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Land use Land Cover Classification using Convolutional Neural Networks

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***Abstract*—Building accurate Land Use Land Cover Maps to identify various land resources, such as forest areas, water bodies, agricultural land, urban areas, etc. have become essential. The information acquired from these Land Cover Maps can be used for various environmental applications and infrastructure planning. Creating automated techniques to generate maps using remotely sensed data using different computer vision and engineering techniques is of great importance. Many attempts have been made to develop Land Use Land Cover classification maps for different study areas. In this research work, we have developed a method to generate a seven-class Land Use Land Cover map using Quantum GIS-tool and the recent Convolutional Neural Network Unet-DenseNet121. Unet deep learning architecture backed with DenseNet121 backbone model is trained to perform classification task on 111,180 patches generated from the study area. The model gives an average Overall-Accuracy of 94.09%, whereas the Matthews-Correlation-Coefficient is 0.66 across all LULC classes, which indicates excellent model performance.**

***Index Terms*— Land Use Land Cover Classification, Deep Learning, Semantic Segmentation, Convolutional Neural Network.**

I. INTRODUCTION

Digital processing of high-resolution satellite images has grown in popularity and is now considered a rapidly growing field of application in computer science engineering and related fields. Images taken from a high-resolution lens of a satellite over a period of time over a specific region are used to capture various land cover features of the region, such as farms, urban areas, water bodies, forest cover, etc. These satellite images can be used for the purpose of creating an accurate Land Use Land Cover (LULC) classification of the site but are not limited to this field [1, 2]. Advancements in technological domains such as open-source data availability, mass storage, high-performance computing, and digital imaging have led to this rapid growth [3]. A high amount of data is present in satellite images and is the key to extracting the best features for image analysis. Remote sensing and computer vision applications require high-resolution satellite images for deep-learning techniques to exploit the image to extract features [4]. Various satellites are present in orbits around the globe, such as geostationary, polar, navigation, remote sensing, etc., with examples such as Landsat-2, Sentinel-2, Landsat-8/9, SPOT, Quickbird, ASTER, Ikonos [5]. On the Earth's Surface, standard Land Cover (LC) types such as soil, farms, water, forest areas, etc. define the characteristics of the Earth's surface. For different applications such as

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climate change [6], bio-diversity, and environmental studies [7] there is a need to have trustworthy and precise information about the location, kind, and extent of LC types.

Remote sensing deals with varied and difficult-to-interpret data and datasets of labeled images do not yet exist in the geospatial field [8]. This research work includes the generation of a Sentinel-2 labeled dataset for seven LULC classes for the study area. Semantic segmentation has been done using a Deep Convolutional Neural Network (CNN) which is trained on the generated dataset. Testing is done using various metrics to check the performance of the model. The paper includes six sections, section 2 gives details of the related works in this area, followed by section 3 provides details of the study area. Sections 4 and 5 give the material used and full implementation detail. The final two sections discuss further information for evaluating the models, results, and conclusion.

II. Related Works

EuroSAT [10] dataset consists of 27,000 labeled patches of Sentinel-2 images for ten LULC classes. These images cover 34 major European cities, but the dataset is very varied and contains data from across the year for many countries. Another major problem with the dataset is that they are not atmospherically correct which can create major issues in the task of LULC classification. Another dataset WH-MAVS [11], provides a high-resolution dataset developed using Google Earth images from Wuhan, China. The dataset contains 47,137 patches belonging to 14 LULC classes. This dataset is highly unbalanced classwise, and the classes do not particularly fall under the required LULC classification.

DeepWaterMap [12] is a fully convolutional neural network model that uses the LandSat image data from across the world to identify water bodies globally. Three versions of DeepWaterMap were trained using Nvidia Tesla P100 GPUs, precision, recall, and F1-Score values for these models range from 0.8 to 0.94. Using LandSat images [13], a machine learning algorithm Multinomial Logistic Model (Mnlogit) is developed using randomly referenced points from Google Earth as training data. The model gives an accuracy ranging from 82-86% for the forest and farm LULC classes but shows average performance for other LULC classes. Another research work is done to identify changes in deforestation using deep learning architectures such as U-Net, SharpMask, and ResUnet on the Amazon Rain Forest. Landsat-8 images have been used along with Multi-layer Perceptron (MLP) and Random Forest (RF) for comparison purposes [14].

