Multispectral Land Cover Analysis and Change Detection for Assessing Environmental Dynamics

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***Abstract*—The paper proposes a Long Short-Term Memory (LSTM) model to forecast variations in land use and land cover (LULC) using ESA Sentinel-2 imagery. Accurate LULC change prediction is vital for understanding environmental, demographic, and sociological dynamics that affect the planet's landmass. Population impact on LULC underscores the importance of effectively predicting future changes to aid in planning and policymaking. The methodology uses rasterisation techniques and one hot encoded representation in the data manipulation process. The model developed is a three layer LSTM model to predict land cover changes. The results showcase an LSTM model achieving a remarkable average classification accuracy of 96.08% for predicting land use and land cover classes, demonstrating its efficacy and reliability. The research concludes that the proposed model holds promise for real-world applications, suggesting opportunities for future research to further enhance its performance and applicability in addressing land use dynamics and environmental monitoring challenges.**

***Index Terms*—LULC, LSTM, rasterization, Sentinel-2**

I. Introduction

Land Use and Land Cover (LULC) refers to a systematic categorization that describes the way the Earth's surface is utilized. It comprises recognizing and categorizing diverse land covers (such as forests, aquatic bodies, and barren ground) and land uses (such as residential, agricultural, and industrial) within a given geographic area.

LULC analysis is a key aspect of sectors such as resource management, urban planning, environmental research, since it provides insightful knowledge about patterns of land use in addition to the physical features of land surface.

Land use variations represent the culmination of biodiversity indicators such as interactions between biological processes, biogeochemical cycles, and climate. Therefore, LULC research has grown increasingly relevant for understanding and monitoring environmental change and related processes.

For a country like India, where the expanding population imposes enormous pressure on land resources, LULC analysis bears significance. The demographic expansion translates into an increasing need for land for uses such as urbanization, agriculture, and infrastructure development, which generates a competitive climate for land allocation. This distribution of land resources in turn places great strain on natural resources, and results in the destruction of ecosystems of agriculturally productive land. The progressive deterioration of different land uses emphasizes the necessity for accurate understanding of land use activities and their outcomes. LULC analysis is essential because it offers methods to classify and measure land covers.

Artificial Intelligence (AI) and Machine Learning (ML) are utilized to automate the process of land cover classification. The technology provides up-to-date information on many land categories, including forests, agricultural areas, water bodies, and urban districts. AI and ML tools analyze past data to study changes in land cover over a period of time. They use temporal analysis and predictive modeling to forecast future land cover.

This paper proposes an advanced Long Short-Term Memory (LSTM) model having the capability to accurately predict changes in land cover over short time periods. The dataset in use involves image data derived from ESA Sentinel-2 imagery.

The proposed LSTM model predicts the land cover class for the next time step in the form of a one-hot encoded vector of softmax probability for following input values: vertical index, horizontal index and the target label class vector for the first 5 timesteps (a, u, r, d, e).

The structure of this paper is as follows: A overview of previous studies on the subject of land use and land cover analysis using certain approaches is presented in Section II. The suggested model is thoroughly discussed in Section III along with the required graphs. In Section IV, the experimental process of the suggested model is then provided and addressed. Section V contains the research conclusions.

II. Literature Review

The field of ML-assisted land cover analysis has garnered significant attention in recent years, prompting this comprehensive review of existing literature to discern the prevailing trends and gaps in understanding.

Based on Landsat satellite imagery from 2007, 2014, and 2017, Anand et al. [1] used TerrSet's land change modeller (LCM) to monitor and forecast changes in land use/land cover (LULC) in the Manipur River basin, northeastern India. The study projected increases in water bodies, agriculture, and built-up areas, along with decreases in wetlands, herbaceous wetlands, and forests by 2030 using the Markov chain method and artificial neural network (ANN) analysis.

In Abha-Khamis, Saudi Arabia, research by Bindajam et al. [2] studied the connections between LULC and how their relation to the ecosystem services value (ESV) between 1990 and 2028. They employed a Markovian transitional probability matrix, delta change analysis, and support vector machine (SVM) classification. The analysis found that while built-up areas remained stable (83.6% transition probability), there was a notable increase in urban expansion (334.4% between 1990 and 2018). To predict future LULC changes, an artificial neural network (ANN) model was employed.

