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# The Potential of Smart Farming IoT Implementation for Coffee Farming in Indonesia: A Systematic Review

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**ABSTRACT:** As one of Indonesia's main export agricultural commodities, coffee farming faces many obstacles, ranging from plant pest organisms to climate and environmental problems. These problems can be solved using smart farming technology. However, smart farming technology has not been applied intensively in Indonesia. This paper aims to analyze the potential for implementing smart farming for coffee in Indonesia. This article presents a systematic review of the information about the potential application of IoT smart farming for coffee farming in Indonesia by applying the PSALSAR (Protocol, Search, Appraisal, Synthesis, Analysis, Report) review method. This study concludes the list of smart farming technologies for coffee that have the potential to be applied in Indonesia. Those technologies are classified based on their application scope: quality control (including subtopics like coffee quality control), climate monitoring, the anticipation of pest organisms, and coffee processing), coffee production planning, and coffee waste utilization. Regarding infrastructure readiness and the need for smart farming technology for coffee, the island of Java has the most potential for implementing smart farming for coffee as soon as possible. The high potential for application in Java is because the telecommunications technology infrastructure is ready, and the land area and coffee production are large.

**KEYWORDS:** Systematic review; coffee farming; smart farming; Internet of Things (IoT); PSALSAR

## 1. Introduction

Coffee has been becoming a prominent agriculture product in Indonesia since long time and already well known for its consumers. In addition, Indonesia is also ranked fourth as a coffee-producing country behind Brazil, Vietnam, and Colombia in 2020. Meanwhile, world coffee consumption has an increasing trend, at least if we look at the data from 2013 to 2018 [1]. These facts demonstrate that coffee continue to be consumed by the world community, and Indonesia potentially has the benefit from coffee farming if it's developed better.

On the other hand, many problems related to coffee production in Indonesia still need to be solved. These problems are classified into the quantity and quality of coffee that is not good enough, caused by coffee pest organisms [2], climate and environmental influence [3],

[4]. The organisms consist of pests, diseases, and nematodes. Regarding climate, coffee in Indonesia is influenced by altitude, rainfall, land, plant material, and the surrounding environment. The problems need to be addressed if coffee in Indonesia is expected to dominate the world's coffee market and positively affect the country's revenues. Various ways can be used to overcome the problems mentioned before. One of many ways is by utilizing smart farming technology, which has been developed in recent decades. Alfred et al. [5] summarize IoT smart farming technology to be applied in rice production and processing in the Asia-Pacific. Ilie [6] describes the techno-economic factors related to implementing smart farming for corn fields at Frizonagra farm in Romania. Muniasamy [7] summarizes machine learning technology for smart farming in desert areas such as Saudi Arabia. O'Shaughnessy et al. [8] compared solutions to smart farming in the United States and the Republic of Korea (ROK). This is all literature related to smart farming, focusing on specific fields of application or certain regions. However, there is no comprehensive review regarding smart farming applications for coffee farming to be implemented in Indonesia.

Many technologies can be applied to solve the problems in coffee farming, and the solutions can be obtained from several sources. De Vita et al. [9] developed plant disease detection using machine learning and convolutional neural networks (CNN) based on the STM32 series microcontroller. Rahul and Rajesh [10] developed a robot to detect sick plants through their leaves and cut them. Collazos-Burbano et al. [11] developed a mechanism for detecting plant leaf characteristics using Ultrasonic Wave Propagation (UWP). This paper is used to detect Arabica coffee leaves. Huang et al. [12] developed an automatic coffee bean detection system based on deep learning. CNN. Drone technology and Synthetic Aperture Radar (SAR) were used by Oré et al. [13] to monitor the growth of coffee, corn, and sugar cane plantations. Carrijo et al. [14] developed an automatic coffee fruit detection system using digital image processing combined with machine learning. The image was taken with a camera carried by a drone directed to fly around the area of the coffee plantation. These sources indicate that the information related to smart farming technology that can be used to solve coffee farming already exists, but the information is still scattered and not yet integrated. In terms of the advantages of IoT technology, many studies have been carried out to solve problems related to coffee farming. Rutayisire et al. [15] built e-Kawa, a pH monitoring system, to maintain the quality of coffee. The pH data is delivered to the coffee washing station and was used to consider the ripe status of the coffee. Rajendran et al. [16] utilized the IoT to develop a security system for food in the coffee industry. Nurwarsito et al. [17] developed a communication system for the stream of microclimate data (RH, temperature, soil moisture, and light intensity) for coffee plantations. These studies have applied IoT technology to coffee farming, but the information is still scattered, and there are no linkages. From the importance of Indonesia's role in the world's coffee farming, problems related to coffee farming in Indonesia, studies related to smart farming in several countries and several sectors, and studies on smart farming in coffee farming, a "systematic review related to the potential of smart farming IoT implementation for coffee farming in Indonesia" is considered urgent to do. This paper aims to analyze the potential for implementing smart farming for coffee in Indonesia. This research was expected to be used as a recommendation or a guide for practitioners and stakeholders in coffee farming to apply smart farming to coffee farming in Indonesia.

