Change Detection and Prediction Model for Land Use and Land Cover Using LTCNN

A report submitted in partial fulfillment of the requirements for the award of the degree of

Bachelor of Technology

in

Department of Computer Science and Engineering

by

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BONAFIDE CERTIFICATE

This is to certify that the project work phase II entitled **"Change Detection and Prediction Model for Land Use and Land Cover Using LTCNN"** is a bonafide record of the work done by

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in partial fulfillment of the requirements for the award of the degree of **Bachelor of Technology** in **Computer Science and Engineering** of the **NATIONAL INSTITUTE OF TECHNOLOGY PUDUCHERRY** during the year 2023 - 2024.

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ABSTRACT

The Earth undergoes continuous transformation due to natural processes and human interventions, necessitating vigilant monitoring to mitigate environmental threats. This project focuses on conducting a thorough change detection (CD) analysis of the Dakshina Kannada region, located along the coast of Karnataka, India.

Spatial and temporal variations in land use and land cover (LULC) are meticulously tracked utilizing LULC maps sourced from the National Remote Sensing Agency, Indian Space Research Organization (ISRO). Leveraging data from the Advanced Wide-Field Sensor (AWiFS) aboard the Resourcesat2 satellite, LULC maps (1:250k) spanning from 2005 to 2018 are scrutinized using a deep learning approach featuring a Liquid Time-Constant Neural Network (LTCNN) with dual encoder-decoder architecture. The model demonstrates an impressive overall accuracy of 90.07%.

In addition to change detection, this study extends its scope to encompass change prediction and change analysis. Change prediction involves forecasting LULC dynamics, resulting in a predicted LULC image for 2030. Meanwhile, change analysis involves a detailed examination of alterations occurring between 2005 and 2030.

Over the 13-year period under examination, discernible variations in LULC patterns emerge, including shifts in urban development, agricultural practices, vegetation dynamics, forest cover, barren land, littoral swamp, water bodies, and current fallow areas. The detection of these changes underscores concerns regarding the region's environmental resilience, particularly its vulnerability to coastal flooding due to escalating urbanization.

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CHAPTER 1

INTRODUCTION

1.1 INTRODUCTION

The Earth's natural resources support intricate ecosystems that have evolved over millennia. While natural ecosystems operate according to their inherent dynamics, human-managed agricultural landscapes are meticulously crafted and controlled, influenced by environmental and biological factors. As the global demand for land intensifies, the need for policies promoting sustainable land management becomes increasingly paramount.

Monitoring Earth's transformations, particularly in land use and land cover (LULC), is crucial for fostering sustainable development. Remote sensing techniques, including satellite imagery analysis, are indispensable tools for detecting these changes.

This study presents a holistic approach to LULC analysis, leveraging the Liquid Time-Constant Neural Network (LTCNN) for change detection, while employing CA-Markov for change prediction and change analysis. LTCNN provides a robust framework for identifying and analyzing changes in land use over time, addressing issues such as pseudo changes and class imbalance.

Using a dataset focused on the Dakshina Kannada region, we evaluate the efficacy of these methods. In addition to LTCNN-based change detection, we extend our analysis to include change prediction using CA-Markov to forecast LULC dynamics for 2030. Furthermore, we conduct detailed change analysis with CA-Markov, examining alterations occurring between 2005 and 2006.

With an overall accuracy of 90.07%, this study underscores the importance of monitoring land use changes and introduces LTCNN and CA-Markov as powerful tools for these tasks. These findings highlight their contributions to improving accuracy in LULC analysis, emphasizing the importance of sustainable land management policies amidst global environmental challenges.

1.2 DEFINITIONS

Remote sensing: Remote sensing is the acquisition of information about an object or phenomenon without direct physical contact. This is typically done using sensors that capture data from a distance, often mounted on satellites, aircraft, or other platforms. Remote sensing is widely used in various fields, including geography, environmental science, agriculture, forestry, and urban planning, to gather data about the Earth's surface, atmosphere, or oceans. The collected information helps in monitoring, analyzing, and making informed decisions about the studied areas.

Land use land cover images (LULC) images: Land use and land cover (LULC) images depict the spatial distribution of different types of land use and the physical coverage of the Earth's surface. Land use refers to human activities on the land, such as residential, agricultural, industrial, or commercial purposes. Land cover, on the other hand, describes the physical characteristics of the land, including natural features like forests, water bodies, or barren areas.

