Analysis of Multi-Temporal Satellite Images for Change Identification and Predictions

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A***bstract*** **- Satellite data are used to monitor certain fields such as deforestation, polar ice loss, and climate change. The rate and extent of forest loss and ice melt, as well as global climate change trends, may all be tracked. Multi-temporal images are satellite photos or aerial photographs acquired by a sensor at different times but corresponding to the same location or area covered by that sensor. Change detection and prediction is essential for detecting changes in aerial images, environmental changes, and determining land utilization and coverage. Neural networks are robust Machine Learning(ML) models that can learn from data and perform many tasks, including image identification, natural language processing, and speech synthesis. Most neural networks lack the ability to adapt to new data inputs that change over time. The proposed study employs an Artificial Neural Networks(ANN) that adapts to the dynamic and unpredictable satellite image detection and prediction.**

Keywords – Artificial Neural Networks, Satellite Images, Change detection and Prediction, Remote Sensing

I. INTRODUCTION

Remote sensing is a highly effective approach for monitoring and managing the environment. The applications include crop production estimation purposes, erosion of soil identification, urban development, forest visualization, and variations in the climate. Satellite imagery and Geographical Information Systems (GIS) images displaying land coverage and usage modifications are critical for a wide range of applications, including environmental science, forest management, water management, farming, and geography. Natural resource management, planning, and monitoring activities rely on reliable land cover data. The methods used to track changes in vegetation vary from comprehensive sampling in the field with plot surveys to intensive examination of data collected via satellite, which has been shown to be less expensive for massive areas than smaller areas of evaluation and investigation.

Change detection is an approach that determines variations in the condition of a thing or occurrence by monitoring it multiple times. [1]. It is employed for detecting multi-temporal improvements by comparing them over two or more periods of time. Monitoring change has been extensively utilized for monitoring farming stress, forest destruction, ecosystem changes, season's evaluation, and so on. [2].

Artificial Neural Networks (ANNs) can effectively manage a wide range of remote sensing data, including multispectral and hyper-spectral images. The flexibility allows them to easily adapt to the many spectral bands and resolutions used in remote sensing applications. ANN have shown effectiveness in a variety of remote sensing applications, including land cover categorization, recognition of objects, vegetation and crop surveillance, and terrain analytics. It has a wide range of applications; include image analysis and character identification, prediction, enhancement and estimations. The flexibility they have qualifies them for a variety of roles in the field. Particularly, networks with a significant number of parameters can be susceptible to overfitting, gathering noise or particular patterns in data used for training that can't be applied effectively to unfamiliar, unidentified information. [3].

During recent years, researchers are focusing on various ways to detect the changes in land cover for effective monitoring of land use and other devastations. The present study demonstrates how ANN methods are used for change detection and prediction of satellite images. This study does not focus on any specific regions and this will mainly review and study the effectiveness of ANN in land change detection.

The remaining section of the study is divided as follows, the literature review section reviewed the various ANN methods in the land cover detection, followed by ANN methods illustrations in section 3. Then the findings and conclusion were given in the next sections..

II. LITERATURE REVIEW

Many researchers have undertaken numerous studies to detect changes in land utilization and coverage trends over time and anticipate the future growth of metropolitan areas. A study in [4] emphasizes measuring the temperature islands phenomenon arising from urbanization and vegetation shifts throughout the past thirty years (1990–2020) in three primary regions of the Punjab province: Sheikhupura, Chiniot, and Pakpattan. The information from Landsat is used for studying the influence of cities with heat islands and changes in land cover in those areas. A study in [5] examines the environmental consequences of rising temperatures using Landsat satellite imagery. To gain insight into these challenges, the approach employs a novel Urban Thermal Field Variance Index (UTFVI), as well as thermal and spectral indices. Land surface temperature (LST) and associated variables are forecasted using a complex strategy that involves regression analysis, the use of cellular automata (CA)-Markov chains, and deep neural network algorithms.

