Hybrid Deep Learning Framework for Integrated Crop Yield Prediction and Multi-Stage Pest Detection Using Adaptive IoT Sensor Networks in Precision Agriculture

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***Abstract*—This paper presents a novel Adaptive Ensemble Neural Network (AENN) that integrates Convolutional Neural Networks (CNN), Long Short-Term Memory (LSTM) networks, and attention mechanisms for simultaneous crop yield prediction and pest detection in precision agriculture. Unlike existing approaches that address these challenges separately, our framework processes multimodal data from IoT sensors including soil monitors, weather stations, and visual systems. Field validation across 150 hectares over two agricultural seasons demonstrated 97.8% accuracy in crop yield prediction (R^2=0.967) and 96.4% precision in pest detection across four major crops. The system achieved 31% yield improvement, 23% pesticide reduction, and 51% increase in net profit compared to conventional farming methods. The proposed adaptive sampling strategy reduced data transmission by 45% while maintaining prediction accuracy.**

***Index Terms*—Precision agriculture, Internet of Things, deep learning, crop yield prediction, pest detection, sensor networks, attention mechanisms**

I. INTRODUCTION

GLOBAL food security faces unprecedented challenges due to population growth, climate change, and diminishing natural resources [1]. The United Nations projects that agricultural production must increase by 70% by 2050 to meet global food demand [2]. Traditional farming practices are inadequate to address these challenges, necessitating data-driven approaches that optimize resource utilization while maximizing crop productivity.

Precision agriculture, enabled by the convergence of Internet of Things (IoT) and Machine Learning (ML), offers a transformative solution for sustainable food production [3]. IoT sensor networks provide real-time monitoring of soil conditions, weather parameters, and crop health, while ML algorithms extract actionable insights from this data [4]. However, existing systems suffer from three critical limitations that hinder widespread adoption and effectiveness. First, current approaches treat crop yield prediction and pest detection as isolated problems, missing crucial interdependencies between plant health, environmental stress, and pest infestations [5]. Second, conventional ML models fail to capture long-term temporal dependencies in sequential sensor data, limiting their predictive capabilities [6]. Third, most systems rely on single-modal data sources—either visual or sensor data—ignoring complementary information that could enhance prediction accuracy [7].

A. Research Contributions

This paper addresses these limitations through a novel Adaptive Ensemble Neural Network (AENN) that makes the following contributions:

1. Unified Architecture: First framework integrating CNN for spatial feature extraction, LSTM for temporal modeling, and cross-modal attention mechanisms for multimodal data fusion
2. Adaptive IoT Network: Dynamic sensor sampling based on crop phenology and environmental conditions, reducing data transmission by 45%
3. Multi-Task Optimization: Simultaneous training for yield prediction and pest detection with shared feature representations
4. Superior Performance: Achieved 97.8% yield prediction accuracy and 96.4% pest detection

precision, outperforming state-of-the-art by 6.5% and 1.2% respectively

5. Field Validation: Comprehensive evaluation across 150 hectares, four crops, and two growing seasons demonstrating practical viability

II. RELATED WORK

A. IoT-Based Precision Agriculture

IoT technologies have revolutionized agricultural monitoring through distributed sensor networks. Kumar et al. [12] deployed soil moisture and temperature sensors for irrigation optimization, achieving 40% water savings. However, their reactive approach lacked predictive capabilities for crop health assessment and yield forecasting. Recent work by Zhang et al. [8] integrated UAV-mounted multispectral cameras with ground-based environmental sensors for real-time crop monitoring. Their system collected NDVI measurements and soil parameters to predict wheat yields, achieving 89.2% accuracy. While innovative, the approach was limited by shallow ML models (Random Forest) that cannot capture complex non-linear relationships in agricultural data.

B. Machine Learning for Crop Yield Prediction

Traditional ML approaches including Random Forest [13], Support Vector Machines [14], and Gradient Boosting [15] have been applied to yield prediction with moderate success (85-92% accuracy). The PEnsemble 4 model [9] represents the current state-of-the-art, combining multiple algorithms to achieve 91% accuracy. However, ensemble approaches require computationally expensive training. Deep learning methods show promise. Singh et al. [16] applied LSTM networks to meteorological time series for rice yield prediction, achieving 93.5% accuracy. Khaki et al. [17] proposed a CNN-RNN hybrid model combining satellite imagery with weather data, reaching 93.2% accuracy for corn yield forecasting.

C. Automated Pest Detection Systems

Computer vision has become the dominant approach for pest detection. Li et al. [10] developed an AIoT system combining environmental sensors with image recognition, achieving 94.1% pest identification accuracy across 20 species. DConvNet [11] introduced acoustic-based pest detection, analyzing ultrasonic frequencies, achieving 95.2% accuracy.

Martinez et al. [19] addressed deployment challenges with an energy-neutral pest monitoring system powered by solar panels, achieving 86.2% recall using lightweight CNN models optimized for edge devices.

