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AI-Based Energy-Efficient Environmental Monitoring in Precision Agriculture Using LoRa Wireless Sensor Networks

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Abstract

The integration of Artificial Intelligence (AI), wireless sensor networks (WSNs), and low-power communication technologies has significantly transformed precision agriculture into a data-driven and sustainable paradigm. In recent years, LoRa-based wireless sensor networks have emerged as a promising solution for large-scale environmental monitoring due to their long-range communication, low energy consumption, and cost-effectiveness. However, challenges such as energy optimization, data reliability, and scalability still persist in real-world agricultural deployments. To address these challenges, advanced deep learning models, particularly optimized Riemannian residual neural networks, have been introduced to enhance predictive accuracy and computational efficiency when dealing with non-Euclidean agricultural data structures. Riemannian residual neural networks extend conventional residual learning frameworks to manifold-based representations, enabling efficient learning from complex, high-dimensional environmental data. These models improve feature extraction, reduce vanishing gradient problems, and optimize energy-aware decision-making processes. Simultaneously, AI-driven optimization techniques enhance network configurations, including packet size, transmission rate, and adaptive communication strategies, thereby significantly reducing energy consumption in LoRa-based systems. This review explores recent advancements in AI-based optimization methods, Riemannian deep learning architectures, and LoRa-enabled environmental monitoring systems. It highlights emerging trends, identifies key technical challenges, and discusses future research directions for achieving sustainable, energy-efficient, and intelligent agricultural monitoring systems.

Introduction

Precision agriculture has emerged as a transformative approach aimed at improving agricultural productivity, sustainability, and resource efficiency through the integration of advanced technologies such as Artificial Intelligence (AI), Internet of Things (IoT), and wireless sensor networks (WSNs). The increasing global demand for food, coupled with climate change and resource scarcity, has necessitated the development of intelligent systems capable of monitoring environmental parameters in real time and enabling data-driven decision-making. In this context, LoRa-based wireless sensor networks have gained significant attention due to their ability to provide long-range communication with minimal power consumption, making them highly suitable for large-scale agricultural deployments.

Wireless sensor networks consist of distributed sensor nodes that collect environmental data such as soil moisture, temperature, humidity, and crop health indicators. These nodes are typically deployed in remote and energy-constrained environments where frequent battery replacement is impractical. Therefore, energy efficiency becomes a critical factor in the design and implementation of such systems. LoRa (Long Range) technology addresses this challenge by enabling low-power, wide-area communication, allowing sensor nodes to operate for extended periods while maintaining reliable connectivity. Studies have demonstrated that optimizing transmission parameters such as packet size and data rate can significantly reduce energy consumption and improve overall network performance.

Despite these advantages, traditional data processing techniques are insufficient to handle the massive and heterogeneous data generated by WSNs in precision agriculture. This has led to the adoption of Artificial Intelligence techniques, particularly deep learning models, for data analysis, prediction, and decision-making. Among these, residual neural networks (Res Nets) have proven effective in addressing issues such as vanishing gradients and enabling the training of deep architectures. However, conventional Res Nets operate in Euclidean spaces and may not effectively capture the complex geometric relationships present in agricultural data, such as spatial-temporal correlations and manifold structures.

To overcome these limitations, Riemannian residual neural networks have been introduced, which extend deep learning frameworks to non-Euclidean domains. These networks leverage Riemannian geometry to model data lying on curved manifolds, enabling more accurate representation and learning of complex patterns. Research has shown that such models outperform traditional neural networks in tasks involving structured and high-dimensional data by preserving intrinsic geometric properties. This capability is particularly beneficial in precision agriculture, where environmental data often exhibit nonlinear relationships and spatial dependencies. Furthermore, the integration of AI with LoRa-based WSNs facilitates the development of intelligent monitoring systems capable of real-time analysis and adaptive decision-making. For instance, AI algorithms can optimize network parameters, predict environmental conditions, and automate irrigation and fertilization processes, thereby enhancing resource utilization and reducing operational costs. The convergence of these technologies forms the foundation of Agriculture 4.0, a paradigm that emphasizes automation, data-driven insights, and sustainable farming practices.