The goal of the study in [6] is to investigate the LULC changes in Aizawl city between 1991 and 2021 using multi-date Landsat images and a cellular automata-ANN (CA-ANN) model to anticipate future scenarios. The research is important to analyze the development of cities in hill areas as well as the past effects of patterns of development along hill zone boundaries for effective land use decisions. The automated categorization of support vector machines (SVM) included in the Orfeo toolbox (OTB) modules has been employed for LULC identification of patterns. Landsat image data is used to determine the impact of LULC change on the Hodna basin (26 thousands kilometres) from the year 2000 to 2020, as well as to estimate various change scenarios up to 2050. Landsat data was analyzed using Maximum Likelihood Supervised Classification (MLSC) with a five-year interval from 2000 to 2020. A simulation has been carried out with ANN and ML methods to estimate the potential change situations for each class of LULC[7].

ML and Artificial Intelligence (AI) have obtained prominence in a wide range of scientific applications, including land cover monitoring. The study in [8] explores the reliability of the ML-based algorithm for classification of random forest (RF) for monitoring LC classes in Kuwait City's metro zone between 2016 and 2021. The study in [9] examined land utilization and land coverage changes during the period from 1991 to 2021, and predicted future changes in Binh Duong province, Vietnam, with the objective to propose a research direction on land use change and associated issues in the study area. The maps of LULC were created with multispectral satellite data and a random forest tree (RFT). Areal analytics and yearly modification rates were utilized to evaluate category changes in land use identification. Geographical Information System technique combined with Artificial Neural Network to analyze a city's previous development trends and anticipate future land transformations. In [10], the land alterations during the preceding three decades of development (1990-2020) were evaluated using classified maps for Jaipur city in India, revealing that the built-up area increased by 46.54%.

The study in [11] identifies and predicts prevalent changes found using SVM for supervised classification and CA-ANN[12] frameworks for predictions in the quantum geographic information systems (QGIS). [13] describes a model by applying predictive analysis to detect anomalous variations in photographs. Neural networks are taught to anticipate "before" and "after" pixel values from a series of photographs. Such networks are then used to forecast expected values for the identical imagery utilized during learning.

III. METHODOLOGY

ANN is employed to detect the Land use Land Cover (LULC) in the satellite images. Two satellite images taken at different times were used in this study and the test images were collected from the web resources. The remotely sensed images are subjected to corrections and pre-processing before being fed into the neural networks. The outcomes of the ANN are compared with Random-Forest (RF) and K-Nearest Neighbor (KNN) techniques.

A. Artificial Neural Networks(ANN)

The early neural networks were multi-layered, with just five levels of input and three layers that were concealed yielded outcomes for a single class. Land classes are being identified using ANN after receiving training information on terrain types. It comprises three layers: the one that inputs the data layer, the hidden layer, and the resultant layer. The input layer accepts the supplied information and transfers them on to the following layer, and then sends the predicted outcome to the resultant layer. The perceptron is made up of numerous neurons that constitute the fundamental building blocks of the brain. To put it simply, every circle indicates a neuron. Perceptrons are thick layers of neurons organized vertically. Each neuron was given weights (w1, w2, w3) and biases, and the subsequent calculations have been carried out.

The activation value was transferred to the following node via weights and the activation function. Each node uses the transfer function to calculate and update the sum of the weights. It then carried out a procedure known as activation. This was the only neuron capable of performing this function. The nodes can then decide whether or not to transmit the message. The ANN adjusted the weights to estimate the signal extension. The activation flowed across the network till it arrived at the desired node[14].

The Figure 1 shows the ANN with water body images as input and it classifies it as water bodies. For instance, if the same water bodies (location) are occupied by buildings in the later stage, it will show different results and in the LULC map it is marked as buildings. The changes in the images are detected and it is represented using different color codes for various categories like vegetation, forest areas, water bodies and buildings.

