PhytoFusion: Deep Representation Learning for Intelligent Plant Phenotyping and Precision Agriculture

Budde Akshitha[1], Karramareddy Sharmila[2*], Ch. Shiva Sai Prasad[3]

[1]PG Student,[2]Associate Professor and Head, [3]Assistant Professor, [1,2,3]Department of Computer Science and Engineering

[1,2,3]Vaagdevi Engineering College, Warangal, 506005, Telangana, India.

[1] akshithabudde630@gmail.com, [3] chandragiri.shiva@gmail.com

*Correspondence: Karramareddy Sharmila(sharmilakreddy@gmail.com)

ABSTRACT

Agriculture has evolved from traditional manual farming practices to intelligent data-driven systems through the rapid advancement of digital technologies and Machine Learning (ML). Traditionally, farmers relied on field observations, experience, and statistical methods to monitor crop conditions and make agricultural decisions. However, the increasing availability of agricultural data collected from Internet of Things (IoT) sensors, weather stations, and satellite imagery has created the need for advanced analytical frameworks capable of processing large-scale and heterogeneous datasets. Conventional agricultural prediction systems often analyze classification and regression tasks independently, resulting in fragmented decision-making, lower prediction accuracy, and inefficient utilization of computational resources. To address these challenges, this research proposes a unified multi-task agricultural prediction framework based on the One Classification and Two Regression Tasks (1CA2RT) approach, which simultaneously performs crop disease classification, Normalized Difference Vegetation Index (NDVI) prediction, and harvest time estimation. The framework employs three existing Machine Learning models, namely Support Vector Machine (SVM)-1CA2RT, AdaBoost (AB)-1CA2RT, and Ridge (R)-1CA2RT, along with a proposed hybrid model named Echo State Network–Light Gradient Boosting Machine (ESN-LGBM)-1CA2RT. The proposed model combines the temporal feature-learning capability of the Echo State Network (ESN) with the efficient gradient boosting mechanism of the Light Gradient Boosting Machine (LGBM) to capture complex nonlinear relationships among soil properties, climatic conditions, and crop characteristics. The ESN generates dynamic reservoir state representations from sequential agricultural data, while the LGBM model utilizes these reservoir features to perform accurate classification and regression tasks with improved computational efficiency. Experimental evaluation demonstrates that the proposed ESN-LGBM-1CA2RT model achieves superior predictive performance compared with the existing baseline models, obtaining excellent classification accuracy along with highly accurate NDVI and harvest time predictions. The proposed framework provides an efficient, scalable, and reliable decision-support system for precision agriculture by integrating multiple prediction tasks within a single analytical architecture.

Key words: Echo state network (ESN), light gradient boosting machine (LGBM), multi-task learning, normalized difference vegetation index (NDVI), precision agriculture, predictive models.

1. INTRODUCTION

Vegetation indices have a crucial role in precision agriculture and crop monitoring by providing a straightforward and reliable assessment of the condition and health of crops [1]. Depending on the vegetation index, information on various aspects of plant growth and development can be monitored, such as chlorophyll content, leaf area, canopy structure, and water status, as shown in fig. 1. This

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information can then be used to optimize prescription rates in precision agriculture, such as variable fertilizer application, irrigation, and pesticide application [2]. This is generally performed by identifying intra-field zones that are underperforming or experiencing stress, and target inputs to those areas to improve crop productivity and yield.

