A Systematic Review of Current Trends in Artificial Intelligence for Smart Farming to Enhance Crop Yield

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***Abstract*—Current technology has been widely applied for development, one of which has an Artificial Intelligence (AI) applied to Smart Farming. AI can give special capabilities to be programmed as needed. In cooperation with agricultural systems, AI is part of improving the quality of agriculture. This technology is no stranger to being applied in basic fields such as agriculture. This smart technology is needed to increase crop yields for various regions by utilizing the current trends paper. This is necessary because less land is available for agriculture, and there is a greater need for food sources. Therefore, this systematic review aims to collect the current trends in AI studies for Smart Farming papers using the latest year features from 2018-2022. This paper is handy for researchers and industry in looking for the latest papers on research to enhance crop yields. The authors utilized Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) of 534 articles from IEEE, ACM, MDPI, IAES, and ScienceDirect. After going through a careful process, 67 papers were found that were judged according to the criteria. After the authors got some of the current trends, the author has discussed several factors regarding the results obtained to enhance crop yields, such as Weather, Soil, Irrigation, Unmanned Aerial Vehicle (UAV), Pest Control, Weed Control, and Disease Control.**

Keywords*— *Artificial Intelligence (AI); Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA); Smart Farming.

I. Introduction

It is no longer strange if the world population can reach 9.1 billion. It is conceivable that the need for food must have increased by 70 percent, and the culture of moving people from rural to urban areas is also a topic of discussion. As the population increases, one can imagine if the land used for agriculture will experience a very drastic decline in the years to come. The most important reasons for reduced food production are improper planning, inappropriate harvesting, unpredictable weather conditions, irrigation techniques, and other matters such as livestock not being maintained [1].

But this can be helped by the development of technology. This progress will greatly impact if a common thread is drawn. Still, it cannot be equated altogether because small farmers and companies are left behind if they do not carry out digital transformation. As a new era of the Internet of Things (IoT) emerges, several companies have seen how to stay ahead of the curve by leveraging open source applications, low-cost sensors, and, more generally, scale-up farmers and small businesses. One area also discussed is Artificial Intelligence (AI), where an algorithm learns independently and contributes to developing new insights [2].

IoT or Internet of Things [3]–[6] also has many research applications because it can use in almost every technology. The current technology in intelligent systems called Smart Farming usually utilizes the IoT. It also offers software and hardware technology solutions to increase agricultural yields. Its implementation in agricultural land has changed over the past decade, starting from using holes and scissors to cultivate fields and machines to harvest crops. Therefore, Smart Farming was introduced because this technique promises efficiency in which farmers take advantage of IoT to be applied to all farming methods and implementation methods [7].

Smart Farming [8]–[11] is widely used in agriculture because it is very helpful. In intelligent surveys, each planted area had various criteria and could be measured from both quantity and quality. Some critical Criteria for Smart Farming, such as nutrients [12], soil [13], pests [14], irrigation [15] etc., determine the ability and suitability of certain types of crops. In most situations, different criteria usually exist in one crop field, let alone for the same crop growing on all available land for agriculture; because it requires a specific analysis of the location needed to map the production of plant products effectively and efficiently [16].

AI or Artificial Intelligence [17]–[21] is the one that is often used both academically and educationally. AI can also be called something that is imitation based on the human mind intelligence. It is implanted in machines to be designed so that machines can think like humans. It is expected to be able to do whatever living things do, so AI can be likened to learning to solve problems. Machine Learning (ML) and Deep Learning (DL) are part of the AI where ML is above DL. But it has the same family under AI. This study becomes the main focus of their research. AI techniques can be applied in this field and combined with IoT and Smart Farming. These techniques can be used to capture detailed and very complex data, after which AI can provide good answers and suggestions for the problems being carried out. Existing AI techniques include Fuzzy Logic and Expert System networks [22].

ML or Machine Learning [23]–[26], has been widely used to help facilitate and solve problems. Other things can also take advantage of DL or Deep Learning [27]–[30] in solving and facilitating important issues. Because ML and DL are part of AI, the author focuses on using them to solve systematic review problems that the author will display.

