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ADVANCING LAND USE AND LAND COVER CLASSIFICATION THROUGH DEEP LEARNING IN REMOTE SENSING AND SATELLITE IMAGERY

A PROJECT REPORT

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Certified that this project report titled "**ADVANCING LAND USE AND LAND COVER CLASSIFICATION THROUGH DEEP LEARNING IN REMOTE SENSING AND SATELLITE IMAGERY**" is the Bonafide work of "**DRON KAUSTUB [Reg No: RA2111043010044], AKSHIKA SINGH [Reg No: RA2111043010036], DEEPTANSHU KHANDELWAL [Reg No: RA2111004010127],** who carried out the project work under my supervision. Certified further that to the best of my knowledge the work reported herein does not form any other project report or dissertation on the basis of which a degree or award was conferred on an earlier occasion on this or any other candidate.

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We hereby declare that the Major Project entitled "**ADVANCING LAND USE AND LAND COVER CLASSIFICATION THROUGH DEEP LEARNING IN REMOTE SENSING AND SATELLITE IMAGERY**" to be submitted for the Degree of Bachelor of Technology is our original work as a team and the dissertation has not formed the basis of any degree, diploma, associateship or fellowship of similar other titles. It has not been submitted to any other University or institution for the award of any degree or diploma.

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ABSTRACT

This study addresses the critical challenge of accurate Land Use and Land Cover (LULC) classification in the rapidly developing Chengalpattu district of India. The research tackles fundamental obstacles in LULC mapping, including spectral confusion between land cover types, computational constraints for large areas, and the transferability of models across heterogeneous landscapes.

The approach utilizes deep learning methods through fine-tuning a ResNet-50 convolutional neural network (CNN) model on a wide dataset of 27,000 remotely sensed images covering ten different LULC classes. The Google Earth Engine integration facilitates the processing of high-resolution multispectral Sentinel-2 satellite imagery at high efficiency. Our model performs well with 97.20% training accuracy and 90.85% validation accuracy, with precision, recall, and F1-scores all over 89%.

Field validation conducted in February 2025 in Chengalpattu validated the model and singled out some problems in classifying complex urban agglomerations and transition areas among land covers. The system effectively separates annual crops, forests, herbaceous vegetation, highways, industrial complexes, pastures, permanent crops, residential areas, rivers, and sea/lake water bodies into color-coded visualizations of the district's land use pattern. The derived LULC maps show Chengalpattu's patchwork landscape, with agricultural areas dominated in central and southern parts, high forest cover in the west, residential and industrial clusters in the north and east.

Sustainable Development Goals:

These results are relevant to Sustainable Development Goal 11 (Sustainable Cities and Communities) and SDG 15 (Life on Land) and provide decision-makers with reliable data for environmental management, urban planning, agricultural management, disaster response, and policymaking based on evidence in this rapidly evolving region. This study shows the potential of cutting-edge deep learning models combined with satellite remote sensing to overcome the multi-faceted challenges offered by diverse topography and rapid urbanization, making a baseline for sustainable development planning.

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LIST OF ABBREVIATIONS

ABBREVIATIONS	MEANING
CNN	Convolutional Neural Network
DEM	Digital Elevation Model
GEE	Google Earth Engine
GIS	Geographic Information System
LULC	Land Use and Land Cover
LSTM	Long Short-Term Memory
NDVI	Normalized Difference Vegetation Index
OBIA	Object-Based Image Analysis
RGB	Red-Green-Blue
SAR	Synthetic Aperture Radar
SEZ	Special Economic Zone
VHR	Very-High-Resolution

CHAPTER 1

INTRODUCTION

1.1 BACKGROUND

Land Use and Land Cover (LULC) classification symbolizes an essential tool in the field of environmental science and the area of geospatial analysis. It contributes specific information about how land resources are allocated and how landscape persists and changes over time. However, understanding the difference between land cover and land use is important. Land cover is the physical material cover of the earth's surface (e.g., vegetation, surface water, bare soil, artificial features), while land use refers to how humans utilize the land (e.g., agriculture, houses, businesses).

The recent pace of LULC change has increased rapidly in part due to anthropogenic (human driven) and natural drivers. Increased urbanization continues to drive large-scale LULC change, as increased built-up environments expand into previously agricultural or natural areas. This can certainly be seen when analyzing satellite imagery of urban metropolitan areas of India, which traditionally urbanized and continue to modify surrounding rural landscape. Additionally, the forest clearing related to agricultural expansion and natural resources extraction continues to be another influential driver of substantial habitat loss and change in regional climate regimes.

The increase in the frequency and severity of climate-related disturbances like fires and floods are altering landscapes across the globe, resulting in measurable changes in land cover and ecological resilience. Historically, LULC classification methods were primarily based on manual interpretation of aerial photographs and field surveys (van Oort, 2006). Such methods were effective, but ultimately time-consuming, labor-intensive, and typically limited in spatial coverage. The increased use of satellite remote sensing data has changed that by providing systematic, consistent, and repeatable observations of the Earth's surface at a variety of spatial and temporal resolutions.

1.2 STATEMENT OF THE PROBLEM

Although remote sensing has made progress recently, challenges remain for LULC classification. Traditional classification techniques often suffer from spectral confusion between certain land cover types, which impacts classification accuracies. Processing large amounts of satellite data for large geographical areas requires substantial processing power and time.

Many existing LULC maps quickly become dated, particularly in very dynamic landscapes, such as cities undergoing rapid urban growth or landscapes undergoing significant environmental degradation. Classification models may not generalize effectively when transferring from a model developed for one area of land cover to another area, resulting in reduced classification performance owing to the geographic variability for land cover characteristics.

Efficiently integrating satellite derived information with existing GIS databases that are also easily accessible and understood by non-technical stakeholders remains a challenge. In the case of India, the hurdles described previously will be exacerbated due to the vast diversity in landscapes, rapid rates of urbanization, and complex agriculture patterns that characterize India. Because of this, accurate and timely LULC data is exceptionally important for the planning of sustainable development in India.

1.3 RESEARCH OBJECTIVES

The main objective of this study is to address the aforementioned issues by developing and implementing a real-time LULC classification system using deep learning techniques and satellite imagery. Specific objectives are to build a sufficiently good deep learning model that can accurately classify multiple LULC classes using Sentinel-2 satellite imagery.

Additionally, the study aims to create a processing pipeline for real-time or preferably near-real-time LULC classification at a district-level in India. It will validate the classification process using Chengalpattu district as a study area. The work will also focus on developing interactive visualization tools to easily convey the LULC information to the community and stakeholders. Finally, the thesis will review and discuss the performance and limitations of the developed system and suggest directions for future work.

1.4 SIGNIFICANCE OF THE STUDY

The above data can be used in environmental monitoring, which is the real-time classification system that will allow for continuous monitoring of environmental change, such as deforestation, urban sprawl, and water body dynamics, and prompt action. Similarly, in urban planning, accurate land use/land cover maps provide critical information to guide urban planners in the allocation of land, infrastructure, and sustainable city development.

Other uses can be for agricultural management that is, the precise crop type and agricultural practice segmentation enable precision agriculture and food security. Disaster management is the timely land use/land cover information that is necessary to evaluate vulnerability to natural disasters and develop appropriate mitigation efforts. Lastly, policy development, which is information from the system's accurate and spatially relevant data, can create evidence-based policies for land use policy and environmental regulation.

1.5 SCOPE AND LIMITATIONS

This study involves the development and application of an advanced CNN-based model tailored for LULC classification. With diligent development and testing, we're implementing this new model to process Sentinel-2 satellite data over the varied landscape of Chengalpattu district. The system will differentiate between ten unique LULC classes, delivering detailed land coverage analysis. To provide this information in a useful and accessible form for a range of stakeholders, we're also creating easy-to-use interactive visualization tools that will return the classified output in a ready-to-understand form.

As with any study, we must acknowledge there are some limitations. The accuracy of the classification is limited by the nature that Sentinel-2 imagery only provides a resolution of 10m x 10m, which might not be high enough to capture very high-resolution land cover detail. Cloud cover and interference in the atmosphere can significantly influence image quality, which may make classification precision suboptimal under certain seasons or conditions. Our testing procedure also depends on reference data availability and quality, which may also be incomplete or biased. Further, the model that we are developing may require being retrained drastically or having its parameters adjusted when deployed in different geographic regions with different landscape conditions not present in our training data.

CHAPTER 2

LITERATURE SURVEY

2.1 EVOLUTION OF LULC CLASSIFICATION TECHNIQUES

Classifying land use and land cover (LULC) has come a long way in the past several decades, moving from a manual interpretation approach to a computationally sophisticated method. The very first techniques were visual interpretation of aerial photographs, which is an effective technique, but spatially limited to small areas and impractical for large scale LULC mapping. The utilization of satellite remote sensing in the 1970s represented a significant advancement by the potential to systematically observe the Earth's surface across varying spatial and temporal resolution.

Early automated approaches to LULC mapping were dominated by pixel-based classification approaches such as maximum likelihood and minimum distance classifiers. These methods utilize spectral signatures to assign each pixel to a specific class. Mixed pixels and heterogeneous landscapes pose challenges for traditional pixel-based approaches that lead to the development of alternative computational approaches to better classify LULC.

Heterogeneous/LULC environments were first explored using object-based image analysis (OBIA) approaches in the early 2000s, as a classification approach that segmented the image into homogeneous objects. This allowed the spatial context of the objects to be better taken into account by the classification algorithm - which obviated some of the traditional "salt and pepper effect" from automated pixel-based classification approaches. There are multiple studies that have demonstrated how OBIA methods, particularly applied to high resolution imagery, provided an efficacious classification method in heterogeneous urban environments.

2.2 DEEP LEARNING IN REMOTE SENSING

In recent years, remote sensing as a tool for LULC classification has undergone a transformation due to the use of deep learning. Deep learning models have proved to be notably adept at identifying complex features extracted from satellite images while producing high latent accuracies. Several recent studies have incorporated deep learning approaches to enhance classification counts of agricultural remote sensing images. For example, Aljebreen et al. [1] published a "River Formation Dynamics" algorithm combined with deep learning for classification purposes.

Jagannathan and Divya [2] applied deep convolutional neural networks (CNNs) to model LULC change, supporting the premise of deep learning being a method of incorporating spatial and temporal variability. Yuan et al. [3] described the creation of the WH-MAVS dataset as significant in the spectrum of the use of remote sensing applications for land use classification. Zaabar et al. [4] showed the utility of combining an object-based, CNN analysis method to mapping coastal zones. These examples indicate that the quality of parameters within a solid dataset and sophisticated algorithms add value to practice and the accuracy of classification.

2.3 SEGMENTATION-BASED APPROACHES

Much progress has been made in LULC classification through segmentation-based model advancements. Fan et al. [5] examined segmentation models in classifying remote sensing imagery, calibrating their form in large part to unfold how state-of-the-art segmentation algorithms improved land cover discernment. Sanchez-Fernandez et al. [6] exhibited self-supervised learning yielding better results than conventional supervised learning with small in-domain datasets while minimizing reliance on large, annotated datasets.

Zhu et al. [7] offered a multitemporal convolutional LSTM model efficiently encoding temporal relationships for land use classification. Dong et al. [8] advanced a feature ensemble deep learning network for improving classification accuracy on very-high-resolution (VHR) optical remote sensing imagery. These developments speak to the effects of segmentation, self-supervised learning, and temporal modeling on LULC classification accuracies.

