

PROFESSIONAL TRAINING REPORT

at

Sathyabama Institute of Science and Technology (Deemed to be University)

Submitted in partial fulfillment of the requirements for the award of
Bachelor of Engineering Degree in Computer Science and Engineering

By

KALATHUR RAKESH
(Reg. No.38110224)

TUMALLAPALLI GANESH
(Reg. No.38110604)



DEPARTMENT OF COMPUTER SCIENCE AND ENGINEERING

SCHOOL OF COMPUTING

SATHYABAMA

INSTITUTE OF SCIENCE AND TECHNOLOGY
(DEEMED TO BE UNIVERSITY)

Accredited with Grade "A" by NAAC

JEPPIAAR NAGAR, RAJIV GANDHI SALAI, CHENNAI - 600 119

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SATHYABAMA

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DEPARTMENT OF COMPUTER SCIENCE AND ENGINEERING

BONAFIDE CERTIFICATE

This is to certify that this Project Report is the bonafide work of **KALATHUR RAKESH(38110224)**, **TUMMALAPALLI GANESH(38110604)** who carried out the project entitled "**AGRICULTURAL LAND CLASSIFICATION**" under my supervision from November 2021 to March 2022.

Internal Guide

DR.A.VijiAmutha Mary M.Tech., PhD

Head of the Department

Dr.s VIGNESHWARI, M.E.,PhD.,

Dr.L.Lakshmanan,M.E.,PhD.,

Submitted for Viva voce Examination held on _____

InternalExaminer

ExternalExaminer

DECLARATION

I **KALATHUR RAKESH(38110224), TUMMALAPALLI GANESH(38110604)** hereby declare that the Project Report entitled **AGRICULTURAL LAND CLASSIFICATION** done by me under the guidance of **DR.A.VIJI AMUTHA MARY,M.Tech.,PhD** is submitted in partial fulfillment of the requirements for the award of Bachelor of Engineering degree in Sathyabama Institute of **Science and Technology.**

DATE : 9-04-2022

PLACE : Chennai

k.rakesh
SIGNATURE OF THE CANDIDATE

ACKNOWLEDGEMENT

I am pleased to acknowledge my sincere thanks to Board of Management of SATHYABAMA for their kind encouragement in doing this project and for completing it successfully. I am grateful to them.

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TRAINING CERTIFICATE



ABSTRACT

Over the last few years, the research into agriculture has gained momentum, showing signs of rapid growth. The latest to appear on the scene is bringing convenience in how agriculture can be done by employing various computational technologies. To implement this project we have used LAND satellite images which contains images of FOREST, AGRICULTURE LAND, URBAN AREA and Range LAND. However, only a few studies have compared the performances of these classifiers with different training sample sizes for the same remote sensing images, particularly the Sentinel-2 Multispectral Imager (MSI). In this study, we examined and compared the performances of the RF, kNN, and SVM classifiers for land use/cover classification using Sentinel-2 image data. An area of 30×30 km² within the Red River Delta of Vietnam with six land use/cover types was classified using 14 different training sample sizes, including balanced and imbalanced, from 50 to over 1250 pixels/class. All classification results showed a high overall accuracy (OA) ranging from 90% to 95%. Among the three classifiers and 14 sub-datasets, SVM produced the highest OA with the least sensitivity to the training sample sizes, followed consecutively by RNN and kNN. In relation to the sample size, all three classifiers showed a similar and high OA when the training sample size was large enough, i.e., greater than 750 pixels/class or representing an area of approximately 0.25% of the total study area. The high accuracy was achieved with both imbalanced and balanced datasets.

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1. INTRODUCTION

we studied the potential of high spatial and temporal resolution Sentinel-1 remote sensing data for different agriculture land cover mapping applications and assessed the new deep learning techniques. We proposed to use two deep RNN approaches to explicitly consider the temporal Correlation of Sentinel-1 data, which were applied on the Camargue region.

We demonstrated that even with the classical approaches (*KNN*, *RF* and *SVM*), good classification performance could be achieved with Sentinel-1 SAR image time series. We experimentally demonstrated that the use of recurrent neural networks to deal with SAR Sentinel-1 time series data yields a consistent improvement in agricultural classes as compared with classical machine learning approaches. The experiments highlight the appropriateness of a specific class of deep learning models (RNNs) which explicitly consider the temporal correlation of the data in order to discriminate among agricultural classes of land cover, typically characterized by similar but complex temporal behaviors.

1.1 MOTIVATION

Both the theory and practice tell us that although land cover (LC) and land use (LU) are closely related, thus many proposed land use classifications are actually mixing land cover and land use where natural and semi-natural vegetation are described in terms of land cover, agricultural and urban areas in terms of land use, and, in particular, the definition of forests is a combination on land cover and land use. Still it is necessary to develop LU classification separately from LC classification due to the differences between these two and the importance of LU statistics for related policy analysis and decision making.

1.2 PROBLEM DEFINITION

We demonstrated that even with the classical approaches (*KNN*, *RF* and *SVM*), good classification performance could be achieved with Sentinel-1 SAR image time series.

We experimentally demonstrated that the use of recurrent neural networks to deal with

SAR Sentinel-1 time series data yields a consistent improvement in agricultural classes as compared with classical machine learning approaches. The experiments highlight the appropriateness of a specific class of deep learning models (RNNs) which explicitly consider the temporal correlation of the data in order to discriminate among agricultural classes of land cover, typically characterized by similar but complex temporal behaviors.

1.3 OBJECTIVE OF PROJECT

In this paper, we studied the potential of high spatial and temporal resolution Sentinel-1 remote sensing data for different agriculture land cover mapping applications and assessed the new deep learning techniques. We proposed to use two deep RNN approaches to explicitly consider the temporal Correlation of Sentinel-1 data, which were applied on the Camargue region.

2. AIM AND SCOPE OF THE PRESENT INVESTIGATION

2.1 Scope:

The proposed LU classification reflects the close relationship and integrative nature of the work on LU databases/datasets by various Departments and Divisions at FAO as discussed in the previous section. It is a consolidated summary of the LU classifications used in WCA2010 and the questionnaires for the dataset “Land” under “Resources”, which are the higher level and more aggregated classes for agricultural land use; the LU classifications used in AGROMAPS and the questionnaires for the dataset “Area Harvested” under “Production,” which in fact are the crop classification as in ICC (discussion on the similarity and difference between the product classification and the crop classification can be found in the document of WCA2010); and the LU classification used in FRA2010, which is those classes for forest land use.

2.2 LIMITATIONS OF PROJECT

only a few studies have compared the performances of these classifiers with different training sample sizes for the same remote sensing images, particularly the Sentinel-2 Multispectral Imager (MSI).