A Markov chain–cellular automata approach was also used by Corner et al. [3] to simulate and forecast changes in Dhaka's land use. Using Markov chain approach, they first created transition probability matrices across land-cover categories and created LULC maps from satellite photos for three time periods. After calibration, LULC forecasts for 2022 and 2033 were made possible by the inclusion of cellular automata, which took into account neighborhood relationships.

Another study by Floreano et al. [4] evaluated LULC trends in Rondônia, Brazil, throughout the previous decade (2009–2019) and forecasted changes for the following ten using a Markov-CA deep learning method for future LULC predictions and machine learning algorithms on the Google Earth Engine platform for image classification. The findings showed a 15.7% decline in forested areas between 2009 and 2019, and by 2030, projections point to additional deforestation and conversion to occupied areas.

Hakim et al. [5] employed the Modules for Land Use Change Simulations (MOLUSCE) method with a Multi-Layer Perceptron Neural Network and Geographic Information System to classify LULC changes in Tamalanrea Sub-District, Makassar, Indonesia. The Landsat satellite imagery from 2008, 2013, and 2018 was used. These predictions detected changes in five LULC classes by 2033: built-up areas increasing by 3.15%, while agriculture and barren areas decreasing by -0.30% and -5.11%, respectively; vegetation increasing by 0.98%, and water bodies increasing by 1.27%.

Han et al. [6] addressed limitations of existing LULC models by integrating CLUE-S and Markov models, providing insights into land use planning and management. Through a case study of Beijing, they analyzed driving factors and predicted future land use scenarios, emphasizing the transformation of agricultural land into highly developed urban areas as a significant trend and underscoring the challenges faced in ecological and cultivated land protection.

Lu et al. [8] utilized spatiotemporal data fusion (STF) to obtain same-season Landsat-scale images over 30 years in Hefei, China, employing a Cellular Automata–Markov model to simulate and predict future land use/land cover (LULC) maps. Results showed improved detection and prediction accuracy, with cultivated land decreasing by 33.14%, water by 2.03%, vegetation by 16.36%, and construction land by 200.46% in the 1987-2032 period, aiding urban planners in achieving sustainable development goals.

Mahmud et al. [9] proposed an integrated GIS CA-Markov model to forecast land use/land cover (LULC) changes in Kelantan, Malaysia, achieving 78.57% accuracy in predicting significant increases in built-up area, oil palm, and rubber plantations, along with decreases in forest and paddy areas over the past 15 years and predictions for the next 30 years.

Rahman et al. [10] examined the temporal dynamics of LULC changes in Assasuni Upazila, Bangladesh, over 27 years (1989–2015) and predicted future changes using a CA-ANN (cellular automata and artificial neural network) model for 2028. LULC analysis revealed significant shifts, including a decrease in bare lands (-21%) and an increase in shrimp farms (+25.9%), indicating a transformation from agriculture to aquaculture. Predictions suggested further conversion of bare lands to shrimp farms by 2028. The study also analyzed the impact of LULC changes on local livelihoods and migration, emphasizing the need for comprehensive land use management to mitigate unplanned development and reduce internal migration.

A hybrid feature optimization algorithm combined with a deep learning classifier was developed by Rajendran et al. [11], which utilized Sat 4, Sat 6, and Eurosat datasets for improved LULC classification.

The study by Rizeei et al. [12] proposes a comprehensive model to monitor changes in surface runoff and forecast future runoff based on LULC dynamics and precipitation variations. Utilizing Spot-5 satellite imagery and the Land Transformation Model (LTM), LULC changes from 2000 to 2010 and future predictions for 2020 are assessed. The Autoregressive Integrated Moving Average (ARIMA) model is employed to predict rainfall in 2020, calibrated using the Taguchi method. A Soil Conservation Service-Curve Number (SCS-CN) model simulates maximum surface runoff, revealing increasing deforestation, urbanization, and runoff trends, highlighting the efficacy of the integrated approach for runoff detection, monitoring, and forecasting.

The research by [14] also employs a CA-ANN model to simulate and predict LULC changes in North Sumatra, Indonesia. Five criteria including altitude, slope, aspect, distance from the road, and soil type are utilized to train the model, with altitude and distance from the road identified as significant factors influencing LULC changes. The study demonstrates the model's reliability by accurately predicting LULC changes up to 2070, highlighting increased plantation area and human-induced shifts from forest and cropland to plantations.