LULC images are commonly used in geographic information systems (GIS) and remote sensing to analyze and monitor changes in land patterns over time. These images play a crucial role in urban planning, environmental management, agriculture, and other fields by providing insights into how land is utilized and how it evolves**.**

Liquid time constant neural networks: Liquid Time Constant (LTC) Neural Networks are an innovative approach to neural network architecture that introduces variability in the time constants of neurons within the network. This dynamic adjustment of time constants allows the network to respond to input data with more flexibility and adaptiveness, enhancing its ability to capture temporal dependencies in complex datasets. LTC Neural Networks build upon the strengths of recurrent neural networks (RNNs) while addressing their limitations in handling long-range dependencies and sensitivity to sequence length. By allowing neurons to have individual and adaptable time constants, LTC Neural Networks can model data more effectively in applications such as time series analysis, speech recognition, and natural language processing. This novel design results in improved performance and generalization across various tasks, offering a significant advancement in the field of neural networks.

Change detection: Change detection is the process of identifying and analyzing changes in a specific area over time, often using satellite images or maps to compare and quantify alterations in land cover, land use, or other features.

Change prediction: Change prediction is a crucial task in various domains that involve analyzing data over time, such as finance, healthcare, and environmental science. This process involves identifying potential shifts in trends or patterns that may impact future outcomes. The ability to accurately predict changes can lead to timely decision-making and risk management, as well as the optimization of resources. Techniques for change prediction often involve monitoring and analyzing data for trends, anomalies, and other indicators of impending changes. As data-driven approaches evolve, advanced machine learning methods such as neural networks and time series analysis are increasingly being used to improve the precision and reliability of change prediction.

Neural Circuit Policies: Neural Circuit Policies (NCPs) are recurrent neural network models inspired by the nervous system of the nematode Caenorhabditis elegans. NCPs leverage neurons modeled using ordinary differential equations, allowing them to exhibit complex temporal dynamics and adapt their response based on input. These models feature sparse, structured wiring that mirrors the efficiency of the biological system, enhancing their performance in control and decision-making tasks. The package provides two neuron models: Liquid Time-Constant (LTC) and Closed-form Continuous-time (CfC). LTCs are known for their adaptive timing and causal dynamical modeling but require numerical solvers that can slow down training. In contrast, CfC models approximate the closed-form solution of differential equations to enhance speed. Both models excel in handling sequential and time-series data. NCPs offer the flexibility of a fully connected network or can use sparse structured wirings, such as the AutoNCP class, which creates a 4-layer recurrent architecture mimicking the sensory, inter, command, and motor neurons of C. elegans. This unique structure combines efficiency and biological inspiration to deliver robust and interpretable neural network models.

1.3 OBJECTIVE

This project aims to build a powerful tool for land use analysis. It uses cutting-edge deep learning techniques like LTCNN to accurately identify and understand how land use patterns change over time. This approach not only improves change detection efficiency but also reveals hidden patterns in the data. This comprehensive approach is crucial for environmental monitoring, urban planning, and managing natural resources.

Beyond just detecting changes, the project goes further by predicting future land use trends with CA-Markov and analyzing historical changes. This holistic view provides a deeper understanding of land use dynamics in the studied area. These additional features make the tool more valuable, allowing it to not only identify current changes but also anticipate future trends and analyze past patterns.

Ultimately, the goal is to create a robust deep learning tool that combines LTCNN, CA-Markov, and other advanced techniques. This tool will be a valuable resource for decision-makers, scientists, and planners, enabling them to make informed choices regarding land use changes, promoting sustainable development and efficient resource utilization.

1.4 MOTIVATION

- Early warning system aided by detection of vulnerable land cover changes.
- Improve agriculture practices by identifying changes in farmable land.
- LTCNNs integrate temporal data efficiently for comprehensive analysis
- LTCNNs excel in detecting subtle temporal changes in LULC patterns, enhancing the identification of gradual shifts over time.

1.5 APPLICATIONS

- Environmental Management
- Agricultural Monitoring.
- Monitoring Urbanization
- Infrastructure Development

1.6 PURPOSE

The purpose of the project is to develop a deep learning model for change detection analysis using LULC images. Leveraging deep learning techniques, the project aims to create an advanced system capable of accurately identifying and analyzing changes in land use and land cover over time. Recognizing alterations in the Earth's surface is essential for environmental monitoring, urban planning, and sustainable resource management. By harnessing the power of deep learning algorithms, the project seeks to build a robust model that efficiently detects and characterizes changes in LULC patterns from satellite imagery.

The project encompasses various key stages, starting with data collection, preprocessing, and feature extraction. Subsequently, the system will undergo training to recognize patterns and variations in land cover across multiple time points. Evaluations of the model's performance will rely on metrics such as accuracy, ensuring a comprehensive assessment of its effectiveness.

Successful implementation of this project aims to provide a valuable tool for environmental scientists, urban planners, and decision-makers. Accurate detection of changes in land use holds significant potential for informed decision-making processes, including sustainable urban development, natural resource conservation, and disaster management. Ultimately, the project endeavors to enhance our understanding of dynamic landscape changes, thereby promoting effective strategies for land use planning and environmental stewardship.