Several examples of Smart Farming systems work on a combination of software and hardware to work optimally. Hardware [31]–[34] is one of the components that often exist in IoT. Hardware has grown a lot because of support from IoT components. It can be carried anywhere, low power with connections utilizing a wireless network to make connections between massive devices in large numbers. But don't forget to use the Graphics Processing Unit (GPU) to be assisted by AI. To collect AI, data can use sensors to get input from the environment. This is mostly done with the use of IoT. Many input can use for Big Data technology assists this software, which supports collecting large amounts of data. The IoT module can collect this information as input from various data processed by sophisticated AI-based software. As a result, AI can provide new decisions for farmers. AI works very effectively and efficiently in analyzing the current trends [35].

Therefore, a need for Smart Farming, IoT, and AI arise. Farmers often monitor and understand crops, which should be done for fieldwork. Therefore, agriculture is always related to equipment and uses that utilize AI. This technology can be used from sowing seeds to harvesting. This also helps in timely harvest reports to minimize operational costs. Given that each country focuses on its agricultural industry, we are waiting for optimal solutions on technology with the hope of sustainable agriculture that does not cause environmental impacts. The latest communication and sensing technologies provide capabilities for on-the-ground monitoring that are helpful for land pickers and farmers. The wireless sensors do an excellent job of real-time crop monitoring with features like giving high accuracy, moreover most usefully, doing early detection of conditions on farmland [16].

Applying these methods is not easy. Industry players, researchers, and the government put new hopes into increasing agricultural production with this technology, but this is not easy if you don't know the current trends in AI for Smart Farming and how to enhance crop yield. Therefore, it is necessary to have a systematic review and look at current trends to see AI and other AI methods that can help in Smart Farming systems. Various ways have been done in agriculture, such as monitoring, measuring, processing to doing good marketing. Many studies have reviewed Smart Farming. Terence and Purushothaman [36] focus on Smart Farming techniques and categorize agricultural techniques in IoT-based agricultural control and monitoring systems, plant diseases, and automatic irrigation systems.

Study [37] has taken several into account: plant classification, disease detection, precision breeding, land cover identification, object recognition of pests, weed detection, phenotype, and smart irrigation. Other studies [35], [38] focus on research in agriculture by conducting systematic reviews on future trends, challenges, etc.

The authors aim to conduct a systematic review and current trends using some of the AI previous studies suitable for Smart Farming to enhance crop yield. Researchers proposed using Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) [39]. The difference with previous studies is that the authors only concentrate on using PRISMA. The other aims of this study include the publisher of the current trends paper focusing on AI for Smart Farming to enhance crop yields, the country's current trends paper focuses on AI for Smart Farming to enhance crop yields.

The contributions of this review are; to make a systematic review of AI for Smart Farming to enhance Crop Yield, look for methods/platforms for AI for Smart Farming to enhance Crop yields, and conduct discussions on the results that can be applied to a specific scope.

Finally, after understanding the background of the Study in part 1, several sections will be made to organize this study systematically. Part 2 explains the methodology that will be used in Smart Farming. Next step 3, the author explains the details of the results of the systematic review search. In Section 4, the researcher will discuss some of the methods used. Finally, the very last Part 5 is the conclusion.

II. Methodology

Many of the best scientific works are being developed or have existed in recent years. The number of studies makes the article. Many authors must analyze from different perspectives to determine what models are suitable. For example, many uses of Smart Farming focus show the fundamental openings and challenges of utilizing this innovation. This work aims to analyze Smart Farming using PRISMA by systematically reviewing Smart Farming. Then, several steps were made to help this systematic review, where there are 3 phases used. Fig. 1 will display the Methodology Flowchart (inspired by a previous study [40]).

