Spectrum of Engineering Sciences
ISSN (e) 3007-3138 (p) 3007-312X
Volume 3, Issue 9, 2025

SAMF-RPL: AN IOT-DRIVEN RPL-BASED SMART AGRICULTURE MONITORING FRAMEWORK FOR PEST DETECTION

Muhammad Usman Danish[*1], **Sana Asghar**[*2], **Shaista Shabbir**[3], **Amreen Shafique**[4], **Areeba Saeed**[5]

[*1, *2]*Department of Computer Science, The Islamia University of Bahawalpur, Bahawalpur, Pakistan*
[3]*Department of Computer Science and Information Technology, University of Kotli, Azad Jammu and Kashmir, Pakistan*
[4]*Department of Computer Science, Mohi-ud-Din Islamic University, Nerian Sharif, Azad Jammu and Kashmir, Pakistan*
[5]*Department of Computer Science, The Government Sadiq College Women University, Bahawalpur, Pakistan*

DOI: https://doi.org/10.5281/zenodo.17224936

Keywords
IoT, Smart Agriculture, IPV6, RPL, SAMF, Pest Detection

Article History
Received: 02 July 2025
Accepted: 12 September 2025
Published: 25 September 2025

Corresponding Author: *
Muhammad Usman Danish
Sana Asghar

Abstract
The Internet of Things (IoT) is revolutionizing the agricultural sector by enabling advanced monitoring solutions that enhance productivity and sustainability. This study addresses the critical challenge of pest and disease detection in wheat farms, with a precise focus on the resource-constrained environments. We proposed a novel Smart Agriculture Monitoring Framework (SAMF) by utilizing the Routing Protocol for Low-Power and Lossy Networks (RPL) to ensure robust and efficient communication. The performance of the proposed SAMF-RPL framework is rigorously evaluated through simulations in the Contiki OS-based Cooja simulator. For a comprehensive analysis, its performance is benchmarked against an alternative framework based on Long-Range (LoRA) technology, termed SAMF-LoRA. The performance is comprehensively compared with multiple Key performance metrics, including Packet Delivery Ratio (PDR), end-to-end delay, and network power consumption. The simulation results demonstrate the significant superiority of the proposed SAMF-RPL framework. It achieves a substantially higher PDR, lower end-to-end delay, and significantly reduced power consumption compared to the SAMF-LoRA benchmark. These findings conclusively validate the efficacy of the RPL-based design, establishing SAMF-RPL as an ideal and efficient solution for automated pest detection in low-power and lossy agricultural networks.

1. Introduction

The current century has witnessed a marvellous evolution in scientific advancements that aim to facilitate humanity with a new meaning of innovation. Likewise, all other sectors of our lives, computer networks have also evolved in a significantly exceptional manner. The IoT is a widely expanding communication technology that falls under the umbrella of computer networks. It comprises multiple heterogeneous sensor nodes that can communicate with each other irrespective of human involvement, where this behaviour distinguishes IoT from conventional computer networks [1]. The applications of IoT are continuously expanding in every sphere of our lives; however, SAMF is one of the prominent applications of IoT. SAMF is a high-tech and effective method for practising agriculture and sensibly growing food. Such systems are mainly based upon the core concepts of IoT, which eliminates the need for physical labour for farmers while simultaneously enhancing productivity [2].

SAMF significantly improves the overall agricultural system by monitoring the field in real-time. It keeps a close eye on various elements such as humidity, temperature, soil, etc. It provides crystal-precise real-time observations [3]. Such environmental data is used to pick appropriate crops for the climatic conditions in which they will be grown and thrive. [4]. A wide variety of sensors are employed in the IoT ecosystem to assess meteorological conditions, including humidity and rainfall, correctly. One of the most well-known uses of the IoT in agriculture is precision agriculture [5]. Precision farming enables farmers to gather data with the help of sensors and analyze that data to make informed and timely decisions [6].

With the integration of IoT, modern greenhouse systems have evolved into intelligent, adaptive environments capable of responding immediately to user commands and dynamically adjusting internal parameters such as temperature. By deploying distributed networks of sensors, these systems continuously capture and transmit real-time data streams, thereby enabling precise and highly granular monitoring of the greenhouse microclimate. The sensor arrays provide measurements of critical environmental variables, including pressure, humidity, temperature, and light intensity, which collectively form a comprehensive dataset describing the state of the greenhouse environment at any given moment. This advancement in sensing and communication technologies has fundamentally transformed conventional agricultural operations, offering unprecedented levels of control and automation. In particular, the monitoring of water usage and overall greenhouse conditions is facilitated through these sensor networks, ensuring that irrigation processes can be executed both intelligently and autonomously. Such capabilities not only optimize resource utilization but also contribute to sustainable agricultural practices by minimizing water waste and maintaining optimal growth conditions for crops [7]. The induction of agricultural drones is the most recent example of this transformation. Crop health examination, crop monitoring, planting, crop spraying, and field analysis are just a few of the jobs that drones are used for on the ground and in the air. An abundance of real-time data from drones has helped the agriculture business soar to new heights and reshape the landscape [8, 9]. A typical model of SAMF is depicted in Figure 1:

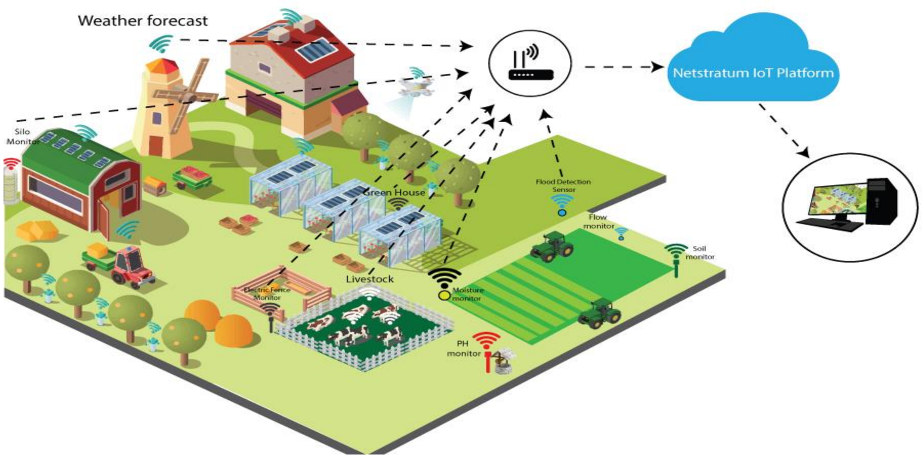

Figure 1: An overview of SAMF

RPL is an IPv6-based communication protocol designed to ensure reliable communications in low-power and lossy networks [10]. When utilizing RPL, the nodes are coupled in a tree topology. Each combination of nodes forms a Directed Acyclic Graph (DAG), which assures that there are no loops in the network's communication. These DAGs are connected to a central root node to construct a single, gigantic DAG known as A Destination-Oriented Directed Acyclic Graph (DODAG) [11]. DODAG Information Object (DIO), DODAG Information Solicitation (DIS), DODAG Advertisement Object (DAO), and DODAG Advertisement Object Acknowledgement (DAO-ACK) are the four types of control packets that are exchanged in this protocol [12].

The root node in RPL is responsible for constructing the baseline topology. As a result, the other nodes in the network receive a DIO packet broadcast by this parent node. This packet contains all of the information about this root node and its destination. Receiver nodes examine these DIO packets and recover critical information that enables them to determine the characteristics of their neighbors and the attributes of the root node to communicate. Following that, the constituent nodes send unicast DAO packets to the root node, indicating that they are ready to participate and communicate with the network [13]. The root nodes then respond with DAO-ACK packets, which confirm that the connection request was legitimate. Nodes are assigned rank numbers, which increase in value as we move away from the root node in the tree.

