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An Implementation of Satellite Image Classification and Analysis using Machine Learning with ISRO LISS IV

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***Abstract*—Image category is a complicated system that can be stricken by many factors. This paper examines modern-day practices, problems, and potentialities of image category. The emphasis is positioned at the summarization of primary advanced category procedures and the strategies used for enhancing category accuracy. In addition, a few essential problems affecting category performance are discussed. This literature evaluate indicates that designing an appropriate image processing system is a prerequisite for a a hit category of remotely sensed records right into a thematic map. Effective use of a couple of functions of remotely sensed records and the choice of a appropriate category approach are especially extensive for enhancing category accuracy. Non-parametric classifiers such as neural network, choice tree classifier, and knowledge-primarily based totally category have an increasing number of turn out to be essential procedures for multi-source records classification. Integration of faraway sensing, geographical data systems (GIS), and professional machine emerges as a brand-new studies frontier. More studies, however, is had to discover and decrease uncertainties with inside the image-processing chain to enhance category accuracy.**

***Keywords*—** Artificial Neural Network (ANN), Machine Learning, Sensor LISS IV, Remote Sensing

I. Introduction

Machine learning is the scientific study of algorithms and statistical models that computer systems use to perform a task without using explicit instructions, relying on patterns and inference. In our program, machine learning algorithms are applied to achieve image processing. In ISRO, to perform image processing the scientists have to first convert the image into data frames and feed this information into a system application where manually they have to change the bands depending on the image and identify objects in the image. This process is time consuming and sometimes can lead to errors as the data is not precise which can lead to inaccurate processing of the data. Our projects build a system that can identify the number of bands of the image and create precise data that can be fed to the system and this data is then processed using the concept of convolutional neural network to obtain feature extraction and object recognition without any manual effort.

The primary concept of the project is to focus on the information which will be obtained by processing of the images or datasets that are made available from the sensor. The sensor that is used for the purpose of our project is LINEAR IMAGE SELF SCANNING SENSOR – IV, also known as LISS-IV. The images on the satellite are captured

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by the sensor which takes high resolution images. The high-resolution satellite images are being provided by RRSC- C ISRO, Nagpur. [1], Satellite image classification is the most important task includes computer-assisted techniques for data analysis, processing and classification. Many techniques are introduced for image classification, such as: neural network (NN), decision trees, genetic programming, statistical machine learning and other analysis methods [2].

The classification of satellite images comprises two main stages: segmentation and classification. The aim of image segmentation is to divide the image into parts which are strongly correlated by the conceptual content of the image. In the light of predefined groups or classes of known attributes [3], while the purpose of the classification is to allot a specific label for each fragment of the image, neural networks are an interest. The power of the neural network classification has been mentioned in recent research [1]. Neural networks give flexibility and the ability to learn complex data to identify classes for image data classification. Thus, by providing small tests, you can achieve highly accurate and robust results. In addition, the neural network approach avoids the problem of specifying the impact each source has on a multi-source statistical analysis. This means that for a multi-source remote sensing data classification, a neural network approach is preferable [4]. Remote sensing is the science of acquiring information about the Earth's surface without actually contact with it, the sensor is designed based on two techniques: passive sensor, or active sensor. Passive sensor receives the illumination reflected by objects from an additional light source, such as the sun. Optical sensors are normally passive sensors that collect various spectral ranges (or bands) that vary in number and width per sensor. Active sensors send radiation and disperse reflections to the targets.

In 2005, Mayank Toshniwal,[1] suggest feed-forward neural networks in the area of satellite image segmentation. New approaches and innovative increments have been added to the standard thoughts. Provides suitably developed neural network architecture with high accuracy. Obtained accuracy and efficiency in terms of standard parameters to achieve accurate image segmentation. It has been concluded that the timeliness of segmentation and problem-solving inadequate training sets can be improved.

