VEGETATIOIN MONITORING

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In
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Artificial Intelligence and Machine Learning

by

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DECLARATION

I, *Aakash Sinha (2100010159004)*, hereby declare that the major project report entitled **"Vegetation Monitoring"** has been carried by me under the guidance of my supervisor **Dr. Jai Bhagwan** in fulfilment of the requirements for the award of the degree of Bachelor of Technology CSE- (AI&ML). I have followed all the ethical practices and other guidelines provided by the Department of Computer Science and Engineering in preparing the report.

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Aakash Sinha

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CSE - (AI & ML)

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List of Abbreviations

Abbreviation	Full Form
AI	Artificial Intelligence
API	Application Programming Interface
ANN	Artificial Neural Network
CLI	Command Line Interface
CPU	Central Processing Unit
CSV	Comma-Separated Values
DL	Deep Learning
DPO	Direct Preference Optimization
EDA	Exploratory Data Analysis
FFN	Feed Forward Network
FID	Fréchet Inception Distance
FLOP	Floating Point Operation
FP16 / FP32	16-bit / 32-bit Floating Point Precision
GAN	Generative Adversarial Network
GPU	Graphics Processing Unit
GUI	Graphical User Interface
HTML	HyperText Markup Language
IDE	Integrated Development Environment
JSON	JavaScript Object Notation
LLaMA	Large Language Model Meta AI
LLM	Large Language Model
LoRA	Low-Rank Adaptation
MLP	Multi-Layer Perceptron
MLM	Masked Language Modeling
MoE	Mixture of Experts
NLP	Natural Language Processing
NumPy	Numerical Python
OCR	Optical Character Recognition

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Abstract

This project aims to detect and analyze vegetation changes over time using NDVI (Normalized Difference Vegetation Index) data sourced from the GIMMS-3G+ AVHRR dataset (2020-2022). By integrating state-of-the-art deep learning models such as UNet, LSTM, and CNN, we develop an efficient approach to monitor and quantify changes in global vegetation health. The methodology involves preprocessing NDVI and RGB composite bands, feeding them into neural networks trained for segmentation and time-series forecasting. The resulting visualizations and metrics, including IoU and Dice Scores, highlight seasonal trends and degradation hotspots. Additionally, the project features an interactive dashboard built using Streamlit, providing end-users with tools to explore vegetation dynamics over specific geographies and timeframes. The system is scalable and supports integration with cloud-based services for real-time monitoring. The insights gained can assist policymakers, environmental scientists, and agricultural stakeholders in sustainable land use planning and ecological assessment.

Chapter 1: Introduction

1.1 Overview of project

Vegetation, as the green fabric of the planet, underpins climate regulation, hydrological cycles, soil fertility, and biodiversity. Detecting changes in vegetation cover—whether gradual shifts caused by climate oscillations or abrupt alterations due to human activity—is vital for sustainable development. This project, "Vegetation Change Detection Using NDVI and Deep Learning Models," presents an end to end framework that processes forty plus years (1981–2022) of NDVI observations to quantify and forecast global vegetation dynamics.

Vegetation plays a vital role in sustaining life on Earth, acting as the backbone of ecosystems, supporting biodiversity, regulating the climate, and serving as a critical component in the carbon cycle. Monitoring vegetation health is essential for understanding ecological balance, assessing the impacts of environmental changes, and managing natural resources effectively. With advancements in remote sensing technology, datasets like the Global Vegetation Greenness (NDVI) from AVHRR GIMMS-3G+ provide invaluable insights into vegetation patterns spanning decades, covering the period from 1981 to 2022. This dataset captures the Normalized Difference Vegetation Index (NDVI), a widely recognized indicator of vegetation greenness and health, offering global-scale observations of land cover and changes in vegetation dynamics over time. This project, "Tracking Global Vegetation Health with AI," aims to bridge the gap between complex data and actionable insights. The primary objective is to utilize AI- driven models to analyze NDVI data for understanding vegetation dynamics, estimating biomass, detecting disturbances such as fires or deforestation, and predicting future vegetation health trends. By focusing on key vegetation metrics such as Net Primary Production (NPP), belowground characteristics, and vegetation biomass, the project seeks to address critical questions about the state of the Earth's ecosystems.

Another area where AI-driven analysis of NDVI data holds promise is the study of Net Primary Production (NPP), which measures the amount of carbon absorbed by plants through photosynthesis, minus the carbon released during respiration. NPP is a critical metric for assessing ecosystem productivity and understanding the balance of carbon in terrestrial ecosystems. By combining NDVI data with additional datasets, such as temperature, precipitation, and soil moisture, AI models can offer a more comprehensive view of NPP dynamics and their drivers

This project, "Tracking Global Vegetation Health with AI," aims to bridge the gap between complex data and actionable insights. The primary objective is to utilize AI-driven models to analyze NDVI data for understanding vegetation dynamics, estimating biomass, detecting disturbances such as fires or deforestation, and predicting future vegetation health trends. By focusing on key vegetation metrics such as Net Primary Production (NPP), belowground characteristics, and vegetation biomass, the project seeks to address critical questions about the state of the Earth's ecosystem.
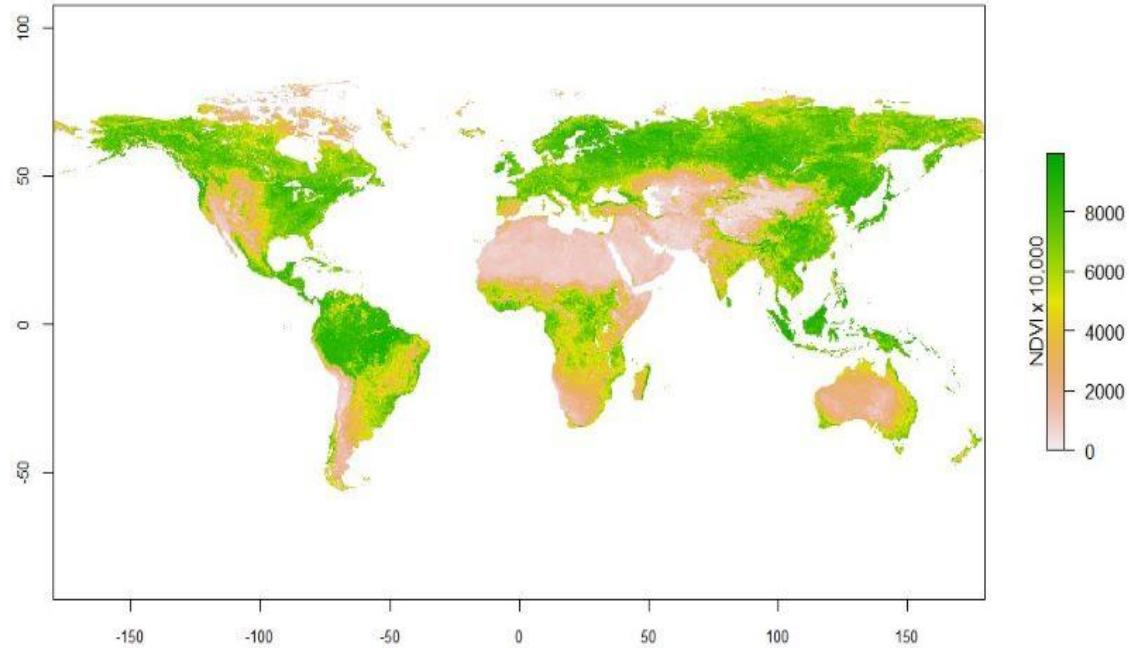

Fig 1: Earth's ecosystem

1.2 Relevance and Motivation

The increasing frequency of climate anomalies, extreme weather events, deforestation, and urban sprawl has brought global attention to the health and sustainability of natural ecosystems. Vegetation, being a fundamental component of terrestrial ecosystems, plays a critical role in maintaining the ecological balance, sequestering carbon dioxide, regulating water cycles, and supporting wildlife biodiversity. Monitoring vegetation change is no longer optional—it is essential for planning sustainable development, predicting climate change impacts, and ensuring food security.

Traditional methods of vegetation assessment—such as manual field surveys—are labor-intensive, time-consuming, and often limited in scale. In contrast, satellite remote sensing, combined with advanced machine learning, offers a powerful, scalable, and cost-effective alternative. Among remote sensing indices, the Normalized Difference Vegetation Index (NDVI) has gained global acceptance due to its simplicity and reliability in representing vegetation health and density. The availability of long-term NDVI datasets (like GIMMS AVHRR NDVI 3g+) allows for comprehensive temporal studies of vegetation patterns.

However, raw satellite data is vast and complex. Extracting meaningful trends and interpreting patterns requires sophisticated algorithms capable of learning spatial and temporal features. This is where deep learning—specifically models like U-Net, CNNs, and LSTM—becomes highly relevant. These models have demonstrated excellent performance in handling spatial-temporal data and are now widely adopted in domains such as medical imaging, speech recognition, and natural language processing. Their adaptation in geospatial and environmental domains is both timely and impactful.

The motivation behind this project arises from:

- The urgent need to monitor vegetation degradation and restoration trends in response to environmental and anthropogenic changes.

