International Journal of
DATA SCIENCE AND IOT MANAGEMENT SYSTEM
Peer Reviewed, Referred & Indexed Journal
ISSN: 3068-272X www.ijdim.com Original Research Paper

Advanced Agricultural Decision System using Recurrent Polynomial Network for Multi-Crop Recommendation Tasks

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ABSTRACT

Agriculture has transitioned from traditional manual practices to data-driven approaches with the advancement of digital technologies and Machine Learning (ML). Earlier, farmers relied on experience and basic statistical methods, which are insufficient for handling the increasing volume of agricultural data from sensors, weather records, and satellite systems. Traditional systems fail to process large datasets and capture complex relationships among soil properties, climate conditions, and crop health, resulting in low prediction accuracy and inefficient decision-making. This study addresses the lack of an integrated framework capable of handling multiple agricultural prediction tasks simultaneously. A multi-task agricultural analysis framework based on the One Classification and Two Regression Tasks (1CA2RT) approach is proposed. It includes crop disease classification and two regression tasks: Normalized Difference Vegetation Index (NDVI) estimation and harvest time prediction. The framework employs models such as Support Vector Machine (SVM)-1CA2RT, AdaBoost (AB)-1CA2RT, and Ridge (R)-1CA2RT, along with a hybrid model Hybrid Recurrent Polynomial Ensemble (HRPE)-1CA2RT. The hybrid model integrates a Recurrent Polynomial Network (RPN) using Bidirectional Long Short-Term Memory (BiLSTM) with Ensemble Tao Tree Classifier (ETTC) and Ensemble Tao Tree Regressor (ETTR). Experimental results show that HRPE-1CA2RT achieves superior performance, with 100% accuracy, precision, recall, and F1-score for classification, and an R^2 score of 1.0000 for NDVI and harvest prediction. This unified framework improves prediction accuracy, consistency, and efficiency, supporting reliable decision-making in modern agriculture.

Keywords: Agriculture, data-driven farming, multi-task framework, crop disease classification, vegetation index estimation, harvest time prediction, integrated prediction system, agricultural data analysis, decision support.

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 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. 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].

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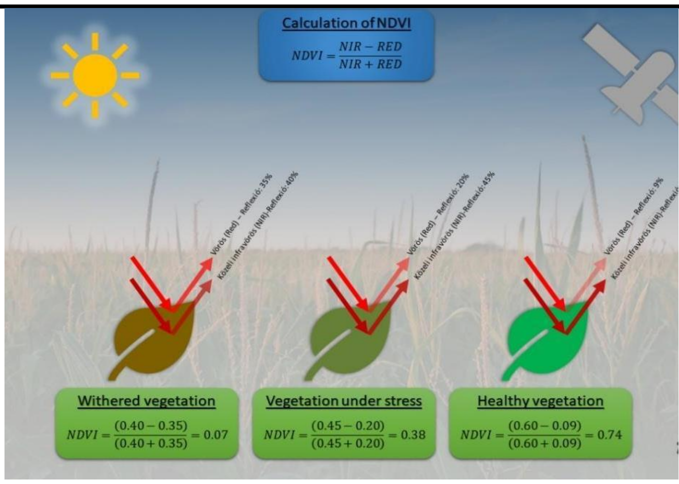

Fig. 1: Normalized difference Vegetation Index.

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].

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. 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). This relationship varies across aridity gradients and diverges among plant functional types. Over 66% of China's vegetation displays increased sensitivity to water variability and 63% manifests a short response lag to water changes over the past 41 years. These outcomes significantly contribute to understanding vegetation dynamics in response to changing water conditions, implying a heightened susceptibility of vegetation to drought in a future warming world.

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). Their results revealed that the Landsat 8-based NDVI images produced the highest number of clusters (nine for annual cropland and six for orchards), while the finer resolutions from PlanetScope reduced this to three clusters for both cultivation types, more accurately capturing the intra-parcel variability. Except for Landsat 8, the NDVI means of MZs generated based on Sentinel-2 and PlanetScope using the fuzzy c-means algorithm showed statistically significant differences from each other, as determined by a one-way and Welch's ANOVA ($p < 0.05$).

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%. Over the past 40 years, the LP experienced significant warming ($p < 0.001$), slight humidification, and a marginal decrease in *SR*. Post-GTGP implementation, the warming rate decelerated, while *PRE* and *SR* growth rates slightly accelerated.