2. 3 LITERATURE SURVEY

2.3.1 Rice crop mapping and monitoring using ERS-1 data based on experiment and modeling results

Authors: T. Le Toan, F. Ribbes, Li-Fang Wang

Abstract: Information on rice growing areas and on rice growth conditions are necessary in rice monitoring programs and in studies on the emission of methane from flooded rice fields. The objective of this paper is to assess the use of ERS-1 SAR data to map rice growing areas and to retrieve rice parameters. The approach

includes first a synthesis of experimental results at two different test areas followed by a development of a theoretical model to interpret the observations. The synthesis of experimental data at two test areas, a tropical site with short cycle rice (Semarang, Indonesia) and a temperate site with long cycle rice (Akita, Japan), has shown that flooded rice fields have characteristic increasing temporal radar responses. When the radar backscattering coefficients are expressed as a function of the rice biomass, the effect of cultural practices and climate (long cycle versus short cycle) is reduced. The observations have been interpreted by a theoretical model, which relies on a realistic description of rice plants and which considers the backscattering enhancement and clustering effects of the scatterers. Good agreement has been obtained between experimental data and theoretical results. The strong temporal variation of the radar response of rice fields is due to the wave-vegetation-water interaction, which increases from the transplanting stage to reproductive stage. By simulations using the validated model, the length of the rice cycle or the rice varieties have shown minor effects on the temporal curve. A method for rice fields mapping has been developed, based on the temporal variation of the radar response between two acquisition dates. Inversion of SAR images into plant height and plant biomass has also been performed. The results appear promising for the use of ERS-1 and RADARSAT data for rice monitoring.

2.3.2 Sentinel-2: ESA's Optical High-Resolution Mission for GMES Operational Services

Authors: Drusch, M.; Bello, U.D.; Carlier, S.; Colin, O.; Fernandez, V.; Gascon, F.; Hoersch, B.; Isola, C.; Laberinti, P.; Martimort, P.; et al.

Abstract: Global Monitoring for Environment and Security (GMES) is a joint initiative of the European Commission (EC) and the European Space Agency (ESA), designed to establish a European capacity for the provision and use of operational monitoring information for environment and security applications. ESA's role in GMES is to provide the definition and the development of the space- and ground-related system elements. GMES Sentinel-2 mission provides continuity to

services relying on multi-spectral high-resolution optical observations over global terrestrial surfaces. The key mission objectives for Sentinel-2 are: (1) To provide systematic global acquisitions of high-resolution multi-spectral imagery with a high revisit frequency, (2) to provide enhanced continuity of multi-spectral imagery provided by the SPOT (Satellite Pour l'Observation de la Terre) series of satellites, and (3) to provide observations for the next generation of operational products such as land-cover maps, land change detection maps, and geophysical variables. Consequently, Sentinel-2 will directly contribute to the Land Monitoring, Emergency Response, and Security services. The corresponding user requirements have driven the design toward a dependable multi-spectral Earth-observation system featuring the Multi Spectral Instrument (MSI) with 13 spectral bands spanning from the visible and the near infrared to the short wave infrared. The spatial resolution varies from 10 m to 60 m depending on the spectral band with a 290 km field of view. This unique combination of high spatial resolution, wide field of view and spectral coverage will represent a major step forward compared to current multi-spectral missions. The mission foresees a series of satellites, each having a 7.25-year lifetime over a 15-year period starting with the launch of Sentinel-2A foreseen in 2013. During full operations two identical satellites will be maintained in the same orbit with a phase delay of 180° providing a revisit time of five days at the equator. This paper provides an overview of the GMES Sentinel-2 mission including a technical system concept overview, image quality, Level 1 data processing and operational applications.

2.3.3 A survey of image classification methods and techniques for improving classification performance

Authors: Lu, D.; Weng, Q. A

Abstract: Image classification is a complex process that may be affected by many factors. This paper examines current practices, problems, and prospects of image classification. The emphasis is placed on the summarization of major advanced classification approaches and the techniques used for improving classification accuracy. In addition, some important issues affecting classification performance are discussed. This literature review suggests that designing a suitable image-processing procedure is a prerequisite for a successful classification of remotely sensed data

into a thematic map. Effective use of multiple features of remotely sensed data and the selection of a suitable classification method are especially significant for improving classification accuracy. Non-parametric classifiers such as neural network, decision tree classifier, and knowledge-based classification have increasingly become important approaches for multisource data classification. Integration of remote sensing, geographical information systems (GIS), and expert system emerges as a new research frontier. More research, however, is needed to identify and reduce uncertainties in the image-processing chain to improve classification accuracy.

2.3.4 On farm assessment of rice yield variability and productivity gaps between organic and conventional cropping systems under Mediterranean climate

Authors: Delmotte, S.; Tuttonell, P.; Mouret, J.C.; Hammond, R.; Lopez-Ridaura, S

Abstract: Organic rice production is characterized by high yield variability and substantial productivity gaps with respect to conventional systems. Variability may be accentuated in areas of erratic climate, such as in the Mediterranean region of *La Camargue* in southern France. While management recommendations for organic cropping systems are not readily available, innovative farmers develop strategies to achieve high, and less variable, yields. The objectives of this study were to identify the main factors affecting yield variability and the farmer management strategies used to sustain crop productivity while reducing input use. Participatory monitoring of farmer fields for yields, yield components, soil condition, weeds and management practices from 1992 to 2009 resulted in a database of more than 380 entries. These data included continuous, discrete and nominal variables. They were explored using classification and regression trees to describe management strategies under conventional and organic systems and to identify and categorise the main variables associated with rice yield variability. Rice yields varied between 0.5 and 10 t ha⁻¹ under conventional and between 0 and 9 t ha⁻¹ under organic management. Weed competition was the main factor affecting yield for both conventional and organic systems. The gap between

current average yields and the estimated yield potential of 10 t ha^{-1} was on average 2.7 t ha^{-1} under conventional and 5 t ha^{-1} under organic management. The latter can be largely attributed to the effect of weed competition. The productivity gap between conventional and organic management fluctuated between c. 1 t ha^{-1} under conducive conditions and c. 4 t ha^{-1} under limiting conditions (e.g., severe salinity problems). Strategies to attain high yields under conventional and organic management differed: Under conventional management, a low initial plant stand associated with early sowing was compensated by high tillering rates induced through N fertilization, while weeds were controlled by herbicides. Under organic management, late sowing allowed a higher initial plant density due to higher temperatures during emergence. This higher density ensured greater competition with weeds and sufficient number of panicles per unit area at harvest. If organic rice production is to be further promoted in Mediterranean regions, such innovations should be supported by technical means such as short cycle varieties adapted to late sowing under high latitudes. Other alternatives to outcompete and/or control weeds without the need for herbicides, notably through irrigation water management, crop rotation or use of cover crops must also be explored. These results indicate that farmer innovations may show possible pathways towards the ecological intensification of current agriculture.

3. EXPERIMENTAL OR MATERIALS AND METHODS, ALGORITHMS USED

3.1 EXISTING SYSTEM:

The analysis is carried out on multitemporal Sentinel-1 data over an area in Camargue, France. The data set was processed in order to produce an intensity radar data stack from May 2017 to September 2017. We improved this radar time series dataset by exploiting temporal filtering to reduce noise, while retaining as much as possible the fine structures present in the images.

3.1.1 Disadvantage:

only a few studies have compared the performances of these classifiers with different training sample sizes for the same remote sensing images, particularly the Sentinel-2 Multispectral Imager (MSI).

3.2 Proposed work:

In this study, we examined and compared the performances of the RF, kNN, and SVM classifiers for land use/cover classification using Sentinel-2 image data. An area of 30×30 km² within the Red River Delta of Vietnam with six land use/cover types was classified using 14 different training sample sizes, including balanced and imbalanced, from 50 to over 1250 pixels/class. All classification results showed a high overall accuracy (OA) ranging from 90% to 95%. Among the three classifiers and 14 sub-datasets, SVM produced the highest OA with the least sensitivity to the training sample sizes, followed consecutively by RNN and kNN.