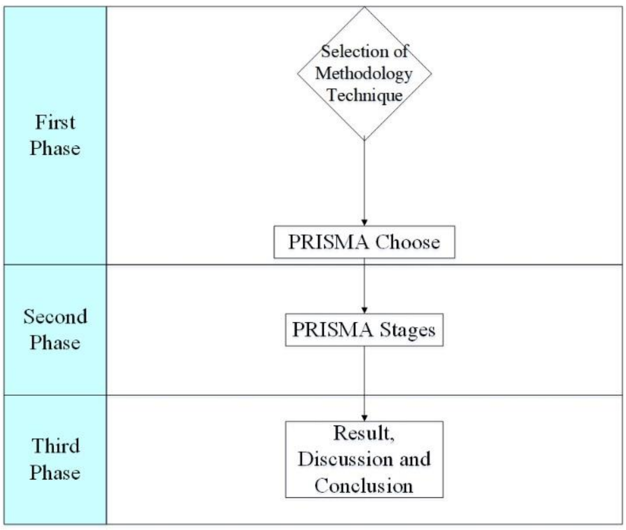

Fig. 1. Methodology Flowchart.

After seeing the display in Fig. 1, the author will elaborate on the criteria, strategies, and assessments that will be used (Inspired by a previous study [40]).

A. Research Strategy

The author makes a strategy. In 2021, research was conducted on a website focused on Smart Farming. The author must be more careful in determining this database, considering its scope and relevance. The databases used are several journals and conferences, such as ACM, IEEE, MDPI, ScienceDirect, and IAES. In 2022, a modern look was carried out within the same database.

At this time, it is done by searching for details of terms, such as ("Artificial Intelligence" OR "AI") and ("Smart Farming Model" OR "Smart Agriculture Model") and ("Smart Farming Enhance Production" OR "Smart Agriculture Enhance Production") and ("Smart Agriculture" OR "Smart Farming") and ("Precision Farming" OR "Precision Agriculture") related to ("IoT" OR "Internet of Things) and ("Agriculture System" OR "Farming System") and ("Deep Learning") and ("Machine Learning") and some related research AI that can enhance the quality of Smart Farming.

The previously mentioned keyword phrases fit have been explained, so based on the search algorithm from the database, the Study needs to have Main keywords that are derived and match the scope of the Study. In this Study, the search does not focus on one type of agriculture but on heterogeneous agriculture.

On the other hand, the author has limited publications, including review articles, conference papers (considered), and research articles. Hence the scope. Furthermore, the publications that are used only focus on using English.

B. Selection Criteria

Searching for several papers from 2018 – 2022, a selection of papers was also carried out, focusing on discussing Smart Farming. It does not mean that other things are ignored. But the impact must show the benefits of Smart Farming and not discuss other points. Several stages were carried out on selecting criteria such as Identification, Screening, Eligibility, and Included. Essential steps that must be taken, such as the focus, must be in the form of paper, for some manuscripts such as editorials, book chapters, and technical and online blogs cannot be included.

C. Quality Assessment

Information obtained from four databases resulted in 534 research papers. After that, identification is made to see several factors. In this Study, identification excluded 207 papers and left 327 papers at screening. After that, it entered the next stage, and there were 155 exceptions, 172 papers were left in the eligibility phase, and the final results were analyzed for 67 papers and excluded 105 papers. Thus, 67 papers have been the center of discussion in this Study.

After doing the steps, the author will focus on classifying existing papers. So that in the next section, the results of the review selection will be discussed.

III. Result

From the results of the methodology in the previous section, in this section, the author will describe the results used to carry out a PRISMA [39] (and inspired by previous pattern Study [38]) concept used, as shown in Fig. 2.