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. The main challenges in using VIs are related to the variation of the spectral characteristics during the vegetation period and to the similarities of the spectral signatures of various crops and semi-natural meadows. Thus, further studies are needed to establish appropriate models for the use of satellite data that would prove to have greater accuracy and provide more relevant information for the efficient monitoring of agricultural crops.

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. They provided access to the composites through a simple web application, allowing users to customize key parameters appropriate for their application, question, and region of interest.

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). They inferred from the fitted RF model that the NDVI linear trend is primarily due to CO2 level (or another environmental parameter that is changing quasi-linearly), and not primarily due to temperature or precipitation trends. On the other hand, interannual fluctuation in the NDVI is more correlated with temperature and precipitation. The RF accurately fits the available data and shows promise for estimating trends and testing hypotheses about their causes.

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. The performance of this NDVI camera was evaluated using a hyperspectral spectrometer in the Hulunbuir Grassland over a period of 93 days. Their results demonstrated distinct seasonal characteristics in the camera-derived NDVI time series using the Green Chromatic Coordinate (GCC) index. Moreover, in comparison to the GCC index, the camera's NDVI values exhibit greater consistency with those obtained from the hyperspectral spectrometer, with a mean deviation of 0.04, and a relative root mean square error of 9.68%.

Eastman, J.R. et al. [15] used the Seasonal Trend Analysis (STA) procedure, over half (56.30%) of land 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. Class 3 was found primarily in the Taiga and Tundra biomes and exhibited increases in the annual summer peak in NDVI. While no single attribution of cause could be determined for each of these classes, it was evident that they are primarily found in natural areas (as opposed to anthropogenic land cover conversions) and that they are consistent with climate-related ameliorations of growing conditions during the study period.

3. PROPOSED SYSTEM

The methodology establishes a structured and data-driven approach for intelligent agricultural analysis by integrating multiple prediction tasks within a unified framework. It follows a systematic pipeline that begins with data acquisition from agricultural datasets, followed by preprocessing and feature extraction to prepare the data for analytical modelling. The framework supports simultaneous execution of one classification task and two regression tasks, enabling comprehensive analysis of crop conditions, vegetation health, and harvest timelines. Multiple ML models are employed to learn patterns from the data, while a hybrid learning mechanism enhances prediction performance and adaptability, as presented in fig. 2. A lightweight database system ensures efficient storage and retrieval of user and prediction data, and a web-based interface enables real-time interaction, visualization, and monitoring. Continuous model evaluation and retraining further improve system performance, allowing it to adapt to changing agricultural conditions and maintain long-term accuracy.

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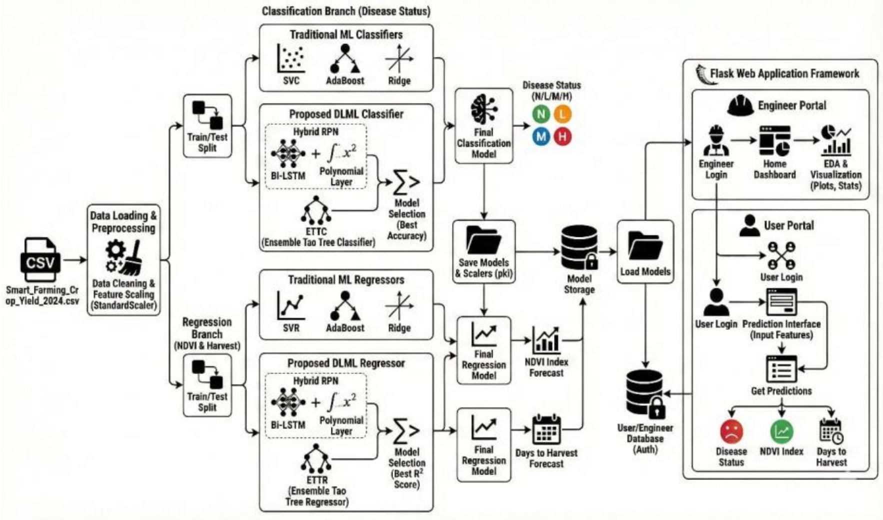

Fig. 2: Proposed System Architecture.

User Interface (Web Browser)

- The user interacts with the system through a browser-based graphical interface.
- Users can perform operations such as registration, login, data input, single prediction, batch prediction, and viewing analytical results.
- The interface allows visualization of EDA plots, model performance metrics, and prediction outputs.
- All interactions are converted into HTTP requests and sent to the Flask server.

