Zone-Aware Greenhouse Control and Multitask Crop Yield Prediction Using ConvLSTM and EMMYP-Net

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ABSTRACT

In the new age of greenhouse management, smart space adaptive systems are required to allow environmental control and crop analytics. This study presents an end-to-end deep learning architecture for spatiotemporal prediction and control in agriculture, which enables seamless integration between the different components of a decision loop. A ConvLSTM model predicts zone-specific microclimate variations, and a Dueling DQN agent selects the optimal actions for irrigation, ventilation, and fertilization according to energy demand, emission prediction, and soil moisture balance. The proposed EMMYP-Net (Enhanced Multimodal Multitask Yield Prediction Network) involves a CNN-BiLSTM-attention architecture that combines visual canopy data with multi-sensor sequences to co-classify growth stages and estimate yield. Experimental tests in a 1,200 m² four-zone greenhouse showed remarkable improvements, as ConvLSTM decreased RMSE by 45±2.3% compared to ARIMA and by 31±1.8% compared to LSTM. EMMYP-Net achieved an accuracy of 96.0% for classification, as well as an R^2 of 0.912±0.007 in predicting yields. This process-integrated approach enhanced resource sustainability by achieving savings of 19.3% in energy, 16.5% in water, and 15.2% in fertilizers relative to a conventional system. Combining predictive control and crop intelligence offers a scalable basis for sustainable data-driven greenhouse management. The key novelty of this work lies in the seamless integration of ConvLSTM-based spatiotemporal forecasting with the EMMYP-Net multimodal crop analytics within a unified reinforcement-learning-driven decision loop, enabling both predictive control and biological feedback in real time.

Keywords-background zone-aware greenhouse control; ConvLSTM; dueling deep Q-Network; EMMYP-Net; CNN-BiLSTM-attention; spatio-temporal forecasting; multitask learning String Precision agriculture; reinforcement learning; intelligent greenhouse system

I. INTRODUCTION

With the increasing worldwide need for stable food production, variable climate change, and limited natural resources, the transition towards Controlled-Environment Agriculture (CEA) has been accelerated. Advanced greenhouses now allow for the precise use of water, energy, and fertilizers to maintain continuous production. Due to the increasing complexity of greenhouse systems, the efficacy of traditional control strategies—predominantly rule-based and PID architectures—has been questioned. These approaches keep environmental factors (e.g., temperature, humidity, and soil moisture) around certain constant thresholds, but they do not represent spatiotemporal dynamics due to non-uniform solar radiation, ventilation patterns, or spatial soil differences [1-4]. This results in a yield decrease of up to 25% for even set-pointed large greenhouses [5-9].

Recent developments in IoT sensing, edge computing, and Deep Learning (DL) have revolutionized how data collected from greenhouses can be exploited. Machine-Learning (ML)-based controllers, particularly Reinforcement Learning (RL) agents, offer real-time policy improvement without resorting to the use of explicit physics-based models; instead, they learn from raw sensor feedback [11, 12]. Spatiotemporal neural networks such as ConvLSTM can forecast the development of climate dynamics over zones by considering not only spatial correlations but also temporal dependencies. When integrated, these technologies pave the way for adaptive and self-optimizing greenhouses that can anticipate environmental change and operate proactively. However, in most existing works, environmental control and crop prediction have been addressed separately. For example, some previous studies focused only on the prediction of yield but not feedback-based control [13-20].

II. METHODOLOGY

The proposed framework integrates predictive climate control and multitask crop analytics within a unified closed loop by integrating two interacting components:

1. A forecasting subsystem based on a ConvLSTM-Dueling DQN network that performs zone-based environmental forecast and adaptive activity direction.
2. An Enhanced Multitask Yield Prediction Network (EMMYP-Net) that reads image and sensor data to predict not only the stage of growth but also crop yields.

