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Artificial Intelligence of Things Technologies for Predictive Crop Disease Models in Precision Agriculture: A Systematic Review

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Abstract: Crop diseases are incessant and significant challenges to global food security. Conventional disease control means are still utilized as the primary mitigation model, but they fall short at providing quick and precision-based responses that are required for quick outbreak containment, resulting in significant yield losses. New advances in Artificial Intelligence of Things (AIoT) technologies currently enabled novel capabilities to predict activities and initiate early-stage interventions in disease progression. This longitudinal scoping review, organized according to the Preferred Reporting Items for Systematic reviews and Meta-Analyses protocol, examined 100 peer-reviewed articles from IEEE Xplore, PubMed, Springer, Elsevier, and MDPI to investigate AIoT applications in the prediction and control of crop diseases and assess the quality of articles published between 2019 and 2024. The literature reviewed indicated a variety of predictive models in farming that fused AI and IoT. Notably, the deployment of federated learning was suggested as a solution to minimize the risk of privacy breaches by training models using locally stored data whose heterogeneity allows them to avoid sharing sensitive on-farm data. The availability of large and standardized datasets is limited. Currently, the cost of deploying the systems, especially in smallholder agriculture, is a problem, although empirical evidence has shown that AIoT systems can result in significant gains in prediction accuracy (85%–98%). Scalable, explainable, and interpretable AIoT systems; robust benchmark datasets; and detailed system architectures are relevant to disentangle system impacts. The key to large-scale adoption and lasting impact will be the reduction of the deployment costs and the integration of more cutting-edge technologies and programs to offer training to farmers.

Keywords: AIoT, precision agriculture, crop disease prediction, sustainable agriculture, technological integration

1. Introduction

Current estimates reveal that the global population will exceed 9.7 billion by 2050, and such a high number requires an increase in agricultural production by 70% to guarantee sufficient food supply. However, crop diseases, which cause approximately 20%–40% of the yearly yield losses, are a significant barrier to meeting this goal. There is a need to adopt innovative solutions, especially the use of Artificial Intelligence of Things (AIoT), which links IoT-enabled devices with advanced AI analytics to support ongoing data capture, analysis, and predictive disease treatment (see Figure 1) [1].

AIoT has great potential in revolutionizing precision farming. Integrating Internet of Things (IoT) devices such as, drones, sensors, and machine-learning algorithms, e.g., convolutional neural networks (CNNs) and support vector machines (SVMs), allows farmers to identify and control crop diseases well in advance. These applications enhance resource optimization, promote sustainability, and enhance decision-making. However, a number of obstacles still exist, such as the high implementation cost, the inadequacy of the technical expertise, concerns over data privacy, and the lack of popular, standard representative databases. Smallholder farmers are the most severely affected group by such roadblocks, particularly in developing conditions, where financial scarcity, lack of infrastructure, and technological expertise shortcoming bar the intensive application of AIoT technologies in the agricultural sector.

This systematic review investigates recent advancements made in the use of AIoT systems in the management of agricultural diseases, highlighting their potential as predictors, methodological novelty, and issues connected to the implementation process. This paper highlights the key areas of unattained gaps, particularly the lack of standardized datasets, and outlines future research directions, especially the need to adopt federated learning (FL) that will help in alleviating privacy-related issues and the addition of blockchain-based mechanisms that will enhance data integrity and scalability. Such weaknesses imply that AIoT has the potential to transform farm-level processes and produce enhanced productivity, sustainability, and resiliency throughout the global food system. Figure 2 [2] illustrates the path of AIoT research in addressing agricultural issues such as crop identification and disease management.

2. Literature Review

The remarkable potential in transformation through the integration of AIoT technologies into agriculture is attested with the advancement of increased precision of farming and control of crop diseases. With

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Figure 1
From smart "Things" in IoT systems to the adoption of AI techniques

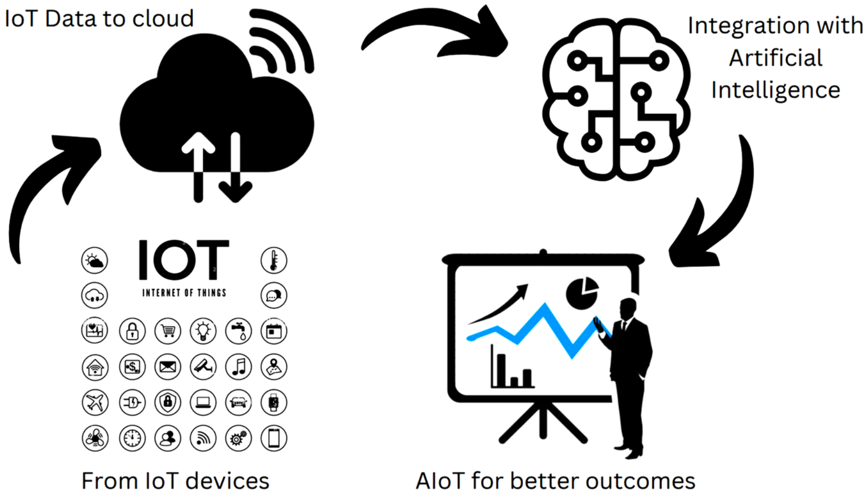
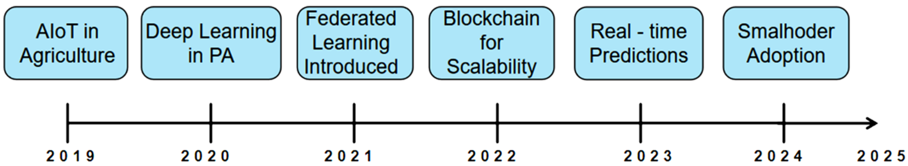