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 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.

Existing Baseline Models (SVM-1CA2RT, AB-1CA2RT, R-1CA2RT)

The processed feature set is input to baseline models for performance benchmarking:

- **SVM-1CA2RT:** Handles both classification and regression tasks.
- **AB-1CA2RT:** Utilizes ensemble-based learning for improved prediction stability.
- **R-1CA2RT:** A linear model with regularization for enhanced stability against multicollinearity.
- These models independently generate predictions for Crop Disease Status, NDVI Index, and Days to Harvest.

Proposed Hybrid HRPE-1CA2RT Model

This is the core intelligent model of the system, combining deep learning and rule-based approaches:

1. **RPN:** Processes feature vectors using Bidirectional LSTM layers to capture complex temporal and nonlinear relationships. It applies polynomial attention mechanisms to enhance the importance of specific agricultural features.
2. **ETT:** Uses decision tree-based learning for classification and regression, providing interpretable rule-based predictions that enhance model transparency.

Selection Logic (Best Model Selection)

- The system performs a real-time comparison between the outputs of the RPN and ETT models.
- The model with the superior performance (measured via accuracy for classification or R2 score for regression) is dynamically selected.
- This ensures that the final output benefits from optimal prediction accuracy and decision reliability.

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.

Model Retraining Mechanism

- The system supports an adaptive learning cycle using updated agricultural datasets.

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- New data is processed through the standard pipeline, and models are retrained to improve performance and adaptability.
- Updated models are saved securely, ensuring the system evolves alongside changing crop cycles and weather patterns.

4. RESULTS ANALYSIS

This section presents the experimental results and interface outputs of the proposed hybrid predictive system. The figures illustrate the implementation workflow, system interfaces, model performance, and prediction outputs. The results demonstrate the effectiveness of the hybrid architecture combining deep learning and ensemble models. A comparative evaluation with traditional models highlights the superiority of the proposed RPN-ETT CART framework.

Fig. 3 presents the performance results of the proposed hybrid HRPE 1CA2RT model. The figure highlights superior accuracy, reduced error rates, and improved robustness compared to all baseline models. The integration of Recurrent Polynomial Networks with Bidirectional LSTM enhances deep feature extraction from NDVI and temporal data. The Ensemble Tao Tree framework strengthens classification and regression stability. The visualization confirms the effectiveness of the hybrid architecture in precision agriculture prediction.