2.4 HIGH-RESOLUTION MAPPING AND CROSS-RESOLUTION LEARNING

Numerous studies have noted the recent emphasis on high-resolution mapping and cross-resolution learning to enhance LULC classification. An example is the introduction of a framework to apply low-resolution labels to high-resolution land cover mapping based on deep learning by Qi et al. [9]. Victor et al. [10] delivered a comprehensive review of prominent deep learning applications in agriculture relevant to precision agriculture, mainly in terms of the contributions by CNN and analogs.

Karra et al. [11] presented a new earth-wide scheme for LULC classification using Sentinel-2 and deep learning methods. Wang et al. [12] delivered a systematic review of LULC classification products that referenced contemporary applications while characterizing new trends and challenges in the study area. Priyanka et al. [13] suggested a new deep learning optimized model denoted DPPNet that demonstrated improved robustness for high-resolution segmentation used in satellite image analysis.

Talukdar et al. [14] compared several types of machine learning classifiers for LULC classification wherein they identified positive and negative aspects of the specific techniques. Brown et al. [15] described the Dynamic World dataset using the recent advancements in LULC classification at a 10m global classification of LULC with near real-time global ability. These contributions will direct LULC classification efforts into a new epoch, where deep learning models consistently demonstrated better precision, scalability and offered quicker detection in near real-time global data.

2.5 GOOGLE EARTH ENGINE FOR LULC CLASSIFICATION

Google Earth Engine (GEE) is a strong and new tool for remote sensing analysis on a large scale, including land use and land cover (LULC) classification. GEE provides a multi-petabyte catalog of satellite imagery and geospatial datasets with cloud-based processing capabilities, so users can process large amounts of data quickly. Several scholars have conducted LULC classification that utilizes GEE. Gorelick et al. [16] provided a detailed overview of the capabilities of GEE and possible uses for the environmental monitoring.

Tsai et al. [17] demonstrated GEE's ability to develop workflows for automated LULC classifiers from Landsat and Sentinel-2 data. Kumar and Mutanga [18] incorporated machine learning algorithms into GEE for LULC classification and illustrated how GEE can handle demanding computational applications. Tamiminia et al. [19] reviewed GEE applications across the remote sensing audience, including mapping LULC, and pointed out the advantages of GEE for computational efficiency and data simplicity.

2.6 RESEARCH GAPS AND OPPORTUNITIES

While advances made through remote sensing and deep learning have augmented LULC classification studies, important gaps are still present. Real-time applicability is a primary challenge among these, since most existing systems examine data post facto, their use for monitoring dynamic conditions and instant decision-making being compromised.

Another significant research deficiency exists in the transferability of models, whose effectiveness with deep learning models typically remains uncertain if used in regions other than where they were specially trained and validated because of heterogeneous landscape conditions. Additionally, the selection of features, especially when using a framework of deep learning with multispectral and temporal features, remains a developing field of study that still requires more mature literature.

Accessibility of results is also a challenge, since it is a problem to make the more complex classification results easily accessible and interpretable by non-technical users like land-use planners and policymakers. Finally, there is a need for more in-depth research into leveraging temporal analysis for LULC classification and the measurement of land cover changes over time. This thesis aims to address some of these gaps by establishing a real-time LULC classification system with interactive visualizations, focusing on an India case study and validation within the Chengalpattu district.

CHAPTER 3

STUDY AREA

3.1 GEOGRAPHIC LOCATION AND EXTENT

Chengalpattu district, situated at the northeastern part of the Tamil Nadu, extends between 12°13' to 12°50' North latitude and 79°43' to 80°13' East longitude and covers an area of 2,791 sq. kms. It is flanked by the Chennai and Tiruvallur districts to the north, Kanchipuram to the west, Viluppuram to the south, and the Bay of Bengal to the east. Such a unique geographical location, with economic implications, makes it one of the key districts in the State of Tamil Nadu.

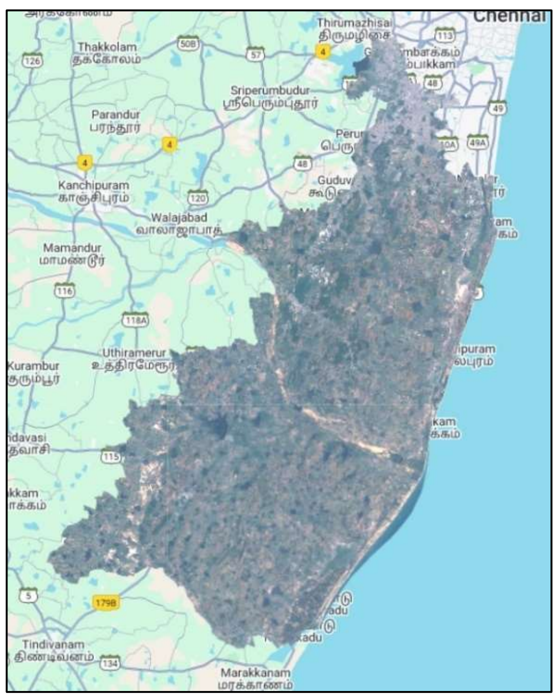

Figure 3.1. Geographical landscape of Chengalpattu

Figure 3.1. shows the geographical landscape of the Chengalpattu district. The district continues to have a diversified geographical landscape that consists of coastal plains,

tropical woodlands along the fertile river basins created by the Palar and Cheyyar rivers, and undulating terrain located in the west due to the foothills of the Eastern Ghats. Chengalpattu district was formed in the year 2019 after being carved out of the Kanchipuram district in order to better manage the rapid urbanization, growth of population, and associated infrastructure demands for the region.

Chengalpattu serves as a significant peri-urban and suburban area due to its proximity to the city of Chennai, with real estate developments, anticipated industrial development, and improved connectivity through developing highway and suburban rail networks. Economic activities in Chengalpattu include diverse agriculture (rice, sugarcane, and groundnut), industrial and IT corridors (Maraimalai Nagar and Mahindra World City), coastal fishing, and tourism surrounding heritage sites like Mahabalipuram.

Chengalpattu experiences a tropical climate with hot summers, a monsoon-dependent agricultural calendar, and composite mild winters. However, there are environmental concerns for sustainable development associated with groundwater depletion, coastal erosion, and urban pollution. Overall, Chengalpattu's location, administrative importance, and economic growth make it an important region of Tamil Nadu's growth trajectory.

3.2 PHYSICAL GEOGRAPHY

3.2.1 Topography

The terrain of Chengalpattu district illustrates a typical example of the Eastern Coastal Plains, with flat to gently undulating topography that gently rises from sea-level along the eastern coast to an altitude of 100 meters in the 'western' interior. The coastal region has large low-lying open plains whose elevation rarely exceeds 10 meters, characterized by sandy and clayey soils, estuaries, and salt marshes before shifting to higher elevation further inland.

The slope descending westward is formed due to displacement related to ancient rivers, most notably the Palar and Cheyyar, that have deposited alluvial soils forming vegetated floodplains juxtaposed with low-lying rocky outcrop and laterite elevation. The platform of the district consists of Precambrian crystalline rocks with granite hillocks and boulders forming in some areas (e.g. Madurantakam) juxtaposed with younger sedimentary deposits in the eastern half.

The range of elevations allows for varying types of ecosystems from coastal mangroves to inland scrub forests and has historically provided an opportunity to manage water use via tanks and seasonal streams. However, in the past few years, urbanization as a result of the expansion of Chennai, quarrying and modification of riverbeds have altered these processors, presenting a transition on landforms in the region that increases opportunities for development but presents challenges for environmental sustainability in an important area.

3.2.2 Climate

Chengalpattu district has a tropical maritime climate with uniformly high temperatures, high humidity, and well-defined monsoon patterns that determine its ecological and agricultural processes. The climate also has the usual pattern of three distinct seasons: hot and dry summer (March to May), the monsoon season (June to December), and mild winter (January to February).

Temperature fluctuations are moderate because of the coastal location of the district, with summer temperatures often reaching above 40°C in interior regions, whereas coastal areas are slightly cooler (35-38°C) because of sea breezes. Temperatures during winter months seldom fall below 20°C, and the most pleasant months are December and January. Humidity is consistently high (70-85% average) throughout the year, especially in coastal mandals such as Mahabalipuram, and generates sultry conditions that enhance the heat index during summer months.

Rainfall regime of the district is controlled by northeast monsoon (October-December) that delivers around 60% of annual precipitation, followed by less frequent rains during southwest monsoon (June-September). Annual rainfall of 1,200 mm is quite spatially variable - coastal blocks experience higher rainfall (maximum 1,400 mm) than western interiors (approximately 1,000 mm). Summer convective thunderstorms (April-May) give relief from heat for a short while but lead to localized flooding. Rain shadow of the Eastern Ghats makes western taluks like Madurantakam relatively dry.

These climatic factors deeply influence the agriculture calendar and natural vegetation of the area. Plantations of cashew and mango thrive in dry western areas, and coconut occupies the coastal belt. High humidity forms tropical dry evergreen forests in protected locations, though most is now cultivated. Climate change effects are beginning to be seen through increased variability in rainfall, more heatwaves, and rising sea levels that are polluting coastal aquifers. Conventional water management systems such as eri (tank) irrigation continue to be important in reducing these climatic stresses and maintaining the district's agrarian economy.

3.2.3 Drainage System

The district is drained by many small rivers and streams, but the most prominent one is the Palar River. The Palar rises in Karnataka's Nandi Hills, flows through the northern edge of the district, and empties into the Bay of Bengal. Although non-perennial and very much dependent on monsoon rain, it provides a vital water source for irrigation, drinking purposes, and recharge of groundwater. But industrial pollution and sand mining have lowered its quality in recent times.

Some other significant water courses are the Cheyyar River, which is a tributary of the Palar, and the Buckingham Canal, an old saltwater navigation canal along the coast. The district also has a large network of traditional tanks and reservoirs, like the Veeranam Tank and Kelavarapalli Dam, that collect rainwater and aid in agriculture. Along the coast, ecologically diverse estuaries, lagoons, and backwaters such as Pulicat Lake and the Muttukadu Backwaters serve as crucial habitats for varied aquatic and avifaunal life.

3.3 SOCIOECONOMIC CHARACTERISTICS

3.3.1 Demographic Profile

Based on the 2011 Census statistics (before the formation of the district), the present area of the Chengalpattu district was inhabited by around 2.5 million people, with a density of nearly 900 people per square kilometer. The population is spread across urban as well as rural settlements, with major urban concentrations in the towns of Chengalpattu (district headquarters), Maraimalai Nagar, and Tambaram. The district has seen its population increase in the past few decades rapidly, owing to the growth of Chennai's me

3.3.2 Economic Activities

Chengalpattu economy offers a rich mix of traditional and new-age industries, defying the notion that the district lags behind others. Agriculture is still the base, with rice being the major crop, complemented by sugarcane, groundnuts, and other vegetables. Plantations along the coast and fishing communities add to the rural living. Industrial-wise, Chengalpattu has seen rapid development, particularly along the Chennai-Bengaluru Industrial Corridor.

There are quite a number of industrial estates and Special Economic Zones (SEZs) that have attracted top industry players in automotive manufacturing, electronics, IT, and pharma. Even the services sector has caught up, with tremendous growth in education, health, logistics, and retail. Tourism also increasingly is adding to the local economy, with the district's scenic coastline, places of heritage interest, and the fact that it is close to Chennai, attracting domestic and overseas tourists.

3.4 LAND USE PATTERNS

The land use pattern of Chengalpattu district unequivocally testifies to its gradual transformation from a largely rural to more urban character. Agricultural Land, dominated by paddy cropping, is still an important land use, influencing most of the rural spaces where irrigation is facilitated by tanks and canals, though subject to increased pressures of urbanization. Forest Cover in the district is very limited, and it comprises mostly scrub and tropical dry deciduous forests, with the Nanmangalam Reserve Forest being one of the significant protected areas.

