1. INTRODUCTION

1.1 ABOUT PROJECT

Remote sensing, the acquisition of information about an object or phenomenon without making physical contact, has revolutionized the way we observe and understand the Earth. The proliferation of satellites and aerial imaging technologies has resulted in an unprecedented volume of high-resolution imagery, capturing diverse aspects of the Earth's surface and atmosphere. These images are invaluable for various applications, including environmental monitoring, urban planning, agriculture, disaster management, and military intelligence.

Traditionally, the analysis of remote sensing images relied on classical image processing and machine learning techniques. These methods typically involve significant human effort in feature extraction and often struggle with the complexity and high dimensionality of remote sensing data. With the growing availability of vast amounts of data, there is a pressing need for more efficient, scalable, and accurate analytical methods.

Deep learning, a subfield of artificial intelligence, has emerged as a powerful tool for image analysis due to its ability to automatically learn hierarchical features from raw data. Convolutional neural networks (CNNs), in particular, have achieved state-of-the-art results in various computer vision tasks, including image classification, object detection, and segmentation. The success of deep learning in these domains has spurred interest in its application to remote sensing image analysis.

In this context, our research explores the deployment of deep learning techniques to address key challenges in remote sensing. We focus on several critical tasks: land cover classification, object detection, and change detection. Land cover classification involves categorizing different regions of an image into predefined classes such as forests, urban areas, and water bodies. Object detection aims to identify and locate specific objects of interest, such as vehicles or buildings, within an image. Change detection entails identifying differences between images captured at different times to monitor temporal changes in the landscape.

This study provides a comprehensive review of recent advancements in deep learning methodologies tailored for remote sensing applications. We analyze the strengths and limitations of various deep learning architectures and techniques, emphasizing their potential to improve the accuracy and efficiency of remote sensing image analysis.

1.2 EXISTING SYSTEM

Traditional methods for analysing remote sensing images largely rely on classical image processing and conventional machine learning techniques. These approaches typically involve manual feature extraction, making them labour-intensive and limited in handling the high-dimensional and complex nature of remote sensing data.
In recent years, deep learning models—especially Convolutional Neural Networks (CNNs)—have shown significant promise in remote sensing tasks such as land cover classification, object detection, and segmentation. Existing systems have used these techniques with the following characteristics:

Advantages:

- High accuracy in tasks like land cover classification.
- Robustness to variability and noise in image data.
- Real-time processing capability for certain use cases.
- Adaptability to various sensors and resolutions.
- Context-aware interpretation using GIS or UAV integrations.

Disadvantages:

- High computational resource requirements.
- Dependence on large, labelled datasets.
- Limited performance in occluded or complex scenes.
- Integration challenges with multi-source data formats.
- Difficulties in generalizing across diverse geographies.

1.3 PROPOSED SYSTEM

To address the limitations of existing systems, the proposed system leverages an advanced deep learning model—**CNN (ResNeXt architecture)**—to automatically learn hierarchical features from raw remote sensing images. The key objective is to enhance object detection accuracy and classification efficiency on high-resolution aerial images.

Highlights of the Proposed System:

- Uses the **RSSOD dataset** featuring 5 object classes: Car, Aeroplane, Vegetation, Tree, and Boat.
- Implements **Convolutional Neural Network (CNN)** for feature extraction and classification.
- Achieves object detection accuracy ranging from **89% to 95%**.
- Minimizes need for handcrafted features by directly learning from image data.

Advantages:

- Improved generalization using modern CNN architectures.
- Reduced need for extensive manual labeling via transfer learning techniques.
- Modular implementation for better scalability and testing.

Limitations:

- Slight inaccuracies in bounding box placements.
- Potential biases from pre-trained CNN layers.
- Requires GPU for efficient training and large-scale inference.

2. REQUIREMENT SPECIFICATIONS

2.1 REQUIREMENT ANALYSIS

This project, Remote Sensing Image Analysis using Deep Learning, focuses on detecting and classifying objects in aerial imagery using Convolutional Neural Networks (CNNs). To achieve this, the following requirements were analysed:

Functional Requirements:

- Ability to upload and preprocess remote sensing datasets.
- Train a CNN model using labelled aerial image data.
- Perform object detection and classify objects such as cars, boats, trees, vegetation, and airplanes.
- Display performance metrics such as accuracy, precision, recall, and confusion matrix.
- Enable user to test object detection on custom uploaded images.

Non-Functional Requirements:

- High model accuracy and robustness.
- Efficient computation with limited system resources.
- Good user interface for interacting with the model (e.g., selecting images, viewing results).

System Requirements:

Hardware Requirements:

- Processor: Pentium IV 2.4 GHz or above
- RAM: Minimum 512 MB
- Hard Disk: Minimum 40 GB
- Monitor: VGA Colour Display

Software Requirements:

- Operating System: Windows
- Programming Language: Python 3.7
- Libraries: TensorFlow, NumPy, Pandas, Matplotlib, Scikit-learn

2.2 SPECIFICATION PRINCIPLES

To ensure a robust and scalable solution, the following specification principles were applied:

Clarity and Completeness:

All requirements have been clearly defined and documented to avoid ambiguity and ensure complete functionality.

Feasibility:

The chosen technologies (Python, CNN, TensorFlow) are open-source and suitable for academic and research applications. The computational demands are well within the capabilities of standard hardware configurations available in academic labs.

Consistency:

Requirements are designed to maintain consistency between different modules such as dataset handling, preprocessing, model training, and prediction.

Modularity:

The system is divided into independent modules:

- Dataset Upload and Preprocessing
- CNN Training and Evaluation
- Object Detection on Test Images

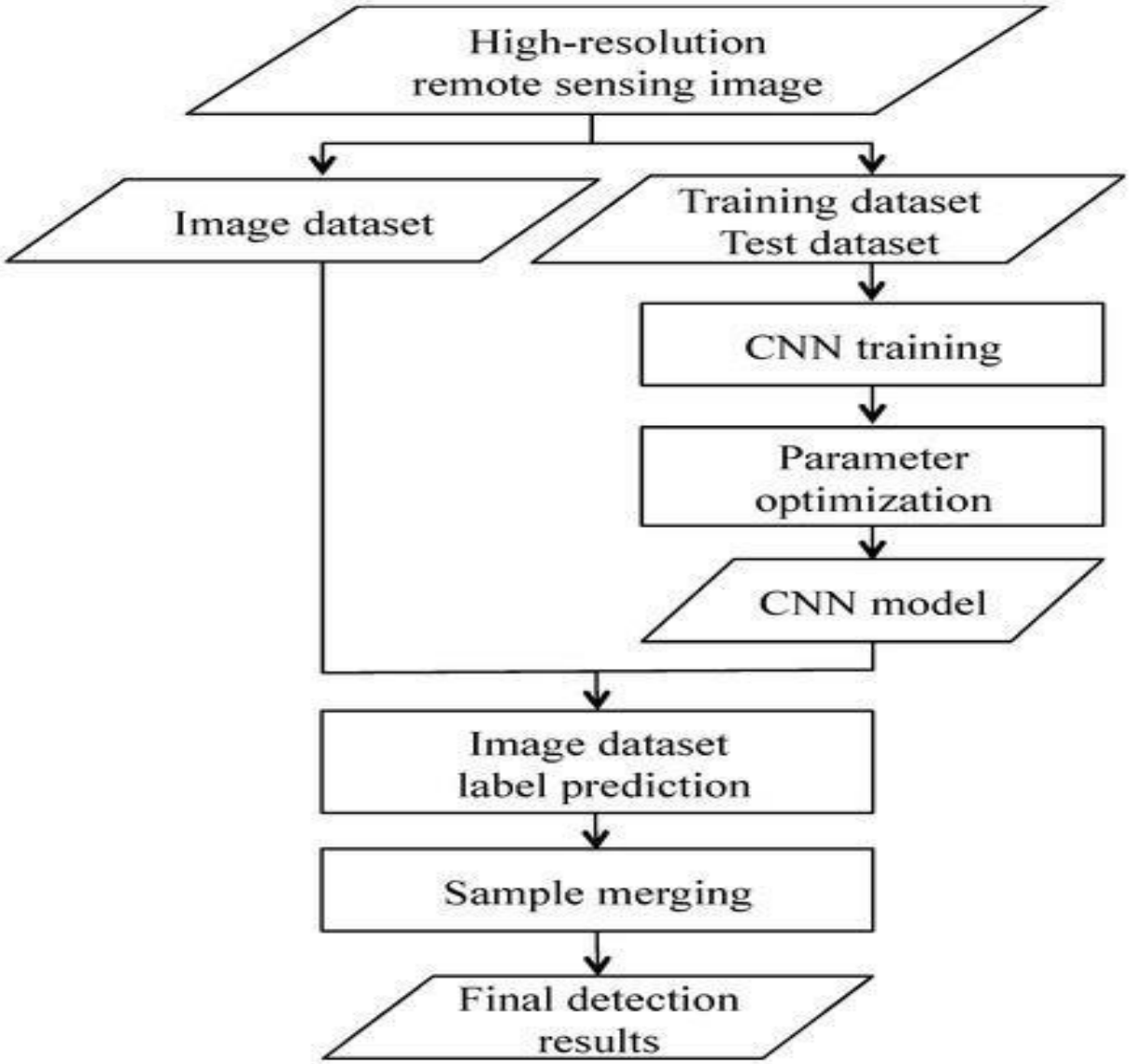
Each module can be developed and tested independently, supporting efficient debugging and upgrades.

Scalability:

The framework supports expansion to include more object categories, newer CNN architectures, and real-time detection capabilities in the future.

3. SYSTEM DESIGN

3.1 ARCHITECTURE/BLOCKDIAGRAM



3.2 UML DIAGRAMS

UML stands for Unified Modeling Language. UML is a standardized general-purpose modeling language in the field of object-oriented software engineering. The standard is managed, and was created by, the Object Management Group.

The goal is for UML to become a common language for creating models of object oriented computer software. In its current form UML is comprised of two major components: a Meta-model and a notation. In the future, some form of method or process may also be added to; or associated with, UML.

The Unified Modeling Language is a standard language for specifying, Visualization, Constructing and documenting the artifacts of software system, as well as for business modeling and other non-software systems.

The UML represents a collection of best engineering practices that have proven successful in the modeling of large and complex systems.

The UML is a very important part of developing objects oriented software and the software development process. The UML uses mostly graphical notations to express the design of software projects.