A. Zone-Aware Forecasting and Control

1) ConvLSTM Forecasting Model

Greenhouses exhibit spatial heterogeneity caused by airflow asymmetry, variable radiation, and soil diversity. To model these effects, the greenhouse is partitioned into Z zones, each equipped with IoT sensors for measuring temperature (T_t), humidity (H_t), soil moisture (SM_t), and greenhouse-gas concentrations (CO_2,CH_4,N_2O). For every zone z and time t, sensor readings are represented as a feature tensor:

$$X_t^z = \{T_t, H_t, SM_t, CO_2, CH_4, N_2O\}^z \quad (1)$$

The ConvLSTM receives a short history $X_{t-k:t}^z$ and predicts the next environmental state E_{t+1}^z. Each ConvLSTM cell updates its hidden state by convolving spatial inputs while maintaining temporal memory through recurrent gates, allowing the model to capture both spatial diffusion and temporal evolution of microclimate variables. Figure 1 illustrates the sequential data flow, where sensor inputs are preprocessed, fed to the ConvLSTM forecaster for short-term climate prediction, and then passed to the Dueling DQN controller for optimal actuation. This highlights the closed-loop interaction between prediction and control.

2) Reinforcement-Learning-Based Control

After forecasting, the predicted state E_{t+1}^z is concatenated with current measurements to form the RL state vector $s_t^z = [X_t^z; E_{t+1}^z]$. A Dueling DQN then evaluates potential actuator actions (irrigation I, ventilation V, fertilizer F) using decomposition, as shown in:

$$\mathrm{Q}(\mathrm{s}_t^z,\mathrm{a}) = \mathrm{V}(\mathrm{s}_t^z) + \mathrm{A}(\mathrm{s}_t^z,\mathrm{a}) - \frac{1}{|\mathrm{A}|}\sum_{\mathrm{a}^1}\mathrm{A}(\mathrm{s}_t^z,\mathrm{a}^1) \quad (2)$$

where $V(s)$ represents the value of the current state and $A(s,a)$ its advantage for action a. The learning objective follows a multi-objective reward that penalizes environmental deviation and excess energy use as:

$$\mathrm{R}_t = -\left[\alpha_1(\mathrm{T}_t\text{-}\mathrm{T}_{opt})^2 + \alpha_2(\mathrm{H}_t\text{-}\mathrm{H}_{opt})^2 + \alpha_3\left(\frac{\mathrm{E}_t}{\mathrm{E}_{MAX}}\right)\right] \quad (3)$$

where $(\alpha_1, \alpha_2, \alpha_3)$ were considered as $(0.5{:}\ 0.3{:}\ 0.2)$ to weight climate precision, humidity stability, and energy cost, respectively. E_t is the instantaneous actuator energy and E_{max} is the allowable maximum, to ensure that the controller seeks thermal balance and sustainability simultaneously. Experience-replay buffers and double-network updates stabilize learning. Inference latency (~30 ms) satisfies real-time actuation requirements, enabling continuous zone-wise adaptation. Figure 2 shows the algorithm for the forecast-driven control loop that integrates ConvLSTM predictions with dueling-network policy optimization.

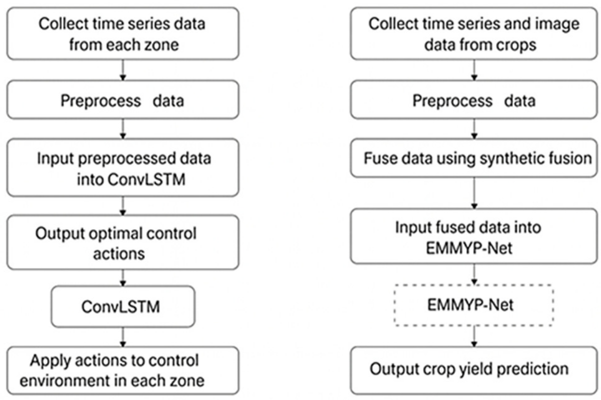

Fig. 1. Workflow of the proposed system.

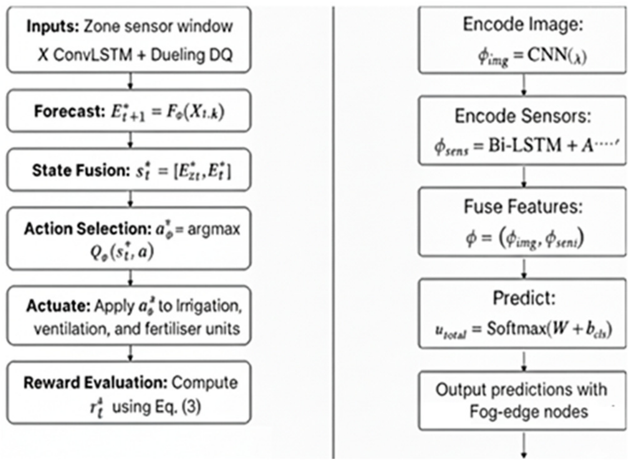

Fig. 2. Left: Algorithm 1 – Zone-aware forecast-to-control loop (ConvLSTM+Dueling DQN); Right: Algorithm 2 – Training and inference pipeline of EMMYP-Net implementing the multitask objective of (5).