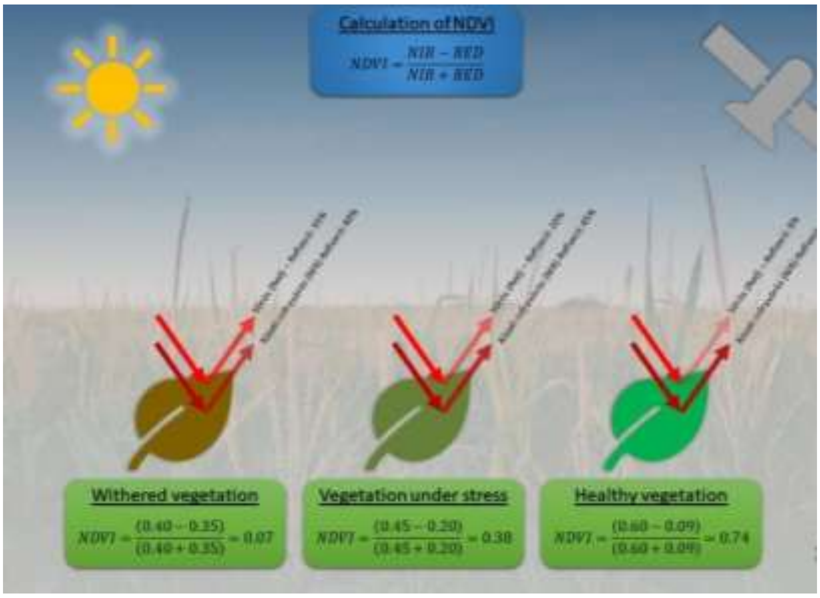

Fig. 1: Normalized difference vegetation index.

Vegetation indices also provide a cost-effective and non-destructive way of crop monitoring, ensuring a widely available and environmentally sustainable approach for assessing crop health [3]. The development of remote-sensing sensors for crop monitoring in both broadband and narrowband bands open immense possibilities for their combination into novel vegetation indices [4]. To date, this has led to the development of 519 total vegetation indices, per Index DataBase. While most of these indices serve a different purpose and have unique advantages and limitations according to sensor type and field conditions, the difficulty of objective assessment of their performance in crop-health monitoring arose. Achieving maximum crop yield at minimum cost is one of the goals of agricultural production. Early detection and management of problems associated with crop yield indicators can help increase yield and subsequent profit [5].

1.1 Research Objective

- To design and evaluate Support Vector Machine (SVM)-1CA2RT, AdaBoost (AB)-1CA2RT, and Ridge (R)-1CA2RT models for performing multi-task agricultural prediction on crop disease classification, NDVI prediction, and harvest time estimation.
- To develop the proposed Echo State Network–Light Gradient Boosting Machine (ESN-LGBM)-1CA2RT model to improve prediction performance for both classification and regression tasks by effectively learning complex agricultural data patterns.
- To compare the performance of SVM-1CA2RT, AB-1CA2RT, R-1CA2RT, and the proposed ESN-LGBM-1CA2RT model based on classification and regression performance metrics, computational efficiency, and overall prediction accuracy for multi-task agricultural analysis.

2. LITERATURE SURVEY

Nițu.A.et al. [6] investigated their distinctiveness and discriminative power in the context of applications for agriculture based on hyperspectral data. More precisely, this paper merges two complementary perspectives: an unsupervised analysis with PRISMA satellite imagery to explore whether these indices are truly distinct in practice and a supervised classification over UAV hyperspectral data.

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They assess their discriminative power, statistical correlations, and perceptual similarities. Tang, H.et al. [7] employed the latest Global Inventory Modelling and Mapping Studies (GIMMS) Normalized Difference Vegetation Index (NDVI4g), an updated version succeeding GIMMS NDVI3g spanning from 1982 to 2022.They integrated this dataset with the multiple scale Standardized Precipitation Evapotranspiration Index (SPEI 1 to 24) to investigate the spatial–temporal variability of sensitivity and lag in vegetation growth in response to water variability across China.Their findings indicate that over 83% of China's vegetation demonstrates positive sensitivity to water availability, with approximately 66% exhibiting a shorter response lag (lag < 1 month).

Kaya, F et al. [8] investigated the impact of spatial resolution on classifying three-year, multi-temporal vegetation indices derived from satellites with coarse (30 m, Landsat 8), medium (10 m, Sentinel-2), and fine spatial resolutions (3.7 m, PlanetScope). The classification was performed using the fuzzy c-means algorithm, with the fuzziness performance index (FPI) and normalized classification entropy (NCE), which were used to determine the optimal number of management zones (MZs). Aslan et al. [9] emphasized the need for comprehensive comparisons and more consistent methodologies in future research. Their work underscores the significant role of Sentinel-2 and AI in advancing precision agriculture, offering valuable insights for future studies that aim to enhance sustainability and efficiency in crop management through advanced predictive models.