3.2.1 Advantage:

1. Its accuracy percentage is 90% to 95% for all classification result.

FEASIBILITY STUDY

The feasibility of the project is analyzed in this phase and business proposal is put forth with a very general plan for the project and some cost estimates. During system analysis the feasibility study of the proposed system is to be carried out. This is to ensure that the proposed system is not a burden to the company. For feasibility analysis, some understanding of the major requirements for the system is essential.

Three key considerations involved in the feasibility analysis are

- ◆ ECONOMICAL FEASIBILITY
- ◆ TECHNICAL FEASIBILITY
- ◆ SOCIAL FEASIBILITY

ECONOMICAL FEASIBILITY

This study is carried out to check the economic impact that the system will have on the organization. The amount of fund that the company can pour into the research and development of the system is limited. The expenditures must be justified. Thus the developed system as well within the budget and this was achieved because most of the technologies used are freely available. Only the customized products had to be purchased.

TECHNICAL FEASIBILITY

This study is carried out to check the technical feasibility, that is, the technical requirements of the system. Any system developed must not have a high

demand on the available technical resources. This will lead to high demands on the available technical resources. This will lead to high demands being placed on the client. The developed system must have a modest requirement, as only minimal or null changes are required for implementing this system.

SOCIAL FEASIBILITY

The aspect of study is to check the level of acceptance of the system by the user. This includes the process of training the user to use the system efficiently. The user must not feel threatened by the system, instead must accept it as a necessity. The level of acceptance by the users solely depends on the methods that are employed to educate the user about the system and to make him familiar with it. His level of confidence must be raised so that he is also able to make some constructive criticism, which is welcomed, as he is the final user of the system.

3.3 ALGORITHMS USED :

Support Vector Machine Algorithm :

Support Vector Machine or SVM is one of the most popular Supervised Learning algorithms, which is used for Classification as well as Regression problems. However, primarily, it is used for Classification problems in Machine Learning.

The goal of the SVM algorithm is to create the best line or decision boundary that can segregate n-dimensional space into classes so that we can easily put the new data point in the correct category in the future. This best decision boundary is called a hyperplane.

SVM chooses the extreme points/vectors that help in creating the hyperplane. These extreme cases are called as support vectors, and hence algorithm is termed as SupportVectorMachine.

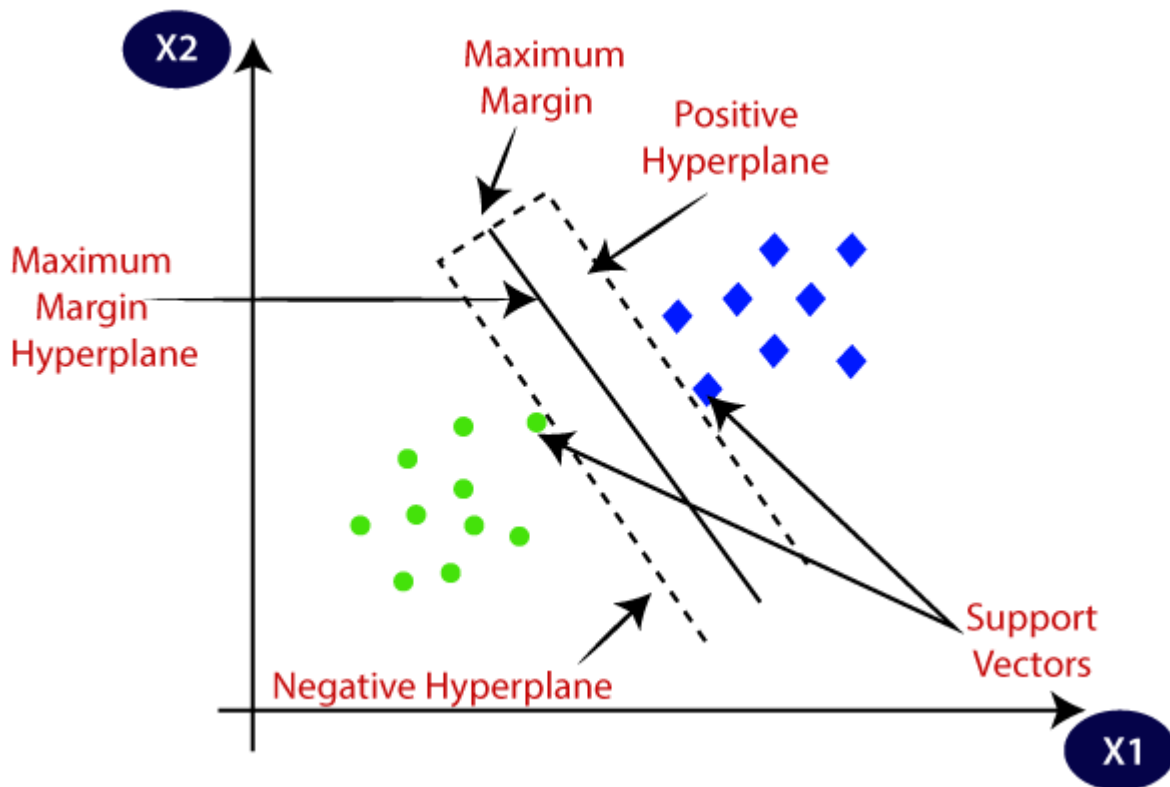


Fig 3.3.1 Classification Using SVM

SVM algorithm can be used for Face detection, image classification, text categorization, etc.

SVM can be of two types:

Linear SVM:

Linear SVM is used for linearly separable data, which means if a dataset can be classified into two classes by using a single straight line, then such data is termed as linearly separable data, and classifier is used called as Linear SVM classifier.

Non-linear SVM:

Non-Linear SVM is used for non-linearly separated data, which means if a dataset cannot be classified by using a straight line, then such data is termed as non-linear data and classifier used is called as Non-linear SVM classifier.

Hyperplane and Support Vectors in the SVM algorithm:

Hyperplane: There can be multiple lines/decision boundaries to segregate the classes in n-dimensional space, but we need to find out the best decision boundary that helps to classify the data points. This best boundary is known as the hyperplane of SVM.

The dimensions of the hyperplane depend on the features present in the dataset, which means if there are 2 features (as shown in image), then hyperplane will be a straight line. And if there are 3 features, then hyperplane will be a 2-dimension plane.

We always create a hyperplane that has a maximum margin, which means the maximum distance between the data points.

Support Vectors:

The data points or vectors that are the closest to the hyperplane and which affect the position of the hyperplane are termed as Support Vector. Since these vectors support the hyperplane, hence called a Support vector.

Convolutional Neural Network:

Convolutional Neural Network is one of the main categories to do image classification and image recognition in neural networks. Scene labeling, objects detections, and face recognition, etc., are some of the areas where convolutional neural networks are widely used.

CNN takes an image as input, which is classified and process under a certain category such as dog, cat, lion, tiger, etc. The computer sees an image as an array of pixels and depends on the resolution of the image. Based on image resolution, it will see as $h * w * d$, where h = height w = width and d = dimension. For example, An

RGB image is $6 * 6 * 3$ array of the matrix, and the grayscale image is $4 * 4 * 1$ array of the matrix.

In CNN, each input image will pass through a sequence of convolution layers along with pooling, fully connected layers, filters (Also known as kernels). After that, we will apply the Soft-max function to classify an object with probabilistic values 0 and 1.

