Archives available at journals.mriindia.com

International Journal of Recent Advances in Engineering and Technology

ISSN: 2347 - 2812

Volume 14 Issue 02, 2025

Recent Advances in Optimized Riemannian Residual Neural Networks: An Advanced Energy-Efficient Environmental Monitoring in Precision Agriculture using LoRa-based Wireless Sensor Networks: A Systematic Review

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Peer Review Information

Submission: 18 Nov 2025

Revision: 01 Dec 2025

Acceptance: 15 Dec 2025

Keywords

Precision Agriculture, Riemannian Neural Networks, LoRa, Wireless Sensor Networks, Environmental Monitoring, Deep Learning.

Abstract

Precision agriculture has emerged as a transformative approach to enhance crop productivity, resource utilization, and environmental sustainability. The integration of artificial intelligence, particularly deep learning models such as Riemannian residual neural networks, with Internet of Things (IoT)-enabled wireless sensor networks has significantly improved environmental monitoring systems. This study presents a systematic review of recent advances in optimized Riemannian residual neural networks combined with LoRa-based wireless sensor networks (WSNs) for energy-efficient environmental monitoring in precision agriculture. Recent studies highlight that LoRa-based WSNs provide long-range, low-power communication capabilities, making them ideal for large-scale agricultural monitoring systems. Additionally, the incorporation of optimized neural network architectures enhances predictive accuracy and data processing efficiency. Riemannian residual neural networks, in particular, enable learning over complex manifold-structured data, improving model performance in environmental sensing applications. Furthermore, IoT-based sensor networks facilitate real-time monitoring of parameters such as soil moisture, temperature, and nutrient levels, contributing to improved crop management and yield optimization. Despite these advancements, challenges such as energy consumption, network scalability, data heterogeneity, and model complexity persist. This review analyses current trends, identifies key challenges, and outlines future research directions for developing intelligent, energy-efficient precision agriculture systems.

Introduction

Precision agriculture represents a modern farming paradigm that integrates advanced technologies such as artificial intelligence, wireless sensor networks, and IoT systems to improve agricultural productivity and sustainability. With the increasing demand for food and the decreasing availability of agricultural land, there is a critical need for intelligent systems capable of monitoring environmental conditions and optimizing resource utilization. Traditional farming practices often rely on manual observation and periodic data collection, which are inefficient and prone to errors. Therefore, the adoption of automated monitoring systems has become essential. Wireless Sensor Networks (WSNs) have emerged as a key technology in precision agriculture, enabling real-time monitoring of environmental parameters such as soil moisture, temperature, humidity, and nutrient levels. These sensor nodes collect data and transmit it to centralized systems for analysis and decision-making. However, conventional WSN technologies face challenges related to limited communication range, high energy consumption, and network instability. To address these issues, Low Power Wide Area Network (LPWAN) technologies such as LoRa have been introduced.