Gowri Ariputhiran, S. Gandhimathi [6] proposed in 2013 to classify and extract the space in high resolution multispectral satellite image categories in urban areas. A multi-spectral satelite image is preprocessed by a Gaussian filter to remove the noise in the image. The functions are then extracted using the Gray Level Co-Event Matrix from the filtered image (GLCM). The extracted characteristics are also classified by means of the Back Propagation Artificial Neural Network (BPANN) and the performance is analyzed in terms of its accuracy, failure rates and sensitivity. The classification results were up to 94.59%, ensuring that in all types of satellite images, the classification has good accuracy.

The hybrid clustering and feeding system of a new Neural Network Classifier were submitted by S. Praveena, Dr. S. P. Singh [3] in 2014 for the mapping of shade, trees, buildings and roads. It begins with the single pre-processing step to make the picture segmentable. The preprocessed image is segmented with the hybrid Artificial Bea Colony (ABC) genetic algorithm developed to produce the effective segmentation in satellite image by hybridizing ABC and genetic algorithms and is classified with the feed-forward neural network classification. The results have been very accurate.

J. Shabnam et al [4] introduced a supervised method of the satellite image classification in paper "Very High-Resolution Satellite Image Classification Using Fuzzy Rule-Based Systems;" Satellite images are classified in five main classes: shade, vegetation, roads, construction and unused land. This procedure utilizes satellite classification image segmentation and fuzzy techniques. It applies to two segmenting levels, first level segmentation identifies shadows, vegetation and roads and classifies them. Segmentation of the second level identifies buildings. It also uses contextual control to classify segments that are not classified.

"Land Cover Classification of Satellite Images using Contextual Information" by Bjorn Frohlich [5] Presents a method for the classification of satellite images into multiple predefined land cover classes. With the support of the training set, this method is automated and uses segment level classification. The classification methods involve contextual characteristics of several predefined classes to enhance classification accuracy.

II. RELATED WORK

The literature relevant to the current study was studied to gain a better understanding of the current state of the field. The findings of this preliminary study are described in this section. A fast and automatic approach to detect objects in images of large size. Experimentation was performed supported by calculations to show that the proposed technique provides faster recognition. A similar attempt was made in to improve the accuracy of object detection in complex satellite images. The solution attempted to mimic the human vision system to improve the accuracy of detection.

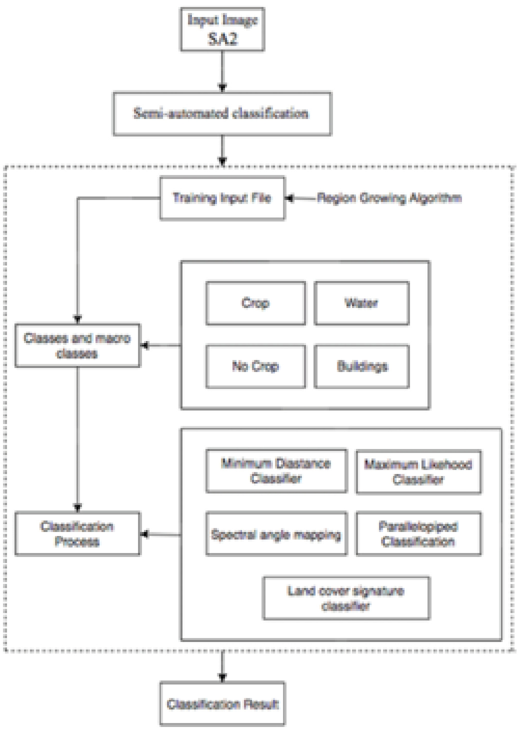

Figure 1. Flow Chart of Overall Process

Reference used a GIS-based application to detect ships in high resolution satellite images. This is used for monitoring maritime activities. In the task of identifying type of aircraft in satellite imagery was done with hierarchical recognition methods. By experimentally comparing different approaches, a superior method was recommended. The identification of vehicles in satellite images was performed. This was done using segmentation followed by classification. The usage of support vector machine for classification in satellite images was discussed.