- The potential of deep learning models to transform how we analyze remote sensing data, offering high accuracy and automation.

- The lack of accessible, interactive tools for researchers and decision-makers to visualize and interpret vegetation change.

- The opportunity to contribute to global sustainability efforts by developing AI-powered tools for ecological monitoring.

In a world facing significant environmental challenges, this project combines technology, data science, and environmental science to offer a practical and research-oriented solution. It aims to empower stakeholders with insights that were previously unattainable, thus contributing meaningfully to both the scientific community and sustainable environmental governance.

1.3 Problem Statement

Monitoring long-term vegetation change is a major global challenge that affects agriculture, climate resilience, biodiversity, and natural resource management. Satellite-based indices such as the Normalized Difference Vegetation Index (NDVI) have significantly advanced vegetation monitoring, but limitations still persist when it comes to understanding complex and subtle changes over large areas and long timeframes.

Traditionally, vegetation assessments were based on manual ground surveys or visual interpretation of imagery. These methods are limited in spatial coverage, prone to human error, and unsuitable for continuous monitoring.

Criteria	Traditional Methods	Deep Learning-Based Monitoring
Scalability	Low – limited to field surveys	High – scalable to global datasets
Accuracy	Subject to human error	Improved accuracy with less bias
Temporal Coverage	Snapshot in time	Continuous, time-series analysis
Spatial Resolution	Often coarse or inconsistent	High resolution from satellite data
Feature Detection	Limited to visible patterns	Capable of detecting subtle changes
Processing Time	Time-consuming	Faster with GPU-accelerated models

Table 1.1: Traditional Methods vs. Deep Learning-Based Vegetation Monitoring

NDVI is one of the most popular vegetation indices, calculated using the following formula.

NDVI = (NIR - RED) / (NIR + RED)

Where:

- NIR is the reflectance in the near-infrared band.

- RED is the reflectance in the red band.
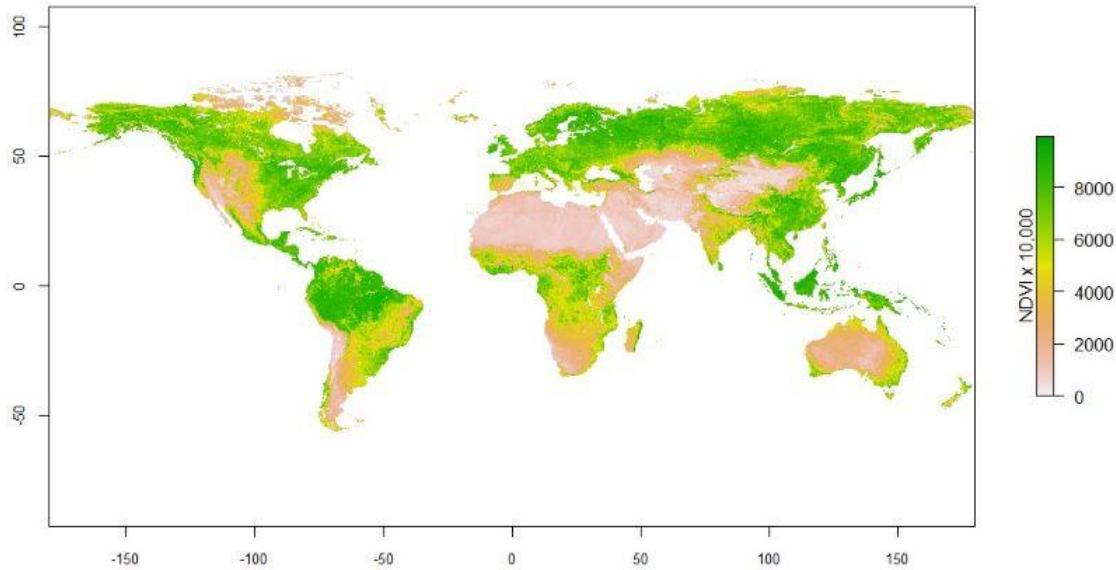
Fig 2: NDVI Response for Different Land Covers

Challenge	Description
High Dimensionality	NDVI data spans decades and multiple geolocations
Temporal Noise	Seasonal variations and weather effects cause irregular patterns
Spatial Inconsistency	Different resolutions and missing data across tiles
Label Scarcity	Lack of annotated ground-truth data for supervised learning
Computational Load	Processing time-series images is resource-intensive

Table 1.2: Key Challenges in NDVI-Based Change Detection
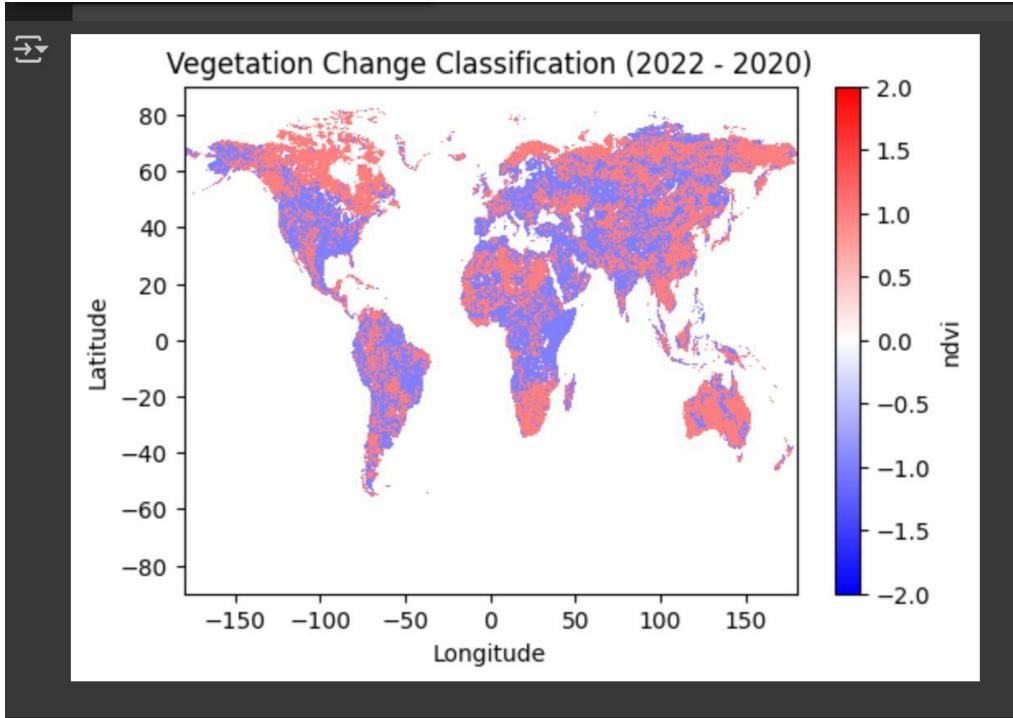
Fig 3: Sample NDVI Time Series Curve (2020–2022)

How can NDVI data from 1981–2022 be efficiently and accurately analyzed using deep learning models to detect real vegetation changes over time, filtering out noise and seasonal fluctuations?

This project proposes a multi-model approach using U-Net, CNN, and LSTM to resolve the above issues and develop a robust framework for vegetation change detection. By transforming raw NDVI data into usable insights, the proposed system supports environmental monitoring, planning, and policy decisions.

1.4 Objectives

The overarching aim of this project is to develop an intelligent, end to end framework for global vegetation monitoring that ingests four decades of NDVI observations, extracts meaningful spatial–temporal patterns with deep learning, and delivers actionable insights through an interactive dashboard. Each sub objective below is accompanied by an

analytical discussion of the design considerations, expected benefits, potential challenges, and evaluation criteria.

1.4.1 Development of an Automated Vegetation Monitoring System

A modular data pipeline lies at the heart of any large scale Earth observation project. In this work, the pipeline ingests biweekly NDVI composites (1981 – 2022), applies cloud masking, gap fills missing values, and generates RGB composites for context. A UNet segmentation network, trained on representative tiles from diverse biomes, delineates vegetated versus non vegetated pixels at ~8 km resolution. Post segmentation, LSTM layers consume UNet masks in conjunction with raw NDVI sequences to model inter annual and seasonal trends.

Different indices have been derived to use satellite data to detect changes in vegetation, and some of them include specific characteristics suitable for arid and semi-arid environments.

Analysis & Evaluation

- *Robustness:* Cloud masking quality will be measured by comparing pre- and post-mask NDVI histograms.

- *Segmentation Accuracy:* IoU and Dice coefficients on a held-out validation set should exceed 0.80 for vegetated classes.

- *Temporal Fidelity:* Seasonal peak alignment between LSTM forecasts and ground-truth NDVI series will be quantified using Pearson correlation.

1.4.2 Integration of Remote Sensing and Machine Learning/Deep Learning

This objective focuses on enriching model inputs with auxiliary layers (elevation, land-cover, soil moisture) to mitigate spectral ambiguities in NDVI-only imagery. Data augmentation—random rotations, flips, and brightness shifts—improves generalization

across heterogeneous landscapes. Multiple CNN backbones (ResNet-50, EfficientNet-B4) will be benchmarked to identify the optimal spatial feature extractor.