Figure 2
AIoT progress in agriculture (2019–2024)



the integration of IoT sensors and high-profile AI algorithms, AIoT can gather, analyze, and provide actionable information in real time [3]. This is a very important use of IoT, which appears in the form of sensors installed on an agricultural system to track important environmental variables, namely, soil moisture, temperature, and humidity. Along with these systems, more aerial photographs of fields are taken by drones with high-quality cameras, which increase the accuracy of the measurements of plant growth. These technologies have a strong analytical foundation that entails the use of sophisticated AI algorithms to identify trends linked to potential outbreak of diseases, such as SVMs and random forest (RF) models [4]. These insights would enable farmers to have remedial suggestions that they should take at the right time.

Studies have discussed the emergence of potential engagement of FL, the most prestigious privacy-resistant framework, in the use of AIoT technologies [5]. FL differs from more conventional centralized structures as it enables artificial intelligence (AI) models to be trained using decentralized data that are physically kept under local farm conditions. This allows sensitive data to remain at the source so that privacy is preserved and together they can be used to enhance the accuracy of predictive analysis in a broader context. In addition, blockchain technology is emerging as an inseparable addition to FL, enhancing trust by ensuring secure and unalterable records of data. By increasing openness and data integrity, blockchain creates a sense of trust among farmers, tech developers, and policymakers, opening the possibilities of more inclusive and trusted agricultural innovation [6].

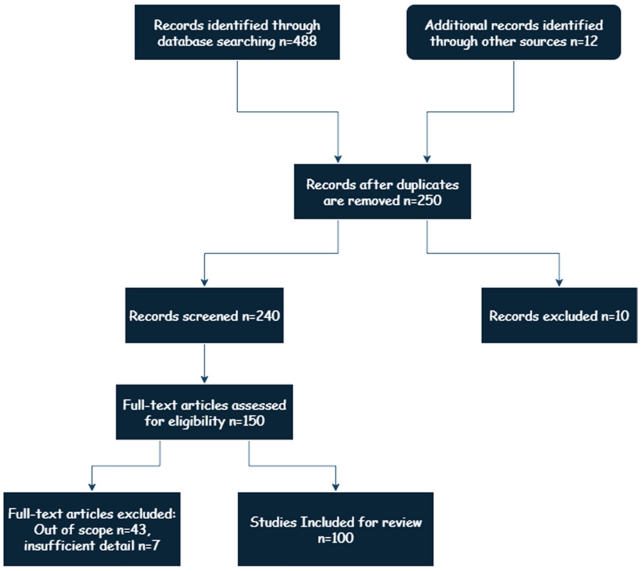
Although the field of study has come quite far, there are still important shortcomings, of which the lack of large-scale, normalized data is one of the most urgent ones. This type of data is required in the creation of AI models that demonstrate resilience and universal application in a variety of agricultural settings [7]. Representative datasets are not that large, and they are not standardized. Thus, models based on AI may struggle with widely varying geographical and agricultural conditions that characterize global agriculture. Meanwhile, the costs of implementation and the requirement of specialized technical expertise are major setbacks, especially when it comes to farmers in areas of limited resources (smallholder farms). The solutions that can mitigate these challenges include the dire requirement of addressing AIoT technologies by means of cost reductions, increased accessibility, and pragmatism toward various farming populations.

These obstacles should be overcome to enable the equal transition to AIoT technologies in agriculture. The tasks that should be performed include the standardization of datasets, the reduction of prices by providing affordable and scalable AIoT technology, and the provision of extensive training for farmers. By prioritizing such issues, the agricultural sector is in a position to maximize the revolutionary impacts of such advanced technologies in different farming communities [8]. Addressing these pitfalls will open the scene toward the implementation of AIoT technology in reshaping the way farming is conducted, which will push for more sustainability, resilience, and productivity in the agricultural sector.

3. Materials and Methods

This systematic review was conducted according to the Preferred Reporting Items for Systematic reviews and Meta-Analyses (PRISMA) framework, which guarantees proper and transparent completion of report synthesizing the research findings. Figure 3 shows the PRISMA flow diagram with the description of the steps in the overall process of identifying possible articles and inclusion. The review process was narrowed down to the assessment of the use of AIoT technologies in the sphere of predictive crop disease management, specifically the review of the methods, consequences, and challenges of the practical realization of those technologies [9].