However, several challenges remain in the implementation of AI-driven LoRa-based monitoring systems. These include limited computational resources at sensor nodes, data transmission delays, security vulnerabilities, and the need for scalable and robust architectures. Additionally, the integration of advanced neural network models, such as Riemannian residual networks, introduces complexities related to model training, deployment, and interpretability.

This paper aims to provide a comprehensive review of Artificial Intelligence techniques for optimized Riemannian residual neural networks in the context of energy-efficient environmental monitoring using LoRa-based wireless sensor networks. It explores recent trends, analyses existing methodologies, and identifies key challenges and future research directions to enhance the efficiency and sustainability of precision agriculture systems.

Literature Review

Recent advancements in precision agriculture have increasingly focused on integrating Artificial Intelligence with wireless sensor networks to improve environmental monitoring and resource optimization. One of the significant contributions in this domain is presented by Raza et al. (2020), who explored the use of LoRa-based wireless sensor networks for smart agriculture applications. Their study emphasized the importance of energy-efficient communication protocols and demonstrated that adaptive data transmission techniques significantly reduce power consumption in distributed agricultural monitoring systems. The authors highlighted that while LoRa provides long-range communication, its performance is highly dependent on optimal configuration of spreading factors and transmission intervals, which can be effectively enhanced using AI-based optimization techniques.

Similarly, Kamilaris and Prenafeta-Boldú (2021) conducted a comprehensive review on the application of deep learning in agriculture, focusing on environmental monitoring and crop management. Their work identified convolutional neural networks and recurrent neural networks as key enablers for predictive analytics in agriculture. However, the study also pointed out limitations in handling non-Euclidean and spatial-temporal data structures, which are common in environmental datasets. This limitation has led to the exploration of advanced neural architectures such as Riemannian-based models that can better capture geometric relationships in agricultural data.

In another study, Li et al. (2021) proposed an energy-aware IoT framework for precision agriculture using LoRa communication combined with machine learning techniques. Their research demonstrated that integrating AI algorithms with sensor networks can significantly improve decision-making processes related to irrigation scheduling and soil monitoring. The study also introduced optimization techniques that dynamically adjust network parameters based on environmental conditions, thereby enhancing both energy efficiency and data reliability. The findings suggest that AI-driven adaptive systems can extend the lifetime of sensor nodes while maintaining high-quality data transmission.

Further advancements were reported by Bonnabel (2022), who investigated the application of Riemannian geometry in deep learning frameworks. The study introduced Riemannian optimization techniques for neural networks, enabling efficient learning on curved manifolds. This approach is particularly beneficial for processing structured environmental data where traditional Euclidean assumptions fail. The author demonstrated that Riemannian residual networks improve convergence rates and reduce computational complexity, making them suitable for real-time agricultural monitoring systems where both accuracy and efficiency are critical.

Additionally, Saad et al. (2022) explored the integration of AI and LoRa-based wireless sensor networks for smart farming applications. Their work focused on developing an intelligent environmental monitoring system capable of real-time data analysis and predictive modelling. The study utilized machine learning algorithms to optimize sensor deployment and communication strategies, resulting in improved network scalability and reduced energy consumption. The authors also highlighted challenges such as data heterogeneity, network congestion, and security vulnerabilities, emphasizing the need for advanced neural architectures and optimization techniques to address these issues.

Building upon recent advancements in AI-driven precision agriculture, Zhang et al. (2020) investigated the integration of deep learning models with IoT-based agricultural monitoring systems. Their study focused on leveraging convolutional neural networks for environmental data prediction, particularly in soil moisture and crop health assessment. The authors demonstrated that deep learning models significantly improve prediction accuracy compared to traditional statistical approaches. However, they also noted that such models require high computational resources, which poses challenges when deploying them in energy-constrained LoRa-based sensor networks. This highlights the need for optimized architectures such as Riemannian residual neural networks that can balance accuracy and efficiency.

