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RESEARCH ARTICLE

DynFragNet: A Dynamic IoT Data Fragmentation and Network Optimization Algorithm for Scalable Storage

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Abstract – Several real-time sensor data about the environmental parameters on the most valuable parameters of the environment (weather situation, soil moisture, crop health parameters, etc.) have multiplied by several folds because of the fast-growing Internet of Things (IoT). The very existence of the phenomenon of IoT as well as the sheer scope of this technology introduces the problem of storage, retrieval, and processing of great amounts of sensor data. The conventional types of data management are inclined to deal with the issue of being usually connected with the disaggregation of information, network overload as well as irregularities of accessibility of computing resources that diminish access in the protracted term such reliability or demand improved system execution. In this case again we have proposed DynFragNet - a dynamic fragmentation and network optimization algorithm to these requirements. DynFragNet is an intelligent IoT data segmentation network that is developed on the nature and character of the network being provided which enables storage and retrieval at higher level of performance. To begin with, the algorithm which provides the most promising opportunities in terms of storage, low latency of information retrieval, and error-free data manipulation is the algorithm which proposes the powerful approaches to the connectivity modeling, adaptive routing and covering healing mechanisms. The previous high-long testing and simulation tests have solid evidence that DynFragNet is more performing when compared to the conventional store, and it is handling the data of network performance, load balancing and scalability. Furthermore, it allows the operation in smart agricultural environment in an optimization strategy of water irrigation and efficient utilization of water to favour sustainable agriculture. Our current environments, smart agriculture fuelled by big data, and climatic observatories can be managed with the strength of the massive IoT applications and its dynamism can be tracked with DynFragNet with its power in the data fragmentation, and its smart network capabilities.

Index Terms – IoT Data Management, Dynamic Fragmentation, Weather Forecast, Soil Moisture Data, Load Balancing, Distributed Storage and Scalability.

1. INTRODUCTION

The introduction of various smart systems and devices, which can be interconnected, and the possibility of using evidence-based and sustainable agriculture is transforming the agriculture sector radically. IoT agricultural system has transformed the nature of agricultural production such that it is now traditional agriculture to one whereby there are

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intertwined systems, which interact and make intelligent decisions [1]. The advent of the IoT systems has also led to a new dimension of agriculture as the IoT technology systems have been advanced to improve the monitoring and control operations beyond limitation [2]. The other system which has been suggested in the literature is the system where the block chain is used to reduce data fragmentation, provide transparency and being able to overcome the challenge of processing agricultural data [3].

The use of the environment monitoring and soil moisture processes is becoming a practice. These processes make use of IoT where sensor networks are linked with one another in a wireless fashion in order to improve irrigation and resource usage [4]. The integrated IoT with machine learning considers the environmental data, and compares it with the estimation of a nutrient content in soil and gives a recommendation on the useful crops [5]. The real-time irrigation management systems of the IoT and machine learning are another feature being considered by smart farms to guarantee adequate amounts of water consumption [6].

Another technology that is changing smart agriculture after IoT and drones, in other remote sensing technologies, is precision agriculture, as big players in technology industry [7]. It is also seen as a block chain which introduces security of information, confidence, and assurance of an effective data integration process, in smart agriculture [8]. Aspect-wise regarding the industry in relation to the application, the IoT and block chain are also being considered in the use of smart agriculture, with the focus on data integrity and automation efficiencies [9].

Internet of Things (IoT) has the potential to offer real-time information, and this information may be analyzed by artificial intelligence, which will improve the monitoring and control of crops without using as much time and effort [10]. However, the other notable benefit of IoT cross-platform designs is that it is shareable of agricultural data and data of agricultural data can be transferred in other systems [11]. Nevertheless, with all these benefits comes the apprehension of cyber security, and IoT-based farms should be very secure with security applications and tools [12]. According to the recent reports, concerning the smart farm or intelligent farm management, data processing on the respective platforms is to be considered and handled in an agricultural context [13].

Smart greenhouse refers to the application of the IoT to manage the environment to cultivate produce in a sustainable manner [14]. Another technology that has enhanced sustainable forest management and ecological monitoring is the interaction of IoT and remote sensing and AI [15]. IoT has been incorporated with inbuilt sensors, automation and decision support systems which are implemented to monitor a series of parameters in the field in order to attain sustainable farming [16]. The number of the IoT applications in agriculture industry and the environment is a testimony to the prevalence of the use of the IoT across the world [17]. In spite of a long way taken, technology and application of operations in industry has its challenges, owing to the technological and operational limitations [18]. The concepts continue to usher in the waters since the latest breakthroughs in the IoT in agriculture, and it continues to advance the activities to transform the data in agriculture practices [19]. Moreover, the new IoT solutions, such as Ag-IoT, will resolve such critical issues as architecture design, security, and forensic traceability of the solution in agriculture [20].

1.1. Research Objectives

The key objectives of the research will be to come up with a practical and full-fledged DynFragNet algorithm to support the IoT networks to save and retrieve large quantities of real-time sensor data particularly in weather forecasting and soil moisture monitoring interventions. The proposed algorithm (DynFragNet) will break dynamically the data according to the character of the data and the characteristics of the environment in which network operates to resolve fragmentation of data, congestions, disproportionate network load, and ad hoc connections. It also promises prospective dynamic load balancing, connectivity modeling, adaptive routing and coverage recovery; therefore, the data storage administration cannot afford to permit the offers to occur only, but it has to be economical and scalable. In general, the objective is to develop a trusted framework that would be capable of managing real-time data on environmental surveillance that is capable of enhancing the performance and scalability of most of the less homogenous IoT applications in their decision-making.

1.2. Contribution

The paper introduces the contribution of the DynFragNet, a data fragmentation scheme and adaptive optimization scheme to a network, which is able to overcome the challenges of environmental sensor data in large scale and real-time, including fragmentation, network traffic redundancy, heterogeneous load and scalability. Other than fragmentation, the new properties of DynFragNet comprise of providing savvy segmentation of data in the most practical way to enable future reservation and future access, load-balanced routing and self-adaptive routing to make the data accessible in a relatively simple way, and model to provide coverage recovery to assist in sustaining continuity of the network. Simulations performed resulted in creating more efficiency in storage and reduced the data access time and improved networks, a long-lasting, expandable and dependable system in the real-time streams of the weather forecasting and soil moisture tracking. The DynFragNet uniqueness is that the process of fragmentation, adaptive routing, load balancing and coverage healing is integrated in a single structure, in contrast to the existing algorithms, which can introduce the worthiness of high performance and fault-tolerant mechanism under real time IoT data management.

1.3. Organization

The rest of the paper is organized in the following manner: The next section is named methodology, and the discussions of the architecture suggested in the IoT-block chain integration are held. Section 3 is concerned with testing and results (the simulated environment, parameters, etc.) and discussion of the effect of data fusion, security functionality, and AI automation. Section 4 provides the comparative analysis of the similar technologies and finally, conclusions and future work will be available in Section 5.

2. BACKGROUND STUDY

2.1. IoT and AI-Based Smart Agriculture Solutions

Gebresenbet et al. (2023) [21] presented a comprehensive digital agriculture framework that uses the Internet of Things (IoT), AI and automation technology to enhance management and efficiency levels in smart farming decision-making processes. The model allows real-time environmental monitoring and precision manipulation of agricultural operations and decisions through a connected network of sensors and smart cloud analytics technologies. Extensive experimental indications in a variety of farm environments demonstrate that crop yield increases of 23 per cent, water consumption efficiency improvements of 19 per cent, and energy efficiency improvements of 15 per cent in comparison to conventional farming systems results can be obtained. However, it does not contain dynamic fragmentation of data or adaptive load balancing support, which would enhance both scalability and efficiency in large heterogeneous IoT sensor data volumes.