He, Q. et al. [10] highlighted a considerable and widespread greening on the LP from 1982 to 2022, evidenced by a *kNDVI* slope of 0.0020 yr^{-1} ($p < 0.001$) and a 90.9% significantly increased greened area. The GTGP expedited this greening process, with the *kNDVI* slope increasing from 0.0009 yr^{-1} to 0.0036 yr^{-1} and the significantly greened area expanding from 39.1% to 84.0%. Vidican, R. et al. [11] showed that VIs appear to be suitable for mapping and monitoring agricultural crops, forage crops, meadows and pastures. Sentinel-1 and Sentinel-2 data were the most utilized sources, while some of the frequently used VIs were EVI, LAI, NDVI, GNDVI, PSRI, and SAVI. In most of the studies, an array of VIs needed to be employed to achieve a good discrimination of crops or prediction of yields.

Robinson, N.P. et al. [12] addressed this deficiency by producing a Landsat derived, high resolution (30 m), long-term (30+ years) NDVI dataset for the conterminous United States. They used Google Earth Engine, a planetary-scale cloud-based geospatial analysis platform, for processing the Landsat data and distributing the final dataset. They used a climatology driven approach to fill missing data and validate the dataset with established remote sensing products at multiple scales. Krakauer, N.Y. et al. [13] analyzed the normalized difference vegetation index (NDVI) from 1981 to 2015 semimonthly, at an 8 km spatial resolution. They used a random forest (RF) of regression trees to generate a statistical model of the NDVI as a function of elevation, land use, CO2 level, temperature, and precipitation. They found that the NDVI increased over the studied period, particularly at low and middle elevations and during the fall (post-monsoon).

Zhao, Q. et al. [14] addressed the limitations and meet the needs of vegetation monitoring research and remote-sensing NDVI validation, his study implemented a novel NDVI camera. The proposed camera incorporates narrowband dual-pass filters designed to precisely separate red and near-infrared (NIR) spectral bands, which are aligned with the configuration of sensors onboard satellites. Through software-controlled imaging parameters, the camera captures the real radiance of vegetation reflection, ensuring the acquisition of accurate NDVI values while preserving the evolving trends of the vegetation status. Eastman, J.R. et al. [15] used the Seasonal Trend Analysis (STA) procedure, over half (56.30%) of land

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surfaces were found to exhibit significant trends. Almost half (46.10%) of the significant trends belonged to three classes of seasonal trends (or changes). Class 1 consisted of areas that experienced a uniform increase in NDVI throughout the year, and was primarily associated with forested areas, particularly broadleaf forests. Class 2 consisted of areas experiencing an increase in the amplitude of the annual seasonal signal whereby increases in NDVI in the green season were balanced by decreases in the brown season. These areas were found primarily in grassland and shrubland regions.

3. PROPOSED METHODOLOGY

This research proposes a structured and intelligent framework for multi-task agricultural prediction by integrating one classification task and two regression tasks within a unified analytical architecture. The system utilizes agricultural datasets containing soil properties, environmental conditions, and crop-related parameters, which are processed through preprocessing, feature selection, and normalization to generate high-quality inputs for Machine Learning (ML) models. The framework simultaneously performs crop disease classification, Normalized Difference Vegetation Index (NDVI) prediction, and harvest time estimation using the One Classification and Two Regression Tasks (1CA2RT) approach. Initially, existing models such as Support Vector Machine (SVM)-1CA2RT, AdaBoost (AB)-1CA2RT, and Ridge (R)-1CA2RT are implemented to establish baseline performance. This research further introduces a hybrid model, Echo State Network–Light Gradient Boosting Machine (ESN-LGBM)-1CA2RT, which combines the temporal feature learning capability of ESN with the efficient boosting mechanism of LGBM to enhance prediction accuracy.