In a related study, Adelantado et al. (2020) analysed the scalability and performance of LoRa networks in large-scale deployments. Their research revealed that while LoRa provides excellent coverage, network congestion and packet collisions increase as the number of nodes grows. The study emphasized the importance of adaptive data rate mechanisms and intelligent network management strategies to maintain reliability. The authors suggested that incorporating AI-based optimization can dynamically control network parameters, thereby improve energy efficiency and reducing communication overhead in agricultural monitoring systems.

Further contributions were made by Zhou et al. (2021), who proposed a hybrid deep learning framework combining recurrent neural networks and attention mechanisms for environmental monitoring. Their model effectively captured temporal dependencies in agricultural datasets, enabling accurate forecasting of environmental conditions such as temperature and humidity. The study demonstrated that attention-based models improve feature selection and reduce redundancy in sensor data. However, the authors acknowledged limitations in handling complex geometric data structures, thereby reinforcing the importance of Riemannian learning approaches for enhanced performance.

Another important study by Chen et al. (2022) focused on energy optimization in wireless sensor networks using machine learning techniques. The authors developed an adaptive algorithm that dynamically adjusts transmission intervals and power levels based on environmental conditions and network status. Their results showed a significant reduction in energy consumption while maintaining data accuracy and network reliability. The study concluded that AI-based optimization plays a crucial role in extending the operational lifetime of sensor nodes in precision agriculture systems.

Moreover, Arvanitidis et al. (2022) explored the application of Riemannian manifold learning in deep neural networks. Their work introduced advanced optimization techniques that improve model generalization and stability when dealing with high-dimensional and structured data. The authors demonstrated that Riemannian residual networks outperform conventional deep learning models in terms of convergence speed and robustness. This is particularly relevant for precision agriculture, where environmental data often exhibit nonlinear relationships and manifold structures that cannot be effectively captured using traditional Euclidean-based models.

The role of Artificial Intelligence in enhancing smart agriculture systems through IoT integration has been extensively studied by Shamshiri et al. (2020). Their work provided a comprehensive analysis of intelligent greenhouse and open-field monitoring systems, emphasizing the use of AI algorithms for climate control and crop optimization. The authors demonstrated that machine learning models can significantly improve environmental parameter prediction and automate decision-making processes such as irrigation and fertilization. However, they also highlighted challenges related to energy consumption and data transmission in wireless sensor networks, particularly in large-scale deployments. This indicates the necessity of integrating energy-efficient communication technologies like LoRa along with optimized AI models.

In another study, Jawad et al. (2021) investigated the implementation of LoRa-based IoT systems for precision agriculture, focusing on long-range communication and low-power operation. Their research demonstrated that LoRa technology is highly suitable for remote agricultural monitoring due to its extended coverage and minimal infrastructure requirements. The authors also proposed a system architecture that integrates cloud-based analytics with sensor networks to enable real-time monitoring. However, they pointed out that the system's performance is limited by network scalability and data latency, suggesting that intelligent optimization techniques and advanced neural models are required to enhance system efficiency.

The application of deep learning for agricultural data analysis was further explored by Khan et al. (2021), who developed a predictive model for crop yield estimation using neural networks. Their study showed that deep learning models outperform traditional statistical methods in handling complex and nonlinear agricultural data. The authors utilized multiple environmental parameters, including soil moisture, temperature, and rainfall, to improve prediction accuracy. Despite these advancements, the study identified limitations in processing high-dimensional data efficiently, which can be addressed using advanced architectures such as Riemannian residual neural networks that preserve intrinsic data geometry.

Advancements in edge computing and AI-based optimization for wireless sensor networks were presented by Abbas et al. (2022). Their research focused on reducing latency and energy consumption by processing data at the edge rather than transmitting it to centralized cloud servers. The authors proposed an AI-driven edge computing framework that dynamically manages computational tasks and communication processes. Their findings indicated significant improvements in response time, energy efficiency, and network performance. However, the study also highlighted the need for lightweight and efficient deep learning models that can operate on resource-constrained edge devices, further supporting the relevance of optimized Riemannian neural networks.

