DETECTION OF LAND COVER CLASSIFICATION USING ARTIFICIAL NEURAL NETWORK (ANN)

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Abstract- The land cover refers to the surface of the Earth, whereas land use describes the activities that take place on the land. Land cover may be anything from water to snow to grassland to deciduous woodland to bare soil. The goal of this research is to develop a method for classifying land cover using ANN. To begin, PCA (Principle Component Analysis) is applied to the input picture as a preprocessing step for dimensionality reduction. Next, the picture that has been preprocessed is taken to the feature extraction stage. In order to extract features, a convolutional filter is used. It is from this set of attributes that statistical features like minimum, maximum, and standard are extracted. In order to train and evaluate these features, the extracted features are transferred. Take a look at the ground truth picture afterwards. Areas of buildings, lakes, and farms are all shown in this ground truth picture.The next step in developing a classification model is to divide these photos into two sets: training and testing. To categorize the model, an ANN classifier is used. Lastly, the input picture's characteristics are tested using the training label of the ground truth image. Accurate predictions of land cover regions are the end outcome of an ANN classifier's successful classification of the extracted picture. Software for simulations, MATLAB, is used in the execution of this project.

1.INTRODUCTION

To better evaluate the effects of natural events or human actions on the environment and to comprehend the long-term functioning of ecosystems, data about the changes in land use and land cover (LULC) dynamics is crucial. The biophysical condition of the Earth's surface is known as land cover, whereas human activities or deliberate modification of land constitute land use. In terms of LULC shifts, we think a land cover transition occurs when different types of land are identified in the same analytical unit twice in a row. One definition of a land cover trajectory is the succession of land cover types in a particular unit of study in three or more observations. This series of changes occurs throughout time. An established and popular approach to land cover trajectory characterization involves stacking the results of several classifiers applied to remote sensing photos taken at different times. Many people have issues with this technique, called post-classification comparison, since it relies on accurate land cover classifications to provide mapped land cover trajectories. So, if the rate of change is smaller than the sum of the individual categorization mistakes, then it is not feasible to assess the change properly. Land cover trajectories that are not legitimate because of mistakes in land cover classifications are those that will never happen in the actual world. It is common practice to conceal invalid trajectories from analysis or fix them in post-classification steps since they are thought of as classification faults. Using a temporal filter and manual editing are two ways to fix these trajectories. If a user-defined set of criteria is violated, such as "areas previously deforested and classified as forest should be renamed as secondary vegetation," then the user-defined classes that provide valid transitions are replaced. These rules have the ability to alter data while taking spectral features into account. Including the temporal characteristics of remote sensing pictures in the analysis helps to prevent problems caused by improper trajectories. As an example, land cover trajectories may be directly classified from a sequence of photos spanning many time periods using either supervised (reference samples are required) or unsupervised (reference samples of trajectories are not). Both approaches, however, have their drawbacks.

Collecting reference samples of land cover trajectories across a series of multi-temporal photographs may be a tedious and time-consuming process that demands a thorough knowledge of the features of various types of change. Additionally, using unsupervised algorithms often yields quite complicated findings.Several global phenomena, including droughts, floods, erosion, migration, and climate change, may be better understood with a better grasp of land use and land cover at different scales. Any sustainable development efforts in any region must include the thorough and ongoing evaluation of LULC. Agricultural land monitoring, groundwater management, social knowledge management of natural resources, geomorphology, and climate change impacts on stream flow and water budgets are just a few of the many scientific fields that rely on detailed LC maps as an input. Land use and land cover (LULC) maps are valuable tools for watershed management and may reveal which areas are most suited for farming. When mapping land cover or monitoring changes over time, remote sensing imagery is usually the go-to choice. The demands for food production, energy generation, and water security are on the rise, and with that comes the need to develop new areas. As a result, the community of hydrologic and water resources models is eager to understand how changing land use affects the water budget. Massive data sets are required to generate low-resolution land cover maps across expansive areas. This calls for very large data storage capacity, powerful processing capabilities, and the ability to adapt to different methodologies. With the release of Google Earth Engine (GEE), these needs were met and the technology was made freely accessible to everyone. GEE is a platform in the cloud that facilitates simple and rapid processing of satellite images by integrating massive volumes of data from various remote sensing sources with a high-performance computing service.

2.LITERATURE SURVEY

2.1 Using a Compound Maximum A Posteriori Approach to Prevent Invalid Transitions in Land Cover Trajectory Classification

Computational Maximum a Posteriori (CMAP) is a land cover categorization technique. By combining our understanding of land cover dynamics with data from many time periods, CMAP is able to provide globally valid land cover trajectories with very few inputs. We used a post-classification comparison approach to examine CMAP in two case studies and compare its land cover trajectories to those of the more traditional Maximum Likelihood (ML) classifier. Classifying land cover using CMAP improves accuracy indices for each date and reduces classification noise. In tropical forests, optical data often outperforms SAR data for land cover classification.

2.2 CFNET: An Optical-SAR-Based Cross-Fusion Network for Joint Land Cover Classification

A cross-fusion network is constructed to categorize land cover using optical and SAR images concurrently. By maximizing the complementary features of the two sensors, a novel fully convolutional network model has the potential to improve the precision of land cover classification. Using a bidirectional cross-gate module will maximize the benefits of fusion. To further validate this model, construct a dataset with many land cover types. Use of a novel modular fully convolutional network model improves landcover classification accuracy. Geographically different contexts, such as heavily inhabited urban areas and less densely populated rural agricultural regions, will make classification more difficult.

2.3 Enhancements to 10 M Resolution Mapping Guangdong, China's Land Cover Classification MULTI-SOURCE REMOTE SENSING DATA USING THE GEAR 3 FROM GOOGLE

At a resolution of 10 m, a comprehensive framework is built to improve the mapping results of land cover classification. Land cover data that illustrates the complex interplay between surface change, human activities, and resource conservation is crucial for environmental preservation, social management, and sustainable development. New high-resolution land cover maps are being made possible with the use of remote sensing data, but how different models, data sources, and included characteristics affect the final classifications is still not entirely clear. Because of this, it can't be used for regional studies that need accurate land cover data. Random forest models outperformed support vector machines, minimum distance, and classification and regression trees. But FROM-GLC10 classified most croplands as grasslands, which is not accurate.