In some cases, initial DIO packets may not reach the candidate child node; in these cases, the candidate child node sends a DIS packet, which contains its request to obtain network information and is received by the candidate child node. The network topology is modified if any inconsistencies are discovered in the network, such as the presence of dead nodes or the presence of attacking situations [14]. Unlike standard networks and protocols [15], the RPL routing protocol is designed to avoid loops instead of eliminating them. To avoid loops, RPL includes two major mechanisms known as the local repair mechanism and the global repair mechanism [11]. When the local repair is activated, the concerned node searches for the parent node or path when a neighbor or link fails. However, the root node will begin a global repair mechanism reconstruction when its local repair network fails to maintain its optimal mode [16].

1.1 Research Motivation

The implementation of IoT technologies within the agricultural sector yields a wide range of benefits, including enhanced efficiency, precision, and sustainability. Nevertheless, several challenges and limitations continue to impede the seamless deployment and large-scale adoption of IoT-based solutions in agricultural environments. Despite the rapid advancement of IoT technologies, a significant proportion of farmers remain unaware of their potential applications and deployment within agricultural practices [17]. Another difficulty is that some people are unwilling to accept new ideas, even though doing so has numerous advantages, because the cost of implementing the IoT in agriculture is prohibitive. Even though sensors are the cheapest component, it would cost more than a thousand dollars in materials and labour to install sensors in every field of the farmers [18].

The IoT agricultural systems collect enormous amounts of data, challenging to keep secure. Someone with unauthorized access to a cloud-based IoT provider's database could steal and manipulate the information. The need to transmit data between a large number of agricultural facilities continues to be a barrier to the widespread adoption of smart farming [19]. To ensure that activities are not disrupted, the connection between these facilities must be reliable enough to endure adverse weather. IoT devices now use a variety of communication protocols, despite efforts to build a single standard in this field [20].

These communication protocols are also responsible for routing data being exchanged among various participating devices [21, 22]. The secure and timely transport and exchange of this data are one of the major smart farming problems. As a result of precision agriculture and IoT technologies, there are more security flaws for data theft and cyber assaults to take advantage of [23]. The robust and synchronized communication among the exchange parties is the key goal of any smart agriculture monitoring framework. Therefore, the selection of an appropriate communication protocol significantly increases. There are some other criteria as well that must be taken into consideration before selecting an ideal communication protocol. In the agriculture space, the communication protocol must be valid enough to accommodate all the spontaneous fluctuations occurring in the traffic flow. The communication sensors may be disturbed by outside environmental conditions, resulting considerable effect on the communication flow of data [24].

1.2 Problem Statement

The authors in [25] proposed an efficient agricultural monitoring system mainly focused on pest and disease monitoring in green fields. The under-contention framework encompasses a collection of Unnamed Arial Vehicles (UAV) that can capture the images of farmland. These images can be utilized to analyse the occurrence of crop pests and diseases. They have proposed an interlinked mechanism by providing profound insights into the specific relationship between pests/diseases and weather parameters. The data containing environmental conditions such as temperature, humidity, and wind pressure is collected by the sensor nodes and then aggregated at a central storage unit. Communication takes place by following the core principles of LoRA technologies. The collected data by UAVs is then analysed in an interlinkage with environmental conditions. Finally, specific statements about farm monitoring are made. We found room for improvement in the communication mechanism that can enhance the effectiveness of that model. Authors have used basic operational concepts of LoRAWAN to regulate the data flow among the network, which demands a considerable amount of system resources for its efficient operation.

Furthermore, the agricultural space is surrounded by tiny sensors that are frequently disturbed by external environmental conditions. This phenomenon disrupts the stable communication flow and makes the network a lossy network. To be more precise, the availability of limited resources and the lossy nature of the communication network demand an adequate communication protocol to cope with such challenges. We aim to solve this problem by implementing RPL, which is mainly designed for low-power and lossy networks.

1.3 Research Questions

This scientific study intends to address the following research questions:

- How can the incorporation of the RPL into an IoT-based monitoring system enhance communication reliability and efficiency in resource-constrained agricultural environments?
- To what extent can RPL serve as a scalable and energy-efficient routing protocol for large-scale smart farming applications, and how does its performance compare with LoRa?
- What improvements in key performance metrics can be achieved through the proposed SAMF-RPL framework, and how do these results validate its suitability for automated pest and disease detection in wheat farms?

2. Related Work

The SAMFs are sometimes susceptible to various crucial performance-related concerns. Many scientific contributions have been made to overcome such issues, and here we have studied some research studies in this domain. Authors [26] describe the design of a chemical sensor to function as part of an IoT system. The data collected from the designated agricultural fields by the NPK sensor is sent to a Google Cloud database, where it may be easily retrieved. To determine whether or not there is a nutritional shortage, the concept of fuzzy logic is used for the information. Python is used to build the hardware prototype and the software embedded in the Raspberry Pi 3 microcontroller. The use of Artificial Intelligence (AI) [27, 28] and image recognition technologies in conjunction with environmental sensors and the IoT is investigated in the study [29] for pest identification. Based on intelligent pest identification and IoT data from the environment, real-time agricultural meteorology and pest identification systems for mobile applications are being investigated. Farmers can use this research to determine the location of pests and the extent of pest infestations, allowing them to accurately apply pesticides at precise times and locations, reducing the amount of agricultural labour required for timely pest control. As a solution to the problem mentioned above, the authors propose an IoT-based Smart Farming decision support system. The proposed model incorporates a multilevel parameter-optimized feature selection algorithm as a classifier based on an Improved Genetic Algorithm (IGA). An additional advantage of the Genetic Algorithm (GA) over other feature subset selection methods is that it offers random search in addition to being a time-saving technique [30]. The authors proposed new agricultural structures based on IoT networks that may be more easily applied to many types of crops and environments. Laboratory and field experiments validated the system's overall effectiveness and durability. Results of the assessments are based on a comparison of the model's precision, accuracy, and processing time with other models, and the results reveal a superiority over other models [31]. The authors presented a Wireless Sensor Network (WSN) architecture based on the IoT to be customized at various design levels for smart agriculture. A multi-criteria decision function is utilized to select a set of cluster heads for use in the field based on data collected by agricultural sensors. Throughput gains of 13.5%, drop ratio gains of 38.5%, latency gains of 13.5%, energy consumption gains of 16% and routing overhead gains of 26.5% were all seen when comparing the proposed framework to alternative solutions in simulation results [32]. The author addresses the power and capabilities of computer-based techniques in their study. By using data analytics and machine learning, a model for forecasting Apple disease in Kashmir Valley apple orchards was constructed, according to the authors. Farmers who took part in a survey about the latest technology and its impact on precision agriculture were also polled to gather further information. Their final discussion focuses on farmers' difficulties integrating new technologies into their farming methods [33]. To create a more dependable smart farming system, a new adaptive network method is proposed. As a more particular example, the proposed adaptive network method works at the application layer of a network. Its adaptability allows it to respond to changes in the network environment by adjusting its protocol. The system can maintain its dependability while monitoring because of an adaptive process that takes advantage of the advantages of both protocols and blends them. According to the findings, there is a significant relationship between the latency of the proposed system and the number of sensors from which it collects data [34]. The authors propose cluster head selection based on cross-layers to tackle the problem of asymmetric energy consumption in wireless sensor networks. The designed framework reduces energy consumption, communication overhead, and end-to-end delay to some extent while boosting network throughput to a higher level compared to current IoT farming methods [35]. The advancement of satellite, sensor networks, and image processing technology has been used to address a variety of problems and difficulties. In recent years, such innovations have been well matched to the needs of intelligent agriculture. Researchers proposed an efficient multi-feature plant management framework to increase the effectiveness of plant monitoring while also considering security issues. The suggested model uses several satellite photos taken over the agricultural region and local images derived from regional data sets to create the final product. The images obtained are analyzed for texture and colour characteristics and then used to classify the photos against various diseases and inadequacies [36]. Temperature and soil moisture parameters impact the growth of agriculture, including elements such as productivity, disease, and yield output. In [37], the temperature quotient is calculated based on the amount of water vapor present in the air and the pressure in the air, both of which are indicators of plant development. Compared to existing thermal comfort procedures, the results are 94% accurate while requiring less time to complete the procedure. The model is created with Arduino Technology. Thingsspeak.com sells the breadboard, which comes with a range of sensors and real-time data sources to get you started [38].

