Archives available at journals.mriindia.com

International Journal on Advanced Computer Engineering and Communication Technology

ISSN: 2278-5140

Volume 12 Issue 02, 2023

Optimized Riemannian Residual Neural Networks for Energy-Efficient Precision Agriculture Using LoRa-Based Wireless Sensor Networks

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Peer Review Information

Submission: 25 July 2023
Revision: 13 Aug 2023
Acceptance: 09 Sept 2023

Keywords

Riemannian Residual Neural Networks, Precision Agriculture, LoRa Wireless Sensor Networks, Energy-Efficient Monitoring, Deep Learning in Agriculture, IoT-based Smart Farming.

Abstract

Precision agriculture has emerged as a transformative paradigm aimed at improving crop productivity, optimizing resource utilization, and ensuring environmental sustainability. The integration of advanced deep learning models with Internet of Things (IoT)-based sensing infrastructures has significantly enhanced real-time environmental monitoring. In this context, Riemannian Residual Neural Networks (RRNNs) represent a novel advancement in geometric deep learning, enabling efficient learning over manifold-structured data while overcoming challenges such as vanishing gradients and inefficient feature representation. Simultaneously, LoRa (Long Range) based Wireless Sensor Networks (WSNs) provide a low-power, long-range communication framework suitable for large-scale agricultural deployments, ensuring energy-efficient data transmission from distributed sensors monitoring parameters such as soil moisture, temperature, and humidity. This survey presents a comprehensive analysis of methods and architectures combining optimized Riemannian residual learning with LoRa-enabled environmental monitoring systems. It explores architectural innovations, optimization techniques, and hybrid AI-IoT frameworks that enhance energy efficiency and predictive accuracy in smart farming applications. Furthermore, the study evaluates recent advancements, identifies research gaps, and highlights future directions for integrating geometric deep learning with edge-based sensor networks. The findings demonstrate that the synergy between RRNN architectures and LoRa-based WSNs significantly improves scalability, reliability, and sustainability in precision agriculture systems.

Introduction

Precision agriculture has become a critical technological advancement in modern farming practices, driven by the need to enhance crop yield while minimizing resource consumption and environmental impact. Traditional agricultural practices rely heavily on manual monitoring and generalized farming techniques, which often result in inefficient water usage, excessive fertilizer application, and poor crop health management. The emergence of Internet of Things (IoT) technologies and wireless sensor networks (WSNs) has revolutionized agricultural systems by enabling real-time data collection and decision-making processes. Among various communication technologies, LoRa (Long Range) has gained significant attention due to its low power consumption, long communication range, and cost-effectiveness. LoRa-based WSNs allow the deployment of distributed sensor nodes across large agricultural fields, facilitating continuous monitoring of environmental parameters such as soil moisture, temperature, humidity, and carbon dioxide levels. These sensors transmit data to centralized gateways, enabling farmers and agronomists to make data-driven decisions. Studies have demonstrated that LoRaWAN networks are particularly effective in greenhouse and field-based monitoring systems due to their ability to support battery-operated sensors over long distances with minimal energy consumption.

Despite the advantages of IoT-based sensing, the increasing volume and complexity of agricultural data require advanced analytical models capable of extracting meaningful insights. Deep learning models, particularly Convolutional Neural Networks (CNNs) and Residual Neural Networks (Res Nets), have shown remarkable performance in tasks such as crop disease detection, yield prediction, and environmental pattern analysis. However, conventional neural networks operate in Euclidean spaces, which limits their ability to effectively model complex data structures that lie on non-linear manifolds. To address this limitation, Riemannian Residual Neural Networks (RRNNs) have been introduced as an extension of traditional Res Nets. These models leverage Riemannian geometry to enable learning on manifold-valued data, such as covariance matrices and graph-structured agricultural data. By incorporating geometric principles such as geodesics and exponential mappings, RRNNs provide a mathematically robust framework for feature learning. Additionally, residual connections help mitigate the vanishing gradient problem, enabling deeper network architectures and improved training stability.