CHAPTER 2

SYSTEM REQUIREMENT SPECIFICATIONS

2.1 Hardware requirement

For training:

Processor: Intel Core I7 2.2 GHz and above

RAM: 16GB and above

Secondary memory: 500MB and above

2.2 Software requirement

- Python3 : Python is an interpreted, high-level and general purpose programming language. It is well known for its code readability. Python is widely used for machine learning and deep learning purposes. Python provides many libraries which can be used for doing different scientific operations.

- Pip: Pip is a package installer for python. Any package in python can easily be installed using pip with just one command.

- Numpy: Numpy is a fundamental package for scientific computing in python. Numpy reduces the use of loops for regularly used scientific operations like matrix addition, multiplication etc. It has various built-in functions to manipulate the data present as an n-dimensional array.

- Tensorflow 2.0 : Tensorflow is an open source library for numerical computation and large scale machine learning. It contains a bundle of machine learning algorithms and models which can be easily used to create deep learning models.

- Keras: Keras is a library that provides a python interface for the artificial neural networks. Keras acts as an interface for the tensorflow library. Tensorflow can act as a backend and keras as an interface can define, train, run the neural network model easily. In this project keras is used for defining, compiling, fitting the model.

- Scikit-learn: It is the most used library to perform machine learning tasks. It contains many tools for machine learning and statistical tasks like regression, clustering etc. In this project the scalers in scikit learn are used to scale the data.

- Operating System: It is installed while installing python itself. It provides many functionalities to do os related operations. In this project, this library is used to gather data from the directories.

- Rasterio: Rasterio is a pivotal library for geospatial raster data, streamlines the handling of datasets in remote sensing and GIS applications. This library's capabilities extend to reading and writing raster files, offering efficiency in tasks such as extracting insights from satellite imagery. In this project, Rasterio could play a key role in seamlessly integrating geospatial data into the machine learning workflow.

- Matplotlib: Matplotlib is a versatile Python library, is widely employed for generating diverse visualizations, including static, interactive, and animated plots. Its extensive toolkit makes it indispensable for data exploration and representation. In this project, Matplotlib's utility lies in visualizing scaled data, enhancing comprehension of the effects of scaling on machine learning models. Whether illustrating feature distributions or showcasing clustering results, Matplotlib's flexibility proves valuable for creating informative visualizations in both geospatial and machine learning analyses.

CHAPTER 3

LITERATURE SURVEY

3.1 Requirement for Research

The use of Liquid Time-Constant Neural Networks (LTCNN) for change detection in Land Use/Land Cover (LULC) images offers a promising approach to addressing key objectives in environmental monitoring and sustainable development. The ability of LTCNN to model complex time-dependent changes in LULC images can enhance the production of accurate change maps, enabling precise identification of alterations in land use and cover over time. Additionally, LTCNN's predictive capabilities can forecast future changes, providing valuable insights into potential environmental shifts.

The approach also supports in-depth change analysis, allowing researchers to assess the underlying patterns and causes of observed changes. By leveraging the adaptability and expressivity of LTCNN, this method can identify trends and dynamics within the data that may otherwise go unnoticed. As part of the requirement gathering for change detection in LULC images, this survey focuses on the application of LTCNN for producing change maps, change prediction, and change analysis, while offering insights into the potential of this neural architecture to enhance the accuracy and efficiency of LULC change detection. Through exploring the methodologies, datasets, and performance metrics employed in these studies, the survey aims to provide a comprehensive overview of the current state of LTCNN applications in LULC change detection and offer recommendations for future research directions.

3.2 Previous Research:

A recent study by Ramin Hasani, Mathias Lechner, Alexander Amini, Daniela Rus, and Radu Grosu (2021), titled "Liquid Time-Constant Networks,"[1] introduces a new class of time-continuous recurrent neural networks (RNNs). These networks are distinct from traditional models because they construct networks of linear first-order dynamical systems modulated by nonlinear interlinked gates, rather than relying on implicit nonlinearities. The resulting model features varying time constants coupled to hidden states and computes outputs using numerical differential equation solvers. These Liquid Time-Constant Networks (LTCs) demonstrate stable and bounded behavior, providing superior expressivity within the family of neural ordinary differential equations and leading to enhanced performance on time-series prediction tasks. Through theoretical analysis, the authors establish bounds over the networks' dynamics and compute their expressive power using the trajectory length measure in a latent trajectory space. They also conduct a series of experiments to manifest the approximation capability of LTCs compared to other classical and modern RNNs.

A recent study by Naik, N., Chandrasekaran, K., Sundaram, V.M. et al. (2023) Dual attention guided deep encoder-decoder network for change analysis in land use/land cover for Dakshina Kannada District, Karnataka, India[9]. The model provides an overall accuracy of 94.11% and the LULC maps from 2005 to 2018 (13 years) are utilized to decide the variations in the LULC, including urban development, agricultural variations, vegetation dynamics, forest areas, barren land, littoral swamp, and water bodies, current fallow, etc.