The rate of Urban and Built-up Area growth has increased significantly in recent decades, especially along major transportation routes such as the Grand Southern Trunk Road (NH-45) and the Chennai (NH-4) highways. Industrial Lands too have occupied a high percentage in the area and concentrated in terms of industrial parks and manufacturing districts like Maraimalai Nagar, Oragadam, and Sriperumbudur (at boundary). Water Bodies such as river, lakes, tanks, and coastal units form a characteristic part and major contributor to the area's morphology in the district.

Lastly, a Transport Network, with its dense concentration of roads, railways, and supporting infrastructure, takes up large tracts of land area, particularly in urban and peri-urban areas. The active interaction between these various land uses in a relatively confined spatial area renders Chengalpattu a compelling case study for LULC classification and tracking, with extensive coverage of land cover classes.

CHAPTER 4

METHODOLOGY

4.1 OVERVIEW OF THE METHODOLOGY

This study's methodology outlines a systematic, multi-stage approach to real-time Land Use and Land Cover (LULC) classification utilizing both deep learning and satellite imagery analysis. The data collection step involves retrieving high-resolution satellite datasets like Sentinel-2, Landsat-8, and MODIS through Google Earth Engine (GEE), while also obtaining key geospatial data such as DEM and NDVI to improve classification accuracy.

The data will then be labeled and annotated through existing LULC maps, field survey materials or OpenStreetMap in order to curate training datasets. The preprocessing step incorporated atmospheric correction and haze and cloud clearing methodologies, image enhancement methods (i.e., pan sharpening), data normalization, and critical exploratory methods including non-parametric tests via means and variances between samples or matches of significance tests.

Data augmentation processed through rotations and flips will also be utilized to expand the volumes of training dataset to help enhance model generalization models. Following data acquisition, a Convolutional Neural Network (CNN) will be developed via transfer learning through neural architectures such as ResNet, or hyperparameter optimization if operating end-to-end. The trained model would then be deployed either with GEE or cloud instances for real-time inference at scales which would involve performing pixel-wise and/or patch-based data classifications before then enhancing with post-processing.

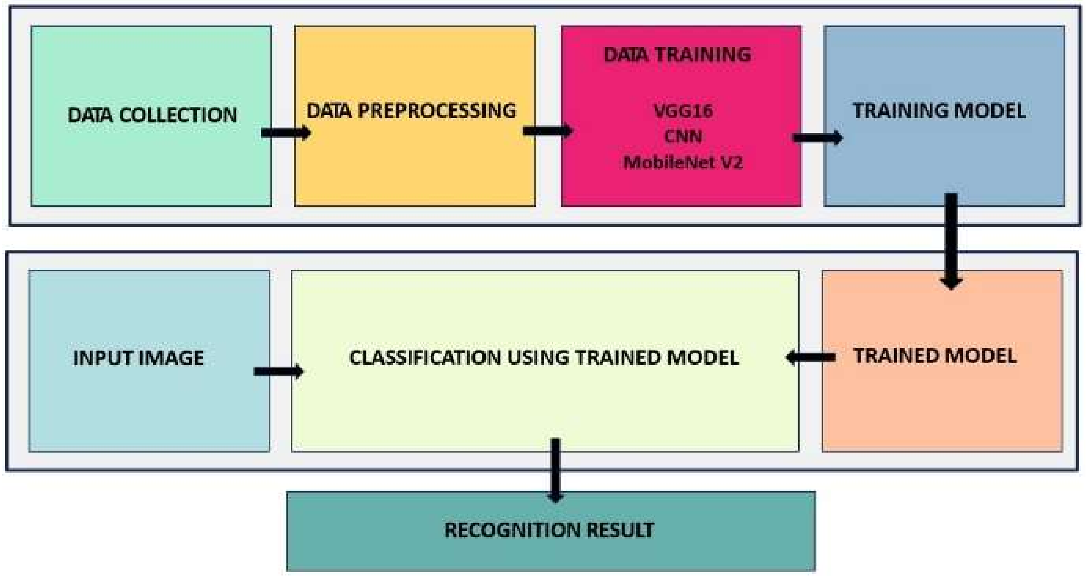

Figure 4.1. Block Diagram

Figure 4.1. illustrates an image classification pipeline that consists of two stages which rely on deep learning. The first stage is the training process, the first step of any deep learning project. In this stage, images are collected from multiple sources (e.g. the internet) and pre-processed to normalize the images. The collection of images that are created in this effort can be used to train multiple deep learning models (such as VGG16, CNN and MobileNet V2). During training, the trained model would ideally learn the dynamics from all images for the purpose of classification, given ideal conditions.

The end outcome of the training is a trained model that provides the ability to classify an unknown image. In the classification or inference stage, the system can pass a new image with unknown class into the trained model, compute the value through the trained neural net and produce the final recognition response—in this case, a predicted class label. Therefore, we can view the pipeline for the task of classifying an image, which includes data preparation, training, inference and deployment.

The last deployment entails visualization and analysis, through which the generated classified LULC maps may be dynamically seen as interactive web dashboards. The accuracy of classification is obtained by Overall Accuracy, Kappa Coefficient, and F1-Score whereas comparisons in terms of time enable end-users to track changes in cover and assess environmental change. The described approach benefits from cloud processing for scalable analysis, automation for easy updates, and precision for capturing the spatial pattern.

Despite the advantages, cloud obstruction included within the landscape, a class imbalance, and the computing time for LULC classification can present challenges, but they may be overcome through the introduction of techniques such as Synthetic Aperture Radar (SAR) data, a weighted loss function, and model quantization. We found the framework useful in supporting real-time LULC classification, and it can be advanced in the future by implementing Transformer-based architectures and developing multi-temporal analytics for better monitoring of land use and land cover change.

4.2 DATA ACQUISITION AND PREPARATION

4.2.1 Satellite Data Source

The Sentinel-2 satellite imagery was selected as the primary data source for this research due to its high spatial resolution (10 m for key bands), multispectral characteristics (13 spectral bands) and free availability. Sentinel-2 is a component of the European Space Agency's Copernicus program and comprehensively cover land surfaces around the world with an approximate 5-day revisit for monitoring the disturbance of the land cover.

There are three data parameters for selection that are temporal coverage, cloud cover percentiles and wavelength bands used. Temporal coverage is the most recent imagery (2023-2024) was prioritized to maintain relevance. Cloud cover percentiles is the imagery with less than 20% cloud cover were selected to reduce the impact from the atmosphere. And lastly the wavelength bands that are used are RGB bands (B2, B3, B4) at 10 m resolution were primarily used along with near infrared (B8) and short-wave infrared (B11, B12) for improved discrimination.

4.2.2 Google Earth Engine Integration

Our analysis leveraged Google Earth Engine's powerful cloud computing platform to ease access, processing, and analysis of Sentinel-2 satellite data through a tailored Python-based workflow. We established a secure API connection between Google Colab and GEE to create an ideal pipeline for data transfer and processing. We used great care in filtering our data by implementing geographic constraints at the district and watershed scale, choosing precise date ranges corresponding to key seasonal trends, and using rigorous cloud cover constraints—preferring images with under 20% cloud cover for best resolution.

In order to further improve image quality, we employed an advanced multi-layer cloud masking technique with the Scene Classification Layer to detect errant clouds and shadow, and additional quality filtering by the QA60 band. Our image processing chain consisted of radiometric normalization to reduce atmospheric distortions, spectral band stacking to form extensive composite strips, and temporal compositing methods based on median and percentile computation to produce seamless cloud-free mosaics.

The data were processed in two output formats lets discuss them. GeoTIFFs for analysis using local GIS tools and TFRecords optimized for integrating deep learning models. We integrated several optimization aspects into our pipeline, such as tile-based processing to efficiently process the entire study area, memory-aware chunking schemes to avoid performance bottlenecks, and quality validation checks automated using standard best practices. This integrated methodology successfully converted raw satellite data into analysis-ready products and preserved the native 10-meter resolution of principal spectral bands.

4.2.3 Data Normalization and Augmentation

The model training and performance were improved as a result of data preparation, which consisted of the techniques such as Normalization, Data Augmentation and Batching. Let's discuss them one by one. Normalization consists of normalizing the pixel values to a range [0,1], so that each spectral band has a consistent scale across digital image objects.

By applying Data Augmentation functions including rotation, flipping, and contrast enhancement, augmentations helped to artificially increase the size of the training dataset and better allowed the models to generalize. Under Batching the data was organized in batches to optimize training models' memory use. The augmentation methods used in the strategy included: Random rotation (0°, 90°, 180°, 270°)- Horizontal and vertical flips- Brightness and contrast adjustments (±10%)- Random crop within the original tile.

4.3 MODEL ARCHITECTURE AND TRAINING

The framework of classification utilized a pre-trained ResNet-50 Convolutional Neural Network (CNN) model fine-tuned for the intention of LULC classification. ResNet-50 was utilized because it is known to have solved image classification issues and has methods of preventing the vanishing gradient issue through the use of residual connections or skip connections that allow for easier flow of gradients through highly deep networks.

To train ResNet-50 for LULC classification, we used a series of basic modifications. We utilized feature extraction using the pre-trained convolutional base of the default ResNet-50 model, with all the convolutional layers frozen. These layers, which were trained on the ImageNet dataset, are shown to extract a rich set of hierarchical image features that are transferable across domains, including our remote sensing data.

We then stripped the top fully connected (dense) layers from the ResNet-50 model because they were designed for a 1000-class ImageNet classification task instead of our LULC classification requirement. We substituted these with fresh dense networks constructed specifically for our LULC classification task.

To avoid overfitting, especially crucial as our relatively modest domain-specific labeled sets are, we added dropout layers with 0.5 dropout rate after the new dense layers. The dropout layer stochastically inactivated 50% of the neurons during training, forcing stronger and more generalizable feature representations from the network. We finally added a SoftMax layer consisting of 10 output neurons (one per each of our 10 LULC classes) to output a probability distribution between the classes towards our multi-class classifier.

For training, we employed categorical cross-entropy loss, which is suitable for multi-class classification problems, and the Adam optimizer due to its adaptive learning rate, which results in faster and more stable convergence. We approached training in two phases: first, we trained only the newly added top layers while keeping the convolutional base frozen; then, to fine-tune the model, we unfroze parts of the deeper layers in the ResNet-50 base to more closely adapt them to our LULC data distributions.

4.3.1 Training Dataset

It was trained on a comprehensive and representative 27,000 remotely sensed image dataset featuring all full attributes, ensuring both significant generalization and accurate high classification rates over all the land use and land cover (LULC) classes. There were three images in our dataset, and each of them made a unique contribution to classification.

Hyperspectral imagery offered a wide spectral range of reflectance information, frequently consisting of hundreds of narrow and continuous spectral bands. Such dense spectral information enabled higher-level discriminability of materials, which made our model capable of separating surface types with subtle spectral differences. This depth of information proved particularly useful in differentiating vegetation types, soil types, and man-made items.

Multispectral images (e.g., satellite images) containing between 4 and 13 bands offered a balanced tradeoff between additional spectral bands and spatial resolution. These images helped identify LULC types while capturing features at acceptable spatial detail. They performed particularly well for medium scales of resolvability, i.e., urban sprawl, field edges, agricultural field form/size, and forest patch edges.