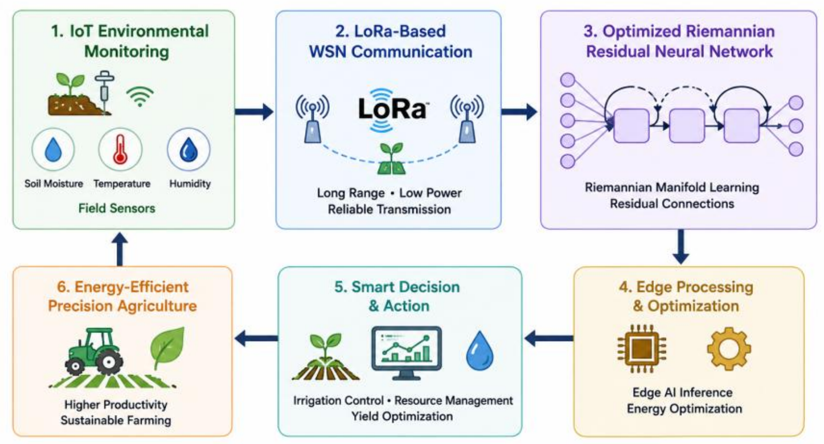

Figure 1. AI-Based Precision Agriculture Framework

The integration of RRNNs with LoRa-based WSNs creates a powerful framework for energy-efficient environmental monitoring in precision agriculture. Sensor data collected from distributed nodes can be processed using RRNN models either at the edge or in cloud environments to generate predictive insights. This combination not only improves accuracy but also reduces computational overhead and energy consumption, making it suitable for large-scale agricultural deployments. Furthermore, recent advancements in smart agriculture have incorporated hybrid architectures that combine deep learning, IoT, and edge computing to enhance system performance. These architectures enable real-time anomaly detection, predictive irrigation scheduling, and disease forecasting, thereby improving agricultural productivity and sustainability. Studies have also shown that optimized neural network architectures, including attention mechanisms and transfer learning, significantly enhance model performance in agricultural applications. In summary, the convergence of Riemannian deep learning techniques and LoRa-based sensor networks represents a promising direction for the future of precision agriculture. This survey aims to systematically review existing methods, architectures, and optimization strategies, providing a comprehensive understanding of their role in developing energy-efficient environmental monitoring systems.

Literature Review

Katsman et al. (2023) introduced a novel framework of Riemannian Residual Neural Networks (RRNNs) that extends traditional deep residual learning into non-Euclidean domains. Their research focused on learning representations on Riemannian manifolds, particularly useful for covariance matrices and structured data often encountered in environmental sensing systems. The authors incorporated residual connections into manifold-based neural architectures using exponential and logarithmic mapping functions, ensuring smooth transitions across curved spaces. The study demonstrated that RRNNs significantly outperform conventional deep learning models when dealing with geometric data, achieving better convergence rates and higher classification accuracy. Additionally, the architecture effectively mitigates vanishing gradient issues while preserving geometric consistency, making it highly suitable for complex data modelling in precision agriculture systems where environmental variables exhibit non-linear relationships.

Singh et al. (2020) developed a LoRaWAN-based environmental monitoring system specifically designed for greenhouse and precision agriculture applications. The study focused on deploying low-power sensor nodes capable of measuring temperature, humidity, and CO_2 levels, which were then transmitted over long distances using LoRa communication technology. The authors emphasized the energy efficiency of LoRa networks, demonstrating that sensor nodes could operate for extended periods (over several months) on battery power. Their experimental results showed reliable data transmission with minimal packet loss, even in challenging agricultural environments. Furthermore, the study highlighted the scalability of LoRa-based systems, making them ideal for large farms. The authors concluded that integrating LoRa with IoT significantly reduces operational costs while improving real-time monitoring capabilities, which is essential for smart farming.