2.4 Regional and International Maps for the Semi-Supervised Categorization of Complex Oceanic SAR Data4 We use spatial data together with statistical features of the complex CP and QP SAR datasets to categorize land coverings. The CP data show similar features to complex quad polarimetric (QP) data from previous RADARSAT missions. A land cover classification system based on spatial information is developed in this study using the statistical aspects of the difficult CP and QP SAR data. Superpixels document the local spatial connection among pixels as their initial function. To elaborate on the global spatial interconnection of superpixels, a graph is constructed above them. Then, labels are propagated from the few detected superpixels to the unlabeled ones, resulting in an estimated land cover classification image with land cover type labels. This method greatly enhances the accuracy of classification. We are not making use of our global spatial dependency. Using the classifier in a QP situation is trickier than in a CP one.

2.5 WH-MAVS: A NOVEL DATASET AND DEEP LEARNING BENCHMARK FOR MULTIPLE LAND USE AND LAND COVER APPLICATIONS[5]

An interactive segmentation network is at the heart of our semi-automatic auxiliary approach for land cover categorization. It makes it easier to research techniques for scene change detection (SCD) and SC. You may use it for a lot of practical land use application jobs as well. This dataset covers almost an entire megacity and is the first of its kind to be publicly accessible, free, georeferenced, and annotated. The WH-MAVS, which covers the center region of Wuhan, China, was created using Google Earth images that had the same spatial resolution and uniform nonoverlapping patch size. Additionally, this model has several interactive modules to enhance the integration of characteristics across scales. Even when U-Net classifies each pixel individually, it's not easy to get a target-specific segmentation effect that's precise enough.

2.6 LAND-COVER CLASSIFICATION WITH HIGH-RESOLUTION REMOTE SENSING IMAGES USING INTERACTIVE SEGMENTATION[6]

Classification of land cover using a semi-automatic auxiliary technique. We provide an interactive segmentation approach that uses user-clicks on the object's inner and outside to direct the model during the segmentation job in the patches. Additionally, this model has several interactive modules to enhance the integration of characteristics across scales. Furthermore, we collect aerial and satellite images of Jiangsu Province, China, and divide it into five common land cover types to generate a large-scale sample library. This sample provided an in-depth analysis of current approaches that rely on deep learning. Despite U-Net's pixel-by-pixel classification capabilities, achieving a target-specific segmentation effect of adequate accuracy remains challenging.

2.7 MAFNET: A MULTIANGLE ATTENTION FUSION NETWORK FOR LAND COVER CLASSIFICATION[7]

For the purpose of land cover categorization, a multi-angle attention fusion network is suggested. An adaptive special-shaped window attention module is included into the deep layer of the network to extract deep semantic information and create the link between global information. The network employs a 50-layer residual network as a feature extraction network. There is also an interactive attention mechanism set up at various angles, and feature maps fused at multiple levels using the multiangle interactive attention fusion module. With this method, land types in remote sensing photos can be accurately classified, and it also has strong generalizability. On the other hand, when it comes to real-world applications, the interconnections between global data are disregarded, and the connection between distant pixels cannot be shown.

2.8 SEMI-MCNN: A SEMISUPERVISED MULTI-CNN ENSEMBLE LEARNING METHOD FOR URBAN LAND COVER CLASSIFICATION USING SUBMETER HRRS IMAGES[8]

The land cover categorization issue is suggested to be solved using a semi-supervised multiple CNN ensemble learning approach, namely semi-MCNN. To make use of massive volumes of unlabeled data, a semi-supervised learning approach was used, taking into account the absence of labelled samples. To make use of massive volumes of unlabeled data, a semi-supervised learning approach was used, taking into account the absence of labelled samples. In this technique, an automated sample selection method termed an ensembled instructor model dataset creation was utilized to choose samples and produce a dataset from vast volumes of unlabeled data automatically. An essential approach to addressing the error propagation issue was to pretrain on the chosen unlabeled data and then fine-tune using the labeled data to fix the errors. when contrasted with cutting-edge land cover classification models, the suggested semi-MCNN performed much better. Though these DL-based solutions have come a long way, they still have a ways to go.

2.9 HIGH-CONFIDENCE SAMPLE GENERATION TECHNOLOGY AND APPLICATION FOR GLOBAL LAND-COVER CLASSIFICATION[9]

A Method and Tool for Generating High-Confidence Samples for Use in Worldwide Land-Cover Classification. In order to back up the employment of deep learning technology for land-cover classification, the technique of creating sample data takes deep learning samples that are derived from high confidence classification results from a range of current high quality classification products. A high-confidence sample is one in which all three of the global land-cover categorization products—from FROM-GLC-2015, GLC_FCS30-2015, and GlobeLand30—share the same discriminating type. Compared to the three land-cover classification products, random forests trained with samples extracted using the sample extraction method outperform them in terms of classification accuracy. However, collecting in-situ samples for LC mapping over expansive regions using conventional reference collection methods is a formidable challenge.

2.10 NATIONAL SCALE LAND COVER CLASSIFICATION USING THE SEMIAUTOMATIC HIGH-QUALITY REFERENCE SAMPLE GENERATION (HRSG) METHOD AND AN ADAPTIVE SUPERVISED CLASSIFICATION SCHEME[10]

The HRSG Method—Semiautomatic High-Quality Reference Sample Generation! A random forest categorization approach that adapts to different climatic zones according to the Koppen-Geiger system. This decision was based on the idea that LC classification accuracy would suffer in large-scale research regions with many climatic zones because the spectral signature of a given LC class might change across these zones. The produced LC maps were tested against several test datasets to ensure a thorough evaluation. It was noted that HRSG can produce high-quality samples unaffected by the properties of scientific LC products, which is relevant to the suggested sample creation approach.

2.11 FULL PARAMETER TIME COMPLEXITY (FPTC): A METHOD TO EVALUATE THE RUNNING TIME OF MACHINE LEARNING CLASSIFIERS FOR LAND USE/LAND COVER CLASSIFICATION[11]

For the purpose of assessing how long it takes machine learning classifiers to process land use data, we have developed an FPTC. RF is a form of ensemble learning. The ensemble technique aims to enhance the classifier's performance by merging many underperforming learners. In RF, ensemble approaches like bagging, boosting, bootstrapping, and so on are used. When working with a robust and intricate model, bagging is the optimal ensemble approach. When faced with limited time and accessible remote sensing data, emergency managers will be able to swiftly choose algorithms in response to natural catastrophes thanks to the accurate prediction of the classification's running time. Lastly, include a batch normalization module that is completely integrated so that you may use all of the time dependency that has been extracted for classification purposes.

2.12 JAGAN: A FRAMEWORK FOR COMPLEX LAND COVER CLASSIFICATION USING GAOFEN-5 AHSI IMAGES[12]

Hyperspectral categorization system using a generative adversarial network and a joint channel-space attention mechanism (JAGAN). The most beneficial feature was obtained via the attention weight map, which was created by merging two joint channel-space attention models; this allowed us to retrain feature-based weights with a greater focus on key features. In addition, JAGAN used two classifiers: sigmoid to verify the authenticity of the input data samples generated by the generator, and softmax to derive the prediction type labels for the input samples. Using GF-5 AHSI pictures, JAGAN successfully improves the classification accuracy for small samples in complicated regional settings.