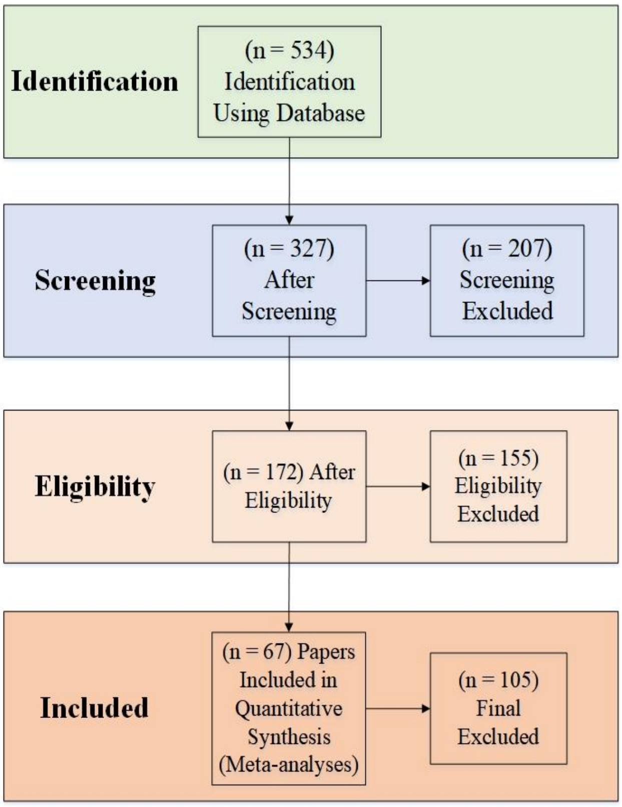

Fig. 2. PRISMA flowchart.

Fig. 2. shows the stages and results of the author's preparation for this systematic review. The author looks for research papers on the internet that are by the research objectives, namely the AI study of current trends in Smart Farming to enhance crop yields. The author will look for what is contained in Smart Farming, focusing on increasing crop yields in several methods, technologies, and algorithms for the current trends.

The author also makes several tables of results from the review based on publishers, making it easier for other researchers to find credible sources. These results are shown in Table I.

TABLE I. PAPERS BY PUBLISHER

Database	Result
IEEE	26
MDPI	15
ScienceDirect	10
ACM	8
IAES	8

Table I shows that most of the papers used in this review are 26 IEEE and 15 MDPI, indicating that these two publishers widely use AI for Smart Farming to enhance crop yields. Then the author makes some results that show the demographics of the database results in Table II.

In Table II, this systematic review shows that many countries that Study (focus on the first author) AI for Smart Farming come from Asia, especially India with 18 articles and China with 13 papers.

TABLE II. PAPERS BY COUNTRY

Country	Result
India	18
China	13
USA	5
Morocco	5
Bangladesh	3
Malaysia	2
South Korea	2
Philippines	2
France	2
Turkey	2
Pakistan	2
Portugal	2
Croatia	1
Greece	1
Finland	1
Vietnam	1
Iran	1
Serbia	1
Mexico	1
Canada	1
South Afrika	1

Next, the author will do a mapping based on the quality of the good paper based on the publisher. This is done by several review papers so that the quality of the review paper is in Table III.

TABLE III. PAPERS BASED ON CRITERIA

Database	Result
Journal	36
Conference	31

In Table III, the authors can see the comparison results from journals and conferences. Many use conference papers as references in this systematic review compared to journals. This shows the current trends for enhancing crop yields are mostly described using conferences.

After that, the author will present the results according to the year the paper was published, which became a reference in preparing this systematic review paper, as shown in Table IV.

TABLE IV. PAPERS BASED ON PUBLICATION YEAR

Publication Year	Result
2018	7
2019	10
2020	13
2021	24
2022	13

Table IV shows publications by year and systematic review of research papers published in 2020, 2021, and 2022. Therefore, research is starting in 2020, 2021, and 2022.

Furthermore, after knowing the criteria of the review paper, the author presents the discussion in the next section. The discussion contains the author's views on current trends and how Smart Farming works and functions in enhancing Crop Yield.

IV. DISCUSSION

This section will discuss what AI applications can drive Smart Farming that will affect crop yields in the current trend paper (2018-2022) derived from a systematic review. This needs to be discussed because any research or paper can help improve a particular topic, but in this discussion, we focus on what AI can do in Smart Farming (not detailed AI methods and their derivatives). Here are the issues that can be used for improvement, as shown in Fig. 3.