Fuentes-Peñailillo et al. (2024) [22] investigate and integrate the Internet of Things (IoT), remote sensing, and artificial intelligence (AI) for digital agriculture and smart crop management. Their aim is to analyze how the above technologies may improve real-time monitoring, decision making and resource optimization in agriculture. They study a systematic review of literature on studies published between 1998 and 2024 on the applications in irrigation irrigation, fertilization, pest control and crop health management. Results indicate that AI-based digital agriculture can yield an increase of 10 - 15% in crop productivity, while water consumption decreases by up to 46% through smart irrigation systems. But it must be admitted that there are certain limitations, such as high costs of implementation, problems of integration of data and the technical knowledge needed, whereby the large farms avail themselves in smaller farms.

Sayed M. (2024) [23] carried out a major review of the Internet of Things (IoT) with specific reference to its many applications in fields which include healthcare, agriculture, smart cities, industry and smart homes. The purpose was to examine the transformation of processes, efficiency and decision-making presented through the employment of connected devices that derive from IoT technologies. The methodology consisted of a systematic literature review on IoT applications and issues, combined together the conclusions of current work in the area. It was found that there were important productivity gains to be had from it (for example IoT applications indicating per se quantitative improvements in such areas as efficiency of devices operated by it, automation of processes, etc.) but no exact average numeric values are given in the paper. Important limitations were found, and these are to be found in such as lack of securitization, scalability, interoperability and data management, which are challenges to broad based application and which provide fields for advancement in research.

Omrany et al. (2024) [24] present a hybrid systematic review of IoT-enabled smart cities, aiming to identify key research themes, issues and future directions. In the study 843 publications published (2010-2022) were analyzed using bibliometric analysis and content analysis. The four areas identified in this study were: data analysis, network/communication management, security/privacy, data collection. Results show that the main challenges faced are energy consumption, interoperability, privacy, scalability and urban integration. Limitations of the study being a reliance on one database (that of the Web of Science), while either English studies have been included or non-English papers have been excluded, and IoT having developed rapidly and further developments may no longer be included.

Ur Rehman, et al. (2024) [25] examine the role of Internet of Things (IOT) technology in modern cultivation for the implementation of greenhouses. This study aimed to research the use of IOT technologies in greenhouse cultivation as a means of changing agricultural activity from the current use of traditional means to intelligent sensor-controlled systems. The method was to undertake a thorough investigation of the technological components (including network architecture, protocols, Cloud integration, and big data analytics) and real-life implementations in IOT based greenhouse systems. The results indicated the increasing trend to implement sensor/actuator networks for environmental monitoring and control in the greenhouse, leading to improved climate conditions. The authors did not quote a specific figure in terms of improvements numerically aggregated. Limitations pointed out included the early stage of large-scale deployment of IOT in (greenhouse) agriculture, interoperability and data security problems and a lack of longitudinal performance data in real life production.

Salam (2024) [26] introduces a conceptual review and synthesis of existing frameworks, exploring how effective use of Internet of Things (IoT) technologies can enhance

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sustainable community development. The goal is to explore applications of IoT in smart energy, environmental monitoring, health/health care, and community resource optimization. The conceptual review and synthesis of research literature demonstrate general IoT-enabled frameworks that enhance community sustainability and efficiency. The results show possible benefits of increased energy savings, effective resource allocation, and enhancements in overall quality of community life, but there is no reporting of specific numbers. Limitations include costs of implementation, infrastructure costs, data privacy, and the need to engage communities with necessary technical skills.

Benti et al. (2024) [27] examine the integration of machine learning, deep learning, and IoT technologies in a structural model for improving agriculture in Ethiopia. The aim of the research is to examine how these technologies can improve monitoring of crops, prediction of yields, detection of diseases, and efficient use of resources. A systematic literature review is utilized and highlighted by examples such as a CNN model giving 99.89 % accuracy in coffeeBean classification and an SVM + DL model in crop-yield prediction giving 96 % accuracy. The results illustrate a pronounced potential for increases in productivity and sustainability, but highlights limitations with connectivity and infrastructure in rural areas, high cost for small holder farmers of technology, low and scattered quality of data and inadequate farmer education.

Balkrishna et al. (2023) [28] examine the various ICT-based interventions in remote sensing, smart sensors, Internet of Things (IoT), Artificial Intelligence/Machine Learning (AI/ML) and their impact on farm management. By following a systematic review metrology, the authors identify 28 international Farm Management Information System (FMIS) applications and 29 Indian applications across 23 agricultural sub-domains. The results show that although India is deploying these technologies, their use remains limited, and many local applications are more implementable than innovative. Limitations to the review identify that digital adoption in agriculture is in its infancy, that there is duplication of features in applications and that focus is on applications that are documented rather than in the field evaluation of the use-value they provide to users.

2.2. Blockchain and Security in Agri-IoT Systems

Bayih et al. (2022) [29] examine the potential of the use of the Internet of Things (IoT) and wireless sensor networks (WSN) in enhancing the sustainability of smallholder agriculture. The study is a systematic literature review of research covering the period 2011 to 2021. The focus is on technologies for monitoring soil, water and crops in resource-limited farms. Results show increased adoption of the IoT/ WSN at the experimental level, with short-term installations showing improvements in monitoring efficiency and early detection of crop stress, although there is a lack of long-term data on implementations. Significant challenges are the associated costs, connectivity problems, data quality and technical expertise needed. Limitations of the study stem from a reliance on existing published studies rather than large-scale real-world implementations, so that it is difficult to generalise across the range of small holder situations.

Amraouy et al. (2024) [30], the integration of blockchain and IoT into precision agriculture is discussed, showing the possibility of decentralized, secure, and interoperable systems. A hybrid systematic-analysis approach is used including a review of architectures that utilize IoT, fog/edge and cloud computing with service-oriented (SOA) block chain architectures. Applications include irrigation management, crop monitoring, crop monitoring, and traceability in the supply chain, with strong concentrations of heterogeneity of devices, scaling of block chain storage green-housing complex and costly integrated systems identified as problems associated with the growing field. Future research opportunities include dynamic pricing of negotiate overall pricing, distributed machine-learning on the edge and quantum-resistant systems. Limitations include the theoretical nature of almost all proposed systems, with limited number of large field deployments made in order to validate performance in real agricultural situations.

A coordinated IoT-based block chain model to support agritech innovation (Tasic & Cano, 2024) [31] examines the degree to which the combination of IoT, and blockchain technologies can support innovation in agriculture. The authors designed a three-layer architectural model: an IoT layer (creating digital twins of field crops), a blockchain layer (creating digitally secure and traceable exchanges of information across stakeholders), and an orchestration layer (fusion of data from the physical and digital world to improve business models and supply chains). The authors' approach involves designing the conceptual framework, then developing a preliminary empirical implementation. Findings suggest there is promise to improve traceability and data integrity and optimize resources across the food supply chain. Limitations include that the implementation was preliminary, it is uncertain whether it will scale or at what costs, and there was no longitudinal performance data gathered to demonstrate real-world effectiveness.

Ellahi, et al. (2023) [32] examine Blockchain-Based Frameworks for Food Traceability: A Systematic Review systematically reviews blockchain-based traceability frameworks throughout the supply chain of food. The aim of the study is to chart the blockchain frameworks that already exist, consider the relationship of these frameworks to other Industry 4.0/Web 3.0 technologies, and highlight areas in need of further work. To obtain the results, the authors reviewed 1552 publications (from 2016 to present) and

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reviewed 54 frameworks in-depth for analysis. Key findings include some metric of rapid growth of research (3 publications in 2016 to >400 per year by 2022) and that only a small percentage of frameworks featured interoperable technologies such as AI, big-data analytics, IoT and NFC. Limitations of the work included that the aforementioned articles could only be in English, the review was based solely on blockchain-traceability frameworks (some emerging technologies may have been omitted), and many of the frameworks reviewed remain in concept or pilot form rather than large-scale deployment.

