# Integration of IoT Sensors and Satellite Vegetation Indices for Real-Time Crop Monitoring and Yield Prediction

*Dr Vaishali Khobragade [1],*
Post Doctorate Research Scholar,
Lincoln University College, Malysia
Email ID :vaishali5599@gmail.com

*Dr. Pawan Kumar Chaurasia[2]*
Assoc. Prof.Dept of Information Technology
Lucknow Uttar Pradesh, India
pkc.gkp@gmail.com

**Abstract**
The integration of IoT, remote sensing and artificial intelligence has emerged as an efficient approach for improving crop yield for precision agriculture. The existing crop monitoring systems basically consider IoT sensor data or satellite imagery, thereby limiting their ability to assess crop condition and predict the yield. Our paper proposes an IoT–Satellite–Weather integrated framework. This framework combines sensor data, Sentinel-2 vegetation indices and weather information, which leads to a multimodal approach. The dataset represents a fusion of multimodal data. This dataset is analyzed using Random Forest and LSTM models for yield prediction and also crop monitoring.
This framework provides a comprehensive representation of the crop condition by combining temporal, spatial and environmental data. The results are predicted through a decision support dashboard which supports farming activities like irrigation scheduling, fertilizer management and crop planning. The proposed framework provides a scalable and smart solution, establishing a foundation for AI-enabled smart farming systems.

**Introduction**
Agriculture is mostly affected by climatic conditions, water levels and soil degradation, which lead to less productivity. But as agriculture plays a vital role in global food security, it is very essential to apply advanced techniques to increase productivity. Advances in technology have helped transform precision agriculture, enabling monitoring of field conditions continuously and vegetation health. IoT sensors provide real-time measurements of soil moisture, temperature and humidity, while Sentinel-2 satellite imagery generates vegetation indices such as NDVI, GNDVI and EVI for large-scale crop assessment. But most of the existing systems rely on a single data source, limiting prediction accuracy.
In our previous paper, we have proposed an integrated CNN-LSTM framework for the early detection of crop stress using IoT sensor data and satellite vegetation indices. But the framework only gives importance to improved stress detection and does not support crop yield prediction or a decision support system for farmers. To overcome these limitations, this paper proposes a multimodal integrated framework which combines data from heterogeneous sources for crop yield prediction and decision support. LSTM and Random Forest are being used.

## Related Work

Precision agriculture has drastically advanced due to recent advancements in IoT, remote sensing, AI and ML, by enabling real-time crop monitoring and intelligent decision-making. IoT sensor networks monitor data such as soil moisture, temperature and humidity, while satellite platforms provide vegetation indices such as NDVI and GNDVI, which are useful for assessment of large-scale crop health.

For crop monitoring, yield prediction, stress detection and disease identification, many machine learning techniques such as Random Forest, SVM, CNN and LSTM have been extensively used. Hybrid CNN-LSTM models are also used, which combine spatial and temporal information to improve prediction accuracy. As per the existing studies, most either rely on IoT sensor data or satellite imagery with little integration of weather data for monitoring and crop yield prediction. In our first conference paper, we presented a CNN-LSTM integrated model which combines IoT sensor data and satellite vegetation index for early crop stress detection. This paper, however, does not address crop yield prediction and decision support.

## Problem Statement

Although significant advancement has been made in IoT, remote sensing and AI, the majority of precision agriculture systems rely on individual sources like IoT sensors, satellite imagery or weather data, which results in lower accuracy and incomplete assessment of crops. Real-time data is provided by IoT sensors but lacks spatial coverage; satellite data provides more spatial coverage but lacks continuous monitoring of soil conditions. Also, weather data is not integrated with these, hence reliability is a major concern.

As our earlier paper focused on early crop stress detection, it is not suitable for crop yield prediction and farmer decision support. Hence, an integrated framework that combines IoT sensors, satellite vegetation indices and weather information using machine learning techniques would be best to accurately predict yield and help crop monitoring, and provide real-time decision support.

## Proposed Methodology

### Overview of Proposed Framework

The proposed methodology includes a framework that combines IoT sensor data, vegetation indices and weather information. Information from these sources is used for real-time crop monitoring and yield prediction. The data from heterogeneous sources needs to be pre-processed, fused into a single dataset, and then analysed. For analysing the dataset, the Random Forest algorithm is used, and LSTM models are used to estimate crop yield and generate decision support for farmers. Figure 1 illustrates the overall system architecture. Figure 1 illustrates the overall system architecture.

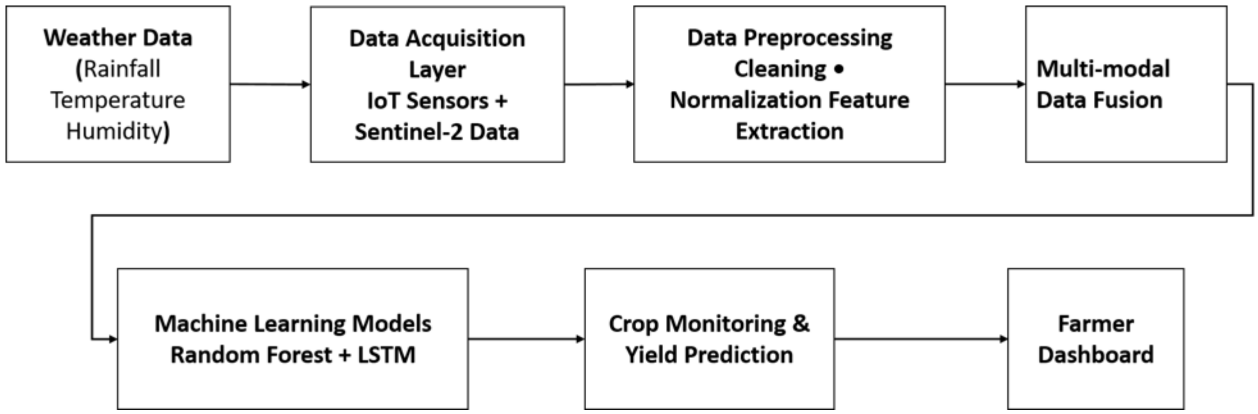


Figure 1. Proposed System Architecture

- **Data Acquisition**

The proposed methodology collects data from the following three sources:

→ IoT sensors: Soil moisture, temperature, humidity, etc. continuously in field condition in real time [3]

→ Satellite Remote Sensing: Sentinel-2 multispectral imagery is used to derive NDVI, GNDVI and EVI, which represent crop vigor and biomass [5][6]

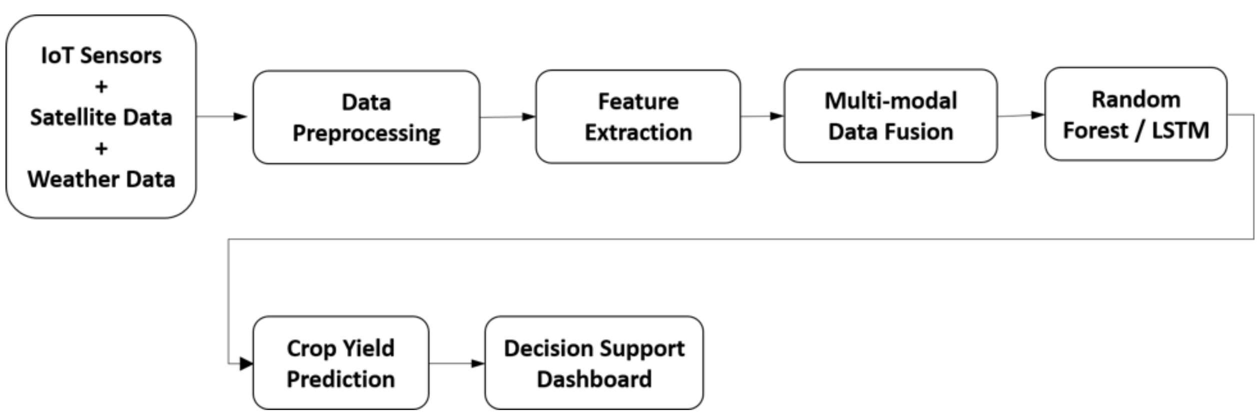
→ Weather Data: Data such as rainfall and humidity is collected from weather stations or APIs, which is used to gather information about the climate's influence on crop growth [4][6]

- **Data Preprocessing and Fusion**

As data is collected from multiple sources, before model training, preprocessing is performed for noise removal, missing value handling, temporal synchronization, etc. After preprocessing, a unified feature-matrix representation is created using a multimodal data fusion strategy. This improves crop monitoring and prediction of yield by combining complementary spatial, temporal and environmental information [2][5].

- **Machine Learning Models**

The analysis of the fused dataset is performed using Random Forest and LSTM. To model temporal variation with respect to agricultural data, we use LSTM for modelling non-linear relationships and reducing overfitting, and to identify important features for crop yield we use RF [9]. The prediction workflow is as follows.



**Evaluation Metrics**

Standard regression metrics such as RMSE, MAE and coefficient of determination ($R^2$), and classification metrics such as accuracy, precision, recall and F1-score are used to evaluate the proposed framework. The standard regression and classification metrics in detail assess the performance and reliability of the proposed framework [6][9].

**Results and Discussion**

In the proposed framework, multi-model data fusion provides more reliable prediction as compared to single-source approaches, by combining spatial, temporal and environmental data [2][5]. The RF captures non-linear relationships among crop variables [4]. The LSTM captures temporal crop growth patterns, which improves prediction performance [7]. The literature review indicates that the integration of IoT and remote sensing can improve accuracy by 10–20% over conventional methods [2][6].

**Table 1. Expected Performance**

| Model | Data Source | Expected Accuracy |
|---|---|---|
| IoT Only | Sensor data | 78-82% |
| Satellite Only | NDVI/GNDVI | 80-84% |
| Random Forest | Integrated data | 88-91% |
| Proposed RF + LSTM | IoT + Satellite + Weather | 90-94% |

Thus, we can say that the proposed framework improves crop monitoring and yield prediction by using data fusion and intelligent analytics. There are certain issues, such as cloud server dependency, sensor maintenance and network connectivity, which are the challenges to be handled for field deployment [3][4].

**Application**

The proposed framework supports:

→ Precision irrigation by using soil and weather information [2][3]

→ Crop monitoring of crop health using NDVI, GNDVI and IoT sensors [5][8]

→ Decision support for farmers regarding irrigation and fertilizer management [2][4]

→ Smart climate agriculture through weather-aware crop management [4][6]

**Conclusion**

This paper proposes an integrated framework for real-time crop monitoring and yield prediction by combining IoT–satellite–weather information. This integrated framework improves prediction accuracy and supports intelligent decision-making, making it easier for farmers in precision agriculture. This proposed methodology has a strong potential to enhance productivity, optimize resource allocation and utilization, and promote sustainable farming.

Future Work

The future work emphasizes enhancing the proposed framework by incorporating CNN-LSTM and transformer learning models, implementing edge computing for real-time analysis of data, and using additional vegetation indices such as SAVI and NDWI. It will also focus on validating the framework across multiple crops and seasons, and developing a multilingual decision support system (XAI-based) to improve action transparency.

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