Plain "Red-Green-Blue" (RGB) images were added because they represent intuitively perceived color combinations that are widely used in manual interpretation pipelines. While limited to just three spectral bands compared to hyperspectral or multispectral imagery, RGB images remained fast and useful for quick visual classification or description of spatial extents. All images in our dataset were manually annotated and geo-referenced to determine spatial accuracy and class integrity. The annotation step incorporated high-resolution reference data (i.e., satellite overlays and topographic maps) and subject matter expertise to provide high-quality ground truth for supervised learning.

Our dataset was created to portray a balance of ten target LULC classes, representing a broad spectrum of ecological and anthropogenically influenced environments. Annual Crop (land with seasonally used purposes for short-term crop growth), Forest (land with planted or natural tree cover consisting of deciduous and evergreen types), Highway (land for principal arteries of transportation with accompanying infrastructure), Industrial (land dominated by warehouses, factories, and heavy-duty buildings), Pasture (land that is mostly grassland used for grazing livestock), Herbaceous Vegetation (non-woody plants, including shrubs, grasses, and forbs), Permanent Crop (land with long-term used purposes, including orchards and vineyards), Residential (habitations of people, including urban and suburban housing), River (inland water courses, including riparian areas) and Sea/Lake (large bodies of water, including saline and freshwater, such as seas, lakes, and reservoirs) are the classes of the dataset used. This heterogeneity of class categories and sources of data guarantees that our model is poised to handle the complexity and heterogeneity of real-world settings.

4.3.2 Training Strategy and Hyperparameter Optimization

4.3.2.1 Dataset Partitioning

All of the 27,000-image dataset was stratified and split into three distinct subsets so that there could be complete model testing and prevention of overfitting. We used 70% of the data for our training set, which we used to train the model parameters and extract feature representations. We had another 15% set aside for validation set, which we used during training to track performance and assist model calibration. The remaining 15% made up our test set, held back from final model testing for the ability to generalize against new data. We employed stratified sampling to keep in each subset a proportionate sample of all ten LULC classes without bias toward overrepresented classes.

4.3.2.2 Model Setup and Layer Freezing

We began with the ResNet-50 model pre-trained from ImageNet weights such that we could utilize transfer learning. We wanted to leverage the abundance of hierarchical features since the model had already learned from a very large image database. The early convolutional layers (the low-level feature extractors) were frozen in place, which allowed us to retain many of those general visualizations, such as edges, textures, and gradient of color.

In the meantime, the subsequent layers (and especially the layers of the last residual blocks) were unfrozen and retrained to adjust to the specific features of the LULC dataset. This fine-tuning helped the network in learning domain-specific features while preserving the overall patterns that could assist in image classification tasks.

4.3.2.3 Learning Rate Scheduling

A learning rate schedule was added to help reach optimum convergence. The training session started with an initial learning rate of 0.001 so that updates could be executed at a reasonable level to allow changes, while not forcing the model to overshoot minima. A ReduceLROnPlateau callback was used, allowing the learning rate to be altered downwards by a factor of 0.1 after several epochs when the model reached a plateau during validation. This helped the model escape local minima and improve learning during later epochs, resulting in more efficient training and better final performance.

4.4 CLASSIFICATION IMPLEMENTATION

4.4.1 Loading Pre-trained Model

First, the model is loaded from the Google Drive pre-trained model. The model is stored as "best_model.pth", and it has the weights and architecture based on the model training. The ResNet-50 architecture will be initialized with the stored parameters and set to evaluation mode for the classification tasks.

4.4.2 Connecting to Google Earth Engine

The study further establishes connection with Google Earth Engine which allows for obtaining satellite imagery. The connection consists of authentication in order to access the Earth Engine API for programmatic querying of the satellite data catalog for parameters of interest. This connection is necessary for obtaining Sentinel-2 imagery for the area of interest.

4.4.3 Processing District Boundary

In order to determine the study area, the drawn district boundary shapefile will be processed. The Chengalpattu district boundary is drawn from the Indian district’s shapefile collection. The selected polygon will be converted to the format that is required with Google

Earth Engine. This geographic drawing will be used to clip the satellite imagery to only capture the study area.

4.4.4 Tiling and Image Acquisition

To acquire Sentinel-2 imagery for the study area, I filtered the image collection based on date range, cloud cover percentage and geographic extent. The images that we selected were processed together into the median composite to allow the reduction of temporal aberrations and cloud shadows, with the RGB bands being extracted from the composite product. The composite image was then segregated into a grid of tiles of 64×64 pixels using a geospatial processing tool. At this point, we identified and eliminated non-relevant tiles (i.e., those outside the district boundary), which in turn focused my computational capacity on the area of relevance.

4.4.5 Classification of Tiles

We predicted the LULC class of each tile with the pre-trained CNN model. The probability of each tile class was provided. From there, the highest probability class was chosen for the tile and saved along with the tile's spatial coordinates so that it could be recomposed into the complete classified map.

4.5 VISUALIZATION AND MAPPING

4.5.1 Color Coding and Map Creation

After classification, each image tile was assigned a predicted Land Use and Land Cover (LULC) class and mapped to a color code (as outlined in Table I) that visually differentiated between the LULC class types (ten in total), to maintain clarity and consistency in the final mapping visualization. To develop the full classified map:Each map tile was filled on the basis of the predicted class labeled with RGB values based on the associated label.

The RGB tiles were then georeferenced and spatially located based on where they originated in the Chengalpattu district (boundary). The spatial orientation ensured that the geographic location of the dataset was accurate, thus making a fully integrated LULC map that is high-resolution and of the entire area of study. This would allow, at a glance, a clear visualization of LULC, as well as a rapid interpretation of spatial trends, fragmentation, and land cover changes that occurred in the Chengalpattu district. It is visually clear which regions were utilized for agriculture, urban settlements, or bodies of water or forest areas.

4.5.2 Interactive Web

MapTo further enhance the site's accessibility and user engagement, the classified LULC map is now made available as an interactive web map using modern geospatial web mapping libraries (e.g., Leaflet.js or Mapbox GL JS). The web visualization interface includes the following components: Base Map The user has access to a geographic/standard base map (e.g., OpenStreetMap or satellite-based imagery) that provides spatial context including roads, topography, administrative boundaries, and natural features.

LULC Overlay Layer is the classified map that is rendered as an overlay layer meaning it zooms/pans as a digital overlay accurately positioned in the base map with geographic coordinates. Legend / Color Ramp allows the user to adjust its opacity to visualize both the classification map results and the terrain below. The interactive legend is displayed in the interface and includes the color codes associated with each LULC class to ensure the user can understand the visualized data without needing to reference external documentation.

The map includes standard GIS navigation capabilities, including the clicking on the map for zoom or pan to clearly explore regions of interest, toggling layers on and off to show or hide each component of the map and click or hover (if implemented) for tile level classification metadata.

4.6 PERFORMANCE EVALUATION

To systematically evaluate the effectiveness of the LULC classification model, a reliable assessment approach based on various quantitative metrics and qualitative analyses was adopted. The assessment approach was designed not only to assess overall model performance but also to identify areas to improve class-wise performance, as well as water related spatial consistency.

4.6.1 Accuracy Performance Metrics

To facilitate a complete evaluation of the model's predictive ability, several metrics were utilized to assess performance, lets discuss about them one by one. Overall Accuracy (OA) represents the number of tile images correctly predicted divided by the total number of tiles in the test set. Overall accuracy indicates and describes the model's performance generally, but due to class imbalance the overall accuracy to individual land use land cover (LULC) class accuracy metric should be interpreted carefully.

Class-wise accuracy is used to calculated class-wise accuracy as the number of samples correctly predicted divided by the actual number of samples in the respective LULC class. This accuracy would help identify which classes the model is performing well or poorly for in class-wise accuracy.

A confusion matrix was generated to capture the distribution of predicted classes and the actual classes. The confusion matrix is beneficial to indicate any misclassification type or systematic confusion such as switching LULC types or picking a similar land cover type (such as Pasture and Herbaceous Vegetation), this is helpful to visualize classify prediction errors.

F1-Score was computed to determine the balance between false positives and false negatives. The F1 score can also be used as an additional score on poorly built datasets. The F1 score is the harmonic mean of precision and recall. Kappa Coefficient is used to find out the agreement between predicted and actual classifications considering chance, we used Cohen's Kappa Coefficient. The larger the Kappa value, the higher the predictive reliability over random chance.

4.6.2 Confusion Matrix Assessment

The confusion matrix revealed a detailed, class-specific view of the model performance that not only showed true positive occurrences, but also false positives and false negatives for each LULC classification. Some insights that arose from the confusion matrix. Certain classes, residential and industrial properties, received occasional misclassification with RM classification. This behavior was expected, characteristics present in object-based models come from the built structures in satellite images, thus sometimes the satellite images are not able to distinguish different buildings.

Herbaceous vegetation (HG) and pasture (FP) were commonly confused because of overlapping spectral and spatial characteristics. Water bodies (i.e. River and Sea/Lake) received minimal misclassification and were classified well. Water bodies received separate and distinct signatures in all image types (RGB, multispectral, hyperspectral) suitable for classification.

4.6.3 Validation

A validation exercise was conducted to generate trust in the classification results through a comparison with ground truth data. Ground truth data utilized a combination of field surveys, expert annotated data sets, and high-resolution satellite images to provide a comparison. The validation involved the following actions such as ground truth data collection, Overlay and Visual Sample Comparison, Quantified Accuracy Assessment and Error Analysis.

Ground Truth Data Collection is the field-based surveys were conducted in selected areas of the Chengalpattu district and were coupled with manually interpreted high-resolution satellite images to create a reliable reference. Overlay and Visual Sample Comparison is the LULC classification map, was overlaid with the ground truth data in GIS software allowing for both spatial inspection and comparison on a pixel-wise basis.

Quantified Accuracy Assessment is using this comparison, the measures of accuracy, and precision, recall, F1-score, and overall accuracy, were recalculated. Areas in disagreement were recorded and analyzed spatially and the Error analysis is the areas in agreement that were used to confirm the model had been effective in certain LULC categories, while areas of disagreement were examined to determine if there were causes such as seasonal variation, image quality, or restrictions from annotation accuracy.

4.7. REALISTIC CONSTRAINTS

4.7.1. Spatial Resolution Constraints

One of the stronger technical constraints related to this project is the spatial resolution of the Sentinel-2 satellite imagery, which offers a maximum resolution of 10 meters per pixel for some spectral bands. While this is still fairly high for open-source satellite information, it still lacks the resolution necessary to digitize fine-scale urban features, such as small buildings, narrow roads, or sub-urban infrastructure.

In rural areas, it could also create mixed pixel effects, where a single pixel contains a mix of land cover types, resulting in classification ambiguities. These constraints reduce the model's capacity to differentiate between similar or spatially related land uses, particularly within heterogeneous and dense built-up areas.

4.7.2. Atmospheric distortion and cloud cover

Another large issue that remote sensed applications face is the impacts of cloud cover, haze, and other atmospheric particles on satellite imagery, which can hide important surface features. While the project plans to apply cloud masking techniques like using Sentinel-2's Scene Classification Layer (SCL) and QA60 band filtering, these are not foolproof measures.

There may still be a few potential cloud shadows, or thin clouds that remain, which could distort spectral reflectance and lead to some misclassification in part of an area that is fogged by clouds. Humidity and other atmospheric variations like air pollution can also change the spectral signature of surfaces, which can affect an organism's model prediction accuracy in certain environmental conditions.

4.7.3. Model Generalizability

While the CNN model has been developed to perform well within Chengalpattu, the transfer of the trained model to other locations is a major limitation. Each area has its own unique topography, climate, land use characteristics, etc., which will impact the spectral properties of the land cover types, just because they belong to the same classes does not guarantee they look sufficiently alike for the model to accurately classify another location. Models should typically be retrained or fine-tuned, especially through domain adaptation, for areas with limited features shown in the training dataset. So, the geographical transferability is less than ideal and limits the ability of the model to scale at a national or global level without re-training or providing additional labeled training data.