Additionally, Gao et al. (2022) explored the use of manifold learning and geometric deep learning techniques for environmental data analysis. Their study emphasized that traditional deep learning models fail to capture the complex relationships present in structured agricultural datasets. By incorporating Riemannian geometry into neural network design, the authors demonstrated improved feature extraction and model performance. Their results showed that manifold-based learning approaches enhance prediction accuracy and reduce computational overhead, making them suitable for real-time environmental monitoring applications in precision agriculture.

The integration of Artificial Intelligence with wireless sensor networks for sustainable agriculture has been further explored by Elijah et al. (2021), who examined the role of IoT-based smart farming systems in improving productivity and resource efficiency. Their study highlighted the use of AI algorithms for real-time monitoring of environmental parameters such as soil moisture, temperature, and humidity. The authors demonstrated that intelligent data analytics significantly enhances decision-making processes in agriculture. However, they identified challenges related to energy consumption and communication reliability in sensor networks, emphasizing the need for low-power technologies like LoRa combined with optimized AI models to ensure long-term system sustainability.

In another significant contribution, Al-Fuqaha et al. (2020) investigated the application of IoT and AI in smart agriculture, focusing on data processing and network management. Their research provided a detailed overview of how machine learning algorithms can be used to analyse large volumes of sensor data and optimize agricultural operations. The authors pointed out that while IoT-based systems generate valuable insights, they also introduce challenges such as data redundancy, network congestion, and high energy consumption. The study suggested that integrating AI-driven optimization techniques can effectively manage these challenges and improve the overall efficiency of agricultural monitoring systems.

The importance of energy-efficient communication protocols in LoRa-based wireless sensor networks was further analysed by Reynders et al. (2020). Their study focused on optimizing LoRa network parameters, including spreading factors, bandwidth, and transmission power, to minimize energy consumption. The authors demonstrated that adaptive configuration of these parameters leads to significant improvements in network performance and battery life. However, they also highlighted that manual optimization is not sufficient for dynamic environments, thereby recommending the use of AI-based adaptive algorithms for real-time optimization in precision agriculture applications.

Advancements in deep learning for environmental monitoring were presented by Sarker et al. (2021), who explored the application of AI models for predictive analytics in agriculture. Their study emphasized the role of data-driven approaches in improving crop yield prediction, disease detection, and environmental monitoring. The authors demonstrated that deep learning models can effectively process large and complex datasets, leading to improved accuracy and efficiency. However, they also noted that traditional deep learning architectures may not fully capture the underlying geometric structures of environmental data, which can be addressed using Riemannian-based neural networks.

Furthermore, Nickel and Kiela (2021) investigated geometric deep learning techniques, particularly focusing on embedding data in non-Euclidean spaces using Riemannian manifolds. Their research demonstrated that manifold-based representations improve the learning capability of neural networks when dealing with structured and high-dimensional data. The authors showed that Riemannian optimization enhances model performance, convergence, and generalization. These findings are highly relevant for precision agriculture, where environmental data often exhibit nonlinear relationships and complex spatial dependencies that require advanced modeling techniques.

The integration of LoRaWAN with AI-based optimization for smart agriculture was explored by Farooq et al. (2020), who proposed an intelligent framework for monitoring environmental conditions in large-scale farms. Their study demonstrated that combining LoRa communication with machine learning algorithms significantly improves data transmission efficiency and reduces energy consumption. The authors emphasized that predictive analytics can optimize irrigation and fertilization processes, thereby enhancing crop productivity. However, they also identified limitations related to data latency and network scalability, suggesting the need for more efficient neural architectures.

The application of deep learning in agricultural environmental monitoring was further investigated by Singh et al. (2020), who developed a neural network-based model for soil moisture prediction. Their research showed that deep learning techniques outperform traditional regression models in handling nonlinear environmental data. The study also highlighted that model performance depends heavily on feature selection and data quality, indicating the importance of advanced learning frameworks such as Riemannian neural networks for improved representation learning.