3. Proposed Methodology

3.1 Implementation Structure and Proposed SAMF-RPL

We have proposed an IoT-based SAMF to detect the presence of pests and diseases in the farmland. The framework consists of 4 steps in which different functionalities are performed at each stage. In the first stage of the proposed framework, the sensor nodes are deployed within the farmland in a scattered pattern. The core purpose of these devices is to acquire environmental data such as temperature, humidity, and wind pressure. The movement of UAVs is planned above the concerned field in a systematic way, where the aerial images of the farmland are captured. The UAVs contain high-quality optical cameras that can easily take good-quality pictures from a long distance [39]. The flying path of these UAVs is planned to depend upon several parameters such as image capturing angles, sun direction, and wind pressure. The data captured by individual UAVs and ground sensors is then transmitted to the central root node responsible for transmitting it to the IoT gateway node. A typical deployment of UAVs and sensor nodes can be shown in Figure 2:

Figure 2: Deployment of Sensors and UAV in open farmland

Here, we will ensure data communication among nodes through the RPL protocol, which is an ideal choice for reliable communication in resource-constrained lossy networks. All the nodes in RPL are arranged in a tree-like topology where all the child nodes aim to send data toward the root node. RPL supports three basic modes of communication: point-to-point, point-to-multipoint, and multipoint-to-point communication [40]. We have followed multipoint-to-point communication, where multiple data transmission streams are directed towards a single node. In open farmland, nodes are situated at long distances, so having communication among these nodes is a significant challenge. RPL comes to overcome such challenges with its strength to communicate in lossy environments by consuming less energy from network resources [41]. A structure of various modes of communication in RPL is shown in Figure 3:

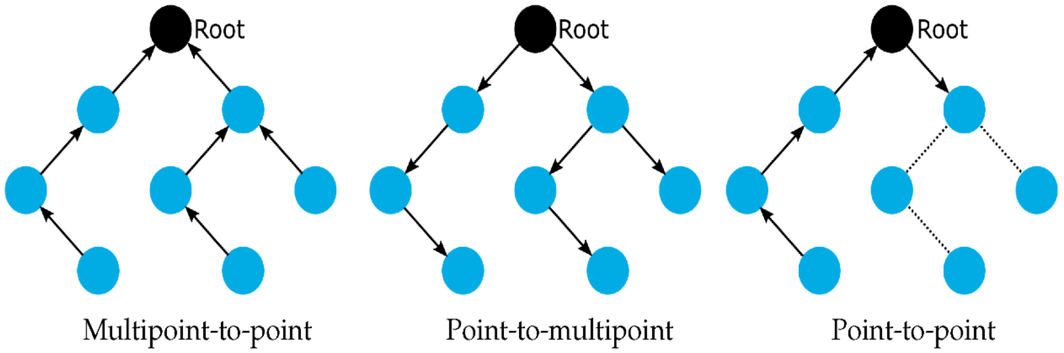

Figure 3: Various Communication Modes in RPL

The IoT gateway node then transmits this data to the cloud, where two significant functionalities are performed, the first one is data analysis, and the second one is data storage. Cloud resources facilitate such communication environments with an efficient means of communication. These resources are available to the monitoring system. They can provide real-time support without costing an excessive burden on the network [42]. The cloud then analyses these optical images taken by UAVs. It then sends them out to the remote farmer who can access the actual situation of his farmland through a mobile interface. An overview of such a communication cycle can be seen in Figure 4:

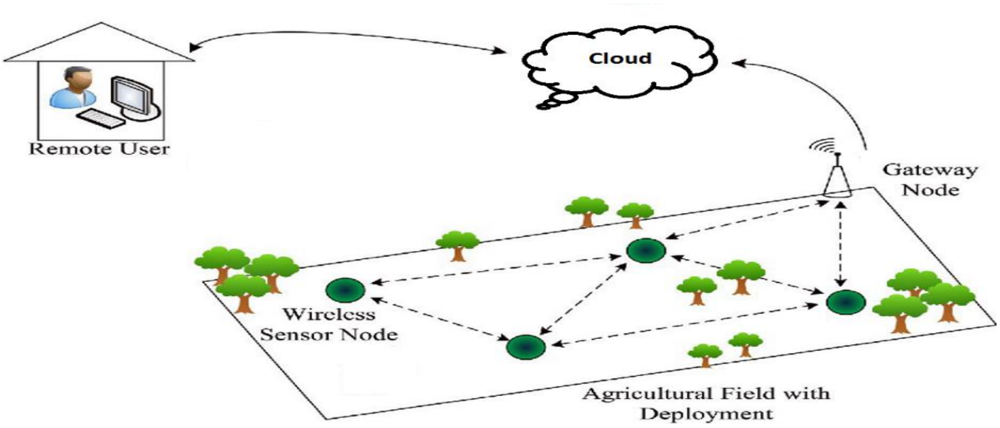

Figure 4: Communication cycle of SAMF

At the cloud, the images are then analyzed concerning the data provided by the sensor nodes. The occurrence of pests and disease can affect the outer surface of plants, where the leaf can turn yellow, red, or some other colour depending upon the strength of the disease. It becomes complicated for the human eye to look at these infected plants because of the relevant colours. Optical sensors can capture high-quality images, where it is easy to have a comprehensive overview of the whole farmland [43, 44]. The infected plants in the farmland look different in colour compared to the healthy plants. Figure 5 depicts an idea of how the optical images look after analysis.

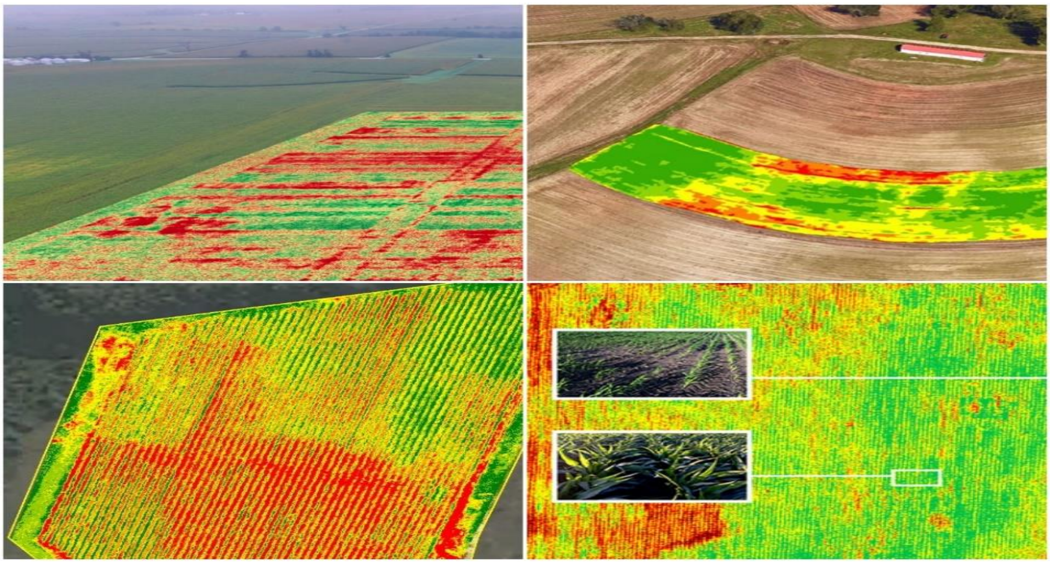

Figure 5: Images taken by UAVs after Analysis

The entire communication of the proposed SAMF is depicted in Figure 6:

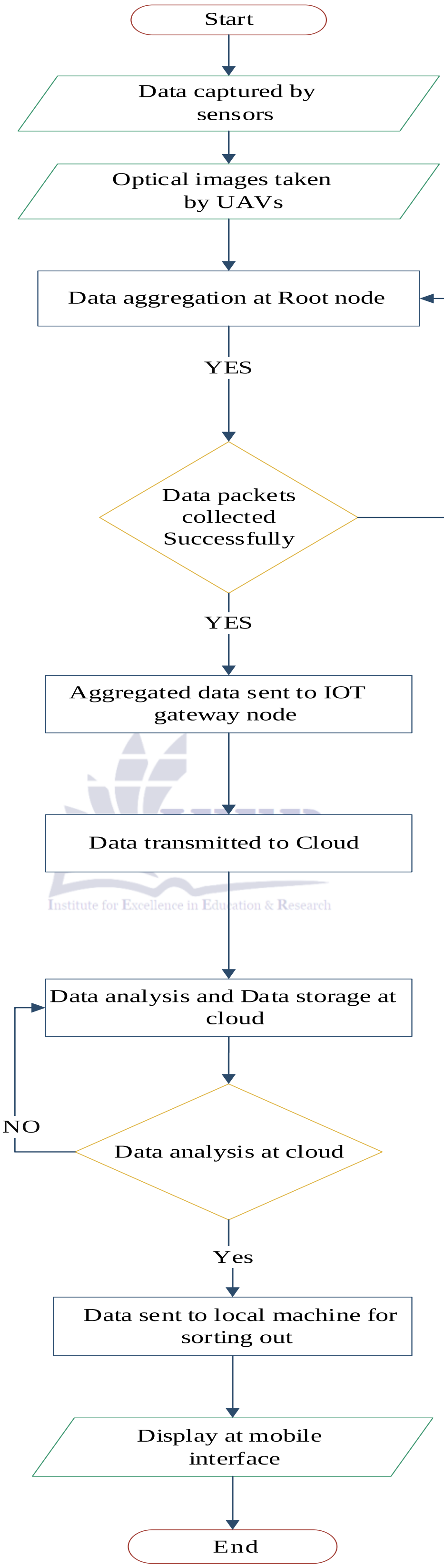

Figure 6: Workflow of the Proposed SAMF-RPL

In an RPL DODAG, these nodes are placed in a tree topology, with pathways connecting the sender and sink nodes between each node [45]. Every node will have a preferred parent node and a route that corresponds to it. To go to the sink node, a neighbour node with the least amount of information is selected as the desired parent when any communication is transferred [46]. The distance between two nodes is defined as the Rank of a node. There will be a concept known as the objective function, which will have its respective path measure that can be used to determine the best possible path to a destination. It determines what a node's Rank should be concerning the objective function utilized in the RPL protocol. In a DODAG formation, the objective function is utilized to select the desired parent node and the routing of messages between them. To make matters more complicated, objective functions use routing metrics to find a path from a parent node to the root node [47].

Workflow of RPL

START
COUNT Self_ Rank
Calculate_ Parent node_ Rank
Calculate Neighbor-Rank
Generalize the routing table
Calculate_ Parent_ Rank (On-demand)
If the previous Rank is suitable for communication
Send DIS to DAG
Obtained the required information through DIO
If DAG is compatible, send DAO
If else
Discard DIO
Discard the new parent
End

The algorithm is further elaborated in Figure 7:

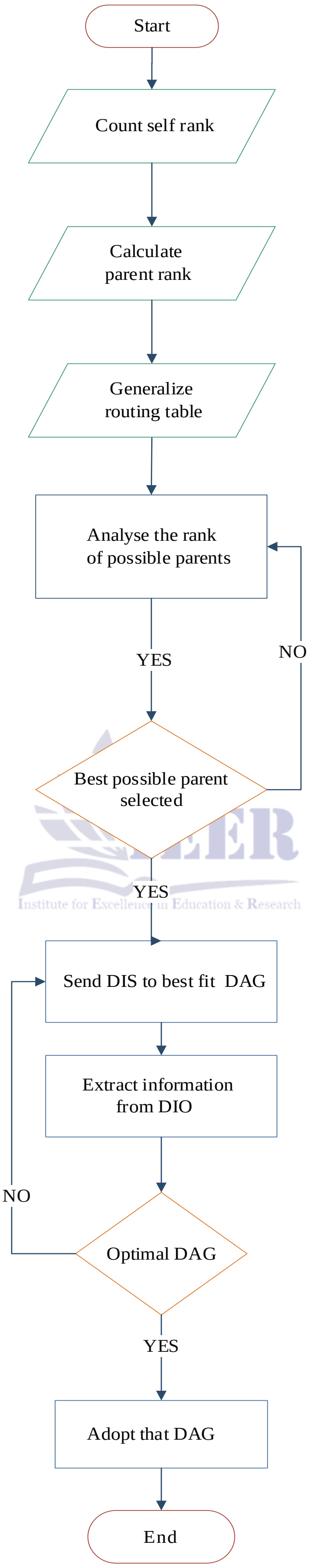

Figure 7: Workflow of RPL

3.2 Performance Evaluation

The performance of RPL is examined in a simulation-based environment where a virtual industrial setup is established. The detailed overview of the simulation setup and performance parameters is elaborated in the upcoming sections.

3.2.1 Simulations Setup

RPL is a broadly used routing protocol for resource-constrained Industrial Internet of Things (IIoT) environments. The word "resource constraint" refers to devices that have limited energy, computational resources, and memory storage capabilities. The Contiki operating system provides a testing environment for low-power and lossy networks, which can be used for network evaluation. The Cooja simulator is designed to work in conjunction with the Contiki operating system and to assist in obtaining a realistic view of scientific contributions that have been proposed. There is a wide variety of other simulation tools available, such as MATLAB, NS-2, and OMNETT++; however, Cooja is widely regarded as the best option for dealing with devices with limited resources. [48]. We have made a fixed topology of 100 nodes using the RPL routing protocol. As we are investigating the actual performance of RPL in large-scale IIoT networks, the nodes are randomly connected in a fixed topology. All these nodes have been placed in a 100-square-meter industrial area. Among all these nodes, the route node is energy-rich. However, all the remaining nodes are considered resource-constrained nodes [49, 50]. The communication model is multipoint to the point where multiple senders aim to send data towards a single receiver, the root node. The traffic model is constant, where a packet size of 12t bytes is transmitted over a carrier frequency of 2.4 GHz. The simulations are run for 2000 seconds, and the performance of the RPL protocol in the scenario mentioned above is evaluated. The simulation setup is listed in Table 1:

Table 1: Simulation Setup

S#	Parameters	Values
1	Routing Protocol	RPL
2	Physical Standard	IEEE 802.15.4
3	Operating Framework	Contiki
4	Simulator	Cooja
5	Operating System	Contiki
6	Version	2.7
7	Mote type	T mots Sky
8	Traffic Model	Constant bit rate
9	Number of nodes	100
10	Node Deployment	Random
11	Deployment area	100 m x 100 m

12	Network Topology	Random/Mesh Fixed
13	Topology type	Random / Mesh
14	Packet Size	127 bytes
15	Channel Data Rate	250 kbps
16	Operating Carrier Frequency	2.4 GHz
17	Simulation Time	The 2000s

3.2.2 Simulation Parameters

The performance of RPL in a large-scale agricultural scenario is evaluated in a diverse range of performance parameters such as PDR, end-to-end delay, and power consumption. The benchmarked algorithm and the proposed algorithm are both designed to monitor the existence of pests in farmland. Therefore, their performance must be compared and analyzed on some real-time performance parameters to get a visionary projection of their actual performance.