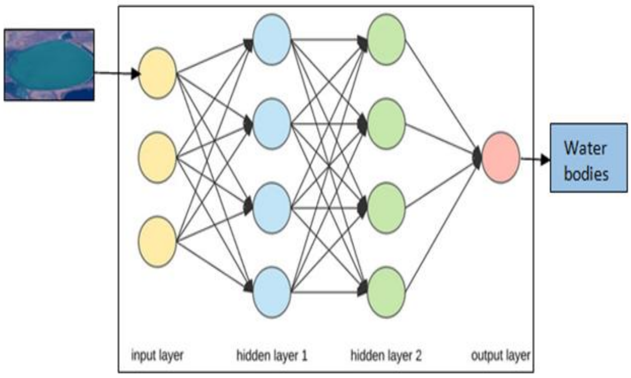


Figure 1 ANN for the classification of satellite images

B. Random Forest Classifier

Random Forest (RF) based land utilization and vegetation classification is a great strategy for categorizing the landscape because it employs an extensive number of decision trees to get reliable outcomes. It is a supervised ML system for classifying multispectral satellite images, which is an efficient and inexpensive method for identifying land utilization and vegetation changes. The higher the number of trees in the RF, the better the accuracy. The Figure 2 presents the working of a random forest algorithm.

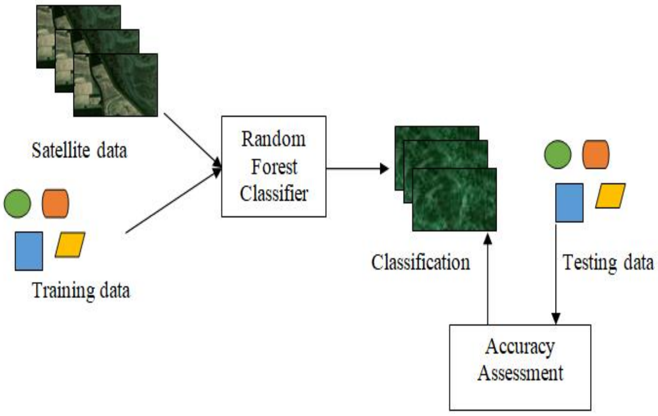


Figure 2 Random Forest Classifier for Satellite Images

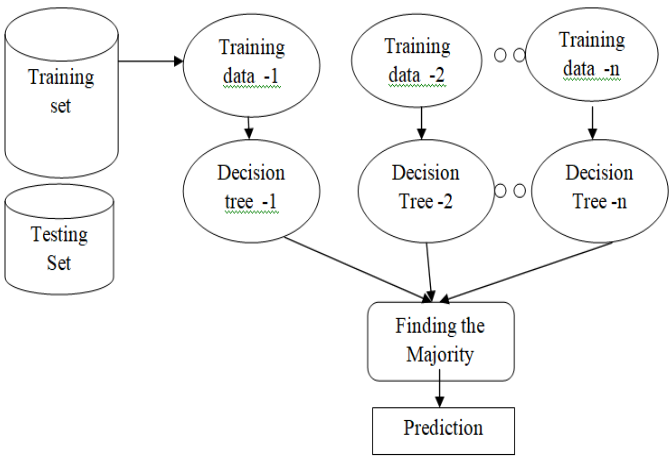


Figure 3 Working of Random Forest Algorithm

The clustered data is used for the initial training data and the splitting of data is shown in Figure 3 and 4