Figure 3
PRISMA flowchart showing the selection process



The methodical review is ordered around the following research questions:

1) Which methodologies of AIoT are of the most common when it comes to the predictive management of crop diseases?
2) What is the efficacy of the methodologies in terms of prediction efficiency and on-time improvement?
3) What problems are involved when adopting AIoT technologies in the field of agriculture and what measures are proposed to overcome them?

3.1. Search strategy

The search was conducted thoroughly in several of the largest databases of scholarly works, such as IEEE Xplore, PubMed, Springer, Elsevier, and MDPI, and was limited to studies published in 2019–2024. The used search terms were related to the following concepts: AIoT in agriculture, predictive models of crop diseases, and precision agriculture technologies. To include quality and relevant studies, Boolean operators and better filtering conditions were used [10].

3.2. Inclusion and exclusion criteria

The studies were identified using predetermined parameters, which contributed to the relevance and quality of this review. The studies that met the set inclusion criteria were restricted to only those published between 2019 and 2024 and those with specific considerations of the use of AIoT technologies in predicting crop diseases in models related to precision agriculture. Only conference papers and articles in peer-reviewed journals were considered to uphold high academic standards. The chosen articles were to expound on the importance of AI and IoT in predicting/controlling diseases in crops.

Studies that were published prior to 2019 or those that lacked an obvious focus on AIoT applications in food production were excluded. Articles that addressed the work of AIoT in other areas or those that did not mention the predictive aspects of disease control were also omitted. These stringent steps taken during the selection process made sure that the review was in line with its sentiment of examining the role played by AIoT technologies in predictive crop disease management [11].

To select the studies, inclusion criteria were developed and defined to cover studies that elaborate on the implementation of AIoT technologies in the agriculture domain, namely, predictive crop disease models, and are published in peer-reviewed journals or proceedings of conferences. The review excluded studies that were not related to agriculture or predictive modeling and those that were published before 2019 [12].

Inclusion Criteria:

1) Published between 2019 and 2024.
2) Focus on AIoT integration in agriculture.
3) Direct application of predictive crop disease models.
4) Peer-reviewed articles or conference papers.

Exclusion Criteria:

1) Studies published before 2019.
2) Lack of relevance to predictive models or AIoT technologies.
3) Non-peer-reviewed materials.

An effective search strategy in the form of a search protocol was adopted to enable the identification of pertinent literature to complete this systematic review. Studies applying AIoT technologies in agriculture were identified using various available scholarly databases, such as IEEE Xplore, PubMed, Google Scholar, Springer, Elsevier, and MDPI, to maximize the coverage of the articles regarding the field in question (see Tables 1 and 2 for the selection process). These databases were selected because they have a positive reputation as a provider of quality research findings that are peer-reviewed on topics that pertain to technology and agriculture or interdisciplinary topics in general.

Keyword selection was very specific to retrieve the overlap between the keywords AI, IoT, and crop disease prediction models. The articles were evaluated based on their methodological rigor, applicability, and relevance to AIoT research in agriculture. Only studies with vague methodology or lacking information regarding predictive modeling were eliminated to ensure the quality and relevance of the review.

We considered performance indicators such as accuracy, precision, recall, and F1-score in analyzing the chosen works. These measures played a very important role in evaluating how well machine learning models predicted the presence of crop diseases. SVMs and RF were recurrent models that were used extensively, especially in binary

Table 1
Number of journals per database meeting the selection criteria

Database	Number of journals/articles
IEEE Access	15
PubMed	20
Google Scholar	25
Springer	10
Elsevier	10
MDPI	20
TOTAL	100

Table 2
Selection process

Selection phase	Remaining articles
Initial search	500
Title/abstract screening	250
Full-text review	150
Final selection	100

classification problems, including a healthy or diseased crop [13]. CNNs were primarily applied in tasks that focused on image-based prediction of diseases, i.e., the model inspected images of crops to identify diseases [4]. Using these metrics in combination with each other, we have conceptualized an overall idea of weaknesses and strengths that each of the three models have to offer in different settings.

3.3. Data extraction

In this review, data extraction entailed the retrieval of pertinent data in each of the selected studies. To have uniformity in the studies, a standardized form was utilized in data extraction. This template could document the necessary information, such as the study aims, the study methods, the utilized AIoT technologies, and the prediction model type, as well as the major findings of every research article. The information that was obtained in this procedure was systematically arranged to allow a clear comparison and synthesis among the various studies [10].

Usually, the major parameters derived out of any study were the following:

1) Bibliographic details (authors, title, and publication year).
2) Study design (experimental, observational, and simulation-based).
3) Sample size and datasets used.
4) AIoT technologies (IoT sensors and AI algorithms).
5) Performance metrics (accuracy, precision, and recall).