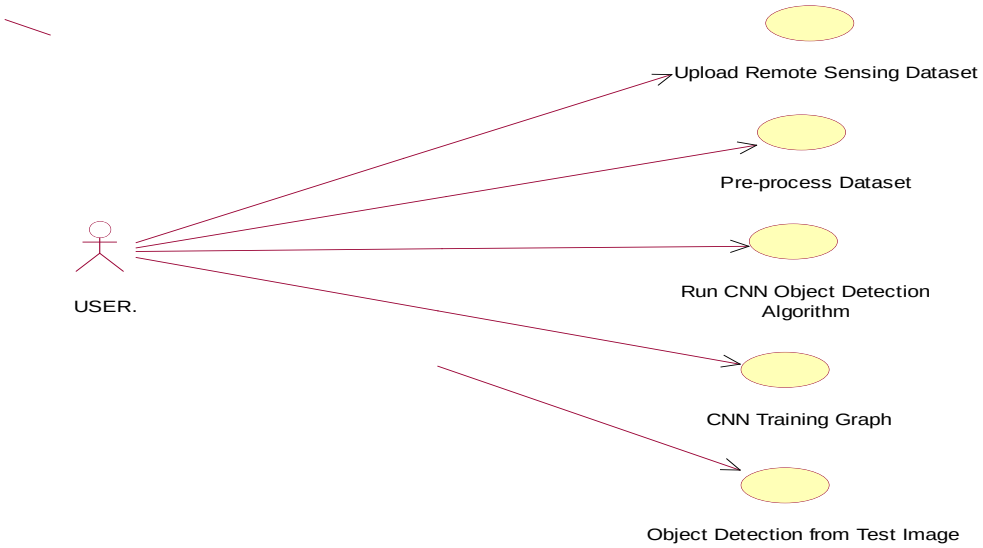
GOALS:

The Primary goals in the design of the UML are as follows:

1. Provide users a ready-to-use, expressive visual modeling Language so that they can develop and exchange meaningful models.
2. Provide extendibility and specialization mechanisms to extend the core concepts.
3. Be independent of particular programming languages and development process.
4. Provide a formal basis for understanding the modeling language.
5. Encourage the growth of OO tools market.
6. Support higher level development concepts such as collaborations, frameworks, patterns and components.
7. Integrate best practices.

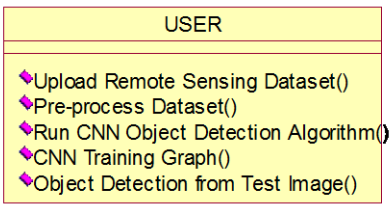
Use case diagram:

A use case diagram in the Unified Modeling Language (UML) is a type of behavioral diagram defined by and created from a Use-case analysis. Its purpose is to present a graphical overview of the functionality provided by a system in terms of actors, their goals (represented as use cases), and any dependencies between those use cases. The main purpose of a use case diagram is to show what system functions are performed for which actor. Roles of the actors in the system can be depicted.



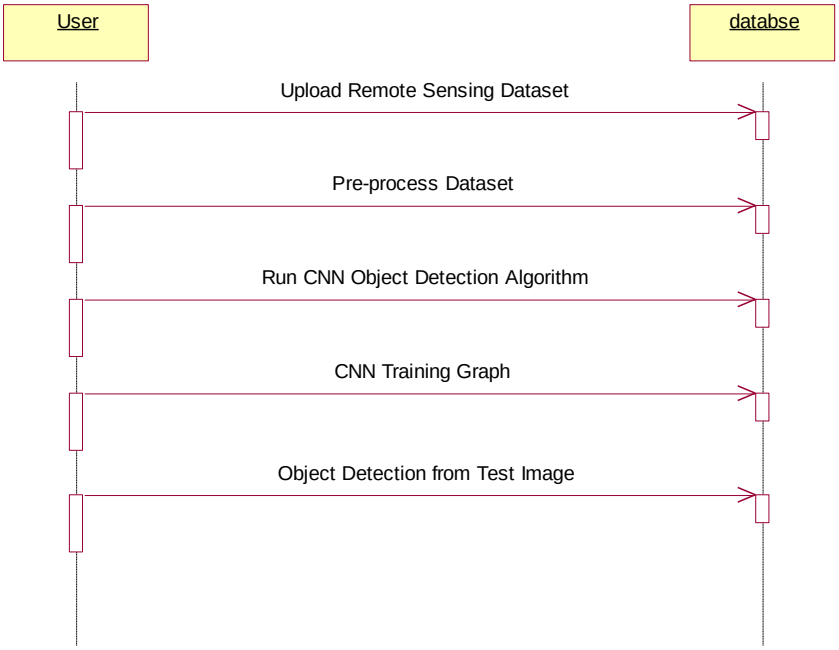
Class diagram:

The class diagram is used to refine the use case diagram and define a detailed design of the system. The class diagram classifies the actors defined in the use case diagram into a set of interrelated classes. The relationship or association between the classes can be either an "is-a" or "has-a" relationship. Each class in the class diagram may be capable of providing certain functionalities. These functionalities provided by the class are termed "methods" of the class.



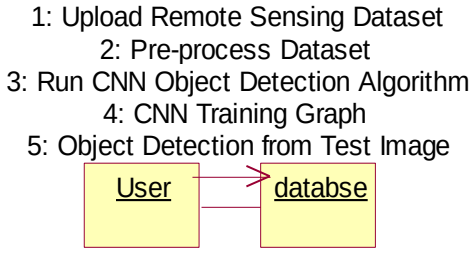
Sequence diagram:

A sequence diagram represents the interaction between different objects in the system. The important aspect of a sequence diagram is that it is time-ordered. This means that the exact sequence of the interactions between the objects is represented step by step. Different objects in the sequence diagram interact with each other by passing "messag



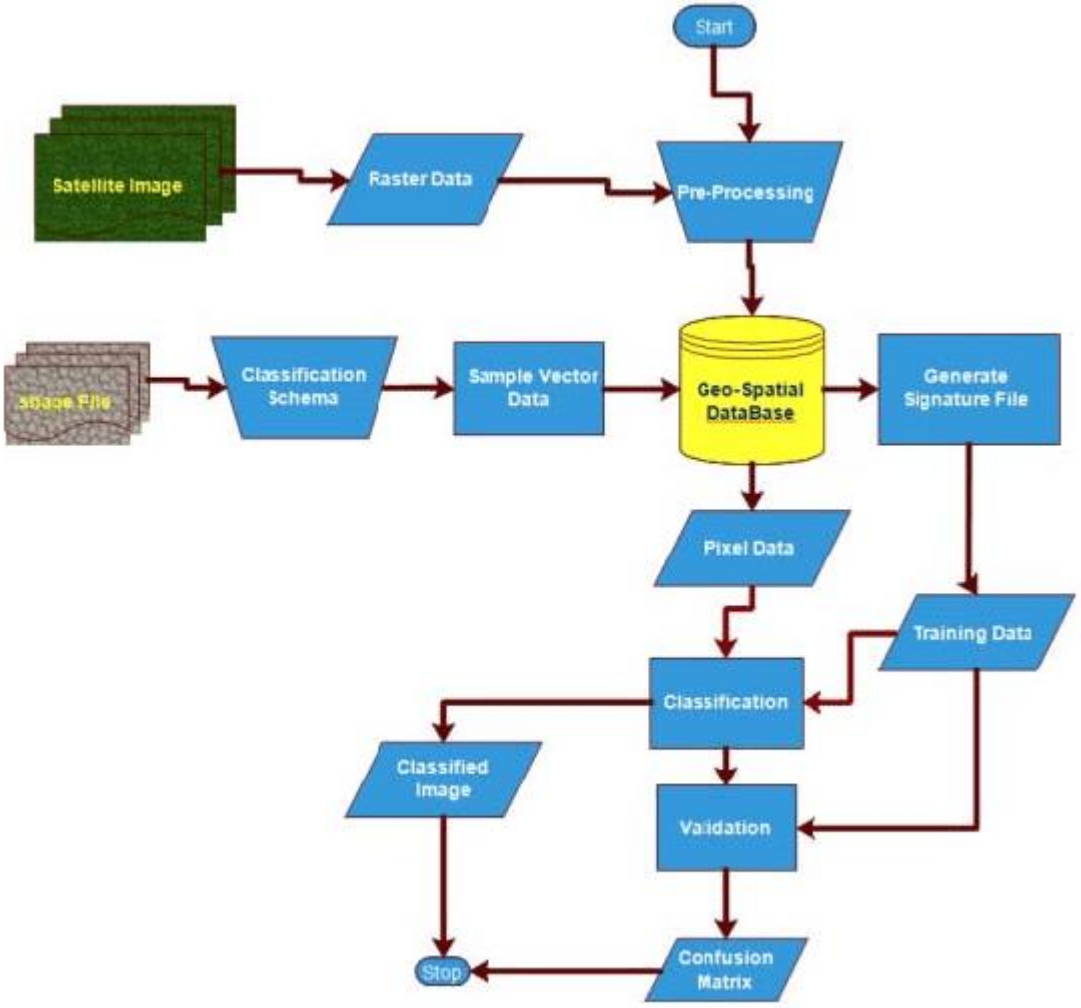
Collaboration diagram:

A collaboration diagram groups together the interactions between different objects. The interactions are listed as numbered interactions that help to trace the sequence of the interactions. The collaboration diagram helps to identify all the possible interactions that each object has with other objects.



3.2.1 DATA FLOW DIAGRAM:

1. The DFD is also called as bubble chart. It is a simple graphical formalism that can be used to represent a system in terms of input data to the system, various processing carried out on this data, and the output data is generated by this system.
2. The data flow diagram (DFD) is one of the most important modeling tools. It is used to model the system components. These components are the system process, the data used by the process, an external entity that interacts with the system and the information flows in the system.
3. DFD shows how the information moves through the system and how it is modified by a series of transformations. It is a graphical technique that depicts information flow and the transformations that are applied as data moves from input to output.



4. IMPLEMENTATION

4.1 PROJECT MODULES: -

The project is implemented using several core modules to facilitate the processing of remote sensing images and performing object detection using deep learning:

1. Upload Remote Sensing Dataset

- Users can upload the RSSOD dataset, which includes classes like Car, Aeroplane, Tree, Boat, and Vegetation.
- The system reads all images and associated bounding boxes to generate training features.

2. Pre-process Dataset

- Images are normalized and split into training and testing datasets.
- Frames are extracted and cropped to contain only detected faces or objects.
- Dataset is shuffled for robust training.

3. Run CNN Object Detection Algorithm

- CNN is trained on the dataset using the ResNeXt model for feature extraction.
- The model is evaluated using performance metrics like Accuracy, Precision, Recall, F1-Score, and Confusion Matrix.

4. CNN Training Graph

- Displays training and validation accuracy vs. epoch to visualize the learning curve of the model.