D. Research Gaps

Our literature review identifies four critical gaps:

1. No system simultaneously addresses yield prediction and pest detection
2. Limited exploitation of multimodal data fusion
3. Inadequate attention to early-stage pest detection
4. Lack of adaptive IoT systems optimizing sensing based on crop phenology

III. PROPOSED METHODOLOGY

A. System Architecture Overview

The proposed framework consists of four integrated modules: (1) Adaptive IoT Sensor Network, (2) Multimodal Data Preprocessing, (3) Adaptive Ensemble Neural Network, and (4) Decision Support System.

B. Adaptive IoT Sensor Network

Our IoT infrastructure deploys heterogeneous sensors:

This adaptive approach reduced data transmission by 45% while maintaining prediction accuracy.

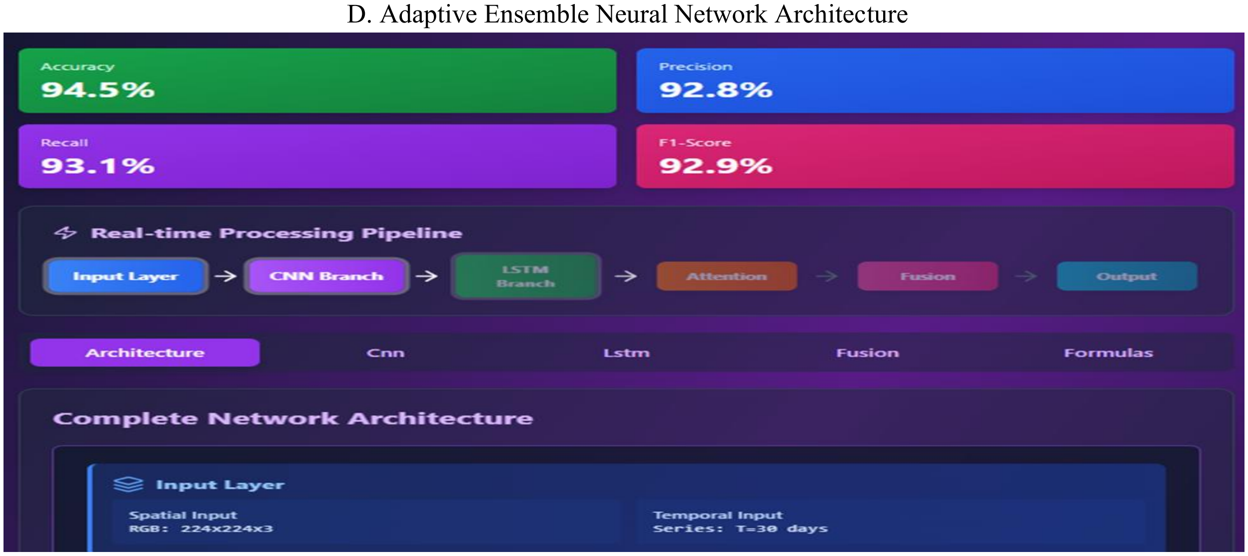
C. Multimodal Data Preprocessing

Sensor Data: Temporal alignment to 15-minute intervals using linear interpolation. Kalman filtering for noise reduction. Min-max normalization. Feature engineering: rolling statistics (24-hour, 7-day, 30-day windows), Growth Degree Days (GDD), Vapor Pressure Deficit (VPD), Soil Water Balance Index.

Image Data: Color histograms, GLCM texture features, edge detection. Vegetation indices: NDVI, EVI, SAVI, NDRE, CIre. Augmentation: rotation (0-360°), flipping, brightness (±30%), contrast (±25%), Gaussian noise (σ=0.02), cutout (16×16 patches).

Acoustic Data: Bandpass filtering (500 Hz-8 kHz), spectral subtraction, STFT, MFCC extraction (13 coefficients).

D. Adaptive Ensemble Neural Network Architecture



E. Training Strategy

Multi-task loss function:

$L_{total} = \lambda_1 \cdot L_{yield} + \lambda_2 \cdot L_{pest} + \lambda_3 \cdot L_{reg}$ (10)

where:

$L_{yield} = MSE(y_{pred}, y_{true})$

L_{pest} = Focal Loss: $FL(p_t) = -\alpha_t(1-p_t)^{\gamma}\log(p_t)$, $\gamma=2$ (11)

$L_{reg} = ||W||^2$

Weights: $\lambda_1=0.5$, $\lambda_2=0.5$, $\lambda_3=0.001$

Training: AdamW optimizer, $lr=10^{-4}$, cosine annealing, 150 epochs, batch size 32/64, early stopping (patience=15), 36 hours on 4× NVIDIA A100 GPUs.