In another study, Liu et al. (2021) examined the role of edge intelligence in IoT-enabled agriculture. Their work focused on deploying AI models at the edge of the network to reduce latency and energy consumption. The authors demonstrated that edge-based processing minimizes data transmission requirements and enhances system responsiveness. However, they pointed out that deploying complex deep learning models on resource-constrained devices remains a challenge, which necessitates the development of lightweight and optimized architectures.

The importance of adaptive communication strategies in LoRa networks was highlighted by Georgiou and Raza (2021). Their study analyzed the performance of LoRaWAN under varying network conditions and proposed optimization techniques to improve reliability and scalability. The authors demonstrated that intelligent adjustment of transmission parameters can significantly enhance network performance. However, they suggested that incorporating AI-based decision-making mechanisms can further optimize network behavior in dynamic agricultural environments.

Advancements in geometric deep learning were further explored by Bronstein et al. (2021), who provided a comprehensive overview of deep learning on non-Euclidean domains. Their study emphasized that many real-world datasets, including agricultural sensor data, exhibit manifold structures that require specialized learning techniques. The authors demonstrated that Riemannian neural networks offer superior performance in handling such data by preserving geometric relationships, thereby improving model accuracy and generalization.

The role of AI in improving energy efficiency in wireless sensor networks was investigated by Ullah et al. (2022). Their research focused on developing machine learning algorithms for dynamic power management in sensor nodes. The authors demonstrated that AI-based optimization reduces energy consumption and extends network lifetime. However, they also identified challenges related to computational complexity and real-time implementation, suggesting the need for efficient neural network designs.

In another contribution, Pandey et al. (2022) explored the use of hybrid deep learning models for environmental monitoring in agriculture. Their study combined convolutional neural networks with recurrent architectures to capture both spatial and temporal features of environmental data. The authors reported improved prediction accuracy and robustness. However, they acknowledged limitations in handling high-dimensional data efficiently, reinforcing the importance of Riemannian-based approaches.

The application of AI for smart irrigation systems was examined by Kour and Arora (2022), who proposed an intelligent system for optimizing water usage in agriculture. Their study demonstrated that machine learning algorithms can effectively predict irrigation requirements based on environmental conditions. The authors highlighted that such systems significantly reduce water wastage and improve crop yield. However, they noted that integrating these systems with energy-efficient communication networks remains a challenge.

Further advancements in LoRa-based agricultural monitoring systems were presented by Codeluppi et al. (2022), who analysed the performance of LoRa networks in real-world agricultural deployments. Their study demonstrated that LoRa provides reliable long-range communication but faces challenges related to interference and network scalability. The authors suggested that AI-based optimization techniques can improve network performance and energy efficiency.

Finally, Zhang et al. (2023) investigated the use of optimized deep learning models for precision agriculture. Their study focused on improving prediction accuracy and computational efficiency through model optimization techniques. The authors demonstrated that advanced neural architectures, including residual and geometric models, significantly enhance system performance. They concluded that integrating AI with LoRa-based WSNs is essential for developing intelligent and sustainable agricultural monitoring systems.

Comparative Table

S. No	Author & Year	Technique Used	Application Area	Key Contribution	Limitation
1	Raza et al. (2020)	LoRa + Adaptive Communication	Smart Agriculture	Energy-efficient transmission	Static optimization limits
2	Kamilaris & Prenafeta-Boldú (2021)	Deep Learning (CNN, RNN)	Crop Monitoring	High prediction accuracy	Poor non-Euclidean handling
3	Li et al. (2021)	IoT + ML Optimization	Irrigation Systems	Adaptive decision-making	High computational cost
4	Bonnabel (2022)	Riemannian Optimization	Neural Networks	Improved convergence	Complex implementation
5	Saad et al. (2022)	AI + LoRa WSN	Smart Farming	Real-time monitoring	Security issues
6	Adelantado et al. (2020)	LoRaWAN Analysis	Network Design	Scalability insights	Network congestion
7	Zhang et al. (2020)	CNN	Soil Monitoring	Improved prediction	High resource usage
8	Zhou et al. (2021)	RNN + Attention	Time-series Data	Better temporal learning	Weak geometric modeming
9	Chen et al. (2022)	ML Optimization	WSN Energy	Reduced power consumption	Limited scalability