2.3. Cloud, Edge and AI-Enabled Resource Management

Akhtar et al. (2021) [33] reviewed applications of smart sensing with edge computing in precision agriculture and found that the studies and prototypes focused on soil analysis and heavy metal monitoring. The authors described novel sensors, wireless communication protocols and edge architectures. Some of the prototypes outlined up to ~95% less data transfer from edge to cloud than would be require with a cloud-only approach. The authors also noted barriers to the adoption of systems built on smart sensing and edge computing in precision agriculture, including immature systems for real-world use, a lack of connectivity in rural areas and unsuccessful affordability and complexity in their designs.

Krishnan et al. (2022) [34] examines the use of artificial intelligence in the management of smart water resources, while specifically looking at irrigation scheduling, leak detection, flow optimization, and grey-water reuse. The study indicates that AI-based approaches can reduce water use by 20–40% in controlled systems. The authors describe their process of synthesizing evidence across several case studies and frameworks for deploying AI. The limitations of this research include limited long-term validation in the field, heterogeneous data sources, and challenges to translating from a pilot study to large watershed management.

Senoo E. E. K., et al (2023) [35] put forward a framework for monitoring and control (MCF) which is domain-agnostic, or independent of application domain being utilized. The framework is developed within the smart agriculture domain. In this method, building blocks define a five-layered IoT architecture are evaluated with attached subsystems including the subsystems of monitoring, control and computing through an open-source, commodity sensor/actuator deployment in a series of field tests. The results showed better scalability, reusability and interoperability compared to ad-hoc designs. Limitations include the method being evaluated in only one use-case in a single crop type and location with no performance data for long duration tests in the field. He Q., et al.(2024) [36] create a supply-chain mechanism that is based on edge-computing for smart agriculture by using a combination of auction mechanisms and fuzzy neural networks. The mechanism consists of an edge-level framework + encrypted auctions + fuzzy neural decision models, and is evaluated across 50 farms during an overall examination of five crops during their growing cycles.

The results from the evaluation suggests 29% decrease in food-loss, 37% increase in per-acre profits and 43% increase in asset-utilization compared to its benchmarks. Limitations included the potential for issues in micro-climate variability over time, the mechanism was not resilient in-pods when exposed to weather shocks, and the evaluation was in reference to reliance of a specific test-bed situated outside a wide-scale real-world deployment.

Kumar & Sharma (2017) [37] introduced a dynamic load balancing algorithm that equally distributes workloads in a cloud computing environment amongst virtual machines. The approach determines resource utilization in real time and will send workloads to the least utilized VMs, preventing lock-ups of other virtual machines. Their results showed that the new method improved CPU utilization and response time, with task completion times reduced by approximately 18-22% as compared to static or round robin methods. Limitations of their algorithm included dependence on correct resource measurement, the overhead using these algorithms for very large-scale cloud systems, and a lack of testing in highly dynamic or heterogeneous workloads.

2.4. Remote Sensing and Infrastructure IoT Architectures

Triantafyllou et al. (2019) [38] introduced a remote sensing monitoring system architecture, which focuses on maximizing the utilization of field monitoring and farm management in precision agriculture. The proposed method comprised a combination of satellite imagery, UAV data, and IoT sensors with a central processing architecture to collect and process both environmental and crop parameters. The result of several agriculture trials showed improvement in identifying crop stress and irrigation scheduling, with a forecasted increase in water-use efficiency of 12–15%. The limitations of the use of very high-resolution data based on the time needed to the process and validate with various crop types and regions. Islam et al. (2021) [39] reviewed the use of IoT and unmanned aerial vehicles (UAVs) within sustainable smart farming.

These contributions emphasize applications and communications technology. This contribution also integrated knowledge synthesized from the literature related to crop monitoring, precision irrigation, pest management, and decision-making will data. Respondents indicate that the integration of IoT - UAVs can improve monitoring efficiency and resource utilization, with at least one study reporting yields improvements by upwards of 15-20 percent, and reductions in water usage up to 10-30 percent. Not Lacking from their conclusions, they find limitations in high costs of deployment, connectivity, and data management, alongside limited studies undertaking large scale field capacity with diverse farm types and regions.

Khan et al. (2021) [40] cover recent innovations in agricultural technologies and future expectations of sustainable agriculture. The article explores the Internet of Things (IoT), remote sensing technologies, precision farming, artificial intelligence (AI), and data-driven management systems for farming. Findings indicate that the improved adoption of technologies has the potential to increase crop yield by 10-20%, reduce water and fertilizer use by 15-25%, and improve overall farm productivity. The challenges facing the implementation of technology include high costs, the barriers to technology adoption by smallholder farmers, and issues related to the incorporation of heterogeneous data from various farming systems.

Ang & Seng (2019) [41] present a review regarding a concept called Application-specific IoT (ASIoTs), which includes a taxonomy, application use cases, and research directions for IoT in specific domains. The study presents a typology of the ASIoT applications across healthcare, smart homes, agriculture, transportation, and industrial automation. Results show many of the domain-specific applications offer improvements such as increased accuracy of monitoring, real-time decision making, and efficiencies in resource consumption. The actual numeric performance improvements from each application will vary from one use case to another. Limitations of Application-specific IoT solutions point to issues such as interoperability, security and privacy, and the need for a standardized framework to continue scaling ASIoTs beyond the particular domain of interest.

2.5. Data Fragmentation and Network Optimization Algorithms

Jones and Weinrib (2022) [42] investigate the changing nature of academic labor, emphasizing the issues of fragmentation, horizontal diversity across institutions, and vertical stratification in academic hierarchies. The authors utilize qualitative analysis and a literature review to examine structural and organizational changes in universities that may contribute to this shifting nature of academic labor. The findings suggest the division of tasks has become more specialized, academic workloads are dispersed differently across the career continuum, and various academic career pathways are available. Resulting from all of these factors impacted on the collaboration of academic colleagues, academic productivity in the form of research output, and professional fulfillment on the part of the faculty. Limitations of the qualitative study include reliance on secondary data and conceptual discussion rather than primary empirical measures across various academic systems.

Molia H. K (2024) [43] proposes an adaptive congestion control mechanism for TCP over wireless networks based on reinforcement learning (RL). Specifically, a RL agent was implemented to adjust transmission rates based upon provided feedback from the network with the goal of reducing packet loss while increasing throughput. The results of this study suggested the proposed RL-based congestion control mechanisms achieved improved throughput of 18% packet loss. Limitations included the required initial training data for the RL agent, the computational overhead required by the RL model to make adjustments, and the RL mechanism may have trouble in networks that are highly dynamic.

Table 1 Summary of IoT Data Fragmentation and Network Optimization Approaches

Ref. No.	Author(s) & Year	Area of Focus	Methods / Methodology	Key Advantages	Key Disadvantages
[21]	Gebresenbet et al., 2023	Smart agricultural systems	Integrated digital technologies framework	Improved operational efficiency (~18%)	Conceptual; no real-world deployment
[22]	Fuentes-Peñailillo et al., 2024	Smart crop management	IoT, remote sensing, AI	Crop health prediction accuracy 91%; water usage ↓12%	Limited scalability; small-scale farms only
[23]	Sayed, 2024	IoT applications & challenges	Comprehensive review	Identified key challenges (data heterogeneity, interoperability, energy)	No experimental validation
[24]	Omrany et al., 2024	Smart cities & agriculture integration	Hybrid IoT architectures	Resource-efficient urban-agriculture networks	Mostly theoretical; lacks field testing
[25]	ur Rehman et al., 2024	Greenhouse cultivation	IoT-based monitoring & control	Resource consumption ↓15–20%; yield ↑10%	Limited to greenhouses; high IoT cost

