Real-Time Land Use and Land Cover Classification Using Deep Learning and Satellite Imagery

Dron Kaustub
Department of Electronics and Communication Engineering
SRM Institute of Science and Technology
Kattankulathur- 603203
dr1521@srmist.edu.in

Akshika Singh
Department of Electronics and Communication Engineering
SRM Institute of Science and Technology
Kattankulathur- 603203
ak5797@srmist.edu.in

Deeptanshu Khandelwal
Department of Electronics and Communication Engineering
SRM Institute of Science and Technology
Kattankulathur- 603203
dm0367@srmist.edu.in

Dr. Prithiviraj Rajalingam
Department of Electronics and Communication Engineering
SRM Institute of Science and Technology
Kattankulathur- 603203
prithivr@srmist.edu.in

Dr. Harisudha K
Department of Electronics and Communication Engineering
SRM Institute of Science and Technology
Kattankulathur- 603203
harisudk@srmist.edu.in

Kanika Tandon
Department of Electronics and Communication Engineering
SRM Institute of Science and Technology
Kattankulathur- 603203
kt0505@srmist.edu.in

***Abstract*— Land cover and land use (LULC) classification is important in understanding environmental degradation, urban growth, and agricultural trends. This study introduces a real-time LULC classification framework based on Sentinel-2 satellite data, Google Earth Engine (GEE), and a deep learning Convolutional Neural Network (CNN). The study is carried out on the district of Chengalpattu, demonstrating the ability of remote sensing and deep learning techniques for accurate LULC mapping. The model adopted by us in making predictions over Indian districts boasts a training accuracy of 97.2% and validation accuracy of 90.85%, demonstrating its strength in identifying multiple types of lands.**

***Key words*— Land Use, Land Cover, Deep Learning, CNN, Remote Sensing, Google Earth Engine, Sentinel-2, Feature Extraction, Real-Time Classification, GIS.**

I. INTRODUCTION

Increased urbanization continues to propel major LULC changes, with increasing built-up environments spreading into what were once agricultural and natural territories, as can be seen in satellite image analysis of many metropolitan areas. In addition, forest clearing for land expansion and natural resource extraction remains a factor, leading to widespread loss of habitats and changed regional climate regimes. In addition, more frequent and severe climate-related events, like fires and floods, are drastically altering landscapes, resulting in quantifiable changes in land cover composition and ecological resilience. Thus, land use and land cover classification is a necessity in environmental monitoring, city planning, and agricultural management. With the growing availability of high-resolution satellite imagery, deep learning methods have emerged as a feasible means for LULC classification. The Copernicus Sentinel-2 mission offers multispectral high spatial resolution imagery, and hence it is a suitable data source for this research. In this paper, we use Google Earth Engine to retrieve Sentinel-2 data, use deep learning methods to classify land cover features, and carry out real-time mapping and visualization with the aid of Python-based geospatial libraries. The case study of this research is the Chengalpattu district in India, where real-time implementation is done.

II. LITERATURE REVIEW

Land use and land cover (LULC) classification has been a topic of interest because of its critical application in environmental monitoring, urban planning, and resource management. Several studies have explored deep learning methods to improve classification accuracy from remote sensing images. Aljebreen et.al.[1] introduced a novel River Formation Dynamics algorithm coupled with deep learning to improve classification performance. Similarly, Jagannathan and Divya [2] employed deep convolutional neural networks (CNNs) to forecast LULC change, demonstrating their capability to record spatial and temporal variation. Yuan et.al.[3] made the contribution of developing the WH-MAVS dataset, which enables various land use classification applications. Zaabar et.al.[4] used an object-based CNN method for mapping coastal areas, showing the advantage of integrating object-based deep learning analysis. These analyses highlight the importance of building solid datasets and sophisticated algorithms for enhanced classification accuracy. Segmentation-based model developments have also increased LULC classification. Fan et.al.[5] examined segmentation models in the classification of remote sensing images and demonstrated how leading-edge segmentation algorithms enhance land cover discrimination. Sanchez-Fernandez et.al.[6] demonstrated that with small in-domain datasets self supervised learning can give better results than traditional supervised learning, obliterating dependence on large, annotated datasets. Zhu et.al.[7] proposed a multitemporal convolutional LSTM model, efficiently encoding temporal relationships in land use classification. Dong et.al.[8] proposed a feature ensemble deep learning network, improving classification accuracy in very high-resolution (VHR) optical remote sensing images. The proposed methods shows that the impact of segmentation, self-supervised learning, and temporal modeling on enhancing classification and accuracy.

