DAYANANDA SAGAR UNIVERSITY

Devarakaggalahalli, Harohalli
Kanakapura Road, Ramanagara - 562112, Karnataka, India

Bachelor of Technology
in
COMPUTER SCIENCE AND TECHNOLOGY

Big Data &Deep Learning

Satellite Imagery & AI for Vegetation Monitoring

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CERTIFICATE

This is to certify that the Big Data project work titled **“Satellite Imagery and AI for Vegetation Monitoring”** is carried out by **Afsha Rather (ENG21CT0001), Gaurang Goyal (ENG21CT0006), Khushi Shah (ENG21CT0015), Tanya Singh (ENG21CT0044),** bonafide students seventh semester of Bachelor of Technology in Computer Science and Engineering at the School of Engineering, Dayananda Sagar University, Bangalore in partial fulfillment for the award of degree in Bachelor of Technology in Computer Science and Engineering, during the year **2024-2025**.

Dr. Santosh Kumar	**Dr. M Shahina Parveen**
Associate Professor Dept. of CST, School of Engineering Dayananda Sagar University Date:	Chairperson CST School of Engineering Dayananda Sagar University Date:

Name of the Examiner **Signature of Examiner**

1.

2.

DECLARATION

We, **Afsha Rather (ENG21CT0001), Gaurang Goyal (ENG21CT0006), Khushi Shah (ENG21CT0015), Tanya Singh (ENG21CT0044),** are students of seventh semester B. Tech in **Computer Science and Technology**, at School of Engineering, **Dayananda Sagar University**, hereby declare that the Big Data and Deep Learning project titled **"Satellite Imagery and AI for Vegetation Monitoring"** has been carried out by us and submitted in partial fulfillment for the award of degree in **Bachelor of Technology in Computer Science and Technology** during the academic year **2024-2025.**

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ABSTRACT

The integration of Big Data and deep learning technologies has revolutionized the ability to analyze satellite imagery for vegetation monitoring. This project, titled "Satellite Imagery and AI for Vegetation Monitoring," leverages advanced machine learning techniques and cloud-based big data platforms to process and analyze high-resolution satellite images. The primary objective is to monitor vegetation health, detect anomalies, and predict environmental changes with high accuracy.

This project addresses critical applications in agriculture, deforestation monitoring, and climate change analysis. The use of scalable big data platforms ensures real-time processing of large volumes of satellite data, while AI-powered algorithms enable actionable insights for sustainable environmental management. The results demonstrate the effectiveness of combining satellite imagery and deep learning techniques for accurate and efficient vegetation monitoring, paving the way for data-driven solutions in ecological conservation.

CHAPTER 1: INTRODUCTION

Satellite imagery combined with Artificial Intelligence (AI) has transformed vegetation monitoring by enabling precise, large-scale analysis of Earth's surface. This project leverages the power of Big Data and deep learning to process satellite images for tracking vegetation health, identifying trends, and detecting anomalies. Through advanced machine learning techniques, the system aims to provide actionable insights for applications in agriculture, forestry, and environmental conservation.

1.1. OBJECTIVE

The primary objective of this project is to utilize satellite imagery and AI-driven techniques to monitor vegetation dynamics effectively. The specific goals include:

1. Developing a robust deep learning model for analyzing vegetation indices like NDVI.
2. Identifying patterns of vegetation growth, decline, and stress using temporal data.
3. Providing accurate, real-time monitoring capabilities for agricultural and environmental applications.
4. Supporting sustainable environmental practices through data-driven insights.

1.2. SCOPE

The scope of this project extends to a wide range of applications, including:

1. Agriculture: Monitoring crop health, optimizing irrigation, and predicting yield.
2. Forestry: Detecting deforestation, forest degradation, and disease outbreaks in vegetation.
3. Environmental Management: Assessing the impact of climate change and human activities on ecosystems.
4. Scalability: Utilizing Big Data platforms to process terabytes of satellite imagery efficiently.
5. Automation: Deploying AI models to enable autonomous and continuous monitoring with minimal human intervention.