Experimentally it was shown that the algorithm can be faster and more accurate using active learning. According to the place of satellite images, infra-red images were used and a sea-land segmentation algorithm was proposed. Grayness and texture of surface were studied to arrive at a Gray Smoothening Ratio as a feature descriptor around which an algorithm was developed to classify and segment the images into sea and land. In addition to this, the algorithm also had a function to fill and gaps that arise due to natural conditions such as fog or cloudy weather. The authors implemented a machine learning technique using Adaboost. The prime point of study in this paper, was to separate circular structures in satellite images. Adaboost, an ensemble of various machine learning classification algorithms to provide a superior classifier, and Haar, a series of statistical feature descriptors were primarily used to implement the tool. Adaboost was trained iteratively and Hear descriptors were directly implemented over the gray-level images so as to avoid segmentation. The final phases used a cascade of Adaboost classifiers so as to avoid re-detection at the various scales of the image. The end result is a separated set of images. The study focuses on retrieving images from high resolution satellite images using CNN based approaches. Multiple datasets were used with strong CNNs to observe strong improvement over existing approach. Reference uses large set of image data to perform surface object recognition. Two methods based on CNN and SVM are proposed and compared. It is found that in the performed experiments, CNN had better performance. Isolated airstrips are identified in satellite images using SVM after preprocessing the images. The algorithm performed very well providing an accuracy of 94%. It was able to identify airstrips among other common linear objects like roads, canals, and other objects [7].

Several annotated datasets of imagery, along with detection and classification activities, have recently appeared. The most important subject of the profound learning used in remotely sensed imagery is the classification of the land cover or construction detection. For example, a dataset of 2100 aerial photographs from the UC Merced Land Use Survey. The images are 256x256 pixels with a distance of 0.3 meters per pixel for a ground sample. The 21 classes include agricultural, road- and water classes, storage and tennis courts as well as facilities classes. Several scientists used CNNs for the UC Merced images into land cover types (VGG, ResNet and Inception) and one reported classification accuracy of up to 98.5%. However, the size, the number, types and geographical diversity of this dataset is very limited. The Space Net dataset comprises high-resolution satellite images of Digital Globe from five cities and building footage. In order to segment images and extract the footprints of construction CNNs have been trained. The geography and usefulness for training a classificatory is limited in this dataset. Ref. includes a list of other data sets for remote sensing. None of them contain the hundreds of thousands of images on a global scale that are required to develop a versatile image classification system [8].

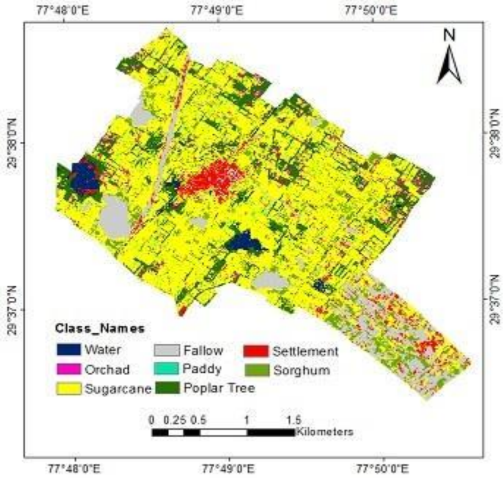

Figure 2. Classified image using decision tree (VI)

