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Land use Land Cover Classification using Deep Neural Network

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***Abstract*—With remote sensor data, land use and land cover classification offers geographical information. The land use land cover classification process considers several factors for urban planning, natural resources management, environment management, and disaster monitoring. The recent advances in deep learning models to classify land use land cover classes. The objective of this research work is to use remote sensing and Geospatial Information Systems to perform land use land cover classification. The customized Sentinel-2 dataset is generated using QGIS to implement a Deep Neural network. In this study, pixel-based classification was performed using the UNet model. Accuracy assessment was performed using Overall Accuracy and F1-Score. The research showed overall classification accuracy of 95.5% and a value of F1-Score is 0.66. The UNet model is suitable for customized datasets to present essential information for sustainable environmental planning.**

***Index Terms*— Remote sensing, Land use land cover, GIS, Deep Neural network, UNet, Sentinel-2.**

I. INTRODUCTION

Land Use Land Cover(LULC) classification is important for mapping and environmental applications, such as urban planning [1], natural resources management, and crop yield prediction [2]. To provide useful land information, remote sensing is essential and often used with GIS techniques. Remote sensing technology has a high potential to perform pixel-based LULC classification. Remotely sensed imagery has traditionally been classified into land cover (LC) and land use (LU). Pixel-based image classification is assigning labels to each pixel of the image [3]. High-resolution remote sensing images provide spectral signatures, texture features, and spatial structure of ground objects which are essential for LULC classification [4]. Sentinel-2 L2A satellite images have been used to research various geographical applications. The effectiveness of Sentinel-2 has been explored, particularly in LULC mapping, and it has demonstrated a high potential for application[5].

Several techniques have been developed for LULC classification, including traditional machine-learning algorithms and advanced deep learning networks. Traditional machine learning algorithms such as the support vector machine (SVM) and the maximum likelihood classifier (MLC) are used to classify images into several classes. The image's low-level features, such as color, geometry characteristics, greyscale and spatial texture, are extracted for classification. These methods are less efficient, costly, and time-consuming for high-resolution satellite imagery[6]. The deep learning architectures allow the high-level feature extraction, and robust features

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from images using a deep multiplayer network [7,8]. In this paper, LULC classification is performed on generated sentinel-2 imagery for the Indian region. The Convolutional Neural Network architecture - UNet has been used for pixel-based LULC classification. Accuracy assessment is done in order to find out how well. The UNet model is performing, and the usefulness of LULC classification using overall accuracy and F1-score.

II. Literature Review

For LULC classification, semantic segmentation is an active topic that provides a pixel-based output map. For image classification, traditional machine learning algorithms have been proposed. Reference [9] implemented SVM and MLC for LULC classification. In this paper, overall accuracy for MLC was between 86.71% and 100%, and for the SVM, 82.15% and 93.17%. In terms of stability of the algorithm MLC model showed less success in converting low dimensional space into high dimensional space. Recently, computer vision and Deep Neural networks(DNN) have great advances in image classification. Reference [10] proposed Convolution Neural Network(CNN) based framework -1D CNN on WorldView-3 MSI dataset. The 1D CNN model extracts patches to find local features from satellite images to improve performance. For the specified study area, the WorldView-3 MSI dataset contains a spectral range of 400 nm to 1040 nm with an average spatial resolution of 1.2 m. The average accuracy of the model is between 85% to 89%.
Reference [11] proposed the recent CNN approach is for semantic segmentation. The model's average accuracy in the training phase is 98%, and the accuracy of the testing phase is 95%. Reference [12] presented deep neural network architectures for semantic segmentation, including UNet and DeepLabV3+ on UOPNOA and UOS2 datasets. For LULC classification number of bands and ground sampling distance are essential components. Reference [13] implemented UNet model and Fine-Grained(FG-UNet) model for pixel-based classification. In this work, models work on a dataset that combines Sentinel-2 L2A time-series images, Corine LandCover (CLC) 2012, and the French National Geographic Institute's "BD Topo". As per the literature review, just a few research has been done using Sentinel-2 as it's a new kind of satellite imagery. Along with that, the UNet model performs better in areas with a lot of texture in terms of LULC classification. More study is needed to analyze Sentinel-2 imagery with the UNet model.

III. Study Area

The selected study area is Khandesh District includes the Jalgaon, Dhule, and Nandurbar districts, and covers a geographical area of more than 20,000 square kilometers. The study area has various characteristics that include different LULC classes such as water, urban land, barren land, agriculture, forest, and fallow land. Analysis of the study area is essential for well-informed decision-making regarding future land uses planning policies. The study area and its corresponding labeled LULC map is represented in Fig. 1.