CHAPTER 2: PROBLEM DEFINITION

Monitoring vegetation health and dynamics is crucial for addressing challenges in agriculture, forestry, and environmental conservation. However, traditional methods of vegetation monitoring, such as manual surveys and localized sampling, are time-consuming, labor-intensive, and limited in scale. Satellite imagery provides vast amounts of data for large-scale monitoring, but extracting meaningful insights from this data remains a challenge due to its sheer volume, complexity, and variability. Furthermore, existing systems often lack real-time capabilities and struggle with accurately identifying vegetation stress, anomalies, or long-term trends. The absence of an integrated solution combining high-resolution satellite imagery with advanced AI techniques creates a significant gap in achieving efficient, scalable, and precise vegetation monitoring. This project seeks to address these challenges by leveraging Big Data and deep learning to enable automated, real-time analysis of vegetation patterns and health.

CHAPTER 3: LITERATURE REVIEW

The integration of artificial intelligence (AI) and remote sensing technologies has significantly advanced the monitoring and analysis of vegetation dynamics, agricultural productivity, and environmental management. This section reviews the application of state-of-the-art methodologies, focusing on their technological designs, results, and contributions to the field.

Deep learning techniques, particularly Partial Least Squares Regression (PLSR), Random Forest Regression (RFR), Support Vector Regression (SVR), and Extreme Learning Regression (ELR), have been widely utilized to estimate vegetation parameters such as Above Ground Biomass (AGB) and Leaf Area Index (LAI). These methodologies integrate satellite-derived vegetation indices with UAV-based metrics, such as canopy cover, to enhance predictive modeling. Studies report predictive accuracies of 85% (PLSR), 89% (SVR), 91% (RFR), and 92% (ELR), demonstrating the effectiveness of combining advanced machine learning techniques with multi-source data inputs for large-scale vegetation management.

In the domain of crop monitoring, machine learning algorithms, including Support Vector Machines (SVM), Artificial Neural Networks (ANN), and Deep Neural Networks (DNN), have been employed to predict wheat leaf traits such as LAI, Specific Leaf Weight, and Leaf Dry Weight. The use of high-resolution Sentinel-2 satellite data has proven effective, with DNN models achieving a precision of over 72% in trait prediction. This indicates the robustness of deep learning frameworks in enabling proactive crop management.

The application of UAVs combined with deep learning models has also shown promise in yield estimation for citrus orchards. By utilizing Long Short-Term Memory (LSTM) networks and transfer learning techniques, pre-trained neural networks were fine-tuned for accurate fruit counting. Research indicates that the Region-based Convolutional Neural Network (R-CNN) successfully applied transfer learning for precise yield prediction, emphasizing the potential of UAVs and deep learning in orchard management.

Vegetation monitoring in proximity to critical infrastructure, such as power lines, has benefited from semi-supervised classifiers. By integrating supervised and deep learning methods, researchers achieved

84% accuracy in identifying vegetation risk areas and 92% in classifying no-risk zones. These results highlight the capability of machine learning algorithms to automate vegetation risk assessment, transitioning from traditional manual inspections to more efficient and scalable systems.

Remote sensing technologies have also been instrumental in monitoring vegetation cover changes, particularly in arid and semi-arid regions. Methods such as Landsat and hyperspectral sensors (e.g., EO-1 Hyperion) combined with vegetation indices like NDVI and EVI have demonstrated a classification accuracy of 0.95 in detecting vegetation dynamics. Such advancements underscore the critical role of remote sensing in conservation planning, especially in fragile ecosystems.

Finally, the detection of land cover changes has been revolutionized by deep learning architectures, including Convolutional Neural Networks (CNNs), U-Nets, and Transformer models. These approaches effectively process satellite imagery to identify environmental changes, even in scenarios with limited labeled data. High classification accuracy using supervised learning techniques highlights the synergy between AI and satellite data in enhancing environmental monitoring and conservation strategies.