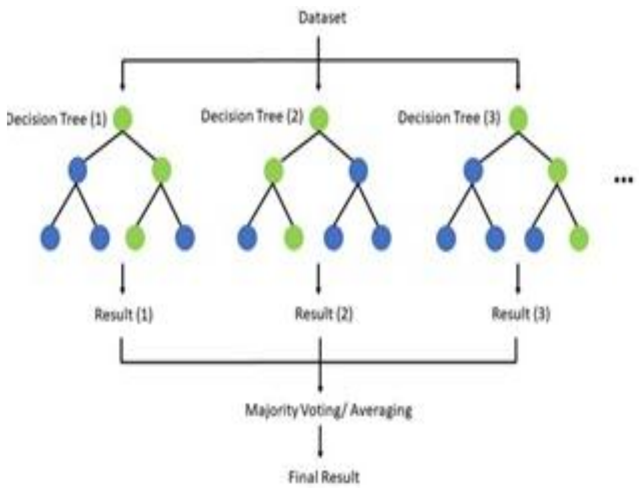


Figure 4 Random Forest classifier

Each decision tree consists of decision nodes, leaf nodes, and a base node. Each tree's leaf node symbolizes the decision tree's ultimate outcome. The final conclusion is chosen by a majority vote. In this case, the majority of the decision trees' output is used as the rain forest system's ultimate result. The Figure 3 depicts a simple random forest classifier. The following stages describe the working Random Forest Algorithm:

Step 1: Take a sample at random from a given data or training collection.

Step 2: For every set of data used for training, this method produces a decision tree.

Step 3: The vote will be determined by calculating the average of the choice trees.

Step 4: Finally, choose the predicted outcome with the most votes as the final result.

Random Forest takes observations at random, constructs a decision tree, and then returns a result based on majority voting. There are no formulas required here

C. K-Nearest Neighbor(KNN)

The main principle behind nearest neighbor techniques is to choose a certain number of samples for training that are closest in distance to the new location and predict their labels. The k-NN algorithm identifies unidentified data points by choosing a most prevalent class among the k-closest instances. In KNN, the parameter 'k' indicates the number of adjacent neighbours to include in the final outcome of the voting process. Euclidean distance is the most popular distance metric to calculate distances between data points.

$$d(\boldsymbol{p},\boldsymbol{q}) = \sqrt{\sum_{i-1}^{N}(q_i - p_i)^2}$$ -------Eq-1

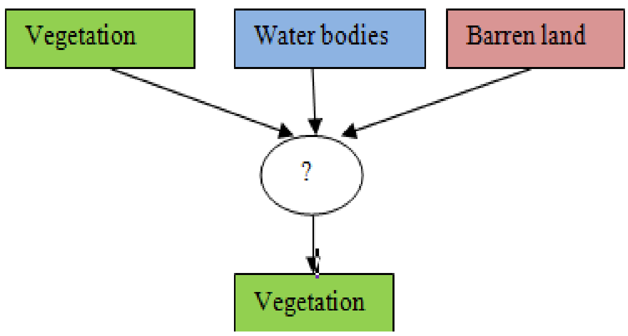


Figure 5 Categorization of lands form satellite images

Figure 5 shows the categories of lands that are categorized from aerial photographs. Depending on the type of land the categories are labelled and it is not restricted to only three as shown in Figure 3.5. The following steps explains the K-Nearest Neighbor algorithm

Step 1: Start the dataset with known categories. In this case, the different types of lands .Then cluster the data using PCA clustering techniques.

Step 2: Add a new type of land with an unknown category.

Step 3: Classify the new type looking at the nearest type based on the majority of votes.

Step 4: If the new type of land is between two categories, don't assign any type of land.

For instance, if the type of land is closest to the vegetation which is represented in green, it is labelled as vegetation if the type of land is new, ie. Unknown type, as represented in Figure 6 as black circle, no category is assigned to the point.