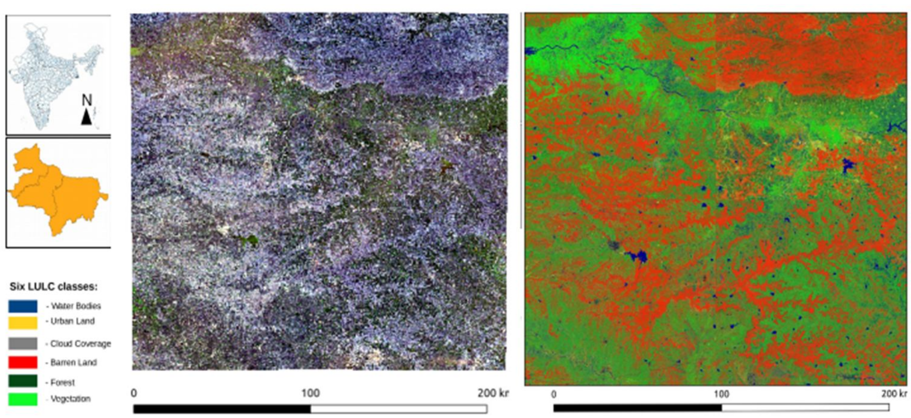

Figure 1. Study Area and LULC map

IV. Implementation

Pixel-based classification of Sentinel-2 imagery is implemented using the proposed methodology. The proposed system is divided into different tasks, which are described in this section. Fig. 2 shows the proposed system workflow.

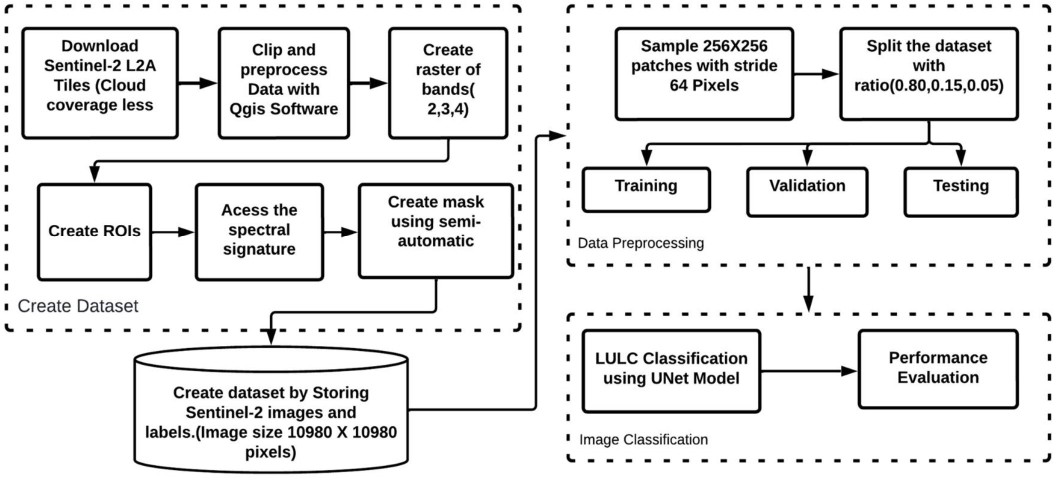

Figure 2. Proposed system methodology

A. Dataset Generation

Satellite images from the study area were obtained from {https://scihub.copernicus.eu/}. For training, four sentinel-2 L2A satellite tiles were used with an image size of 10980x10980pixels and spatial resolution of 10m per pixel for Data. For this work, Sentinel-2 images with bands 2,3,4 are considered, which provide meaningful information for LULC classification. QGIS tool [14] is used to create the labeled dataset. The first step to creating a mask is to perform the segmentation of images by clipping and preprocessing. The virtual raster of the three bands 2,3,4 is created using the QGIS tool. After creating a virtual raster, create a region of interest(ROI) to prepare for training. Supervised classification is performed to create a mask for the sentinel-2 image. The masking process is useful for the Representation of raster data.

B. Data Preprocessing

The image size and labeled mask size are 10980x10980pixels which are relatively large, and the entire image can not be provided as an input to the model. To train the model, each image and mask is divided into a small patch with a size of 256x256 pixels. The dataset was created with 1,14,134 images and a corresponding mask. The dataset is separated into training, validation, and testing datasets for the further classification process. Among them, 117,707 images and masks were used for training, 22,070 for validation, and the remaining 7,357 for testing.