5. Object Detection from Test Image

- Users can upload new images for detection.
- The trained CNN model predicts and highlights objects using bounding boxes.

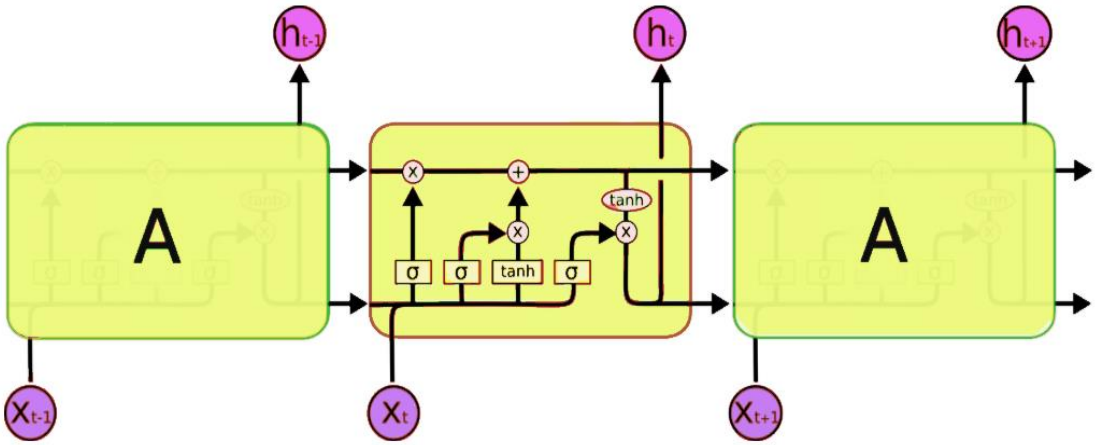
4.2 ALGORITHMS: -

1. Convolutional Neural Network (ResNeXt)

- A CNN architecture that introduces cardinality (the size of the set of transformations) as an essential dimension.
- It improves representational power while maintaining computational efficiency.
- ResNeXt uses grouped convolutions and performs better than standard ResNet on image recognition tasks.

2. Long Short-Term Memory (LSTM)

- LSTM is a special kind of Recurrent Neural Network capable of learning long-term dependencies.
- It is used here to process sequences of image features extracted from video frames.
- LSTM helps in understanding temporal relationships between frames**.**

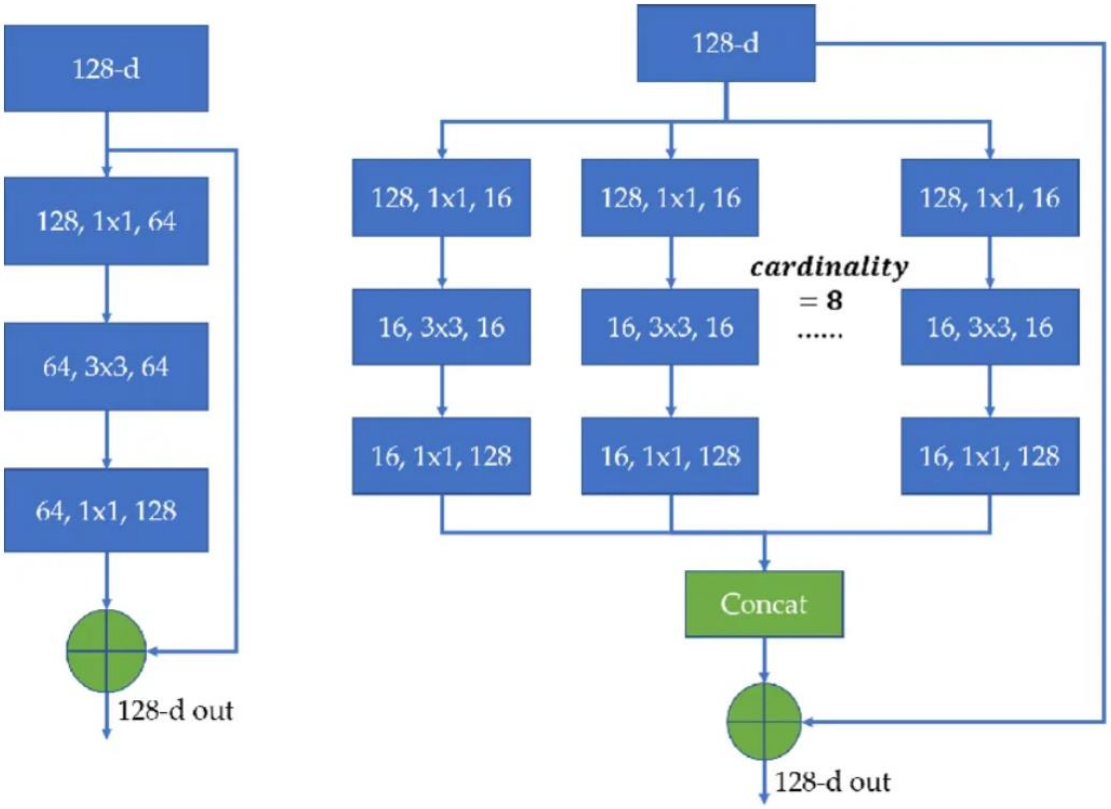


Key Steps:

- Feature extraction using ResNeXt from each frame.
- Sequential processing of frame features using LSTM.
- Final prediction based on the temporal analysis of the sequence.

3.ResNeXt:

- ResNeXt is a Convolutional Neural Network (CNN) architecture, which is a deep learning model. ResNeXt was developed by Microsoft Research and introduced in 2017 in a paper titled "Aggregated Residual Transformations for Deep Neural Networks."
- ResNeXt uses the basic ideas of the ResNeXt (Residual Network) model, but unlike ResNeXt, it uses "groups" instead of many smaller paths. These groups contain multiple parallel paths, and each path is used to learn different features. This allows the network to learn more features more effectively, increasing its representational power.

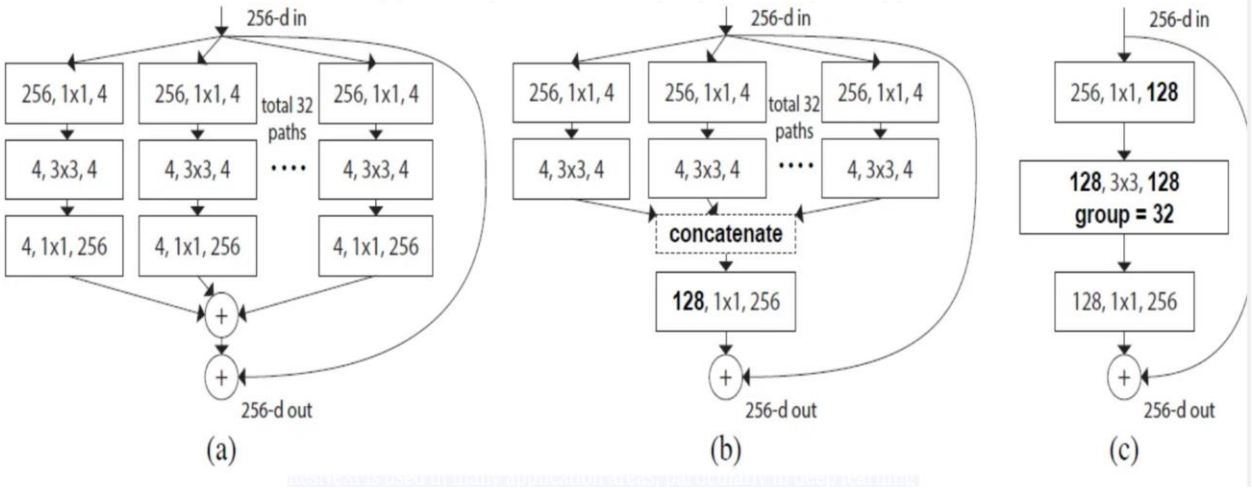


The main features and advantages of ResNeXt are:

1. Parallel Paths: ResNeXt is based on the use of multiple parallel paths (or groups) in the same layer. This allows the network to learn a broader and more diverse set of features.

2. Depth and Width: ResNeXt combines two basic methods, both increasing the depth of the network and increasing the width of the network by increasing the number of groups in each layer. This allows using more parameters to achieve better performance.

3. State-of-the-Art Performance: ResNeXt has demonstrated state-of-the-art performance on a variety of tasks. It has achieved successful results especially in image classification, object recognition and other visual processing tasks



ResNeXt is used in many application areas, particularly in deep learning problems working with visual and text data, such as image classification, object detection, face recognition, natural language processing (NLP) and medical image analysis. This model performs particularly well on large data sets and is also a suitable option for transfer learning applications.