A recent study by Makram Chahine, Ramin Hasani, Patrick Kao, Aaron Ray, Ryan Shubert, Mathias Lechner, Alexander Amini, and Daniela Rus (2023), titled "Robust Flight Navigation Out of Distribution with Liquid Neural Networks,"[2] presents a method for creating robust flight navigation agents that can perform vision-based fly-to-target tasks beyond their training environment, even under drastic distribution shifts. This study focuses on the challenge of enabling agents to generalize to new environments with drastic scenery changes that they have never encountered before. The authors designed an imitation learning framework using liquid neural networks, a brain-inspired class of continuous-time neural models that are causal and adapt to changing conditions. The liquid agents effectively distill tasks from visual inputs and ignore irrelevant features, allowing them to transfer their learned navigation skills to new environments. In experiments comparing several other state-of-the-art deep agents, the study demonstrated that liquid networks exhibit exclusive robustness in decision-making, both in their differential equation and closed-form representations.

A recent study by Ramin Hasani, Mathias Lechner, Alexander Amini, Lucas Liebenwein, Aaron Ray, Max Tschaikowski, Gerald Teschl, and Daniela Rus (2022), titled "Closed-form Continuous-time Neural Networks,"[3] introduces a novel approach to address the performance limitations of continuous-time neural processes built by differential equations (DE). The authors present a tightly-bounded closed-form approximation of an integral appearing in the dynamics of liquid time-constant networks (LTCs), a challenge that previously had no known closed-form solution. This approximation allows for efficient modeling of the interaction between neurons and synapses in artificial neural networks. This advancement leads to models that train and perform inference much faster, between one and five orders of magnitude faster compared to differential equation-based counterparts. These closed-form networks offer remarkable scalability and performance in time series modeling, representing a significant breakthrough in understanding and scaling neural models.

3.3 Challenges and Limitations:

The introduction of new classes of recurrent neural networks and other advanced neural models presents several challenges and limitations. In the context of change detection in Land Use/Land Cover (LULC) images, the quality and availability of satellite imagery can significantly affect performance. Inconsistent data resolution and cloud cover can hinder the accuracy of detection, and obtaining frequent and consistent imagery is essential for capturing short-term changes, though longer intervals may reduce precision.

In the case of neural networks, the complex nature of the models can make them sensitive to image preprocessing, including normalization and correction. This sensitivity adds complexity to deploying the models effectively in real-world scenarios. Additionally, the computational demands of training and analyzing these models, especially on large-scale datasets, require substantial resources and can hinder scalability.

For the study of visual navigation tasks using liquid neural networks, achieving consistent performance across drastically different environments can be difficult due to the varied environmental features and potential semantic gaps between learned representations and real-world conditions. These models' reliance on sophisticated numerical solvers may limit their practicality in real-time applications.

Moreover, efficiently modeling the interaction between neurons and synapses using closed-form approximations introduces challenges in terms of managing sensitivity to preprocessing and handling large-scale data. These challenges underscore the need for careful tuning and nuanced algorithm design to achieve consistent performance across different data types and contexts.

3.4 Future Directions:

In the future, the integration of advanced neural network models such as liquid time-constant neural networks (LTCNNs) may lead to significant advancements in sequential decision-making tasks and vision-based navigation. LTCNNs offer unique features such as varying time constants coupled to hidden states, computed via numerical differential equation solvers. This leads to stable and bounded behavior, superior expressivity, and enhanced performance in time-series prediction tasks. Further integration of these models with multi-sensor data sources, including optical, radar, and hyperspectral imagery, could enhance autonomous systems across various domains such as robotics and environmental monitoring. This combination of data types may provide a more comprehensive understanding of environmental changes and improve the adaptability of autonomous systems to diverse and dynamic environments. Future research directions may focus on refining LTCNNs and other neural network models to handle complex real-world data more effectively, potentially through exploring novel architectures such as advanced recurrent neural networks and attention mechanisms. This can help improve adaptability, generalization, and efficiency across different contexts and applications. Regarding Land Use/Land Cover (LULC) images, the integration of multi-sensor data and advanced neural network models will enhance the ability to detect and monitor environmental changes more accurately and efficiently. Utilizing optical, radar, and hyperspectral sources will lead to a more comprehensive understanding of landscape changes, while leveraging LTCNNs can improve the interpretation and generalization of data across different contexts. Automation and real-time change detection will play a pivotal role in enabling continuous monitoring for applications such as disaster response, urban planning, and environmental conservation. Developing temporal fusion models that integrate data from various sources and resolutions can further enhance long-term monitoring capabilities. Additionally, addressing ethical considerations such as privacy and responsible use of remote sensing data for change detection will be essential. Collaborative research efforts, creation of benchmark datasets, and initiatives to encourage crowdsourcing and citizen science participation will contribute to the advancement and standardization of change detection methodologies. Combining insights from multiple disciplines and fostering open access to data and methodologies will drive progress towards more robust, scalable, and interpretable solutions for various applications related to LULC and beyond.