The concept of automated image understanding from video for public security applications is well known and well explored in many domains. Jang and Turk, for example, proposed a vehicle identification system based on the SURF algorithm of function detection. A number of studies have proposed and analyzed the concept of automatic CCTV image analysis and detection of dangerous situations. The automatic fire detection system based on temporary fire intensity variations was proposed by Marbach et al. These and similar solutions take a similar approach to research and address a less complex problem. This is also the case for observational and deduction systems based on the detection and estimation of the human silhouette. Chen et al. propose a good overview of the silhouette representation. This approach is applied in Velastin et al crowd density management system and Lo et al congestion detection system. Dever et al. proposed an automated identification robbery system based on a pose estimation by actors. As part of the UK-based MEDUSA project, Darker et al. proposed the initial concept of an automated detection of gun crime. This team has also worked to identify the signs that an individual carries a hidden weapon. Next emerged the first experiments of the same team using CCTV as an automated firearms sensor. FISVER, a smart public safety framework for video surveyed vehicles with the ability to identify general objects, including artefacts, is an example of a newer approach. In addition, Arslan et al. proposed a threat evaluation solution using visual hierarchy and ontology of conceptual firearms. Dee and Velastin present a good overview of current developments in automated CCTV monitoring systems. It should also be mentioned that other promising approaches are available in similar scenarios in the detection of dangerous objects. Yong et al showed that the detection with microwave sweep frequency radar of metal objects like guns and knives is possible. As shown by Mery et al., objects can also be recognized with X-ray image. Such approaches are restricted in practical terms by cost and health risks. Video-based firearm detection is also a measure of prevention and can be linked to the acoustic gunshot detection [9,10].

Our approach was based on various instruments designed to detect and recognize objects. In this work as well as in other research aimed at safe applications and computer forensics, we have successfully applied MPEG-7 visual descriptors. The INACT Tool (an ingenious advanced image cataloguing tool for child abuse fighting) and the INSTREET Tool are examples (an application for urban photograph localization). Hazardous object detection is a particular case of general object detection that can be performed by methods such as the principal component analysis (PCA) that is also used in this work.

III. PROPOSED WORK

In ISRO Dataset, to perform image processing the scientists have to first convert the image into data frames and feed this information into a system application where manually they have to change the bands depending on the image and identify objects in the image. Our projects build a system that can identify the number of bands of the image and create precise data that can be fed to the system and this data is then processed using the concept of convolutional neural network to obtain feature extraction and object recognition without any manual effort. In our project also we will be training the machine to classify water body, land, forest, roads. Also, we will be making python scripts to convert the images into different bands so that a image can be taken in RGB format.

The proposed satellite image classification consists of two phases: training, and classification. Each phase contains some stages within, Figure 2 shows the detailed stages of each phase, In the proposed method, the training phase is responsible on enroll the database information that needed to implement the next phases. The classification phase is designed to employ the information stored in the database for classification purpose. Both the training and classification phases are based on using back propagation artificial neural network (BPANN) to recognize input features that resulting a classified image. This requires to pass through a preprocessing and preparing stages. The following sections give more explanations about each stage of the proposed method.

A. Training Dataset

For the purpose of supervised training, a specific classified image is used as reference images. This reference image is used to determine the class that each pixel belongs to in the material image. The reference classified image for year 2000 used to train the designed BPANN, while Table I presents the information on image classes of the reference image. Such reference image was achieved from the Iraqi ecological Survey Corporation (IGSC), which contains five classes.

B. Training Phase

Result In the training implementation, the number of iterations through research and experimentation was determined to be 1000 for each training process of one pixel or till reaching a proper accuracy score (i.e., mean square error; MSE= 0.001), where the study ratio used is 0.5. These limits provided the most confident results when weights start with random initial values from 0-1 that are adjusted time to time until the weight behavior reaches true values.