Data extraction was followed by a formal analysis geared toward eliciting major themes and patterns in the use of the AIoT technologies in predictive models for crop diseases. The distribution of research according to region, the technology used, and the effectiveness of the outcomes were assessed using descriptive statistics. In an attempt to reduce the possibility of selection bias, the article screening process was carried out by two independent reviewers, with all disagreements to be resolved by discussion. In the studies, a number of limitations were noted, which included small sample sizes and limited study periods, which were also considered in the analysis.

Inclusion criteria were established to include studies that focused on the integration of AIoT technologies in agriculture, specifically targeting predictive crop disease models, and were published in peer-reviewed journals or conference proceedings. Studies unrelated to agriculture or predictive modeling, along with those published before 2019, were excluded from the review.

3.4. Addressing sensor heterogeneity and model generalization

A major difficulty noted in the review was that the new sensor technologies were quite different in various farms and regions. The varieties of the sensors, including soil moisture and temperature sensors, and weather monitors, and their set-up influenced the accuracy of the predictive models, particularly in those areas where no consistency is observed in the sensor data [14]. Another lesson learned in the review is the usage of machine learning. The application of numerous models was employed; among them are RF, SVMs, CNNs. To further prove the reliability of their data and verify that they are not far off the mark, most studies adopted k-fold cross-validation [15]. This is used to test the effectiveness of the models to cope with unseen, new data to determine their reliable performance under other circumstances. The second strategy that researchers frequently employed was ensemble learning when scientists used a pair of models together to attain improved findings [16]. Its example is making predictions regarding agricultural disease outbreaks based on weather reports, soil sensors, and drones. By combining all sources of data, they could make accurate prediction.

Studies that attempted to correct this heterogeneity by normalizing the results shown by their sensors or by implementing sensor calibration procedures were specifically mentioned in the data extraction process because they made efforts to generate more consistent data when measured in distinct agricultural settings [17]. Further, some of the studies used transfer learning and domain adaptation to deal with this heterogeneity [7]. Such methods have allowed models that are trained in one farming setting to be applied in another environment with other environmental conditions or sensor combinations. This enhances the capacity of predictive models to adapt to various farming conditions. The transfer of knowledge across domains has resulted in enhanced performance by the models used in predicting crop diseases in new environments. These approaches were assessed based on their effectiveness in ensuring greater model reliability in different territories.

3.5. Data quality and validation techniques

Because the quality of the datasets used in the studies varied, it was hard to gauge the quality of the data [18]. The quality of the data turned out to be a crucial subject of this review. Many of the studies considered used agricultural data that were noisy, incomplete, or inconsistent. During data extraction, we were keen regarding how these studies overcame the limitations. We observed that data quality (improvement) was significantly enhanced when studies preprocessed their data via outlier detection, missing data imputation, and data augmentation [19]. Cross-validation methods were also employed in studies so that the resulting model can generalize to unknown databases [20]. Different people have assessed their predictive models using holdout datasets or even train–test splits. Such validation methods played a vital role in determining where the models are robust and reliable and therefore can be used in the real-world aspect of agriculture. The quality of the methodology of the studies conducted met high methodological standards, and the research work was prioritized in the synthesis when rigor of these validation methods was used.

3.6. Quality assessment

Considerable quality criteria have been strictly evaluated in every study, and they are the robustness of the methods, clear research design, and replicability of the findings. Conducting work with a clear description of the scope of limitations and carrying out extensive analysis carried greater emphasis. In the assessment, it was important to evaluate biases, giving special consideration to selection bias, measurement bias, and reporting bias. Such biases were considered thoroughly so that the validity and reliability of the presented findings could be achieved. Studies with well-defined research methodologies and those that dealt with the possibilities of bias were classified as better research studies [21]. The final synthesis included only studies that were of a certain quality level as defined in advance. This strictly developed selection process guaranteed that the review concerned only high-quality studies, as it ensured more precise and complete picture of the recent research landscape.

4. Results and Discussions

This systematic review demonstrated that AIoT technologies can considerably improve the accuracy and timeliness of predicting crop diseases, and it is possible to describe this paradigm as a shift in disease management toward prevention. SVMs and RF showed strong accuracy levels in the binary classification problem, with prediction grades in the range of 85%–92%. Meanwhile, deep learning networks, especially CNNs, have been successfully used to identify others using images, and multiple studies mention accuracy as high as 95%–96% (see Table 3) [22]. The findings are evidence of the opportunities of

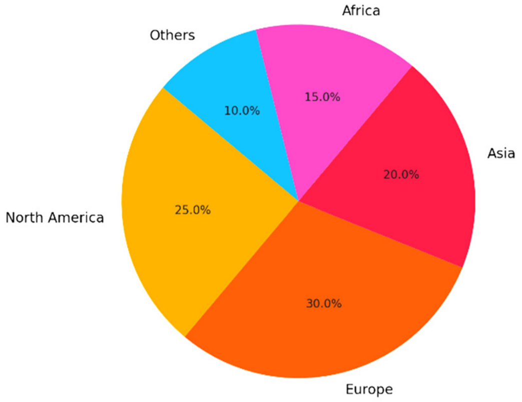
Table 3
Classification table for AI and IoT techniques