CHAPTER 4

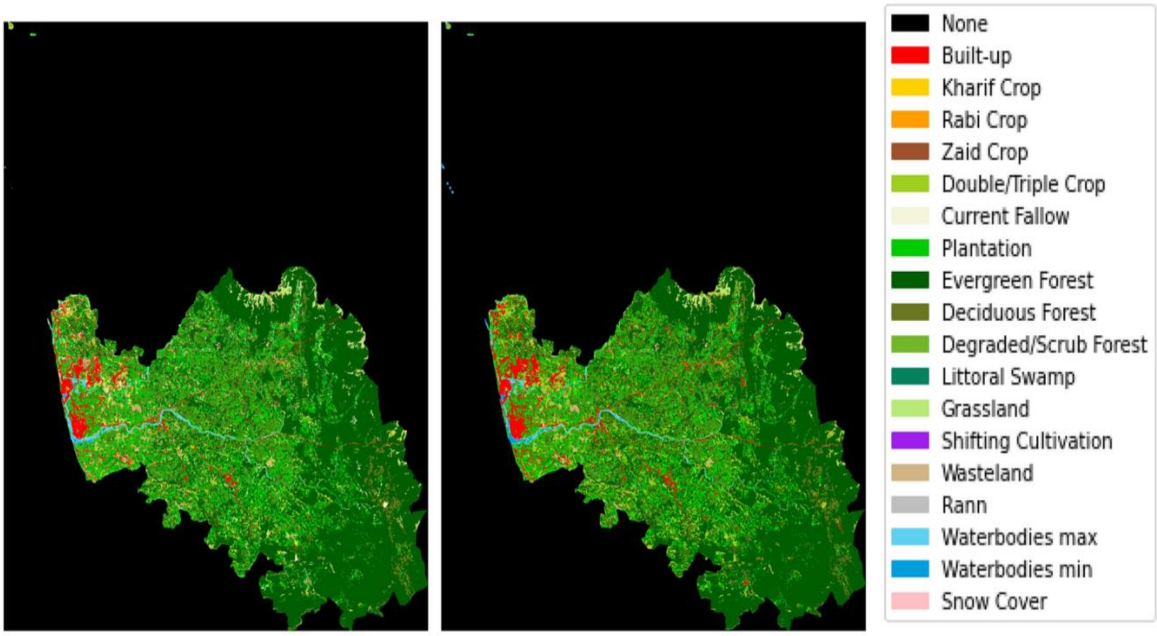
IMPLEMENTATION & RESULTS

4.1 DATA COLLECTION

4.1.1 Dataset for NeuroMapNet Model

The National Remote Sensing Centre, Hyderabad, part of the Indian Space Research Organization (ISRO) provided pre-classified LULC data for the study. This web-based utility, known as Bhuvan, allows users to explore a set of map-based content and obtain spatial data. Bhuvan generates maps for Land Resource analysis at the end of each year using multi-temporal Indian Remote Sensing Satellite(IRS) Resourcesat-1/2 (P6) AWiFS for time series data.

The image details of the study area is 1975 × 2372 pixels. The LULC map for the Dakshina Kannada region for the year 2005–2006 and 2017–2018 is used as input to the model. There are 18 class labels in the received dataset. Only 15 were identified during the analysis as per the received dataset. Shifting cultivation, Rain, and Snow cover are not present for the Dakshina Kannada region.