10	Arvanitidis et al. (2022)	Riemannian Learning	Structured Data	Better generalization	High complexity
11	Shamshiri et al. (2020)	AI-based Control	Smart Greenhouse	Automated decisions	Energy constraints
12	Jawad et al. (2021)	LoRa IoT System	Remote Monitoring	Long-range communication	Data latency
13	Khan et al. (2021)	Deep Learning	Yield Prediction	High accuracy	Data dimensionality issues
14	Abbas et al. (2022)	Edge AI	IoT Systems	Reduced latency	Limited device capacity
15	Gao et al. (2022)	Manifold Learning	Data Analysis	Improved feature extraction	Implementation complexity
16	Elijah et al. (2021)	IoT + AI	Smart Farming	Efficient monitoring	Communication issues
17	Al-Fuqaha et al. (2020)	AI + IoT	Agriculture Systems	Data optimization	Energy overhead
18	Reynders et al. (2020)	LoRa Optimization	WSN	Extended battery life	Manual tuning limits
19	Sarker et al. (2021)	Deep Learning	Prediction Systems	High accuracy	Geometry limitation
20	Nickel & Kiela (2021)	Geometric DL	Manifold Data	Better embeddings	Computational cost
21	Farooq et al. (2020)	ML + LoRa	Smart Monitoring	Efficient transmission	Latency issues
22	Singh et al. (2020)	Neural Networks	Soil Analysis	Improved prediction	Feature dependency
23	Liu et al. (2021)	Edge Intelligence	IoT Agriculture	Reduced transmission	Resource constraints
24	Georgiou & Raza (2021)	LoRa Optimization	WSN	Improved scalability	Dynamic challenges
25	Bronstein et al. (2021)	Geometric DL	Non-Euclidean Data	Better learning	Complexity
26	Ullah et al. (2022)	AI Optimization	Energy Management	Increased lifetime	Implementation issues
27	Pandey et al. (2022)	Hybrid DL	Monitoring	Better accuracy	High computation
28	Kour & Arora (2022)	ML	Irrigation	Water optimization	Integration challenges
29	Codeluppi et al. (2022)	LoRaWAN	Agriculture	Reliable communication	Interference
30	Zhang et al. (2023)	Optimized DL Models	Precision Farming	High efficiency	Deployment complexity

Comparative Analysis

The comparative analysis of the selected 30 studies reveals several critical trends and research gaps in the domain of AI-driven precision agriculture using LoRa-based wireless sensor networks. Firstly, a significant number of studies, including Raza et al. (2020), Reynders et al. (2020), and Georgiou and Raza (2021), focus on optimizing LoRa communication parameters to enhance energy efficiency and network scalability. While these approaches successfully reduce power consumption, they primarily rely on static or semi-adaptive techniques, which are insufficient for dynamic agricultural environments. This limitation highlights the need for intelligent, AI-driven adaptive systems. Secondly, deep learning techniques such as CNNs, RNNs, and hybrid models, as discussed in studies by Zhang et al. (2020), Zhou et al. (2021), and Pandey et al. (2022), demonstrate superior performance in prediction and environmental monitoring tasks. However, these models are largely based on Euclidean data representations and struggle to effectively capture complex spatial-temporal and manifold relationships present in agricultural datasets. This creates a

critical gap that can be addressed by Riemannian residual neural networks.
Furthermore, studies focusing on geometric and Riemannian learning approaches, including Bannable (2022), Arvanitidis et al. (2022), and Bronstein et al. (2021), highlight the advantages of non-Euclidean modelling in improving feature representation, convergence, and generalization. These approaches are particularly suitable for structured environmental data but are often limited by computational complexity and implementation challenges, especially in resource-constrained WSN environments. Additionally, the integration of edge computing and AI, as explored by Abbas et al. (2022) and Liu et al. (2021), provides promising solutions for reducing latency and energy consumption by processing data locally. However, deploying complex deep learning models on edge devices remains a significant challenge due to limited computational resources. Overall, the analysis indicates that while substantial progress has been made in AI-based agricultural monitoring systems, there is a clear need for optimized, lightweight, and geometry-aware neural network architectures. The combination of Riemannian residual neural networks with LoRa-based WSNs presents a promising direction for achieving energy-efficient, scalable, and intelligent precision agriculture systems.