2.13 DYNAMIC MONITORING AND ANALYSIS OF LAND-USE AND LAND-COVER CHANGE USING LANDSAT MULTITEMPORAL DATA IN THE ZHOUSHAN ARCHIPELAGO, CHINA[13]

Using Landsat Multitemporal Data, we dynamically monitor and analyze changes in land use and land cover. Preprocessing, categorization, and analysis of pattern evolution are the major components of multitemporal remote sensing pictures used for the dynamic monitoring and analysis of LUCC. The pre-processing of remote sensing images entails three steps: cropping, atmospheric correction, and radiometric calibration. A physical radiance value is first obtained by converting the digital quantizing result using calibration parameters. After that, in order to fix the atmospheric correction and get rid of the radiance inaccuracy produced by atmospheric absorption and scattering, the "fast line-of-sight atmospheric analysis of spectral hypercubes" (FLAASH) model is used. The findings provide light on the characteristics of LUCC's geographical and temporal evolution.

2.14 FUSING MULTISEASONAL SENTINEL-2 IMAGERY FOR URBAN LAND COVER CLASSIFICATION WITH MULTIBRANCH RESIDUAL CONVOLUTIONAL NEURAL NETWORKS[14]

Using the latest state-of-the-art residual convolutional neural networks (ResNet), a straightforward and effective decision-level fusion method for predicting urban land cover from multiseasonal Sentinel-2 pictures has been developed. Extensively evaluated the method in a cross-validation way throughout a seven-city research region in central Europe. Quantitative and qualitative findings showed that the suggested fusion method outperformed several baseline methods, such as observation- and feature-level fusion. There are still some lingering misunderstandings among the courses, despite the generally positive outcomes.

2.15 LAND-COVER CLASSIFICATION WITH TIME-SERIES REMOTE SENSING IMAGES BY COMPLETE EXTRACTION OF MULTISCALE TIMING DEPENDENCE[15]

An Informer network-based land-cover categorization algorithm with great accuracy. Before we can get the characteristics of the local critical moments, we need to keep the series length short enough that the ProbSparse self-attention mechanism may take multiscale temporal dependencies into account. The second step is to exploit the land-cover time series to its maximum potential by calculating the correlation between each instant and all of the others, as well as the correlation between the significant moments. The method's performance was comparable to that of long short-term memory. However, the model will get more difficult to train as the number of parameters increases in relation to the number of network layers.

3.ANN ARCHITECTURE

Neural networks (NNs) and artificial neural networks (ANNs) are computer systems that mimic the structure and function of the brain's natural neural networks. Through the use of a network of linked units or nodes called artificial neurons, an ANN is able to simulate the activity of actual brain neurons. Like the synapses in a real brain, each connection may potentially transmit a signal to another cell. One of the main functions of an artificial neuron is to receive impulses, process them, and then transmit those signals to other neurons.The "signal" at a connection is a real number, and the output of each neuron is computed as a non-linear function of the total of its inputs. These connections are called edges. As learning continues, the weights of neurons and edges often alter. You may change the signal strength at a connection by changing the weight. To activate, a neuron must first determine if the sum of all signals is strong enough. Layers of neurons are the standard arrangement. It is possible for several levels to alter their inputs in different ways. Along their journey from the input to the output layers, signals may make many traversals of the layers. Terminated based on predetermined criteria.

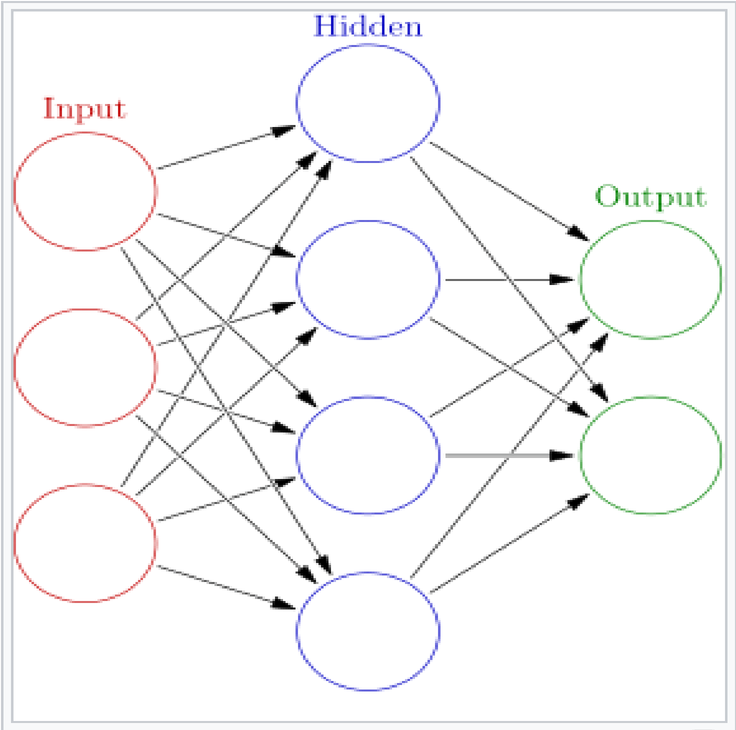

Figure 3.1: ANN Architecture

Supervised learning describes this process. Without being explicitly coded with task-specific rules, these systems "learn" to execute tasks by analyzing instances. Data models An early motivation for ANNs was a desire to use the human brain's structure to solve problems that traditional algorithms struggled with. They quickly stopped trying to be faithful to their biological ancestors and instead focused on enhancing empirical outcomes. A network of connections between neurons enables the transmission of information from one neuron to another. Using weights, the network creates a directed graph.

TYPICAL STRUCTURE OF ANN MODEL

In a typical architecture, artificial neural networks (ANNs) use a stack of processing components called neurons to perform various tasks. Typically, these neurons are organized in a three-layer structure: an input layer, an output layer, and a hidden layer or layers nestled between them. Neurons link the input and output layers to the outside world. The model of an ANN consists of numerous neurons that are either completely or partly connected to each other via connection connections that have varying weights. An ANN's model is always tweaking the connection weights to make input/output behavior conform to the outside world. As a result, the true connection between input and output data forms the basis of an ANN's primary goal.