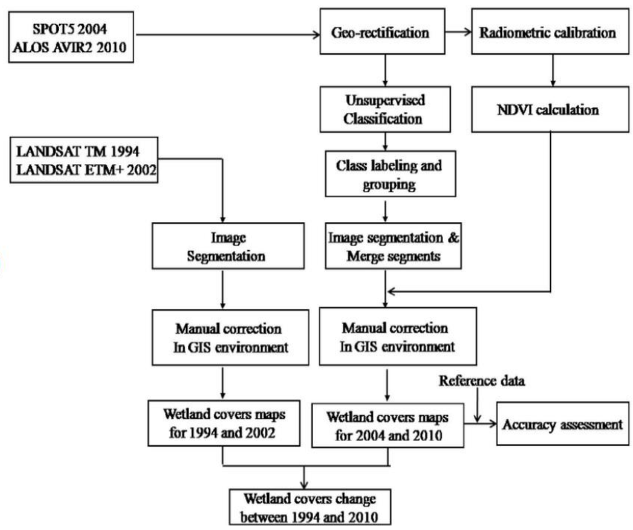

Figure 3. Flow Diagram of Proposed Work

Regardless of the initial value, the weight is oriented towards its true values with thousands of workouts; they are far from their true values at events when training iterations are increased, it is also apparent that in the final iterations the weights settle to some values, and no change can take place when the training iterations are increased. For this reason, at every training iteration, the MSE calculated between the BPNN results and the true class value is lowered until the best weight values are achieved. The MSE's behavior of training the weight for a sample pixel shows that for sufficient specific training iterations, the MSE approaches a zero while the MSE's behavior for more workout iterations in which the MSE does not determine the nil value but continues to be specifically low. The weights behavior during the training period is almost oriented to real values, and the decrease in mode can increase little because of the spectral homogeneity found in the current image block, which demonstrated not monotonous behavior to correct weights. However, until the training phase is over, weights continue to embrace the corrected path to real values. This result ensures that an acceptable classification result was achieved by sufficient iteration and learning ratio.

C. Classification Phase Result

The classification process is based on the use of the database containing the appropriate final weights for the classified image. The table shows some results statistic that is necessary to estimate the classification performance of the same reference satellite image using the proposed BPANN; those are pixel number (Np) and classification percentages (Pc) for each class of the class in the resulting image. The classification percentage is a partial percentage of every class according to the results of the classification and the sum of all participating percentages is 99 percent. The proposed grading score was shown to be 99 percent, indicating that there is no pixel left without the grading in the image given.

D. Classification Score

The classification score proposed is shown to be 99% which indicates that no pixel remains unclassified in the given image. It is shown that the proposed classification score was 99%, which indicates that there is no pixel in the given image is left without classification.

E. Generalizing and validating Outcome

The validation and generalization tests are used by the proposed BPANN method to classify other satellite images, that are not previously classified, mean that other data not used in neural network training is used. The classification result for the period 2003 of satellite images the exact classification result measures are listed in the table In comparison with the original classification, it is shown that the value of the true classification is 98%, When a misclassification of 1% in class 1 and 2% in class 1% in category 2 is, the misclassification of the entire resulting image is 2%. The designed system has successfully classified the validation image correctly with 98 percent accuracy, which means that a generalization was achieved by the proposed system and that new image data can successfully be classified in a good percentage,