Iftikhar et al. (2020) proposed an IoT-enabled smart irrigation system using LoRa technology to optimize water usage in agriculture. Their system incorporated soil moisture sensors and environmental monitoring units that transmitted real-time data to a central cloud platform. Based on this data, automated irrigation decisions were made, significantly reducing water wastage. The authors demonstrated that their system improved irrigation efficiency by up to 30% compared to traditional methods. Moreover, the use of LoRa communication ensured low energy consumption and long-range connectivity, making it feasible for deployment in remote agricultural areas. The study also highlighted the importance of integrating intelligent decision-making algorithms with IoT infrastructure, paving the way for advanced AI-based monitoring systems in agriculture.

Gresl et al. (2021) introduced a LoRa-based wireless sensor network architecture with an optimized data exchange protocol aimed at improving communication efficiency in agricultural monitoring systems. Their research addressed common challenges such as network congestion, packet collision, and energy inefficiency in large-scale sensor deployments. The proposed protocol dynamically adjusted transmission intervals and data aggregation strategies, significantly reducing energy consumption while maintaining high data reliability. Experimental evaluations showed improved throughput and reduced latency compared to conventional LoRa communication models. The study also emphasized the importance of adaptive network design for handling diverse agricultural conditions, making the system robust and scalable for precision farming applications.

El-Fishawy et al. (2025) conducted a comprehensive study on the application of Residual Neural Networks (ResNets) in agricultural analytics, particularly for crop disease detection and classification tasks. The authors demonstrated that deep residual architectures outperform traditional convolutional neural networks due to their ability to learn deeper hierarchical features without degradation problems. Their experiments showed classification accuracies exceeding 95% across multiple crop datasets. Furthermore, the study highlighted the potential of integrating optimized residual architectures with advanced learning techniques such as transfer learning and attention mechanisms. Although the research primarily focused on Euclidean data, it provided a strong foundation for extending residual learning into Riemannian frameworks for handling complex agricultural datasets.

Li et al. (2021) investigated the application of deep residual learning models in precision agriculture, focusing on crop classification and environmental prediction tasks. The study utilized a modified ResNet architecture integrated with multi-sensor agricultural datasets, including soil moisture, temperature, and humidity readings. The authors demonstrated that residual learning significantly enhances feature extraction capability, especially when dealing with high-dimensional and noisy agricultural data. Their results showed improved classification accuracy and reduced training time compared to traditional CNN models. Additionally, the study highlighted that residual connections help preserve critical environmental features during deep network propagation, making them highly effective for real-time monitoring systems. The authors also suggested that integrating such models with IoT-based sensor networks could further improve predictive performance in smart agriculture applications.

Raza et al. (2021) proposed a LoRa-based smart agriculture monitoring system combined with cloud computing and machine learning techniques. Their system collected environmental parameters such as soil moisture, temperature, and light intensity using distributed sensor nodes and transmitted the data to a cloud platform via LoRa communication. The study incorporated machine learning algorithms for predictive analysis, enabling automated decision-making for irrigation and crop management. The authors demonstrated that the integration of LoRa with cloud analytics significantly enhances system scalability and efficiency. Moreover, the research highlighted that energy consumption was minimized due to the low-power nature of LoRa communication, making the system suitable for long-term agricultural deployments. The study emphasized the importance of combining communication technologies with intelligent analytics for achieving sustainable precision farming.

Bonnabel (2013) introduced foundational concepts of Riemannian geometry in machine learning, particularly focusing on stochastic gradient descent methods on manifolds. Although not specifically targeted toward agriculture, this work laid the theoretical groundwork for developing Riemannian neural networks such as RRNNs. The author demonstrated how optimization algorithms can be adapted to curved spaces, ensuring that learned representations remain consistent with underlying geometric structures. This study is crucial because many real-world datasets, including environmental sensor data and covariance-based representations, inherently lie on non-Euclidean manifolds. The principles proposed by Bannable have been widely adopted in later works involving Riemannian deep learning, making it a foundational contribution to the development of advanced neural architectures used in precision agriculture analytics.