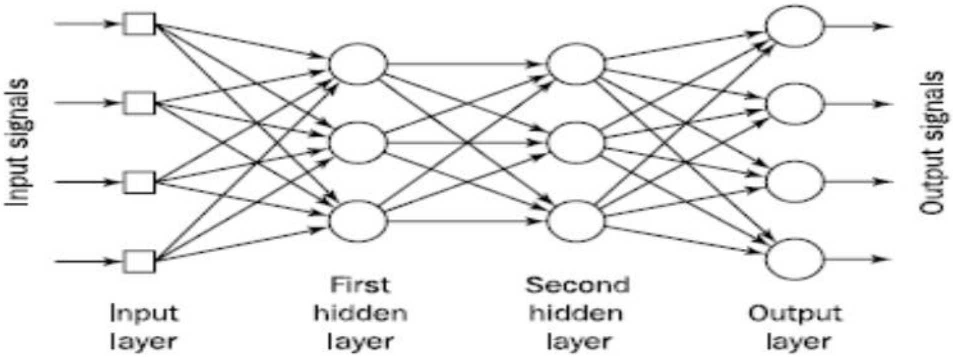

Figure 3.2: Typical structure of ANNs model with two hidden layer

The building blocks of an ANN are a set of virtual neurons. The connections between neurons, which mimic the actual axon-synapse-dendrite connections, are like a network of nodes. A node's impact on another is proportional to the weight of its connection.

The first and foremost layer of an artificial neural network (ANN) is the input layer. This is the layer that receives all of the data that the network needs to function, including text, numbers, audio files, picture pixels, and more.

The second layer is the hidden layer, and it is important to the ANN model. Like a perceptron, there may be only one hidden layer, or there may be several. These hidden layers perform a number of mathematical operations on the input data in order to detect patterns.

Third, the output layer is where we get the outcome we were after, thanks to the careful calculations done in the intermediate layer.

Artificial neural networks use several mathematical processing steps. There are a lot of units stacked on top of each other. A neuron is a unique unit. The input units of the input layer receive various environmental inputs. After that, the data makes its way to the hidden unit, which changes its format so that the output units may utilize it.

4.IMPLEMENTATION OF ARTIFICIAL NEURAL NETWORK

4.1 IMAGE PROCESSING WITH MATLAB

Learn how to use the Image Processing Toolbox in MATLAB with the help of this tutorial. Not all of MATLAB's functions are covered in this course. Going to Help\MATLAB Help in the MATLAB window is a great way to get any questions that this lesson doesn't address addressed. Modified versions of MATLAB's help examples make up a large portion of this course. Image processing programs benefit greatly from the assistance tool's abundance of filter examples.

```
clc
clear
close all
%Image Acquisition
[aa bb]=uigetfile('.jpg');
a = imread([bb aa]);
Data = a;
figure,imshow(Data)
[row,col,num_feature] = size(Data);
load Label
num_class = size(unique(Label),1);
clear a;
%Assign Parameters
train_num_array = [30, 150, 150, 100, 150, 150, 20];
num_PC = 3;
Layernum = 5;
```

```
w=21;
win_inter = (w-1)/2;
epsilon = 0.01;
K=20;
```

4.2 EXTRACT FEATURES

When getting data ready for machine learning jobs, including classification using ANNs and other similar approaches, feature extraction is an essential first step. Data preparation is the process of changing the shape of raw data so that it may be better used for analysis and training models. Reducing the data's dimensionality while capturing essential information and trends is the aim.

```
%Extract Features
StackFeature= cell(Layernum,1);
for l=1:Layernum
    randidx = randperm(row*col);
    StackFeature{l}.centroids = zeros(w*w*num_PC,K);
    disp(['Extracting the features of the ',num2str(l),'th layer...']);
    if l==1
      XPCA = PCANorm(reshape(double(Data), double(row * col), double(num_feature)),double(num_PC));
       XPCAvector = XPCA;
       minZ = min(XPCAvector);

maxZ = max(XPCAvector);
XPCAvector = bsxfun(@minus, XPCAvector, minZ);
XPCAvector = bsxfun(@rdivide, XPCAvector, maxZ-minZ);
XPCA_cov = cov(XPCA);
[U S V] = svd(XPCA_cov);
whiten_matrix = U * diag(sqrt(1./(diag(S) + epsilon))) * U';
XPCA = XPCA * whiten_matrix;
XPCA = bsxfun(@rdivide,bsxfun(@minus,XPCA,mean(XPCA,1)),std(XPCA,0,1)+epsilon);
XPCA = reshape(XPCA,row,col,num_PC);
X_extension = MirrowCut(XPCA,win_inter);

for i=1:K
   index_col = ceil(randidx(i)/row);
   index_row = randidx(i) - (index_col-1) * row;
```

```
        tem = X_extension(index_row-win_inter+win_inter:index_row+win_inter+win_inter,index_col-win_inter+win_inter:index_col+win_inter+win_inter,:);
        StackFeature{l}.centroids(:,i) = tem(:);
    end
    StackFeature{l}.feature = extract_features(X_extension,StackFeature{l}.centroids);
    XPCAvector = PCANorm([StackFeature{l}.feature],num_PC);
    minZ = min(XPCAvector);
    maxZ = max(XPCAvector);
    XPCAvector = bsxfun(@minus, XPCAvector, minZ);
    XPCAvector = bsxfun(@rdivide, XPCAvector, maxZ-minZ);
    clear StackFeature{l}.centroids;
else
  XPCA = PCANorm(StackFeature{l-1}.feature,num_PC);
  XPCA_cov = cov(XPCA);
  [U S V] = svd(XPCA_cov);
  whiten_matrix = U * diag(sqrt(1./(diag(S) + epsilon))) * U';
  XPCA = XPCA * whiten_matrix;
  XPCA = bsxfun(@rdivide,bsxfun(@minus,XPCA,mean(XPCA,1)),std(XPCA,0,1)+epsilon);
  XPCA = reshape(XPCA,row,col,num_PC);
  X_extension = MirrowCut(XPCA,win_inter);
  for i=1:K
     index_col = ceil(randidx(i)/row);
     index_row = randidx(i) - (index_col-1) * row;
        tem = X_extension(index_row-win_inter+win_inter:index_row+win_inter+win_inter,index_col-win_inter+win_inter:index_col+win_inter+win_inter,:);
        StackFeature{l}.centroids(:,i) = tem(:);
    end
    StackFeature{l}.feature = extract_features(X_extension,StackFeature{l}.centroids);
    XPCAvector = PCANorm(StackFeature{l}.feature,num_PC);
    minZ = min(XPCAvector);
    maxZ = max(XPCAvector);
```

```
            XPCAvector = bsxfun(@minus, XPCAvector, minZ);
            XPCAvector = bsxfun(@rdivide, XPCAvector, maxZ-minZ);
            clear StackFeature{l}.centroids;
        end
        clear X_extension;
    end
    %Generate Label
    for layernum=Layernum
        X_joint = [];
        for i=1:layernum
  X_joint = [X_joint StackFeature{i}.feature];
end
X_joint = [X_joint reshape(Data,row*col,num_feature)];
X_joint=double(X_joint);
X_joint_mean = mean(X_joint);
X_joint_std = std(X_joint)+1;
X_joint = bsxfun(@rdivide, bsxfun(@minus, X_joint, X_joint_mean), X_joint_std);
randomLabel = cell(num_class,1);
for i=1:num_class
  index = find(Label==i);
  randomLabel{i}.array = randperm(size(index,1));
end
%Split Training adn Test Data
  X_train = [];
  X_test = [];
  y_train = [];
  y_test = [];
  for i=1:num_class
    index = find(Label==i);
    randomX = randomLabel{i,1}.array;
    train_num = train_num_array(i);
    X_train = [X_train;X_joint(index(randomX(1:train_num)),:)];
    y_train = [y_train;Label(index(randomX(1:train_num)),1)];
  X_test = [X_test;X_joint(index(randomX(train_num+1:end)),:)];
```

```
    y_test = [y_test;Label(index(randomX(train_num+1:end)),1)];
  end
```