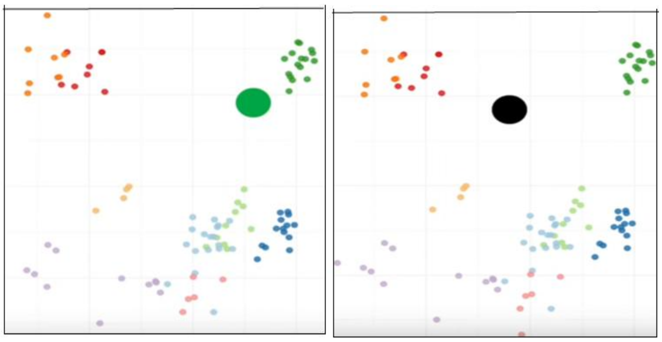


Figure .6 KNN Nearest points-Known & unknown category

IV. Findings and Discussions

There are numerous advantages and disadvantages in utilizing the RF method and one of most important benefits is that it reduces the risk of overfitting in addition to the duration of training time needed. Furthermore, it offers exceptional precision and the RF method is efficient in handling large datasets and generates very precise forecasts by checking the closeness of missing information.. RF regression analysis is not adequate for extrapolating data. Despite linear regression, this employs past observations to determine values beyond the observed limit. RF's are more complex than decision trees and this model requires more training time than other models. For each and every prediction, each decision tree must provide output based on the incoming data. It suffers with high-imbalanced data, variable interpretation, cardinality categorical variables, time series forecasting and hyperparameter sensitivity.

KNN is a non-parametric technique that predicts using a dataset's nearest neighbours, allowing it to handle complex decision boundaries. It excludes the phase of training and the information itself is a modelling that will be used in subsequent predictions, making it incredibly fast. There is no training phase, so new data can be added at any time without influencing the model. At the same time, it fails to work well with massive databases since calculating distances between every instance of data would be prohibitively costly. It does not operate properly with high dimensions, since it complicates the distance calculation procedure by calculating distance for each dimension separately. Moreover, it is sensitive to missing data and data with noise and also the data in all dimensions should be properly scaled.

ANNs are used to quickly evaluate the learned target function. It is fault tolerant, therefore even if one or more cells in the ANN get corrupted, the creation of outputs is unaffected. They can tolerate extended training periods, learn from events, and make decisions based on similar situations. It is capable of performing numerous functions at the same time. Because of its limited broader band, the multispectral dataset is unable to produce the expected results. Various studies have shown that the ANN is suitable for handling such datasets. It has the ability to scale according to the problem size and complexity. The disadvantages are the lack of transparency and no rules to govern their structures. The ANN, RF and KNN is used to classify the satellite images for change detection and it is implemented in python with the Scilkit library. Each method used in this study has its own advantages and disadvantages.

Figure 7(a) ERS -1 image b)ERS-1 Image(after one year)

A sample input images in Figure 7 a) and b) show the ERS-1 images taken at different times are used in this study. This was taken to monitor the land utilization and deforestation for 5 years from 1993-1997 in a tropical rainforest[15].The methods used in this study are evaluated using 5 samples of images taken at different times and in different locations.

Figure 8 shows the results of the application of ANN, RF and KNN methods in the above images for change detection.

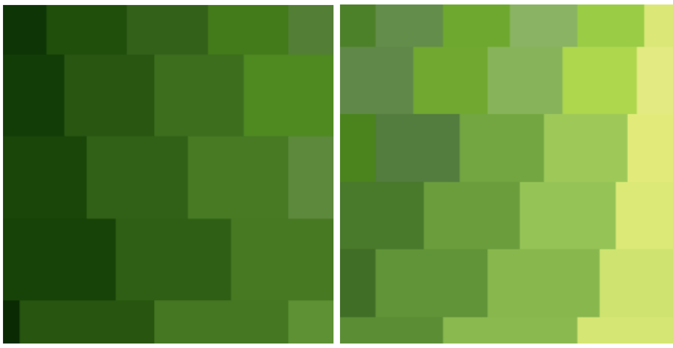


Figure 8 Color Maps for the above images- ANN

The color maps generated by ANN are found to be effective in detecting the changes in the land utilization and coverage.

Performance Evaluation of the ANN methods is computed using the metrics viz, Accuracy, Precision, Log loss and Mean Square Error(MSE). The dataset were collected randomly from the web resources for the demonstration purpose. The assessment is performed using appropriate libraries in python .The metrics are as follows..

a) Accuracy- Accuracy simply indicates how frequently the classifier properly predicts [16] and it is calculated as below

Accuracy =(TP + TN) / (TP + TN + FP + FN) --Equation-1

b) Precision - proportion of accurately predicted attacks to all attacks forecasted[16]