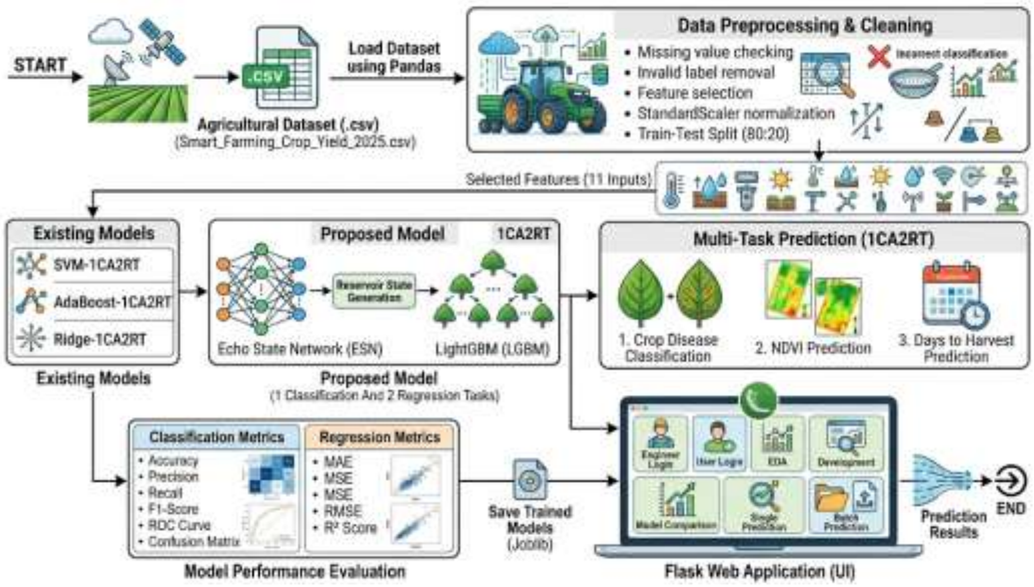

Fig. 2: Proposed system architecture agricultural decision system using recurrent polynomial network for multi-crop recommendation tasks.

Flask Web Server (app.py): The Flask backend receives user requests and routes them to appropriate modules. It manages authentication, session handling, prediction workflows, and data visualization. The server coordinates communication between the user interface, ML models, and the database. It also handles model loading, saving, and triggering retraining when required.

SQLite Database (agriculture.db): The database stores persistent information such as user credentials and registration details. It ensures secure storage of user data using encrypted passwords. The Flask server interacts

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with the database for authentication and data retrieval. It provides efficient and lightweight data management for system operations.

Raw Data (CSV Input): The agricultural dataset serves as the primary input source for analysis. It contains features such as soil moisture, soil pH, temperature, rainfall, humidity, sunlight hours, pesticide usage, yield, latitude, and longitude. This data is fed into the preprocessing pipeline for further analysis.

Data Preprocessing & Feature Extraction (ml_models.py): The dataset undergoes cleaning, normalization, and transformation to ensure high-quality inputs. Numeric features are standardized using scaling techniques to maintain feature parity. Irrelevant or inconsistent data is handled to prevent noise from affecting model performance. Feature vectors are generated and passed to the various ML models.

Prediction Results & Target Output: The system generates precise predictions for three essential agricultural targets:

- **Target 1:** Crop Disease Status
- **Target 2:** NDVI Index
- **Target 3:** Days to Harvest

- Results and model-wise comparisons are displayed in an intuitive format on the user interface.

4. RESULTS AND DISCUSSION

The implementation of the proposed agricultural prediction framework follows a structured workflow that integrates data preprocessing, Machine Learning (ML), and web-based deployment within a unified execution environment. The system performs One Classification and Two Regression Tasks (1CA2RT) using existing models and the proposed Echo State Network–Light Gradient Boosting Machine (ESN-LGBM)-1CA2RT model. Standardized agricultural features are processed through the ESN to generate dynamic reservoir state representations, which are utilized by the LightGBM model for accurate classification and regression. The Flask-based web application provides secure user interaction, prediction services, and visualization of analytical results. This implementation ensures efficient computation, improved prediction accuracy, and scalable deployment for intelligent agricultural decision support.