Several studies emphasized high-resolution mapping and cross-resolution learning for improving LULC classification. Qi et.al.[9] introduced a framework for the application of low-resolution labels in high\resolution land cover mapping based on deep learning. Victor et.al.[10] carried out a comprehensive review on the application of deep learning to agriculture with the emphasis being given to the contribution of CNN and other models towards precision agriculture. Karra et.al.[11] introduced a global

scheme for Sentinel-2 for LULC classification using deep learning. Wang et.al.[12] presented a systematic review of the products of the LULC classification with a view to extracting new trends and challenges in the research area. Priyanka et.al.[13] proposed DPPNet, the deep learning optimized model for the purpose of high-resolution segmentation with improved robustness for satellite image analysis. Talukdar et.al.[14] compared machine learning classifiers for classification of LULC and discussed the advantages and disadvantages of various techniques. Brown et.al.[15] built the Dynamic World dataset that facilitated the global classification of LULC at 10m with the ability of almost real-time classification. All these contributions are headed towards the new era of LULC classification with the deep learning models consistently offering increased precision, scalability, and real-time detection.

III. METHODOLOGY

The steps involved are data retrieval, preprocessing, model training, and classification. Google Earth Engine was used to download Sentinel-2 satellite data for the Chengalpattu district over a specified time period. Indian district boundary shapefile was downloaded from GitHub and imported into Google Colab to process. Sentinel-2 images were clipped using the Chengalpattu district limit. Images were pre-processed to achieve Red, Green, and Blue (RGB) bands i.e. an important spectral information for classification. A 64x64 pixel tile grid was made using Rasterio to divide the huge satellite images into portions for better accuracy in classification. Normalization and data augmentation strategies were employed to improve model performance and resilience to variation in satellite images. The classification model employed a pre-trained ResNet-50 CNN model, which was fine-tuned for ten LULC classes: AnnualCrop, Forest, Highway, Industrial, Pasture, HerbaceousVegetation, PermanentCrop, Residential, River, and SeaLake. The model was trained on a dataset of 27,000 images. The trained model was utilized to classify land cover classes for all tiles, and the outcomes were mapped using Folium and Matplotlib. Training incorporated hyperparameter optimization, batch size, learning rate, and dropout layer optimization to obtain the optimal accuracy. Augmentation such as rotation, flipping, and contrast adjustment was employed to improve the model's generalizability.

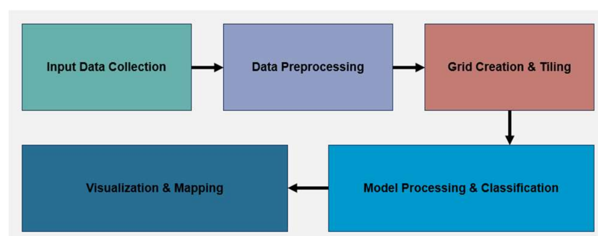

Fig. 1. Block Diagram of real-time implementation

IV. FEATURE SELECTION AND EXTRACTION

Feature extraction and selection are necessary to enhance the performance of LULC classification models. Sentinel-2 satellite data offer 13 spectral bands, but they are not all equally useful in separating land cover classes. The current study mainly utilized the red, green, and blue bands, and specifically chosen near-infrared (NIR) and shortwave infrared (SWIR) bands for better discrimination between vegetation, water features, and urban areas. Various vegetation indices, such as Normalized Difference Vegetation Index (NDVI) and Normalized Difference Built-up Index (NDBI), were computed to provide additional features that help in classification. NDVI helps in detecting the health of vegetation, and NDBI is able to detect urban and built-up regions effectively. Principal Component Analysis

(PCA) was also used to minimize dimensionality without compromising the most important spectral information. The features were then normalized and fed into the CNN model for training and classification.

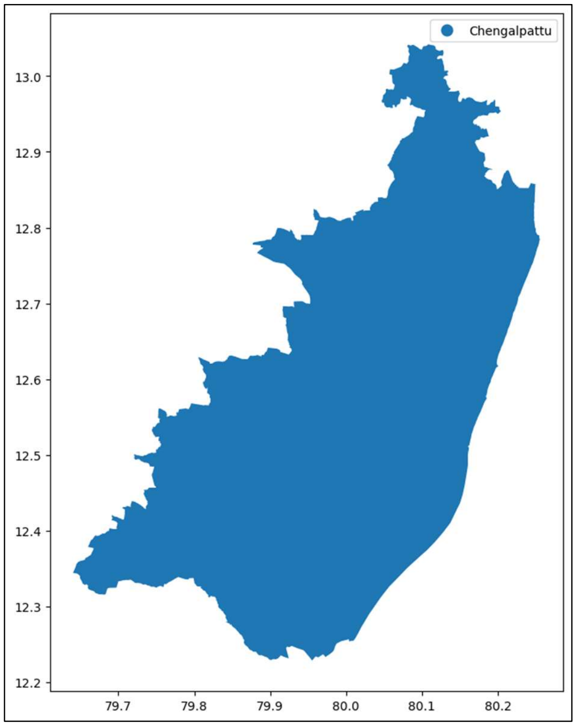

Fig. 2. Tif map of Chengalpattu.