4.3 SAMPLE CODE:-

```
from tkinter import messagebox
from tkinter import *
from tkinter import simpledialog
import tkinter
import matplotlib.pyplot as plt
from tkinter import ttk
from tkinter import filedialog
from sklearn.metrics import precision_score
from sklearn.metrics import recall_score
import pickle
import os
import numpy as np
from sklearn.metrics import accuracy_score
from sklearn.model_selection import train_test_split
from sklearn.metrics import confusion_matrix
from sklearn.metrics import f1_score
import seaborn as sns
import cv2

from keras.callbacks import ModelCheckpoint
import keras
from keras.models import Sequential, Model, load_model
from keras.layers import Conv2D, MaxPooling2D
from keras.layers import Dense, Dropout, Lambda, Activation, Flatten, Input
from keras.preprocessing.image import ImageDataGenerator
from keras.optimizers import Adam, RMSprop, SGD
```

```
main = Tk()
main.title("Remote Sensing Image Analysis using Deep Learning")
main.geometry("1300x1200")

global filename, dataset
global trainImages, testImages, trainLabels, testLabels, trainBBoxes, testBBoxes, cnn_model
labels = ['Car', 'Vegetation', 'Airplane', 'Boat', 'Tree']
global X, Y, boundings

def convert_bb(img, width, height, xmin, ymin, xmax, ymax):
    bb = []
    conv_x = (200. / width)
    conv_y = (200. / height)
    height = ymax * conv_y
    width = xmax * conv_x
    x = max(xmin * conv_x, 0)
    y = max(ymin * conv_y, 0)
    x = x / 200
    y = y / 200
    width = width/200
    height = height/200
    return x, y, width, height

def addBoxes(img, label_file, name):
    boxes = []
    yy = []
    height, width = img.shape[:2]
    if os.path.exists("Dataset/YOLO_labels/"+label_file+"/"+name):
        file = open("Dataset/YOLO_labels/"+label_file+"/"+name, 'r')
        lines = file.readlines()
        file.close()
        if len(lines) > 0:
            for i in range(len(lines)):
                line = lines[i]
                line = line.split(" ")
                x1, y1, x2, y2 = getBox(img, line[1], line[2], line[3], line[4])
                x1, y1, x2, y2 = convert_bb(img, width, height, x1, y1, x2, y2)#normalized
bounding boxes
                boxes.append([x1, y1, x2, y2])
                yy.append(int(line[0].strip()))
    return np.asarray(yy), np.asarray(boxes)

#fucntion to upload dataset
def uploadDataset():
    global X, Y, boundings
    text.delete('1.0', END)
    filename = filedialog.askdirectory(initialdir=".") #upload dataset file
    text.insert(END,filename+" loaded\n\n")
    if os.path.exists('model/X.txt.npy'):
```

```
        X = np.load('model/X.txt.npy')#save all processed images
        Y = np.load('model/Y.txt.npy')
        boundings = np.load('model/bb.txt.npy')
    else:
        boundings = []
        X = []
        Y = []
        for root, dirs, directory in os.walk('Dataset/RSSOD_train_HR'):#if not processed images
then loop all annotation files with bounidng boxes
            for j in range(len(directory)):
                name = directory[j]
                name = name.replace(".png", ".txt")
                img = cv2.imread("Dataset/RSSOD_train_HR/"+directory[j])
                #img = cv2.resize(img, (64, 64))
                yy1, box1 = addBoxes(img, "labels_1class", name)
                yy2, box2 = addBoxes(img, "labels_2classes", name)
                yy3, box3 = addBoxes(img, "labels_4classes", name)
                yy4, box4 = addBoxes(img, "labels_5classes", name)
                yy = []
                box = []
                for m in range(0, 20):
                    box.append(0)
                for m in range(0, 5):
                    yy.append(0)
                start = 0
                for i in range(len(box1)):
                    if start < 20:
                        x1, y1, x2, y2 = box1[i]
                        box[start] = x1
                        start += 1
                        box[start] = y1
                        start += 1
                        box[start] = x2
                        start += 1
                        box[start] = y2
                        start += 1
                        yy[yy1[i]] = 1
                        label += 1
                for i in range(len(box2)):
                    if start < 20:
                        x1, y1, x2, y2 = box2[i]
                        box[start] = x1
                        start += 1
                        box[start] = y1
                        start += 1
                        box[start] = x2
                        start += 1
                        box[start] = y2
                        start += 1
                        yy[yy2[i]] = 1
```

```
                label += 1
            for i in range(len(box3)):
                if start < 20:
                    x1, y1, x2, y2 = box3[i]
                    box[start] = x1
                    start += 1
                    box[start] = y1
                    start += 1
                    box[start] = x2
                    start += 1
                    box[start] = y2
                    start += 1
                    yy[yy3[i]] = 1
                    label += 1
            for i in range(len(box4)):
                if start < 20:
                    x1, y1, x2, y2 = box4[i]
                    box[start] = x1
                    start += 1
                    box[start] = y1
                    start += 1
                    box[start] = x2
                    start += 1
                    box[start] = y2
                    start += 1
                    yy[yy4[i]] = 1
                    label += 1
        if len(box) > 0:
            print(str(box)+" "+str(yy))
            img = cv2.resize(img, (200, 200))#Resize image
            img = cv2.cvtColor(img, cv2.COLOR_BGR2RGB)
            boundings.append(box)
            X.append(img)
            Y.append(yy)

    X = np.asarray(X)#convert array to numpy format
    Y = np.asarray(Y)
    boundings = np.asarray(boundings)
    np.save('model/X.txt',X)#save all processed images
    np.save('model/Y.txt',Y)
    np.save('model/bb.txt',boundings)
text.insert(END,"Remote Sensing Dataset Loaded\n\n")
text.insert(END,"Total images found in dataset : "+str(X.shape[0])+"\n")
text.insert(END,"Objects or Labels Found in Dataset : "+str(labels))
unique, count = np.unique(np.argmax(Y, axis=1), return_counts=True)
height = count
bars = labels
y_pos = np.arange(len(bars))
plt.bar(y_pos, height)
plt.xticks(y_pos, bars)
```

```
    plt.xlabel('Objects Type')
    plt.ylabel('Count')
    plt.title("Dataset Class Labels Graph")
    plt.show()

def preprocess():
    text.delete('1.0', END)
    global trainImages, testImages, trainLabels, testLabels, trainBBoxes, testBBoxes
    global X, Y, boundings
    indices = np.arange(X.shape[0])
    np.random.shuffle(indices)
    X = X[indices]
    Y = Y[indices]
    boundings = boundings[indices]
    split = train_test_split(X, Y, boundings, test_size=0.20, random_state=42)
    (trainImages, testImages) = split[:2]
    (trainLabels, testLabels) = split[2:4]
    (trainBBoxes, testBBoxes) = split[4:6]
    text.insert(END,"Dataset Image Processing & Normalization Completed\n\n")
    text.insert(END,"Total Images found in dataset : "+str(X.shape[0])+"\n")
    text.insert(END,"Total features found in each Image : "+str((X.shape[1] * X.shape[2] *
X.shape[3]))+"\n\n")
    text.insert(END,"80% dataset records used to train ML algorithms :
"+str(trainImages.shape[0])+"\n")
    text.insert(END,"20% dataset records used to train ML algorithms :
"+str(testImages.shape[0])+"\n")
    text.update_idletasks()
    img = cv2.imread("Dataset/RSSOD_train_HR/airplane_085.png")
    cv2.imshow("Processed Image", img)
    cv2.waitKey(0)

def calculateMetrics(algorithm, predict, y_test):
    a = accuracy_score(y_test,predict)*100
    p = precision_score(y_test, predict,average='macro') * 100
    r = recall_score(y_test, predict,average='macro') * 100
    f = f1_score(y_test, predict,average='macro') * 100
    text.insert(END,algorithm+" Accuracy  :  "+str(a)+"\n")
    text.insert(END,algorithm+" Precision : "+str(p)+"\n")
    text.insert(END,algorithm+" Recall    : "+str(r)+"\n")
    text.insert(END,algorithm+" FScore    : "+str(f)+"\n\n")
    text.update_idletasks()

    conf_matrix = confusion_matrix(y_test, predict)
    plt.figure(figsize =(6, 5))
    ax = sns.heatmap(conf_matrix, xticklabels = labels, yticklabels = labels, annot = True,
cmap="viridis" ,fmt ="g");
    ax.set_ylim([0,len(labels)])
    plt.title(algorithm+" Confusion matrix")
    plt.ylabel('True class')
    plt.xlabel('Predicted class')
```

```
    plt.show()

def runCNNAlgorithm():
    text.delete('1.0', END)
    global trainImages, testImages, trainLabels, testLabels, trainBBoxes, testBBoxes,
cnn_model
    #define input shape
    input_img = Input(shape=(200, 200, 3))
    #Create YoloV4 layers with 32, 64 and 512 neurons or data filteration size
    x = Conv2D(32, (3, 3), padding = 'same', activation = 'relu')(input_img)
    x = Conv2D(32, (3, 3), padding = 'same', activation = 'relu')(x)
    x = MaxPooling2D((2, 2))(x)
    x = Conv2D(64, (3, 3), padding = 'same', activation = 'relu')(x)
    x = Conv2D(64, (3, 3), padding = 'same', activation = 'relu')(x)
    x = MaxPooling2D((2, 2))(x)
    x = Flatten()(x)
    #define output layer with 4 bounding box coordinate and 1 weapan class
    x = Dense(64, activation = 'relu')(x)
    x = Dense(64, activation = 'relu')(x)
    x_bb = Dense(20, name='bb',activation='softmax')(x)
    x_class = Dense(Y.shape[1], activation='sigmoid', name='class')(x)
    #create CNN Model with above input details
    cnn_model = Model([input_img], [x_bb, x_class])
    #compile the model
    cnn_model.compile(Adam(lr=0.0001), loss=['mse', 'binary_crossentropy'],
metrics=['accuracy'])
    if os.path.exists("model/cnn_weights.hdf5") == False:#if model not trained then train the
model
        model_check_point = ModelCheckpoint(filepath='model/cnn_weights.hdf5', verbose =
1, save_best_only = True)
        hist = cnn_model.fit(trainImages, [trainBBoxes, trainLabels], batch_size=32,
epochs=30, validation_data=(testImages, [testBBoxes, testLabels]),
callbacks=[model_check_point])
        f = open('model/cnn_history.pckl', 'wb')
        pickle.dump(hist.history, f)
        f.close()
    else:#if model already trained then load it
        cnn_model = load_model("model/cnn_weights.hdf5")
    predict = cnn_model.predict(testImages)#perform prediction on test data
    predict = predict[1]
    predict = np.argmax(predict, axis=1)
    y_test1 = np.argmax(testLabels, axis=1)
    calculateMetrics("Deep Learning CNN Algorithm", predict, y_test1)

def values(filename, acc, loss):
    f = open(filename, 'rb')
    train_values = pickle.load(f)
    print(train_values)
    f.close()
    accuracy_value = train_values[acc]
```

```
    loss_value = train_values[loss]
    return accuracy_value, loss_value


def graph():
    acc, loss = values("model/cnn_history.pckl", "accuracy", "val_accuracy")
    plt.figure(figsize=(10,6))
    plt.grid(True)
    plt.xlabel('EPOCH')
    plt.ylabel('Accuracy')
    plt.plot(acc, 'ro-', color = 'green')
    plt.plot(loss, 'ro-', color = 'blue')
    plt.legend(['Training Accuracy', 'Validation Accuracy'], loc='upper left')
    plt.title('CNN Algorithm Training & Validation Accuracy Graph')
    plt.show()

def predict():
    global cnn_model, labels
    filename = filedialog.askopenfilename(initialdir="testImages")
    img = cv2.imread(filename)
    img = cv2.resize(img, (200, 200))
    img1 = img.reshape(1,200,200,3)
    predict_value = cnn_model.predict(img1)#perform prediction on test data using extension
model
    predict = predict_value[0]#get bounding boxes
    predict = predict[0]
    predicted_label = predict_value[1][0]
    flag = True
    start = 0
    label = labels[np.argmax(predicted_label)]
    while flag:#now loop and plot all detected objects
        if start < 20:
            x1 = predict[start] * 200
            start += 1
            y1 = predict[start] * 200
            start += 1
            x2 = predict[start] * 200
            start += 1
            y2 = predict[start] * 200
            start += 1
            print(str(x1)+" "+str(y1)+" "+str(x2)+" "+str(y2)+" "+label)
            if x1 > 0 and y1 > 0 and x2 > 100 and y2 > 0:
                cv2.rectangle(img, (int(x1), int(y1)), (int(x2), int(y2)), (255,0,0), 1, 1)
                cv2.putText(img, str(label), (int(x1),
int(y1+50)),  cv2.FONT_HERSHEY_SIMPLEX,0.7, (0, 0, 255), 1)
        else:
            flag = False
    img = cv2.resize(img, (400, 400))
    cv2.imshow("Predicted Output", img)
    cv2.waitKey(0)
```

```
def close():
    main.destroy()

font = ('times', 16, 'bold')
title = Label(main, text='Remote Sensing Image Analysis using Deep Learning')
title.config(bg='gold2', fg='thistle1')
title.config(font=font)
title.config(height=3, width=120)
title.place(x=0,y=5)

font1 = ('times', 13, 'bold')
ff = ('times', 12, 'bold')

uploadButton = Button(main, text="Upload Remote Sensing Dataset",
command=uploadDataset)
uploadButton.place(x=20,y=550)
uploadButton.config(font=ff)

processButton = Button(main, text="Preprocess Dataset", command=preprocess)
processButton.place(x=300,y=550)
processButton.config(font=ff)

cnnButton = Button(main, text="Run CNN Object Detection Algorithm",
command=runCNNAlgorithm)
cnnButton.place(x=510,y=550)
cnnButton.config(font=ff)

graphButton = Button(main, text="CNN Training Graph", command=graph)
graphButton.place(x=850,y=550)
graphButton.config(font=ff)

predictButton = Button(main, text="Object Detection from Test Image", command=predict)
predictButton.place(x=20,y=600)
predictButton.config(font=ff)

closeButton = Button(main, text="Exit", command=close)
closeButton.place(x=300,y=600)
closeButton.config(font=ff)

font1 = ('times', 12, 'bold')
text=Text(main,height=22,width=150)
scroll=Scrollbar(text)
text.configure(yscrollcommand=scroll.set)
text.place(x=10,y=100)
text.config(font=font1)

main.config(bg='DarkSlateGray1')
main.mainloop
```