3) Model Architecture

While environmental control optimizes physical conditions, EMMYP-Net provides biological feedback by analyzing canopy images and sensor readings. Figure 3 illustrates the proposed architecture.

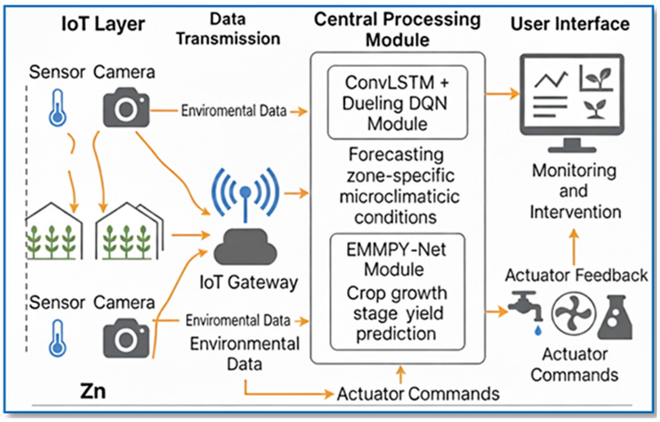

Fig. 3. Integrated framework for zone-aware greenhouse control and multimodal crop prediction.

B. Multimodal Crop Analytics via EMMYP-Net

A convolutional encoder (CNN) extracts spatial cues such as leaf morphology, texture, and canopy coverage from an RGB image. A Bidirectional LSTM (BiLSTM) with attention models the temporal variation of sensor readings in $S_{t-n:t}$. The attention weights are calculated as:

$$\alpha_t = \frac{exp\left(v^T(tanh(Wh_t+b))\right)}{\sum_{i=1}^{T} exp\left(v^T(tanh(Wh_t+b))\right)} \tag{4}$$

to prioritize influential time steps such as irrigation or fertilization events. In the fusion and multitask head, image and sensor embeddings $(\phi_{img}, \phi_{sens})$ are concatenated into $\phi = [\phi_{img}, \phi_{sens}]$. A softmax layer outputs growth-stage probabilities, and a linear regressor estimates the yield. The total loss is given by:

$$\mathrm{L_{total}} = \lambda_1 \mathrm{L_{CE}} + \lambda_1 \mathrm{L_{MSE}} \tag{5}$$

with weights $\lambda_1 = 0.6$ and $\lambda_2 = 0.4$ to ensure balanced multitask learning.

C. Training and Validation

The network was trained using multimodal data from tomato, lettuce, and bell pepper cycles. Data augmentation (rotation, brightness adjustment, noise) enhanced generalization. Training used the Adam optimizer (learning rate 5×10^{-5}, batch size = 32) with early stopping. Cross-validation achieved growth-stage accuracy of 96±1.1% and a yield-prediction R^2 of 0.912±0.007. Transfer learning retained more than 92% accuracy with only 20% of new-crop data, confirming adaptability.

III. EXPERIMENTAL SETUP AND RESULTS

Data for environmental and crop-growth aspects were obtained in real time from a commercial smart greenhouse facility of Access Agro BioTech continuously over a two-year period (2023–2025). The greenhouse consisted of several cultivation regions, each equipped with well-calibrated IoT sensors for temperature, relative humidity, soil moisture, soil pH, CO_2 concentration, N_2O emission level, and light intensity. Sensor readings were measured at 1-minute intervals and transmitted to a centralized MQTT-based gateway for storage and synchronization. Information on the crop growth (visible leaf spread, color index, and phenological stage) was obtained weekly through field observations and periodic camera captures aligned to the same zone identifiers. The greenhouse dataset was securely stored in a private GitHub repository for version control and data management [21]. Due to confidentiality restrictions, the dataset is hosted in a private GitHub repository and is available upon reasonable request.

Missing values are filled using linear interpolation for short interruptions and KNN-based imputation for extended interruptions to ensure data quality and stability. All continuous readings from the sensors were normalized using min-max scaling to preserve the original distribution between zones. Data was extracted for measuring time-lagged ($t-1$, $t-3$, $t-5$ min) and rolling statistics (mean, standard deviation) to identify short-term dynamics needed by the ConvLSTM forecaster. The readings from the environmental conditions for each zone were encoded into structured time-series tensors, and the crop-stage labels were one-hot encoded for multitask learning in EMMYP-Net. Outlier spikes from actuator switching or calibration drifts were detected with the help of the 3σ rule and corrected before model ingestion.