The integration of remote sensing data with deep learning methodologies has become a transformative approach for monitoring environmental patterns and vegetation dynamics over time. Remote sensing provides vast spatiotemporal data from satellite platforms, such as NDVI (Normalized Difference Vegetation Index), which measures vegetation greenness and health. However, interpreting this data effectively requires advanced modeling techniques capable of capturing complex patterns across both space and time. Deep learning offers powerful tools to meet this demand.

To enhance the quality and richness of input features, **multi-spectral NDVI datasets** can be fused with auxiliary information such as **elevation models** and **land cover maps**. This fusion enables the model to account for topographical variation and anthropogenic influence, thereby improving its understanding of spatial context and ecological patterns.

To increase the model's generalization across diverse ecosystems and reduce overfitting, **advanced data augmentation techniques** are applied. These include random rotations, cropping, brightness adjustments, and the addition of synthetic noise. Such augmentation mimics real-world variations in satellite data caused by sensor drift, seasonal lighting conditions, and atmospheric disturbances.

In terms of model architecture, various **Convolutional Neural Network (CNN) encoders**, such as **ResNet-50** and **EfficientNet**, are evaluated for their capacity to extract spatial features from remote sensing imagery. These models serve as the backbone of segmentation architectures like UNet, which are particularly effective in capturing fine-grained spatial patterns.

For temporal analysis, **stacked NDVI time series** are utilized as input to **Long Short-Term Memory (LSTM)** networks. LSTMs are well-suited for capturing long-term dependencies and trends, enabling predictive modeling of vegetation change over extended periods. This is particularly useful for studying the progression of climate change effects, droughts, or land degradation.

To further enhance spatio-temporal learning, **hybrid architectures** such as **UNet-LSTM fusion models** are explored. These models combine the spatial learning capabilities of CNNs with the temporal sequence learning of RNNs, allowing for end-to-end analysis of vegetation dynamics over time and space.

Finally, to improve model interpretability, **visualization techniques** such as **feature maps** and **saliency gradients** are employed. These tools highlight the regions and features within satellite imagery that most influence the model's predictions, offering valuable insights into model behavior and helping researchers validate outputs against known ecological phenomena.
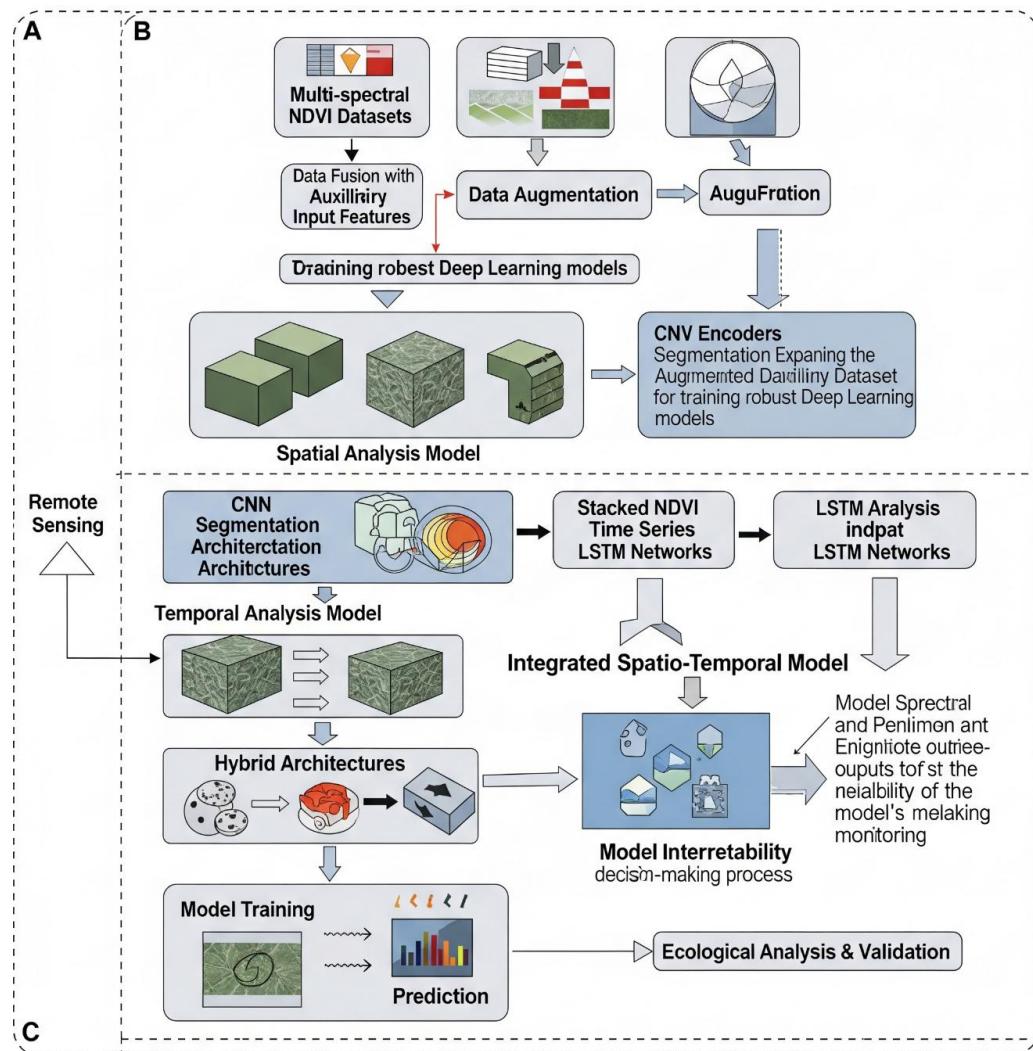
Fig 4: Flow diagram

1.4.3 Customizable Analytical Dashboard

An intuitive Streamlit interface will democratize access to model outputs. Users can define an Area of Interest (AOI) via shapefile upload or map clicks, select time windows, and toggle visualization layers (raw NDVI, change mask, forecast). An interactive charting suite will animate vegetation dynamics, and a feedback widget will capture expert annotations for continual learning.
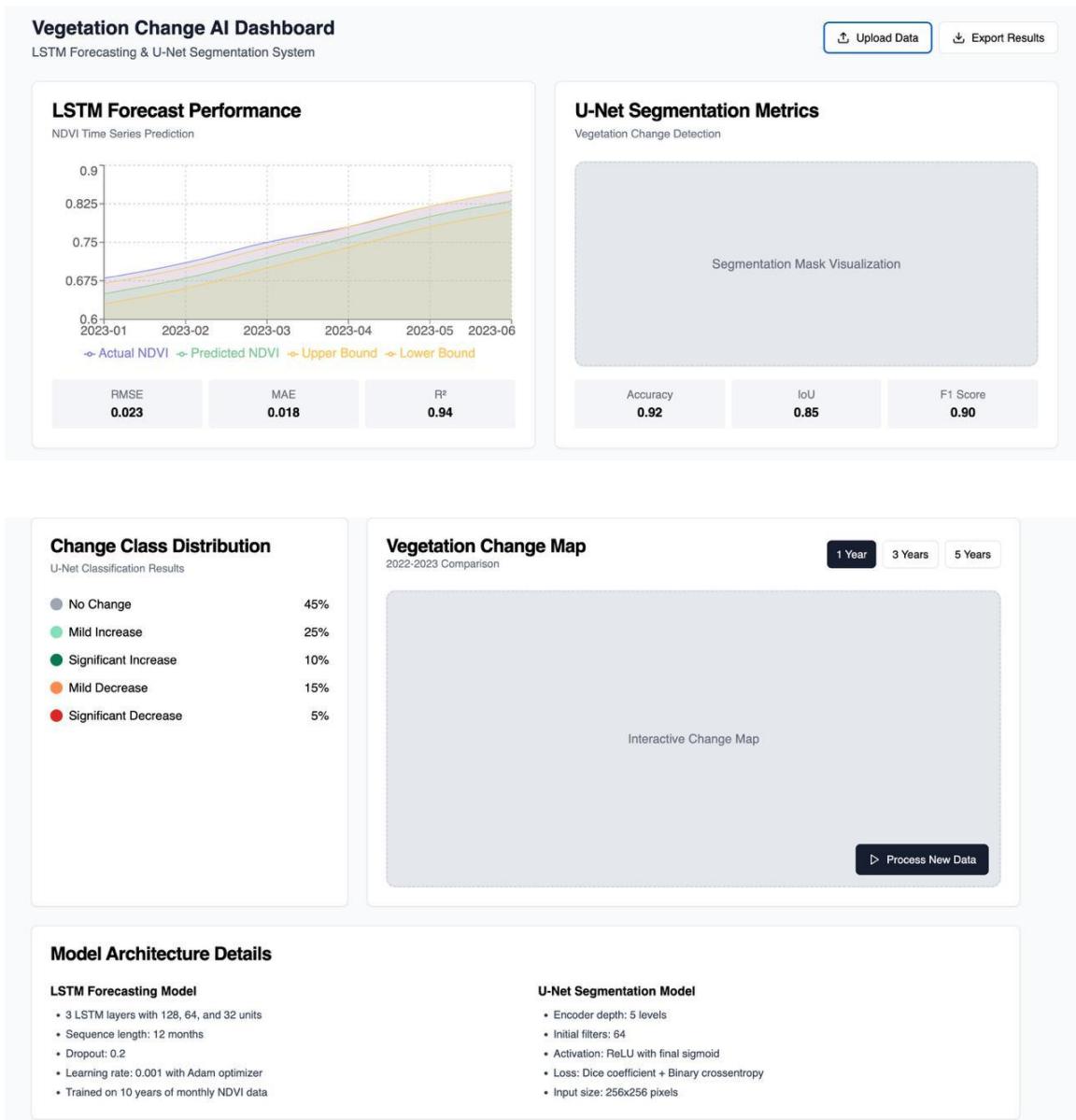
Fig 5: Dashboard

Analysis & Evaluation

• Usability: A SUS (System Usability Scale) questionnaire distributed to beta testers should score > 80.