5. TESTING AND RESULTS

5.1 TESTING METHODS

The purpose of testing is to discover errors. Testing is the process of trying to discover every conceivable fault or weakness in a work product. It provides a way to check the functionality of components, sub-assemblies, assemblies and/or a finished product It is the process of exercising software with the intent of ensuring that the Software system meets its requirements and user expectations and does not fail in an unacceptable manner. There are various types of test. Each test type addresses a specific testing requirement.

TYPES OF TESTS

Unit testing

Unit testing involves the design of test cases that validate that the internal program logic is functioning properly, and that program inputs produce valid outputs. All decision branches and internal code flow should be validated. It is the testing of individual software units of the application. it is done after the completion of an individual unit before integration. This is structural testing, that relies on knowledge of its construction and is invasive. Unit tests perform basic tests at component level and test a specific business process, application, and/or system configuration. Unit tests ensure that each unique path of a business process performs accurately to the documented specifications and contains clearly defined inputs and expected results.

Integration testing

Integration tests are designed to test integrated software components to determine if they run as one program. Testing is even driven and is more concerned with the basic outcome of screens or fields. Integration tests demonstrate that although the components were individually satisfaction, as shown by successfully unit testing, the combination of components is correct and consistent. Integration testing is specifically aimed at exposing the problems that arise from the combination of components.

Functional test

Functional tests provide systematic demonstrations that functions tested are available as specified by the business and technical requirements, system documentation, and user manuals. Functional testing is centered on the following items:

Valid Input	: identified classes of valid input must be accepted.
Invalid Input	: identified classes of invalid input must be rejected.
Functions	: identified functions must be exercised.
Output	: identified classes of application outputs must be exercised.
Systems/Procedures	: interfacing systems or procedures must be invoked.

Organization and preparation of functional tests is focused on requirements, key functions, or special test cases. In addition, systematic coverage pertaining to identify Business process flows; data fields, predefined processes, and successive processes must be considered for testing. Before functional testing is complete, additional tests are identified, and the effective value of current tests is determined.

System Test

System testing ensures that the entire integrated software system meets requirements. It tests a configuration to ensure known and predictable results. An example of system testing is the configuration-oriented system integration test. System testing is based on process descriptions and flows, emphasizing pre-driven process links and integration points.

White Box Testing

White Box Testing is a testing in which in which the software tester has knowledge of the inner workings, structure and language of the software, or at least its purpose. It is purpose. It is used to test areas that cannot be reached from a black box level.

Black Box Testing

Black Box Testing is testing the software without any knowledge of the inner workings, structure or language of the module being tested. Black box tests, as most other kinds of tests, must be written from a definitive source document, such as specification or requirements document, such as specification or requirements document. It is a testing in which the software under test is treated, as a black box .You cannot "see" into it. The test provides inputs and responds to outputs without considering how the software works.

Unit Testing

Unit testing is usually conducted as part of a combined code and unit test phase of the software lifecycle, although it is not uncommon for coding and unit testing to be conducted as two distinct phases.

Test strategy and approach

Field testing will be performed manually and functional tests will be written in detail.

Test objectives

- All field entries must work properly.
- Pages must be activated from the identified link.
- The entry screen, messages and responses must not be delayed.

Features to be tested

- Verify that the entries are of the correct format
- No duplicate entries should be allowed
- All links should take the user to the correct page.

Integration Testing

Software integration testing is the incremental integration testing of two or more integrated software components on a single platform to produce failures caused by interface defects.

The task of the integration test is to check that components or software applications, e.g. components in a software system or – one step up – software applications at the company level – interact without error.

Test Results: All the test cases mentioned above passed successfully. No defects encountered.

Acceptance Testing

User Acceptance Testing is a critical phase of any project and requires significant participation by the end user. It also ensures that the system meets the functional requirements.

Test Results: All the test cases mentioned above passed successfully. No defects encountered.

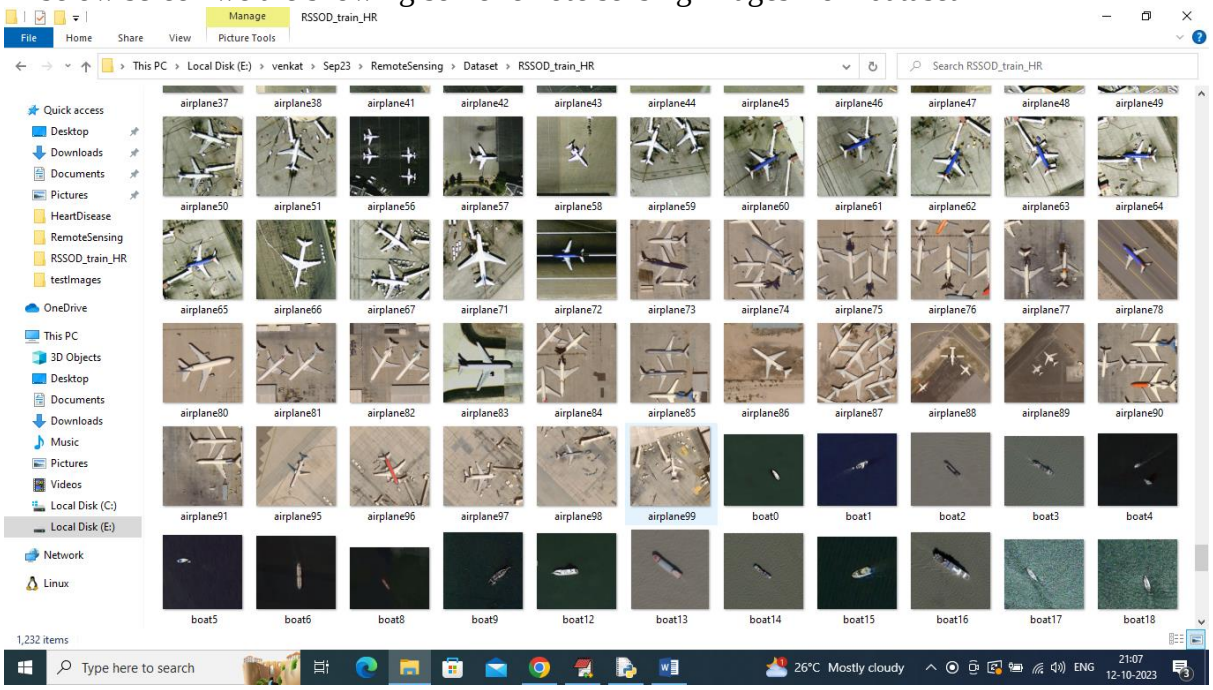
6. RESULTS

In propose work we are employing deep learning Convolution Neural Network to analyze and detect objects from Remote Sensing or Serial images. In the past many algorithms were introduced to detect objects from normal images and very few work has been done on remote images. So, we employed CNN algorithm to detect objects from aerial images.

In proposed work CNN algorithm objects detection accuracy is recorded between 89 to 95%. No CNN algorithms are 100% accurate so our algorithm able to identify objects correctly but bounding boxes of detected objects is little less accurate.

To train CNN algorithm we have utilized RSSOD remote sensing images dataset which can be downloaded from below website
https://data.mendeley.com/datasets/b268jv86tf/1

In below screen we are showing some remote sensing images from dataset



Above dataset consists of 5 different classes, such as Car, Aeroplane, Vegetation, Tree and Boat and by using the above dataset we will train and test CNN performance on remote sensing images.