4.3 CLASSIFICATION USING ANN

ANNs are layered networks of linked nodes that mimic the way the human brain works computationally. When it comes to classification, ANNs really shine at discovering intricate data patterns and correlations, which allows them to provide reliable predictions or sort inputs into predetermined categories. %Intelligent object recognition for classification.

```
labels=ANN_Classify(X_train,y_train,y_test, X_test,Label, X_joint);

  X_result = drawresult(round(labels)',row,col, 2);

  figure,imshow(X_result);

  imwrite(X_result,strcat('Result',num2str(layernum),'.png'),'png');

end
```

After the characteristics of the data are received by an input layer, the input is transformed by one or more hidden layers using weighted connections. During training, the network learns the underlying patterns by adjusting these connections using a dataset with known results. The ultimate outcome of the categorization process is generated by the output layer.

4.4 CLASSIFICATION OF LAND COVER AREAINTRODUCTION

The land is the characterized and measurable surface of the planet, which is also a hub for environmental problems. Land objects and land essential components are its defining features. It defined land resources more narrowly and broadly in recent times. A land resource was defined broadly to include several elements, including climate, water, soil, landforms, flora, and fauna, as well as all socio-economic systems that interact with land uses such as agriculture and forestry within a certain system boundary. Understanding land use and land cover is crucial for many reasons, including but not limited to: modeling water and carbon cycles, ecosystem dynamics, climate change, food and energy security for a rising population, and the development, loss, and degradation of land. Assessing the environmental implications of land use and its effects on the supply of ecosystem services, such as eutrophication, pollution, biodiversity loss, and climate change, is an equalizing tax assessment in several states.Changes in land cover, as a result of land management decisions, affect between seventy-one and seventy-six percent of the world's arable land. Environmental change detection analysis (e.g., where the change happens, what kind of change it is, and how it is happening) comprehending and evaluating the effects of landscape changes on the air, climate, and sea level taking into account changes in land dynamics, the effects on habitats and biodiversity, and the use of monitoring tools in managing natural resources, landscapes, and policy.

Along with sustainable development aims to enhance national capacity and quantify land deterioration, the United Nations Convention to prevent desertification seeks land degradation neutrality (LDN). Insights into LULC have been provided in a number of literature reviews. The review studies conducted since the year 2000 have been summarized in this report. The terms "Land-use" and "Land-cover" have been defined differently in the many academic works published over the years. To better explain meaning, they have further divided out each region independently based on the unique topic of interest. Land-use refers to the function of the land, such as agricultural or recreational usage, whereas land-cover refers to the overall state of the land.Alternatively, land-cover describes certain features and patterns of landscapes. Many new methods for classifying land use and land cover (LULC) have emerged in recent years, thanks to developments in remote sensing and high-resolution image processing. There is a lot of data fluctuation at high resolutions, which is a worry for LULC classification. If unseen instances were obtained at various times or places, the benchmark datasets used to test and evaluate classification algorithms may not capture enough variability to generalize.Patterns of land use and cover undergo dramatic shifts as a result of development pressure. Efforts are being made by public administrators to track the pace of urbanization and evaluate its effects via the efficient detection, monitoring, and analysis of changes in land use. The most effective approach for giving such information is remote sensing analysis, which uses data from multi-temporal satellite sensors with their regular and synoptic coverage. Finding out what changed between two or more dates is what change detection is all about. Variations in the surface's spectral response provide the basis of remote sensing-based change detection.

4.5 PROPOSED WORK

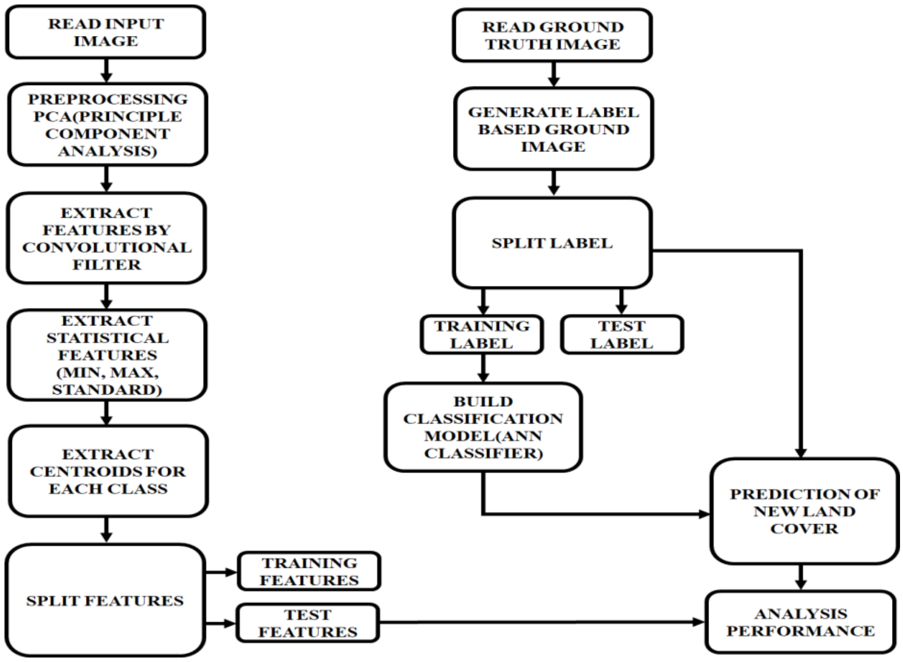

Figure 4.5 : Block Diagram of Proposed System

First, PCA (Principle Component Analysis) was used to preprocess the input picture. One application for it is to make things simpler. Utilizing the preprocessing procedure, undesired characteristics are eliminated and necessary features are extracted from the input picture. Additionally, it simplifies things. Feature extraction is the next step after preprocessing the photos. In order to extract features, a convolutional filter is used. From this feature extraction approach, statistical characteristics such as minimum, maximum, and standard are extracted using it. In order to train and evaluate these features, the extracted features are transferred. Take a look at the ground truth picture afterwards.Images of houses, water, and agricultural landscapes are included in this ground truth picture. Next, the photos are split into two parts: training and testing, so that a categorization model may be built. An Artificial Neural Network classifier analyzes the model and assigns a classification. The last step in feature testing is to apply the training label from the ground truth picture to the input image. Accurate prediction of land cover areas is the end result of effectively classifying the received picture using an ANN classifier. Software for simulations, MATLAB, is used in the execution of this project.