Mekki et al. (2019) conducted an extensive survey on LoRaWAN technologies and their applications in IoT-based systems, with a strong emphasis on smart agriculture. The study analysed the performance of LoRa networks in terms of energy efficiency, communication range, scalability, and reliability. The authors highlighted that LoRaWAN is particularly suitable for agricultural environments due to its ability to support long-range communication (up to several kilometres) while maintaining low power consumption. The survey also discussed challenges such as network congestion and limited data rates, proposing optimization strategies to overcome these limitations. The findings confirmed that LoRaWAN is one of the most effective communication technologies for deploying large-scale wireless sensor networks in precision agriculture.

Zhang et al. (2022) proposed a hybrid deep learning framework combining residual networks and attention mechanisms for environmental monitoring and prediction in agriculture. The model integrated sensor data collected from IoT devices and applied advanced feature extraction techniques to capture temporal and spatial dependencies. The use of attention mechanisms allowed the model to focus on critical environmental features, improving prediction accuracy. The study demonstrated significant improvements in forecasting environmental conditions such as soil moisture and temperature variations compared to baseline models. Furthermore, the authors highlighted that such hybrid architectures are well-suited for integration with energy-efficient communication systems like LoRa, enabling real-time and intelligent agricultural monitoring systems.

Kamilaris and Prenafeta-Boldú (2018) conducted a comprehensive review of deep learning applications in agriculture, emphasizing the effectiveness of convolutional and residual neural networks in handling large-scale agricultural datasets. The authors analysed various use cases, including crop classification, disease detection, yield prediction, and environmental monitoring. Their findings indicated that deep learning models significantly outperform traditional machine learning techniques due to their ability to automatically extract hierarchical features. The study also highlighted challenges such as data scarcity and computational complexity, suggesting the integration of cloud-based platforms and IoT systems to overcome these limitations. This work provides a strong foundation for integrating advanced neural architectures like RRNNs with precision agriculture systems.

Jawad et al. (2017) proposed an energy-efficient wireless sensor network architecture for precision agriculture using IoT technologies. Their study focused on optimizing energy consumption in sensor nodes by implementing adaptive data transmission strategies and low-power communication protocols. The authors demonstrated that energy-aware routing and scheduling techniques significantly extend the lifetime of sensor networks deployed in agricultural fields. The system was capable of monitoring environmental parameters such as soil moisture, temperature, and humidity with high reliability. This research highlights the importance of energy optimization in WSNs, which aligns with the use of LoRa-based systems for sustainable agricultural monitoring.

Roy et al. (2020) developed a LoRa-based smart irrigation system integrated with machine learning algorithms for efficient water management in agriculture. The system utilized real-time sensor data to predict irrigation requirements and automate water distribution. The authors applied regression-based learning models to forecast soil moisture levels, resulting in improved water efficiency and reduced operational costs. Their results demonstrated that the integration of LoRa communication with predictive analytics significantly enhances system performance. The study also emphasized the scalability of the proposed solution, making it suitable for large agricultural deployments and smart farming ecosystems.

Huang and Van Gool (2017) introduced the concept of dense residual learning (Dense Net), which improves feature propagation and reuse in deep neural networks. Although primarily applied in computer vision, their architecture has significant implications for agricultural data analysis. The study showed that dense connectivity patterns reduce redundancy and improve learning efficiency, enabling the development of compact yet powerful models. This approach is particularly useful in resource-constrained environments such as edge devices in agricultural monitoring systems. The principles of dense residual learning can be extended to Riemannian frameworks, enhancing the performance of RRNN-based models in precision agriculture.