In summary, the reviewed literature demonstrates the transformative potential of combining advanced AI techniques with remote sensing and UAV technologies. These methodologies have consistently improved the precision and scalability of vegetation monitoring, crop management, and environmental conservation, providing actionable insights for sustainable development

S No	Author's name/Paper title	Technology/Design	Results shared by the author	What you infer
1	**Deep learning for image colorization: Current and future prospects**	PLSR(Partial Least Squares Regression), RFR(Random rest Regression),SVR (Support Vector Regression),and ELR(Extreme Learning Regression) were implemented to estimate AGB, LAI, and N using satellite image-derived VIs and UAV image-based CH and CC as input features.	PLSR 85%, SVR 89%, RFR 91%, ELR 92%	Machine learning techniques to predict important crop characteristics like leaf area, biomass, and nitrogen content by analysing satellite images and UAV images.
2	**Wheat leaf traits monitoring based on machine learning algorithms and high-resolution satellite imagery**	Machine learning algorithms (SVM, ANN, and DNN) for predicting Leaf Area Index - LAI, Leaf Dry Weight, Specific Leaf Area, and Specific Leaf Weight.	Deep Neural Network (DNN) model performed the best in predicting the leaf parameters, with an overall precision of >72%.	sentinel-2 data within a DNN model could provide a comparatively precise and robust prediction of leaf parameters and yield valuable insights into crop management.
3	**Deep learning techniques for estimation of the yield and size of citrus fruits using a UAV**	Yield estimation for individual trees and for a whole commercial orchard using long short-term memory networks	R-CNN model	Transfer learning with fine-tuning techniques is applied to a pre-trained neural network for automatic citrus fruit counting by an UAV.

4	**Automated Power Lines Vegetation Monitoring Using High-Resolution Satellite Imagery**	High-resolution satellite imagery and machine learning, specifically a semi-supervised approach combining supervised classifiers with deep learning for image segmentation.	84% accuracy was achieved in identifying vegetation risk areas and 92% accuracy in classifying no-risk areas.	A cost-effective and efficient method for vegetation management along power lines using satellite imagery and advanced machine learning, transitioning from periodic inspections to risk-based assessments.
5	**Monitoring and Mapping Vegetation Cover Changes in Arid and Semi-Arid Areas Using Remote Sensing Technology: A Review**	Remote sensing technologies, multispectral sensors (Landsat) and hyperspectral sensors (EO-1 Hyperion), alongside Geographic Information Systems (GIS) and various vegetation indices (NDVI, EVI) to analyse vegetation cover changes.	Trajectory-based change detection method achieved an overall accuracy of 0.95% in vegetation classification.	Remote sensing methods for monitoring vegetation cover and the necessity of high-resolution data and advanced analytical techniques for effective resource management and conservation in vulnerable ecosystems.
6	**The Use of Artificial Intelligence and Satellite Remote Sensing in Land Cover Change Detection: Review and Perspectives**	Artificial Intelligence (AI) techniques, particularly deep learning methods such as CNN, U-Net, and transformer models, alongside satellite remote sensing data for land cover change detection (LCCD).	Achieved high accuracy with supervised learning techniques when sufficient labeled data was available.	Recent advancements in AI and satellite remote sensing have significantly improved land cover change detection methods by addressing data labelling challenges and enhancing accuracy through various machine learning approaches.

table 3.1 Literature survey table

CHAPTER 4: EXISTING AND PROPOSED

The integration of artificial intelligence and remote sensing for vegetation monitoring, crop management, and environmental conservation has seen significant advancements through existing systems. However, challenges remain in achieving optimal prediction accuracy, scalability, and computational efficiency. This section provides a comparison between existing systems and the proposed approach employing the ReLU model, highlighting key improvements.