3.2.2.1 Packet Delivery Ratio (PDR)

Our performance metrics include PDR which provides an analytical insight regarding the efficient communication of a SAMF. It exhibits the actual number of packets received in a ratio to the total number of packets sent from source to destination nodes in the network. PDR plays a phenomenal role to investigate the actual performance of a lossy network as such networks have vital chances of communication packet loss. The PDR of a communication session is calculated through equation (1)

$$\text{Packet Delivery Ratio} = \frac{\Sigma(\text{Total packets received by all destination node}}{\Sigma(\text{ Total packets sent by all source}} \text{ - (1)}$$

3.2.2.2 End-to-End delay

The time it takes for a data packet to travel from the transmitter node to the receiver node is referred to as the end-to-end delay. While evaluating the performance of an optimal agricultural monitoring system, the system with the least end-to-end delay is regarded as the best choice. We have investigated the performance of both SAMFs on end-to-end delay to figure out the best SAMF for resource-constrained and lossy networks based on a large-scale agricultural farmland. This delay is calculated through equation (2)

End-to-End delay: T (h1) + T (h2) + T (h3) ------- T (hn) ------------------------- (2)

3.2.2.3 Power Consumption

The power consumed by a SAMF to effectively perform its operation provides an investigatory insight regarding the efficiency of a system. In a resource-constrained environment, the system must be capable of operating under less power consumption [51]. Therefore, we have evaluated and compared the performance of both schemes under the power consumption, which is a phenomenal attribute for evaluating the real-time performance of an ideal communication system. In our simulation scenario, we have comparatively evaluated the performance of both schemes in terms of power consumption, where four types of power are generally aggregated to calculate the total power consumption of a concerned system, as mentioned in equation (3)

P (Total) = P (Sending) + P (Reception) + P (Sleeping) + P (Receiving) ------------ (3)

4. Results and Discussions

The performance of SAMF-RPL and LoRA is evaluated in terms of PDR as well, where it can be seen that when there were 10 nodes in the network, the PDR was 99.8% for SAMF-RPL and 99.7%for SAMF-LoRA. When we added 10 more nodes to the network, the PDR was 99.3% for SAMF-LoRA; however, the proposed SAMF-RPL shows a slightly increased PDR of approximately 99.6%. Similarly, in a network of 30 nodes, SAMF-LoRA shows a PDR of about 98.8% and the proposed SAMF-RPL has delivered a PDR of 99.2%. The sequence goes on and on. The performance is further evaluated in a network of 40 nodes, where SAMF-LoRA seems to provide a PDR of about 98.2%. That PDR is comparatively low because the proposed SAMF-RPL provides a PDR of 98.9%. The performance of both candidate technologies is evaluated in a network of 50 nodes, where SAMF-LoRA is depicting an end-to-end delay of 97.9%. The proposed SAMF-RPL seems to beat SAMF-LoRA with a PDR of 98.3%, as projected in Figure 8:

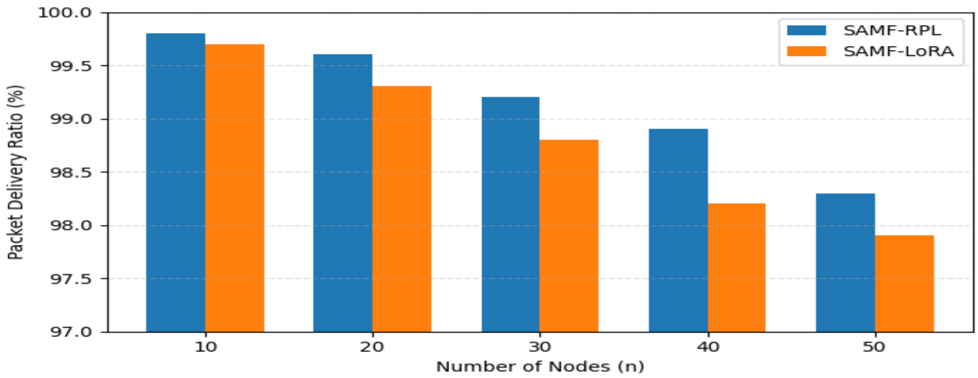

Figure 8: Packet Delivery Ratio Analysis of Nodes 0-50

The performance of SAMF-RPL and SAMF-LoRA is further evaluated in terms of PDR when there were 60 nodes in the network; the PDR was 97.9% for SAMF-RPL and 97.4%for SAMF-LoRA. When we add 10 more nodes to the network, the PDR was 96.9% for SAMF-LoRA; however, the proposed SAMF-RPL shows a slightly increased PDR of approximately 97.4%. Similarly, in a network of 80 nodes, SAMF-LoRA shows a PDR of about 96.4% and the proposed SAMF-RPL has delivered a PDR of 96.9%. The sequence goes on and on. The performance is further evaluated in a network of 90 nodes, where SAMF-LoRA seems to provide a PDR of about 95.9%. That PDR is comparatively low because the proposed SAMF-RPL provides a PDR of 96.3%. The performance of both candidate technologies is evaluated in a network of 100 nodes where SAMF-LoRA is depicting a PDR of 95.3%. The proposed SAMF-RPL seems to beat SAMF-LoRA with a PDR of 95.9%, as shown in Figure 9:

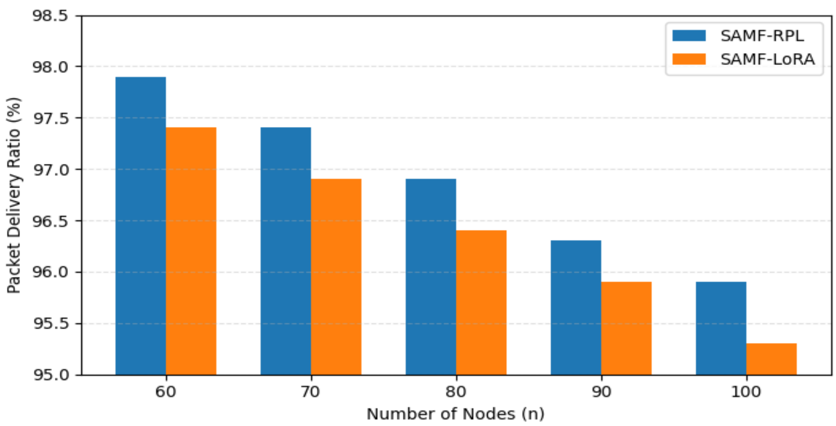

Figure 9: Packet Delivery Ratio Analysis of Nodes 51-100

The performance of SAMF-RPL and LoRA is evaluated in terms of End-to-End delay. It can be seen that when there were 10 nodes in the network, the delay was 6ms for SAMF-LoRA and SAMF-RPL. When we added 10 more nodes to the network, the delay was 12.9ms for SAMF-LoRA; however, the proposed SAMF-RPL shows a slightly lower duration of approximately 12.5ms. Similarly, in a network of 30 nodes, SAMF-LoRA shows an end-to-end delay of 19ms, but that delay was noticed as 18.5ms in the case of the proposed SAMF-RPL. The sequence goes on and on, where the performance is further evaluated in a network of 40 nodes, where SAMF-LoRA provides an end-to-end delay of about 29ms. That delay is comparatively high because the proposed SAMF-RPL has shown a delay of 26ms. The performance of both candidate technologies is evaluated in a network of 50 nodes, where SAMF-LoRA depicts an end-to-end delay of 41ms. The proposed SAMF-RPL seems to beat SAMF-LoRA with a delay of 35ms, as can be witnessed in Figure 10:

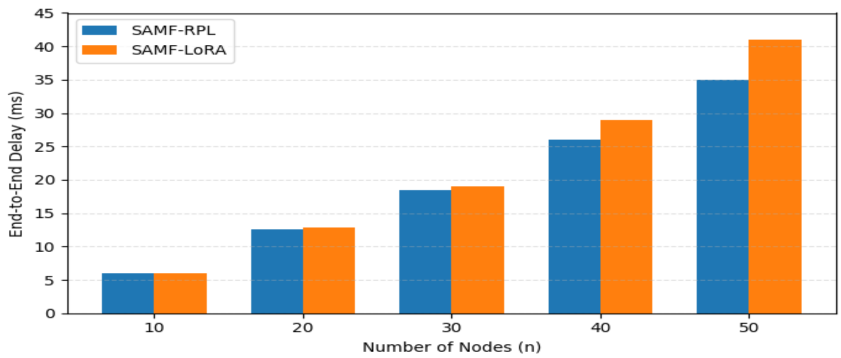

Figure 10: End-to-End delay Analysis of Nodes 0-50

To get deep insight into the actual performance of both technologies, the network size is increased to 60 nodes, where SAMF-LoRA has acquired an end-to-end delay of 49ms. However, the proposed SAMF-RPL again outclasses the previous technology with an end-to-end delay of 44ms. In a network of 70 nodes, the end-to-end delay was 63ms and 53.5ms in the case of SAMF-LoRA and SAMF-RPL. The same performance pattern can be seen when there were 80 nodes in the network. The delay was 72ms for SAMF-LoRA and 64.5ms for our proposed SAMF-RPL. The same results appear in a network of 90 nodes, in which the delay was 83ms and 75ms in the case of SAMF-LoRA and SAMF-RPL. Furthermore, finally, in a network comprising 100 nodes, the end-to-end delay was 97ms for SAMF-LoRA. However, the proposed SAMF-RPL has shown significantly better results with a delay duration of about 83ms, as can be seen in Figure 11:

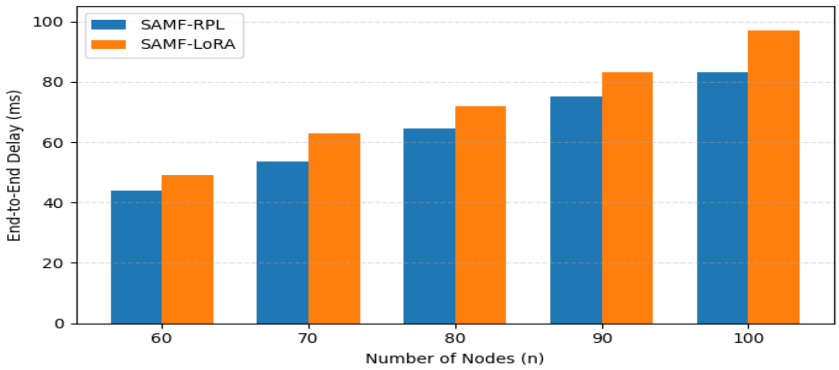

Figure 11: End-to-End delay Analysis of Nodes 51-100

The performance of SAMF-RPL and LoRA is evaluated in terms of power consumption. It can be seen that when there were 10 nodes in the network, the system consumed 0.39mW for SAMF-RPL and 0.38mW for SAMF-LoRA. When we added 10 more nodes in the network, the power consumption was 0.63mW for SAMF-LoRA; however, the proposed. SAMF-RPL shows a slight decrease in power consumption, making it approximately 0.62mW. Similarly, in a network of 30 nodes, SAMF-LoRA consumed power of about 0.53mW, and the proposed SAMF-
:
RPL consumed power of 0.49mW. The sequence goes on and on. The performance is further evaluated in a network of 40 nodes, where SAMF-LoRA seems to consume the power of 1.32mW, which is comparatively high because the proposed SAMF-RPL consumes only 0.8mW of power. The performance of both candidate technologies is evaluated in a network of 50 nodes, where SAMF-LoRA depicts a power consumption of 1.49mW. The proposed SAMF-RPL seems to beat SAMF-LoRA with a reduced power consumption of about 1.25mW as projected in Figure 12

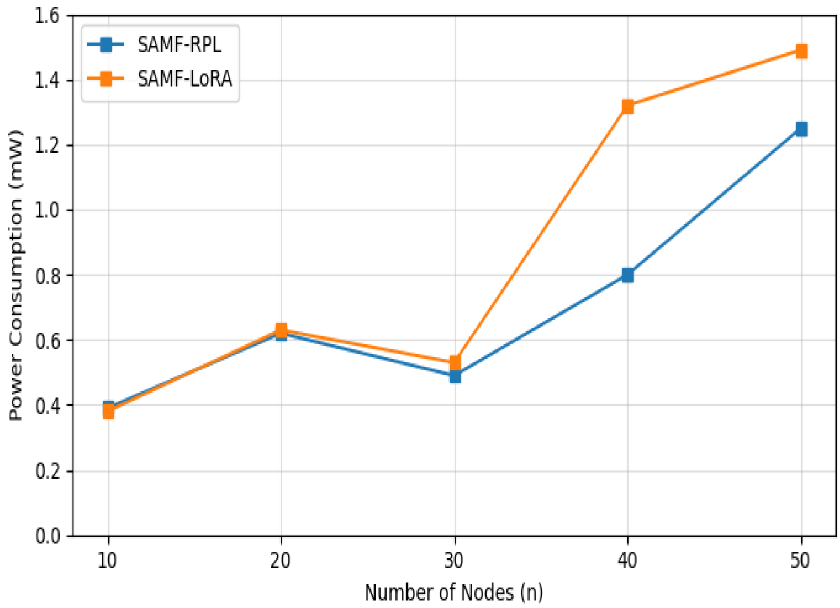

Figure 12: Power Consumption Analysis of Nodes 0-50

The performance of SAMF-RPL and LoRA is further evaluated in terms of power consumption when there were 60 nodes in the network; the power utilization was 1.12mW for SAMF-RPL and 1.59 mW for SAMF-LoRA. When we add 10 more nodes in the network, the power consumption becomes 1.42mW for SAMF-LoRA, proposed SAMF-RPL shows a slightly increased power consumption of approximately 1.39mW. Similarly, in a network of 80 nodes, SAMF-LoRA consumed power of 1.53mW and proposed SAMF-RPL consumed power of 1.41mW. The sequence goes on and on, and the performance is further evaluated in a network of 90 nodes where SAMF-LoRA seems to consume the power of about 1.68mW, which is comparatively high, as the proposed SAMF-RPL consumes the power of about 1.53mW. The performance of both candidate technologies is evaluated in a network of 100 nodes, where SAMF-LoRA is utilizing 1.73mW of power, while the proposed SAMF-RPL seems to outclass SAMF-LoRA with a reduced power consumption of about 1.69mW, as can be seen in Figure 13:

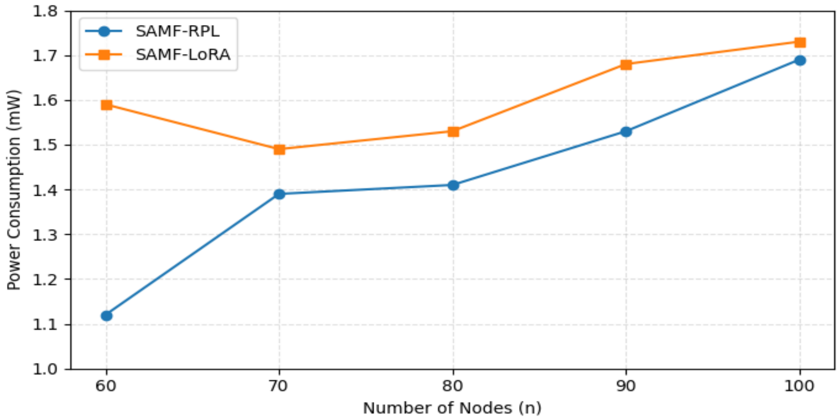

Figure 13: Power Consumption Analysis of Nodes 51-100

The summary of comparative results analysis between SAMF-LoRA and SMF-RPL is also summarized in Table 2:

Table 2: Summary of Comparative Result Analysis

Number of Nodes	PDR (%)		End-to-End delay (ms)		Power Consumption (mW)	
	SAMF-LoRA	SAMF-RPL	SAMF-LoRA	SAMF-RPL	SAMF-LoRA	SAMF-RPL
10	99.7	99.8	6	6	0.38	0.39
20	99.3	99.6	12.9	12.5	0.63	0.62
30	98.8	99.2	19	18.5	0.53	0.49
40	98.2	98.9	29	26	1.32	0.8
50	97.9	98.3	41	35	1.49	1.25
60	97.4	97.9	49	44	1.59	1.12
70	96.9	97.4	63	53.5	1.49	1.39
80	96.4	96.9	72	64.5	1.53	1.41
90	95.9	96.3	83	75	1.68	1.53
100	95.3	95.9	97	83	1.73	1.69

5. Conclusion

This study presents SAMF-RPL, an IoT-based RPL-driven agricultural monitoring framework designed to tackle the critical challenge of pest and disease detection in wheat farms operating under resource-constrained conditions. By leveraging the IPv6-based RPL, the framework ensures efficient and resilient communication, even in lossy networks prone to frequent disruptions. The proposed system was rigorously validated using the Contiki OS-based Cooja simulator, with its performance benchmarked against a LoRa-based alternative, SAMF-LoRA. The simulation outcomes consistently demonstrate the superiority of SAMF-RPL. Specifically, the framework achieved higher packet delivery ratios, lower end-to-end delays, and reduced power consumption when compared to SAMF-LoRA. These results confirm the effectiveness of the RPL-based approach, establishing SAMF-RPL as a reliable and resource-efficient communication framework for agricultural IoT systems. Beyond technical performance, the findings highlight the potential of SAMF-RPL to support large-scale deployments in rural and resource-limited environments, where sustainability and reliability are vital. By ensuring stable and energy-conscious monitoring, the framework strengthens the role of IoT in precision agriculture and lays the foundation for more intelligent, automated pest detection systems. Overall, SAMF-RPL provides a practical, scalable, and energy-efficient solution, advancing the integration of IoT technologies into sustainable farming practices.

REFERENCES

[1] S.-L. Peng, S. Pal, and L. Huang, *Principles of internet of things (IoT) ecosystem: Insight paradigm*. Springer, 2020.

[2] B. Almadani and S. M. J. I. A. Mostafa, "IIoT based multimodal communication model for agriculture and agro-industries," vol. 9, pp. 10070-10088, 2021.

[3] M. Ayaz, M. Ammad-Uddin, Z. Sharif, A. Mansour, and E.-H. M. J. I. a. Aggoune, "Internet-of-Things (IoT)-based smart agriculture: Toward making the fields talk," vol. 7, pp. 129551-129583, 2019.

[4] H. Jiang, X. Li, F. J. M. Safara, and Microsystems, "IoT-based agriculture: Deep learning in detecting apple fruit diseases," p. 104321, 2021.

[5] H. N. Saha, R. Roy, M. Chakraborty, C. J. A. i. a. u. t. I. Sarkar, and m. learning, "Development of IoT-based smart security and monitoring devices for agriculture," pp. 147-169, 2021.

[6] P. S. Chatterjee, N. K. Ray, and S. P. J. I. T. o. C. E. Mohanty, "LiveCare: An IoT-Based Healthcare Framework for Livestock in Smart Agriculture," vol. 67, no. 4, pp. 257-265, 2021.

[7] B. B. Sharma, N. J. I. J. o. A. Kumar, and E. I. Systems, "IoT-based intelligent irrigation system for paddy crop using an internet-controlled water pump," vol. 12, no. 1, pp. 21-36, 2021.

[8] A. F. Suhaimi *et al.*, "IoT Based Smart Agriculture Monitoring, Automation and Intrusion Detection System," in *Journal of Physics: Conference Series*, 2021, vol. 1962, no. 1: IOP Publishing, p. 012016.

[9] L. Kanuru, A. K. Tyagi, S. Aswathy, T. F. Fernandez, N. Sreenath, and S. Mishra, "Prediction of Pesticides and Fertilizers using Machine Learning and Internet of Things," in *2021 International Conference on Computer Communication and Informatics (ICCCI)*, 2021: IEEE, pp. 1-6.

[10] K. N. Qureshi, S. S. Rana, A. Ahmed, and G. Jeon, "A novel and secure attacks detection framework for smart cities industrial internet of things," *Sustainable Cities and Society*, vol. 61, p. 102343, 2020.

[11] M. Zaminkar, F. Sarkohaki, and R. J. I. J. o. C. S. Fotohi, "A method based on encryption and node rating for securing the RPL protocol communications in the IoT ecosystem," vol. 34, no. 3, p. e4693, 2021.

[12] Z. A. Almusaylim, A. Alhumam, and N. J. A. H. N. Jhanjhi, "Proposing a secure RPL based internet of things routing protocol: a review," vol. 101, p. 102096, 2020.

[13] A. Verma and V. J. T. o. e. t. t. Ranga, "Mitigation of DIS flooding attacks in RPL-based 6LoWPAN networks," vol. 31, no. 2, p. e3802, 2020.

[14] D. Airehrour, J. A. Gutierrez, and S. K. J. F. G. C. S. Ray, "SecTrust-RPL: A secure trust-aware RPL routing protocol for Internet of Things," vol. 93, pp. 860-876, 2019.

[15] M. S. Saeed and N. Sherafzal, "Networking and protocols for AI-based healthcare networks," in *Artificial Intelligence-Based Smart Healthcare Systems*: Elsevier, 2025, pp. 121-142.