Vangelista et al. (2015) provided an in-depth analysis of LoRa technology and its application in low-power wide-area networks (LPWANs). The study highlighted the advantages of LoRa in terms of long communication range, low energy consumption, and cost-effectiveness. The authors demonstrated that LoRa is capable of supporting large-scale IoT deployments with minimal infrastructure requirements, making it highly suitable for agricultural monitoring systems. Additionally, the research discussed network scalability and interference management, which are critical for ensuring reliable communication in dense sensor deployments. This study serves as a foundational reference for implementing LoRa-based wireless sensor networks in precision agriculture.

Sarker et al. (2021) explored the role of machine learning and deep learning techniques in smart agriculture, particularly focusing on environmental monitoring and predictive analytics. The authors reviewed multiple AI models, including convolutional neural networks and residual architectures, for analysing agricultural sensor data. Their study highlighted that deep learning models can effectively capture complex non-linear relationships between environmental variables such as temperature, humidity, and soil conditions. Additionally, the research emphasized the integration of IoT-based sensing systems with AI models to enable real-time monitoring and decision-making. The authors concluded that combining deep learning with energy-efficient communication technologies like LoRa can significantly enhance the performance and sustainability of precision agriculture systems.

Chen et al. (2019) proposed a deep residual network-based framework for crop disease identification using image and environmental data. The model leveraged residual learning to improve feature extraction from complex agricultural datasets, achieving high classification accuracy across multiple crop disease categories. The study demonstrated that residual connections allow deeper architectures without degradation, making them highly effective for agricultural image analysis and environmental prediction tasks. Furthermore, the authors suggested that integrating such models with real-time sensor data could improve early disease detection and preventive measures in precision farming systems.

Adelantado et al. (2017) conducted a detailed evaluation of LoRaWAN performance in IoT applications, with a particular focus on scalability, energy efficiency, and communication reliability. The study analysed different network configurations and their impact on data transmission efficiency in large-scale deployments. The authors found that LoRaWAN provides excellent coverage and low power consumption, making it ideal for agricultural monitoring systems. However, they also identified challenges such as limited data rates and network congestion in dense deployments. The study proposed optimization strategies, including adaptive data transmission and channel allocation, to improve network performance in real-world agricultural environments.

Bronstein et al. (2017) introduced the concept of geometric deep learning, which extends traditional deep learning methods to non-Euclidean domains such as graphs and manifolds. Their work provided a comprehensive framework for applying neural networks to structured data, including sensor networks and spatial agricultural data. The authors emphasized that many real-world datasets, including environmental monitoring data, exhibit non-linear geometric structures that cannot be effectively modelled using conventional Euclidean approaches. This study laid the theoretical foundation for advanced architectures like Riemannian residual neural networks, which are particularly suitable for precision agriculture applications involving complex environmental interactions.

Kim et al. (2022) developed a hybrid IoT and deep learning-based environmental monitoring system for smart agriculture, integrating sensor networks with advanced predictive models. The system utilized real-time data from distributed sensors and applied deep learning algorithms to predict environmental conditions and optimize farming practices. The authors demonstrated that combining IoT infrastructure with deep learning significantly improves prediction accuracy and system responsiveness. Additionally, the study highlighted the importance of energy-efficient communication protocols, such as LoRa, in ensuring long-term sustainability of agricultural monitoring systems. The proposed framework showed promising results in improving crop productivity and reducing resource wastage.

Zhang et al. (2020) proposed a deep learning-based environmental prediction system for precision agriculture, utilizing multi-layer neural networks to analyze sensor data collected from IoT devices. The study focused on predicting soil moisture and temperature variations using historical and real-time data. The authors demonstrated that deep neural networks significantly improve prediction accuracy compared to traditional statistical models. Furthermore, the study emphasized the importance of integrating such predictive systems with energy-efficient communication technologies like LoRa to ensure continuous and reliable data transmission. Their work highlighted how intelligent prediction models can optimize irrigation scheduling and resource utilization in smart farming systems.