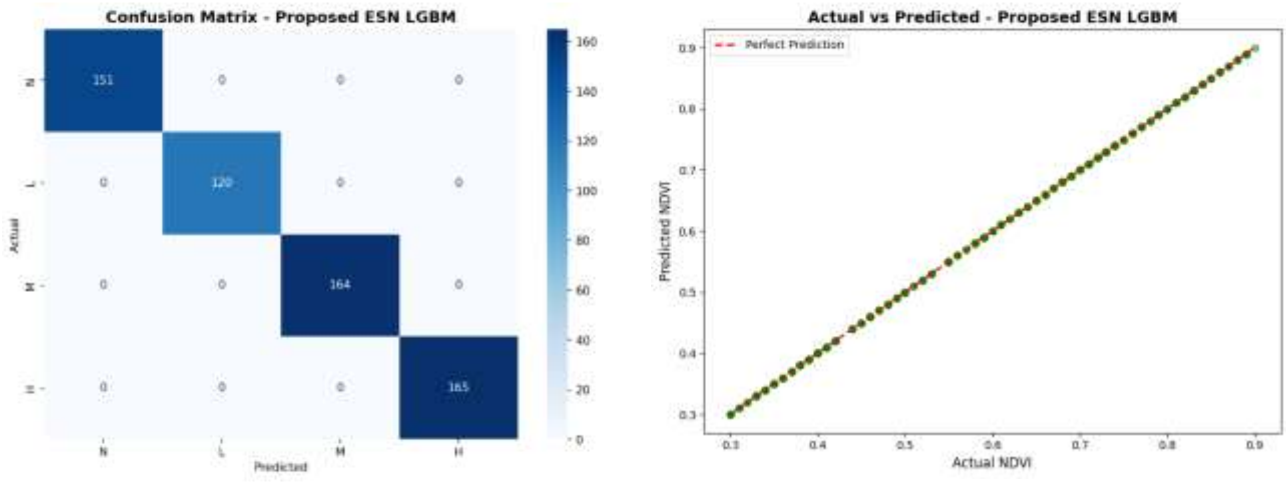

Fig. 3: Presents performance metrics of proposed ESN-LGBM model

Fig. 3 presents the performance evaluation results of the proposed Echo State Network–Light Gradient Boosting Machine (ESN-LGBM)-1CA2RT model. The figure demonstrates superior classification and regression performance compared with the existing baseline models by achieving higher prediction accuracy and lower error values. The