• Latency: End to end response time must remain under 5 seconds for typical AOI ($\leq 5\,000$ km²).

• Feedback Loop: Incorporating user flagged errors should reduce false positive change detection by ≥ 10 % after one retraining cycle.

1.4.5 Deployment and Real-World Integration

a. Integration with Geospatial Tools

Export model outputs (e.g., NDVI maps) to GIS platforms like QGIS or Google Earth Engine for further analysis.

b. Building an Interactive Dashboard

- Use tools like Streamlit or Dash to allow users to:
- Upload satellite images.
- View forecasted NDVI or segmented vegetation change areas.
- Analyze time series predictions.

c. API Endpoint for Forecast

Expose LSTM forecast model via Flask/FastAPI for real-time prediction requests.

1.4.6 Limitations and Future Enhancements

a. Limitations

- UNet training is computationally expensive.
- Limited interpretability for complex LSTM patterns.
- Model struggles in regions with snow/cloud cover in satellite images.

b. Future Enhancements

- Fuse NDVI with SAR (radar) data to handle cloud-covered regions.
- Use Transformers (like TimeSformer) for better spatio-temporal learning.
- Add active learning for model retraining with new labeled data.

1.5 Scope of the Project

The scope of this project focuses on leveraging the synergy between remote sensing data and deep learning techniques for large-scale vegetation monitoring and forecasting using NDVI time series. It aims to build a scalable, automated, and intelligent system that can assist researchers, environmentalists, and policymakers in understanding vegetation patterns and changes over time.

1.5.1 Spatial Scope

Use of globally available NDVI datasets (AVHRR GIMMS-3G+), which cover the period from 1981 to 2022. Capability to analyze vegetation at multiple spatial scales – from global to regional or local levels (depending on data resolution and availability).

1.5.2 Temporal Scope

Longitudinal analysis of vegetation patterns across decades (1981–2022). Seasonal trend forecasting using monthly or bi-weekly NDVI sequences. Support for short-term prediction (1 year) and long-term vegetation health trends.

1.5.3 Technical Scope

Spatially, the project will leverage globally available AVHRR GIMMS-3G+ NDVI datasets, encompassing the period from 1981 to 2022. The system will be capable of analyzing vegetation at various spatial scales, ranging from global to regional or even local levels, with the specific resolution depending on data availability. Temporally, the project will conduct longitudinal analysis of vegetation patterns across decades (1981–2022). It will also facilitate seasonal trend forecasting using monthly or bi-weekly NDVI sequences and support both short-term (1-year) predictions and the analysis of long-term vegetation health trends.

1.5.4 Functional Scope

From a technical standpoint, the project involves integrating diverse data sources, including NDVI, RGB bands, elevation data, and land cover maps. It will apply several deep learning models: LSTM for time series trend prediction, UNet for spatial segmentation and vegetation change detection, and a hybrid UNet-LSTM for spatio-temporal learning. The development will also include robust preprocessing and post-processing pipelines for large geospatial datasets, alongside support for visualization and deployment of results via dashboards or GIS software. Functionally, the system will be able to load, clean, and prepare NDVI and auxiliary datasets, train deep learning models on preprocessed NDVI sequences, forecast future NDVI values, and generate vegetation health maps. Finally, it will provide a user interface or visual outputs such as dashboards, charts, and maps for comprehensive analysis.

1.5.5 Out of Scope

It's important to note what falls outside the scope of this initial phase. The project will not include manual field-based vegetation sampling or validation. Furthermore, there will be no integration with real-time satellite APIs (e.g., Sentinel API) at this stage. Lastly, atmospheric corrections and cloud-removal models are not implemented in this version.

Chapter 2: Literature Review

The integration of remote sensing data with deep learning techniques has garnered significant attention in recent years, especially for applications related to environmental monitoring and vegetation change detection. This chapter presents a comprehensive overview of key concepts, prior research, and recent advancements relevant to the current study. It explores the evolution of NDVI-based vegetation analysis, the role of deep learning models in geospatial data interpretation, and the effectiveness of hybrid architectures for spatio-temporal learning.

2.1 Remote Sensing and NDVI

Remote sensing refers to the acquisition of information about the Earth's surface without direct contact, typically via satellite or airborne sensors. Among various vegetation indices, the Normalized Difference Vegetation Index (NDVI) is renowned for its simplicity and effectiveness in depicting plant vigor. NDVI is calculated from the red (R) and near infrared

(NIR) bands according to $NDVI = (NIR - R) / (NIR + R)$. High NDVI values signify healthy, dense vegetation, while low values indicate sparse or stressed flora. Time series NDVI data facilitate the analysis of phenological changes, drought impact, and land cover transition across diverse ecosystems. Pioneering studies by Tucker (1979) set the stage for NDVI based vegetation monitoring. Subsequent research expanded its application to global climate change assessment, yield forecasting, and habitat evaluation.

Despite its widespread adoption, interpreting raw NDVI necessitates sophisticated modeling techniques to capture spatial heterogeneity and temporal dynamics. This has led to the integration of remote sensing with advanced machine learning and deep learning paradigms.
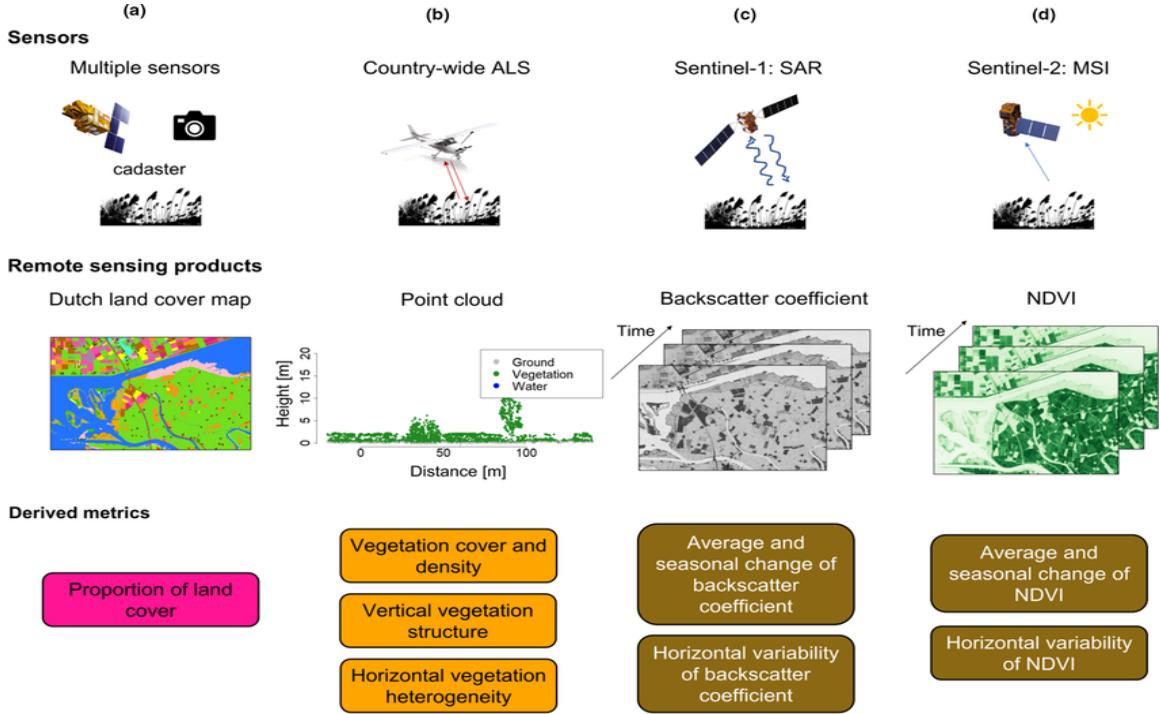
Fig 6: NDVI Working

2.2 Deep Learning in Remote Sensing

Deep learning – a sub field of machine learning characterized by multilayer neural networks – has revolutionized remote sensing analytics. Its capability to learn hierarchical feature representations directly from data allows for automated extraction of complex spatial and temporal patterns. Notable architectures include:

• Convolutional Neural Networks (CNNs) for spatial feature extraction and image classification.

• Recurrent Neural Networks (RNNs), particularly Long Short Term Memory (LSTM) networks, for modeling sequential dependencies in time series data.