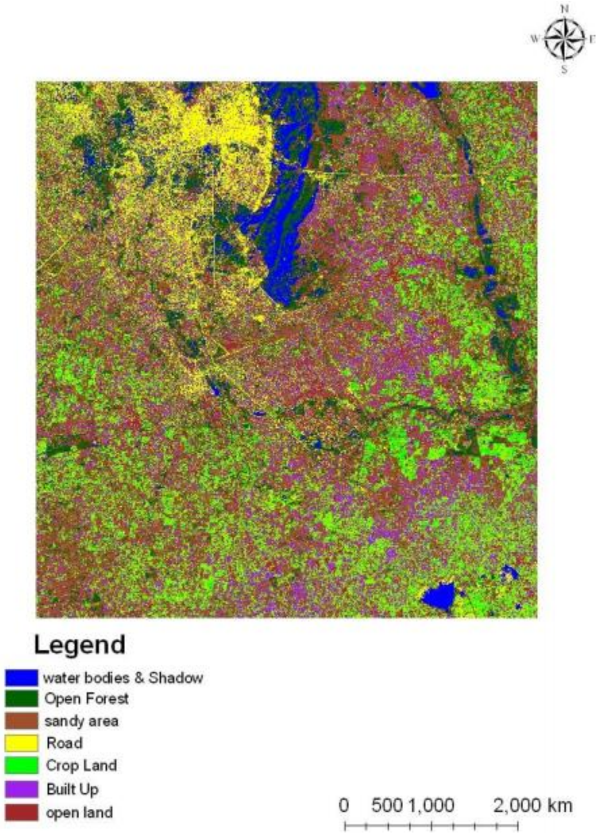

Figure 4. Classified images of LISS IV by Unsupervised Classification using CNN

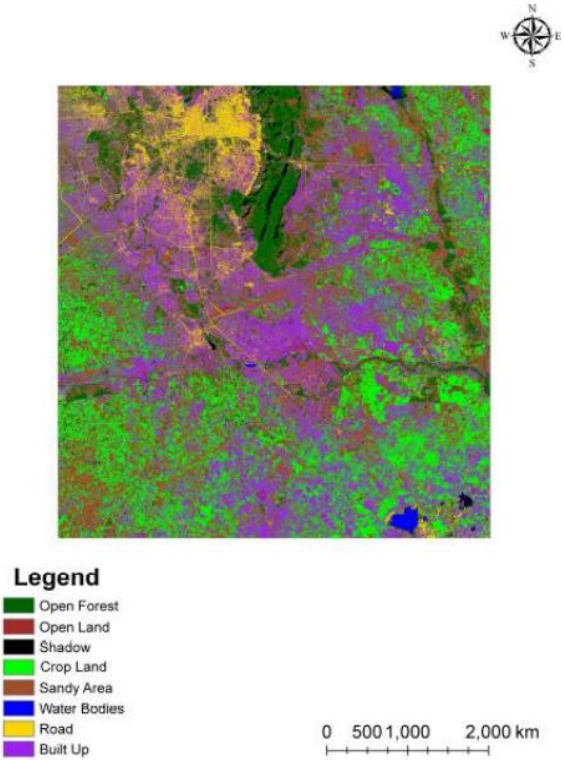

Figure 5. Classified images of LISS IV by Ssupervised Classification

Table shows the results of an evaluation, whereby NP1 is the number of pixels in each class of the resulting graded image, NP2 is the number of pixels in each group of the actual classified image, TC is the number of true classified image pixels compared to a real graded image, PTC is the percentage of true graded image pixels, FC the number of false images, Class data set determination makes the results of the classification more reliable. It was found that the appropriate block size helps the classifier greatly to determine the best class for the test picture, which leads to optimal classification for each block. In the water class, an extended homogenous region, a maximum classification error happens, this error is absolutely due to a failure in the partitioning stage that can be overestimated when non-uniform partitioning methods such as quad tree are used. Whereas in residential classes which are more detailed classes, a minimal classification error occurs, this shows that the proposed method has been successful in the satellite image classification process, ensuring better performance and efficient use of the process.

The final results of the research and experiment are the use of code and artificial networks that can reach classification findings of up to 99%. However, it is imperative to use the supervised training method in BPNN to use preclassified images with other training data ready-to extract systems. As a future work, suggest that use unsupervised training methods in artificial neural networks to overcome this obstacle.

IV. Experimental Results

A. *Login Module*

By this module user able to access the system features by providing its credential such as username and password and able to enable other module service.

Figure 6. Login Module

B. Image Selection

In we have to select the Image ID where it gives area 1 km x 1 km area of particular place. Further this image is divided into multiple parts.