4.7.4. Data Quality and Availability

The quality and quantity of labeled training data is of critical importance to the performance of any supervised deep learning model. In this project, a training dataset of over 27,000 manually labeled image tiles was generated requiring significant time for annotation, verification, and ground truth. In many cases, however, availability or access to high-quality, up to date, labeled datasets is not guaranteed.

Often land use planning regions can include parts of the world where there is either too much complexity in land use relationships, or they do not have a mapping infrastructure with enough detail to justify or quality for using a supervised deep learning model. Relevant reference data including (but not limited to) missing, outdated, and biased data can introduce noise into the model and or limit its robustness, particularly in transitional or ecologically sensitive areas.

4.7.5. Computational Resources

Even with cloud environments (e.g. Google Colab and Google Earth Engine) there are still many computational challenges expected in model development and implementation: tens of thousands of image tiles to train a deep learning model - requiring heavy processing GPUs, large RAM and larger, optimized storage pipelines. Furthermore, preprocessing steps that the model will need, such as cloud filtering, tile generation and georeferencing are also computationally demanding and time-consuming, which can hinder the ability to refine or improve the model in environments with limited resources or in efforts to scale the model to larger areas or datasets with larger spatial resolution.

4.7.6. Temporal Dynamics

An important but sometimes overlooked limitation, is the absence of temporal diversity in the image inputs. The vast majority of classification tasks in this project rely on single-season, or static composite imagery, and do not take into consideration seasonal changes in land cover, cropping, deforestation, lake fluctuation, or urban development. Temporal dynamics in the data could result in misclassification within areas that have different appearances throughout the year. The addition of multi-temporal or time-series data would improve model performance, but would require the increased complexity of data acquisition, processing, and model training.

4.8 ENGINEERING STANDARDS

4.8.1. IEEE and Remote Sensing Protocols

This project proceeded along strictly defined protocols established by IEEE and the European Space Agency (ESA) for remote sensing. The project made use of Sentinel-2 satellite images (after ESA's Copernicus Programme) following ESA's Level-2A products for atmospheric correction, radiometric correction, cloud masking, and generation of land cover classification products.

Use of Scene Classification Layer (SCL) and QA60 cloud band, these EPS levels and specifications are in compliance with saying internationally recognised. As the use of and by IEEE GRSS (Geoscience and Remote Sensing Society) conforms to monitorability, repeatability and certainty, and FREE of bias; therefore, the satellite images were truly consistent for the analysis and classification of geospatial data and the LIEMS (land use and ethnobiological classification).

4.8.2. Machine Learning Standards

The approach described above in this project represents best practice in the field of machine learning engineering; a ResNet-50 convolutional neural network trained on an ImageNet dataset is used to leverage transfer learning to reduce training time and improve model generalizability. For model training, the Adam optimizer with categorical cross-entropy loss function were tuned suitably.

4.8.3. Geospatial Standards

This project employs geospatial data according to professional standards that the GIS and remote sensing community have developed in recent years. The project avoids any inherent spatial disturbance because GeoTIFF raster model (images) files will allow the author to store high quality and high-fidelity georeferenced raster data. The use of TFRecords files optimizes the use of deep learning workflows using TensorFlow.

For instance, the mapping and data processing all occur in Google Earth Engine (GEE) which is a cloud-based platform that follows Open Geospatial Consortium (OGC) standards for distributed scalable geospatial analysis, and where the unit areas (district boundaries) and contributes (regional vectors) area represent using Esri shapefile specifications and referenced in WGS 84 which is the global positioning system (GPS) standard for position location data. This provides a high level of certainty about where the spatial data falls, and that it is interoperable, accurate and able to work within modern GIS tools like QGIS or ArcGIS.

4.8.4. Visualization and User Interface Standards

To promote more effective interpretation and access to LULC classification results, the project provides a modern web-based visualization tool that follows web standards for the development of web pages, accessibility, and particular GIS user interface standards. Interactive maps are modeled via libraries such as Leaflet.js and Mapbox, which follow HTML5, CSS3, and WebGL standards.

The visualization interface includes geospatial overlays, layers that can be toggled on and off, legends, and real-time interaction with the map, which provides users with the proper navigational tools to view, explore and interpret classified land cover data. As noted, available tools are designed to be user friendly and accessible to both technical and non-technical stakeholders so that the output of the classification system may inform planning and decision making across disciplines.

4.9. MULTIDISCIPLINARY ASPECTS

4.9.1. Electronics and Computer Engineering

At its essence, the project embodies Electronics and Computer Engineering in the use of computational and deep learning processes. The proposed Convolutional Neural Networks (CNNs)—and referring to ResNet-50 implies that the project deals with image processing and neural network development—account for some of the most important aspects of the project. The project takes advantage of established engineering processes of data normalization, augmentation (rotation, flipping, changing contrast), and multiplies the number of batches to increase performance and robustness of the model.

The project also involves the use of Google Colab, a cloud environment for training different models, and Google Earth Engine (GEE)—cloud computing with just enough power and capability for processing geospatial data—was implemented as a way to run the model, quicker by processing the geospatially-derived data and changing the landscape of open-source mapping and realization of the intersection of cloud computing and AI engineering and how they need to work together to solve larger issues with remote sensing systems.

4.9.2. Remote Sensing and Geoinformatics

The project rests on a foundation of remote sensing and geoinformatics principles. The principal dataset, which is high-spatial resolution Sentinel-2 (S2) satellite data, requires a series of geospatial data processing operations in a workflow that includes items such as (1) radiometric correction; (2) cloud mask using the QA60 and SCL layers; (3) spectral band stacking; and (4) tiling.

The above items are common practice when it comes to geoinformatics methods designed to translate raw satellite data into outputs ready for analysis then classification. For example, mapping land covers across spatial and temporal extents entails adhering to the specifications of geospatial science to a which ultimately applies unique processing techniques to produce products that conform to geoinformatics standards such as spatially referenced formats that provide a georeference reference system like GeoTIFF.

4.9.3. Environmental Science and Urban Planning

From an environmental science perspective, the project is useful for mapping and monitoring the management of ecosystems. Since it delineates land cover types of forests, cropland, surface water, and built-up areas, the model is a useful values model for environmental assessments, biodiversity conservation, and management of commons. It is applicable to United Nations Sustainable Development Goals (SDGs), especially SDG 11 Sustainable Cities and Communities, and SDG 15 Life on Land. Urban planners can explicitly use the category of built-up areas for measuring urban sprawl, managing sustainable land use, and assessing the environmental impact of development actions in rapidly urbanizing areas such as Chengalpattu.

4.9.4. Geography and Earth Sciences

The project's consideration of the physical geography of Chengalpattu includes many aspects of both geographic and Earth science dimensions, such as topography and vegetation patterns, as well as climate and hydrology. The elevation range in the study area, from coastal plains inland into uplands, was utilized both for model training and for validation, so that variability in land cover related to the terrain could be appropriately accounted for.

The seasonal changes as well as the natural drainage system, including rivers like the Palar and Cheyyar, were considered in the classification process as a part of the geographic understanding of the study area. These geographic context aspects can help in the interpretation of land use changes and deeper understandings of how natural systems are being impacted.

4.9.5. Public Policy and Governance

The last layer of this project's multidisciplinarity ties into public administration, land governance and policy making. The LULC maps (especially when deployed as an interactive solution on the web) are a decision-support system for government, urban developers, broiler plant planners, and responders to disasters. Timely and near timely, the system allows for responses to environmental degradation, encroaching urbanization and climate change. Provided with scientifically tested, spatially aware and visually interpretable evidence, we are closing the divide between technical research and its implementation in public policy and governance.

CHAPTER 5

ONSITE RESEARCH & GROUND VALIDATION

5.1 FIELD VERIFICATION METHODOLOGY

Our study methodology involved essential ground validation to validate the accuracy of our CNN-based LULC classification model. Field study was conducted in various locations scattered across Chengalpattu district in the state of Tamil Nadu, India, in February 2025. This ground validation process was critical for deciding the model performance on the ground versus the real ground conditions and establishing ground truth data points. We chose strategically several representative sites corresponding to various LULC classes predicted by our model, covering a wide range of landscape types in the district for extensive validation.

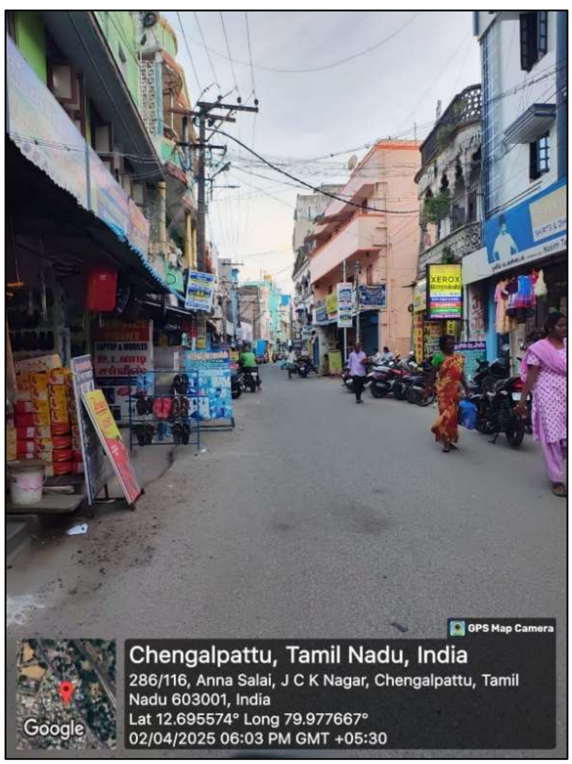

Figure 5.1. Residential Zone in Chengalpattu

Figure 5.1. is a residential zone in Chengalpattu, JCK Nagar. This urban settlement has typical characteristics of fast-growing semi-urban centers in India, including high-density housing patterns with an occasional commercial establishment along the streets. The mixed land use pattern evident in this location posed challenging classification problems for our model, especially in differentiating zones with purely residential use from those with mixed commercial-residential uses. The high-resolution spatial heterogeneity evident here highlighted the importance of using high-resolution images in precise urban LULC classification.

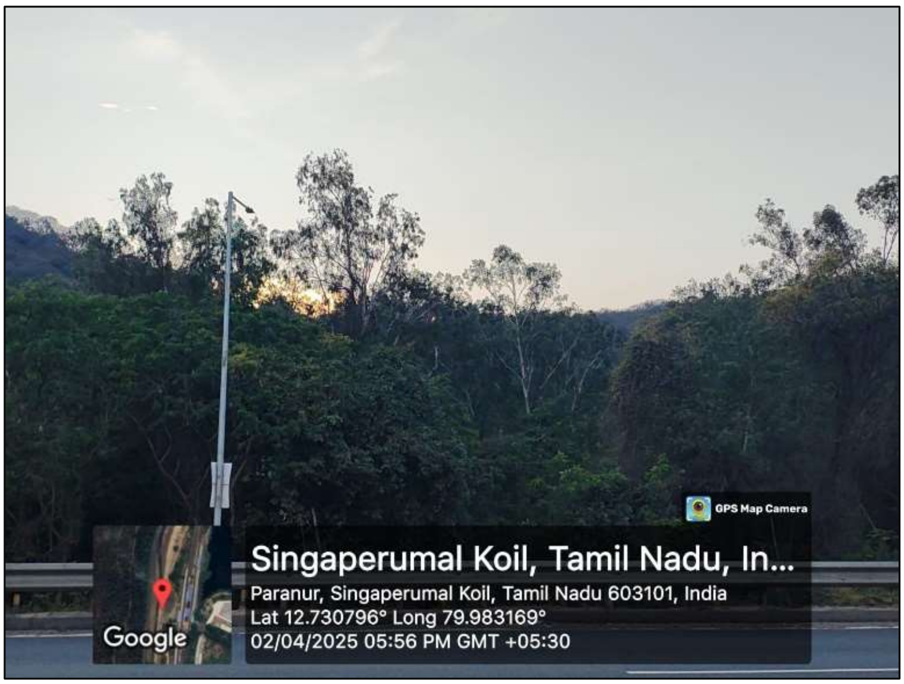

Figure 5.2. Forest Cover In Singaperumal Koil

Figure 5.2. shows a forest cover in Singaperumal Koil with medium canopy density dominated by deciduous cover. The photo shows the typical secondary forest growth structure of the area, with trees of different heights and some gaps in the canopy observable. The forest edge visible in the image shows the boundary zone between forest and modified land, which was difficult for remote sensing classification because there were continuous trends in spectral signatures. This site provided valuable ground truth information to verify our forest classification parameters.