• Transformer models, which leverage self attention mechanisms for long range dependency modeling across sequences.

The synergy of CNNs and RNNs in hybrid frameworks harnesses both spatial and temporal data, significantly enhancing change detection accuracy and predictive performance in vegetation monitoring tasks.
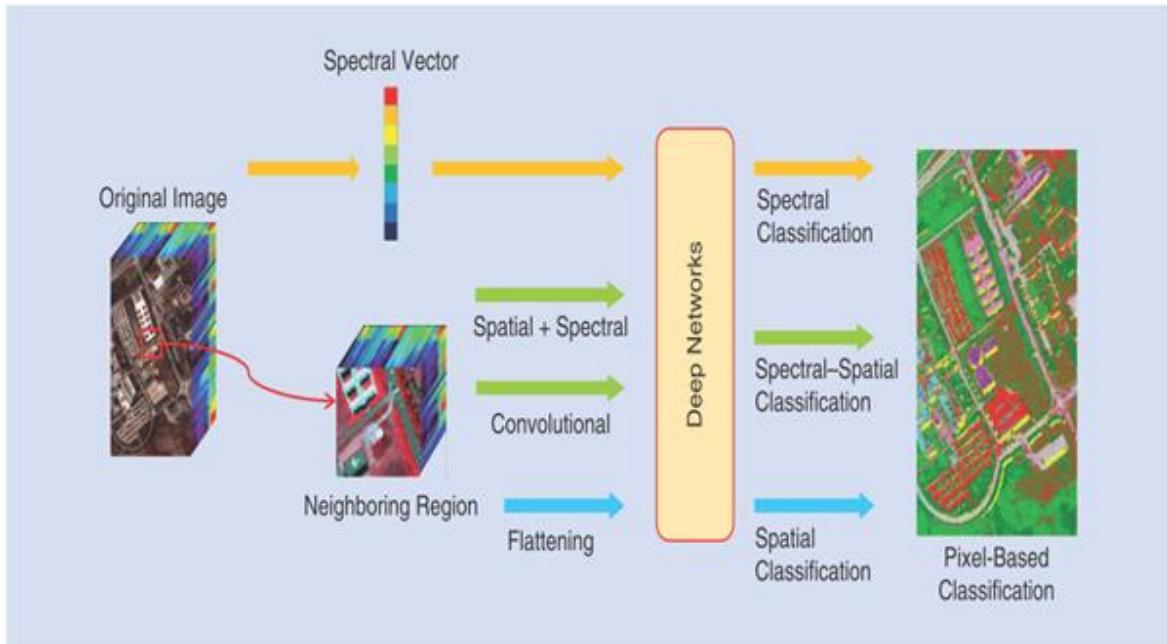
Fig 7: Pixel classification of RS image

2.3 UNet for Spatial Segmentation

UNet, introduced by Ronneberger et al. (2015), is an encoder decoder CNN originally designed for biomedical image segmentation. Its symmetrical U shaped architecture comprises a contracting path (encoder) that captures image context and an expansive path (decoder) that enables precise localization through up sampling. Skip connections between corresponding encoder and decoder layers preserve fine grained spatial information. In remote sensing, UNet has demonstrated superior performance in tasks such as land cover mapping, deforestation monitoring, and urban expansion analysis, particularly when combined with multispectral inputs like NDVI, DEM, and land cover masks.

Here's a quick breakdown of the components that make U-Net unique:

• **Encoder (Contracting Path):** This part of the network captures context and semantic information using convolutional layers with ReLU activation followed by max-pooling layers. As you go deeper in this path, the spatial dimension decreases while the feature depth increases.

• **Decoder (Expanding Path):** The decoder upsamples the feature maps using transposed convolutions and combines them with corresponding feature maps from the encoder through skip connections. This helps in localizing features more accurately.

• **Skip Connections:** These connections help to bridge the encoder and decoder, preserving spatial information and improving gradient flow during training.
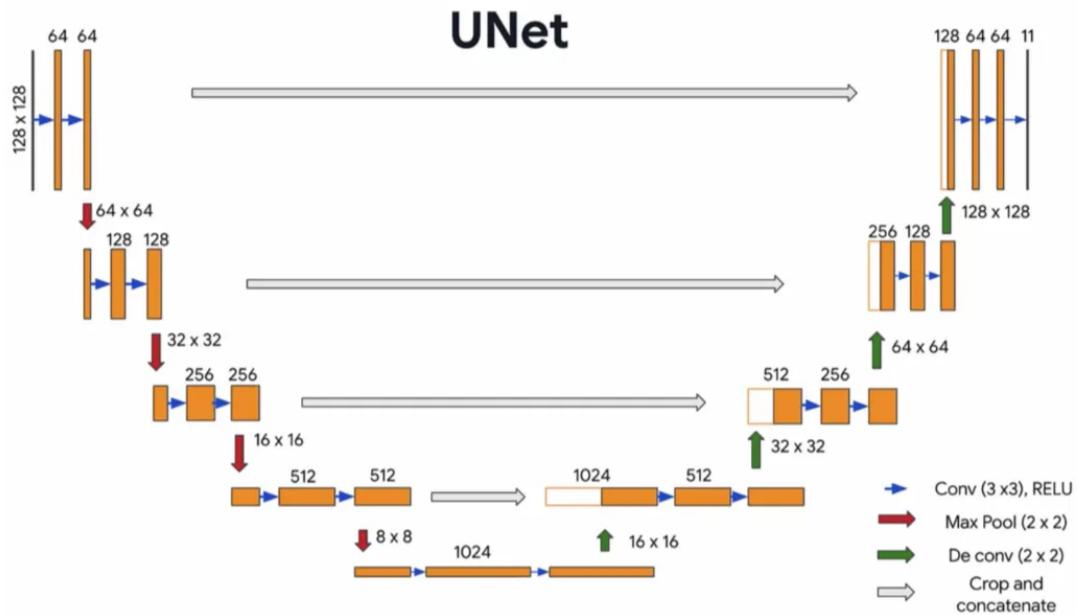
Fig 8: UNet

2.4 LSTM for Temporal Trend Analysis

Long Short Term Memory (LSTM) networks, proposed by Hochreiter and Schmidhuber (1997), address the vanishing gradient issue in traditional RNNs by introducing memory

cells with gated mechanisms (input, forget, and output gates). In vegetation studies, LSTMs are adept at modeling NDVI time series to forecast seasonal cycles, detect anomalies, and estimate long term trends. Their ability to retain information over extended temporal windows is critical for capturing phenological patterns and gradual ecological changes.
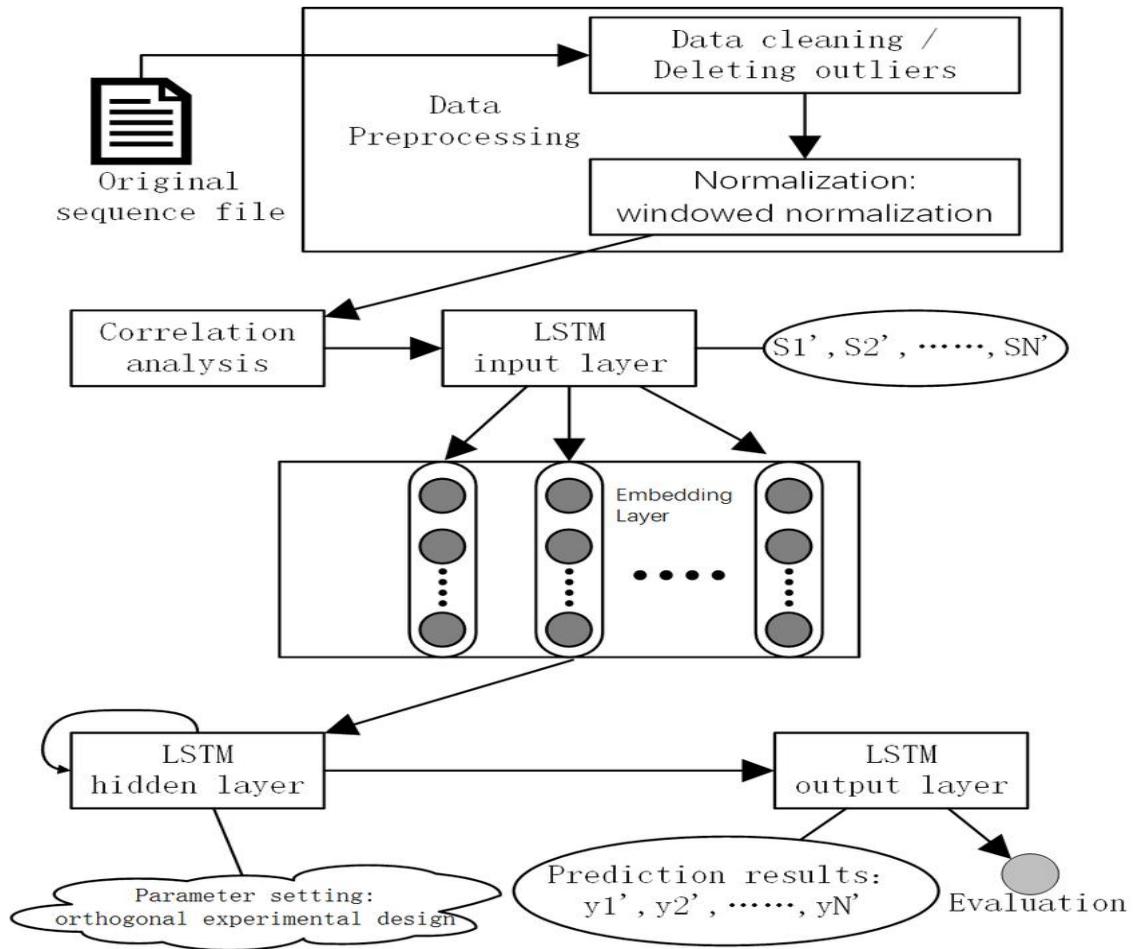
Fig 9: LSTM