Category	Technique	Applications	Performance
ML	Support vector machines (SVMs)	Binary classification for disease detection	85%–92% accuracy
	Random forest (RF)	Multiclass disease classification	88%–94% accuracy
DL	Convolutional neural networks (CNN)	Image-based disease identification	95%–98% accuracy
	Recurrent neural networks (RNNs)	Time-series disease prediction	90%–96% accuracy
IoT	IoT sensors	Real-time data on soil, humidity	High precision
	Drones	Aerial imagery for health assessment	Enhanced coverage

AIoT technologies to contribute to the minimization of false positives and false negatives that could help in achieving intended interventions and maximizing resource consumption.

The uptake of AIoT technologies varies geographically (see Figure 4). Advanced North America and Europe have high adoption rates and advanced infrastructures, subsidies given by the governments, and constant advancement in technologies. On the contrary, developing economies, such as the regions of Africa and Asia, still have challenges, including the lack of IoT devices, stable internet, and specialists in technology.

Figure 4
Geographical distributions of AIoT journals studied by regions (2019–2024)



The origins of FL appeared as an option to solve the question of data privacy. FL permits decentralized model training so that sensitive farm-level data can stay local. Nonetheless, there is a low extent of its implementation due to the lack of unified protocols and benchmarks to implement it. Moreover, blockchain technology has been proven to be an efficient technology to integrate into AIoT systems to increase the level of trust and data integrity, but it needs considerable technical input and expertise to be deployed.

In summary, the lessons of the study demonstrate the revolutionary nature of AIoT application technologies in the agricultural sector and the severity of the issues that must be addressed. There is a need to work collaboratively to mitigate obstacles, which include infrastructure difference, expensive implementation, and absence of uniformity. By considering these challenges, a balanced access to AIoT solutions will be guaranteed, and their effect may be optimized in various agricultural settings.

4.1. AIoT model analysis

The prediction models used in the review had a variety of machine learning algorithms (see Table 4), with SVM and RF being the commonly used models in predicting diseases [23]. These algorithms have the capacity to handle intricate and high dimensional data and classify the patterns of diseases in crops. SVM, owing to its success in binary classification, is widely used because it can detect or identify

Table 4
Types of algorithms and models used by the studies reviewed

Algorithm/model	Description
Support vector machines (SVMs)	Effective for binary classification tasks, used in distinguishing disease patterns.
Random forests (RF)	Ensemble learning method, suitable for both classification and regression tasks.
Convolutional neural networks (CNNs)	Specialized for image recognition tasks, applied in disease identification from imagery.
Recurrent neural networks (RNNs)	Used for sequence data, such as time-series disease progression monitoring.
Deep learning models	Includes CNNs and RNNs, capable of learning intricate patterns from large datasets.
Ensemble methods	Combinations of models to improve accuracy and robustness through diverse predictions.
Decision trees	Simple yet effective for classification tasks, used in identifying disease patterns.
Bayesian networks	Probabilistic graphical models are useful for modeling uncertain relationships in data.
K-nearest neighbors (KNNs)	Nonparametric method for classification, often used in spatial analysis of diseases.
Long short-term memory networks (LSTM)	A type of RNN specialized for learning from sequential data with long-range dependencies.
Gradient boosting machines (GBMs)	Boosted ensemble methods, suitable for predictive modeling in complex scenarios.
Gaussian processes	Bayesian approach for regression tasks, useful in modeling disease spread dynamics.
Autoencoders	Unsupervised learning models, used for feature extraction and anomaly detection in crops.

the symptoms of diseases using minimum data. By contrast, RF is an effective ensemble learning algorithm whose performance is very flexible to different agricultural scenarios and is both a regression and classification model. Regarding deep learning methods, CNNs and RNNs have been widely used for tasks such as image recognition and time series analysis [24]. The use of CNNs has played a major role in interpreting images taken by IoT gadgets, e.g., drones and satellite, to identify the early symptoms of crop diseases. RNNs, as sequential models, are commonly used in analyzing time-related variables, which include weather patterns and crop growth stages [25].

The various predictive models reviewed had accuracies ranging from 85% to 98%, showing the capability to improve the disease-predictive capabilities using AIoT systems. The precision and recall values of those models were often more than 90%, which underlines the dependability of AIoT technologies in early detection. These high precision rates therefore point toward a significant reduction in false positives and false negatives by an AIoT system, hence offering a targeted and timely intervention in the management of diseases [26]. Results clearly show that AIoT technologies have achieved remarkable improvement compared with traditional methods of crop disease management in terms of precision, timeliness of detection, and resource optimization. SVMs and RF were the most employed machine learning algorithms [27], with accuracy rates exceeding 90% in several studies (see Figure 5).