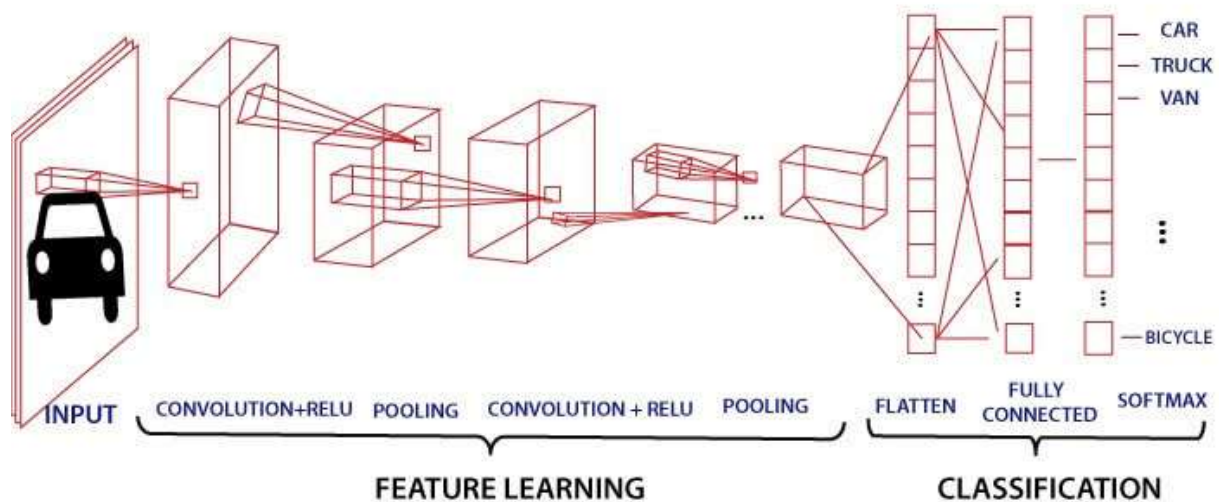


Fig 3.3.2 Classification Using CNN

Convolution Layer

Convolution layer is the first layer to extract features from an input image. By learning image features using a small square of input data, the convolutional layer preserves the relationship between pixels. It is a mathematical operation which takes two inputs such as image matrix and a kernel or filter.

Convolutional Neural Network

Convolution of an image with different filters can perform an operation such as blur, sharpen, and edge detection by applying filters.

Strides

Stride is the number of pixels which are shift over the input matrix. When the stride is equaled to 1, then we move the filters to 1 pixel at a time and similarly, if the stride is

equal to 2, then we move the filters to 2 pixels at a time. The following figure shows that the convolution would work with a stride of 2.

Padding

Padding plays a crucial role in building the convolutional neural network. If the image will get shrink and if we will take a neural network with 100's of layers on it, it will give us a small image after filtered in the end.

Pooling Layer

Pooling layer plays an important role in pre-processing of an image. Pooling layer reduces the number of parameters when the images are too large. Pooling is "downscaling" of the image obtained from the previous layers. It can be compared to shrinking an image to reduce its pixel density. Spatial pooling is also called downsampling or subsampling, which reduces the dimensionality of each map but retains the important information. There are the following types of spatial pooling:

Max Pooling

Max pooling is a sample-based discretization process. Its main objective is to downscale an input representation, reducing its dimensionality and allowing for the assumption to be made about features contained in the sub-region binned.

Max pooling is done by applying a max filter to non-overlapping sub-regions of the initial representation.

Average Pooling

Down-scaling will perform through average pooling by dividing the input into rectangular pooling regions and computing the average values of each region.

Fully Connected Layer

The fully connected layer is a layer in which the input from the other layers will be flattened into a vector and sent. It will transform the output into the desired number of classes by the network.