To implement this project, we have designed following modules

1. Upload Remote Sensing Dataset: using this module we can upload dataset to an application and then read all images and bounding boxes to generate training features

2. Pre-process Dataset: using this module we will normalize, shuffle and split dataset into train and test

3. Run CNN Object Detection Algorithm: In this module CNN will get trained on training features and then its performance will be evaluated using test data features. Performance evaluation will be done in terms of accuracy, precision, recall, Confusion Matrix and FSCORE

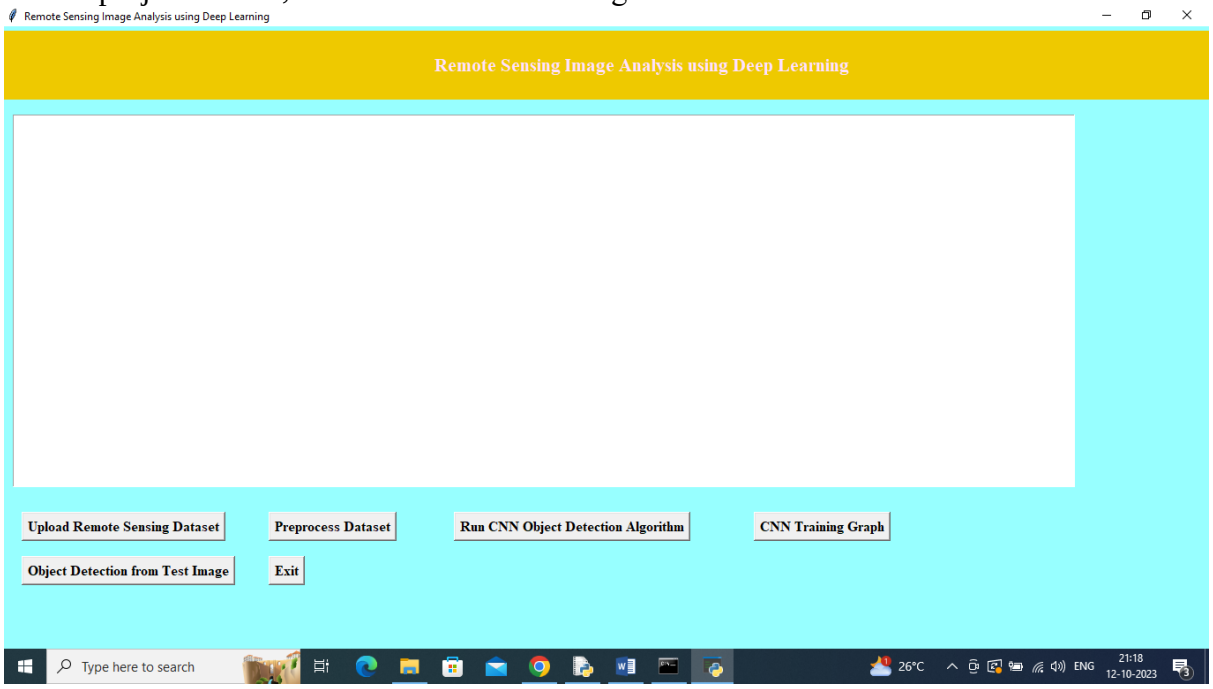
4. CNN Training Graph: using this module we will plot CNN training and validation accuracy graph

5. Object Detection from Test Image: using this module we will upload test image and then CNN will detect and predict objects from input image.

SCREEN SHOTS

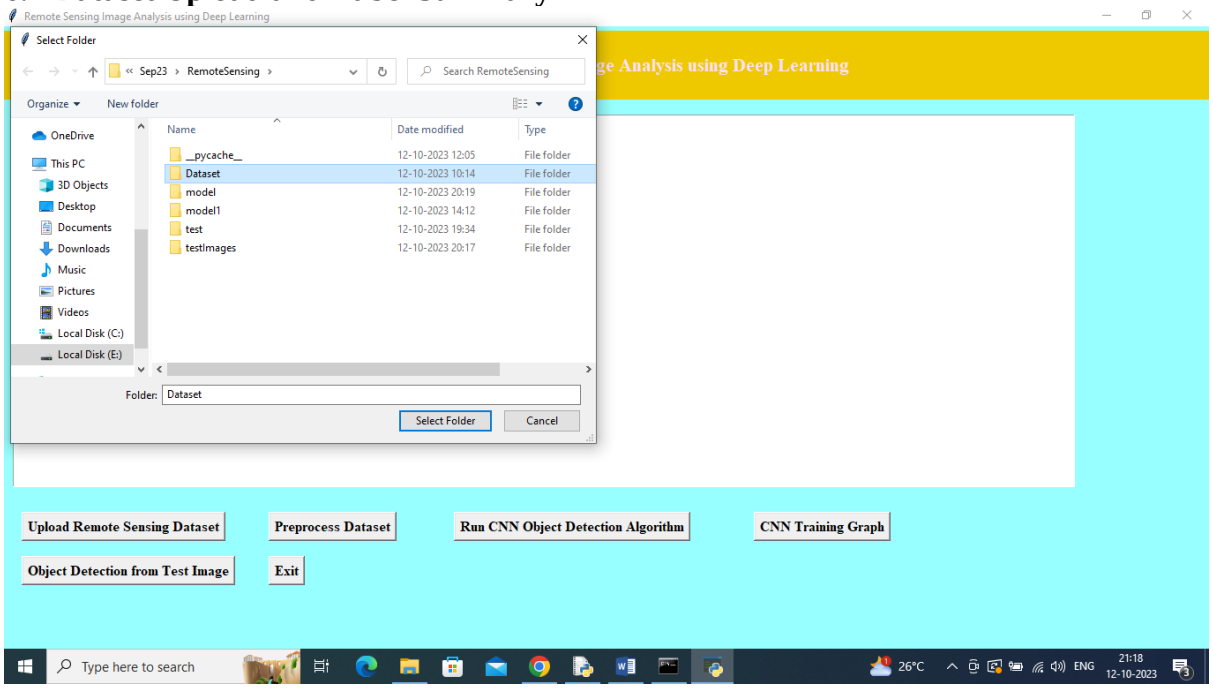
6.1 Project Initialization: -

To run project double, click on 'run.bat' file to get below screen

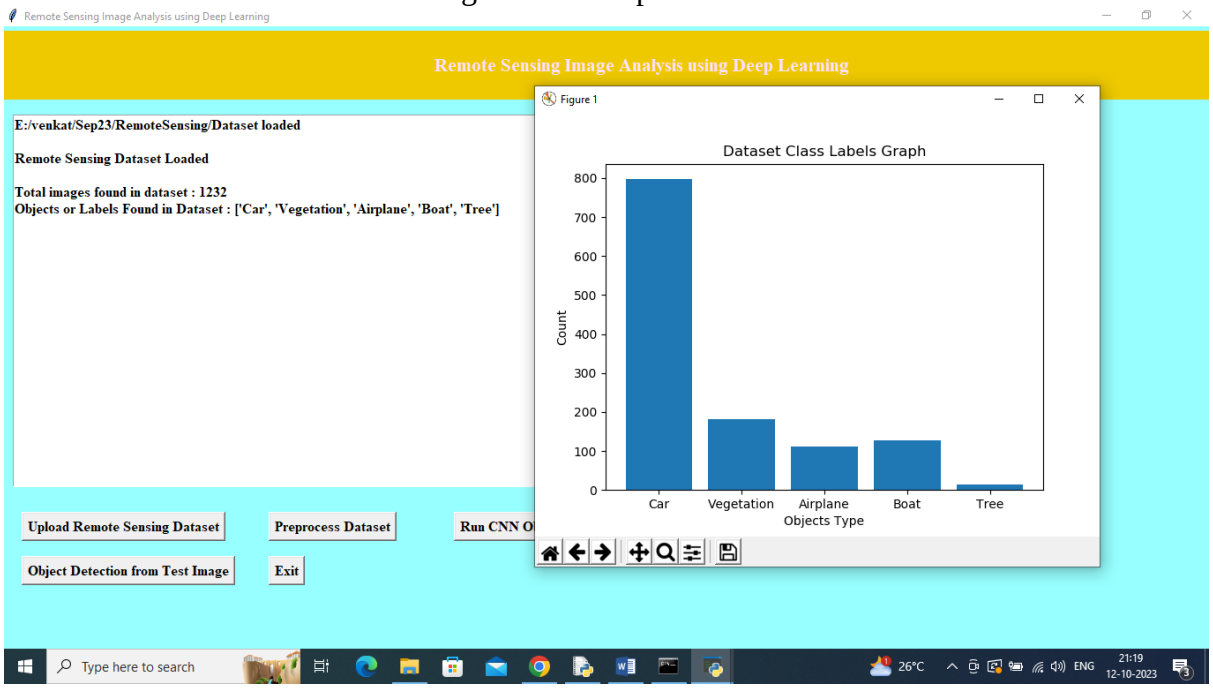


In the above screen click on 'Upload Remote Sensing Dataset' button to upload dataset and get below output

6.2 Dataset Upload and Label Summary

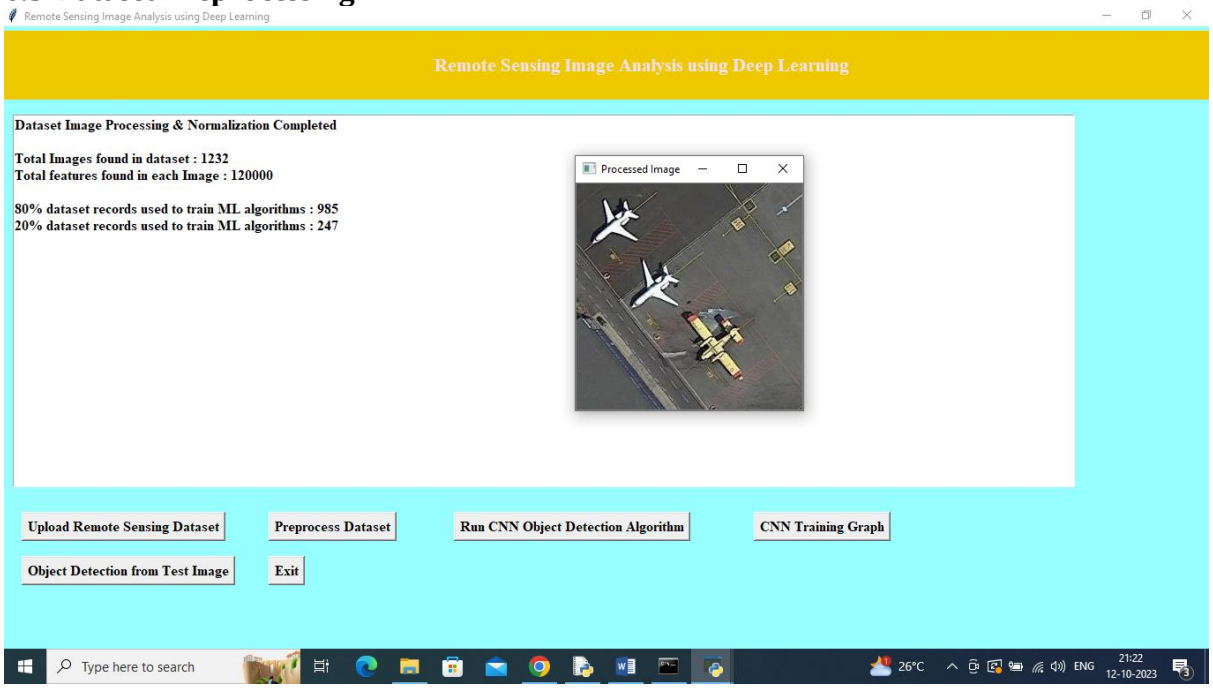


In above screen selecting and uploading 'Dataset' folder and then click on 'Select Folder' button to load dataset and then will get below output