III. Study Area

The study area is 100 x 200 km in size, which covers the north-western part of Maharashtra, as seen in Fig. 1, representing both the satellite image and the generated labeled LULC classification. The study area includes different LULC classes such as farms, barren regions, lakes, forest areas, rivers, hilly areas, etc.

IV. Material Used

European Space Agency (ESA) in the year 2015 launched the Copernicus Sentinel-2 space program. The primary purpose of the Copernicus program is to monitor the change in land surface conditions, emergency management, security as well as climate change. Sentinel-2A and 2B are two satellites present in the Sentinel-2 mission, which are polar-orbiting satellites phased at 180° to each other. The satellites capture image at resolutions of 10, 20, and 60 meters [9]. Out of 13 spectral bands, only the RGB bands at 10m resolution were used to generate the dataset and train the models.

V. Implementation

This section gives the complete details of the implementation, from downloading Sentinel-2 tiles to generating the entire dataset for our study area to training the CNN model on the generated dataset. The detailed workflow diagram is given in Fig. 2.

A. Download Sentinel-2 Tiles

Sentinel-2 tiles are downloaded from the Copernicus Open Access Hub or the Python API with the package ‘sentinelsat’ using the URL https://apihub.copernicus.eu/apihub. The study area used for this research comprises atmospherically corrected two Sentinel-2 L2A images [9].

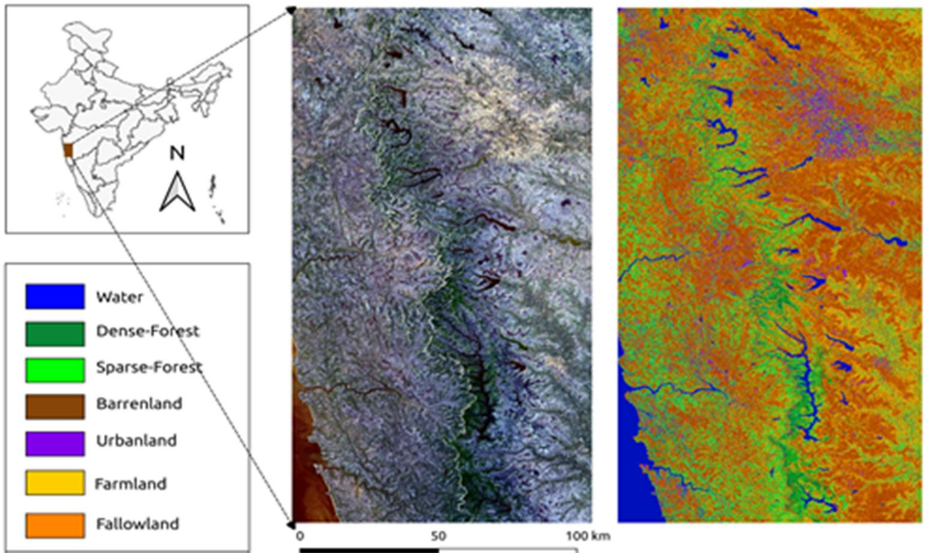

Figure [1]. Study Area

B. Pre-processing

Downloaded Sentinel-2 products are of category L2A, which are atmospherically corrected and do not require much pre-processing. Optimum Index Factor (OIF) calculation is done on the 13 bands, which gives the statistical value for selecting the optimum combination of three bands. Mosaicking and Layer-stacking are done on the bands to generate the complete study area using Geospatial Data Abstraction Library (GDAL).

C. Labeled Data Generation

The labeled dataset is generated using Quantum GIS (QGIS) which provides the Semi-Automatic Classification Plugin (SCP) to create a labeled dataset for our study area. Various Regions of Interest (ROIs) polygons are provided as training input to the SCP plugin to classify the LULC classes for the study area. Dataset created contains seven LULC classes, namely water, dense-forest, sparse-forest, urban-land, barren-land, farm-land, and fallow-land.