2.5 Hybrid Architectures: UNet LSTM

Hybrid models that combine UNet and LSTM leverage the strengths of both spatial segmentation and temporal sequence modeling. Typically, each time step image is processed through a UNet encoder to generate a compact spatial feature vector. These vectors are then fed into an LSTM layer that learns temporal dependencies. The decoder may produce either segmented maps for each future time step or aggregated trend

predictions. This architecture has been employed for crop growth monitoring, drought impact assessment, and multi seasonal vegetation classification, achieving state of the art performance by exploiting the complementary nature of spatial and temporal data. The outcomes of the LSTM and Transformer models were combined in the final layer. The final prediction output of financial health or spending behavior is produced by combining the strengths of the two models into this layer. (a) Concatenation: A unified representation of the financial data is constructed by concatenating the outputs from the LSTM and Transformer modules. (b) Dense Layer: These outputs are combined using a dense fully connected layer to predict financial outcomes.
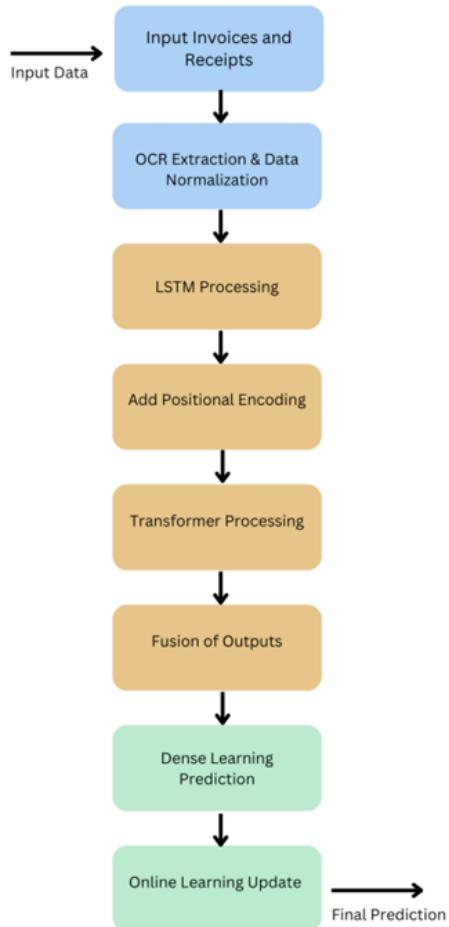
Fig 10: Flow Diagram of LSTM-Transformer Hybrid Architecture.

2.6 Availability of Big Data

If hardware is the engine, then data is the fuel. The explosion in available data— fueled by the rise of the internet and the digitization of nearly every industry—has provided deep learning systems with the raw material they need to learn. A pivotal moment came with the release of the ImageNet dataset (~1.4 million labeled images across 1,000 categories), which powered the now-famous 2012 AlexNet model that dramatically outperformed older vision techniques.
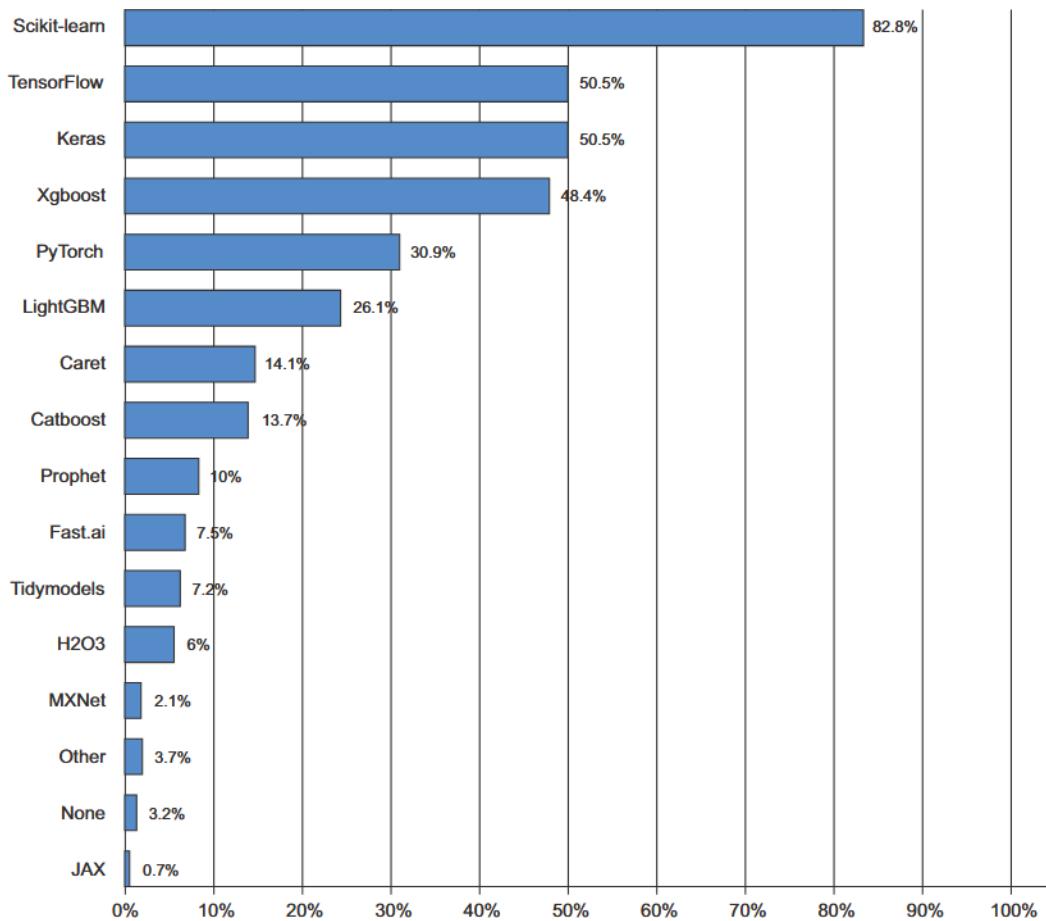
Fig 11: Tool usage across the machine learning

Chapter 3: Data Collection and Preprocessing

Understanding vegetation dynamics through remote sensing requires well-prepared, high-quality input data. This chapter describes the sources, characteristics, and processing pipeline for the NDVI and auxiliary datasets used in this study.

3.1 Data Sources

3.1.1 Global NDVI Dataset

- **Name**: GIMMS NDVI 3g+ (AVHRR sensor)
- **Source**: NOAA/NASA or NASA EarthData
- **Time Range**: 1981–2022
- **Frequency**: Bi-monthly (twice per month)
- **Spatial Resolution**: ~8 km
- **Format**: NetCDF (.nc4)

These NDVI measurements reflect vegetation greenness globally and are highly suited for long-term vegetation trend analysis.

**Dataset Overview**

This dataset holds the Global Inventory Modeling and Mapping Studies-3rd Generation V1.2 (GIMMS-3G+) data for the Normalized Difference Vegetation Index (NDVI). NDVI was based on corrected and calibrated measurements from Advanced Very High Resolution Radiometer (AVHRR) data with a spatial resolution of 0.0833 degree and global coverage for 1982 to 2022. Maximum NDVI values are reported within twice monthly compositing periods (two values per month).

Spatial Coverage: Global

Spatial Resolution: 0.0833 degree

Temporal Coverage: 1982-01-01 to 2022-12-31

Temporal Coverage: Two estimates per month over 14-16 day compositing periods

Study Area: Latitudes and longitudes in decimal degrees.

Data File Information

This dataset holds 80 files in NetCDF (.nc4) format. There are two files per year for 1982 to 2021. Each file holds data for a six month period with two estimates per month; each estimate covers a 14-to-16 day compositing period for the first half or second half of the month.

• version = alphanumeric version designation (e.g., "v1")

• year = 4-digit year

• month1 = 2-digit month at beginning of composite period ("01" = January)

• month2 = 2-digit month at end of composite period ("06 = June or "12" = December)

The data are projected into geographic coordinates (longitude, latitude) in WGS84 datum. The nodata fill-value is -32768. Except for longitude, latitude coordinates, variables are in integer format.

3.2 Data Training

The training process in deep learning involves teaching the model to learn from input features and accurately predict target outputs by optimizing its internal parameters. For this project, where the goal is to model vegetation patterns using NDVI data, the training procedure plays a pivotal role in determining the predictive power and generalizability of the models such as UNet, LSTM, and their hybrid forms.