(a) LULC Map of 2005-06 (b) LULC Map of 2017-18 (c) LULC classes

Figure 4.1 LULC data and description of each LULC Class

4.2 ARCHITECTURE

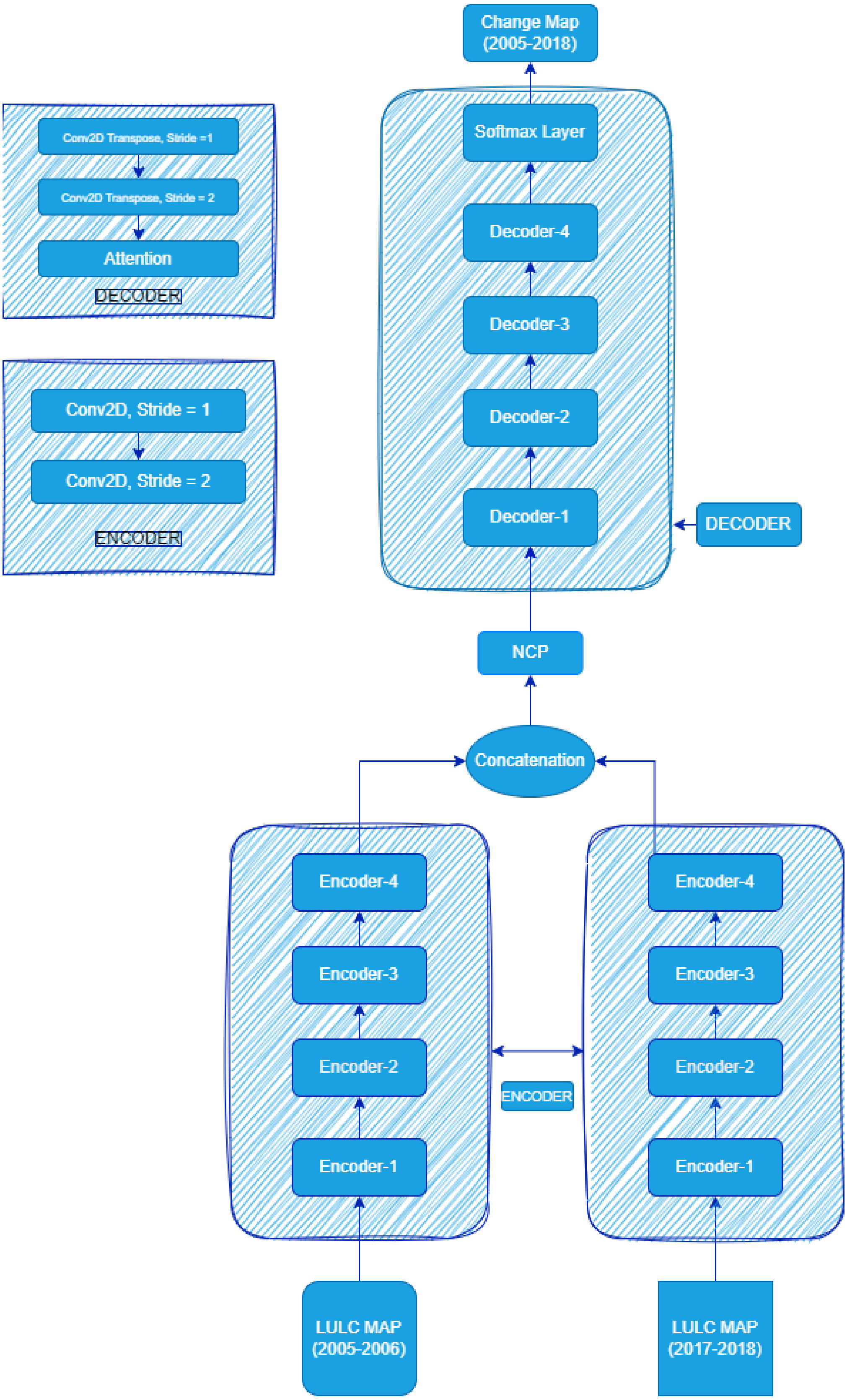


Figure 4.2 NeuroMapNet Architecture

4.2.1 NeuroMapNet

NeuroMapNet," is an encoder-decoder architecture designed for enhanced change detection in land use/land cover (LULC) images. It incorporates Neural Circuit Policies (NCPs) between the encoder and decoder modules, adding advanced neural circuitry to the model for improved performance. NeuroMapNet takes two time series LULC images as input at the encoder, processing them to learn discriminative, multiscale features critical for the task of change detection.

Unlike traditional encoder-decoder architectures, NeuroMapNet does not use skip connections; instead, it leverages NCPs to integrate adaptive temporal dynamics and handle spatial, channel, and temporal dimensions more effectively. This unique approach allows the network to model complex relationships within the input data, leading to more accurate and nuanced predictions.

At the decoder, the network produces a change map based on the input images, identifying areas of transformation or differences between the two time series LULC images. NeuroMapNet uses strided convolutions for efficient downsampling and applies sparse categorical cross-entropy loss for model optimization, ensuring accurate and robust performance in generating precise change maps. This innovative approach to LULC change detection showcases the power of integrating biologically inspired neural networks for low-level vision tasks and image analysis.

4.2.2 LTCNN

Leaky-Integrator Neural Model:

The leaky-integrator neural model captures the dynamics of a neuron's membrane potential. It is modeled by the equation:

$dx(t)/dt = -x(t)/\tau + S(t)$

Where:

$x(t)$ is the neuron's state (e.g., membrane potential) at time

τ is the time constant of the neuron.

$S(t)$ is the synaptic input at time

Conductance-Based Synapse Model:

The conductance-based synapse model describes the behavior of synaptic input based on the neuron's state and other factors. It is modeled by the equation:

$S(t) = f(x(t), I(t), t, \theta)(A - x(t))$

Where:

$f(x(t), I(t), t, \theta)$ is a function that describes the synaptic input dynamics based on the neuron's state, current input, time, and additional parameters θ.

A is a constant representing the reversal potential of the synapse.