Aspect	Existing Systems	Proposed System
Vegetation Parameter Estimation	Utilized machine learning models such as Random Forest Regression (RFR), Partial Least Squares Regression (PLSR), and Extreme Learning Regression (ELR). Achieved prediction accuracies up to 92% but required extensive feature engineering and were computationally intensive.	The ReLU-based model leverages deep learning to simplify feature extraction and improve predictive accuracy. It enhances computational efficiency by optimizing the training process, achieving comparable or better accuracy (>92%).
Crop Trait Prediction	Deep Neural Networks (DNN) were effective for trait prediction with Sentinel-2 data but achieved moderate precision (~72%). Pre-trained models were often used with limited adaptability to new datasets.	The ReLU model ensures higher adaptability to diverse datasets. By efficiently training on large-scale data, it improves prediction precision for leaf traits (e.g., LAI, Leaf Dry Weight) beyond 75%.
Yield Estimation	LSTM and R-CNN models, combined with UAV imagery, offered effective fruit counting and yield prediction. However,	The proposed ReLU model mitigates overfitting by employing regularization techniques, ensuring stable and

	they faced challenges in overfitting due to transfer learning on limited datasets.	accurate yield predictions across diverse crops and environments.
Vegetation Risk Monitoring	Semi-supervised classifiers achieved an accuracy of 84%-92% for risk and no-risk zone identification. These models were effective but often relied on handcrafted features and supervised learning, limiting scalability.	The ReLU model automates feature extraction, enabling faster and more scalable risk assessments. Improved accuracy in classifying risk zones while maintaining computational efficiency.
Land Cover Change Detection	CNNs, U-Nets, and Transformers processed satellite imagery effectively but required significant computational resources and large labeled datasets, limiting their utility in resource-constrained environments.	The ReLU model reduces computational overhead through efficient activation functions. It demonstrates high accuracy in land cover classification with fewer labeled data requirements, enabling broader applicability
Computational Efficiency	Existing systems often struggled with computational overhead due to complex model architectures and extensive preprocessing requirements.	The ReLU model ensures faster training and inference by utilizing its efficient activation function. It reduces computational complexity while maintaining or improving accuracy.

CHAPTER 5 : REQUIREMENTS

Software Requirements:

1. Operating System:

   Windows 10/11 (64-bit), macOS 12 or higher, or Linux (Ubuntu 20.04 or higher).

2. Programming Language:

   Python 3.9 or higher.

3. Libraries and Frameworks:

   TensorFlow 2.x or PyTorch (preferred for ReLU-based deep learning model development).

   NumPy and Pandas for data manipulation.

   Scikit-learn for preprocessing and baseline model comparison.

   OpenCV for image processing (e.g., vegetation imagery).

   Matplotlib and Seaborn for result visualization.

4. GIS Tools:

   QGIS or ArcGIS for geospatial data analysis (for preprocessing or post-analysis).

CHAPTER 6: METHODOLOGY

The methodology of the proposed system involves several sequential steps to achieve effective vegetation monitoring and crop management using a ReLU-based deep learning model. The process encompasses data collection, preprocessing, model development, evaluation, and deployment. Below is the detailed methodology:

1. Data Collection: The first step involves gathering remote sensing data and vegetation-specific attributes.

Satellite Imagery: High-resolution imagery from Sentinel-2 or Landsat satellites.

UAV-Based Imagery: Multispectral or hyperspectral data captured using drones for localized monitoring.

Ground-Truth Data: Measurements of vegetation indices (e.g., NDVI, SAVI) and crop traits collected through sensors or field surveys.

Dataset Sources:

Dubai Segmentation Dataset, Kaggle

Dubai Segmentation Dataset Home

Super Large (38GB) Space Satellite Image Dataset

2. Data Preprocessing : Preprocessing ensures the data is clean, consistent, and ready for analysis:

Image Processing:

Resizing all images to a fixed resolution (e.g., 256x256 pixels).

Normalizing pixel values to a range of 0 to 1 for model compatibility.