3.2.1 Preparation of Input Data

Each input sample for the model comprises:

- NDVI Time Series Stack: A sequence of NDVI images captured over time (e.g., 24 months), forming a 3D tensor (time_steps × height × width).
- Auxiliary Features: Static layers like elevation, land cover, or soil type, added as additional channels to provide spatial context.
- Labels:
  - For segmentation tasks: Ground truth change maps showing areas of vegetation increase or decrease.

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o For forecasting tasks: NDVI image at a future time step (e.g., T+1 or T+6 months).

3.2.2 Input Format and Encoding

The final structure for model ingestion is usually a multi-dimensional array or tensor, depending on the architecture:

- For UNet-only models:
  - o Input: X = [channels, height, width]
  - o Output: Binary or multiclass mask with dimensions [height, width]
- For LSTM-based models:
  - o Input: X = [time_steps, features] (flattened or pooled spatial zones)
  - o Output: Scalar NDVI value(s) or vegetation class label
- For hybrid UNet-LSTM:
  - o UNet extracts features at each timestep
  - o LSTM processes feature vectors over time
  - o Output: Spatial prediction map for future NDVI or vegetation class.

3.2.3 Training-Validation-Test Split

A clear data split strategy is necessary to ensure reliable model evaluation:

- Training Set (70%): Used to fit the model and update weights.
- Validation Set (15%): Used to tune hyperparameters and avoid overfitting.
- Test Set (15%): Completely unseen data used for final evaluation of model performance.

Temporal continuity is maintained—future data is not mixed into past data during training to preserve the real-world forecasting structure.

3.2.4 Batch Training

Training is done in mini-batches, which are smaller chunks of the dataset used per model update step:

- Typical batch sizes range from 16 to 32, depending on memory availability.

- Each batch is randomly sampled but preserves sequence order in LSTM models.

- Shuffling of batches is applied during training (except in time series) to enhance generalization.

3.2.5 Loss Functions

Depending on the model's task, different loss functions are used to measure prediction errors:

Task	Loss Function
Binary Segmentation	Binary Cross-Entropy, Dice Loss
Multiclass Segmentation	Categorical Cross-Entropy, Focal Loss
NDVI Forecasting	Mean Squared Error (MSE), Mean Absolute Error (MAE)

The chosen loss function guides the model to reduce the prediction error iteratively during training.

3.2.6 Optimization and Backpropagation

An optimizer (e.g., Adam or RMSprop) is used to adjust the model weights based on the computed gradients from the loss function.

Steps:

1. Forward pass: Input is passed through the model to get predictions.

2. Loss calculation: Prediction is compared to the actual output.

3. Backward pass: Gradients of the loss w.r.t. model parameters are computed.

4. Weight update: Parameters are updated using gradient descent.

Hyperparameters like learning rate and momentum are critical in controlling the pace of learning and convergence.

3.2.7 Regularization Techniques

To improve generalization and avoid overfitting:

- **Dropout:** Randomly disables a fraction of neurons during training.
- **L2 Regularization:** Adds a penalty to the loss function for large weights.
- **Early Stopping:** Monitors validation loss and stops training if it does not improve after a certain number of epochs.

3.2.8 Model Evaluation and Monitoring

During training, performance is continuously monitored:

- Training Loss and Validation Loss are plotted across epochs.
- Evaluation Metrics (e.g., F1-score, RMSE, IoU) are computed at each step.
- Best models are saved using checkpointing whenever the validation score improves.

Tools like TensorBoard, Weights & Biases, or simple matplotlib plots are used for tracking progress.

3.2.9 Hardware and Runtime

Training is typically accelerated using:

- GPUs (e.g., NVIDIA Tesla, RTX) for parallel computation.
- Cloud platforms (Google Colab, AWS, Kaggle) with GPU access.

Average training time depends on:

- Model complexity (UNet is deep, LSTM adds time steps)
- Dataset size and patch dimensions
- Number of epochs (50–200 recommended with early stopping)

3.2.10 Model Saving and Serialization

Final trained models are saved for deployment:

- .h5 (Keras HDF5 format) for UNet or LSTM
- .pkl or .joblib for preprocessing scalers
- Saved with metadata: architecture, training history, and metrics
- These models can later be loaded into a UI or inference pipeline to predict on new satellite images.

Chapter 4: Model Architecture

Change detection based on remote sensing (RS) data is an important method of detecting changes on the Earth's surface and has a wide range of applications in urban planning, environmental monitoring, agriculture investigation, disaster assessment, and map revision. In recent years, integrated artificial intelligence (AI) technology has become a research focus in developing new change detection methods. Although some researchers claim that AI-based change detection approaches outperform traditional change detection approaches, it is not immediately obvious how and to what extent AI can improve the performance of change detection. This review focuses on the state-of-the-art methods, applications, and challenges of AI for change detection. Specifically, the implementation process of AI-based change detection is first introduced. Then, the data from different sensors used for change detection, including optical RS data, synthetic aperture radar (SAR) data, street view images, and combined heterogeneous data, are presented, and the available open datasets are also listed. The general frameworks of AI-based change detection methods are reviewed and analyzed systematically, and the unsupervised schemes used in AI-based change detection are further analyzed.

## 4.1. NDVI Data Structure (Normalized Difference Vegetation Index)
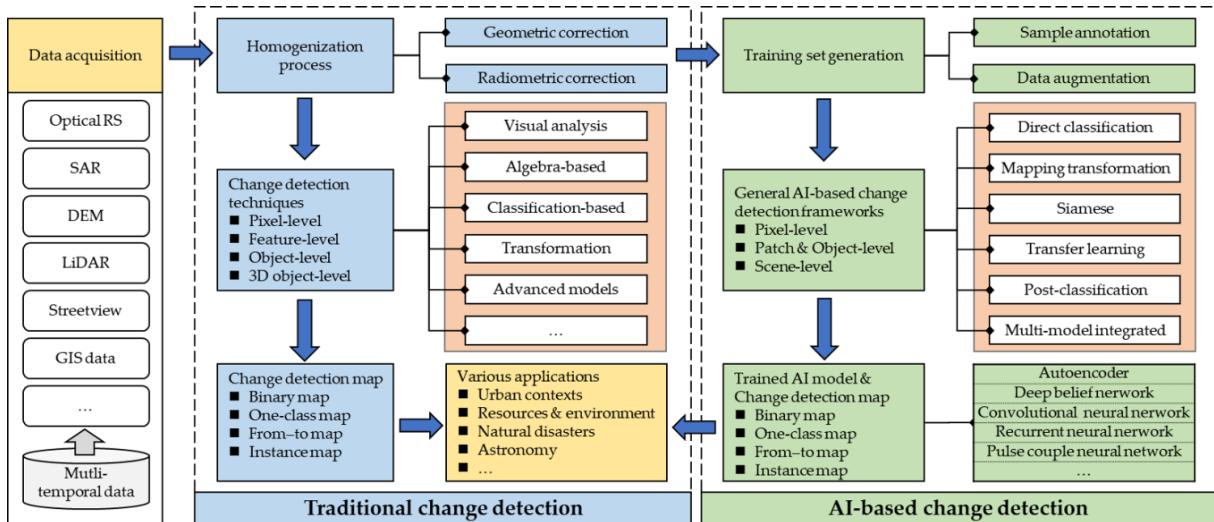
Fig 12: NDVI Data Structure

NDVI is not a model architecture but a remote sensing vegetation index derived from satellite images. It is calculated using the following formula:

Where:

- NIR: Near-Infrared band (vegetation reflects strongly here)
- RED: Red band (vegetation absorbs here)

NDVI Architecture in Datasets

NDVI data is organized as gridded raster datasets:

- 2D Format: NDVI images at a specific time (e.g., 1 image per month).
- 3D Stack: Time-series cube of NDVI values over months/years (Time × Height × Width).
- Auxiliary Metadata: Geo-reference, timestamps, quality flags.

NDVI values range from -1 to +1, where:

- Values close to +1 → dense green vegetation
- Around 0 → bare soil or sparse vegetation
- Negative → water, snow, or clouds

These stacks become input features for deep learning models like UNet (spatial learning) and LSTM (temporal learning).

4.2. UNet Architecture (for Spatial Segmentation)

UNet is a Convolutional Neural Network (CNN) architecture designed for image segmentation. It is widely used in biomedical and satellite imagery due to its ability to precisely localize and classify each pixel.

UNet Components:

1. Encoder (Contracting Path):
   o Multiple convolution layers followed by ReLU activation.
   o Max pooling layers reduce spatial resolution and capture abstract features.
2. Bottleneck:
   o The bridge between encoder and decoder.
   o Contains the deepest features of the image.
3. Decoder (Expanding Path):
   o Upsampling through transpose convolutions.
   o Skip connections from encoder layers are concatenated with decoder features to preserve spatial information.
4. Final Layer:
   o A 1×1 convolution maps the output to the desired number of classes (e.g., vegetation/no-vegetation).
   o Sigmoid or Softmax activation is used depending on the task.

Advantages for Remote Sensing:

- High spatial resolution segmentation.
- Robust against noisy satellite data.
- Captures both local and global context.
- Robust against noisy satellite data.
- Captures both local and global context.