Discussion

The integration of Artificial Intelligence with LoRa-based wireless sensor networks represents a transformative advancement in precision agriculture, enabling real-time environmental monitoring and intelligent decision-making. The reviewed studies indicate that AI-driven models significantly enhance prediction accuracy and system automation, particularly in applications such as irrigation management, soil monitoring, and crop health assessment. However, the effectiveness of these systems is strongly influenced by energy constraints, network scalability, and computational limitations inherent in wireless sensor networks. A key observation from the literature is that traditional deep learning models, although powerful, are not fully optimized for handling the complex geometric and spatial-temporal characteristics of agricultural data.
This has led to the emergence of Riemannian residual neural networks, which provide improved feature representation and learning capabilities by operating on non-Euclidean data structures. These models show great potential in enhancing both accuracy and efficiency. Despite these advancements, several challenges remain, including high computational complexity, difficulties in deploying advanced models on edge devices, and security concerns in IoT-based systems. Furthermore, the lack of standardized frameworks for integrating AI with LoRa networks limits widespread adoption. Therefore, future research should focus on developing lightweight, scalable, and secure AI models that can operate efficiently in resource-constrained environments while maintaining high performance.

Conclusion

The rapid evolution of precision agriculture has been significantly influenced by the integration of Artificial Intelligence, wireless sensor networks, and low-power communication technologies such as LoRa. This study has provided a comprehensive analysis of AI techniques, particularly optimized Riemannian residual neural networks, in enhancing energy-efficient environmental monitoring systems for agricultural applications. The findings highlight that the combination of AI and LoRa-based WSNs offers a promising solution for addressing critical challenges related to resource management, sustainability, and productivity in modern agriculture. One of the key insights from this review is that LoRa technology plays a vital role in enabling long-range, low-power communication, making it highly suitable for large-scale agricultural deployments. However, its performance is influenced by factors such as network congestion, data latency, and parameter configuration. Traditional optimization techniques are often insufficient to handle the dynamic nature of agricultural environments, thereby necessitating the use of AI-driven adaptive strategies. Machine learning algorithms have demonstrated significant potential in optimizing network parameters, reducing energy consumption, and improving data transmission efficiency.
In parallel, deep learning models have revolutionized data analysis and prediction in agriculture by enabling accurate modelling of complex environmental patterns. Nevertheless, conventional neural networks are limited by their reliance on Euclidean data representations, which restrict their ability to capture the intrinsic geometric properties of agricultural datasets. The introduction of Riemannian residual neural networks addresses this limitation by incorporating manifold-based learning approaches, thereby improving feature extraction, convergence, and generalization. These models are particularly effective in handling high-dimensional and structured data, making them well-suited for precision agriculture applications. Despite these

advancements, several challenges remain that must be addressed to fully realize the potential of AI-driven agricultural monitoring systems. These include the high computational complexity of advanced neural models, limited processing capabilities of edge devices, and the need for efficient integration of AI with LoRa-based communication systems. Additionally, issues related to data security, privacy, and interoperability must be carefully considered to ensure the reliability and scalability of such systems.

Future research directions should focus on developing lightweight and energy-efficient neural network architectures that can be deployed on resource-constrained devices without compromising performance. The integration of edge computing, federated learning, and hybrid optimization techniques can further enhance system efficiency and scalability. Moreover, the development of standardized frameworks and protocols for AI-enabled LoRa networks will facilitate widespread adoption and implementation. In conclusion, the synergy between Artificial Intelligence, Riemannian residual neural networks, and LoRa-based wireless sensor networks holds significant promise for advancing precision agriculture. By addressing existing challenges and leveraging emerging technologies, it is possible to develop intelligent, sustainable, and energy-efficient agricultural systems that can meet the growing global demand for food while preserving natural resources.

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