D. Patch Creation

A total of 111,180 patches are created from the entire study area, and their corresponding labeled masks to generate a dataset to train the model. GDAL and Rasterio geospatial python libraries are used to generate overlapping patches of size 64 x 64. 70% i.e., 77,826 patches are considered for training and 30% i.e., 16,677 are used for validation and testing each.

E. Models Training

Unet architecture [15] developed for semantic segmentation on biomedical images using data augmentation is implemented along with the DenseNet121 [16] backbone, which is pre-trained on the 2012 ILSVRC ImageNet dataset. Out of a total of 12,145,992 parameters for the model, 85,632 are non-trainable and 12,060,360 are trainable. Tensorflow and segmentation model libraries are used to implement the CNN model. Hyper-parameters such as a batch size of 32 images, learning rate of 0.001, optimizer Adam and a total of 150 epochs are used. Image pre-processing tasks are done on Dell Precision T1700 Workstation with Intel Xeon E3-1271 with 3.6 GHz for all eight cores with 32GB of memory. Model training is done on the Nvidia DGX workstation equipped with Nvidia Tesla V100 GPUs with 32 GB memory each.

F. Testing

Model testing is done on a batch size of 16 images to calculate the confusion matrix for the seven LULC classes. Metrics such as Recall (RE), Precision (PR), Overall-Accuracy (OA), F1-Score (F1), and Matthews-Correlation Co-efficient (MCC) are used for model evaluation. Prediction is also made on the test images for the model.

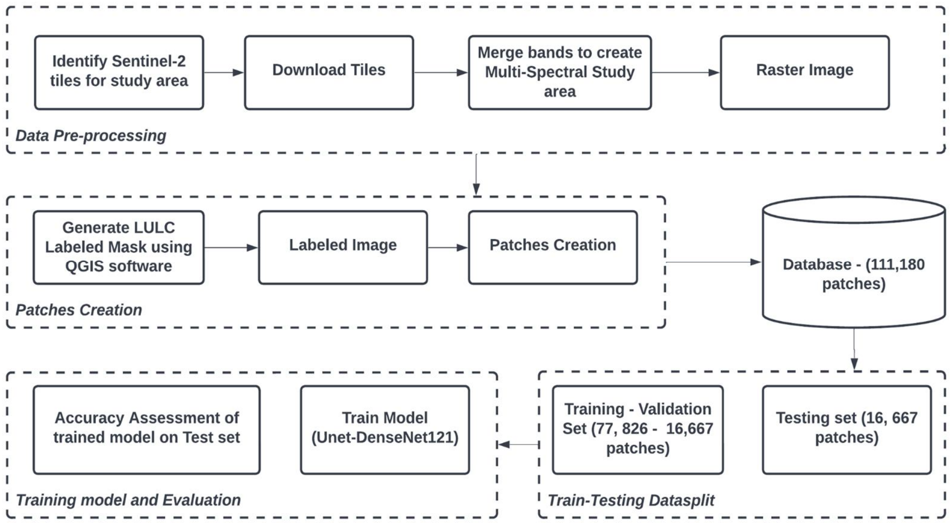

Figure [2]. Work Flow

VI. Results

For evaluating the performance of the trained CNN model, various metrics such as Overall-Accuracy (OA), Recall (RE), F1-Score (F1), Precision (PR), and Matthews Correlation Coefficient (MCC) are used. The confusion matrix and the performance evaluation metrics are given in Fig. 3 and Fig. 4. which represent the different LULC class predictions done on the test images. It can be observed from the Confusion Matrix that the model gives maximum True Positives for all the seven LULC classes. The Overall-Accuracy (OA) of the model for the seven LULC classes ranges from 99% to 87%, with the consolidated average for all classes being 94%. MCC evaluation metric value lies between -1 to +1, with -1 indicating poor model performance and +1 indicating good performance. The MCC value for our model ranges from 0.95 to 0.61, which shows that the model is showing excellent performance for the task of semantic segmentation. The prediction on the test patches can be seen in Fig. 5.