C. Image Classification

In this paper, the most popular CNN model for pixel-based classification that is UNet [15,16] is selected for LULC classification. The UNet model is trained on a created dataset that contains six LULC classes Water, Agriculture, Urban land, Barren Land, Forest, and Cloud. The overall size of the dataset is too large, therefore training of the UNet model is performed using the Nvidia DGX workstation. For the training model, a batch size of 16 is considered to overcome the out-of-memory problem. The UNet model is trained with softmax activation function and ADAM optimizer. Categorical cross-entropy is used as a loss function to keep track of the training and validation accuracy of the model. The UNet model is trained on 100 epochs to give better learning ability.

V. RESULTS

For evaluation of the UNet model, eight random images of size 256x256 pixels are selected. To analyze the model's performance, five evaluation metrics are considered, including Precision, Recall, Overall Accuracy(OA), F1-score, and (Intersection over union) IOU [17]. These performance metrics give high-level information about the quality of the model's classification output. The mathematical representation of the various evaluation metrics used are shown in (1) to (5). True Negative(TN), False Negative(FN), False Positive(FP), and True positive(TP) are considered in the following equations.

$$Precision = \frac{TP}{(TP+FP)} \qquad (1)$$

$$Recall = \frac{TP}{(TP + FN)} \quad (2)$$

$$Overall\ Accuracy = \frac{TP + TN}{(TP + TN + FP + FN)} \quad (3)$$

$$F1\text{-}Score = \frac{2 * Precision * Recall}{Precision + Recall} \quad (4)$$

$$IOU = \frac{TP}{(TP + FP + FN)} \quad (5)$$

The UNet models perform better pixel-based classification for all six LULC classes. The average OA is 95.5%, and the F1-score value of 0.66. The classwise comparison of LULC classification with the respective UNet model is represented in table I. For the UNet model, barren land has the highest F1-score, IOU, with values of 0.94 and 0.89, respectively. Water Bodies are classified with OA of 97%, F1-score of 0.70, and IOU of 0.54. For the UNet model cloud class has the lowest performance with OA, F1-score, and IOU values of 99% and 0.04,0.02, respectively. Forest and vegetation classes were classified with OA of 96% and 91%, F1-score of 0.74 and 0.85, and IOU of 0.58 and 0.74, respectively. The Classification results are calculated from the confusion matrix [18] of the UNet model shown in Fig. 3. The UNet model achieved classwise Overall Accuracy(OA) ranging from 91% to 99%. The patches prediction of UNet model is presented in the format Sentinel-2 image, actual ground truth image with predicted images in Fig. 4.

Figure 3. UNet Confusion matrix

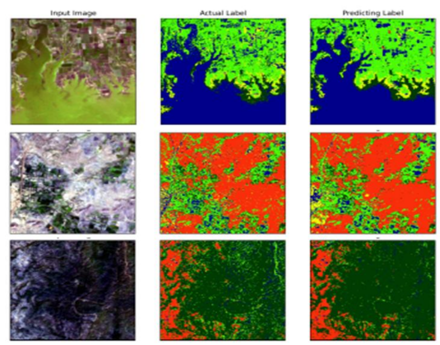

Figure 4. Results

TABLE I. PER CLASS LAND USE LAND COVER CLASSIFICATION ACCURACY FOR UNET MODEL

Metrics	Water Bodies	Urban Land	Cloud	Barren Land	Forest	Vegetation
Precision	0.67	0.63	0.02	0.97	0.67	0.83
Recall	0.74	0.70	0.22	0.91	0.82	0.88
OA	0.97	0.97	0.99	0.93	0.96	0.91
F1-Score	0.70	0.66	0.041	0.94	0.74	0.85
IOU	0.54	0.50	0.024	0.89	0.58	0.74

VI. CONCLUSION

Land use land cover plays an essential role in the management and monitoring of geographical programs at a different level. With the world's population growing exponentially, the necessity to optimize land, urban, and agricultural planning has been more important. To understand land for agriculture, forest, and urban development LULC map is required. To perform LULC classification in this study, a customized dataset of Sentinel-2 L2A images with 1,47,134 patches with a size of 256x256 pixels was constructed. LULC classification has been performed using a deep learning-based semantic segmentation model-UNet. According to the LULC classification results, the OA and F1-score of the UNet model are 95% and 0.66, respectively. The result of the UNet model for six LULC classes with respective overall accuracy ranges between 91% to 99%. In the future, we aim to explore more advance and recent CNN models for semantic segmentation to promote Deep Neural Network architectures and to design different approaches for LULC classification using Transfer Learning with the previously implemented models that will extract high-level features and will help to enhance accuracy.

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