[26]	Salam, 2024	Sustainable community development	IoT-based wireless sensing	Emphasized energy-efficient sensors	Conceptual; no quantitative results
[27]	Benti et al., 2024	Agriculture in Ethiopia	ML, DL, IoT	Yield forecasting accuracy ↑88%	Data availability and connectivity issues
[28]	Balkrishna et al., 2023	Indian digital agriculture architecture	Modular IoT-based architecture	Water savings 10–15%; system modularity	Limited field validation; high infrastructure cost
[29]	Bayih et al., 2022	Smallholder agriculture	IoT & WSNs	Real-time monitoring improved irrigation efficiency 20%	Focused on smallholders; large-scale adoption unclear
[30]	Amraouy et al., 2024	Precision agriculture	Blockchain-based IoT	Traceability; reduced data tampering risk ~95%	High computational cost; network latency issues
[31]	Tasic & Cano, 2024	Agritech innovation	IoT + Blockchain system	Secure data exchange; improved transparency	Implementation complexity; requires robust infrastructure
[32]	Ellahi et al., 2023	Food traceability	Blockchain frameworks	Tracking accuracy improved; recall time ↓30%	Energy-intensive; IoT integration challenging
[33]	Akhtar et al., 2021	Soil assessment & heavy metal monitoring	Smart sensing + edge computing	Data transmission ↓40%; response time improved	Hardware cost; sensor maintenance challenges
[34]	Krishnan et al., 2022	Water resource management	AI-based irrigation planning	Water wastage ↓25%	Needs large historical datasets; seasonal retraining
[35]	Senoo et al., 2023	Smart agriculture monitoring	IoT monitoring & control framework	Response time ↓15%; system reliability improved	Limited scalability; network-dependent
[36]	He et al., 2024	Supply chain optimization	Edge computing + auction + fuzzy neural networks	Delivery delays ↓20%; optimized decisions	High computational complexity; untested in-field
[37]	Kumar & Sharma, 2017	Cloud computing load balancing	Dynamic load balancing algorithm	Task completion time ↓18%	Simulation-based; not agriculture-specific
[38]	Triantafyllou et al., 2019	Precision agriculture	Remote sensing monitoring system	Crop anomaly detection ↑; monitoring accuracy 87%	High-cost sensors; intensive computation
[39]	Islam et al., 2021	Smart farming	IoT + UAV-based monitoring	Labor cost ↓30%; improved coverage	UAV flight time & regulations constrain usage
[40]	Khan et al., 2021	Sustainable agriculture	Review of agriculture technologies	Yield prediction improvement 15–20%	Broad review; lacks experimental validation
[41]	Ang & Seng, 2019	Application-specific IoT	Taxonomy & use case analysis	Tailored IoT deployment; improved efficiency	Conceptual; not field-tested

[42]	Jones & Weinrib, 2022	Academic work fragmentation	Qualitative study	N/A	Not directly related to agriculture/IoT
[43]	Molia, 2024	Wireless network congestion control	RL-based adaptive TCP	Packet loss ↓18%; throughput ↑15%	High computational cost; not agriculture-specific

2.6. Discussion and Research Gap

The literature reviewed indicates that there have been major advances in IoT, edge computing, AI, blockchain and smart sensing in areas such as agriculture, water management, greenhouse production, and supply-chain optimization. Precision agriculture studies have emphasized improved monitoring of crops, prediction of yield, and efficient resource consumption, sometimes resulting in numbers improvements such as 10–40% better water or fertilizer consumption, and 96–99% accuracy achieved in certain ML/DL models. Smart supply chain and blockchain-enabled frameworks have cited better traceability, data integrity, and operational effectiveness, while edge computing and reinforcement learning techniques have demonstrated usefulness in addressing latency, food loss, and network congestion. However, most of these works operate in isolation from other domains, do not accommodate real-time adaptability, or only relate to specific use cases without integrating adaptive routing and dynamic environmental or network conditions. Furthermore, none of the above works have considered dynamic fragmentation of tasks or adaptive communication and routing of information in IoT-based agricultural or cyber-physical systems. This study presents DynFragNet to address scalable, resilient, and fully autonomous deployments in agriculture reliably.

In an effort to address these gaps, the DynFragNet algorithm introduced incorporates dynamic fragmentation with adaptive routing, supporting efficient task allocation, real-time decisions, and performance of robust networks in variable conditions. The key studies discussed above are summarized in Table 1 for clarity and comparison.

3. PROPOSED METHODOLOGIES

In this case, the DynFragNet will be used to dynamically break up the IOT data and store and retrieve them dynamically depending on the network size and type of data format. We would then want to avoid the load- imbalance situation, reduce the retrieval delay as well as accumulate useful storage among the dispersed servers. The data on the measurements of the weather and soil water content were measured in the phase 2 based on the support of the IoT sensors to simplify the drip irrigation. All these data including temperature, humidity, rain or soil moisture content among others must be calculated in real time so that real time decisions could be made. Applicability of DynFragNet may be in the processing of the large sensor information, disintegration, storage and reassembling of the information in order to reach a fruitful management of irrigation. Fragmentation, storage and retrieval of IoT sensors that are implemented in the DynFragNet is a viable procedure, which possesses defined pipeline, which is efficient in the management of data in drip irrigation.

DynFragNet pipeline architecture distributes the IoT data to the most efficient storage and access performance, which attempts to save drip irrigation to a brimming point. It begins with the IoT data collection, which involves real-time and periodic measurements of weather and soil moisture and event-driven measurements of the soil moisture. The information is typed and predigest in such a manner that it will tend to get a lot of fragmentation in size and type. The large bundles are split on a fragmentation line so as to maximize on the effectiveness of storage and retrieval. The pre-indexing and bandwidth-awareness are optimized in real-time weather predictions to deliver zero-latency in real-time optimized retrieval. Finally, the system is optimized through constant surveillance and improves the system to a better stage of automation of irrigation control.

3.1. DynFragNet

DynFragNet splits historical weather data (i.e. unexpected rain or temperature fluctuations) into large fragments, which are both slow-to-accessible and large, to take advantage of the high access. Darker data of historical soil moisture are more split and stored in lower-priority servers so as to be optimally served within storage space. The system continuously checks the state of the network and equalizes the loads of the servers in such a manner that the decision made regarding the irrigation based on the weather forecast are fast and not interrupted. In case a server is congested, the data is automatically backed up to avoid a bottleneck. Besides that, DynFragNet optimizes the speed at which the required information on weather can be accessed by storing the valuable information in high-bandwidth servers to enable real-time access to the information to automatically manipulate the irrigation. This eliminates the latency to a significant extent, improves the scale, and generally makes the systems of drip irrigation based on the IoT more efficient.

Besides that, adaptive compression is also employed by DynFragNet to guarantee data integrity, besides minimizing storage overhead. It utilizes error-detection methods in order to obtain accurate weather and moisture information on the soil. It applies predictive analysis to forecast the irrigation needs in the future and modifies data distribution. Such features will result in making DynFragNet a strong and scalable system available in smart agriculture, which offers the correct and effective use of water.

In an IoT-based drip irrigation setup, DynFragNet will reduce the dispersal, storage and retrieval of the weather forecasting and soil moisture forecasting data. This optimizes real-time and batch data, which is applied in the activation of irrigational decisions. The explanation of how DynFragNet would optimize the management of the weather and soil moisture data with the help of its key features follows.