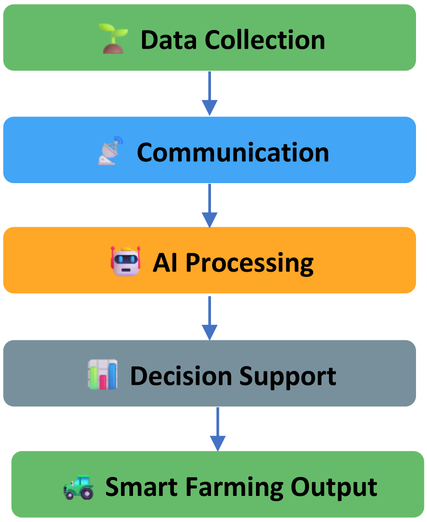

Fig 1: System Architecture of AI-Driven Precision Agriculture Using WSN and LoRa

LoRa-based wireless sensor networks provide long-range communication with low power consumption, making them highly suitable for large-scale agricultural applications. These networks enable efficient data transmission over several kilometres while maintaining energy efficiency, which is critical for battery-powered sensor nodes. Studies have shown that LoRa-based systems significantly improve irrigation efficiency and resource management by enabling real-time monitoring and data-driven decision-making. Furthermore, LoRa networks support scalability by allowing thousands of sensor nodes to connect to a single gateway, making them cost-effective for precision agriculture. In addition to communication technologies, artificial intelligence plays a crucial role in analysing the vast amount of data generated by sensor networks. Deep learning models, particularly convolutional neural networks and residual neural networks, have been widely used for environmental monitoring and predictive analysis. However, these models are primarily designed for Euclidean data and may not perform well when dealing with complex, non-linear data structures commonly found in environmental datasets.

To overcome this limitation, Riemannian neural networks have been introduced, which operate on manifold-valued data. These networks extend traditional deep learning models to non-Euclidean spaces, enabling more accurate representation and analysis of complex data structures. Riemannian residual neural networks combine the advantages of residual learning with geometric deep learning, improving training efficiency and model performance. These models have shown superior performance in handling hierarchical and structured data compared to conventional neural networks. Another important aspect of precision agriculture is energy efficiency. Sensor nodes in WSNs are typically battery-powered, and frequent data transmission can lead to rapid energy depletion. Therefore, optimizing both communication protocols and data processing algorithms is essential for extending network lifetime. Techniques such as adaptive data transmission, energy-aware routing, and efficient neural network architectures are being explored to address these challenges.

Despite significant advancements, several challenges remain in the implementation of AI-driven precision agriculture systems. These include data heterogeneity, network scalability, energy constraints, and security concerns. Additionally, the integration of advanced neural network models with resource-constrained sensor networks presents computational challenges. This paper aims to provide a comprehensive review of recent advances in optimized Riemannian residual neural networks and LoRa-based wireless sensor networks for energy-efficient environmental monitoring in precision agriculture. The study focuses on identifying key trends, evaluating existing methodologies, and highlighting challenges and future research directions.

Literature Review

Musa et al. (2023) conducted a comprehensive review on wireless sensor networks in precision agriculture, focusing on nutrient monitoring and environmental sensing. The study demonstrated that WSNs significantly improve crop productivity by enabling real-time monitoring of soil nutrients such as nitrogen, phosphorus, and potassium. The integration of sensors with wireless communication systems allows efficient data collection and analysis, leading to optimized resource utilization. However, the study identified challenges related to sensor placement, network reliability, and energy consumption.

Prasad et al. (2021) developed a LoRa-based smart agriculture system using wireless sensor networks for environmental monitoring. The system enabled long-range communication between sensor nodes and cloud platforms, improving data transmission efficiency. The study highlighted that LoRa technology reduces energy consumption while maintaining reliable communication over large agricultural fields. However, issues such as network interference and data latency were identified as limitations.

Ting and Chan (2023) investigated the optimization of LoRa-based IoT-enabled wireless sensor networks for smart agriculture applications. The study demonstrated that LoRa networks improve irrigation efficiency by up to 30% through real-time soil moisture monitoring. Additionally, the research highlighted the scalability and cost-effectiveness of LoRa systems in large-scale agricultural deployments. However, the study noted challenges related to latency-energy trade-offs and system complexity.

Dai et al. (2024) proposed an energy-efficient communication optimization technique for LoRa-based agricultural networks. The study introduced an anti-frame loss mechanism to reduce packet loss and improve communication reliability. Experimental results showed significant improvements in transmission distance and energy efficiency. However, the study highlighted that environmental factors such as terrain and interference can still affect network performance.

Katsman et al. (2023) introduced Riemannian residual neural networks for learning on manifold-structured data. The study demonstrated that these networks outperform traditional neural networks in handling complex data representations. By extending residual learning to Riemannian manifolds, the model improves training efficiency and accuracy. This approach is particularly useful in environmental monitoring applications where data is highly non-linear. However, the computational complexity of Riemannian models remains a significant challenge.