Liquid Time Constant Neural Network:

The Liquid Time Constant Neural Network (LTCNN) combines these two models to create a more dynamic and flexible network. The LTCNN is modeled by the equation:

$dx(t)/dt = - [1/\tau + f(x(t), I(t), t, \theta)]x(t) + [f(x(t), I(t), t, \theta]A$

This equation captures the neuron's state changes, incorporating both the leaky-integrator model and conductance-based synapse model. The combined model provides adaptive behavior in response to different inputs, allowing the network to handle complex temporal patterns in data.

The LTCNN enhances the project's capabilities by providing a biologically inspired, temporally aware neural network architecture. This network can adapt its response based on the input data, leading to more accurate and robust performance in change detection and analysis tasks within LULC images.

4.3 RESULTS

4.3.1 Overall Accuracy:

The NeuroMapNet Model utilizes LULC maps to compute Overall Accuracy (OA), crucial for assessing its performance in land use and cover classification.

$$\mathrm{OA} = \frac{\mathrm{TP} + \mathrm{TN}}{\mathrm{TP} + \mathrm{TN} + \mathrm{FP} + \mathrm{FN}}.$$

The Overall Accuracy of the model is 90.07%

4.3.2 Change Map

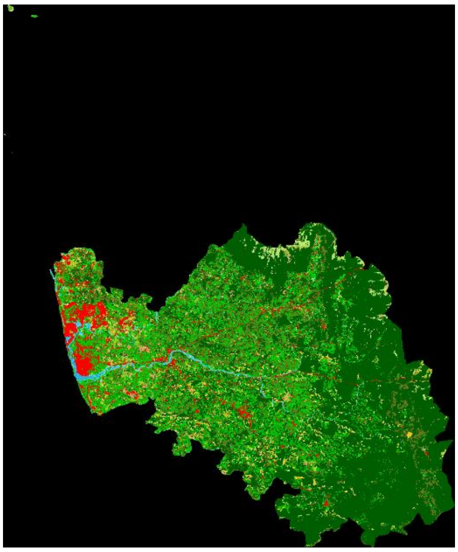
Figure 4.3 Change Map

The image illustrates the alterations in land use and land cover (LULC) patterns from 2005 to 2018, offering insights into the dynamics of landscape transformation over the specified time span.

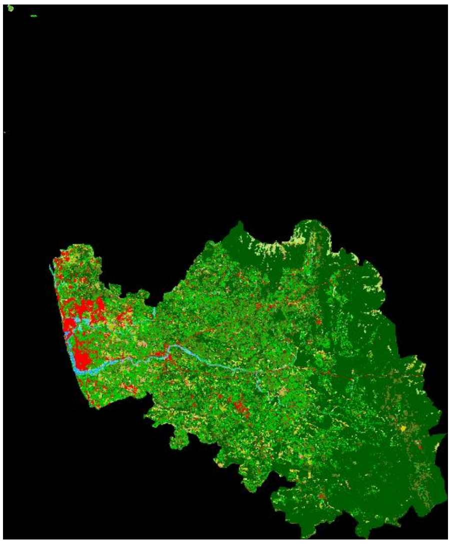
4.3.3 Change Prediction

cellular automata (CA) Markov model is used for the prediction of land use/land cover (LULC) images for the year 2030. The CA Markov model combines the strengths of cellular automata and Markov chain models to simulate and predict future changes in LULC based on historical data and observed transition probabilities. In this approach, the current state of each land use category in the image is represented as a cell in a grid, and its future state is determined by a set of rules that account for the states of neighboring cells. Additionally, the Markov model aspect captures the transition probabilities between different land use classes over time.

This combination allows for modeling both local spatial interactions and temporal dynamics, providing a more comprehensive and realistic representation of how land use and cover may evolve in the future. By training the model with historical LULC data and observed transitions, you can generate predictions for the year 2030 that take into account both the spatial patterns and temporal trends of LULC changes. This approach helps to inform urban planning, environmental management, and policy decisions by offering insights into potential future scenarios for land use and cover.



YEAR 2005



YEAR 2030

Figure 4.4 Original LULC image of 2005 and Predicted LULC image of 2030

Comparison of Land Use and Land Cover: On the left, an image captured in 2005 provides a snapshot of the landscape at that time. On the right, a predicted image for 2030 illustrates anticipated changes in land use and land cover over the intervening years. This visual comparison offers insights into the evolving dynamics of our environment and informs future planning and conservation efforts

4.3.4 Change Analysis

Category	Values in 2005-2006	Values in 2030	Change (%)
Class 0	3211890	3211890	0.00
Built-up	66335	69817	5.25
Kharif Crop	27819	22586	-18.81
Rabi Crop	15064	11505	-23.62
Zaid Crop	2425	1893	-21.92
Double/Triple Crop	23046	28362	23.07
Current Fallow	19835	22790	14.90
Plantation	300071	298450	-0.54
Evergreen Forest	788783	787757	-0.13
Deciduous Forest	179393	181222	1.02
Degraded/Scrub Forest	1510	1580	4.64
Littoral Swamp	15	14	-6.67
Grassland	9835	9854	0.20
Shifting Cultivation	0	0	0.00
Wasteland	18520	16182	-12.62
Rann	0	0	0.00
Waterbodies max	15068	16969	12.62
Waterbodies min	5088	4185	-17.73
Snow Cover	0	0	0.00