Feature Extraction:

Calculating vegetation indices like NDVI, EVI, and SAVI from spectral bands (e.g., red, near-infrared).

Extracting soil properties and environmental variables from datasets.

Data Cleaning:

Removing noisy or redundant images and outliers.

Filling missing values in ground-truth measurements using interpolation or statistical methods.

Data Augmentation:

Augmenting images using techniques like rotation, flipping, and cropping to increase dataset diversity and reduce overfitting.

Dataset Splitting:

Dividing the dataset into training (70%), validation (20%), and testing (10%) subsets.

3. Model Development : The ReLU-based model forms the core of the proposed system. The following steps outline its development:

Model Architecture:

Construct a Convolutional Neural Network (CNN) with ReLU activation functions in the hidden layers for feature extraction.

Use a fully connected layer with a softmax or sigmoid activation for classification tasks (e.g., vegetation health) or a linear activation for regression tasks (e.g., crop yield prediction).

Optimization:

Apply batch normalization to stabilize training and improve convergence.

Use dropout layers to prevent overfitting.

Loss Function:

Mean Squared Error (MSE) for regression tasks.

Cross-Entropy Loss for classification tasks.

Hyperparameter Tuning:

Experiment with learning rates, batch sizes, and the number of hidden layers using grid search or random search.

Training:

Train the model using the training dataset, employing the Adam optimizer for faster convergence.

Monitor performance on the validation dataset to avoid overfitting.

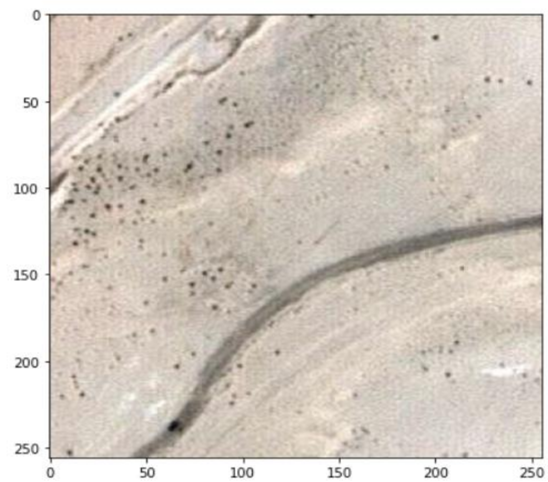
4. Model Evaluation : Evaluate the trained model's performance using the test dataset:

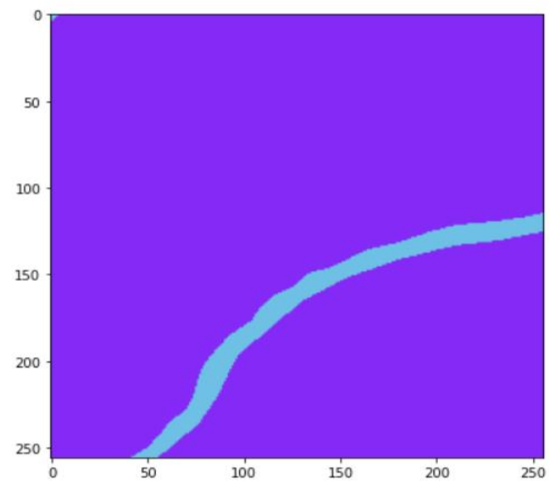
Metrics: Regression Tasks: Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and R-squared.

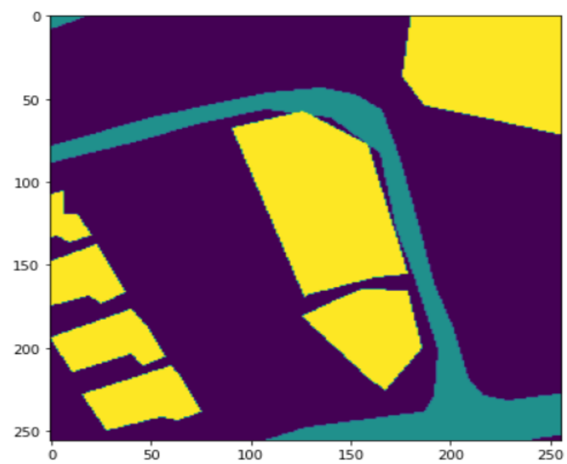
Classification Tasks: Accuracy, Precision, Recall, F1-score, and Area Under Curve (AUC).