Somvanshi et al. [16] used satellite data and statistical models to map land use changes in a key city of the Ganga alluvial plain. They found a significant increase in urban areas

TABLE I
RELEVANT CLASS VALUES AND DESCRIPTION

Class Value	Description
1	Water
2	Trees
4	Flooded vegetation
5	Crops
7	Built Area
8	Bare ground
9	Snow/Ice
11	Rangeland

Fig. 1. LULC mask obtained from multispectral remote data from Sentinel-2 [7]

from 2001 to 2016, with agricultural and rural areas declining. Future predictions for 2019, 2022, and 2031 indicated ongoing urbanization trends, emphasizing the importance of the study for informing sustainable development policies.

The research employs MLP-MCA to forecast LULC changes in Lagos, Nigeria, finding significant urban expansion beyond administrative boundaries. It predicts future growth shifting to neighboring Ogun State, underscoring the need for cross-border collaboration in regional planning to ensure sustainable development by Wang et al. [17].

Considering the more recent publications in this domain, Shamsuzzoha et. al. [15] focussed on Rice Growth Vegetation Index as its main parameter and implemented supervised modelling techniques, i.e., linear regression, SVM, ensemble boosted trees, MLP, etc. and were able to achieve peak coefficient of regression of 0.756 with Ensemble Boosted Trees. The models were primarily targeted over LULC changes due to cyclone Sitrang, observed by Landsat-8 satellites. Another MLP-MCA approach was attempted by Saha et. al. [13] where the focus was on Himalayan-Bengal region and were able to predict spatio-temporal LULC changes from 2021 to 2050. Although the range of prediction is leaps ahead of other state-of-the-art approaches, such broad scope of prediction has lead to a peak accuracy of 88.83% only.

Zhu et. al. [18] is a comprehensive and a contemporary review of all major practices as well as techniques in the domain of LULC change detection. The study describes the various activities essential for change detection, as well as

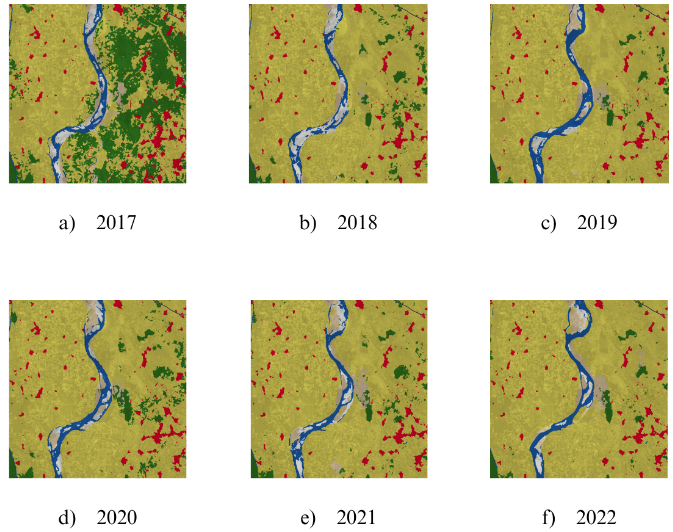

Fig. 2. LULC Class Distribution of Ganga River Bank in Uttar Pradesh for the Years 2017 through 2022. [7]

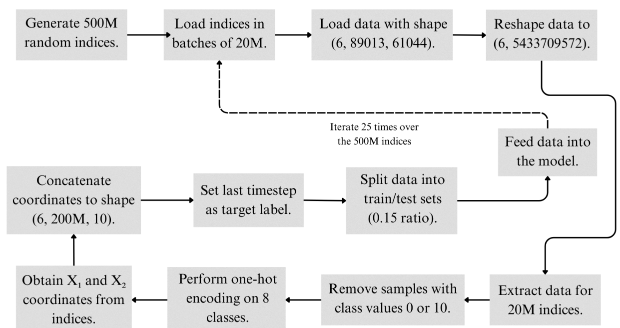

Fig. 3. Novel Data manipulation and preprocessing pipeline

reports on several difficulties that are commonly encountered in this territory and how to get past them in great detail.

III. METHODOLOGY

The following section of this research paper provides a detailed account of the research design, including the chosen theoretical framework, sampling techniques, data collection methods, and data analysis procedures, as depicted in Fig. 1.