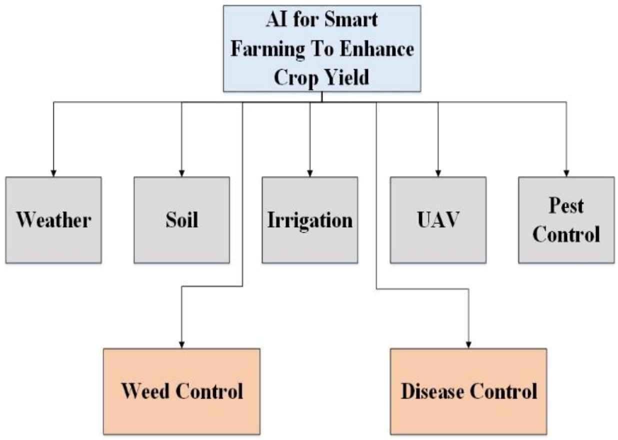

Fig. 3. Smart Farming Improvement Concept.

After understanding several concepts of AI (DL or ML) for enhancing Smart Farming on crop yields (see Fig. 3.), the author then tries to describe some discussions related to the image.

A. *Weather*

The weather is an everyday thing that happens in agriculture. Their influence in the world of agriculture affects the performance of crop yields, so several studies are needed to help AI understand the weather in Smart Farming applications.

Shandilya and Khanduja [41] said several studies have focused on climate, weather, and Smart Farming, but most research requires a significant increase in the cost. This Study uses AI in weather. But Focus AI in the study-specific used SARIMAX algorithm.

Kamatchi and Parvathi [42] Explained using predictive analysis. One of the AI methods, the Artificial Neural Network (ANN) technique, has successfully performed the best crop analysis based on weather conditions. The ANN technique is used in suitable groupings for data mining and machine learning categorization.

Tarik and Jamil [43] take an approach that utilizes AI applied in agriculture. Using Convolutional Neural Networks (CNN) to prevent the number of production results. By taking advantage of the many meteorological and weather. Then proceed to the data processing phase, such as normalization, filtering, and segmentation.

Therefore, in this Study, the author will present the focus of weather on AI for Smart Farming of the current trends paper on enhancing crop yields, which can be done in Table V.

TABLE V. WEATHER STUDY TO ENHANCE CROP YIELD

References	Topic	Solution
[41], [42], [44]–[46]	Weather	Forecast and Predictions
[43]	Weather	Weather Data

B. Soil

In Smart Farming, it is unavoidable to utilize the land. Smart Farming requires suitable and qualified soil to increase crop yields. This discussion discusses the role of AI in improving soil quality which will be applied to Smart Farming.

Suhag *et al.* [47] Explained there is no denying that farmers and landowners face challenges due to the ever-increasing population. One effective solution is to use new technologies such as AI and IoT. Therefore, AI-assisted manufacturing has advanced a lot in farming methods, and all the task conducted by farmers has been made easier with AI. Different work cases will be mapped beforehand in the system, learning new things. Technologies such as precision agriculture use AI technology for mapping diseases in crops, Soil nutrition, and overcome by AI technology (especially Robotic to harvest the crop).

Anand *et al.* [48] explained that monitoring nutrients in the soil are very important because one of the impacts is increasing agricultural yields and productivity, efficiency, and effectiveness. Soil monitoring is based on basic parameters such as water content and temperature so that farmers can estimate the situation. one result of the right decisions being made: is the choice of areas to plant to help tillers or farmers. In this case, ML (Hybrid algorithm) has an important role in detecting the type of soil.

Rodić *et al.* [49] Explained the big role in IoT in terms of inputs that make the system smart in various things like digital and physical. As previously explained, the intelligent system has not only provided a solution but effectively assisted the task of sensing soil moisture to ensure optimal water usage. With the help of several other technologies, such as LoRa can provide cost-effective and energy-efficient devices that have unique advantages over existing solutions. This Study uses Long Short-Term Memory (LSTM). This algorithm is one of the DL.