VII. Conclusion

Land Use Land Cover (LULC) analysis is an important component for various planning and management applications like Natural resource management, Wildlife protection, Route alignment, and Urban planning. Agriculture and Forest areas play a vital role in developing countries such as India, as more than half of the population in India depends on farming as their main income source, whereas forests are important for socio-economic growth.

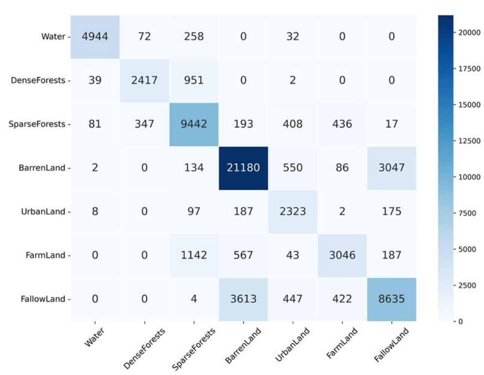

Figure [3]. Unet-DenseNet121 Confusion Matrix

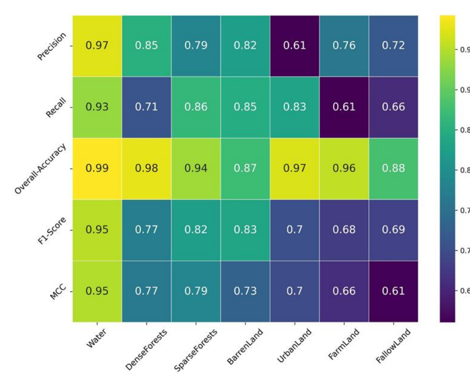

Figure [4]. Unet-DenseNet121 Metrics

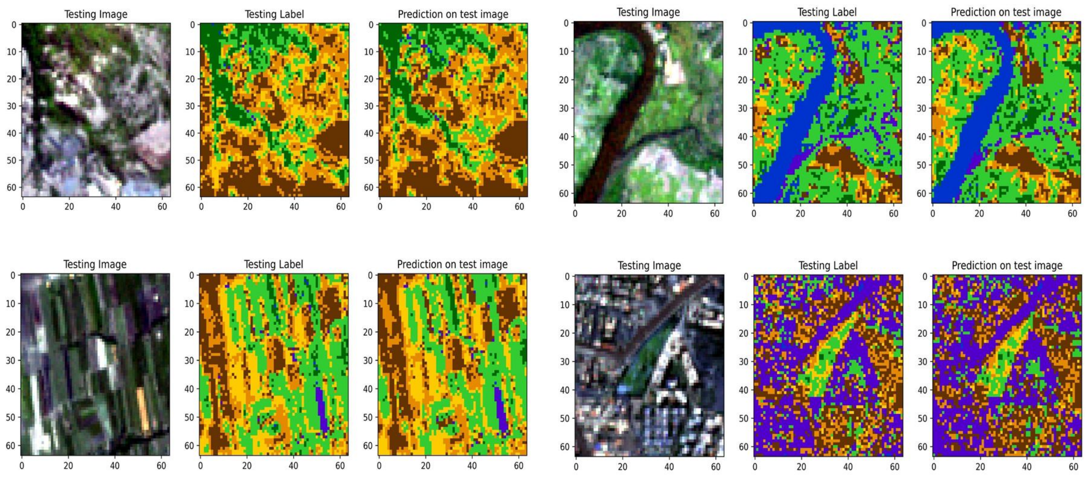

Figure [5]. Unet-DenseNet121 Patches Prediction

In this research work, we have successfully generated a LULC dataset containing 111,180 labeled patches for our specific study area using Sentinel-2 satellite images. A state-of-the-art Convolutional Neural Network (CNN) model has been trained to perform the task of semantic segmentation. The Unet-DenseNet121 model performs significantly well, as seen from the results, with an average OA of 94%. Currently, only two Sentinel-2 tiles are being considered from across India. To create a benchmark dataset, more tiles can be used to generate a more diverse LULC dataset. Other CNN architecture models can also be identified and trained to check improvement in LULC classification accuracy.

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