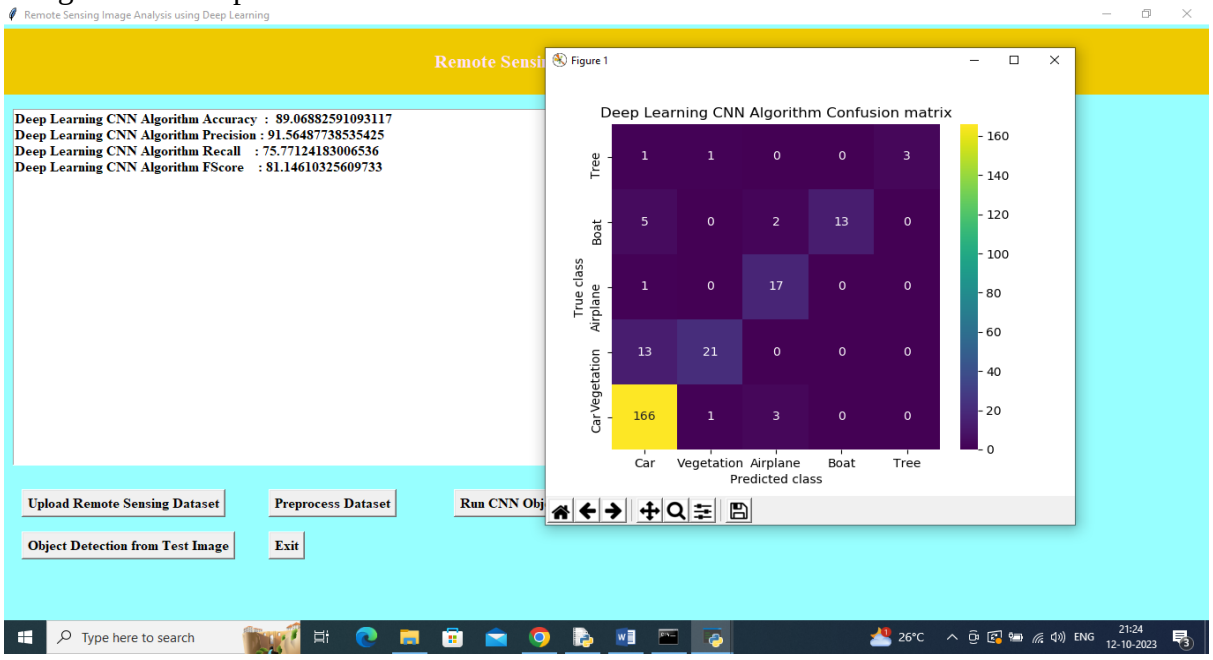
In the above screen can see dataset loaded and then can see available labels and in graph x-axis represents Labels and y-axis represents number of images found under that label. Now close above graph and then click on 'Pre-process dataset' button to process images and get below output

6.3 Dataset Preprocessing



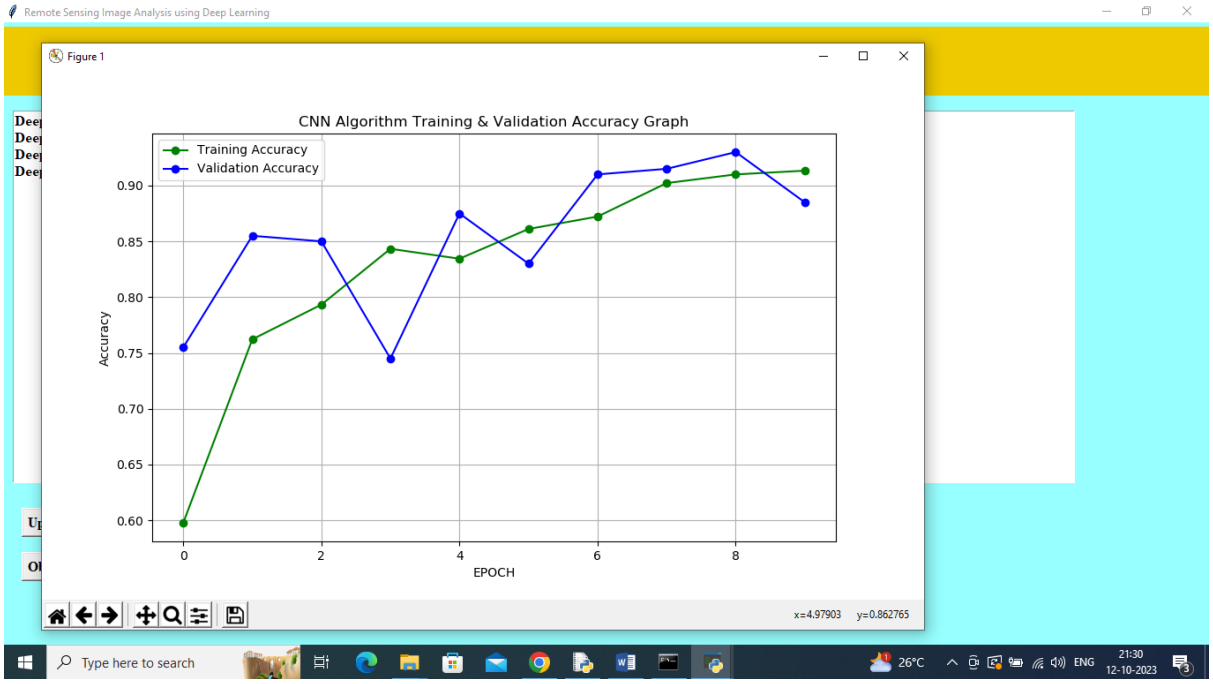
6.4 CNN Model Training and Evaluation

In above screen can see total loaded images and number of features available in each image and then can see training and test size and then can see processed sample image and now close above image and then click on 'Run CNN Object Detection Algorithm' button to train CNN and get below output



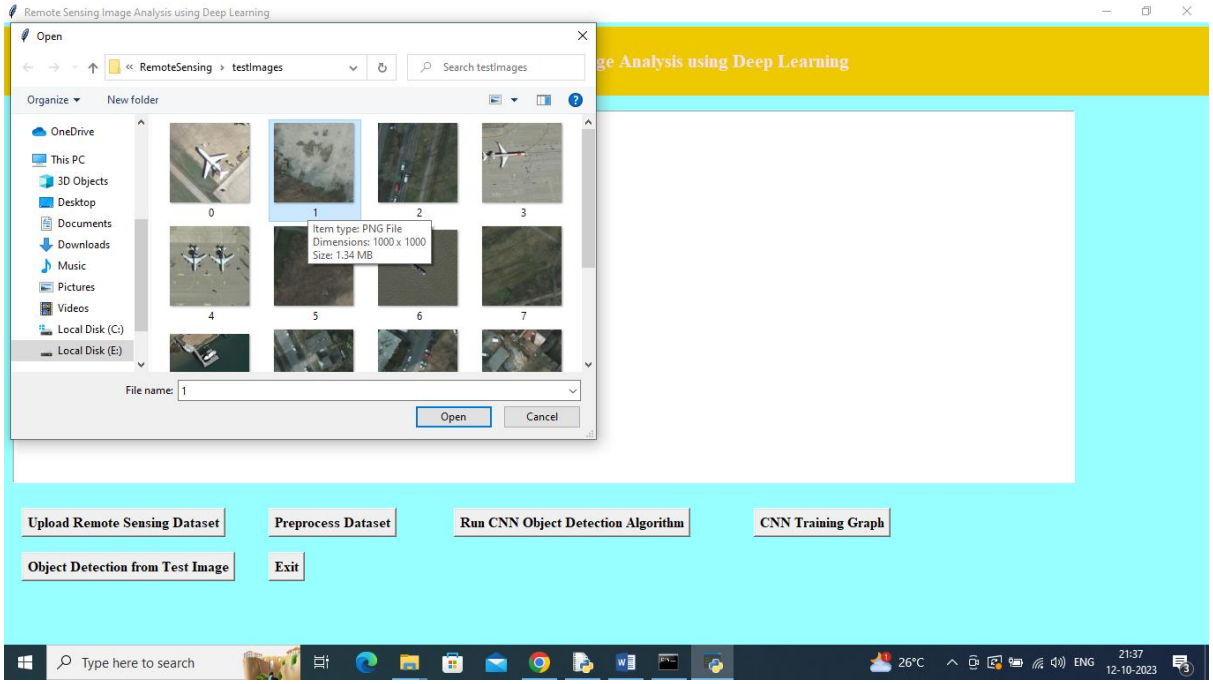
6.5 Training Progress Visualization

In above screen CNN training complete and it got an accuracy of 89% and can see other metrics like precision, recall and FSCORE. In Confusion matrix graph x-axis represents Predicted Labels and y-axis represents True Labels and all counts in diagonal boxes represents correct prediction count and remaining boxes represents incorrect prediction count. Now close above graph and then click on 'CNN Training Graph' button to get below graph



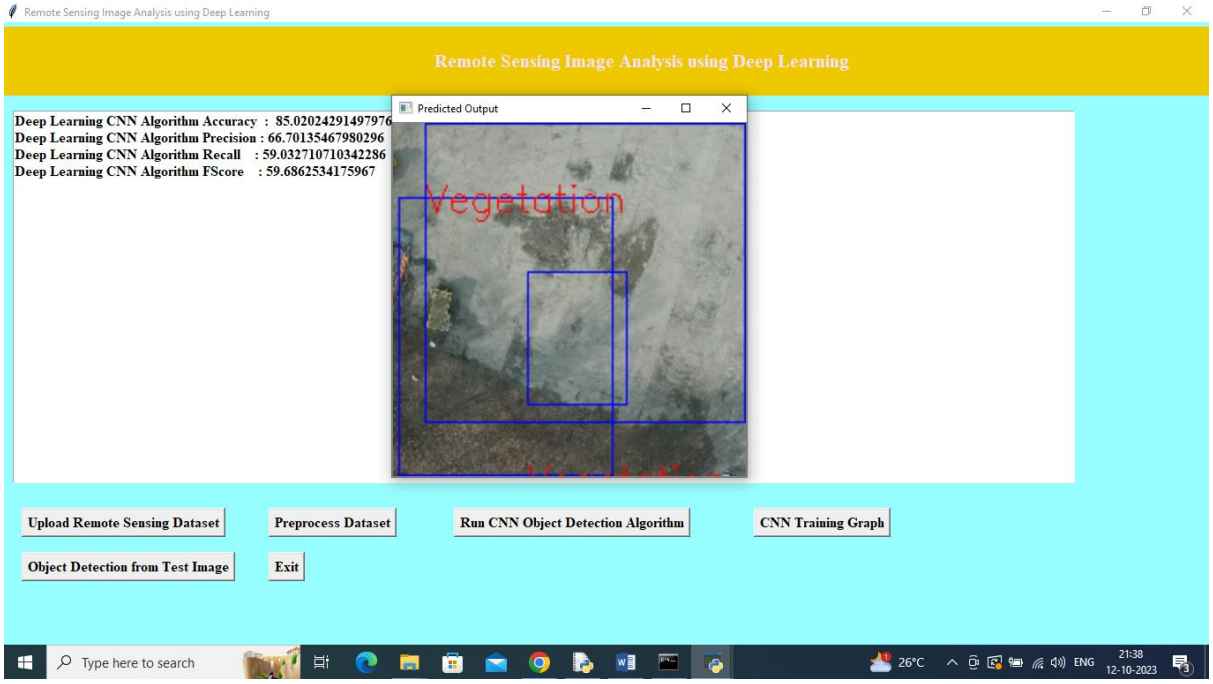
6.6 Object Detection on Test Images

In above graph x-axis represents training epoch and y-axis represents training and validation accuracy where the green line is for training accuracy and blue line for validation accuracy and with each increasing epoch both training and validation accuracy got increased and now close above image and then click on 'Object Detection from Test Image' button to upload test image like below screen