Reshma *et al.* [50] Another breakthrough in agricultural land management, as previously described, can be improved by measuring soil characteristics. This information and data need to be withdrawn and stored in the cloud and then re-analyzed on the land using AI. so that farmers and land pickers can properly utilize resources and direct farming methods wisely to optimize results. This Study can use supervised learning like Support vector machines (SVM) and Decision Trees to convey his recommendations.

The authors present some soil studies on AI for Smart Farming of the current trend studies that can support enhanced crop yields and Smart Farming in soil-focused agriculture, as shown in Table VI.

C. Irrigation

An important component in increasing crop quality is the need for good water, one of which can be made from a good irrigation system. In this section, we will focus on the role of AI in improving irrigation quality that can be applied to agriculture.

Goap *et al.* [58] On Agriculture sector requires a lot of water, but freshwater supply is running low. This happens because the method used is conventional with many challenges such as lack of utilization of water use efficiency. In addition, there is a lot of global warming and climate change that often impact the amount of rain intensity required to meet the availability. Sustainable irrigation is one step in achieving food security. Algorithms using ML (Support Vector Regression (SVR) + k-means) show fewer errors and improve accuracy. The approach used can be proposed to assist in making effective irrigation decisions.

TABLE VI. SOIL STUDY TO ENHANCE CROP YIELD

References	Topic	Solution
[47]	Soil	Nutrition
[51]	Soil	Classification
[48]	Soil	Detection System
[49]	Soil	Humidity Sensing
[52], [53]	Soil	Moisture Prediction and Forecast
[54]	Soil	Moisture Evaluation
[55], [56]	Soil	Prediction
[57]	Soil	Estimate Soil Moisture
[50]	Soil	Analysis

Kwok and Sun [59], On technology in ML can be used for learning and is very important in agriculture. In recent years, many studies have taken advantage of machine learning as part of AI. The utilization of DL in irrigation systems today is highly developed and developed by research and industry. On an irrigation system, leveraging deeper and more specific learning with DL can adjust the water intensity on the kinds of plants.

Murthy *et al.* [60], On scheduling irrigation, is very important, especially because traditional irrigation uses a lot of water, which causes fatal things such as water pollution and water wastage. By utilizing (Weather-aware Runoff Prevention Irrigation Control (WaRPIC)), the recording of the data obtained to form a machine learning model focused on predicting the Maximum Allowable Run Time (MAR).

There are many more Irrigation applications focused on AI for Smart Farming applications in the current trends paper on increasing crop production that focus on its application in irrigation, as shown in Table VII.

TABLE VII. IRRIGATION STUDY TO ENHANCE CROP YIELD

References	Topic	Solution
[58]	Irrigation	Management
[59], [61]–[66]	Irrigation	System
[60]	Irrigation	Control
[67]	Irrigation	Timing Decision
[68]	Irrigation	Predictive

D. Unmanned Aerial Vehicle (UAV)

Rapid advances in technology make Smart Farming take advantage of it, one of which is UAVs, because it is unmanned and can be controlled anywhere. This section will discuss the application of AI-based UAVs that will help Smart Farming

Psiroukis *et al*. [69] Explained that broccoli is a plant that requires handling and is highly valued in agriculture and requires special care in the post-harvest and growing season. Broccoli heads are susceptible to damage because they are harvested by hand. In addition, it is first necessary to identify the land cultivation segment (Using Faster R-CNN and CenterNet). So, UAV research aims to automate architectural processing utilizing deep learning.

Li *et al.* [70] conducted high-resolution result mapping is needed to determine the pattern of spatial yield variability. In determining this, there are important factors because it affects new insights and variability of management results in viewing agricultural products. In UAV, machine learning (random forest regression (RFR) and SVR models) methods can imp0rove the prediction of the results. A machine learning model can be used to perform different vegetation indications.