Precision = TP / (TP+FP) **------** -Equation -2

True positives (TP) and false positives (FP) are represented in the formula above.

c) Log loss: It assesses the degree of divergence between anticipated probability and original label. The smaller the log loss value, the more accurate the model will be. In a perfect model, the log loss value is zero. As an example, if accuracy is the number of correct projections that correspond to the original label, Log Loss value is a measure of uncertainty in our predicted labels based on how they deviate from the real label. Its value ranges between 0 and 1 [17].

$$LogLoss = \frac{-1}{N}\sum_{i=1}^{N}\sum_{j=1}^{M} x_{ij} * \ log(p_{ij})$$ --Equation-3

n = number of samples, M =Number of attributes and $\mathbf{y_{ij}}$ represents i^{th} sample of j^{th} class or not and pij is the probability of i^{th} sample of j^{th} class.

d) Mean-Squared-Error: It is the square of the differences between the actual and anticipated values. Lower the value of MSE, higher the performance of the algorithm[18]

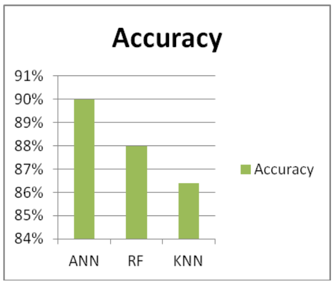
$$\boldsymbol{MSE = \frac{1}{N}\sum_{i=1}^{N}(predicted - input)^2}$$ -----Equation-4

The parameters used in the calculation of accuracy and precision derived from the confusion matrix It is a two-dimensional matrix that contains data on both original and expected classes. It is expressed in a confusion matrix with only four choices, as follows:

- True Positive: traffic identified correctly as attacks
- True Negative: traffic that is accurately classified as typical
- False Positive: communications that are not recognized as attacks
- False Negative: traffic that is considered regular yet is marked as an assault

Table:1 Performance Evaluation

Methods	Accuracy	Precision	Log loss	MSE
ANN	90 %	0.92	4.35	0.15
RF	88 %	0.87	6.54	0.23
KNN	86.4%	0.83	7.01	0.39



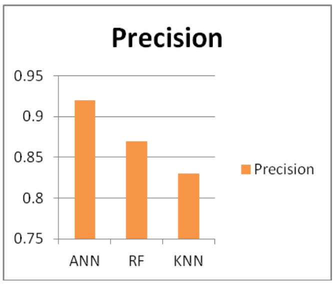
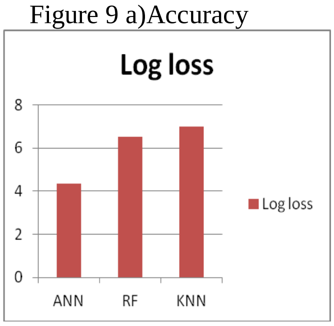


Figure 9 a)Accuracy b) Precision



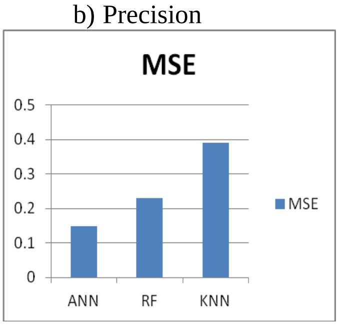


Figure 9 c)Log loss d) MSE

The performance of and classification algorithms for change detection in satellite images has been evaluated and it is tabulated in the Table-I. The table-1 data and figure 9 a) to d) shows that the ANN outperforms the other approaches utilized in this investigation. Hybrid techniques can help to increase the performance of the algorithm utilized in this study.

V. Conclusion

The change detection algorithms using ANN are analysed and it is compared with the RF and KNN method. The performance of the ANN shows efficiency compared to the other two methods. The ANN for classification for change detection offers better efficiency with regard to recall, accuracy, precision and F-score. ANN methods show notable performance in many of the studies and it is found to be best fit for classification models in certain scenarios. The usage of classification models depends on the applicability of the problems and it varies depending on the complexity of the problem.

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