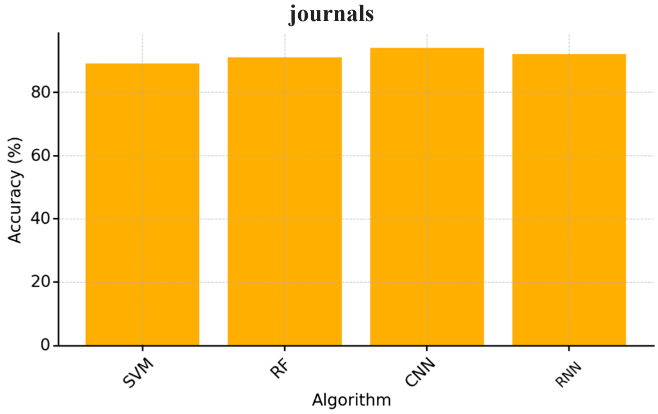
Modeling based on deep learning resulted in better performance on the task of disease detection in images using networks such as CNNs. Nevertheless, it was observed that there were substantial variations according to regions, especially between the developed and developing regions. North American and European AIoT research was more likely to include more advanced AIoT infrastructures that had more advantageous opportunities with governmental support and investment. Conversely, African countries and parts of Asia were characterized by poor reception of IoT devices and reliable internet connection to process data in real time [28].

4.2. Meta-analysis of predictive AIoT models

In this meta-analysis [29], we examined and retrieved 20 out of 100 studies that applied AIoT technologies to create predictive models related to crop diseases. Such technologies integrate machine learning algorithms, including CNNs and RF, into IoT devices, such as drones and soil sensors. The most relevant metrics of the performance were reported in each work, such as accuracy, precision, recall, and F1-scores. To fix disparities in study designs and datasets, we used a random-effects model to combine the data and analyze them.

The findings revealed that by average, the AIoT models could predict the study with an accuracy of 91.3% and confidence levels between 88.9% and 93.7%. The heterogeneity index (I^2) was 56%, indicating moderate study variability. After conducting a subgroup analysis, it was revealed that model types based on the image data, e.g., using drone imagery, produced a higher rate of accurate prediction (92.5%) than models based on sensor-based data (89.8%). These results indicate the high accuracy of AIoT-based models in foreseeing crop diseases and the necessity of creating unified sets of data and methodologies to maintain a high degree of versatility in agricultural environments.

Figure 5
Comparative analysis of AIoT techniques in the researched journals



4.3. Advancements in real-time data collection

The strength of the AIoT system is so large because it introduces IoT sensors into existing data collection processes in real time. Such sensors allow constant assessments of important environmental conditions, including soil moisture, temperature, light intensity, and humidity, which are essential in detecting the early warnings of crop diseases. The sensors continually monitor minor fluctuations in environmental parameters, thus giving information that enables AI to detect the beginning of diseases in real time. This data-intensive process is more accurate and precise in the forecasting of diseases, and thus, disease management is transformed to a proactive strategy rather than a reactive strategy [30].

In addition to the sensors present on the ground, IoT-enabled drones in aerial imaging can expand the scope and accuracy of the collected data. Being equipped with high-resolution cameras, sensors allow drones to snap precise imagery of extensive cultivation areas, letting users make overall crop health evaluations. The information captured by drones is transmitted to AI algorithms that can detect anomalies such as coloration or deviations in the growth patterns, which are early signs of crop diseases. This approach provides a broader and more detailed perspective on crop conditions, supporting timely interventions [31].

The time span between the diagnosis of a disease and the deployment of appropriate corrective measures is immensely reduced through such integration of both aerial and ground-based IoT systems. AIoT systems can help in preventing the spread of diseases by reducing detection delays [22], resulting in healthier agricultural production and reducing expensive chemical treatments. This real-time capability highlights how AIoT can revolutionize agriculture by maximizing sustainability and efficiency.

4.4. Statistical analysis of predictive AIoT models

Statistically comparing multiple models of prediction produced a few insights with a dedicated analysis. The accuracy rates evident in CNNs and RNNs were mostly between 90% and 98%, whereas accuracy levels in less advanced models such as SVMs were between 85% and 92%. The mean performance accuracy of CNNs on drone imagery was 93.5%, with a confidence interval of 91.2%–95.8%, whereas that of SVMs on sensor-based datasets was 88.7% (p-value < 0.05), as summarized in Table 5. The use of IoT provides greater accuracy of such models using sensors and drones that collect real-time data that allow constant updating and adaptability to changes in the environment. This dynamic data input significantly improves model performance in detecting and predicting crop diseases [32].