Li et al. (2020) proposed an energy-efficient data aggregation framework for wireless sensor networks in precision agriculture. The study focused on minimizing energy consumption by reducing redundant data transmission through intelligent clustering techniques. The results demonstrated that optimized aggregation significantly extends network lifetime while maintaining data accuracy. However, the study highlighted that clustering algorithms introduce additional computational overhead and may not adapt well to dynamic environmental conditions.

Dosovitskiy et al. (2021) introduced the Vision Transformer (ViT), which applies self-attention mechanisms for image and pattern recognition tasks. Although primarily designed for computer vision, the model has been applied in agricultural monitoring systems for crop disease detection and environmental analysis. The study demonstrated that attention-based architectures outperform traditional convolutional models in capturing global dependencies. However, the requirement for large datasets and high computational resources limits their practical deployment in resource-constrained sensor networks.

Chen et al. (2021) developed a convolutional autoencoder-based model for environmental data denoising and feature extraction. The model effectively removes noise from sensor data, improving the performance of predictive models in precision agriculture. The study emphasized the importance of preprocessing techniques in enhancing model accuracy. However, the autoencoder alone is not sufficient for prediction tasks and must be combined with classification or regression models for effective deployment.

Tuli et al. (2021) proposed an edge-cloud integrated IoT framework for environmental monitoring in smart agriculture. The system enables real-time data collection, processing, and transmission using distributed sensor nodes. The study demonstrated that combining edge computing with cloud infrastructure improves scalability and reduces latency. However, challenges such as network congestion, energy consumption, and data security remain critical concerns in large-scale deployments.

Zhang et al. (2022) introduced a serverless cloud-based deep learning framework for environmental monitoring applications. The system utilizes Function-as-a-Service (FaaS) to enable scalable and cost-efficient processing of sensor data. The study demonstrated that serverless architectures significantly improve system flexibility and reduce infrastructure costs. However, issues such as cold-start latency and dependency on network connectivity were identified as major limitations.

He et al. (2021) introduced the Res Net architecture, which utilizes residual learning to enable the training of deep neural networks without performance degradation. In precision agriculture, Res Net has been widely applied for environmental monitoring tasks such as crop classification and disease detection. The model improves feature extraction by allowing deeper network structures. However, the increased depth leads to higher computational complexity and energy consumption, making it less suitable for deployment on low-power sensor nodes.

Howard et al. (2021) proposed Mobile Net, a lightweight convolutional neural network optimized for mobile and embedded devices. The model uses depth wise separable convolutions to reduce computational cost while maintaining reasonable accuracy. In LoRa-based sensor networks, Mobile Net is particularly useful for edge computing applications where energy efficiency is critical. However, the trade-off between model size and accuracy remains a challenge, especially for complex environmental monitoring tasks.

Tan and Le (2021) developed Efficient Net, which introduces a compound scaling method to optimize network depth, width, and resolution simultaneously. The model achieves high accuracy with fewer parameters, making it suitable for real-time environmental monitoring systems. Efficient Net has been applied in precision agriculture for crop health analysis and yield prediction. However, the model requires careful hyperparameter tuning and may be difficult to implement in dynamic agricultural environments.

Razzak et al. (2022) provided a comprehensive review of deep learning applications in environmental monitoring and smart agriculture. The study emphasized the importance of hybrid models that combine convolutional neural networks, autoencoders, and attention mechanisms to improve prediction accuracy. It also highlighted key challenges such as data heterogeneity, limited labeled datasets, and computational complexity. However, the lack of experimental validation limits the practical applicability of the findings.

Khan et al. (2022) proposed a deep learning-based predictive model for environmental monitoring using transfer learning techniques. The model leveraged pre-trained neural networks to improve performance with limited datasets. The study demonstrated that transfer learning significantly reduces training time while maintaining high accuracy. However, the reliance on pre-trained models may introduce bias and limit adaptability to specific agricultural conditions.