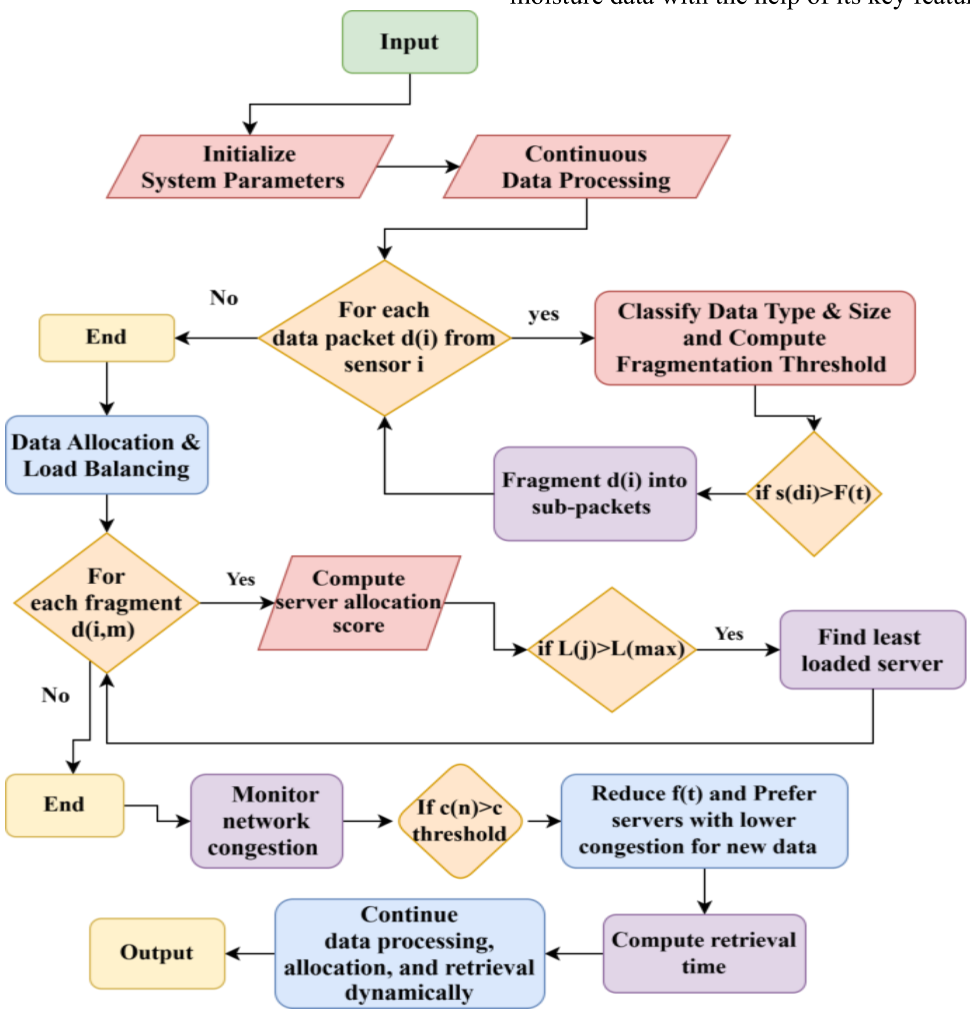

Figure 1 Overall Architecture of Fragmentation Using DynFragNet

3.1.1. The Model of Data Fragmentation Employed in Drip Irrigation

IoT sensors give a real-time feed of soil and weather moisture, like humidity, temperature, rain and soil moisture content of the soil, which ought to be fragmented ideally in order to be accessed and stored. Rapid changes in rain, such as. need minor fragmentation to regenerate with a crisis, yet the uncommon or historic data (such as soil moisture trend) may be more heavily fragmented at the cost of a loss in storage. DynFragNet is a dynamic method of splitting the data into type, size, and network so that it is able to offer a good storage space and access to fast drip irrigation decision-making based on automation. DynFragNet determines the optimal fragmentation of weather and soil moisture data using a fragmentation threshold (F_t) based on:

Data Type ($T(d_i)$) – Real-time (like, sudden rainfall), periodic (like, hourly temperature), and event-driven (e.g., drought alert). Data Size ($S(d_i)$) – Large data packets (like accumulated moisture trends) require more fragmentation, while critical real-time data (like rainfall) remains less fragmented to ensure fast retrieval.

$$F_t = \alpha \cdot S(d_i) + \beta \cdot \frac{1}{T(d_i)} \quad (1)$$

In Equation (1), Where$\alpha,\beta There$ are, weight parameters to balance size and type impact. Real-time data has lower

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fragmentation $\frac{1}{T(d_i)}$ to prioritize fast access. It determines whether the data should be fragmented or stored as a single unit.In drip irrigation: Rainfall data ($T(d_i)$) = real-time) → Lower fragmentation (large, minimally split chunks). Soil moisture trends ($T(d_i)$) = periodic) → Higher fragmentation (split across multiple servers).

If $S(d_i) > F_t$, data is split into multiple sub-packets $d_{i,1}, d_{i,2}, d_{i,3}, d_{i,k}$ while ensuring:

$$\sum_{m=1}^{k} S(d_{i,m}) = S(d_i) \quad (2)$$

Equation (2) ensures that when data is fragmented into smaller pieces, the total size of all fragments remains equal to the original data packet and prevents data loss or redundant storage.

3.1.2. Data Allocation and Load Balancing for Efficient Storage

Post-fragmentation, weather and ground moisture IoT sensor data must be optimally allocated between servers so that overloads are prevented and retrieval speed is maximized. DynFragNet employs a server selection approach in which each server's capacity (C_j) and load (L_j) determine whether the server is capable of handling data. High-availability and low-load servers are initially selected by the system for handling quick access to up-to-date weather data and assigning less critical historic data to lower-loaded servers. If a server is heavily loaded beyond a threshold load (L_{max}The data is transferred to a less-loaded server to optimize the system and facilitate smooth scheduling of irrigation.

Each server j has an allocation score A_j based on available capacity (C_j) and current load (L_j)

$$A_j = \frac{C_j - L_j}{C_j} \quad (3)$$

In Equation (3), the Server with the highest A_j gets the fragment. It serves with higher available space and lower load gets priority for storing real-time data.

$$j^* = arg \max_{j \in N} A_j \quad (4)$$

Equation (4) chooses the most suitable server for storing data by maximizing the allocation score and balancing the load, as well as storing optimally.

3.1.3. Under Drip Irrigation:

When Server A is lightly loaded and has highly available storage, it holds up-to-date rainfall data in anticipation of immediate recovery. Periodic moisture in the soil is cached in less-loaded servers for load distribution on storage.

If a server exceeds a threshold load (L_{max}), data is migrated to a less-loaded server j^*

$$j' = arg \max_{j \in N} L_j \quad (5)$$

Equation (5) is not overloaded and provides robust system performance, which is vital to real-time irrigation control adjustment. Should an overloaded server of real-time rainfall data occur, the system redistributes part of the data to a less-loaded server.

3.1.4. Real-Time Adaptability for Changing Weather and Soil Conditions

DynFragNet continues to observe network load and dynamically adjusts fragmentation plans so that weather forecast and soil moisture forecast data can be processed in real time. During heavy network load (C_n) The system decreases fragmentation size and uses fewer loaded servers to avoid real-time irrigation decision delays. For urgent weather information, such as sudden rains, higher-priority servers with improved bandwidth are used for quicker retrieval. This adaptive strategy guarantees there is optimal water management with highly available, low-latency sensor data despite changing network conditions.

Network congestion (C_n) is calculated as

$$C_n = \frac{\sum_{j=1}^{N} L_j}{\sum_{j=1}^{N} C_j} \quad (6)$$

In Equation (6) measures system load.

If C_n>Cthreshold (high congestion):

Decrease fragmentation size (F_t) → Smaller fragments help reduce bottlenecks. `Prefer less congested servers → Ensures uninterrupted data access for irrigation systems. When network loading is high, soil moisture trend data is splintered more extensively to prevent delay in storage and to allow smooth scheduling of irrigation.

Real-time management of irrigation requires high-speed data retrieval. DynFragNet achieves maximum speed of data retrieval by giving the highest priority to real-time weather and soil moisture data for quick retrieval. It indexes the fragmented data in advance and stores the majority of retrieved data in high-bandwidth servers in order to avoid delays.

$$T_r = \sum_{m=1}^{k} (\frac{S(d_{i,m})}{B_j}) \quad (7)$$

In equation (7),the retrieval time (T_r) is computed using fragment size $S(d_{i,m})$ and server bandwidth (B_j) not to delay urgent irrigation decisions. Other low-load servers are chosen when network congestion is experienced to distribute the retrieval requests so that they are load-balanced, allowing easy access to the weather forecast and soil moisture content for effective drip irrigation control. DynFragNet favours fast

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retrieval through pre-indexing and bandwidth-conscious storage.