5.METHODOLOGY OF ANN ALGORITHM

5.1 DATA PREPARATION

Data Collection

Collect digital elevation models (DEMs), climatic data, land use/land cover maps, and supplementary data such as hyperspectral or multispectral satellite photography. The research area's features may be gleaned from these datasets.

Preprocessing

Remove noise, calibrate the data, and apply radiometric and atmospheric adjustments to the cleaned and pre-processed satellite images. At this point, we know the data is prepared for analysis.

5.2 FEATURE EXTRACTION

Retrieve useful information from the supplementary data and satellite images. Land cover characteristics may be captured by these features, which can include spectral bands, texture, plant indices, terrain properties, and other such derived metrics.

Training Data Preparation

In order to train your model, you need to compile a labeled training dataset that includes the study region's land cover classifications. In order to train the classification model, this dataset is used.

Model Training

Use the training dataset to train a classification algorithm like CNN, Random Forest, or Support Vector Machines (SVM). Patterns and correlations between the land cover classifications and extracted characteristics are learned by the algorithm.

Min-Max Algorithm

In games with n players, often with 2 players, the minimax algorithm is used to find the next move via a recursive process. In this game, every position and situation matters. With the use of a position assessment function, we can determine the probability of a player reaching that location. The player then chooses a move that maximizes the minimum value of the situation, taking into account the opponent's possible next move. Positions are typically assigned finite values as estimates of the degree of belief that they will lead to a win for one player or another. This is typically only achievable at the very end of complex games like chess or go, since looking forward to the completion of the game is computationally impractical except towards the end. One example is the chess computer Deep Blue, which used a heuristic assessment function and looked twelve moves ahead to defeat the reigning world champion, Garry Kasparov. You may compare the algorithm's actions to exploring a gaming tree. In a tree structure, the effective branching factor is the mean of the number of children at each node, or the mean of the number of permissible movements at each location. Even if it's less than exponential when considering forced movements or repeated locations, the number of nodes that need to be searched often grows exponentially with the number of plies. Therefore, the number of nodes that need to be examined for a game's analysis is roughly the branching factor increased to the power of the number of plies.

5.3 LAND CLASSIFICATION

An ANN is a kind of machine learning that has the ability to address a wide range of practical issues that are challenging to address using conventional programming techniques. The land cover categorization task may be accomplished using a multi-layer feed forward network in various network topologies. A network that has a single hidden layer.... Reference datasets created via GPS field surveys and high-resolution drone photos using the back-propagation technique are used to train a multi-layer feed-forward network. An technique for learning known as back-propagation is really just a variant of gradient descent. During each iteration, the backpropagation algorithm iteratively calculates the error and adjusts the network weights to reduce the discrepancy between the network outputs and the actual outputs. After training, the network's weights remain constant, allowing it to categorize inputs into different outputs. Scientists now have the most accurate image of Earth's ecosystem distribution and land use patterns ever created thanks to land cover maps. In order to better manage natural resources and accomplish other research and worldwide monitoring goals, scientists and policymakers rely on accurate land cover maps. Boston University in Boston, Massachusetts, created the maps of the land cover. Using information gathered by NASA's Terra satellite's Moderate Resolution Imaging Spector (MODIS) radiometer. The digital library of Earth photos acquired between November 2000 and October 2001 forms the basis of the maps.The maps, which have a spatial resolution of 1 kilometer (.6 mile), are a huge improvement over earlier maps in terms of clarity and detail, according to Mark Fried, one of the researchers working on the project. With each revolution of the satellite, the MODIS sensor's perspective of a specific spot on Earth changes. The integration of these many perspectives into a unified picture is a significant improvement above previous maps. With the advancements in remote sensing technology, MODIS is able to gather data of better quality than its predecessors. The team was able to automate a large portion of the categorization because to advancements in data processing, cutting the time it took to create maps from months or even years to just under one week. Eleven kinds of natural vegetation, including savannahs, wetlands, deciduous and evergreen forests, and more, are included in each of the seventeen land cover categories produced by MODIS.The maps also show places that are used for agriculture as well as areas with little or no vegetation, such as deserts, cities, and areas covered in perpetual snow. Forest resource management, enhanced water and energy cycle estimations, climate modeling, and the global carbon exchange among land, life, and the atmosphere are all significant applications. Modeling the carbon cycle is associated with GHG emissions from human activities and their removal by GHG sinks, such as plants that fix atmospheric carbon dioxide via photosynthesis. The United States is one of many countries that compile these inventories every year to better understand and foretell the effects of climate change. Land cover maps in combination with other weekly measurements from MODIS. "For every square kilometer, the MODIS land cover product tells us exactly what kinds of vegetation are present, such as mature trees, clear cutting, fresh fire scars, and agricultural crops. We can now estimate the net change in vegetation cover each year. As a result, we are getting closer to a complete picture of the world's carbon sinks and sources.

6.RESULT AND WORKING

6.1 MATLABWINDOW

The core of MATLAB is a new language that has to be learned in order to properly use its capability. Aptly grasps the fundamentals of MATLAB and rapidly progresses to expertise. Paid with innovative, highly productive computer capability that will revolutionize the workplace. Programming in a scalar, non-interactive language like C or FORTRAN takes a very long time. This enables us to solve many technical computing issues, particularly those using matrix and vector formulations, much faster. A matrix laboratory is what the acronym MATLAB stands for. The initial intention of MATLAB was to make the matrix programs created by the LINPACK and EISPACK projects more accessible.