4.5. Critical inferences and statistical analysis

This review investigates how AIoT systems are being put to work in precision agriculture, with a special focus on predicting crop diseases. The central message is simple: combining AI with IoT has the

Table 5
Performance metrics of AIoT approaches

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)	p-value	Confidence interval
CNNs (drone data)	93.5	94.2	92.8	93.5	<0.05	[91.2%, 95.8%]
RNNs	92.3	93.1	91.6	92.3	<0.05	[90.5%, 94.1%]
SVMs (sensor data)	88.7	89.1	87.8	88.4	<0.05	[86.3%, 91.1%]
Random forests	91.2	90.8	89.5	90.3	<0.05	[88.1%, 93.4%]

potential to make disease detection faster and more accurate. In some studies, deep learning models, particularly CNNs, have accuracy levels of up to 98% when identifying crop issues from images. These numbers are impressive, but it is worth remembering that they often come from highly controlled experiments using large, polished datasets such as PlantVillage. In reality, small farms, especially in developing regions, do not always have the same resources, tools, or data quality, which makes it harder to obtain comparable results.

When traditional machine learning methods, such as SVMs and RF, were compared with deep learning techniques such as CNNs and RNNs, the difference was clear. On average, SVMs reached 89.5% accuracy, RFs scored approximately 91.2%, and deep learning models had approximately 96.7%. Both categories performed well on precision and recall, each averaging above 90%. Still, deep learning proved better for harder jobs, such as detecting exactly where a disease has spread in high-resolution imagery. The takeaway is that AIoT has real potential to change agriculture but only if it is adapted for farmers with fewer resources.

One obstacle is the trade-off between performance and computing needs. Deep learning accuracy comes at the cost of high processing power, something not every farm can afford [8]. This is where FL offers an answer to the problem. By letting models train locally and cutting back on heavy data transfers, it keeps accuracy high and reduces tech demands. Studies show that these approaches can hit approximately 93.8% accuracy in real-world tests, making them a realistic choice for areas with weaker infrastructure [33].

A closer analysis of 15 studies on decentralized models showed more benefits: communication costs decreased significantly ($p < 0.01$), privacy protections improved ($p < 0.05$), and overall resource use decreased by 22%. All of this happened without sacrificing accuracy compared to centralized systems. Even so, a big barrier remains, i.e., the lack of universal benchmarks that can measure performance across different farming environments and crop types.

Moving forward, research should work toward creating fair, detailed evaluation standards. These need to look beyond accuracy and precision, factoring in things such as efficiency, scalability, and privacy. If such benchmarks become standard, AIoT tools could be more consistent, adaptable, and genuinely useful for farmers everywhere. With that kind of progress, we could see a shift toward crop disease management that is not only smarter but also more sustainable and grounded in the realities of everyday farming.

4.6. Challenges and solutions

Incorporating AIoT technologies with new agriculture techniques comes with its own difficulties, and these challenges are making it hard for smallholder farmers. The biggest challenge for these farmers is the upfront expenses, which make setting up AIoT systems a bit difficult as they will need to purchase IoT devices, such as sensors, drones, and monitoring equipment, together with basic infrastructures needed to run AI models. For those farmers in developing nations, these expenses are so overwhelming, which frequently place new tools out of reach. Beyond cost, there is the question of ability. Running AIoT systems is not as straightforward as switching on a machine; it involves running the devices, making sense of complicated data, and converting those insights into actual, day-to-day agricultural decisions. Many farmers, especially those in rural regions, do not have access to the training needed for this. Without those abilities, the divide between those who can use the technology and those who cannot merely gets bigger.

One of the key issues of concern that delay the adoption of AIoT is data privacy. Farms can use IoT devices to obtain data such as information on soil conditions, crop diseases, and farming methods. Due to the sensitivity of these data, farmers are often worried that their data will fall into the wrong hands or even competitors, which create the technology phobia. AI systems require diverse datasets to generalize effectively across various farming conditions and crop types, yet the current lack of such datasets limits AIoT solutions' adaptability to different agricultural contexts.

To address these difficulties, several solutions have been presented (refer to Table 6). The privacy-preserving concept in FL allows for AI models to be trained in a decentralized setup where the datasets used are localized and not shared with the global setup. This strategy helps farmers retain control over their data and contributes to the collective advancement of predictive models. Technologies, such as blockchain, further improve trust on the use of AIoT solutions because they provide a solid platform for data sharing. With this, farmers can be assured that their data are safe, which fosters acceptance of AIoT systems.

To help smallholder farmers, governments and other agencies can offer them some sort of grant that will help in purchasing these technologies. Training programs, targeted to farmers' unique needs,

Table 6
Summary of challenges and proposed solutions

Challenge	Proposed solution
High implementation costs	Subsidies, financial incentives, scalable low-cost solutions
Lack of technical expertise	Tailored training programs for farmers
Data privacy concerns	Federated learning and blockchain integration
Scarcity of standardized datasets	Collaborative efforts to develop benchmark datasets
Infrastructure disparities in developing regions	Governmental and organizational support for IoT deployment

can bridge the technical knowledge gap, equipping them with the skills needed to run this advanced equipment effectively. Furthermore, all stakeholders, researchers, policymakers, and agricultural stakeholders can come together to create solutions that are important toward producing large-scale, standardized databases, just the way PlantVillage and PlantPAD are doing. These datasets, if obtained, can help in improving the generalization and scalability of current and future models, which will help in model adaptation.