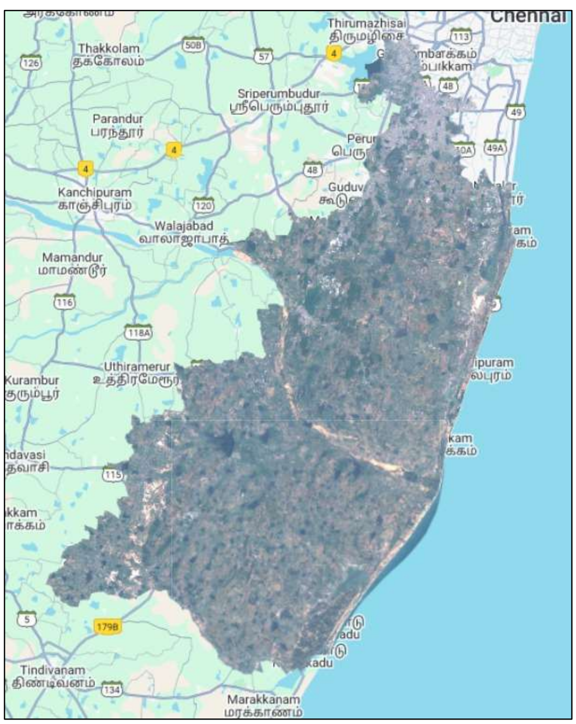

Fig. 3. Locating map of Chengalpattu on Google Earth Engine.

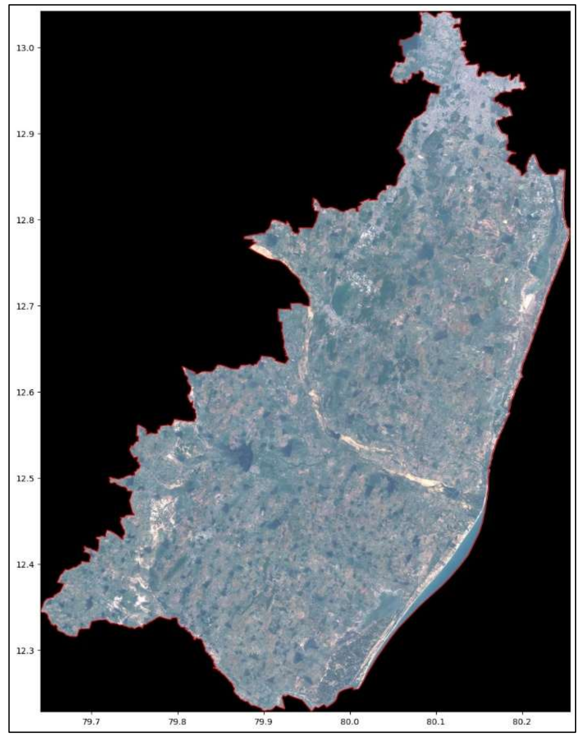

Fig. 4. Traced map of Chengalpattu.

V. REAL-TIME VISUALIZATION AND MAPPING

Real-time visualisation plays an important role in effective LULC monitoring. Classified images and results were georeferenced by Folium in which the classed regions can be interactively explored. Following classification, the maps were kept in Google Drive. Coloured tiles were used to identify different land cover classes. The final map of LULC was placed over a world map to provide spatial reference. Interactive web-based visualization tools were integrated to allow users to toggle between different time periods and analyze land use changes dynamically.

TABLE I. Colour Mapping

Class/Land Cover	**Colour**
Annual Crop	Light Green
Forest	Forest Green
Herbaceous Vegetation	Yellow Green
Highway	Black
Industrial	Red
Pasture	Medium Sea Green
Permanent Crop	Chartreuse
Residential	Magenta
River	Purple
Sea/Lake	Blue

VI. DATASET AND HARDWARE AND SOFTWARE USED

The data used in the research consist of 27,000 images divided into hyperspectral, multispectral, and RGB images. Hyperspectral images offer a vast spectral range for effective material discrimination, whereas multispectral images achieve a balance between spectral richness which is applicable for LULC classification. RGB images provide a simple and effective method of visual classification, especially in urban scenes. The data is annotated and georeferenced, offering high reliability for training deep learning models. The hardware and software configuration for this study was such that computational efficiency and processing speed were optimized. Cloud processing via Google Colab circumvented the need for local costly machines. The computational requirements were an Intel i5/i7 processor or equivalent, NVIDIA Tesla T4 or K80 with CUDA support, and 8GB RAM (16GB for large datasets). The development environment used was Python 3.8+, PyTorch for deep learning, GDAL for geospatial data processing, Folium for interactive visualization on maps, Rasterio for processing satellite imagery, and Google Earth Engine API for data fetching. The use of all these tools provided an effective and scalable platform for LULC classification and display.