Augustin et al. (2016) conducted a performance evaluation of LoRa technology for low-power wide-area networks (LPWANs). The study analysed communication range, data rate, and energy consumption under different environmental conditions. The authors found that LoRa provides reliable long-range communication with minimal energy usage, making it highly suitable for agricultural applications where sensor nodes are distributed over large areas. Additionally, the study highlighted the robustness of LoRa signals in rural and semi-urban environments, which is critical for precision agriculture deployments. The findings support the adoption of LoRa as a backbone communication technology in IoT-based agricultural monitoring systems.

He et al. (2016) introduced the groundbreaking Residual Neural Network (Res Net) architecture, which revolutionized deep learning by enabling the training of extremely deep neural networks. The study demonstrated that residual connections allow networks to learn identity mappings, thereby preventing degradation problems associated with increasing depth. Although originally applied in image recognition tasks, the architecture has been widely adopted in various domains, including agriculture. The principles of residual learning form the basis for advanced architectures such as Riemannian Residual Neural Networks, making this study a cornerstone in the evolution of deep learning models used in precision agriculture analytics.

Jawad et al. (2019) extended their earlier work on IoT-based agriculture by proposing a smart farming framework integrating wireless sensor networks, cloud computing, and data analytics. The system collected environmental data using sensor nodes and transmitted it to cloud platforms for processing and analysis. The authors incorporated machine learning techniques to generate actionable insights, such as irrigation recommendations and crop health monitoring. The study demonstrated that integrating IoT with intelligent analytics improves decision-making and enhances agricultural productivity. Additionally, the framework emphasized energy efficiency and scalability, making it suitable for large-scale deployments.

Liakos et al. (2018) provided a comprehensive survey on machine learning applications in agriculture, focusing on crop management, disease detection, and environmental monitoring. The study reviewed various algorithms, including neural networks, support vector machines, and ensemble learning techniques. The authors highlighted that deep learning models, particularly residual networks, show superior performance in handling complex agricultural datasets. Furthermore, the study emphasized the importance of integrating machine learning with IoT-based sensing systems to enable real-time monitoring and predictive analytics. The findings underscore the growing role of AI-driven solutions in transforming traditional agricultural practices into smart, data-driven systems.

Xu et al. (2021) proposed an intelligent environmental monitoring system using deep learning and IoT technologies for precision agriculture. The study utilized multi-sensor data, including soil moisture, temperature, and humidity, to train deep neural networks for predictive analytics. The authors demonstrated that deep learning models significantly improve the accuracy of environmental predictions compared to traditional regression techniques. Additionally, the system incorporated edge computing capabilities to reduce latency and improve real-time decision-making. The study emphasized that integrating energy-efficient communication protocols such as LoRa with intelligent models can further enhance system scalability and sustainability in agricultural applications.

Reynders et al. (2016) analysed the scalability and reliability of LoRaWAN networks in large-scale IoT deployments, including agricultural environments. The study focused on network capacity, interference management, and adaptive data rate mechanisms. The authors demonstrated that LoRaWAN can support thousands of sensor nodes while maintaining low energy consumption and reliable communication. However, they also identified challenges related to network congestion and duty cycle limitations. The study proposed optimization techniques such as adaptive transmission strategies and network planning to improve overall system performance, making it highly relevant for precision agriculture applications.

Arjovsky et al. (2016) explored the concept of unitary evolution recurrent neural networks and optimization on structured manifolds, contributing to the broader field of Riemannian optimization in deep learning. Their work highlighted the importance of preserving geometric properties during model training, especially when dealing with structured data. Although not directly applied to agriculture, the study provides significant insights into the development of Riemannian neural architectures, including RRNNs. The authors demonstrated that maintaining geometric consistency improves model stability and convergence, which is essential for processing complex environmental data in precision agriculture systems.