Hoummaidi *et al.* [71] focus on sustainable agriculture, which is the focus of food security. Some governments are starting to rely on new technology. Agricultural applications also depend on efficient land monitoring. However, in the traditional case, monitoring is carried out on field surveys, and it is very expensive, slow, and rare. By utilizing remote sensing using UAV drones to be efficient and not waste a lot of time-insensitive agricultural mapping. Then research is carried out by utilizing the method Unmanned Aerial Systems (UAS) and DL as solutions for good mart Farming and sustainable agriculture.

Because there are many studies on UAV on AI for Smart Farming, the author is looking for a current trend paper to increase crop yields in Smart Farming. as shown in Table VIII.

TABLE VIII. UAV STUDY TO ENHANCE CROP YIELD

References	Topic	Component
[69], [72]	UAV	Classification
[70], [73]	UAV	Prediction
[71]	UAV	Mapping

E. Pest Control

All farmers understand that pests are enemies of the world of agriculture, especially in large numbers. AI can tackle pests by understanding such patterns and early detection. In this section, we will discuss to focus on AI in reducing pests that will be applied to Smart Farming

According to his survey study in [74], agriculture is the primary food source. More than 90% of the population gets their food source from agriculture in some countries. But there are problems, one of which is pests as a cause of reduced or lost crops in the agricultural world. Therefore, technology is needed to classify pests that can help detect pests, which is very important to minimize pest movement. The experiment utilizes this proposed classification accuracy with different combinations of the learning rate, ResNeXt-50 (32 × 4d), data augmentation, and transfer learning.

Hu *et al.* [75] discuss knowledge about accurate identification of pests has an important role in deciding to control pests. According to him, it is necessary to investigate the identification of pests in the field with characteristics such as their protective colour, methods for identifying pests based on YOLOv5 technology, and near-infrared imaging.

Nam and Hung [76] found that highly toxic pests could negatively affect crop yields in the final phase and even product quality in the industry. Therefore, everyone agrees to minimize pests and even needs to detect the task of maximizing these crops to make decisions on minimizing the relevant pests. However, this has challenges, such as classifying insect species using the Deep Convolutional Neural Network (CNN), part of machine learning.

Mique and Palaoag [77] focus on detecting rice diseases and pes and controlling and managing agricultural land attacked by pests so that the crop yields. By utilizing modern technology, diseases and pests are found in agriculture, especially in rice fields. This work uses CNN to control pests are plonia; knowledge of farmers about various rice diseases and pests and his work on how to control this pest needs to be considered; This work focuses on finding suitable solutions mechanisms for smallholder reporting. Utilizing image management and CNN, it is necessary to develop applications for detecting diseases and pests of rice.

Pests are bothersome even for agriculture and the final products managed in industry, but to minimize pests is not only using pesticides. The next Table IX will explain some of Pest Control on AI for Smart Farming, the current trends paper related to overcoming, identifying, controlling, and even minimizing pest growth.

TABLE IX. PEST CONTROL STUDY TO ENHANCE CROP YIELD

References	Topic	Solution
[74], [78]–[80]	Pest Control	Pest Classification
[75]–[77], [81]–[84]	Pest Control	Pest Identification or Detection
[85]	Pest Control	Pest Prediction

F. Weed Control

Weeds are considered very important because they affect the nutrients present in the land. Other things can also affect agricultural yields from agricultural harvests. In this section, the author will discuss how to control weeds.

Reedha *et al.* [86] explained that controlling weeds and food crops is the main crop production and agriculture. Because basically, weeds take the same nutrients as plants. Therefore, weeds harm crop yields if they cannot be controlled. Mapping and detection of weeds is an important step. Utilizing the deep learning approach can provide good performance in many sensing tasks. In its investigate visual transformers (ViT) and UAV technology can help.

Garibaldi-Márquez *et al.* [87] explain that Weed discrimination in the environment is challenging to overcome in Smart Farming practices, for example, weed control. Many methods are used. Developing a good practice system recognizes weeds and their crops. Its utilization is based on CNN and compared with the shallow learning approach.