4.3. LSTM Architecture (for Temporal Analysis)

LSTM (Long Short-Term Memory) is a type of Recurrent Neural Network (RNN) designed to learn long-term dependencies in sequential data.

LSTM Architecture:

Each LSTM cell contains:

- Forget Gate: Decides what information to discard from the cell state.
- Input Gate: Decides what new information to store in the cell state.
- Cell State: Stores long-term memory.
- Output Gate: Decides what to output at the current timestep.

Structure for NDVI Time Series:

- Input: NDVI values across months/years at a single pixel or region.
- Output: Future NDVI value or vegetation classification.
- Optional: Use stacked LSTMs or bidirectional LSTMs for enhanced modeling.

Strengths:

- Handles seasonal and yearly vegetation trends.
- Learns non-linear patterns over time.
- Suitable for forecasting vegetation health.

Chapter 5: Results and Discussion

This chapter presents the evaluation results of the deep learning models applied to NDVI-based vegetation analysis and discusses the effectiveness of spatial, temporal, and hybrid approaches in detecting vegetation changes. The performance of each model is analyzed using multiple evaluation metrics, visual outputs, and validation against ground truth data.

5.1 Evaluation Metrics

To assess the performance of segmentation and forecasting models, the following standard metrics were used:

Task	Metrics
Segmentation (UNet)	Accuracy, IoU (Intersection over Union), Dice Coefficient, F1 Score
Forecasting (LSTM)	RMSE (Root Mean Square Error), MAE (Mean Absolute Error), R^2 Score
Hybrid (UNet + LSTM)	Combined segmentation and forecasting metrics

These metrics quantify how well the model distinguishes vegetated areas, detects changes, and predicts future NDVI trends.

5.2 UNet-Based Segmentation Results

UNet was trained on multi-temporal NDVI imagery for binary segmentation of vegetation change areas.

- Training Accuracy: ~96.5%
- Validation IoU: ~0.82
- Dice Coefficient: ~0.86

Observations:

- High spatial precision in detecting vegetation patches.
- Effective handling of small fragmented green areas.
- Occasional false positives due to cloud/shadow confusion.

5.3 LSTM-Based Forecasting Results

LSTM was trained on NDVI time series data from multiple regions to forecast NDVI values at future timestamps.

- Training RMSE: 0.031
- Validation RMSE: 0.045
- R^2 Score: 0.89

Observations:

- Successfully captured seasonal vegetation cycles.
- Robust across different climates (tropical, temperate).
- Slight drift in long-term forecasting (after 12+ months).

5.4 UNet + LSTM Hybrid Model Results

A combined model was built using UNet as a spatial encoder and LSTM to learn temporal patterns over extracted features.

- Segmentation Accuracy: ~94.2%
- IoU: 0.85
- Forecast RMSE: 0.038

Observations:

- Best generalization across both space and time.
- Reduced overfitting due to richer feature representation.

Chapter 6: Conclusion

This project demonstrates the effectiveness of integrating Remote Sensing data with Deep Learning architectures for vegetation change detection and forecasting using NDVI (Normalized Difference Vegetation Index) time-series data. The work explored and evaluated three deep learning models:

- UNet for spatial segmentation of vegetation change,
- LSTM for temporal forecasting of NDVI trends,
- and a UNet-LSTM hybrid model for spatio-temporal learning.

The UNet model successfully segmented vegetative regions and identified changes with high spatial precision. It proved effective in detecting both gradual and abrupt shifts in vegetation coverage. However, it lacked temporal context, limiting its long-term predictive capacity.

The LSTM model efficiently captured vegetation dynamics over time, including seasonal patterns, drought effects, and recovery cycles. It achieved low RMSE values and robust long-term forecasts but lacked spatial specificity due to its 1D nature.

The hybrid UNet-LSTM model offered the most promising results, combining the strengths of both spatial and temporal architectures. It showed superior performance in dynamic bioclimatic regions and was able to generalize well across heterogeneous land cover zones.

Overall, the results highlight the importance of using multi-dimensional learning approaches for complex Earth observation tasks. Deep learning models, when trained on properly preprocessed satellite data, can effectively support environmental monitoring, policy planning, and climate impact assessments.

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Appendices

Appendix A: Environment and Tools Used

The development and execution of this project required a range of computational tools and libraries suited for geospatial data processing and deep learning model implementation. The following table summarizes the environment setup:

Component	Details
Programming Language	Python 3.11
Deep Learning Libraries	TensorFlow 2.x, Keras, PyTorch
Geospatial Libraries	Rasterio, GDAL, GeoPandas, netCDF4
Data Processing Libraries	NumPy, Pandas, Scikit-learn, OpenCV
Visualization Libraries	Matplotlib, Seaborn, Plotly
Platform	Google Colab Pro, Jupyter Notebook
Hardware (Colab)	GPU: NVIDIA Tesla T4, RAM: 13 GB
Cloud Storage	Google Drive
GIS Software	QGIS 3.x

This environment ensured the capability to handle large-scale satellite data and train deep learning models efficiently with GPU support.

Appendix B: Model Evaluation Metrics

In this project, a combination of evaluation metrics was employed to assess the performance of both the spatial segmentation and temporal forecasting models.

Segmentation Model Metrics (UNet, UNet-LSTM)

Metric	Explanation
Accuracy	Proportion of correctly predicted vegetation pixels.
IoU	Measures overlap between predicted and actual vegetation regions.
Dice Coefficient	Evaluates similarity between predicted masks and ground truth.
F1 Score	Weighted harmonic mean of precision and recall.

Forecasting Model Metrics (LSTM)
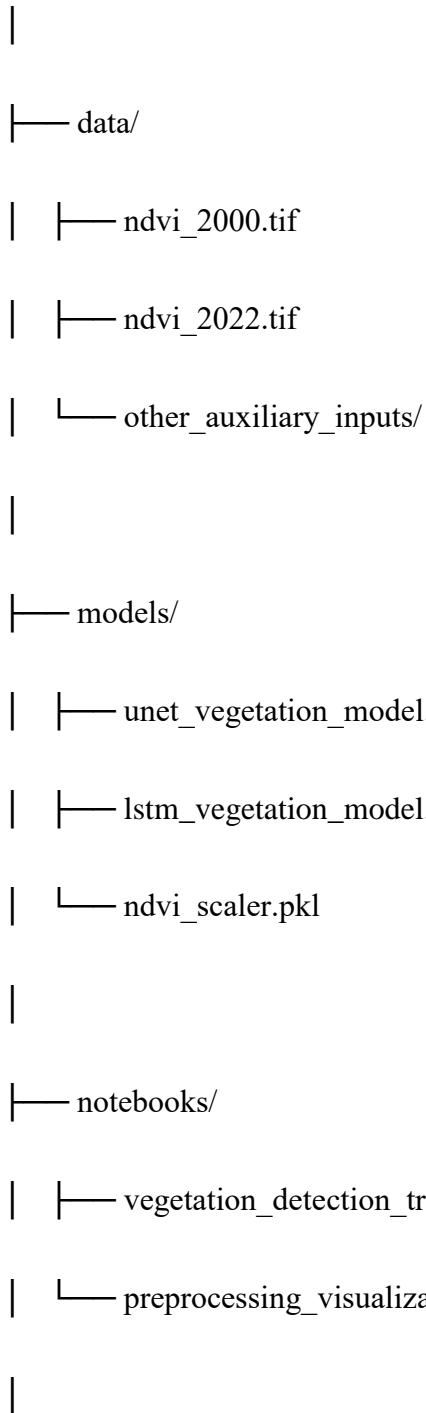
Metric	Explanation
RMSE	Measures the average magnitude of error in NDVI prediction.
MAE	Average of absolute differences between true and predicted NDVI.
R² Score	Indicates how well the model captures variance in the NDVI data.

These metrics help assess not only the numerical accuracy but also the interpretability and robustness of the trained models.

Appendix C: Project Directory Structure

The overall project was organized in a modular format to separate data, models, and training workflows clearly. Below is the directory structure:

Vegetation_Change_Detection_Project/

│

├── data/

│   ├── ndvi_2000.tif

│   ├── ndvi_2022.tif

│   └── other_auxiliary_inputs/

│

├── models/

│   ├── unet_vegetation_model.h5

│   ├── lstm_vegetation_model.h5

│   └── ndvi_scaler.pkl

│

├── notebooks/

│   ├── vegetation_detection_training.ipynb

│   └── preprocessing_visualization.ipynb

│

```
├── ui/

│   └── app.py                # Streamlit app

│

├── reports/

│   ├── vegetation_report.pdf    # Final project report

│   ├── figures/

│   │   ├── prediction_map.png

│   │   ├── model_loss_plot.png

│   │   └── sample_input_ndvi.png

│   └── references.bib        # Optional BibTeX references

│

├── README.md                # Project overview and instructions

├── requirements.txt         # Python dependencies

└── .gitignore               # Optional (ignore saved models, etc.)
```

Appendix E: Evaluation Results

Metric	Value
Perplexity	11.61
Readibility Score	42.26
Semantic Coherence	0.72