Figure 5.3. Highway Corridor in Chengalpattu

Figure 5.3. depicts a highway corridor along the Grand Southern Trunk Road of Chengalpattu. The photograph clearly demonstrates the typical linear infrastructure features with surrounding commercial growth constituting a confusing mixed-use region. The presence of automobiles, roadside facilities, and utility buildings produces a characteristic spectral signature which our model needed to distinguish from other urbanized areas. This site validated our model's capability to properly identify transportation infrastructure, which is a critical component of LULC classification for monitoring urban development and planning in rapidly developing regions.

Figure 5.4. Pasture Field in Chengalpattu

Figure 5.4 is a photograph of a Varadaraja Nagar pasture field that is an agricultural transition area. The photo includes grazing livestock and herbaceous cover patches that characterize the pasture lands in the area. Dispersed woodland and signs of human disturbance across the landscape reflect the semi-managed character of the parcels. These range lands experience variability by season with the vegetation coverage and health, which pointed toward the importance of temporal processes for LULC classification. The proximity to residential areas visible in the background also indicates the fine-grained classification boundaries our model had to navigate.

5.2 ANALYSIS OF LAND USE PATTERNS IN CHENGALPATTU

The field survey found a number of interesting trends in the land use pattern of Chengalpattu. Residential areas of Chengalpattu are marked by intense urban development with mixed commercial activity along major roads. These urban settlements exhibited characteristic features of fast-developing semi-urban settlements, with multi-story residential apartments punctuated by small-scale enterprises. The urban fabric portrays signs of spontaneous growth as opposed to planned growth, providing classification challenges due to complex land use patterns.

The forest cover studied in Singaperumal Koil presented moderate canopy cover with predominantly deciduous cover types. The forest margins had some signs of encroachment and anthropogenic stress, as with visible transitions from natural forest to human-altered habitats. These boundary zones posed specific difficulties for remote sensing classification since the transition zones have spectral signatures somewhere between defined classes. Highway corridors of Grand Southern Trunk Road were characterized by standard linear infrastructural features that had accompanied commercial growth and thus formed complex mixed-use neighborhoods requiring careful stratification within our schema.

The grassland pastures observed at Varadaraja Nagar were a peculiar instance of agricultural alteration, featuring grazing cattle and herbaceous patches. These locations featured seasonally fluctuating conditions highlighting the importance of temporal factors to include in LULC mapping. The field results verified that pastureland in the region tended to be close to residential development, creating complex classification boundaries which our model had to deal with through sophisticated feature identification.

5.3 ENVIRONMENTAL AND SOCIOECONOMIC CONTEXTS

Chengalpattu district offers an interesting study site based on its high-speed transition from being largely an agricultural land-use area to having a combination of industrial, residential, and commercial complexes. Its close proximity to Chennai, India's one of the key metropolises, has triggered much of this shift. The past ten years have witnessed population growth and urbanization at a fast pace in the district, which put natural resources under pressure as well as the conventional land use system.

The water bodies of the district, including lakes, ponds, and the Palar River basin, are significant as far as the maintenance of ecological balance and agricultural productivity is concerned. Our observation in the field revealed conclusive trends towards alarming rates of encroachment and pollution in some of the water bodies, reflective of the environmental cost of premature development. The rural landscape showed a refined mosaic of different styles of cultivation from traditional paddy to intensive high-value horticulture, a reflection of the economic change occurring in the area.

Industrial zones have expanded significantly, especially along main transportation corridors, creating jobs but also environmental concerns related to pollution and resource use. The socioeconomic structure of the district is changing very fast, with historical village settlements evolving into peri-urban settlements with new infrastructure requirements and consumption patterns. Such dynamics pose challenges and demand urgency for effective and timely LULC monitoring as a basis for sustainable development planning.

5.4 IMPLICATIONS FOR MODEL VALIDATION AND REFINEMENT

The outcome of the field study provided us with critical feedback for validating and refining our LULC classification model. By comparing model predictions with ground truth over multiple land use classes, we established both the strengths and weaknesses of the classification technique. The residential classes had trouble distinguishing between pure residential and mixed commercial-residential areas, which means a need for higher spatial resolution data or additional training samples for these complex urban classes.

Forest classification accuracy was overall high, though edge effects and gradual transitions between forested and non-forested areas created classification challenges which could be mitigated with incorporation of edge detection routines or transition zone classes. Highway segments were well detected by our model given their characteristic linear shape and spectral signatures, validating the utility of our methodology for transportation infrastructure classification. The validation of pasture field showed seasonality that impacted classification accuracy and indicated the significance of multi-temporal analysis for future versions of the model.

This ground truth validation experiment showed that while our CNN-based classification system performed well overall, some context-specific issues persist. These findings informed our follow-up model improvement process, such as focused retraining using more examples from problematic transition zones and the inclusion of temporal information to more effectively track seasonal land use patterns. The field validation ensured that our technical methodology was correct, and at the same time, gave guidance on future improvements for enhancing classification accuracy in intricate semi-urban and transitional environments typical of fast-growing districts such as Chengalpattu.

CHAPTER 6

RESULTS AND ANALYSIS

This chapter introduces the overall results received from the real-time Land Use and Land Cover (LULC) classification system applied for the Chengalpattu district. This analysis involves performance evaluation of a model, unseen data validation, visual interpretation of classified maps, and the overall classification output.

6.1 MODEL PERFORMANCE METRICS

The deep learning model used here proved to exhibit strong performance when classifying different land cover categories in the Chengalpattu district. Table 6.1 collates the essential performance metrics garnered during training and validation.

Table 6.1. Model Performance Metrics

Metric	**Value (%)**
Training Accuracy	97.20
Validation Accuracy	90.85
Precision	91.34
Recall	89.76
F1-Score	90.54
R^2 Score	0.893

The CNN model classified with an accuracy of 97.20% during training, indicating outstanding performance on the training set. Evidently, validation accuracy of 90.85% indicates outstanding generalization performance, and it is therefore implied that the model captured significantly the distinguishing features of different land cover classes without overfitting the training dataset.

The high precision value of 91.34% indicates a low false positive rate, while the recall value of 89.76% shows the model's ability to correctly identify most instances of each class. The balanced F1-score of 90.54% further confirms the model's overall effectiveness. The R^2 score of 0.893 indicates that the model explains approximately 89.3% of the variance in the land cover classification, which is quite satisfactory for the complex terrain of Chengalpattu district.

6.2 VALIDATION ON UNSEEN DATA

For additional evaluation of the generalization capability of the model, we checked it on untested satellite imagery downloaded from Google Maps. They were specifically picked to be contrasting from the training dataset to judge the model's real-world effectiveness.

Figure 6.1. Input Satellite image of SRM

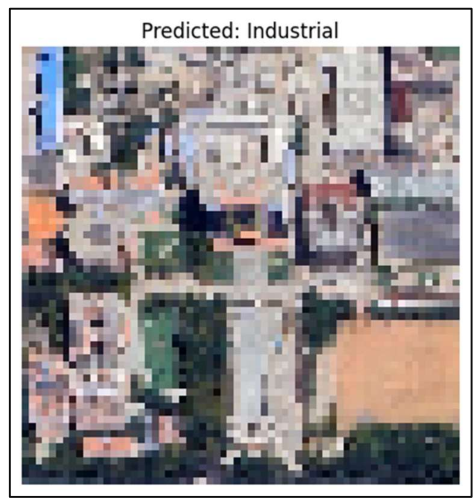

Figure 6.2. Output Prediction

Figure 6.1. shows the satellite image of SRM College campus, which was not in the training dataset. When this image was passed through our model, it correctly identified the region as "Industrial" (Figure 6.2.), corresponding to the built-up environment of an educational institution campus. This correct classification proves the model's capability to label built-up regions with institutional features even though it was not particularly trained on educational infrastructure. It should be mentioned that the model classifies schools as "Industrial" as a result of comparable structural and spectral features of satellite imagery.

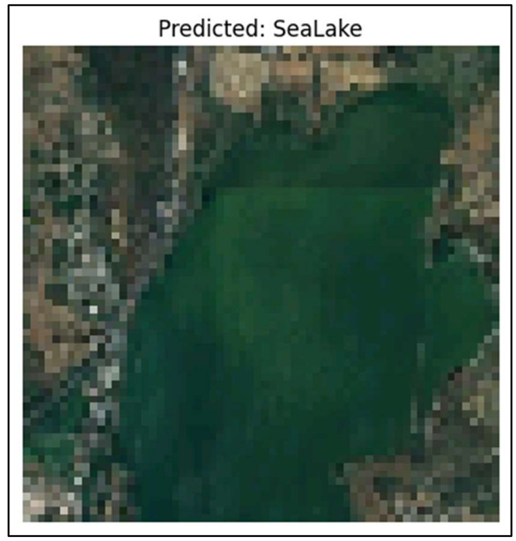

Figure 6.3. Input image of Chengalpattu lake **Figure 6.4. Output Prediction**

Figure 6.3. is a satellite image of Chengalpattu Lake, which is another area outside the training data. The model correctly classified this water body as "Sea/Lake" (Figure 6.4.), recognizing the spectral signature of standing water bodies. This correct classification on unseen data further confirms the model's success in separating water features from other land cover classes.

A notable finding from these tests of validation is that the model works well even when input images are not of the same size as the training data. Although the optimal situation would be the use of satellite imagery of identical dimensions to the training data (64x64 pixels), our model proved to be quite flexible in terms of different image sizes yet retaining high prediction accuracy. This flexibility is vital for real-world applications where standard imagery might not always be available.

6.3 IMPLEMENTATION PROCESS AND VISUALIZATION

Implementation involved a series of operations to transform raw satellite data into a map of LULC classification of the Chengalpattu district in fine detail. Steps involved are highlighted through a set of figures demonstrating the data acquisition to final classification workflow.