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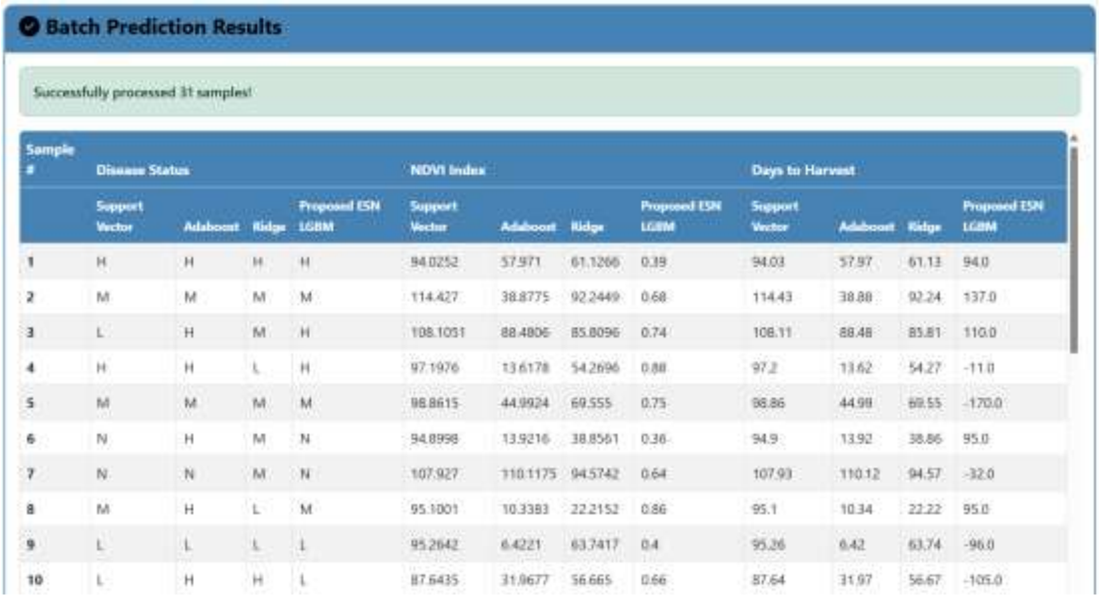
integration of the Echo State Network (ESN) effectively extracts dynamic reservoir feature representations, while the Light Gradient Boosting Machine (LGBM) performs efficient classification and regression using these optimized features. The obtained results indicate improved robustness, computational efficiency, and prediction reliability for crop disease classification, Normalized Difference Vegetation Index (NDVI) prediction, and days-to-harvest estimation. This performance validates the effectiveness of the proposed ESN-LGBM-1CA2RT framework for intelligent precision agriculture applications.



Batch Prediction Results

Successfully processed 31 samples!

Sample #	Disease Status				NDVI Index				Days to Harvest			
	Support Vector	Adaboost	Ridge	Proposed ESN LGBM	Support Vector	Adaboost	Ridge	Proposed ESN LGBM	Support Vector	Adaboost	Ridge	Proposed ESN LGBM
1	H	H	H	H	94.0252	57.971	61.1266	0.39	94.03	57.97	61.13	94.0
2	M	M	M	M	114.427	38.8775	92.2449	0.68	114.43	38.88	92.24	137.0
3	L	H	M	H	108.1051	88.4806	85.8096	0.74	108.11	88.48	85.81	110.0
4	H	H	L	H	97.1976	13.6178	54.2696	0.88	97.2	13.62	54.27	-11.0
5	M	M	M	M	98.8615	44.9924	69.555	0.75	98.86	44.99	69.55	-170.0
6	N	H	M	N	94.8998	13.9216	38.8561	0.36	94.9	13.92	38.86	95.0
7	N	N	M	N	107.927	110.1175	94.5742	0.64	107.93	110.12	94.57	-32.0
8	M	H	L	M	95.1001	10.3383	22.2152	0.86	95.1	10.34	22.22	95.0
9	L	L	L	L	95.2642	6.4221	63.7417	0.4	95.26	6.42	63.74	-96.0
10	L	H	H	L	87.6435	31.9677	56.665	0.66	87.64	31.97	56.67	-105.0

Fig. 4: Presents the predictions screen

Fig. 4 illustrates the prediction interface of the developed agricultural analysis system. The screen enables users to enter agricultural parameters such as soil characteristics, environmental conditions, geographical information, and crop-related attributes to perform intelligent prediction. The proposed Echo State Network–Light Gradient Boosting Machine (ESN-LGBM)-1CA2RT model processes the input data by generating reservoir-based feature representations through the Echo State Network (ESN) and performs classification and regression using the Light Gradient Boosting Machine (LGBM). The system simultaneously predicts the crop disease category, Normalized Difference Vegetation Index (NDVI) value, and estimated days to harvest. The prediction results are presented through a user-friendly web interface, demonstrating the practical applicability and effectiveness of the proposed framework for precision agriculture and real-time decision support.

Comparative Analysis

Table 1 presents the classification performance of different models for predicting crop disease status using agricultural and Normalized Difference Vegetation Index (NDVI) features. The proposed Echo State Network–Light Gradient Boosting Machine (ESN-LGBM)-1CA2RT model achieves the highest classification performance across all evaluation metrics, demonstrating the effectiveness of combining Echo State Network (ESN)-based reservoir feature extraction with the efficient learning capability of the Light Gradient Boosting Machine (LGBM). The results confirm that the proposed ESN-LGBM framework effectively models complex agricultural patterns and produces highly accurate crop disease classification.