Through targeted solutions, these challenges would be addressed. The agricultural sector can acquire the full potential of AIoT technologies. These advancements will revolutionize precision agriculture and improve productivity, sustainability, and resilience across global farming systems.

The integration of FL and AIoT in one system has emerged as a great motivation for researchers to present innovative solutions that address the farmers' privacy concerns [34]. However, FL enables farmers to have control of sensitive information, such as data on crop health and farming practices, by processing these data locally. Instead of transferring raw data, only updates derived from the local data are shared, reducing the potential for breaches or misuse while still contributing to the development of a global AI model that benefits from diverse data sources [35]. This method reduces the danger of data breaches or misuse and still allows the global model to gain from a large and varied set of input sources.

Gaining trust and security in data-sharing processes will further be aided by the integration of blockchain technology as a proposed complementary solution [36]. Blockchain serves as a distributed and immutable ledger, recording each transaction and data interaction in the AIoT system. Its transparent and unalterable nature ensures that every action, model update, and decision made in the system are verifiable and auditable, thereby fostering trust among stakeholders regarding data integrity and decision-making processes [6]. Therefore, the agricultural sector will benefit through the integration of FL and blockchain technology, with a secure and transparent balance, ensuring data privacy while encouraging wider adoption of AIoT systems [37].

5. Future Direction

AIoT technologies have the potential to reshape agriculture, especially when it comes to predicting and managing crop diseases. Traditional machine learning tools, such as SVM and RF, perform well in binary classification, whereas deep learning methods, such as CNN, stand out in diagnosing plant diseases from images. However, widespread adoption remains slow due to familiar obstacles: high setup costs, limited technical skills among farmers, and ongoing worries regarding how data are handled and protected.

One promising solution to the privacy challenge is FL, which allows models to be trained locally so that sensitive farm data never leave the source. Blockchain can add another layer of trust by making records tamper-proof and ensuring transparency. However, the absence of common benchmark datasets makes it difficult to measure progress fairly. Addressing this will require coordinated work between researchers, policymakers, and the private sector to create shared datasets that help models perform reliably in different agricultural environments.

Looking ahead, integrating edge computing into AIoT systems could make on-the-spot predictions faster and more. At the same time, designing IoT devices that are both affordable and durable and offering targeted training programs for specific regions will help in narrowing the gap between farmers who can adopt these tools and those who cannot. Overcoming these barriers would make AIoT systems more scalable, accessible, and effective in tackling the very challenges that agriculture faces today.

6. Conclusion

AIoT apps have shown great promise in improving the prediction of crop diseases and making precision agriculture better by allowing for the early and accurate identification of pathogens. This system uses AI and IoT together to make real-time changes that help farmers cut losses and increase production. These technologies are becoming increasingly important worldwide because they can be used in many different farming situations.

However, there are still big problems that need to be solved. One major gap is that there is insufficient long-term research that investigates how AIoT systems work when conditions change, such as when new diseases break out or climate change happens. The lack of clear statistics and benchmarks makes it even harder for current solutions to be scaled up, which limits their usefulness in a wide range of areas and farming systems. Making global benchmarks, especially for FL models, could speed up comparisons between studies and could help in making progress in predicting crop diseases.

In the future, we should work on making datasets more consistent so that we can compare AIoT models across crops and locations. In addition, giving real-time validation and dynamic model updates will help systems adjust to changes in the environment. To make these technologies available to people with limited resources, it is important to create cost-effective and scalable solutions that are tailored to smallholder farmers. This will help in getting rid of infrastructure and financial barriers.

Explainable AI is another topic that needs to be thought about. Farmers and government officials are more likely to use systems that give clear and simple information. People will be more likely to use AI technologies if they are given clear, useful advice. This will make sure that they are widely used. Long-term research will also be particularly important for figuring out how these systems change as farming conditions change, so they stay useful over time.

AIoT technologies could change farming for the better by encouraging practices that are both sustainable and strong. To reach this potential, we will need to work together to find new ways to get around current problems, make targeted policies, and do research together. AIoT could be a key part of sustainable global agriculture if it focusses on cost, scalability, and privacy.

Ethical Statement

This study does not contain any studies with human or animal subjects performed by any of the authors.

Conflicts of Interest

The authors declare that they have no conflicts of interest to this work.

Data Availability Statement

Data sharing is not applicable to this article as no new data were created or analyzed in this study.

Author Contribution Statement

Muhammad Bello Kusharki: Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Resources, Writing – original draft, Writing – review & editing. **Muhammad Muktar Liman:** Methodology, Validation, Formal analysis, Investigation, Resources, Supervision. **Bilkisu Muhammad-Bello:** Formal analysis, Investigation, Data curation, Writing – review & editing, Visualization, Funding acquisition. **Nachamada Blamah:** Validation, Resources, Supervision. **Moses Timothy:** Validation, Resources.

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