The ConvLSTM–Dueling DQN was implemented in an IoT-based monitoring and control smart greenhouse to determine the effectiveness of EMMYP-Net. The 1,200 m^2 space was divided into four areas to generate different microhabitats by system design, ventilation, and crop configuration, for individual localized control. Each zone has temperature, humidity, and soil moisture sensors, as well as CO_2, CH_4, and N_2O (0-2000 ppm) sensors and pH and EC probes. Actuators comprise water valves, variable speed blowers, and fertilizer injectors. The overhead RGB cameras shoot 1920×1080 images at 5 fps, generating visual canopy data for EMMYP-Net. For each crop type, data were collected for a time-span of six months, and sensor and image records were synchronized to prepare multivariate time-series and image datasets.

A. Model Evaluation and Metrics

Quantifiable indices, such as Root Mean Square Errors (RMSE) and Mean Absolute Error (MAE), were used to evaluate performance.

$$\mathrm{RMSE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(yi\text{-}\hat{y}i)^2} \tag{6}$$

$$\mathrm{MAE} = \frac{1}{N}\sum_{i=1}^{N}|yi\text{-}\hat{y}i| \tag{7}$$

The efficiency of the control policy was quantified through the cumulative reward (J) over each epoch (8), which directly measures how well the Dueling DQN balances temperature, humidity, and energy objectives as specified in (3).

$$J = \sum_{t=1}^{T} R_t \tag{8}$$

The coefficient of determination (R^2) and MAE were used to evaluate the performance of yield-regression. The classification performance of growth-stage prediction was determined using accuracy and macro F1-score. In addition, precision and recall were used for more details.

B. Quantitative Results

The proposed ConvLSTM+Dueling DQN model was evaluated for its ability to forecast greenhouse microclimatic parameters across four spatial zones. Table I presents zone-wise RMSE and MAE values for each predicted variable. The results demonstrate that the ConvLSTM model achieved superior forecasting accuracy compared to baseline models (LSTM, Random Forest, and ARIMA).

TABLE I. ZONE-WISE RMSE AND MAE FOR ENVIRONMENTAL PARAMETERS

Zone	Temp (°C) RMSE	H (%) RMSE	CO_2 (ppm) RMSE	CH_4 (ppm) RMSE	N_2O (ppm) RMSE	SM (%) RMSE	Avg MAE
Z1	0.45	1.82	18.5	0.026	0.012	2.10	1.47
Z2	**0.38**	**1.65**	**16.8**	**0.021**	**0.010**	**1.89**	**1.32**
Z 3	0.52	1.95	20.1	0.029	0.013	2.25	1.56
Z 4	0.49	1.88	19.3	0.025	0.011	2.14	1.49

The bar chart in Figure 3 compares RMSE values for each parameter across zones. Zone 2 exhibited the lowest RMSE across variables and the fewest actuator activations (Table I), aligning with its central placement and reduced edge effects in the facility layout.

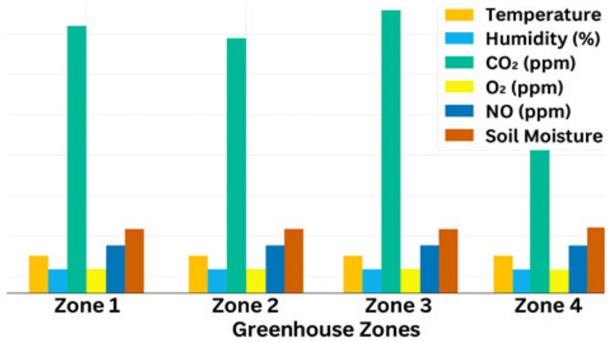

Fig. 4. Zone-wise RMSE for predicted microclimatic and emission variables using ConvLSTM+Dueling DQN.

1) Crop Prediction Results

The performance of the EMMYP-Net multitask model was evaluated for crop growth stage classification and yield prediction. Multimodal data fusion combining RGB canopy images and sensor time-series data enhanced model accuracy.