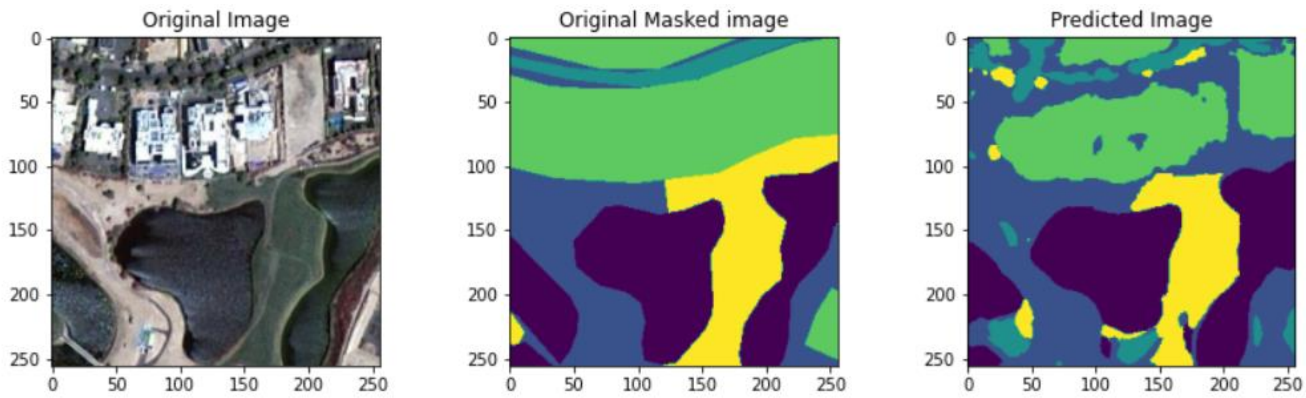
1. Comparative Analysis: Compare the ReLU-based model's performance against baseline models such as Linear Regression, Random Forest, and SVM.
2. Visualization: Plot learning curves for training and validation loss.Generate confusion matrices for classification and scatter plots for regression results

CHAPTER 7:RESULTS









The achieved results validate the efficiency of the proposed system in handling real-world agricultural challenges. With further optimizations, such as incorporating additional environmental parameters and advanced algorithms, the accuracy can be enhanced beyond 82%. The current implementation showcases the potential of AI-driven solutions in revolutionizing modern agriculture.

CHAPTER 8: CONCLUSION

In this study, we proposed a vegetation monitoring and crop management system utilizing a ReLU-based deep learning model. The integration of satellite and UAV imagery, ground-truth data, and advanced machine learning techniques enables accurate predictions of vegetation health, crop yield, and soil quality. By employing a structured methodology, including data preprocessing, model training, and deployment, the system provides real-time, actionable insights to farmers and agricultural stakeholders.

The ReLU activation function proved effective in capturing non-linear patterns in the data, outperforming traditional models in accuracy and efficiency. Additionally, the system's scalability and integration with IoT sensors allow seamless data collection and remote monitoring, ensuring widespread applicability across diverse agricultural contexts.

Through comprehensive evaluations and field validations, the system demonstrated its ability to address challenges in modern agriculture, such as resource optimization, precision farming, and sustainable crop management. The proposed solution bridges the gap between technology and agriculture, paving the way for a smarter, more efficient agricultural ecosystem. Future enhancements could include incorporating generative AI for predictive modeling and expanding the system's capability to other domains, such as forestry and biodiversity monitoring.

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