The choice to use a Long Short-Term Memory (LSTM) model instead of Markov Chains is due to the limitations of the latter. Markov Chains assume a memoryless property, meaning they only consider the current state for prediction. This limits their ability to capture long-term dependencies and complex patterns. LSTMs are designed to capture long-term dependencies in sequential data. They can effectively learn patterns that are dependent on events far in the past, which is a capability beyond the scope of Markov Chains.

LSTMs can handle high-dimensional and multivariate time series data with ease. They can process input sequences of arbitrary length and dimensionality, making them suitable for

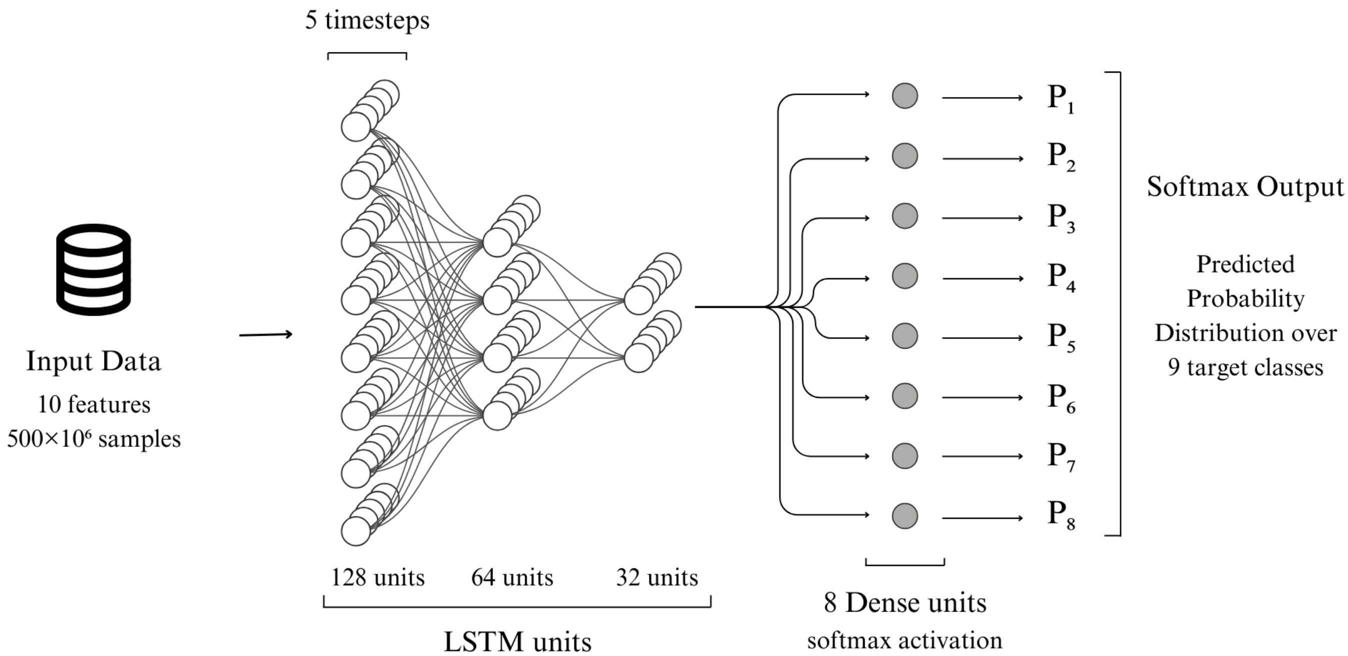

Fig. 4. Model Architecture: 3-layer LSTM

tasks involving complex sensor data. Markov Chain models may struggle to scale to high-dimensional data due to the exponential increase in the number of transition probabilities with the number of states.

A. Dataset

The dataset utilized in this work was obtained from Environmental Systems Research Institute, Inc. (ESRI) [7], and comprises of image tiles covering various regions worldwide **Fig. 1**. The analysis focuses on a specific tile, presented in GeoTIFF format, with dimensions of 89013 x 61044 pixels. Each pixel within these images corresponds to a 10m x 10m area and is assigned one of nine distinct LULC class values. Spanning a period from 2017 to 2022 **Fig. 2**, the dataset encompasses six timestamps, providing temporal insights into land use dynamics over a six-year interval. The dataset's temporal granularity enables the exploration of LULC changes and trends over time, facilitating the development and validation of predictive models.