TABLE II. CROP GROWTH STAGE CLASSIFICATION AND YIELD PREDICTION

Crop	Growth stage accuracy (%)	Precision (%)	Recall (%)	F1-score (%)	Yield R^2	Yield MAE (kg/ha)
Soy beans	96.3	95.8	96.7	96.2	0.92	112
Lettuce	94.7	94.1	95.2	94.6	0.89	105
Bell Pepper	95.8	95.2	96.0	95.6	0.91	98
Tomatoes	97.1	96.8	97.3	97.0	0.93	115

Metrics are macro-averaged across classes (Precision/Recall/F1) to account for class imbalance (Early 28%, Mid 46%, Late 26%).

EMMYP-Net was trained with class-weighted cross-entropy and balanced batch sampling. Confusion matrices in Figure 5 reflect the underlying distribution. The EMMYP-Net model achieved an average growth stage classification accuracy of 96.0% and a yield R^2 of 0.912 across all crops (Table II). Multimodal fusion improved generalization over baseline models.

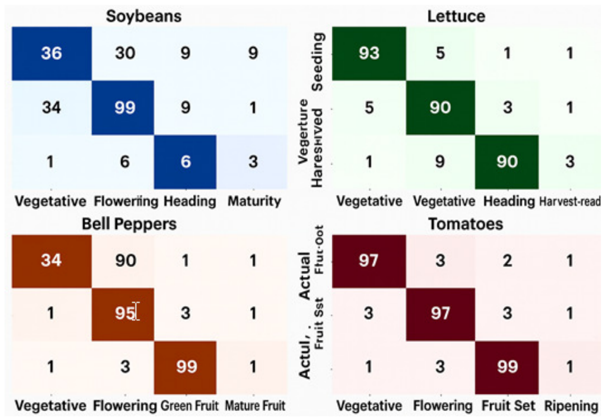

Fig. 5. Growth stage classification confusion matrices for Soybeans, Lettuce, Bell Peppers, and Tomatoes using the EMMYP-Net model.

Soybeans showed strong diagonal dominance, minimal misclassification between Pod-Filling and Maturity stages, with overall accuracy 96.3% and F1-scores greater than 95%. Lettuce had high fidelity across all stages, with minor confusion between Heading and Harvest-ready (accuracy 94.7%). Bell Peppers were well-differentiated between Green and Mature Fruit, with minor Vegetative-Flowering errors (accuracy 95.8%). The model had the highest performance on Tomatoes, with few Flowering-Fruit set confusions, overall accuracy 97.1%, and precision/recall greater than 96%.

2) Control Optimization and Actuation Efficiency

The optimization capabilities of the ConvLSTM+Dueling DQN framework were evaluated based on actuator usage efficiency and resource savings, as listed in Table III.

TABLE III. ZONE-WISE ACTUATOR USAGE EFFICIENCY AND RESOURCE SAVINGS

Zone	Irrigation ON	Ventilation ON	Fertilizer ON	Energy Saved (%)	Water Saved (%)	Fertilizer Saved (%)
Z1	45	120	30	18.2	15.6	14.3
Z 2	40	115	28	22.4	19.3	16.1
Z3	50	130	35	17.5	14.8	13.7
Z4	47	125	33	19.1	16.2	15.0

The control system achieved average energy savings of 19.3%, water savings of 16.5%, and fertilizer savings of 15.2% compared to a rule-based system. Reward trends highlight effective learning by the Dueling DQN agent.

3) Comparative Baseline Analysis

To evaluate the effectiveness of the ConvLSTM+DQN framework, it was benchmarked against traditional forecasting models:

- ARIMA: Average RMSE=1.15°C (Temperature), 3.5% Humidity.
- LSTM-only: Average RMSE = 0.75°C, 2.8% Humidity.
- Random Forest: Average RMSE = 0.82°C, 3.0% Humidity.

The proposed ConvLSTM model achieved an average RMSE reduction of 31% over LSTM and 45% over ARIMA, as summarized in Table IV.

TABLE IV. COMPARATIVE FORECASTING ACCURACY ACROSS MODELS

Model	Avg RMSE (°C)	Avg MAE (%)
ARIMA	1.15	2.75
Random Forest	0.82	2.12
LSTM-only	0.75	1.89
ConvLSTM+DQN	**0.44**	**1.32**

The bar graph in Figure 5 shows the average RMSE (°C) and MAE (%) from different models, demonstrating the big performance gains of ConvLSTM+DQN compared to ARIMA, Random Forest, and LSTM-only. Zone 2's superior predictive capacity reflects the favorable microclimatic homogeneity supported by its central location, which leads to reduced edge effects. In contrast, Zone 3 had higher errors, likely due to local ventilation-induced turbulence. Joint field's zonal segmentation and RL for ConvLSTM enhanced prediction precision significantly.