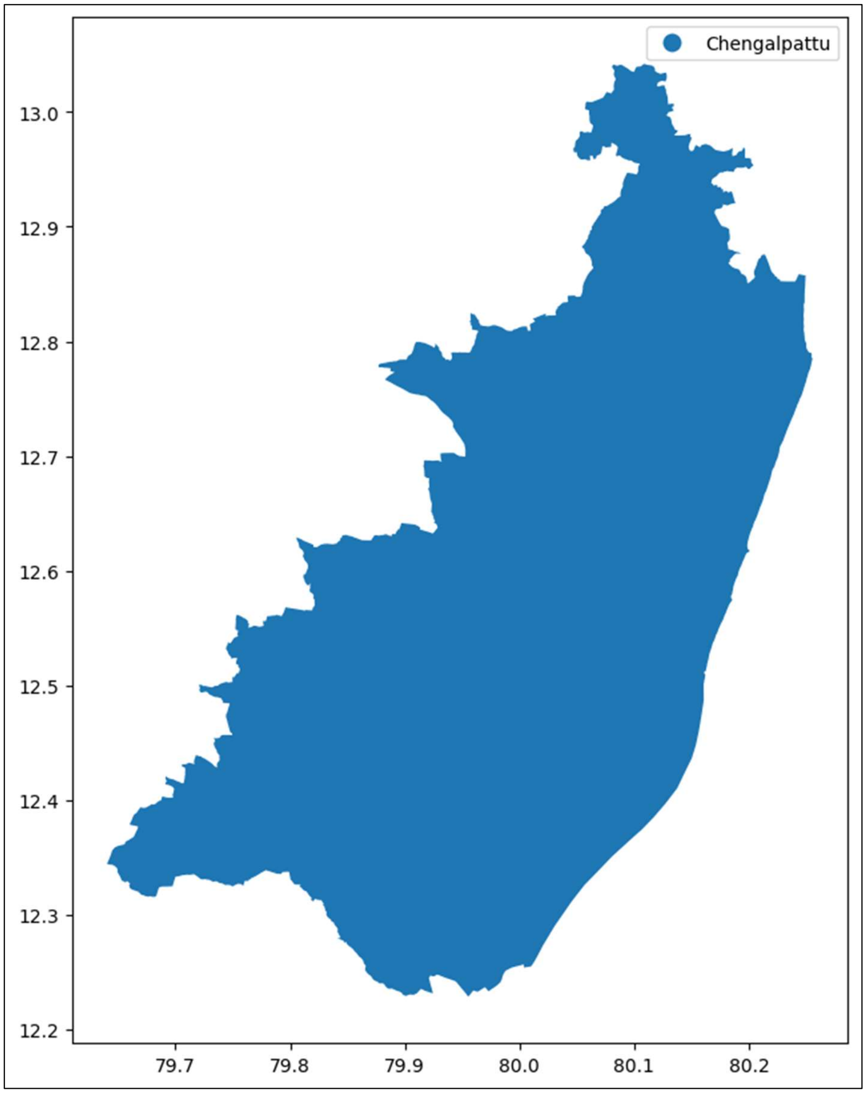

Figure 6.5. Tif map of Chengalpattu.

Figure 6.5. is the Tif map of Chengalpattu. This picture is derived from the Indian district map dataset, which provides district images of all districts in Tif format. The Tif format is particularly valuable as it stores the geographical coordinates of all districts, allowing for precise plotting on a geospatial canvas. This base map serves as the foundation for subsequent processing steps and ensures that our analysis is spatially accurate within the administrative boundaries of Chengalpattu district.

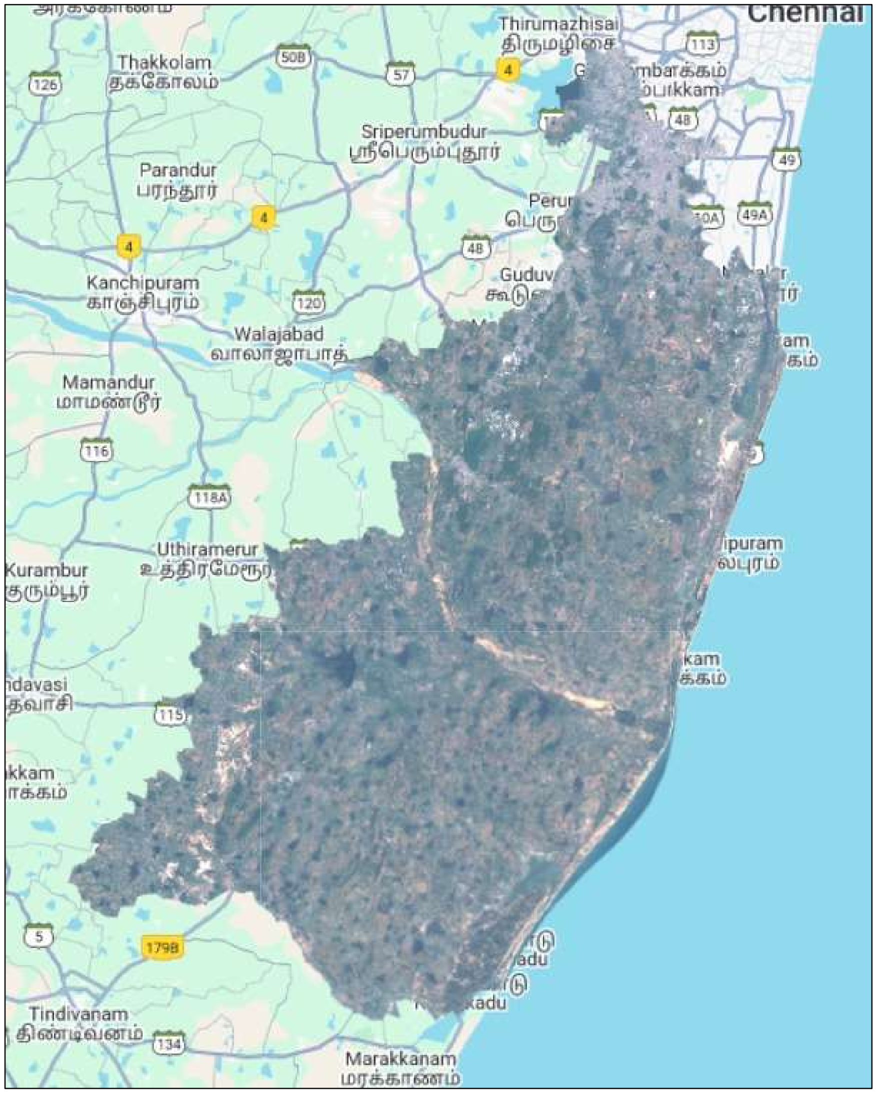

Figure 6.6. Locating map of Chengalpattu on Google Earth Engine.

Figure 6.6. shows the locating map of Chengalpattu on Google Earth Engine. In this figure, we can observe that the Tif picture from Figure 6.5. is traced on the map of Chengalpattu that we obtained from Google Earth Engine. This is a critical step towards overlaying our administrative boundary data on the actual satellite imagery, so that we're only extracting terrain information for our area of interest. The accurate overlay allows us to avoid extracting data outside our area of interest and concentrate computational effort on the Chengalpattu district.

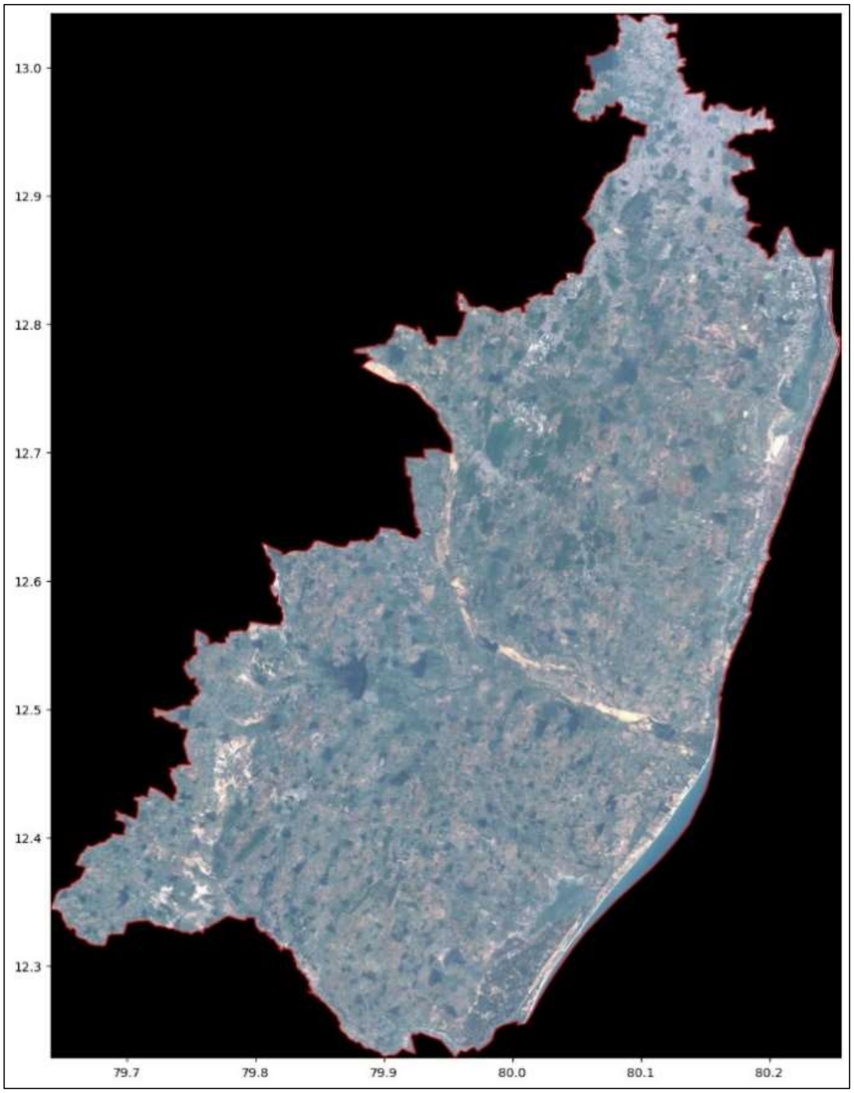

Figure 6.7. Traced map of Chengalpattu.

Figure 6.7. depicts the traced map of Chengalpattu. Here, we take the previous image and crop only the Chengalpattu part, plotting it on a black page to reduce extraneous elements that appeared in the Google Earth Engine imagery. This clean representation of the district boundary serves as a mask for extracting the specific satellite data needed for our classification task. The black background provides a clear visual separation between the area of interest and surrounding regions, facilitating subsequent processing steps.

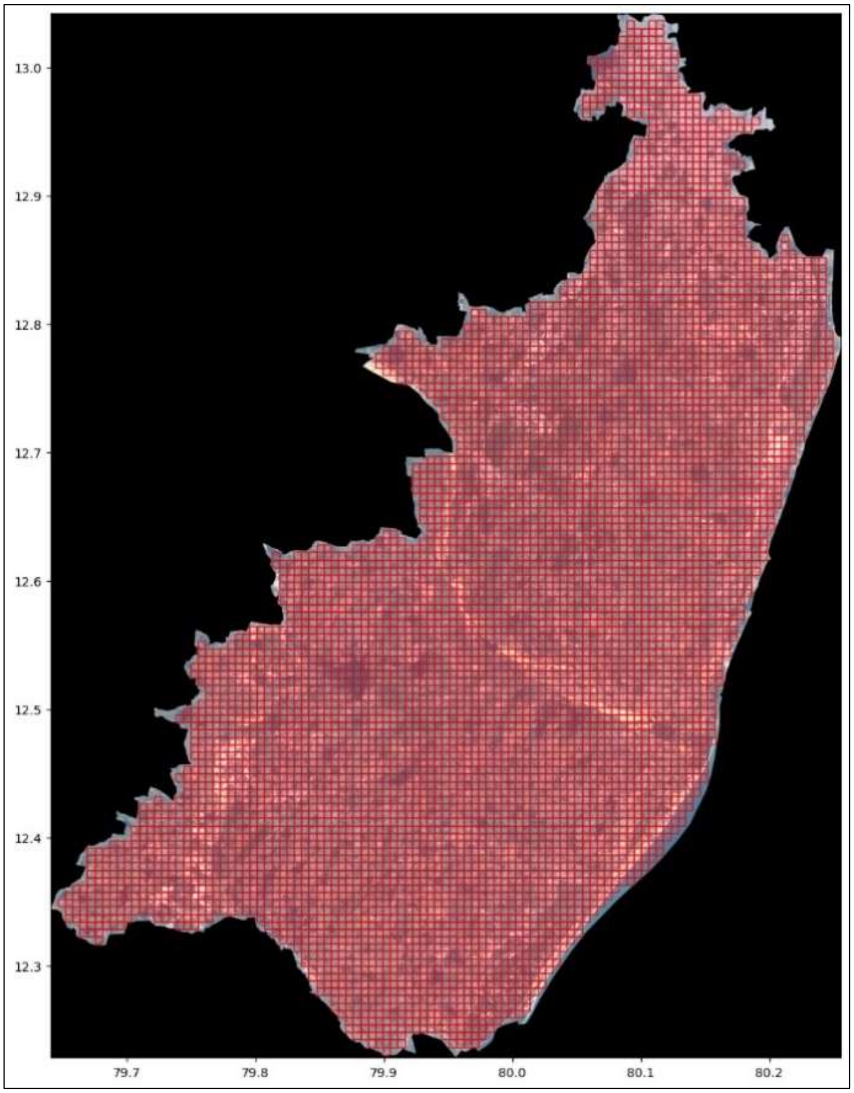

Figure 6.8. Chengalpattu Map with Grid Overlay.