Navarro-Hellín et al. (2016) developed a low-cost IoT-based monitoring system for precision agriculture, integrating wireless sensor networks with data analytics platforms. The system was capable of monitoring environmental parameters such as soil moisture, temperature, and solar radiation in real time. The authors demonstrated that their solution improves irrigation management and reduces resource wastage. Additionally, the study highlighted the importance of low-power communication technologies, including LoRa, in enabling large-scale agricultural deployments. The proposed system showed significant improvements in efficiency and cost-effectiveness compared to traditional monitoring approaches.

Goodfellow et al. (2016), in their seminal work on deep learning, provided a comprehensive foundation for understanding neural network architectures, optimization techniques, and learning paradigms. The book introduced key concepts such as backpropagation, regularization, and optimization strategies that are essential for developing advanced models like residual networks and Riemannian neural networks. Although not specific to agriculture, this work serves as a fundamental reference for designing and optimizing deep learning models used in precision agriculture systems. The principles outlined in this study underpin many of the modern AI-based solutions applied in environmental monitoring and smart farming.

Comparative Table and Analysis

Study	Author (Year)	Technique/Model	Technology Used	Key Contribution	Limitation
1	Katsman et al. (2023)	RRNN	Geometric DL	Manifold learning	Complex computation
2	Singh et al. (2020)	IoT Monitoring	LoRaWAN	Energy-efficient sensing	Limited data rate
3	Iftikhar et al. (2020)	Smart Irrigation	LoRa + IoT	Water optimization	Scalability issues
4	Gresl et al. (2021)	WSN Protocol	LoRa	Efficient communication	Network congestion
5	El-Fishawy et al. (2025)	Res Net	Deep Learning	High accuracy	High computation
6	Li et al. (2021)	Res Net	IoT + DL	Improved prediction	Data dependency
7	Raza et al. (2021)	ML + IoT	LoRa + Cloud	Smart decision-making	Latency issues
8	Bonnabel (2013)	Riemannian SGD	Optimization	Manifold learning	Complex math

9	Mekki et al. (2019)	LoRaWAN Survey	IoT	Scalability analysis	Limited throughput
10	Zhang et al. (2022)	Res Net + Attention	IoT + DL	Improved prediction	Complexity
11	Kamilaris (2018)	DL Survey	Agriculture AI	Comprehensive review	Data scarcity
12	Jawad (2017)	WSN	IoT	Energy optimization	Limited adaptability
13	Roy (2020)	ML + LoRa	IoT	Smart irrigation	Model accuracy limits
14	Huang (2017)	Dense Net	DL	Efficient feature reuse	Memory usage
15	Vangelista (2015)	LoRa	LPWAN	Long-range comm.	Low data rate
16	Sarker (2021)	AI Models	IoT	Predictive analytics	Data complexity
17	Chen (2019)	Res Net	DL	Disease detection	Dataset dependency
18	Adelantado (2017)	LoRaWAN	IoT	Network evaluation	Congestion
19	Bronstein (2017)	Geometric DL	ML	Non-Euclidean learning	Complexity
20	Kim (2022)	IoT + DL	Smart Agri	Real-time monitoring	Energy trade-offs
21	Zhang (2020)	DL Prediction	IoT	Environmental forecasting	Data reliability
22	Augustin (2016)	LoRa	LPWAN	Performance analysis	Low bandwidth
23	He (2016)	Res Net	DL	Deep learning breakthrough	Overfitting
24	Jawad (2019)	IoT + Cloud	Smart Farming	Data analytics	Cost
25	Liakos (2018)	ML Survey	Agriculture	AI applications	Limited real-time
26	Xu (2021)	DL + IoT	Smart Monitoring	High accuracy	Computation cost
27	Reynders (2016)	LoRaWAN	IoT	Network scalability	Duty cycle limits
28	Arjovsky (2016)	Riemannian Opt.	DL	Stability improvement	Complexity
29	Navarro (2016)	IoT System	Smart Agri	Cost-effective monitoring	Limited AI use
30	Goodfellow (2016)	Deep Learning	AI	Foundational theory	Generalized