Figure 4.5 Change Percentage from 2005-2006 to 2030

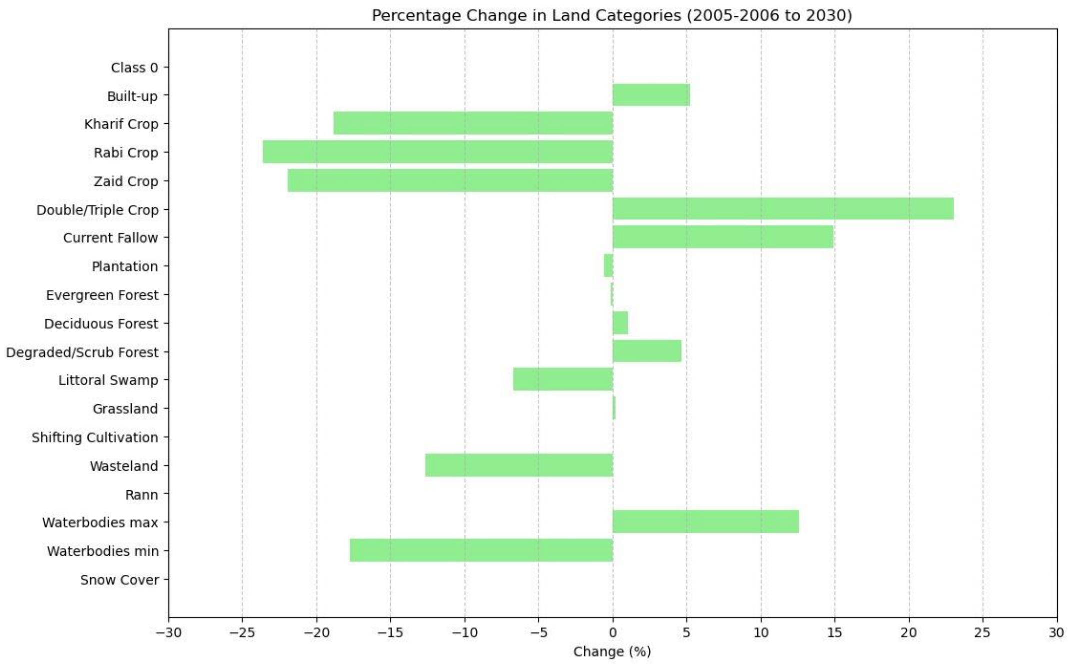


Figure 4.6 Representation of Change Percentage of categories from 2005-2006 to 2030

Category: This column lists the different LULC categories under consideration, ranging from "Class 0" to "Snow Cover," including categories such as Built-up, Crop types (Kharif, Rabi, Zaid), Forest types (Evergreen, Deciduous, Degraded/Scrub), Waterbodies, and others.

Values in 2005-2006: The corresponding values represent the land area (in Sq.Km) occupied by each LULC category during the time period of 2005-2006.

Values in 2030: These values depict the projected land area(in Sq.Km) for each LULC category in the year 2030, providing insights into the anticipated changes in land use over time.

Change (%): This column presents the percentage change in land area for each LULC category between the years 2005-2006 and 2030. Positive values indicate an increase in land area, while negative values signify a decrease. This metric offers a quantitative measure of the changes occurring within each LULC category over the specified time period.

Overall, this data provides valuable insights into the dynamic nature of land use and land cover, offering information on both historical trends and projected changes, which can inform decision-making processes related to environmental management, urban planning, and resource allocation.

CHAPTER 5

CONCLUSION

5.1 Change Detection and prediction model in LULC Images using LTCNN

In conclusion, this project demonstrates the strength of combining advanced computer vision and machine learning techniques for change detection and prediction in land use/land cover (LULC) images. The successful implementation of the LTCNN architecture within an encoder-decoder framework allows for accurate detection and analysis of changes in LULC over time, providing valuable insights into temporal variations and supporting applications such as environmental monitoring and land management.

Meanwhile, the use of the cellular automata (CA) Markov model for predicting future LULC images for the year 2030 offers nuanced projections by blending spatial modeling with probabilistic transitions. This approach provides a realistic forecast of potential shifts in land use, aiding strategic planning and sustainable practices.

Together, these methodologies showcase the potential of harnessing cutting-edge technologies for geospatial analysis, contributing to proactive measures in response to evolving land use patterns and addressing critical challenges in environmental management. The project's innovative approach paves the way for ongoing excellence in the field of remote sensing and geospatial studies.

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