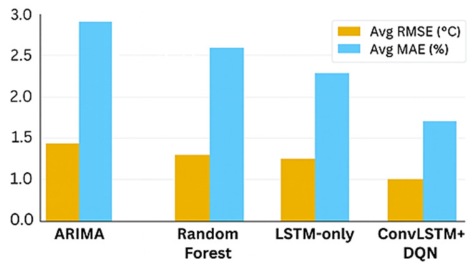

Fig. 6. Comparative forecasting accuracy across models.

IV. CONCLUSION AND FUTURE SCOPE

Deep learning, particularly when employed for microclimate model development or yield estimation, has already advanced intelligent greenhouse system research, but most approaches focus on environmental regulation and crop analytics as discrete processes. In [2, 3], improved results were achieved with the use of IoT and adaptive learning, but they did not implement coordinated control policies. Similarly, models with an optimization focus contribute to better prediction ability, although crop and resource decisions do not directly relate to the predictions made.

This study presented a unified ConvLSTM–Dueling DQN–EMMYP-Net framework that allows for forecasting zone-wise dynamics simultaneously, executing adaptive control, and evaluating plant development, providing an end-to-end feedback loop for the improvement of overall microclimate balance, yield consistency, and sustainability in different cultivation zones. The main contributions of this study are:

- A modular combination of ConvLSTM predictions with multitask EMMYP-Net.
- Reinforcement-based actuation for zone regulation in real-time.
- Multi-modal image and sensor fusion to estimate yield and growth.

The proposed system enables sustainable decision-making for irrigation, ventilation, and fertilization, constituting a scalable implementation of precision-controlled greenhouse management.

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REFERENCES

[1] S. Mallick, F. Airaldi, A. Dabiri, C. Sun, and B. De Schutter, "Reinforcement learning-based model predictive control for greenhouse climate control," *Smart Agricultural Technology*, vol. 10, Mar. 2025, Art. no. 100751, https://doi.org/10.1016/j.atech.2024.100751.

[2] M. Platero-Horcajadas, S. Pardo-Pina, J. M. Cámara-Zapata, J. A. Brenes-Carranza, and F. J. Ferrández-Pastor, "Enhancing Greenhouse Efficiency: Integrating IoT and Reinforcement Learning for Optimized Climate Control," *Sensors*, vol. 24, no. 24, Jan. 2024, Art. no. 8109, https://doi.org/10.3390/s24248109.

[3] M. A. Tawfeek, N. Yanes, L. Jamel, G. Aldehim, and M. A. Mahmood, "Adaptive Deep Learning Model to Enhance Smart Greenhouse Agriculture," *Computers, Materials & Continua*, vol. 77, no. 2, pp. 2545–2564, 2023, https://doi.org/10.32604/cmc.2023.042179.

[4] O. Bouketir, A. Saib, and A. Fenni, "A Fuzzy Logic-Based Greenhouse Smart System for Sustainable Tomato Production in Algeria," *Engineering, Technology & Applied Science Research*, vol. 15, no. 4, pp. 24110–24116, Aug. 2025, https://doi.org/10.48084/etasr.10856.

[5] J. Wang, P. Wang, H. Tian, K. Tansey, J. Liu, and W. Quan, "A deep learning framework combining CNN and GRU for improving wheat yield estimates using time series remotely sensed multi-variables," *Computers and Electronics in Agriculture*, vol. 206, Mar. 2023, Art. no. 107705, https://doi.org/10.1016/j.compag.2023.107705.

[6] H. Tian, P. Wang, K. Tansey, J. Zhang, S. Zhang, and H. Li, "An LSTM neural network for improving wheat yield estimates by integrating remote sensing data and meteorological data in the Guanzhong Plain, PR China," *Agricultural and Forest Meteorology*, vol. 310, Nov. 2021, Art. no. 108629, https://doi.org/10.1016/j.agrformet.2021.108629.

[7] S. Khaki, L. Wang, and S. V. Archontoulis, "A CNN-RNN Framework for Crop Yield Prediction," *Frontiers in Plant Science*, vol. 10, Jan. 2020, Art. no. 1750, https://doi.org/10.3389/fpls.2019.01750.