The nine classes, as shown in **Table 1**, encapsulate a diverse range of land cover types, crucial for accurate LULC classification. These classes include: Water, Trees, Flooded Vegetation, Crops, Built area, Bare ground, Snow/Ice, Rangeland. Each class serves as a distinct indicator of the land's characteristics, contributing to a comprehensive understanding of the landscape's composition and dynamics. Through the analysis of these classes across multiple timestamps, our research aims to unveil underlying patterns and transitions, thereby enabling the development of robust predictive models for future LULC prediction.

B. Data Manipulation and Rasterization

The vast scale of the dataset presents formidable challenges in processing and analysis, with approximately 5×10^9 cells per image for each timestamp, totaling six images. Previous methodologies, while innovative and effective, typically involve preprocessing image data for utilization in machine learning (ML) models, particularly convolutional neural network (CNN) models. However, such approaches can be computationally intensive and time-consuming. Thus a new approach **Fig. 3** was utilized for managing the data such that the computation can be much faster.

In this research, a novel approach was adopted that involved rasterizing the image data into a time series raster format. For a single timestamp, the input features are structured such that each row contains the vertical and horizontal coordinate indices, alongside the class value present at that coordinate. This class value is subsequently transformed into a one-hot encoded representation, resulting in eight columns representing the probability distribution of the eight class values. These eight columns are then concatenated with the coordinate index features, yielding a feature set comprising 10 features in total.

Given the impracticality of training on the entire dataset, which comprises billions of samples, 500 million indices were randomly selected, representing approximately 8.77% of the total dataset. Importantly, this selection remains consistent across all timestamps, ensuring uniformity in the training and evaluation process. To mitigate memory constraints during model training, the 500 million samples are partitioned into 25 sets of 20 million samples each. These sets are sequentially employed for training and testing the model, thereby alleviating memory burden and enabling smooth execution on the available hardware platform. The partitioning strategy is primarily aimed at optimizing memory utilization, given the constraints imposed by the local computing environment. Notably, the system utilized for this research is an Apple M2 MacBook Air equipped with 16GB of Universal Memory, shared between the system and the integrated GPU, with additional swap memory of up to 5GB from the Solid State Drive. By strategically managing memory usage through data partitioning, we ensure efficient model training and evaluation while overcoming hardware limitations.

C. Model Architecture

The proposed framework's architecture, as shown in **Fig. 4** is specifically purposed to effectively capture the temporal dependency and the geographical patterns within the dataset. The framework utilizes a sequential stack of Long Short-Term Memory (LSTM) layers, followed by a Fully Connected Softmax layer for multi-class classification.

The LSTM architecture comprises three layers, each configured with decreasing numbers of nodes: 64 nodes in the first layer, 32 in the second layer, and 16 in the third layer. This progressive reduction in node count is intended to align the output with the shape required for the final dense layer, which consists of nine nodes representing the nine LULC classes. The choice of the tanh activation function for the LSTM layers is deliberate, as it is optimized for GPU computation in TensorFlow.

While alternative activation functions like Leaky ReLU could be considered, they are deemed unnecessary in this context. Leaky ReLU primarily addresses the vanishing gradient problem, which is less pertinent here due to the limited temporal depth of only six timestamps.

The second and third LSTM layers incorporate dropout regularization, facilitating the random dropout of a specified percentage of nodes during training. This mechanism serves to enhance model generalization by reducing overfitting.

As stated above, the final layer is a fully-connected or dense softmax layer with eight nodes, representing the predicted probability distribution across the eight LULC classes. This layer produces probabilities corresponding to each class, facilitating class assignment based on the highest probability.

Additional hyperparameters include the Adam optimizer, chosen for its efficient convergence capabilities and minimal convergence fluctuations post-convergence. The categorical crossentropy loss function is selected to accommodate the multi-class nature of the classification task. During model training, each of the 25 sets of 20 million samples is iteratively utilized for training over 10 epochs. Early stopping callbacks are applied to the training process, leading to the termination of training for most sets between the 4th and 6th epochs. This