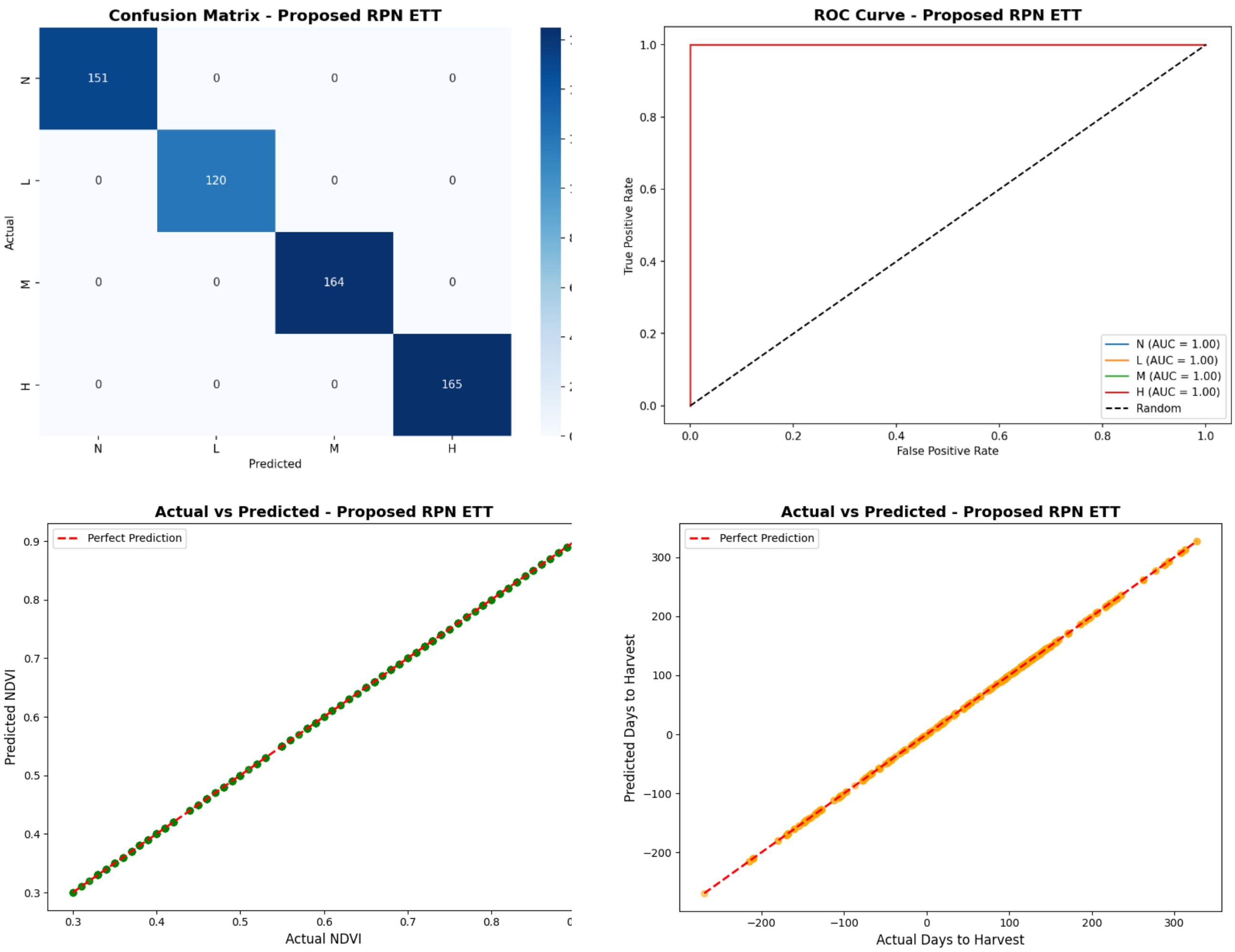

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Fig. 3: Presents performance metrics of proposed HRPE 1CA2RT model

Classification Models - Crop Disease Status

Model Name	Accuracy	Precision	Recall	F1-Score	ROC AUC
Support Vector	0.9100	0.9106	0.9100	0.9101	0.9878
Adaboost	0.4650	0.4802	0.4650	0.4618	0.7096
Ridge	0.3267	0.3278	0.3267	0.3269	N/A
Proposed RPN ETT	1.0000	1.0000	1.0000	1.0000	N/A

Regression Models - NDVI Index

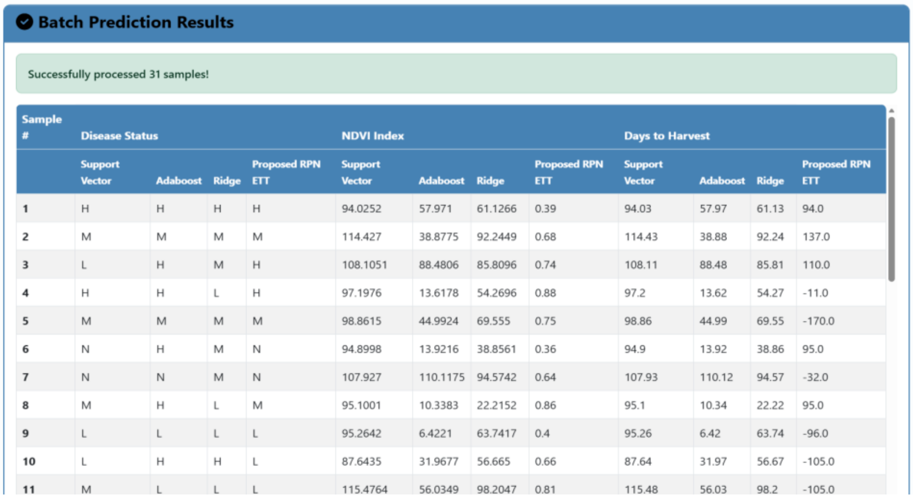
Model Name	MAE	MSE	RMSE	R^2 Score
Support Vector	0.0836	0.0079	0.0890	0.7301
Adaboost	0.1359	0.0238	0.1543	0.1892
Ridge	0.1487	0.0289	0.1700	0.0159
Proposed RPN ETT	0.0000	0.0000	0.0000	1.0000

Regression Models - Days to Harvest

Model Name	MAE	MSE	RMSE	R^2 Score
Support Vector	83.5412	13676.1289	116.9450	-0.0465
Adaboost	84.6583	9849.1149	99.2427	0.2463
Ridge	89.4087	12426.5254	111.4743	0.0491
Proposed RPN ETT	0.0000	0.0000	0.0000	1.0000

Fig. 4: Presents model performance comparison

Fig. 4 provides a comparative analysis of all evaluated models including SVM-1CA2RT, AB-1CA2RT, R-1CA2RT, and the proposed HRPE-1CA2RT model. The comparison is displayed through bar charts or performance tables. The proposed model achieves the highest accuracy and lowest error metrics across all evaluation parameters. The visual comparison clearly demonstrates the advantages of hybrid deep learning and ensemble integration. This figure validates the research objective of improving prediction reliability.