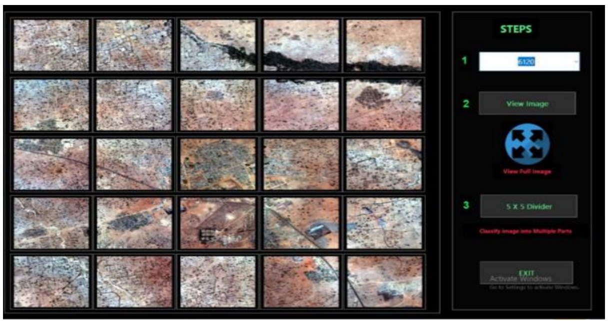

Figure 7. Image Selection Module

C. *Satellite Image Object Prediction*

In this we have to select the types of objects that we want to detect from the satellite image and have to click on the image to make prediction. Then click on the button to predict object from image. Here we can predict different types of objects from satellite image such as Cars, Roads, Trees, Bikes, Homes, River, Healthy water, Waste water, Railway route, Trucks, etc.

Figure 8. Image Prediction Module

D. Representation of Prediction in Graph

In this we will able to see the detected object count as per object occur in satellite image and graphical view representation in different charts. In this module it will show the prediction of object from satellite image in different charts format such as, Pie chart Bar Chart Scatter Graph Doughnut Chart Scatter Connected Graph.

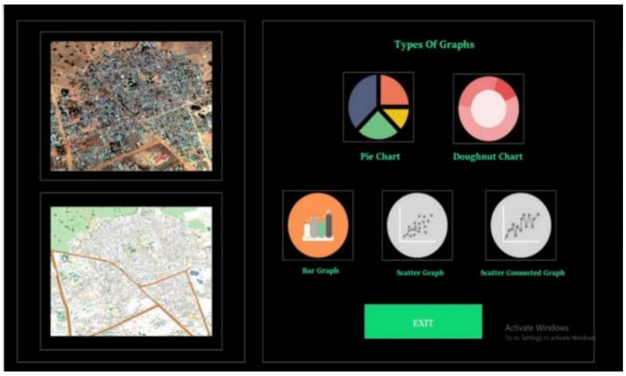

Figure 9. Graph Representation Module

E. Output of Image

By this module we will able to save the predictions of our model in different chat view and predicted image as well.

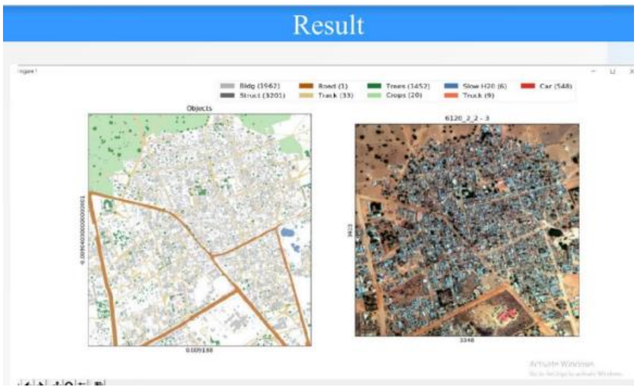

Figure 10. Output Module

V. CONCLUSION

Satellite imagery holds a large amount of information. However, to use this information, it needs to be extracted from the raw image data. Object recognition is a method that can help the extraction of information from satellite images. Two object recognition approaches, one supervised and one unsupervised, were chosen based on their performance observed in earlier studies. These algorithms were then evaluated on satellite images as a part of this study. CNN was used on a two-object data set to evaluate their performances and identify the approach which is comparatively better. Using the normalized values, it was found that CNN performed poorly in comparison to support vector machine.

VI. FUTURE WORK

Image class strategies and their efficacy with reference to variations in spectral and spatial resolutions have been analyzed via the prevailing study. The overall performance of exceptional class approach turned into evaluated in phrases of accuracy. It turned into discovered that LISS IV datasets may be categorized as much as degree three of land use/land cowl instructions of NRSC. Increasing the extent of class degrades the accuracy of class. It may be concluded that Surface water our bodies and Built Up and Roads are higher categorized via way of means of the Fuzzy Logic classifier compared to the MLC and Unsupervised Classification. That's why Fuzzy Logic Classification is the higher Method to categorise LISS-IV dataset. Further enhancements want to be carried out to apply a mixture of class strategies to broaden automatic approaches for guidance of land use maps from remotely sensed multispectral records.

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