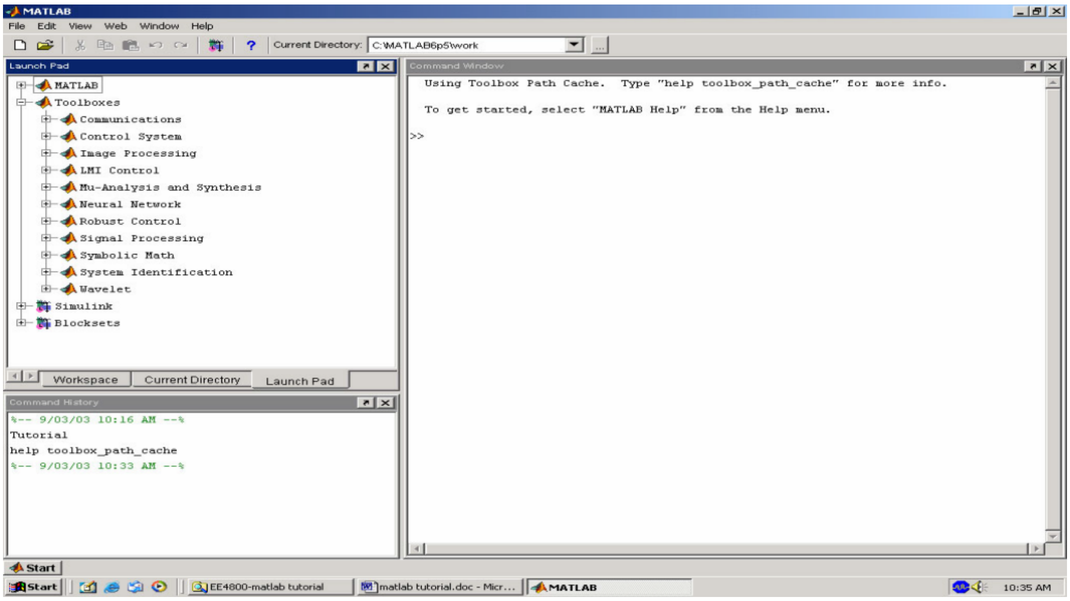

Figure 6.1: MATLAB Window

On the right side of the screen, you can see the Command Window. You may use this window to input instructions into MATLAB and see how they're executed. On the bottom left of the screen, you'll see the Command History window, which shows all the commands that have been put into the Command Window lately. One window, accessible by tabs in the top left corner of the screen, may hold up to three separate windows. The user is informed of the presently used M-files in the first window, the Current Directory. The Workspace pane, the second window, shows the size and use of all variables at the moment. The Launch Pad window, the third window, is crucial since it provides quick access to all of the various toolboxes; Image Processing being one of them.
To get a new prompt, write code after the >> prompt and hit return. Be sure to include a semicolon after each line of code if you do not want it to be shown in the MATLAB Command Window thereafter. The cod will be printed in the command window just under the cursor if a semicolon is not present.

6.2 SIMULATION OUTPUT

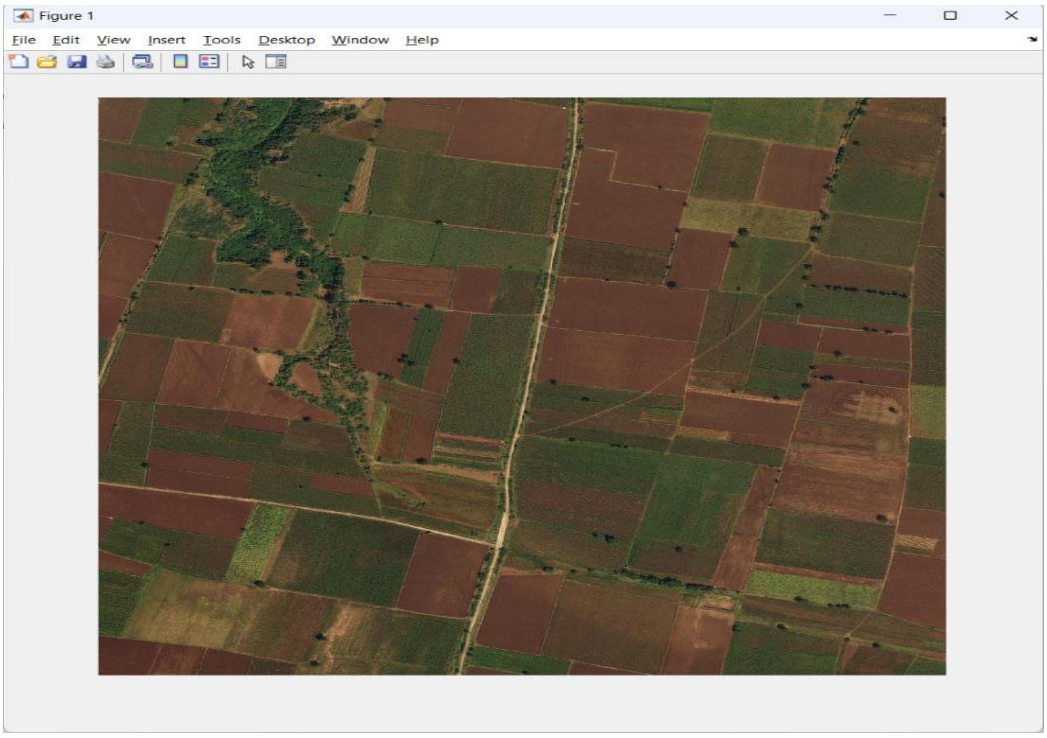

Figure 6.2: Input land cover image

Figure 6.2 shows that input land cover image. Land cover means what covers the surface of the earth and land use describes how the land is used.

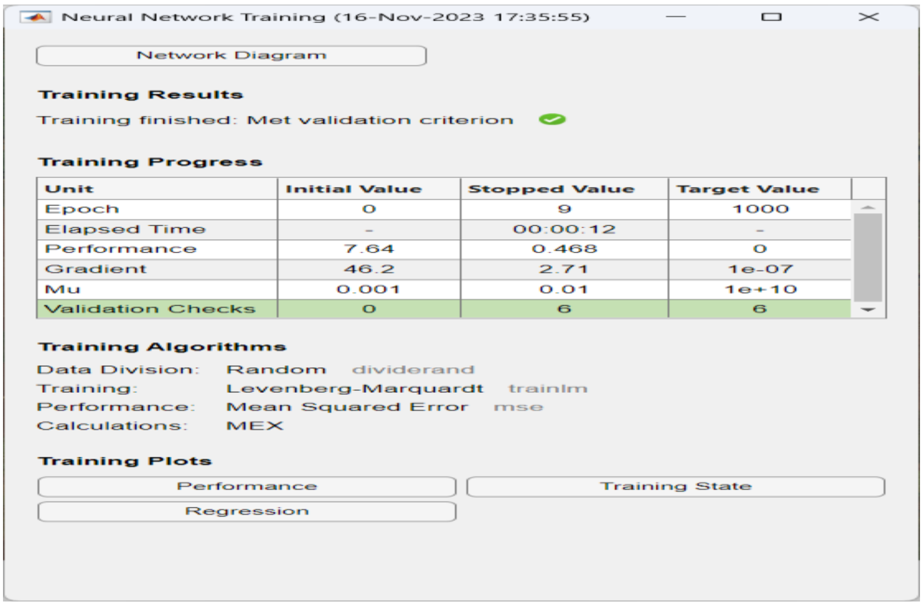

Figure 6.3: Training Process

Figure 6.3 represents that training process image. The ground truth image includes examples of images of buildings, water, and agricultural landscapes.