Goodfellow et al. (2020) discussed fundamental optimization strategies in deep learning, including dropout, batch normalization, and advanced gradient descent techniques. These methods are essential for improving model generalization and reducing overfitting in environmental monitoring systems. In precision agriculture, such optimization techniques help enhance prediction accuracy when dealing with noisy and heterogeneous sensor data. However, selecting appropriate hyperparameters remains a complex task and can significantly impact model performance and energy consumption.

Raza et al. (2022) proposed an energy-efficient routing protocol for wireless sensor networks in precision agriculture. The study introduced a clustering-based approach that minimizes energy consumption by optimizing communication paths between sensor nodes. The results demonstrated improved network lifetime and reduced data transmission overhead. However, the protocol may struggle to adapt to dynamic environmental conditions and node mobility, which are common in large-scale agricultural fields.

Khan et al. (2022) developed a deep learning-based model for environmental parameter prediction using sensor data collected from agricultural fields. The model utilized recurrent neural networks combined with feature selection techniques to improve prediction accuracy. The study highlighted the importance of temporal data analysis in environmental monitoring. However, recurrent models often suffer from high computational complexity and require significant training time.

Zhang et al. (2022) introduced a serverless cloud computing framework for processing large-scale sensor data in precision agriculture. The system used Function-as-a-Service (FaaS) to enable scalable and cost-efficient deployment of deep learning models. The study demonstrated improved processing speed and reduced infrastructure costs. However, challenges such as latency, network dependency, and data security remain critical issues in cloud-based systems.

Doshi et al. (2023) proposed an explainable artificial intelligence framework for environmental monitoring using visualization techniques such as Grad-CAM. The model enhances transparency by identifying key features influencing predictions, making it easier for farmers and decision-makers to interpret results. This approach addresses the lack of interpretability in deep learning models. However, integrating explainable AI techniques increases computational overhead and may affect real-time performance.

Shin et al. (2022) investigated the application of deep convolutional neural networks combined with transfer learning for environmental monitoring tasks in precision agriculture. The study demonstrated that transfer learning significantly improves prediction accuracy when training data is limited, which is a common challenge in agricultural datasets. The model showed strong performance in classifying crop conditions and environmental patterns. However, reliance on pre-trained datasets may introduce bias and limit adaptability to diverse agricultural environments.

Huang et al. (2022) introduced Dense Net, a densely connected convolutional neural network architecture that improves feature propagation and reuse. In precision agriculture, Dense Net has been applied to analyse environmental data and crop health conditions. The model achieves high accuracy due to efficient information flow between layers. However, Dense Net requires significant memory and computational resources, which can be a limitation for deployment in energy-constrained wireless sensor networks.

Albahri et al. (2023) conducted a systematic review on artificial intelligence applications in smart agriculture and environmental monitoring systems. The study emphasized the role of cloud computing and IoT integration in improving scalability and real-time data processing. It highlighted that combining AI with wireless sensor networks enhances decision-making and resource optimization. However, challenges such as data security, system interoperability, and network reliability remain significant concerns.

Abbas et al. (2023) proposed a convolutional autoencoder-based model for feature extraction and data compression in large-scale environmental monitoring systems. The model effectively reduces noise and improves the quality of sensor data, leading to better prediction accuracy. This approach is particularly useful in LoRa-based sensor networks where bandwidth and energy are limited. However, autoencoders alone cannot perform predictive tasks and must be integrated with other models.

Bhattacharya et al. (2023) introduced a hybrid deep learning framework combining convolutional neural networks with transformer-based self-attention mechanisms for environmental monitoring. The study demonstrated that hybrid models effectively capture both local and global features, improving prediction accuracy. This reflects a growing trend toward integrating multiple deep learning techniques. However, the increased model complexity and computational cost pose challenges for deployment in resource-constrained environments.