Razfar *et al.* [88] Explain if research focusing on Weed detection is a part that is often used to implement Smart Farming in implementing IoT. Species such as Weeds are responsible for 45% of crop losses due to the struggle for nutrients from native plants. Therefore, the weed detection method was used to reduce this percentage. This study focuses on detection methods using deep learning models to look for weeds in soybean plantations. The study used ResNet50, three custom CNN Models, and MobileNetV2.

Haichen *et al.* [89] is an effective way to increase crop yields. In the application in smart agriculture, in identifying effective, accurate, and reliable weeds in controlling the location of weeds, in proposing VGG16+SVM weed classification algorithms to optimize the algorithm.

Ukaegbu *et al.* [90]. Explaining machine learning applications is very clear and gaining more popularity. There are better algorithms, such as the DL algorithm for classification, signal identification, and crack detection. The DL algorithm has a wider application than other machine learning systems. Weed detection research CNN, using transfer learning focus in the previously ResNet50 model, then proceed to performance evaluation using random forest (RF).

Many more recent research trends focus on Weed Control on AI for Smart Farming of crop yields in agriculture, be it precision or Smart Farming. Table X shows some of the current trends papers focusing on information and systems management.

TABLE X. WEED CONTROL STUDY TO ENHANCE CROP YIELD

References	Topic	Solution
[86], [87], [89], [91], [92]	Weed Control	Weed Classification
[88], [90], [93]–[98]	Weed Control	Weed Identification and Detection

G. Disease Control

Plant diseases are becoming new material in the increased learning broadly to be studied scientifically. Usually focuses on the biological characteristics of the disease. Identifying plant diseases has recently been proven to require special attention. Early detection of disease can help maintain plant quality.

Luna *et al.* [99] used tomato plants. In the ancient method of knowing the disease, an examination is carried out, and the treatment of diseases in tomatoes is still done manually by practice. System development is needed to perform tasks such as detecting plant diseases for users so that they do not always do everything manually. There are general signs of damage such as bacterial, fungal disease, nematodes, and viruses originating, resulting in death on the underside of the leaf or yellowing and black spots on the bottom of the leaf. The research used in this study is CNN. Anomalies were used by F-RCNN trained to detect.

Afzaal *et al.* [100] Other crops are also very susceptible to various diseases, which has led to an increase in the world of agriculture and industry. To improve the quality of plants, plants must protect plants from all kinds of harmful diseases. The available options include ancient ways to identify plant diseases to achieve this goal. This includes inspections carried out anciently or simply by prescribing disease. But this ancient method was time-consuming, and not just anyone thought a disease had to be an expert. Other solutions such as using pesticides in crop production, only the use of chemical pesticides can be detrimental and cause poor food quality. On the other hand, farmers also need to increase labor costs. So, according to the author, early detection of plant diseases (using Mask R-CNN architecture) is necessary to increase crop yields.

There are many more studies regarding diseases in plants. Because basically, this disease can reduce the harvest quality and make the Smart Farming system not good. Table XI will show some of the AI current trends papers for Smart Farming that addresses plant disease problems.

TABLE XI. DISEASE CONTROL STUDY TO ENHANCE CROP YIELD

References	Topic	Solution
[47], [77], [99]–[103]	Disease Control	Disease Detection and Identification
[104]–[106]	Disease Control	Disease Classification
[107]	Disease Control	Recognition

V. CONCLUSION

This Study focuses on conducting a systematic review in AI for Smart Farming of current trends papers to enhance crop yields. This review helps find the current trends paper related to enhancing crop yields in Smart Farming technology. In this review, the authors utilize PRISMA, which has successfully retrieved 534 articles in databases spread across IEEE, ScienceDirect, ACM, IAES, and MDPI. At the end of the process, the authors get 67 AI studies for Smart Farming of current trends papers that can enhance crop yields. The author also discusses several factors that can enhance crop yields in Weather, Soil, Irrigation, Unmanned Aerial Vehicle (UAV), Pest Control, Weed Control, and Disease Control. On the other hand, these AI factors significantly affect the performance of Smart Farming. Further research can be reviewed using other methods such as statistical models, system recommenders, and multi-agents.

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