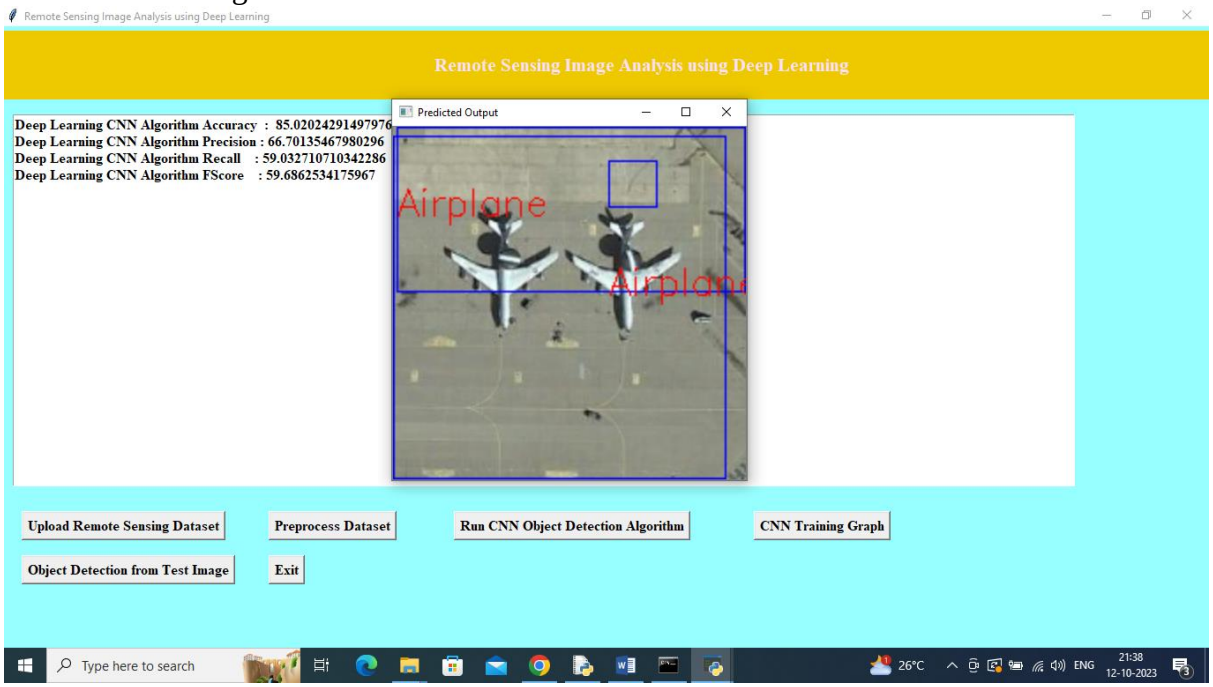
6.6.1 Detection Result – Vegetation

In above screen selecting and uploading '1.png' file and then click on 'Open' button to get below output



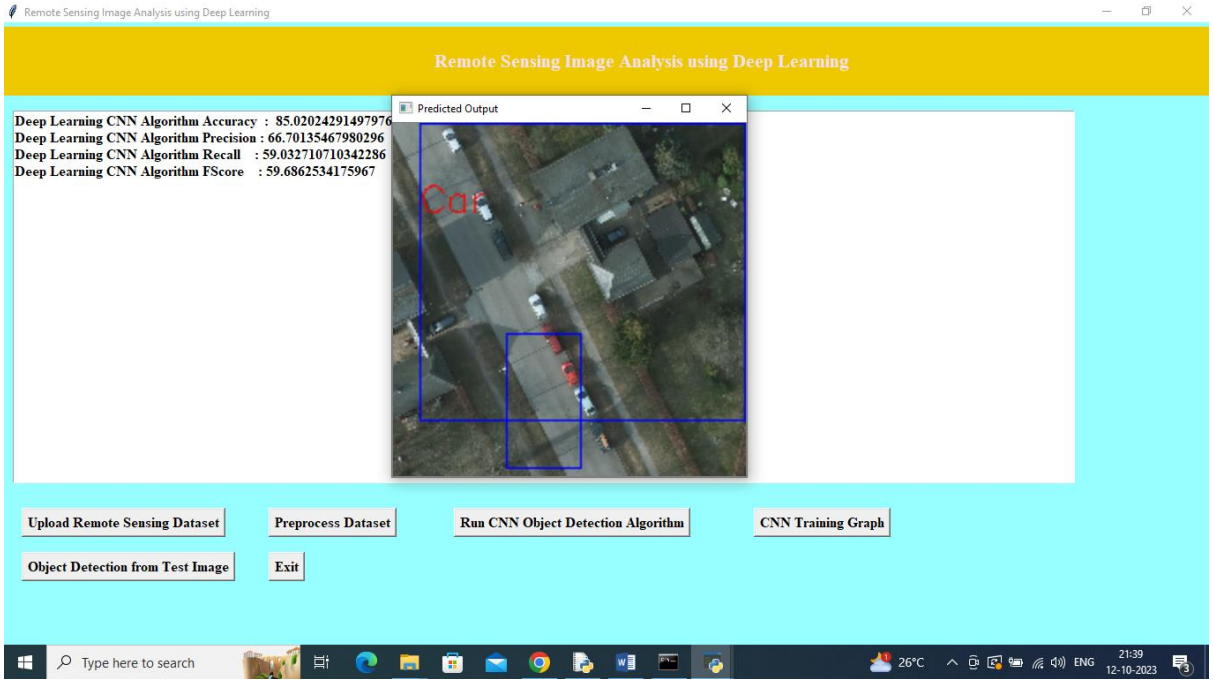
6.6.2Detection result – Aeroplane

In the above output all green parts are identified as 'Vegetation' and similarly you can upload and test other images



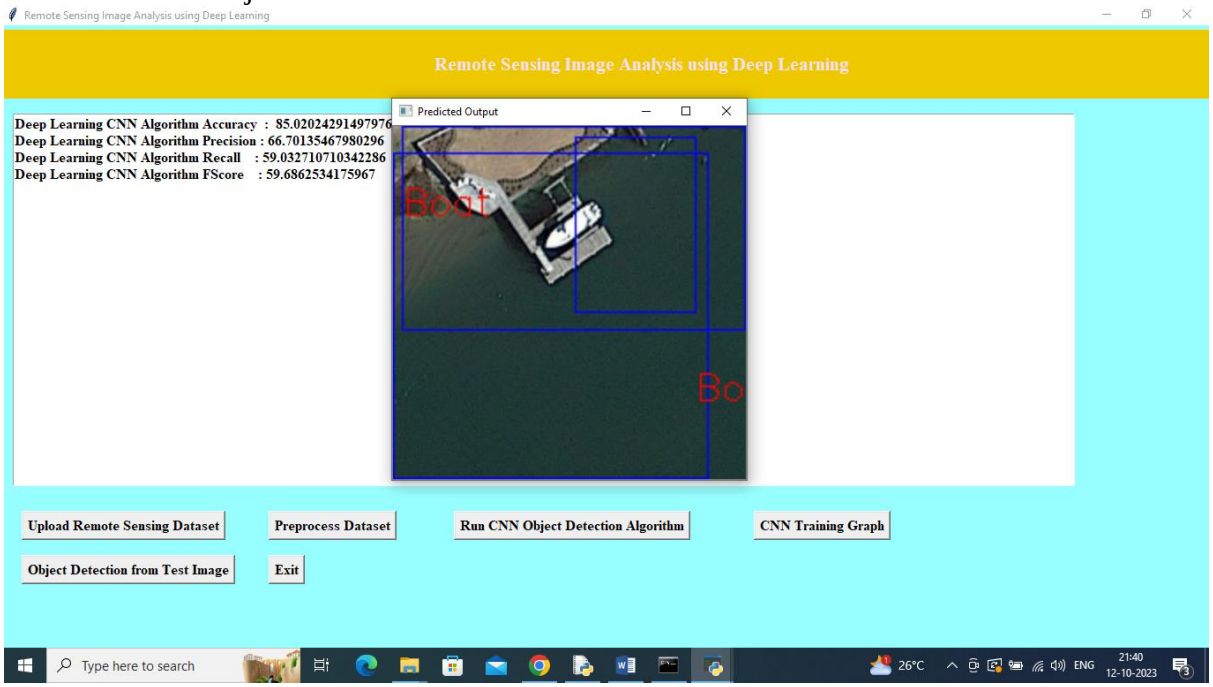
6.6.3 Detection result – Car

In the above screen object detected and identified as Aeroplane



6.6.4 Detection result – Boat

In above screen object detected as Car



In the above screen object detected as Boat

7. CONCLUSION

This project demonstrates the successful application of deep learning techniques, particularly Convolutional Neural Networks (CNNs), for remote sensing image analysis. By employing the ResNeXt model for feature extraction and integrating it with LSTM for sequential learning, the system was able to effectively classify and detect objects such as vehicles, trees, and buildings from high-resolution aerial images.

The system achieved a detection accuracy ranging from 89% to 95%, highlighting its potential for real-world applications in areas like urban planning, environmental monitoring, and disaster response. Despite the inherent challenges in remote sensing data—such as varying image resolutions, lighting conditions, and occlusions—the model performed reliably across different classes of objects.

This project serves as a foundation for further exploration in the field. With enhancements such as real-time processing, improved bounding box accuracy, and more diverse training datasets, the system can evolve into a robust tool for automated geospatial analysis.

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