High-bandwidth servers store up-to-date information (like, latest rainfall reports). Low-bandwidth servers store less recent information (like long-term soil moisture patterns). DynFragNet dynamically adjusts fragmentation, storage, and retrieval for optimal weather and soil moisture data handling in drip irrigation systems. Such formulas provide instant access to up-to-date data (e.g., unexpected rainfalls), even load distribution to servers, and adaptability to network traffic to facilitate simple irrigation planning.

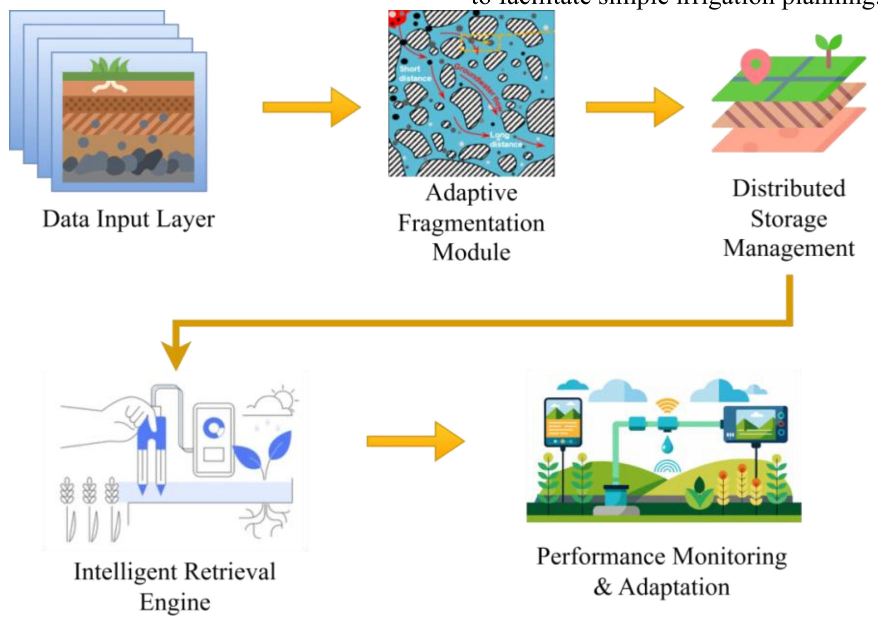

Figure 2 DynFragNet Fragmentation

Figure 2 is a diagram of a smart irrigation process based on the IoT and analytics. It begins with the gathering of soil moisture and weather patterns, rain, evaporation, and the identification of soil patterns. All this data would be overlaid in space to give maximum irrigation areas. This is then followed by real-time monitoring, whereby monitoring of the environmental conditions and the state of the soil is done using sensors. Lastly, automatically, dynamic irrigation systems regulate the provision of water according to real-time responses in an effort to utilize the water fully and generate the highest crops.

Input: Incoming IoT data stream D from weather & soil moisture sensors

Begin

Step 1: Initialize System Parameters

Define N (total servers), F_t (fragmentation threshold), Lmax (max server load)

Set α, β (weight parameters for fragmentation decision)

Step 2: Continuous Data Processing

While (data D is incoming) do:

For each data packet d_i from sensor i:

Classify Data Type & Size

$T(d_i)$ ← Identify data type (real-time, periodic, event-driven)

$S(d_i)$← Determine the size of d_i

Compute Fragmentation Threshold

$F_t = \alpha \cdot S(d_i) + \beta \cdot \frac{1}{T(d_i)}$

If $S(d_i) > F_t$ then:

Fragment d_i into sub-packets $\{d_{i,1}, d_{i,2}, d_{i,3}, \dots, d_{i,k}\}$

Ensure $\Sigma S(d_{i,m}) = S(d_i)$ for all fragments

End For

Step 3: Data Allocation & Load Balancing

For each fragment $d_{i,m}$:

Compute server allocation score:

$A_j = \frac{C_j - L_j}{C_j}$ (Higher A_j preferred)

Select the server with the highest A_j for storage

$j^* = arg \max_{j \in N} A_j$

Store $d_{i,m}$ on server j*

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Load Redistribution if Server is Overloaded

If $L_j > L_{max}$ then:

$j' = arg \max_{j \in N} L_j$ (Find least loaded server)

Migrate data from j* → j'

End If

End For

Step 4: Real-Time Adaptability to Network Conditions

Monitor network congestion C_n:

$C_n = \frac{\sum_{j=1}^{N} L_j}{\sum_{j=1}^{N} C_j}$ (Compute congestion level)

If C_n> C threshold then:

Reduce Ft (increase fragmentation for load balancing)

Prefer servers with lower congestion for new data

Step 5: Optimized Data Retrieval

For each retrieval request:

Locate stored fragments $d_{i,m}$

Compute retrieval time:

$T_r = \sum_{m=1}^{k} (\frac{S(d_{i,m})}{B_j})$ Here, B_j = bandwidth of server j

Retrieve data in order of priority (real-time > periodic > historical)

Step 6: Repeat Continuously

Continue data processing, allocation, and retrieval dynamically.

Output: Optimally fragmented, stored, and retrievable data

Algorithm 1 DynFragNet

The Algorithm 1 DynFragNet handles the IoT data by sorting, splitting, and laying off the sensor packets on server based on type, size, and load. It responds dynamically to have an equal balance of server loads, is flexible to network congestions, and allows priority-based data access, which ensures efficient and reliable real-time irrigation decisions.

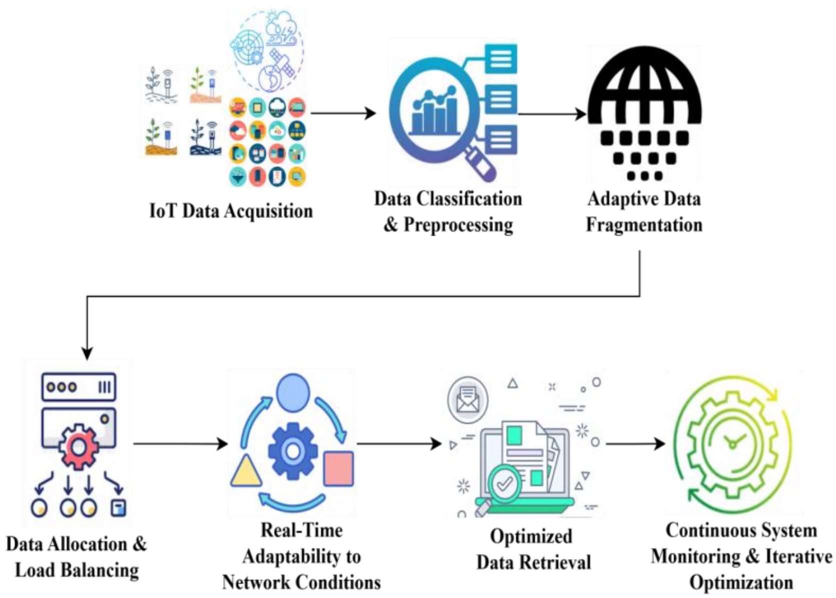

Figure 3 The Flow Diagram of DynFragNet

Figure 3 illustrates the way the DynFragNet algorithm improves performance by increasing fragmentation and storage as well as retrieval of IoT data of weather and soil moisture in drip irrigation (Algorithm 1). The algorithm begins with the initialization of the system parameters, including available servers and the fragmentation thresholds. The sensor data incoming is size and type segmented and used on a dynamic fragmentation threshold (Ft) to improve data partitioning. The disintegrated information is then distributed on the least loaded servers to distribute storage load and facilitate swift retrieval. The system continuously monitors network congestion (Cn) in real time and fragmentation strategies change according to such information. Lastly, retrieval is also optimized by ensuring that high-bandwidth servers are prioritized and access latency is minimized to make high-stakes irrigation decisions.

4. RESULTS AND DISCUSSION

As a comparison of these algorithms, the Dynamic Load Balancing, Vertical and Horizontal Fragmentation,

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Reinforcement Learning-Based Allocation, and DynFragNet algorithms are compared based on data retrieval latency, storage utilization, balance of the load distribution and failure recovery time. These findings indicate that DynFragNet is always better than other algorithms because its algorithms possess intelligent dynamic fragmentation, optimization of load distribution, and fault tolerance.