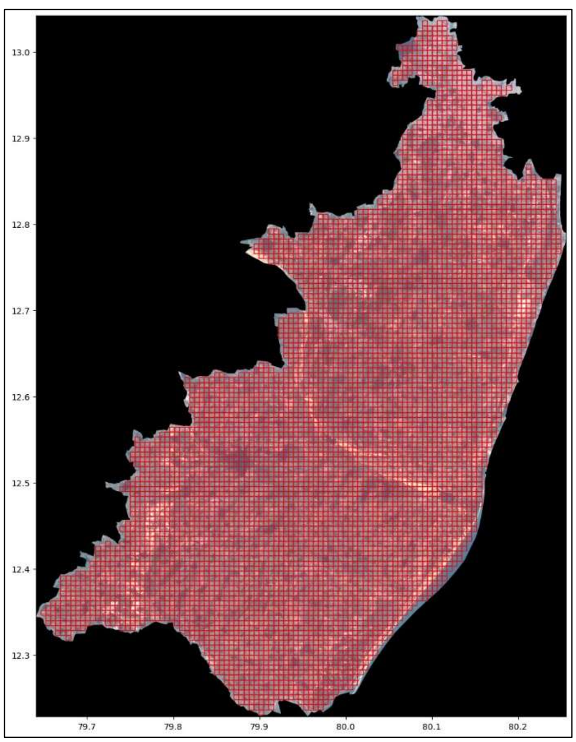

Fig. 5. Chengalpattu Map with Grid Overlay.

VII. EXPERIMENTAL RESULTS

The classification model was validated using Chengalpattu district images. The CNN model was trained with accuracy of 97.2% and the validation accuracy of 90.85%. The LULC map generated could classify varied land cover classes correctly. The predicted tiles were color-coded based on pre-established categories, which rendered interpretation easy. The interactive visualization offered real-time analysis features for urban planners and environmental scientists. A confusion matrix was used to evaluate class-wise accuracy, where good classification performance in classes such as Residential, Forest, and Industrial was indicated with minor misclassifications reported in River and Herbaceous Vegetation.

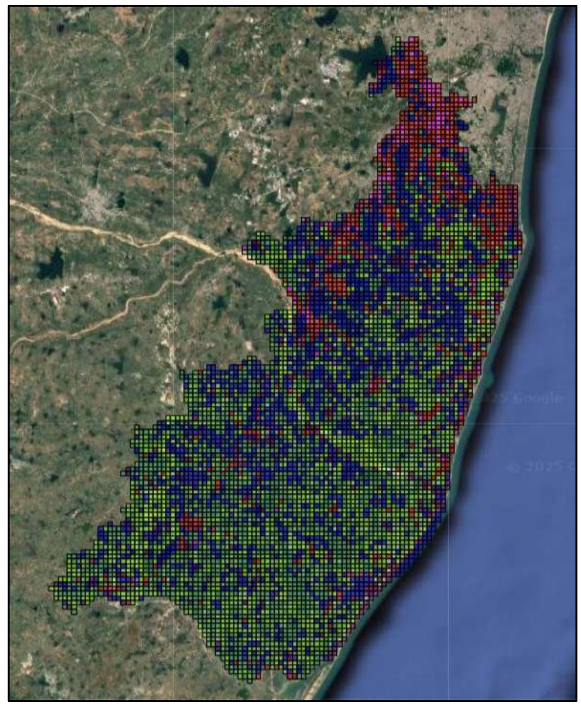
Fig. 6. Predicted Classification of Chengalpattu.

VIII. CONCLUSION

The present research proves the viability of employing satellite imagery and deep learning for real-time LULC mapping. Google Earth Engine, along with an optimized CNN model, offers a low-cost and scalable solution to land cover mapping. Future research will investigate how to integrate more spectral bands and temporal analysis into the research to enhance classification accuracy and monitor land-use changes over time. Impacts of this work are profound to environmental monitoring, sustainable urbanization, and disaster management. Enhancement can include application of transformer-based deep learning structures to enhance accuracy and season variability robustness for classification. Another enhancement can come from incorporating satellite imagery with finer resolution and adopting cloud computing technology for processing of large data quantities to support more real-time capability. Adding more LULC classes to the model and augmenting the training dataset with greater geographic diversity will further enhance the generalizability and accuracy of the classification system.

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