[16] A. Verma and V. J. I. S. J. Ranga, "Security of RPL based 6LoWPAN Networks in the Internet of Things: A Review," vol. 20, no. 11, pp. 5666-5690, 2020.
[17] A. R. de Araujo Zanella, E. da Silva, and L. C. P. J. A. Albini, "Security challenges to smart agriculture: Current state, key issues, and future directions," vol. 8, p. 100048, 2020.
[18] P. K. R. Maddikunta *et al.*, "Unmanned aerial vehicles in smart agriculture: Applications, requirements, and challenges," vol. 21, no. 16, pp. 17608-17619, 2021.
[19] B. B. Sinha and R. J. F. G. C. S. Dhanalakshmi, "Recent advancements and challenges of Internet of Things in smart agriculture: A survey," vol. 126, pp. 169-184, 2022.
[20] R. Z. Ekaputri, D. Jumiarni, B. Usman, B. Karyadi, and E. P. J. E. J. P. K. M. Putra, "The Potential of Hydroponics as a Solution for Food Security and Economics Resilience: Issues and Challenges of Smart-Agriculture," vol. 5, no. 2, pp. 493-505, 2021.
[21] A. Shafique, A. A. Farea, and K. N. Qureshi, "AI as a new paradigm for distributed healthcare networks," in *Artificial Intelligence-Based Smart Healthcare Systems*: Elsevier, 2025, pp. 97-118.
[22] T. Iqbal, G. Wu, Z. Iqbal, M. B. Mahmood, A. Shafique, and W. Guo, "PypiGuard: A novel meta-learning approach for enhanced malicious package detection in PyPI through static-dynamic feature fusion," *Journal of Information Security and Applications,* vol. 90, p. 104032, 2025.
[23] F. Bu and X. J. F. G. C. S. Wang, "A smart agriculture IoT system based on deep reinforcement learning," vol. 99, pp. 500-507, 2019.
[24] I. Mistry, S. Tanwar, S. Tyagi, N. J. M. s. Kumar, and s. processing, "Blockchain for 5G-enabled IoT for industrial automation: A systematic review, solutions, and challenges," vol. 135, p. 106382, 2020.
[25] D. Gao, Q. Sun, B. Hu, and S. J. S. Zhang, "A framework for agricultural pest and disease monitoring based on internet-of-things and unmanned aerial vehicles," vol. 20, no. 5, p. 1487, 2020.
[26] G. Lavanya, C. Rani, P. J. S. C. I. GaneshKumar, and Systems, "An automated low cost IoT based Fertilizer Intimation System for smart agriculture," vol. 28, p. 100300, 2020.
[27] S. Islam, D. Javeed, M. S. Saeed, P. Kumar, A. Jolfaei, and A. N. Islam, "Generative AI and cognitive computing-driven intrusion detection system in industrial CPS," *Cognitive Computation,* vol. 16, no. 5, pp. 2611-2625, 2024.
[28] A. Shafique, M. S. Saeed, D. Javeed, and K. N. Qureshi, "AI Models and Ethical Considerations in Research," in *Next Generation AI Language Models in Research*: CRC Press, 2024, pp. 170-190.
[29] C.-J. Chen, Y.-Y. Huang, Y.-S. Li, C.-Y. Chang, and Y.-M. J. I. A. Huang, "An AIoT based smart agricultural system for pests detection," vol. 8, pp. 180750-180761, 2020.
[30] A. P. Kale, S. P. J. C. Sonavane, and E. i. Agriculture, "IoT based Smart Farming: Feature subset selection for optimized high-dimensional data using improved GA based approach for ELM," vol. 161, pp. 225-232, 2019.

[31] P. Sumathi, R. Subramanian, V. Karthikeyan, and S. J. I. J. o. C. S. Karthik, "Soil monitoring and evaluation system using EDL-ASQE: Enhanced deep learning model for IoT smart agriculture network," vol. 34, no. 11, p. e4859, 2021.

[32] K. Haseeb, I. Ud Din, A. Almogren, and N. J. S. Islam, "An energy efficient and secure IoT-based WSN framework: An application to smart agriculture," vol. 20, no. 7, p. 2081, 2020.

[33] R. Akhter, S. A. J. J. o. K. S. U.-C. Sofi, and I. Sciences, "Precision agriculture using IoT data analytics and machine learning," 2021.

[34] M. R. Ramli, P. T. Daely, D.-S. Kim, J. M. J. C. Lee, and E. i. Agriculture, "IoT-based adaptive network mechanism for reliable smart farm system," vol. 170, p. 105287, 2020.

[35] H. B. Mahajan, A. Badarla, A. A. J. J. o. A. I. Junnarkar, and H. Computing, "CL-IoT: cross-layer Internet of Things protocol for intelligent manufacturing of smart farming," vol. 12, no. 7, pp. 7777-7791, 2021.

[36] J. Santhosh, P. Balamurugan, G. Arulkumaran, M. Baskar, and R. J. W. P. C. Velumani, "Image Driven Multi Feature Plant Management with FDE Based Smart Agriculture with Improved Security in Wireless Sensor Networks," pp. 1-17, 2021.

[37] M. S. Mekala and P. J. M. Viswanathan, "CLAY-MIST: IoT-cloud enabled CMM index for smart agriculture monitoring system," vol. 134, pp. 236-244, 2019.

[38] N. Penchalaiah, J. Nelson Emmanuel, S. Suraj Kamal, and C. Lakshmi Narayana, "IoT Based Smart Farming Using Thingspeak and MATLAB," in *ICCCE 2020*: Springer, 2021, pp. 1273-1295.

[39] J. Kim, S. Kim, C. Ju, and H. I. J. I. A. Son, "Unmanned aerial vehicles in agriculture: A review of perspective of platform, control, and applications," vol. 7, pp. 105100-105115, 2019.

[40] P. Srikanth and S. P. Shetty, "A Review on RPL for Low Power Lossy Networks," 2020.

[41] H.-S. Kim, J. Paek, D. E. Culler, and S. J. A. T. o. S. N. Bahk, "PC-RPL: Joint control of routing topology and transmission power in real low-power and lossy networks," vol. 16, no. 2, pp. 1-32, 2020.

[42] K. Adhinugraha, W. Rahayu, T. Hara, and D. J. F. G. C. S. Taniar, "On Internet-of-Things (IoT) gateway coverage expansion," vol. 107, pp. 578-587, 2020.

[43] S. K. Mishra, B. Sahoo, P. P. J. J. o. K. S. U.-C. Parida, and I. Sciences, "Load balancing in cloud computing: a big picture," vol. 32, no. 2, pp. 149-158, 2020.

[44] K. Ashokkumar, D. D. Chowdary, and C. D. Sree, "Data analysis and prediction on cloud computing for enhancing productivity in agriculture," in *IOP Conference Series: Materials Science and Engineering*, 2019, vol. 590, no. 1: IOP Publishing, p. 012014.

[45] X. J. M. P. i. E. Niu, "Optimizing DODAG build with RPL protocol," vol. 2021, 2021.

[46] T. Zhang, T. Zhang, X. Ji, and W. Xu, "Cuckoo-RPL: cuckoo filter based RPL for defending AMI network from blackhole attacks," in *2019 Chinese Control Conference (CCC)*, 2019: IEEE, pp. 8920-8925.

[47] M. Jyothisree and S. Sreekanth, "Design and Implementation of RPL in Internet of Things," in *Advances in Decision Sciences, Image Processing, Security and Computer Vision*: Springer, 2020, pp. 707-718.

[48] A. Kertész, T. Pflanzner, and T. J. J. o. G. C. Gyimóthy, "A mobile IoT device simulator for IoT-Fog-Cloud systems," vol. 17, no. 3, pp. 529-551, 2019.

[49] D.-T. Ta, K. Khawam, S. Lahoud, C. Adjih, and S. Martin, "LoRa-MAB: A flexible simulator for decentralized learning resource allocation in IoT networks," in *2019 12th IFIP Wireless and Mobile Networking Conference (WMNC)*, 2019: IEEE, pp. 55-62.

[50] M. Laaouafy, F. Lakrami, O. Labouidya, N. Elkamoun, and R. Iqdour, "Comparative study of localization methods in WSN using Cooja simulator," in *2019 7th Mediterranean Congress of Telecommunications (CMT)*, 2019: IEEE, pp. 1-5.

[51] M. S. Saeed *et al.*, "Power management in smart grid for residential consumers," in *International Conference on P2P, Parallel, Grid, Cloud and Internet Computing*, 2017: Springer, pp. 415-423.