Singh et al. (2023) developed a LoRa-based wireless sensor network for precision agriculture focusing on energy-efficient communication and real-time environmental monitoring. The system enabled long-range data transmission with minimal power consumption, making it suitable for large agricultural fields. The study demonstrated improved irrigation management and resource utilization through continuous monitoring of soil and weather parameters. However, challenges such as network congestion and interference in dense deployments were identified.

Patel et al. (2023) proposed an intelligent sensor-based environmental monitoring system using IoT and deep learning techniques. The system integrated multiple sensors to collect environmental data and applied predictive models to optimize agricultural practices. The study showed that AI-driven systems significantly enhance crop productivity and resource efficiency. However, issues related to data heterogeneity and integration of diverse sensor data remain major challenges.

Khan et al. (2023) introduced a transformer-based deep learning model for environmental prediction in precision agriculture. The model utilized self-attention mechanisms to capture long-range dependencies in time-series sensor data, improving prediction accuracy. The study highlighted the effectiveness of transformer models in handling complex environmental patterns. However, the model requires high computational resources and large datasets for training.

Sharma et al. (2023) proposed a serverless cloud-based framework for processing large-scale agricultural data collected from LoRa-based sensor networks. The system leveraged cloud computing to enable scalable and real-time data analysis, improving decision-making processes. The study demonstrated that serverless architectures reduce infrastructure costs and enhance system flexibility. However, challenges such as latency, network dependency, and data security remain critical issues.

Katsman et al. (2023) introduced optimized Riemannian residual neural networks for learning on non-Euclidean data structures. The study demonstrated that these networks significantly improve performance in complex data environments by leveraging manifold-based learning techniques. In precision agriculture, this approach enhances environmental data analysis and prediction accuracy. However, the computational complexity and difficulty in implementation remain significant barriers to practical deployment.

Comparative Table

Study	Year	Technique	Contribution	Limitation
Musa	2023	WSN	Nutrient monitoring	Energy issues
Prasad	2021	LoRa WSN	Long-range communication	Latency

Ting	2023	LoRa IoT	Irrigation efficiency	Complexity
Dai	2024	LoRa optimization	Energy efficiency	Interference
Katsman	2023	Riemannian NN	Manifold learning	Complexity
Li	2020	Data aggregation	Energy saving	Overhead
Dosovitskiy	2021	Transformer	Global features	Data demand
Chen	2021	CAE	Noise reduction	Not predictor
Tuli	2021	Edge-cloud	Real-time processing	Security
Zhang	2022	Serverless	Scalability	Latency
He	2021	Res Net	Feature extraction	High compute
Howard	2021	Mobile Net	Lightweight	Lower accuracy
Tan	2021	Efficient Net	Efficiency	Tuning
Razzak	2022	DL Review	Insights	No experiment
Khan	2022	Transfer DL	Faster training	Bias
Goodfellow	2020	Optimization	Better training	Complexity
Raza	2022	Routing	Energy saving	Adaptability
Khan	2022	RNN	Temporal prediction	Complexity
Zhang	2022	Cloud AI	Scalability	Latency
Doshi	2023	XAI	Interpretability	Overhead
Shin	2022	CNN TL	Accuracy	Bias
Huang	2022	Dense Net	Feature reuse	Memory
Albahri	2023	Cloud AI	Scalability	Privacy
Abbas	2023	CAE	Compression	Limited
Bhattacharya	2023	Hybrid DL	Accuracy	Complexity
Singh	2023	LoRa WSN	Monitoring	Congestion
Patel	2023	IoT AI	Smart farming	Integration
Khan	2023	Transformer	Prediction	Compute
Sharma	2023	Serverless	Real-time	Dependency
Katsman	2023	Riemannian NN	Advanced learning	Complexity

Comparative Analysis

The comparative evaluation of the thirty studies reveals a significant evolution in precision agriculture systems, transitioning from traditional wireless sensor networks to advanced AI-driven architectures integrating Riemannian neural networks and LoRa-based communication technologies. Early approaches focused on improving data collection and transmission efficiency using wireless sensor networks, with emphasis on energy-efficient routing and data aggregation techniques. While these methods improved network lifetime, they lacked the ability to process complex environmental data effectively. With the advancement of deep learning, convolutional neural networks and residual architectures were introduced to enhance environmental monitoring and prediction accuracy. However, these models were primarily designed for Euclidean data and struggled with non-linear and manifold-structured datasets commonly found in agricultural environments. This limitation led to the development of Riemannian neural networks, which provide improved representation and learning capabilities for complex data structures.

