
A Comprehensive Review on Weather Anomaly Detection and Risk Prediction for Smart Agriculture

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Abstract.

Agriculture is considered a major pillar of India's socio-economic development. Agriculture is highly sensitive to climatic variations, such as droughts, floods, and temperature fluctuations. Accurate detection of weather anomalies and timely prediction of associated risks plays very important role for increasing agricultural productivity and sustainability. The emergence of the Internet of Things (IoT) and deep learning technologies have been instrumental in recent years in enabling smart agriculture. The paper presents a literature review of numerous studies dedicated to the topic of weather anomaly detection and risk prediction through the use of different methods, such as Long Short Term Memory (LSTM) autoencoders, Convolutional Neural Networks (CNNs), Transformer-based models, and ensemble learning methods applicable to the analysis of large-scale agricultural and meteorological data. The study also identifies recent advancements, various model performance parameters, and also highlights critical research gaps. Finally, a roadmap for future research methodology is proposed to enhance intelligent decision-making in smart agriculture.

Keywords. Smart Agriculture; Deep Learning; Anomaly Detection; LSTM; CNN; IoT; Risk Prediction.

1. INTRODUCTION

Global economy is based on agriculture. Human survival is very dependent on the food security and economic stability. Farming is very sensitive to the environment and climatic changes that include alteration in temperature, irregular rains and extreme climatic conditions. The conventional agricultural forecasting systems are not suitable to identify and forecast real-time weather anomalies. Deep learning is currently a popular machine learning method to derive valuable information out of large scale data. Weather anomaly detection can be defined as the detection of deviations that are unusual or unexpected that arise as a result of climatic anomalies. Risk prediction is concerned with how these

weather anomalies are predicted to affect crop yield. Combining weather anomaly and risk prediction allows building smart systems that facilitate proactive decision-making. With further development of the Internet of Things (IoT) and Artificial Intelligence, smart agriculture provides predictive analytics and real-time observation. Recent studies prove that it is necessary to combine sensor-based systems with machine learning algorithms to identify anomalies and forecast risks. However, such problems as data reliability, computing capacities and a lack of integrated structures persist. The paper gives a review of the recent literature on intelligent systems to identify weather anomalies and forecasting risk.

2. RELATED WORK

Rua Y. Aburasain [1] introduced an Enhanced Black Widow Optimization integrated with a Hybrid Deep Learning-based Intrusion Detection (EBWO-HDLID) approach for smart agriculture. The method aims to identify intricate behavioural patterns and pinpoint potential critical security vulnerabilities, enhancing the system's reliability and security. In [2] LoRaWAN was used to connect sensing devices to LSTM autoencoders for continuous monitoring of the microalgae culture and the detection of anomalies. Another hybrid strategy was introduced in [3] where the integration of LSTM autoencoder with One Class Support Vector Machine (OCSVM) was used to analyze daily meteorological observation data taken in East Java from 2015 to 2024. All these developments, however, fall short of achieving strong generalization of the models and the ability to accurately recognize the diversity of environmental conditions. Recent research in smart agriculture has increasingly explored hybrid deep learning approaches for analyzing weather irregularities and crop-related patterns. Method of IoT-enabled ensemble learning models, and optimized CNN architectures have demonstrated improved performance in anomaly detection and decision-making processes [4], [5]. However, most of these approaches rely heavily on historical datasets and provide limited capability for real-time risk forecasting.

The recent research in the field of smart agriculture combines deep learning with IoT to detect anomalies and anticipate risks [6]. Machine learning models (SVM, Random Forest, DNN) and big data frameworks (CNN-LSTM with Spark) enhance monitoring, scalability and decision making [7],[8]. Unsupervised IoT algorithms like K-Means and Isolation Forests can be used to do real-time detection with minimum labelled data [9]. The recent development in smart agriculture combines the concept of deep learning with intelligent sensing to detect weather anomalies in real time and predict risks. UAV frameworks based on transformers and lightweight TSMixer models can improve the precision and effectiveness of detection, whereas AI-based ensemble models can be enhanced to resist extreme weather conditions [10], [11], [12]. Nevertheless, scalability, real-time deployment, sparse data processing, and the ability to incorporate predictions into actionable strategies are still a problem, and more integrated and intelligent systems are needed.

In recent studies on smart agriculture, one of the crucial aspects has been the securing of IoT systems so that they can achieve dependable and trustworthy data to detect anomalies and predict risks. Deep learning models are optimized, lightweight edge-based intrusion detectors, and hybrid frameworks such as GMLP-IDS enhance the detection accuracy and

information integrity [13], [14]. However, they are primarily utilized to combat cyber security threats and are not combined with environmental anomaly detection, which highlights the need to integrate the frameworks that can differentiate between cyber-attacks, sensor malfunctions, and actual weather anomalies. Recent progress in precision agriculture leverages deep learning techniques alongside multimodal data to enhance anomaly detection and risk prediction. Frameworks such as IMSF Net with AROS use UAV, satellite, and sensor data to monitor crops precisely and CNN-based frameworks (e.g., VGG, ResNet) identify visual anomalies, including diseases and weeds [15], [16].

3. RESEARCH GAP

Based on the literature review, there are several gaps identified in the existing literature. Studies have so far focused on anomaly detection or risk prediction, but have not tried to combine them in a single model. There are several factors that can influence agricultural data reliability, such as sensor failures, environmental conditions, and cybersecurity threats. Current approaches tend to identify anomalies after they have happened instead of forecasting potential anomalies prior to their occurrence. High computing resources can also be required by advanced models, which is not suitable for use in edge devices. Furthermore, the challenges of limited use of multimodal data, poor model interpretability and lack of cybersecurity and environmental monitoring integration are still significant.

4. FUTURE DIRECTIONS

The development of integrated intelligent systems combining anomaly detection, risk prediction and decision making is suggested for future research. Early warning systems and useful recommendations should be offered to help farmers take timely actions in such systems. The lightweight models would be compatible with the edge devices, and the integration of data from sensors, satellites, UAVs and weather sources would enhance accuracy of the models. Reliable data can be provided by secure IoT architectures and the explainable AI can help in making the system decisions understandable and trustworthy. Systems to be developed in the future should also be adaptable, scalable and continuously learnable as the environment and climate shift.

5. CONCLUSION

The review highlights the importance of deep learning and hybrid models in detecting weather anomalies and predicting risks in smart agriculture. Techniques such as LSTM, GAN, CNN, and ensemble models can identify complex patterns in IoT and environmental data. However, challenges remain in real-time prediction, computational complexity, scalability, sensor fault detection, explainability, and multimodal data integration. Future research should focus on unified, lightweight, scalable, explainable, and multimodal models to improve agricultural resilience and sustainability under changing climatic conditions..

6. REFERENCES

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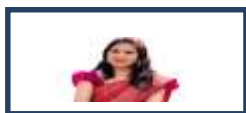
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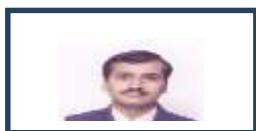
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