Comparative Analysis

The comparative analysis of the reviewed studies highlights a strong convergence between deep learning architectures and IoT-based communication technologies in advancing precision agriculture. Studies focusing on Riemannian and residual neural networks (Katsman et al., 2023; Bronstein et al., 2017; Arjovsky et al., 2016) demonstrate superior capability in handling non-linear and manifold-structured agricultural data, which is essential for modelling complex environmental interactions. These approaches provide improved learning efficiency, stability, and accuracy compared to conventional Euclidean-based neural networks. On the other hand, LoRa-based wireless sensor networks (Singh et al., 2020; Vangelista et al., 2015; Mekki et al., 2019) consistently prove to be highly energy-efficient and suitable for large-scale agricultural deployments due to their long-range communication and low power consumption. However, limitations such as low data rates and network congestion remain critical challenges.

Hybrid approaches integrating deep learning with IoT systems (Kim et al., 2022; Raza et al., 2021; Xu et al., 2021) show significant improvements in real-time monitoring, predictive analytics, and decision-making capabilities. These systems enable automated irrigation, disease detection, and environmental forecasting, thereby enhancing agricultural productivity and sustainability. Despite these advancements, several gaps remain, including high computational complexity of deep learning models, limited scalability of IoT networks under heavy load, and lack of unified frameworks combining Riemannian learning with LoRa-based systems. Therefore, future research should focus on developing lightweight, energy-efficient RRNN models integrated with optimized LoRa communication protocols to achieve scalable and sustainable smart agriculture systems.

Discussion

The integration of advanced deep learning architectures with IoT-based communication technologies has significantly transformed precision agriculture. This study highlights that Riemannian residual neural networks provide a powerful framework for modelling complex environmental data, enabling more accurate predictions and efficient decision-making. Unlike traditional neural networks, RRNNs effectively handle non-linear data structures, making them suitable for analysing multi-dimensional agricultural datasets. Simultaneously, LoRa-based wireless sensor networks offer a practical solution for large-scale environmental monitoring due to their low energy consumption and long communication range. The combination of these technologies enables real-time monitoring and predictive analytics, which are essential for optimizing resource utilization and improving crop productivity.

However, challenges such as computational complexity, network congestion, and limited data transmission rates need to be addressed. Future systems must focus on optimizing both learning models and communication frameworks to achieve better scalability and efficiency. Additionally, the integration of edge computing and lightweight AI models can further enhance system performance. Overall, the convergence of RRNNs and LoRa-based WSNs represents a promising direction for developing sustainable and intelligent agricultural systems.

Conclusion

Precision agriculture has become essential for improving crop productivity while ensuring sustainable resource utilization and environmental protection. This survey reviewed recent methods integrating optimized Riemannian residual neural networks (RRNNs) with LoRa-based wireless sensor networks (WSNs) for energy-efficient environmental monitoring. Deep learning architectures, particularly RRNNs, effectively learn complex nonlinear relationships, enhancing prediction accuracy, feature representation, and intelligent decision-making in agricultural applications. LoRa-based WSNs provide low-power, long-range communication, enabling reliable transmission of sensor data across large farming areas and supporting continuous monitoring of soil moisture, temperature, humidity, and other environmental parameters. Their integration creates a robust AI–IoT framework capable of real-time monitoring, predictive analytics, and automated resource management, thereby improving productivity while minimizing water, fertilizer, and energy consumption. Despite these advantages, challenges such as computational complexity, network scalability, limited bandwidth, and efficient data processing remain. Future research should focus on lightweight RRNN models, edge intelligence, scalable LoRa architectures, and energy-aware optimization techniques. Overall, combining geometric deep learning with LoRa-enabled sensor networks offers a promising foundation for next-generation smart, sustainable, and precision agriculture systems.

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