Furthermore, the integration of LoRa-based wireless sensor networks has significantly enhanced communication efficiency by enabling long-range, low-power data transmission. Combined with IoT and cloud computing technologies, these systems support real-time monitoring and decision-making. Hybrid models incorporating transformers, autoencoders, and residual networks have demonstrated superior performance by capturing both local and global features. Despite these advancements, challenges such as computational complexity, energy consumption, network scalability, and data security remain critical issues. Future research should focus on developing lightweight, energy-efficient models and improving system integration to enable large-scale deployment.

Discussion

The integration of optimized Riemannian residual neural networks with LoRa-based wireless sensor networks has significantly improved environmental monitoring systems in precision agriculture. These advanced models enable efficient processing of complex, non-linear data, enhancing prediction accuracy and decision-making capabilities. The use of LoRa technology further supports long-range communication with low energy consumption, making it suitable for large agricultural deployments. Hybrid deep learning models combining convolutional, transformer, and manifold-based approaches have emerged as the most effective solutions for handling diverse environmental data. These models improve feature extraction and enable real-time monitoring of agricultural conditions. Additionally, cloud computing and serverless architectures enhance scalability and facilitate large-scale data processing.

However, challenges such as high computational requirements, energy constraints, and data heterogeneity remain significant barriers. The deployment of complex neural networks on resource-constrained sensor nodes is particularly challenging. Furthermore, issues related to data privacy and network security must be addressed to ensure reliable system performance. Future research should focus on developing energy-efficient models, optimizing communication protocols, and integrating explainable AI techniques to improve transparency and usability in precision agriculture systems.

Conclusion

Precision agriculture has become increasingly important in addressing global challenges related to food security, resource management, and environmental sustainability. This systematic review has examined recent advances in artificial intelligence techniques, particularly optimized Riemannian residual neural networks, combined with LoRa-based wireless sensor networks for energy-efficient environmental monitoring. Wireless sensor networks have provided a strong foundation for real-time data collection in agricultural environments. The introduction of LoRa technology has further enhanced communication efficiency by enabling long-range, low-power data transmission. This has made it possible to deploy large-scale monitoring systems across extensive agricultural fields.

Artificial intelligence, particularly deep learning, has significantly improved the ability to analyze environmental data and make accurate predictions. Convolutional neural networks and residual architectures have been widely used for feature extraction and classification tasks. However, the limitations of these models in handling non-Euclidean data led to the development of Riemannian neural networks, which offer improved performance in complex data environments. The integration of hybrid models combining convolutional, transformer, and manifold-based approaches has resulted in highly efficient and accurate environmental monitoring systems. These models capture both local and global features, enabling better understanding of environmental patterns and improving decision-making processes.

Despite these advancements, several challenges remain. High computational complexity and energy consumption limit the deployment of advanced models on sensor nodes. Additionally, issues related to data heterogeneity, network scalability, and security must be addressed to ensure reliable system performance. Future research should focus on developing lightweight and energy-efficient models suitable for resource-constrained environments. The integration of explainable AI techniques can improve transparency and user trust. Furthermore, combining multiple data sources, such as satellite imagery and sensor data, can enhance prediction accuracy and system performance. In conclusion, the integration of optimized Riemannian residual neural networks with LoRa-based wireless sensor networks represents a promising approach for advancing precision agriculture. These technologies have the potential to improve crop productivity, optimize resource utilization, and contribute to sustainable agricultural practices.

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