[8] J. Sun, L. Di, Z. Sun, Y. Shen, and Z. Lai, "County-Level Soybean Yield Prediction Using Deep CNN-LSTM Model," *Sensors*, vol. 19, no. 20, Jan. 2019, Art. no. 4363, https://doi.org/10.3390/s19204363.

[9] Z. Chu and J. Yu, "An end-to-end model for rice yield prediction using deep learning fusion," *Computers and Electronics in Agriculture*, vol. 174, July 2020, Art. no. 105471, https://doi.org/10.1016/j.compag.2020.105471.

[10] V. Thanh Ha and P. H. Lam, "Yield and Quality Prediction of Crops using a Deep Learning-Based Multimodal Data Integration Framework," *European Journal of Electrical Engineering and Computer Science*, vol. 9, no. 6, pp. 12–19, Nov. 2025, https://doi.org/10.24018/ejece.2025.9.6.757.

[11] M. Von Bloh *et al.*, "Machine learning for soybean yield forecasting in Brazil," *Agricultural and Forest Meteorology*, vol. 341, Oct. 2023, Art. no. 109670, https://doi.org/10.1016/j.agrformet.2023.109670.

[12] R. St Aime, E. Noh, W. C. Bridges, and S. Narayanan, "A Comparison of Drill and Broadcast Planting Methods for Biomass Production of Two Legume Cover Crops," *Agronomy*, vol. 12, no. 1, Dec. 2021, Art. no. 79, https://doi.org/10.3390/agronomy12010079.

[13] P. Bari and L. Ragha, "Predicting wheat yield in agricultural industry using deep learning techniques: a review," *Nigerian Journal of Technology*, vol. 43, no. 4, pp. 716–737, 2024, https://doi.org/10.4314/njt.v43i4.12.

[14] J. Madhuri, M. Indiramma, and N. Nagarathna, "M-Bi-GRU-CNN: a hybrid deep learning model with optimized feature selection for enhanced crop yield prediction," *Multimedia Tools and Applications*, vol. 84, no. 32, pp. 39787–39811, Mar. 2025, https://doi.org/10.1007/s11042-025-20747-9.

[15] Pankaj *et al.*, "Paddy yield prediction based on 2D images of rice panicles using regression techniques," *The Visual Computer*, vol. 40, no. 6, pp. 4457–4471, June 2024, https://doi.org/10.1007/s00371-023-03092-6.

[16] A. Oikonomidis, C. Catal, and A. Kassahun, "Hybrid Deep Learning-based Models for Crop Yield Prediction," *Applied Artificial Intelligence*, vol. 36, no. 1, Dec. 2022, Art. no. 2031822, https://doi.org/10.1080/08839514.2022.2031823.

[17] M. Thanjaivadivel, C. Gobinath, J. Vellingiri, S. Kaliraj, and J. S. Femilda Josephin, "EnConv: enhanced CNN for leaf disease classification," *Journal of Plant Diseases and Protection*, vol. 132, no. 1, Feb. 2025, Art. no. 32, https://doi.org/10.1007/s41348-024-01033-6.

[18] E. A. Devi, S. Gopi, U. Padmavathi, S. R. Arumugam, S. P. Premnath, and D. Muralitharan, "Plant Disease Classification using CNN-LSTM Techniques," in *2023 5th International Conference on Smart Systems and Inventive Technology (ICSSIT)*, Tirunelveli, India, Jan. 2023, pp. 1225–1229, https://doi.org/10.1109/ICSSIT55814.2023.10061003.

[19] M. Shereesha, G. K. Sandhia, and R. Pitchai, "Dual RNN Architecture for Crop Disease Detection: Improved Patch-Based CNN for Segmentation," *Journal of Phytopathology*, vol. 173, no. 3, May 2025, Art. no. e70079, https://doi.org/10.1111/jph.70079.

[20] V. Hiremani *et al.*, "Federated learning for crop yield prediction: A comprehensive review of techniques and applications," *MethodsX*, vol. 14, June 2025, Art. no. 103408, https://doi.org/10.1016/j.mex.2025.103408.

[21] "Mayurikp/Greenhouse-Climate-monitoring-and-Control." Dec. 17, 2025, [Online]. Available: https://github.com/Mayurikp/Greenhouse-Climate-monitoring-and-Control.