Figure 6.8. presents the Chengalpattu Map with Grid Overlay. In this critical preprocessing step, the entire district image is divided into numerous small grid cells to facilitate detailed analysis. The coordinates of every grid intersection are computed and saved to be used later. Every grid cell constitutes a square image that is an input to our deep learning model. This grid-based method supports parallel processing and allows the classification to be done at a fine spatial resolution, retaining local variations in land cover types within the district.

6.4 CLASSIFICATION RESULTS AND COLOR MAPPING

The final classification outcomes are represented by a color-coded map presenting the various land cover classes in the Chengalpattu district visually. Table 6.2 gives the color mapping scheme employed to visualize the ten land cover classes in our research.

Table 6.2. Color Mapping for Land Cover Classes

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

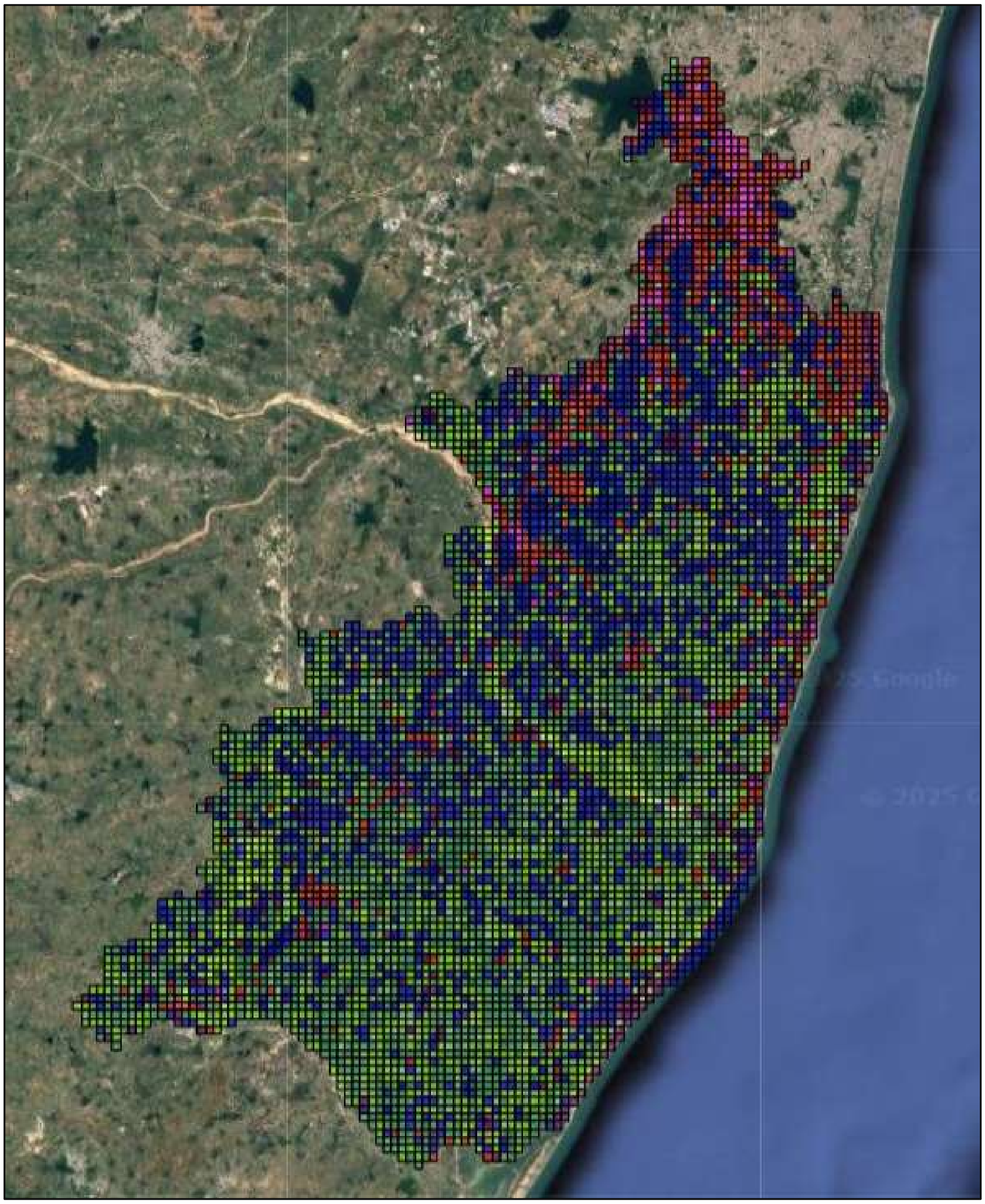

Figure 6.9. Predicted Classification of Chengalpattu.

The Predicted Classification of Chengalpattu is depicted by Figure 6.9. This final output map is a product of our entire classification process, where every pixel is mapped to one of the ten land cover categories by the model predictions. The visualization in color coding illustrates the spatial pattern of different land cover types in the district. The land class map indicates that Chengalpattu consists of a mosaic landscape where Agricultural lands (Annual Crop and Permanent Crop) are in the center and south, and there is dense forest cover in the western districts.

Residential and industrial regions are located in intensive clusters in the north and east districts. Road networks (Highways) consist of inter-connected lines through the landscape, connecting principal settlements. Water bodies like lakes and rivers are obviously revealed in purple and blue, defining the hydrological aspects of the district.

The map reveals a typical peri-urban environment with juxtaposed urban, agricultural, and natural environments. The transitional areas between diverse land cover are ecologically and in urban planning terms of specific interest, being here often indicative of zones of change and of probable environmental pressure. The delineation of such boundaries is informative with regard to planning for sustainable development and managing the environment of the district.

The good classification accuracy on both validation data and new images proves the strength of our deep learning method. The CNN model obtains the spectral and spatial features of various land covers well, making discrimination accurate even on complicated and heterogeneous landscapes. The real-time application with Google Earth Engine and Python geospatial libraries illustrates the feasibility of this method for real-time monitoring and analysis of land use and land cover changes in the Chengalpattu district.

CHAPTER 7

CONCLUSION

This work has demonstrated the feasibility of real-time Land Use and Land Cover (LULC) classification in the Chengalpattu district. The current work showed that advanced deep learning algorithms, based on high-resolution satellite imagery and processed using cloud-based platforms, can be successful for LULC classification. We used a fine-tuned ResNet-50 Convolutional Neural Network (CNN) trained on a very large, robust, and diverse dataset of over 27,000 pooled annotated satellite image tiles.

The model achieved satisfactory performance when model performance was evaluated, including training accuracy of 97.20% and validation accuracy of 90.85%. The high precision, recall, and F1-scores (>89%) suggested that model performance is strong and reliable for all land cover categories. The model was validated by ground surveys conducted in February 2025 and was shown to classify a wide variety of rural, urban, and mixed covers including agricultural fields, water bodies, forests, urban residential areas, and highways.

The system provides meaningful contributions to the disciplines of geospatial analysis and environmental monitoring, especially for the case of rapidly urbanizing areas. It fills the gap between conventional, time-consuming LULC mapping methods and contemporary needs for real-time, high-resolving, and scalable classification models. The successful linkage with Google Earth Engine (GEE) facilitated effective processing and visualization of data, making it available and potentially applicable to planners, policymakers, and researchers.

In spite of its virtue, the model revealed weakness over some highly complex urban and transitional areas where spectral overlap and space heterogeneity created classification problems. These results underscore the importance of ongoing refinement, particularly where anthropogenic land changes are most active. On the whole, this research provides a solid foundation for the use of deep learning in large-scale, real-time LULC monitoring and highlights its indispensable role in informing sustainable land use planning, disaster management, and policy decision-making.

RECOMMENDATIONS FOR FUTURE WORK

The contributions of this research, there are a few recommendations for improving future assessments. For example, classification of seasonal land classes should benefit from using multi-temporal satellite data that would provide more dynamic observation of land cover change. Higher resolution satellite data and object-based image analysis (OBIA) methods may improve accuracy of land use in urban and transitional contexts where land use is typically more complicated with spectrally ambiguous classes.

An additional area to focus on would be geographic transferability of the model. In addition to expanding the existing training data set to cover more representative areas, using transfer learning or domain adaptation methods could also help. Although it's unknown how well transformer models will function in geospatial contexts, anything that includes transformer-based models (e.g., Vision Transformers, or ViTs) certainly has potential for enhancing spatial pattern classification in a range of settings.

Finally, integrating social, economic, and climate information would create a more useful analysis platform of land use, aiding in the creation of sustainable planning. As a final note, developing interactive dashboards or tools that include methods for real-time surveillance and alerts would make results easier to understand and more likely to be applied by non-technical application contexts.

ETHICAL BINDINGS

The moral obligation of the project "Operational Real-time Land Use and Land Cover (LULC) Classification for Chengalpattu District Using Deep Learning and Satellite Remote Sensing" is our pledge to undertake research with utmost ethical standards in the field of environmental monitoring and land use management. The project, which involves the classification of land use patterns using advanced convolutional neural networks and satellite imagery, has been carried out with unwavering dedication to transparency, accountability, and responsible innovation.

Throughout this research, we have maintained strict respect for intellectual property rights, properly acknowledged all open-source tools, datasets, and prior research, and adhered rigorously to institutional and legal guidelines. The system created is meant only for environmental monitoring, sustainable urban planning, agricultural management, disaster response preparation, and policymaking based on information—not for any kind of unauthorized surveillance, land appropriation, or environmentally harmful activities.

This binding also emphasizes our adherence to ethical handling of data, providing privacy concerns in areas of high population density, mitigating potential bias in the training data, and ongoing evaluation of societal impacts. We recognize that what accompanies the release of technology that informs land management decisions and are dedicated to ensuring that our system of classification is guided by ethical principles, is ecologically sustainable, respects indigenous land rights, and is fair to resource distribution across the Chengalpattu district.

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Paper Title: Real-time Classification of Land use and cover using Deep Learning and Satellite Imagery

Abstract:
Land cover and land use (LULC) classification is important in understanding environ-mental 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 valida-tion accuracy of 90.85%, demonstrating its strength in identifying multiple types of lands.

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