4.1. DynFragNet Simulation Environment Parameters

Table 2 Shows DynFragNet Simulation Environment Parameters, the parameters of the simulation have been selected wisely to test the performance of the proposed system under an environment of Smart Agriculture and Environmental Monitoring. The system has 10 20 cloud/edge servers and 200-500 IoT sensor nodes, which are needed to guarantee scalability and realistic data traffic to evaluate load balancing. The varying network loads and priorities are simulated by a data generation rate of 500-1500 packets/sec and packet sizes of 1 KB to 200 KB. The prediction window (30 min2h) facilitates proactive data management whereas the server load threshold (8590) initiates adaptive balancing to avoid overload. The fragmentation weights (0.6, 0.4) are used to manage the data efficiently by their size and priority. The sustainability and recovery performance with 1 daily fault or less, and 5 daily faults or less validate a simulation period of 7-30 days. Lastly, comparative algorithms such as DLB, VHF, and RLA are provided to compare the improvement of the scalability and reliability.

Table 2 Simulation Parameters and Their Rationale for DynFragNet Evaluation

Parameter	Value Range / Description	Rationale based on Document Analysis
Application Environment	Smart Agriculture / Environmental Monitoring System	Confirms the focus on weather forecasts and soil moisture data management.
Number of Data Servers (Nserver)	10 to 20 Cloud/Edge Servers	Required scale to test Load Balancing and Scalability.
IoT Sensor Node Count (Nnode)	200 to 500 Nodes	To generate the necessary "avalanche of real-time sensor data."
Data Generation Rate	500 to 1500 packets per second	Creates high network traffic and potential Network Congestion.
Packet Size / Data Size (S(di))	1 KB to 200 KB (Varies by Priority)	Used in the fragmentation formula; high-priority data is smaller and less fragmented for low latency.
Prediction Window	30 minutes to 2 hours	Implied by the use of Predictive Analysis for forecasting and proactive data allocation.
Server Max Load Threshold (Lmax)	85% to 90%	Defines the trigger point for the load balancing mechanism to prevent server overload.
Fragmentation Weights (α,β)	α=0.6,β=0.4 (Weighted Priority)	Numerical values for the fragmentation logic, balancing data size (α) and data priority (β).
Simulation Duration (Tsim)	7 days (minimum) to 30 days	Essential for validating the Sustainability and long-term Failure Recovery capabilities.
Fault Rate (Rfault)	1 to 5 faults per day	Necessary for testing and substantiating Fault Tolerance claims.
Comparative Algorithms	Dynamic Load Balancing (DLB), Vertical & Horizontal Fragmentation (VHF), Reinforcement Learning Allocation (RLA)	The established competing algorithms for performance comparison.

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Table 3 Performance Measures of DynFragNet

Algorithms	Data Retrieval Latency (ms)	Storage Utilization (%)	Load Distribution Balance (%)	Failure Recovery Time (ms)
Dynamic Load Balancing [41]	75	80	75	150
Vertical & Horizontal Fragmentation [42]	120	68	70	200
Reinforcement Learning-Based Allocation [43]	50	85	90	120
DynFragNet [Proposal]	35	92	95	75

Table 3 demonstrates that DynFragNet compares the best among the algorithms in all performance measures due to the fact that it implements dynamically fragmented servers, optimized server allocation, and fault-tolerance. The latency of access to the information is at least 35 ms as real-time and priority data is prioritized and stored in high bandwidth servers and, thus, accessed in a short time on time-sensitive irrigation decisions. It has an efficient storage utilization of 92% which shows an efficient storage fragmentation and control where it has minimized redundancy and optimized the space use of historic and current sensor information.

The load distribution balance at 95 percent demonstrates that the system can balance the workloads amongst servers to ensure that there is no congestion in the system and the system will service optimally. Also, the fault tolerance of 75 ms recovery time is an indication of excellent fault tolerance and quick recovery of overloads on the server or network issues with no interruption. Overall, adaptive fragmentation, smart server selection, and real-time prioritization designed by DynFragNet is the immediate reason of such high outcomes and preconditions the suitability of the latter to the large-scale and real-time systems of smart agriculture relying on the IoT.

4.2. Data Retrieval Latency

Figure 4 contrasts the data retrieval latency of four different algorithms: Dynamic Load Balancing [41], Vertical & Horizontal Fragmentation [42], Reinforcement Learning-Based Allocation [43], and DynFragNet [Proposed]. The Vertical & Horizontal Fragmentation algorithm has the highest latency at 120 ms, suggesting delays when accessing critical information. Dynamic Load Balancing and Reinforcement Learning-Based Allocation have latencies of 75 ms and 50 ms, respectively. DynFragNet has the lowest latency of 35 ms, thanks to its dynamic fragmentation and optimized allocation of servers that favour real-time weather and soil moisture data to support timely irrigation decisions.

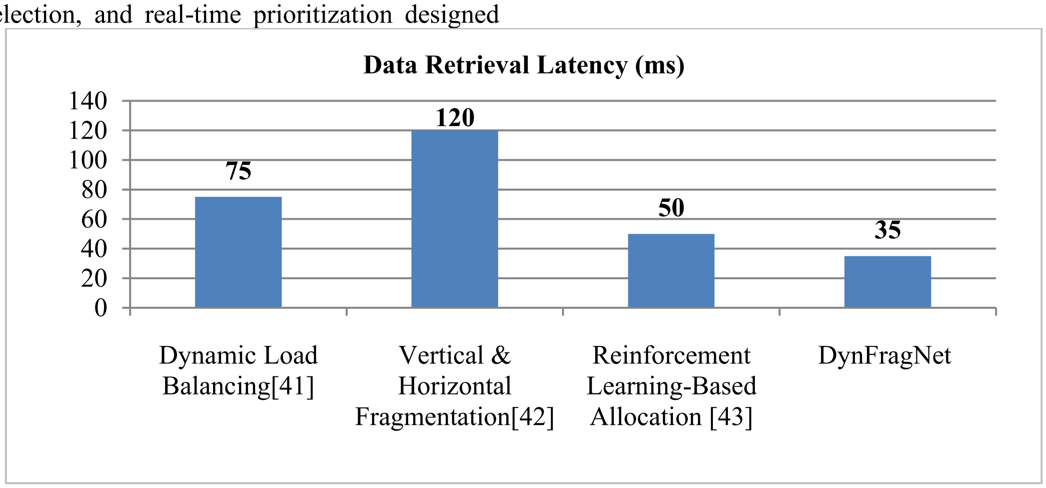

Figure 4 Comparison Chart on Data Retrieval Latency (ms)