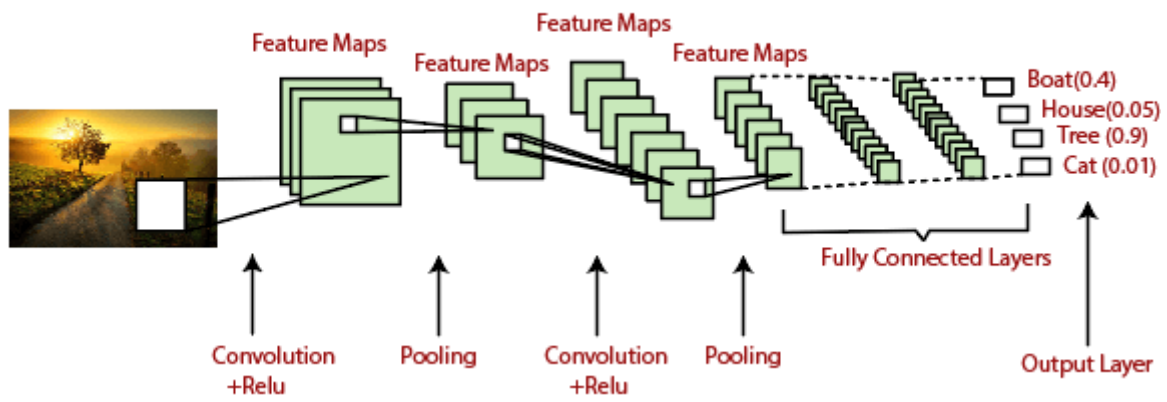


Fig 3.3.3 Convolutional Neural Network

3.4 SYSTEM ARCHITECTURE

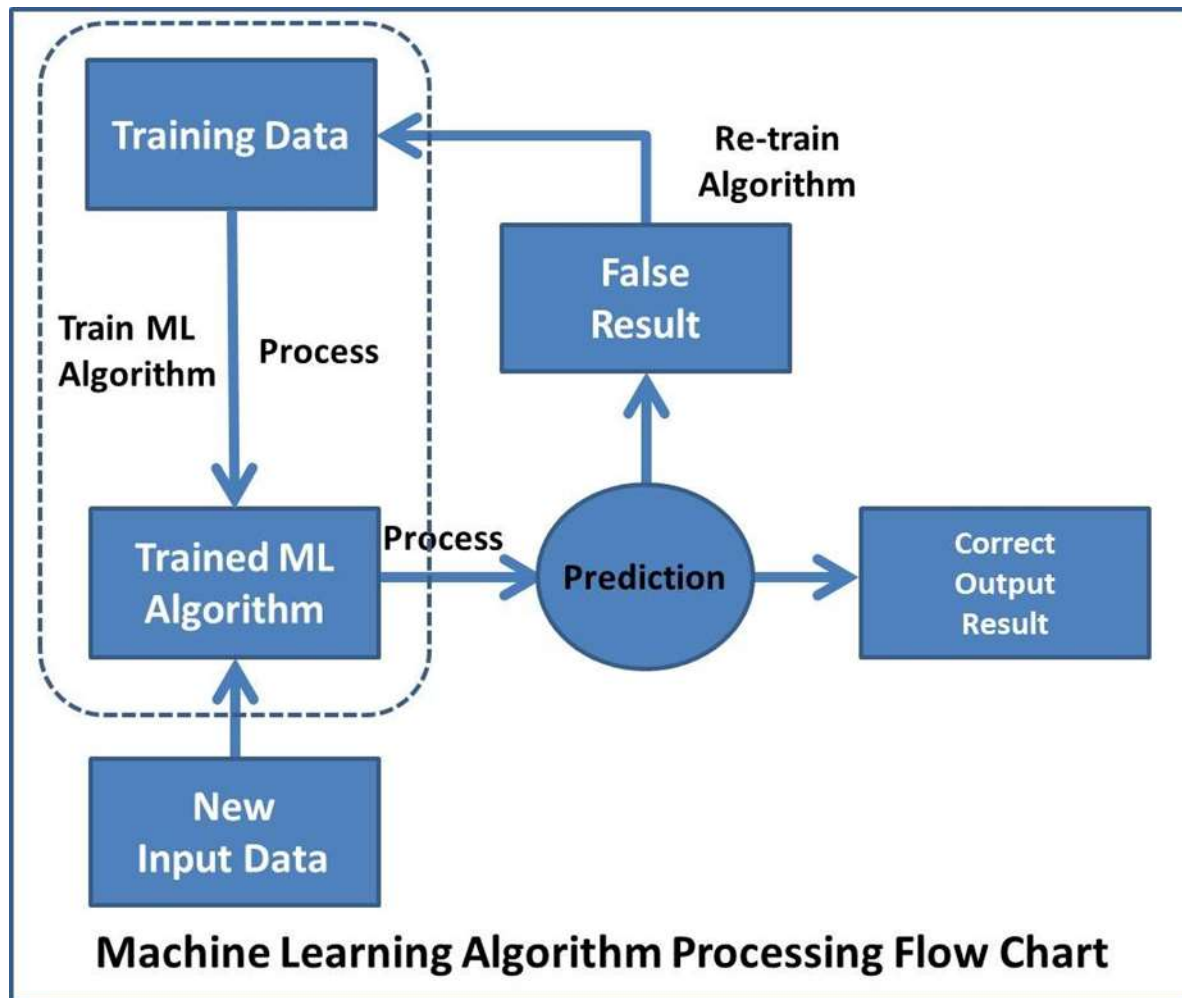
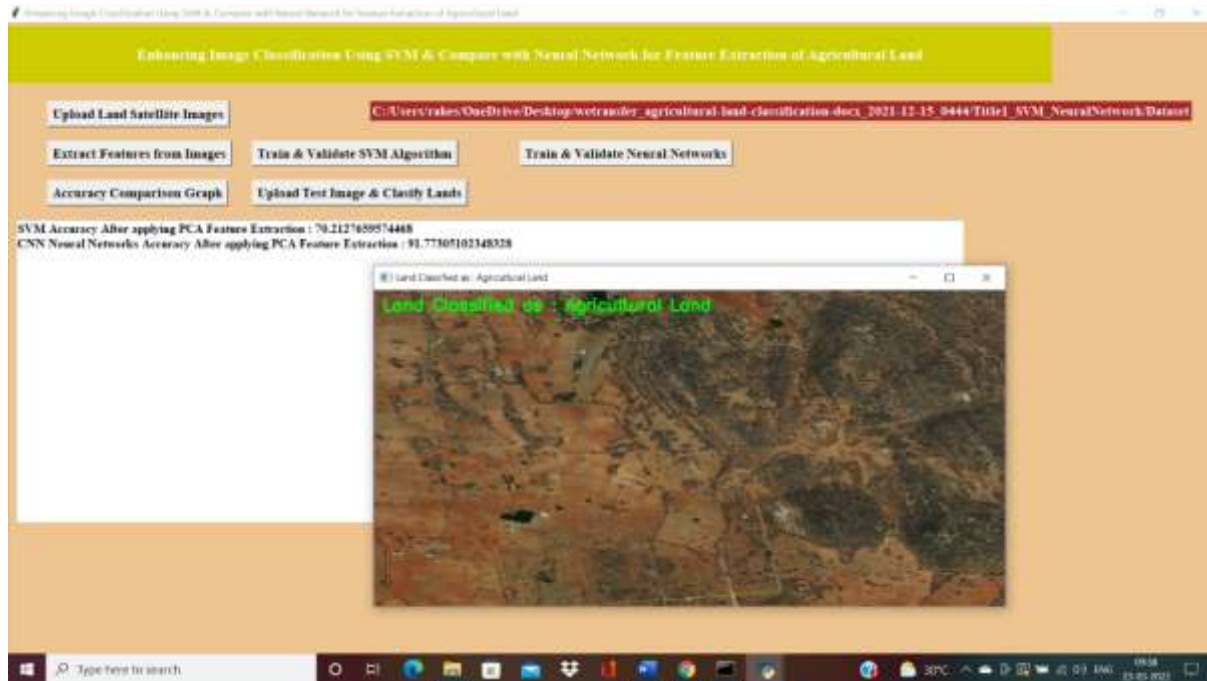


Fig 3.4 System Architecture

CHAPTER 4

RESULTS AND DISCUSSION, PERFORMANCE ANALYSIS

Results :



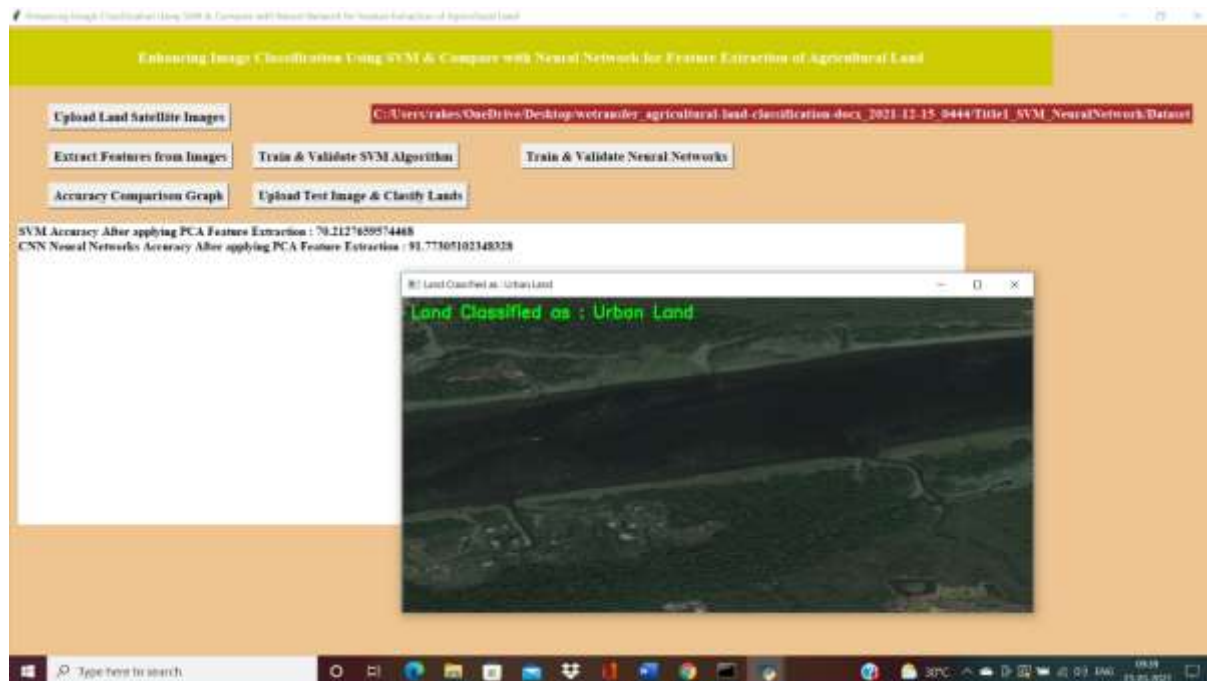


Fig 4.1 Results

Performance:





Fig 4.2 Performance

5 SUMMARY AND CONCLUSIONS

Classification results showed a high overall accuracy (OA) ranging from 90% to 95%. Among the three classifiers and 14 sub-datasets, SVM produced the highest OA with the least sensitivity to the training sample sizes, followed consecutively by RNN and kNN. In relation to the sample size, all three classifiers showed a similar and high OA

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1. <https://www.w3schools.com/python>
2. <https://www.tutorialspoint.com/python/index.htm>
3. <https://www.javatpoint.com/python-tutorial>
4. <https://www.learnpython.org/>

Appendix:

A.SCREEN SHOTS

Interface:



Fig 5.1 Interface

Loading Dataset:

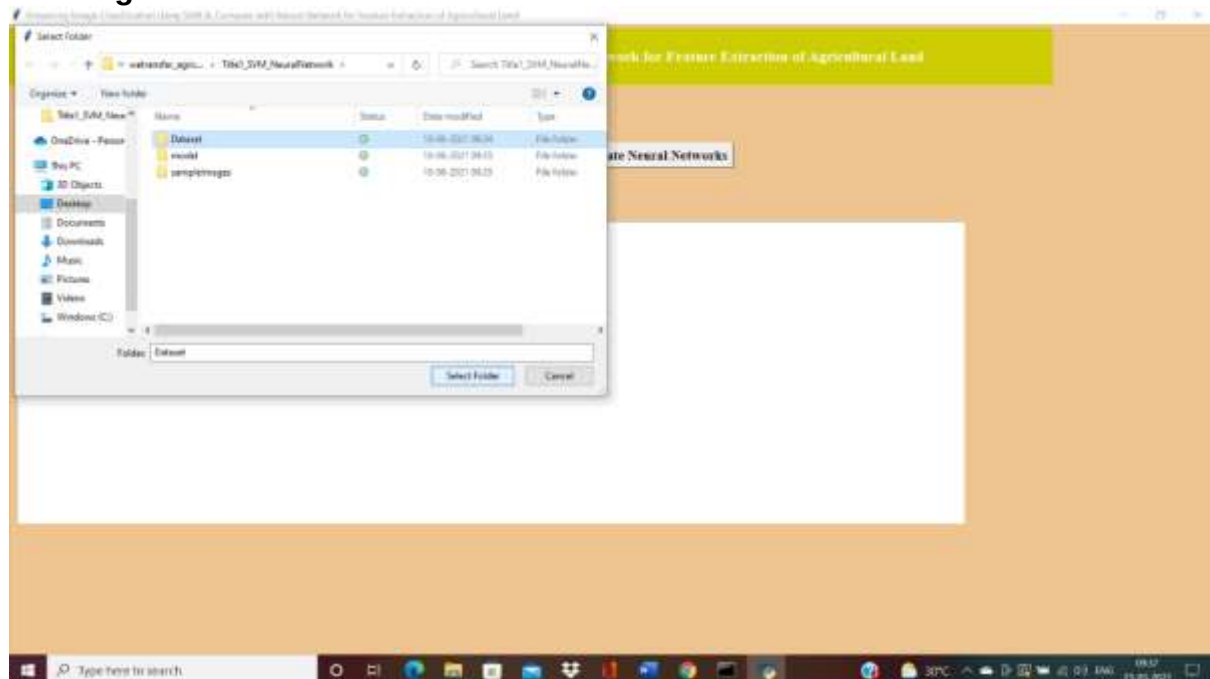


Fig 5.2 Loading Dataset

Feature Extraction:



Fig 5.3 Feature Extraction

SVM Accuracy:



Fig 5.4 SVM Accuracy

CNN Accuracy:



Fig 5.5 CNN Accuracy

Comparison SVM vs CNN:

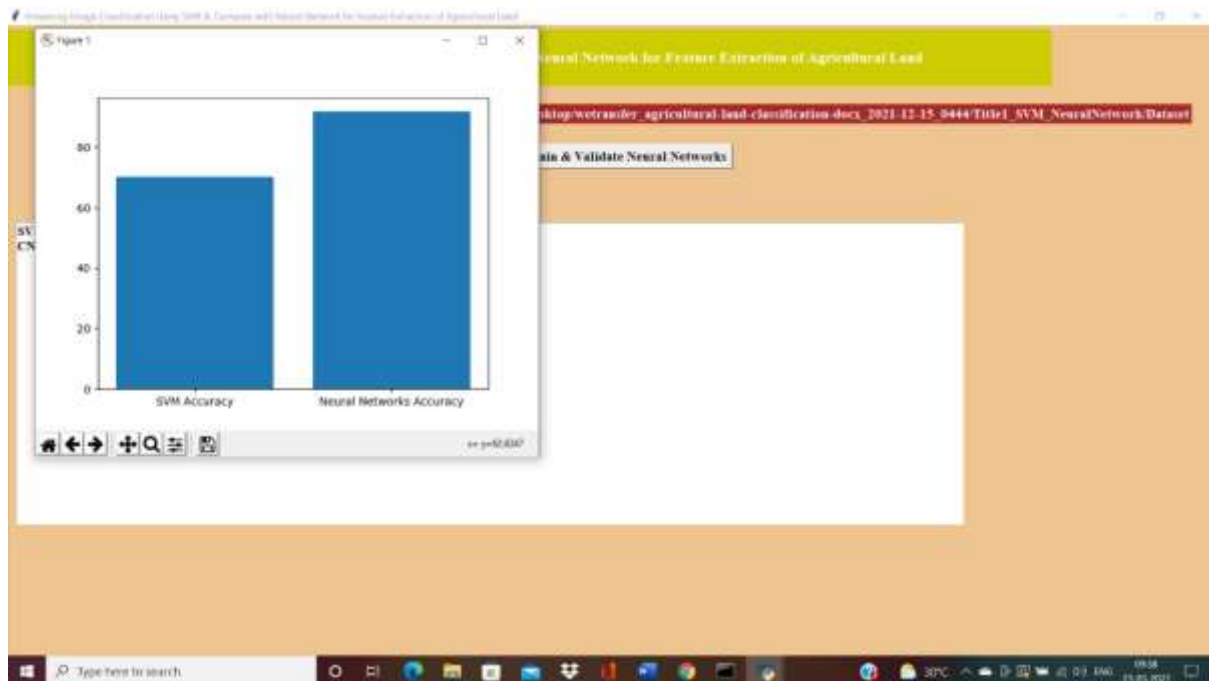
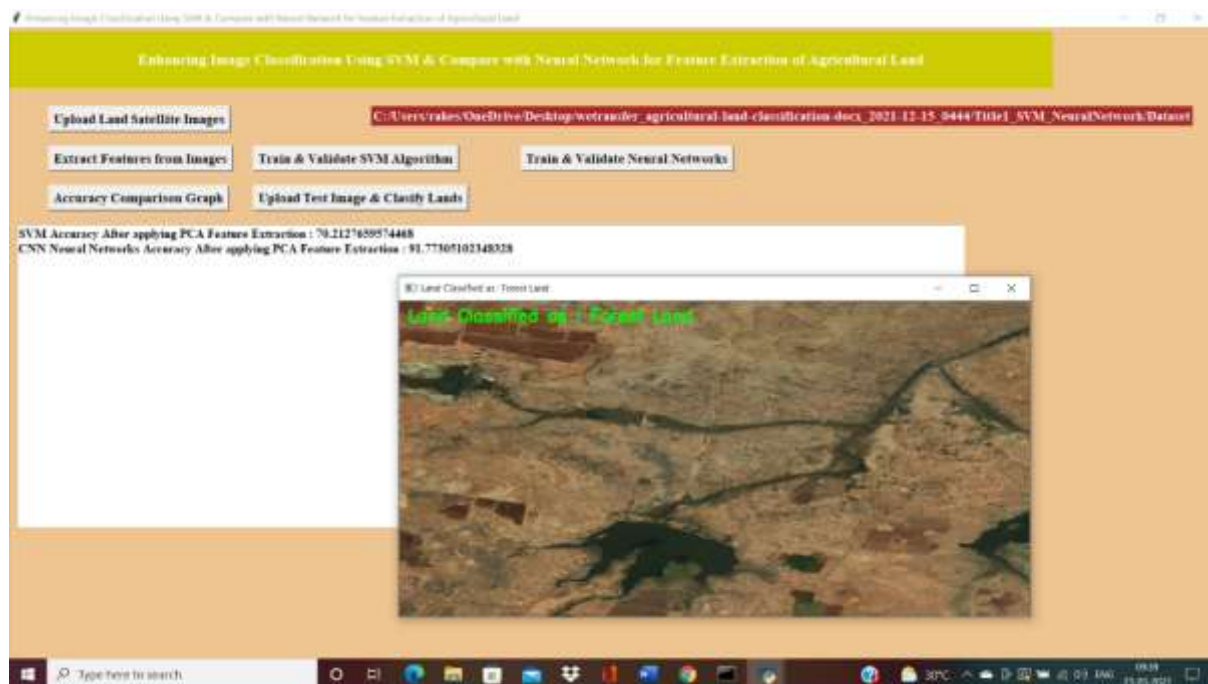
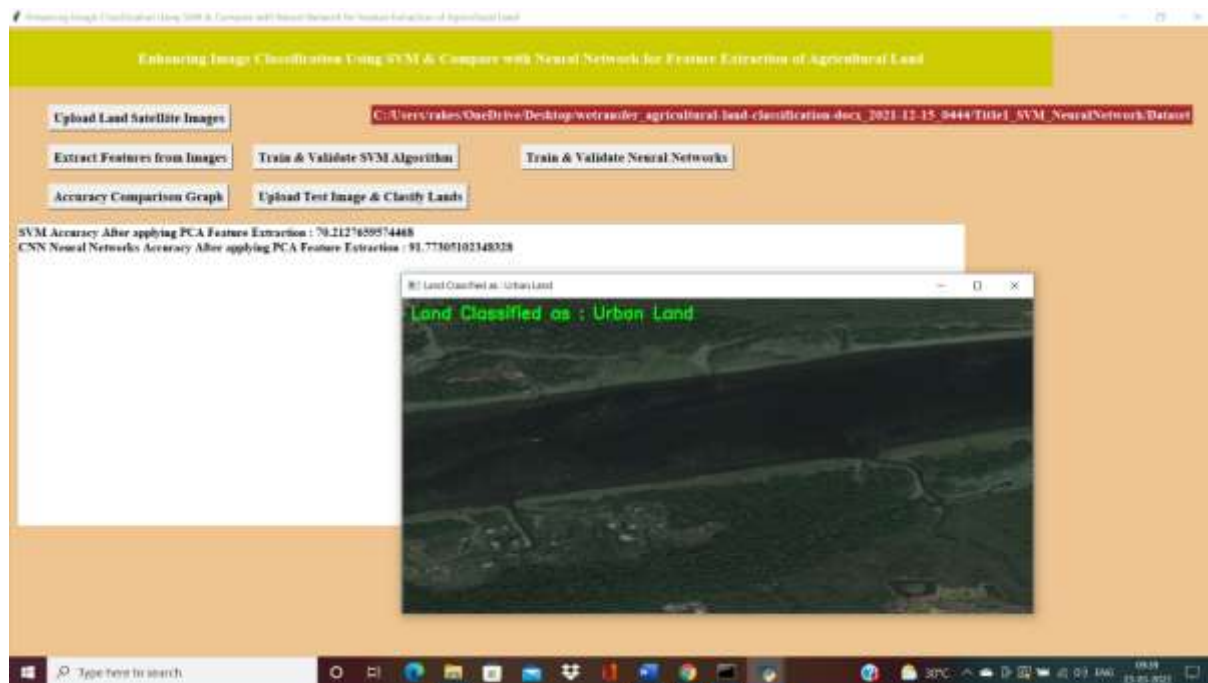


Fig 5.6 Comparision SVM vs CNN

Classification Results:



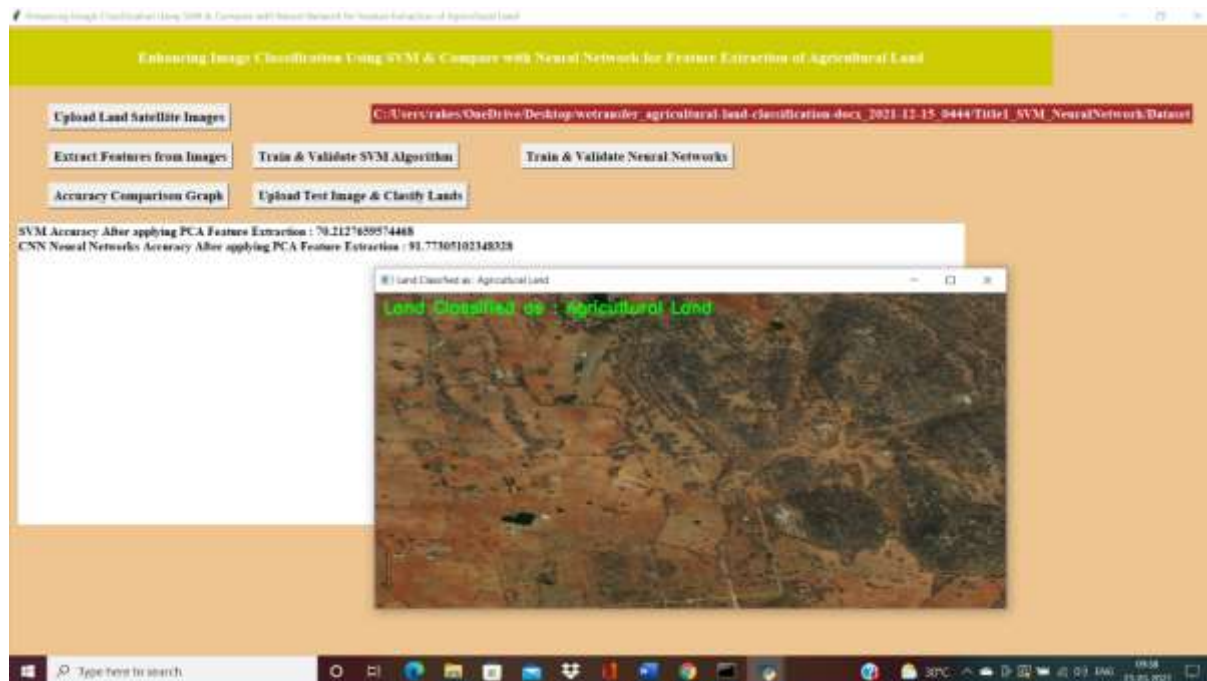


Fig 5.7 Results

B.SOURCE CODE

```
from tkinter import messagebox
from tkinter import *
from tkinter import simpledialog
import tkinter
from tkinter import filedialog
import matplotlib.pyplot as plt
import numpy as np
from tkinter.filedialog import askopenfilename
import os
import re
import numpy as np
import pandas as pd
```

```

from sklearn.metrics import accuracy_score
from sklearn import svm
from sklearn.model_selection import train_test_split

import cv2
from keras.utils.np_utils import to_categorical
from keras.layers import MaxPooling2D
from keras.layers import Dense, Dropout, Activation, Flatten
from keras.layers import Convolution2D
from keras.models import Sequential
from keras.models import model_from_json
import pickle
from sklearn.decomposition import PCA

main = tkinter.Tk()
main.title("Enhancing Image Classification Using SVM & Compare with Neural
Network for Feature Extraction of Agricultural Land")
main.geometry("1300x1200")

global filename
global svm_acc,neural_network_acc
global classifier
global X,Y
global svm_x,svm_y
global X_train, X_test, y_train, y_test

labels = ['Urban Land','Agricultural Land','Range Land','Forest Land']

def upload():
    global filename
    filename = filedialog.askdirectory(initialdir=".")
    pathlabel.config(text=filename)
    text.delete('1.0', END)
    text.insert(END,filename+" loaded\n");

def extractFeatures():
    global X,Y
    global svm_x,svm_y
    global X_train, X_test, y_train, y_test
    text.delete('1.0', END)
    X = np.load('model/X.txt.npy')
    Y = np.load('model/Y.txt.npy')
    svm_y = Y

    svm_x = np.reshape(X, (X.shape[0],(X.shape[1]*X.shape[2]*X.shape[3])))
    text.insert(END,"Number of features in images before applying PCA feature
extraction : "+str(svm_x.shape[1])+"\n")
    pca = PCA(n_components = 100)

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svm_x = pca.fit_transform(svm_x)
text.insert(END,"Number of features in images after applying PCA feature
extraction : "+str(svm_x.shape[1])+"\n")
X_train, X_test, y_train, y_test = train_test_split(svm_x, svm_y,
test_size=0.2)
text.insert(END,"Total Images Found in dataset : "+str(len(X))+"\n")

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def runSVM():
    text.delete('1.0', END)
    global svm_acc
    global X_train, X_test, y_train, y_test
    cls = svm.SVC()
    cls.fit(X_train, y_train)
    prediction_data = cls.predict(X_test)
    svm_acc = accuracy_score(y_test,prediction_data)*100
    text.insert(END,"SVM Accuracy After applying PCA Feature Extraction :
"+str(svm_acc)+"\n")

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def runNeuralNetworks():
    global X,Y
    global neural_network_acc
    global classifier
    Y1 = to_categorical(Y)
    if os.path.exists('model/model.json'):
        with open('model/model.json', "r") as json_file:
            loaded_model_json = json_file.read()
            classifier = model_from_json(loaded_model_json)
            classifier.load_weights("model/model_weights.h5")
            classifier._make_predict_function()
            print(classifier.summary())
            f = open('model/history.pckl', 'rb')
            data = pickle.load(f)
            f.close()
            acc = data['accuracy']
            neural_network_acc = acc[19] * 100
            text.insert(END,"CNN Neural Networks Accuracy After applying PCA
Feature Extraction : "+str(neural_network_acc)+"\n")
        else:
            classifier = Sequential()
            classifier.add(Convolution2D(32, 3, 3, input_shape = (64, 64, 3), activation
= 'relu'))
            classifier.add(MaxPooling2D(pool_size = (2, 2)))
            classifier.add(Convolution2D(32, 3, 3, activation = 'relu'))
            classifier.add(MaxPooling2D(pool_size = (2, 2)))
            classifier.add(Flatten())
            classifier.add(Dense(output_dim = 256, activation = 'relu'))
            classifier.add(Dense(output_dim = 4, activation = 'softmax'))

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    print(classifier.summary())
    classifier.compile(optimizer = 'adam', loss = 'categorical_crossentropy',
metrics = ['accuracy'])
    hist = classifier.fit(X, Y1, batch_size=32, epochs=20, shuffle=True,
verbose=2)
    classifier.save_weights('model/model_weights.h5')
    model_json = classifier.to_json()
    with open("model/model.json", "w") as json_file:
        json_file.write(model_json)
    f = open('model/history.pckl', 'wb')
    pickle.dump(hist.history, f)
    f.close()
    f = open('model/history.pckl', 'rb')
    data = pickle.load(f)
    f.close()
    acc = data['accuracy']
    neural_network_acc = acc[19] * 100
    text.insert(END,"CNN Neural Networks Accuracy After applying PCA
Feature Extraction : "+str(neural_network_acc)+"\n")

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def graph():
    height = [svm_acc,neural_network_acc]
    bars = ('SVM Accuracy', 'Neural Networks Accuracy')
    y_pos = np.arange(len(bars))
    plt.bar(y_pos, height)
    plt.xticks(y_pos, bars)
    plt.show()

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def predict():
    filename = filedialog.askopenfilename(initialdir="sampleImages")
    image = cv2.imread(filename)
    img = cv2.resize(image, (64,64))
    im2arr = np.array(img)
    im2arr = im2arr.reshape(1,64,64,3)
    img = np.asarray(im2arr)
    img = img.astype('float32')
    img = img/255
    preds = classifier.predict(img)
    predict = np.argmax(preds)

    img = cv2.imread(filename)
    img = cv2.resize(img, (800,400))
    cv2.putText(img, 'Land Classified as : '+labels[predict], (10, 25),
cv2.FONT_HERSHEY_SIMPLEX,0.7, (0, 255, 0), 2)
    cv2.imshow('Land Classified as : '+labels[predict], img)
    cv2.waitKey(0)

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font = ('times', 14, 'bold')
title = Label(main, text='Enhancing Image Classification Using SVM & Compare
with Neural Network for Feature Extraction of Agricultural Land')
title.config(bg='yellow3', fg='white')
title.config(font=font)
title.config(height=3, width=120)
title.place(x=0,y=5)

font1 = ('times', 13, 'bold')
uploadButton = Button(main, text="Upload Land Satellite Images",
command=upload)
uploadButton.place(x=50,y=100)
uploadButton.config(font=font1)

pathlabel = Label(main)
pathlabel.config(bg='brown', fg='white')
pathlabel.config(font=font1)
pathlabel.place(x=460,y=100)

featuresButton = Button(main, text="Extract Features from Images",
command=extractFeatures)
featuresButton.place(x=50,y=150)
featuresButton.config(font=font1)

svmButton = Button(main, text="Train & Validate SVM Algorithm",
command=runSVM)
svmButton.place(x=310,y=150)
svmButton.config(font=font1)

nn = Button(main, text="Train & Validate Neural Networks",
command=runNeuralNetworks)
nn.place(x=650,y=150)
nn.config(font=font1)

graphbutton = Button(main, text="Accuracy Comparison Graph",
command=graph)
graphbutton.place(x=50,y=200)
graphbutton.config(font=font1)

predictb = Button(main, text="Upload Test Image & Clasify Lands",
command=predict)
predictb.place(x=310,y=200)
predictb.config(font=font1)

font1 = ('times', 12, 'bold')
text=Text(main,height=20,width=150)
scroll=Scrollbar(text)

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text.configure(yscrollcommand=scroll.set)
text.place(x=10,y=250)
text.config(font=font1)
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main.config(bg='burlywood2')
main.mainloop()
```