To create a classification model, these images are then divided into training and testing processes.

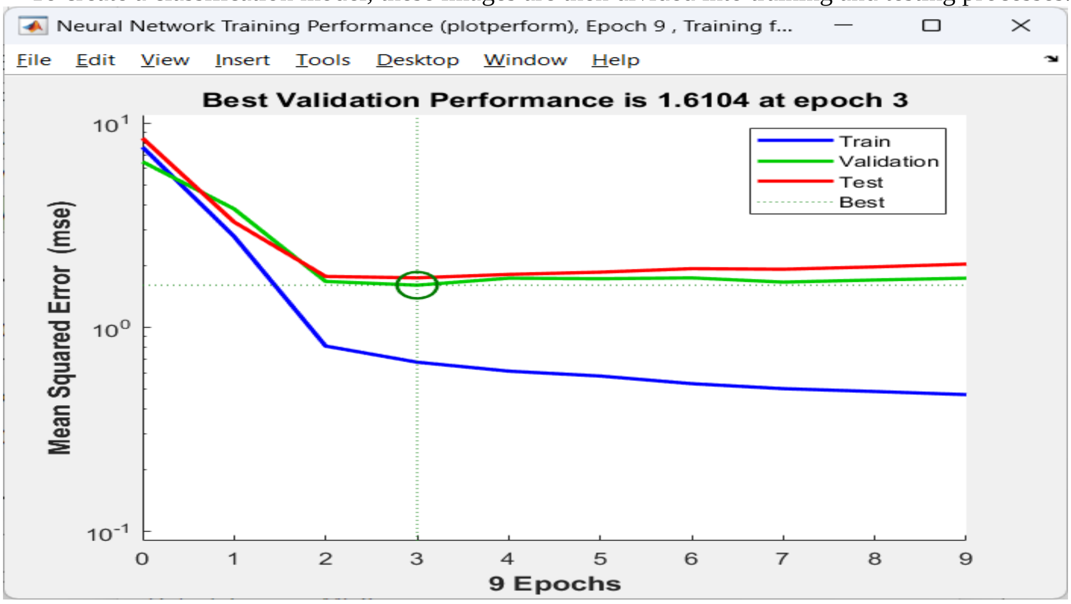

Figure 6.4: Validation Process

Figure 6.4 represents that best validation performance. These performance shows that train, test, best and validation level.

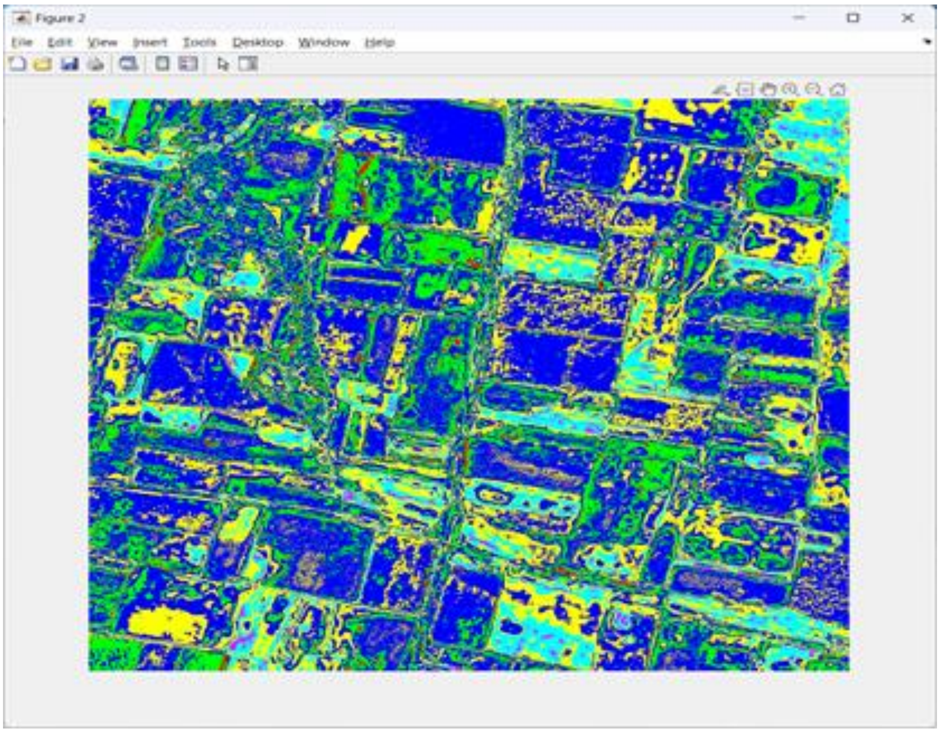

Figure 6.5: Final Output image

In figure 6.5, you can see the final product picture. Accurate prediction of land cover areas is the end result of effectively classifying the received picture using an ANN classifier.

CONCLUSION AND FUTURE WORK

Implementation of a land cover categorization system using an ANN classifier is the focus of this research. At first, the input picture was preprocessed using PCA, which stands for Principle Component Analysis. It was used to reduce dimensionality. By applying this preprocessing procedure to the input picture, unnecessary features are removed and useful ones are extracted. Feature extraction is done on the pictures after preprocessing. The use of a convolutional filter was made for the purpose of feature extraction. The feature extraction method allows for the extraction of statistical characteristics such as minimum, maximum, and standard. The retrieved features are used for training and testing these features. Agricultural landscapes, houses, and lakes are all examples of what is known as a ground-truth picture. The next step in creating a classification model is to divide these images into training and testing sets. The model was sorted using a classifier that is based on an artificial neural network. Finally, the input picture's characteristics are tested using the training label from the ground truth image. The recovered picture was successfully categorized using an ANN classifier, and the result is a reliable estimate of the land cover areas. In order to complete this assignment, the MATLAB program is used. In order to improve accuracy, our study may be developed in the future to use the Hybrid algorithm approach. In order to enhance the classification accuracy even more, we will investigate a more effective strategy for the Hybrid algorithms.

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