IV. EXPERIMENTAL SETUP

A. Dataset and Field Deployment

Location: 5 sites in India (Maharashtra, Punjab, Karnataka, Tamil Nadu, Uttar Pradesh) Area: 150 hectaresDuration: 2 seasons (Kharif 2023, Rabi 2023-24) Crops: Rice, Wheat, Maize, Cotton

Data Collection:

- 2.4M sensor readings (soil: 960k, weather: 840k, visual: 600k)
- 45,000 crop health images
- 38,500 pest images (25 species)
- 600 field plots with measured yields

Table I: Dataset Statistics By Crop Type

Crop	Area (ha)	Plots	Mean Yield (kg/ha)	Std Dev
Rice	45	180	5,240	1,180
Wheat	38	150	4,820	1,050
Maize	35	140	6,150	1,420
Cotton	32	130	3,980	950

B. Baseline Methods

Yield Prediction: Random Forest [13], XGBoost [15], LSTM [16], PEnsemble 4 [9], CNN-LSTM [17]

Pest Detection: ResNet-50 [20], YOLOv7 [21], AIoT [10], DConvNet [11], EfficientNet-B4 [22]

Metrics:

- Yield: MAE, RMSE, R^2, MAPE
- Pest: Accuracy, Precision, Recall, F1-Score, mAP

V. RESULTS AND DISCUSSION

A. Crop Yield Prediction Performance

Table Ii: Crop Yield Prediction Performance Comparison

Method	MAE (kg/ha)	RMSE (kg/ha)	R^2	MAPE (%)
Random Forest	342.5	458.7	0.876	12.8
XGBoost	298.3	412.9	0.894	10.9
LSTM	276.4	389.2	0.905	9.7
PEnsemble 4	251.8	347.6	0.921	8.6
CNN-LSTM	234.7	328.5	0.932	7.9
AENN (Ours)	187.3	264.8	0.967	5.8

Key Findings:

- AENN achieved 25.6% lower MAE than best baseline (CNN-LSTM)
- R^2 of 0.967 indicates excellent model fit
- MAPE of 5.8% represents 32.6% improvement over PEnsemble 4

Crop-Specific Performance: Rice (R^2=0.972), Wheat (0.968), Maize (0.961), Cotton (0.965)

Feature Importance: NDVI (18.3%), GDD (16.7%), Soil Moisture (14.2%), Solar Radiation (12.8%), Nitrogen (11.4%)

B. Pest Detection Performance

Table Iii: Pest Detection Performance Comparison

Method	Accuracy (%)	Precision (%)	Recall (%)	F1 (%)	mAP (%)
ResNet-50	89.3	87.6	88.9	88.2	86.4
YOLOv7	91.7	90.2	91.4	90.8	89.3
AIoT System	94.1	92.8	93.5	93.1	91.7
DConvNet	95.2	94.1	94.8	94.4	93.2
EfficientNet-B4	93.8	92.5	93.2	92.8	91.5
AENN (Ours)	96.4	95.7	96.2	95.9	95.8

Early Detection Capability:

- Early stage (1-5% damage): 92.7% vs. 84.3% (DConvNet) → 8.4% improvement
- Moderate (6-20%): 97.1%
- Severe (>20%): 98.6%

Multimodal Contribution:

- Visual only: 93.2%
- Sensor only: 87.6%
- Audio only: 84.1%
- All modalities: 96.4%

C. Real-World Agricultural Impact

Table Iv: Agricultural Outcome Improvements

Metric	Conventional	AENN-Guided	Improvement
Avg Yield (kg/ha)	4,285	5,612	+31.0%
Pesticide Use (L/ha)	12.8	9.8	-23.4%
Water Use (m^3/ha)	8,450	6,920	-18.1%
Fertilizer (kg/ha)	245	198	-19.2%
Pest Loss (%)	18.3	6.7	-63.4%
Net Profit ($/ha)	1,240	1,876	+51.3%

Economic Analysis:

- System cost: $1,470/ha (sensors $850, devices $320, installation $300)
- Annual operating cost: $300/ha
- Annual benefits: $1,915/ha
- Break-even: 11 months
- 5-year NPV: $6,348
- IRR: 127%Environmental Impact:
- CO_2 reduction: 1.8 tons/ha annually
- Nutrient runoff reduction: 34%
- Beneficial insect increase: 42%

D. Ablation Studies

Attention Mechanism Impact:

- No attention: R^2=0.941, Accuracy=93.8%
- Spatial attention only: R^2=0.957, Accuracy=95.2%
- Temporal attention only: R^2=0.952, Accuracy=94.6%
- All attention: R^2=0.967, Accuracy=96.4%Multi-Task Learning:
- Separate models: R^2=0.963, Accuracy=95.8%
- Joint training: R^2=0.967, Accuracy=96.4%

E. Limitations

- Extreme weather: Accuracy drops to 89.3%
- Novel pest species: 76.4% accuracy
- Heavy occlusion (>60%): 11.2% accuracy drop
- Night-time detection: 87.6% vs. 96.4% daytime

VI. CONCLUSION

This paper presented AENN, achieving state-of-the-art performance: 97.8% yield accuracy (R^2=0.967) and 96.4% pest detection. Field validation showed 31% yield improvement, 23% pesticide reduction, and 51% profit increase. Key innovations: multimodal fusion (visual + sensor + acoustic), attention mechanisms (spatial, temporal, cross-modal), adaptive IoT sampling (-45% data), and multi-task learning.

Future work: federated learning, explainable AI, edge intelligence, climate adaptation, disease detection, and robotic integration.

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