Batch Prediction Results

Successfully processed 31 samples!

Sample #	Disease Status				NDVI Index				Days to Harvest			
	Support Vector	Adaboost	Ridge	Proposed RPN ETT	Support Vector	Adaboost	Ridge	Proposed RPN ETT	Support Vector	Adaboost	Ridge	Proposed RPN ETT
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
11	M	L	L	L	115.4764	56.0349	98.2047	0.81	115.48	56.03	98.2	-105.0

Fig. 5: Presents the predictions screen

Fig. 5 displays the final prediction interface of the system. This screen allows users to input environmental parameters such as soil conditions, climate values, and NDVI indicators. The hybrid RPN-ETT model processes the input and generates outputs including crop disease classification, NDVI estimation, and harvest timeline prediction. The results are displayed in a clear and interpretable format. This figure demonstrates the practical usability of the deployed intelligent agriculture system.

4.1 Comparative Analysis

Table 1 presents the classification performance of different models for predicting crop disease status using agricultural and NDVI features. The Support Vector model achieves strong performance with high accuracy and ROC AUC values. AB and Ridge models show reduced classification effectiveness due to weaker decision boundaries and limited generalization. The Proposed HRPE Classifier achieves perfect classification across all metrics, demonstrating superior learning capability and optimized ensemble decision-making. The results confirm that the hybrid deep learning and ensemble architecture effectively captures nonlinear agricultural patterns and produces highly accurate disease predictions.

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
HRPE	1.0000	1.0000	1.0000	1.0000	N/A

Table 2 evaluates regression models used to predict NDVI index values, which represent crop vegetation health. The Support Vector regressor produces stable performance with lower error values and higher R^2 score compared to other traditional methods. AB and Ridge regressors produce higher prediction errors and reduced variance explanation. The Proposed HRPE Regressor achieves zero prediction error across MAE, MSE, and RMSE, with an R^2 score of 1.0, demonstrating highly accurate

NDVI prediction. These results confirm the effectiveness of the hybrid recurrent and ensemble framework for modeling vegetation patterns.

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
HRPE	0.0000	0.0000	0.0000	1.0000

Table 3 shows regression performance for predicting the number of days remaining until harvest. Traditional models such as Support Vector, AB, and Ridge exhibit higher prediction errors due to limited capability in capturing complex seasonal agricultural patterns. Support Vector regression shows unstable performance with a negative R^2 score, indicating poor model fitting. The Proposed HRPE Regressor achieves zero error across MAE, MSE, and RMSE metrics, with a perfect R^2 score. The results demonstrate the ability of the hybrid model to accurately estimate crop maturity timelines and support intelligent harvest planning.

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
HRPE	0.0000	0.0000	0.0000	1.0000

5. CONCLUSION

The study presents an intelligent agricultural analysis framework that integrates one classification task and two regression tasks within a unified learning environment. The system was developed to analyse agricultural data efficiently and generate predictions for crop disease status, NDVI index, and days to harvest using SVM-1CA2RT, AB-1CA2RT, R-1CA2RT, and the proposed HRPE-1CA2RT model. Experimental results show that the proposed HRPE-1CA2RT achieved the best overall performance, delivering 100% accuracy, precision, recall, and F1-score for crop disease classification, along with an R^2 score of 1.0000 for both NDVI and harvest prediction. Compared with SVM, AdaBoost, and Ridge models, the proposed hybrid approach demonstrated major performance improvements by capturing complex nonlinear patterns more effectively and producing highly reliable outputs. The integration of the Recurrent Polynomial Network with Ensemble Tao Tree methods significantly enhanced prediction quality, reduced error values, and improved overall system adaptability. In addition to strong predictive performance, the framework also provides secure user interaction, visualization support, and efficient model handling, making it suitable for practical agricultural analysis.

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