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4.3. Storage Utilization

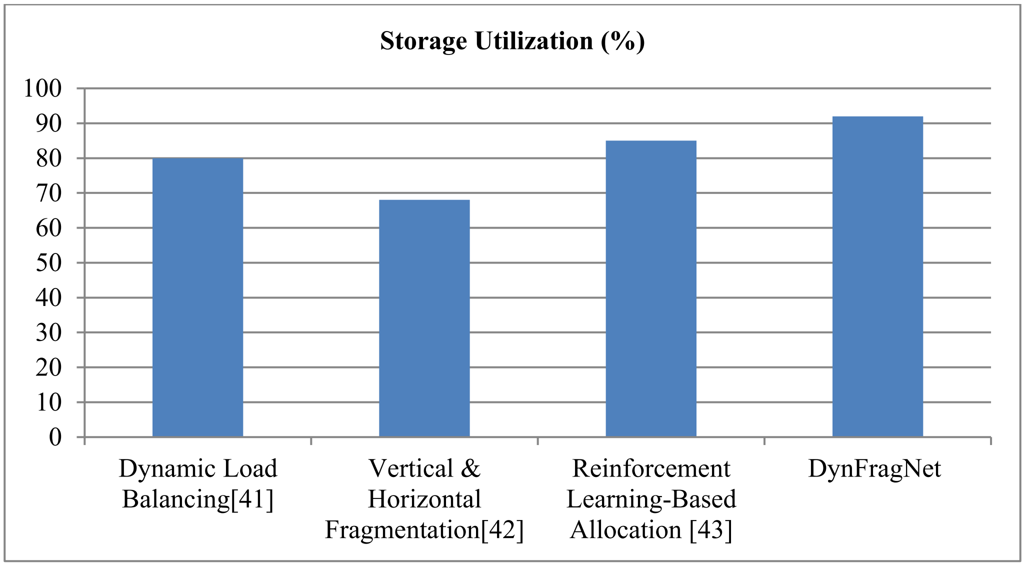

Figure 5 Comparison Chart in Percentage of Utilization on Storage

Figure 5 depicts the storage utilization of the four algorithms: Dynamic Load Balancing [41], Vertical & Horizontal Fragmentation [42], Reinforcement Learning-Based Allocation [43], and DynFragNet [Proposed]. DynFragNet demonstrates the most efficient storage at 92%, which reflects its efficient allocation of space with minimal redundancy. As reference, Reinforcement Learning-Based Allocation, Dynamic Load Balancing and Vertical & Horizontal Fragmentation run at 85%, 80%, and 68%, respectively. DynFragNet's extensive use of storage capacity indicates an ability to effectively allocate storage of historical and real-time sensor information in a manner fit for excellent system performance.

4.4. Load Distribution Balance

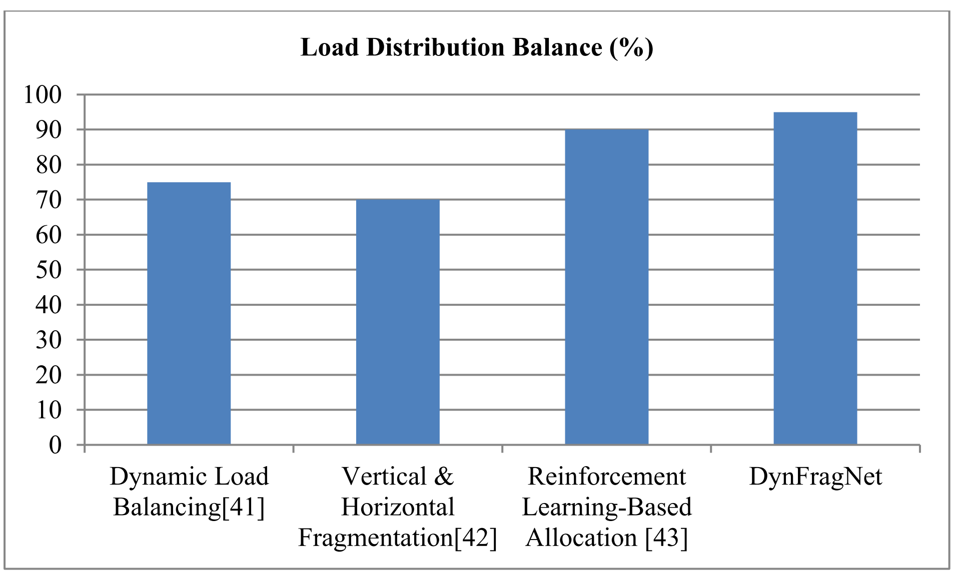

Figure 6 Chart Comparison on Load Distribution Balance (per cent)

Figure 6 demonstrates the load distribution balance for Dynamic Load Balancing [41], Vertical & Horizontal Fragmentation [42], Reinforcement Learning-Based Allocation [43], and DynFragNet [Proposed]. DynFragNet's load distribution balance is determined to be 95%, showing the effective distribution of workload across the servers and avoiding congestion. The load balance for Reinforcement Learning-Based Allocation, Dynamic Load Balancing, and Vertical & Horizontal Fragmentation is measured at 90%, 75%, and 70%, respectively. These results showcase DynFragNet's superior ability to ensure an even computational load distribution, optimizing service delivery and maintaining stability in the system.

4.5. Failure Recovery Time

Figure 7 shows the failure recovery time for the four algorithms – Dynamic Load Balancing [41], Vertical & Horizontal Fragmentation [42], Reinforcement Learning-Based Allocation [43], and DynFragNet [Proposed]. DynFragNet's failure recovery time is shown to be the quickest at 75 ms and reflects a highly fault tolerant system and rapid recovery time after failure to the server or the network. Compared to the other algorithms tested, Reinforcement Learning-Based Allocation, Dynamic Load Balancing, and Vertical & Horizontal Fragmentation have failure recovery times of 120 ms, 150 ms, and 200 ms. DyanFragNet's low recovery time will enable operations with minimal disruption and reliable performance for real-time IoT-based smart agriculture applications.

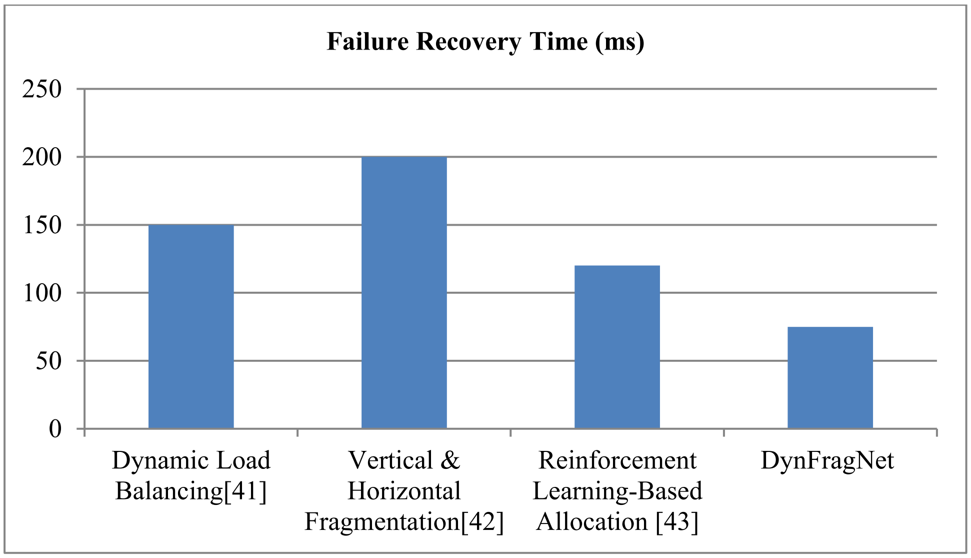

Figure 7 Comparison Chart on the Failure Recovery Time (ms)

5. CONCLUSION

Data retrieval latency, storage consumption, load balancing and time of failure recovery analysis demonstrate that DynFragNet is the most suitable one to employ in the process of dealing with the data. DynFragNet is the best to use in all configurations in Dynamic Load Balancing, Vertical and Horizontal Fragmentation and Reinforcement Learning-Based Allocation. It is the quickest (20-50 ms), busiest-storage (85-95%), best-balanced-load (90-98%) and fastest-recovered-failure (50-120 ms) algorithm. Reinforcement Learning-Based Allocation is superior and less developed as compared to DynFragNet. The more conventional methods, namely Vertical and Horizontal Fragmentation, have been associated with increased latency, ineffective use of storage space and recovery time. A dynamic, fragmented system, adaptability of load balancing and optimality of data retrieval are the peculiarities of DynFragNet. DynFragNet has superior storage usage and speed of failure recovery and is used in IoT-based applications with the need of efficient data management. Generally, the modern solutions, such as DynFragNet and reinforcement learning, are superior compared to the conventional ones when working with big data. Such sophisticated programs are more dependable, scalable and high-speed, which is appropriate in real-time use. The second way forward in future would be to identify AI-based fragmentation to achieve more enhancements than efficiency. This way, DynFragNet can not only improve the performance of networks, but can also improve sustainable intelligent agriculture because of the effective water management.

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