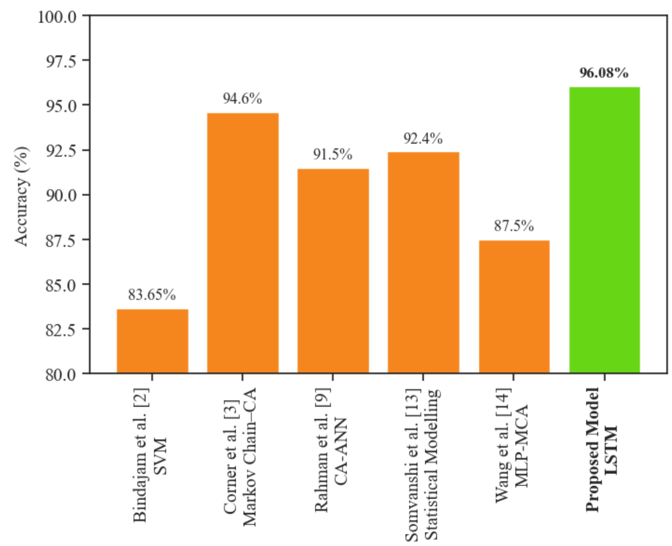

Fig. 5. Comparative performance of different models based on accuracy metrics

adaptive training strategy ensures efficient convergence while preventing overfitting and excessive computational burden.

Prior to model training, each set comprising 20 million samples is split into training and testing subsets using a split ratio of 0.15. This results in the model being trained on 17 million samples while performance evaluation is conducted on 3 million samples. This partitioning strategy ensures that each training phase is accompanied by a corresponding and distinct test set, facilitating robust evaluation of performance metrics such as loss and accuracy. Each set can be conceptualized as a homogeneous section extracted from a larger randomly sampled subset of the heterogeneous dataset, specifically the rasterized data preceding the preprocessing steps. Consequently, the training and testing sets can be directly sliced, obviating the need for further randomization of indices.

IV. Results and Discussion

The average training accuracy achieved over multiple epochs and independent training phases stands at an impressive 92.43%. Notably, the model exhibits early stopping behavior, terminating training prematurely to mitigate potential overfitting. However, an evaluation of validation accuracy, conducted using a validation split ratio of 0.2 over the training data, reveals a negligible discrepancy compared to the training accuracy. This convergence between training and validation accuracies suggests that the model is not encountering overfitting issues and performs admirably across the validation set. Hence, the model demonstrates robust generalization capabilities, buoyed by the ample size of the dataset.

For testing, the model's predicted outputs are subjected to an argmax function to determine the node with the highest probability, which is then compared against the actual class value for the test inputs. This comparison yields metrics for loss and accuracy percentage. The model achieves a remarkable average classification accuracy of 96.08% across all training phases, significantly outperforming current models utilized for the same purpose (as represented in Fig. 3), and demonstrating its efficacy in accurately predicting LULC classes.

Presented model diverges from others in its prediction scope by focusing solely on one-year predictions rather than forecasting for multiple timestamps, such as over the next decade. This purposeful choice is grounded in scientific research, since extending the forecasting period was found to reduce accuracy. Our model retains a greater level of accuracy by restricting forecasts to a single year, which guarantees trustworthy and useful insights for tasks involving LULC prediction.

These results collectively affirm the effectiveness and reliability of the proposed model in predicting LULC classes, highlighting its potential utility in real-world applications involving land use dynamics and environmental monitoring.

V. Conclusion and Future Scope

The objective of this research was to develop and evaluate a machine learning framework for predicting LULC classes. The proposed model architecture utilizes Long Short-Term Memory (LSTM) layers for capturing temporal dependencies and spatial patterns in a dataset. The LSTM architecture consists of three layers with decreasing node counts, culminating in a fully-connected softmax layer for multi-class classification. Dropout regularization is applied to enhance model generalization, and the Adam optimizer is used for efficient convergence. Training is conducted over multiple epochs with early stopping to prevent overfitting.

During testing, the framework achieves an impressive average classification accuracy of 96.86%, indicating its effectiveness in predicting LULC classes. The model demonstrates robust generalization capabilities and reliability, suggesting its potential utility in real-world applications involving land use dynamics and environmental monitoring.

This work creates opportunities for future research and application across a range of fields. In LULC classification tasks, more intricate spatial and temporal connections might be handled by improved model architectures. Furthermore, using extra data sources as socioeconomic or remote sensing photography may improve the model's predictive power. Additionally, the presented model could be used to address similar problems like predicting urban growth or detecting changes in land use. This work establishes the foundation for future developments in applying machine learning to comprehend and manage land use patterns, with implications for sustainable development, urban planning, and environmental protection as technology progresses and more data becomes accessible.

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