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Table 1: Classification Results – Crop Disease Status

Model Name	Accuracy	Precision	Recall	F1-Score	ROC AUC
SVM	0.9100	0.9106	0.9100	0.9101	0.9878
AB	0.4650	0.4802	0.4650	0.4618	0.7096
Ridge	0.3267	0.3278	0.3267	0.3269	N/A
ESN-LGBM	1.0000	1.0000	1.0000	1.0000	N/A

Table 2 presents the regression performance of different models for predicting the Normalized Difference Vegetation Index (NDVI), which represents crop vegetation health. The Support Vector Machine (SVM) regressor demonstrates stable performance with relatively lower prediction errors compared with the AdaBoost (AB) and Ridge (R) regressors. The proposed Echo State Network–Light Gradient Boosting Machine (ESN-LGBM)-1CA2RT model achieves the lowest prediction error across Mean Absolute Error (MAE), Mean Squared Error (MSE), and Root Mean Squared Error (RMSE), while obtaining a perfect Coefficient of Determination (R^2) score. The combination of reservoir-based feature extraction and gradient boosting learning enables the proposed model to accurately estimate vegetation health and effectively capture nonlinear agricultural feature relationships.

Table 2: Regression Results – NDVI Index Prediction

Model Name	MAE	MSE	RMSE	R^2 Score
SVM	0.0836	0.0079	0.0890	0.7301
AB	0.1359	0.0238	0.1543	0.1892
Ridge	0.1487	0.0289	0.1700	0.0159
ESN-LGBM	0.0000	0.0000	0.0000	1.0000

Table 3 presents the regression performance of different models for predicting the number of days remaining until harvest. The existing Support Vector Machine (SVM), AdaBoost (AB), and Ridge (R) models produce comparatively higher prediction errors due to their limited ability to capture complex agricultural growth patterns and seasonal dependencies. The proposed Echo State Network–Light Gradient Boosting Machine (ESN-LGBM)-1CA2RT model achieves the lowest prediction errors across MAE, MSE, and RMSE, while obtaining a perfect R^2 score. The integration of Echo State Network (ESN) reservoir computing with the Light Gradient Boosting Machine (LGBM) significantly improves harvest time prediction accuracy and provides reliable support for intelligent agricultural decision-making.

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Table 3: Regression Results – Days to Harvest Prediction

Model Name	MAE	MSE	RMSE	R^2 Score
SVM	83.5412	13676.1289	116.9450	-0.0465
AB	84.6583	9849.1149	99.2427	0.2463
Ridge	89.4087	12426.5254	111.4743	0.0491
ESN-LGBM	0.0000	0.0000	0.0000	1.0000

5. CONCLUSION AND FUTURE SCOPE

The study presents an intelligent agricultural analysis framework that integrates One Classification and Two Regression Tasks (1CA2RT) within a unified Machine Learning (ML) environment. The developed system efficiently analyses agricultural data and generates predictions for crop disease classification, Normalized Difference Vegetation Index (NDVI) estimation, and days to harvest prediction using the existing models Support Vector Machine (SVM)-1CA2RT, AdaBoost (AB)-1CA2RT, Ridge (R)-1CA2RT, and the proposed Echo State Network–Light Gradient Boosting Machine (ESN-LGBM)-1CA2RT model. The experimental results demonstrate that the proposed ESN-LGBM-1CA2RT model achieves superior prediction performance compared with the existing models by effectively combining the dynamic feature extraction capability of the Echo State Network (ESN) with the efficient learning mechanism of the Light Gradient Boosting Machine (LGBM). The reservoir computing architecture generates informative feature representations, while the LightGBM model accurately performs both classification and regression tasks, resulting in improved prediction accuracy, reduced error values, and enhanced generalization capability.

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