## 2. Agriculture 4.0

Agriculture has undergone evolution throughout human history. The need for agriculture is in line with the human need for survival. Until now, the agricultural technology phase has reached the level of agriculture 4.0, although several authors have tried to formulate the definition of agriculture 5.0 [18–21]. An explanation al. [18] regarding the evolution of agriculture technology from 1.0 to 4.0 is a fairly clear and representative explanation of world history. This description of the evolution of agriculture from 1.0 to 4.0 was adapted from Huang et al. [18]. Agriculture 1.0 is characterized by agriculture with a dominant combination of human and animal power. The fuel used is still based on firewood. Agriculture 2.0 uses mechanical technology to help humans solve their agricultural problems. In this phase, the main fuel is coal. Agricultural 3.0 began to use automation technology in its activities. Information technology began to be used simply in this phase. The main fuel used was also petroleum. Agriculture 4.0 is a phase that can be considered the most up-to-date at this time because it has extensively used AI and IoT technology. This phase is also called the "smart agriculture" phase. The fuel used has also begun to integrate petroleum-based fuels with thermal, hydro, and nuclear-based energy. Liu et al. [22] define Agriculture 4.0 based on five main technologies: IoT, robotics, AI, big data, and blockchain. The explanation of each technology that plays an important role in Agriculture 4.0 includes:

- IoT is used predominantly for monitoring conditions in plantation or livestock areas. Potential problems in the IoT aspect are, of course, the problem of communication stability and network distribution that is still not uniform in places where it is needed.
- Robotics can be used for automation in livestock and agriculture, for example, for automatic feeding applications, automatic pesticide spraying, and 3D food printing. Potential problems still need to be solved regarding the autonomous algorithm, accurate detection, and intelligence mechanisms of the robot.
- AI and Big Data can be used complementarily for Agricultural Decision Support System applications, predictive analysis of agricultural systems, and to support robotics technology to be smarter. Potential problems that must be solved include the difficulty of integrating researchers and farmers as users and the existence of crucial social and ethical issues in using data for smart agriculture.
- Blockchain can be used for security issues in livestock and agricultural systems and matters concerning data integrity and reliability, such as smart contracts. The potential problems lie in interoperability and scalability.

## 3. Methodology

Grant and Booth [23] classified review papers into 14 types, one of them is a systematic review. Davis et al. [24] stated that systematic review is the gold standard of paper reviews since the steps are systematic, transparent, and reproducible (others can reproduce or copy). This paper conducts a systematic review using guidelines from Kitchenham [25] and Mengist et al. [26]. PSALSAR is used because this method has clear steps. Furthermore, this method is an improvement on another popular method known as Search, Appraisal, Synthesis, and Analysis (SALSA). The steps in this paper's systematic review can be abbreviated into PSALSAR [26], which are:

a. Protocol: define the scope of the study.
b. Search: plan your search strategy;
c. Appraisal: selecting a paper from the search step based on some quality criteria;
d. Data Synthesis consists of data extraction and categorization;
e. Analyze: data analysis;
f. Report: writing a report and coming to a conclusion.

### *3.1. Protocol*

The study scope in this review paper is divided into several factors: technology, smart farming, smart agriculture, and coffee farming. Several technologies are deployed in smart farming that are discussed in this paper. In contrast, this paper identifies some potential that can be maximized for coffee farming, especially related to their performance through smart farming in coffee processing and growth. This paper tries to find out "What technology has been deployed in global smart farming that can be implemented to solve problems in coffee farming, especially in Indonesia?".

### *3.2. Search Strategy*

The data were derived from the search results for papers within IEEE databases. The IEEE database was selected because it is anticipated that the search results will pertain exclusively and technically to electrical technology derivatives. The search approach used a combination of technology and coffee-related keywords. For instance, "Smart Farming" AND "Coffee" OR "Internet of Things" AND "Coffee." On March 31, 2022, the search operation was conducted. The Table 1 provides a summary of the search results for articles.

**Table 1.** Search string and its result.

| Search String | Result | Search String | Result |
|---|---|---|---|
| "Smart Farming" AND "Coffee" | 1 | "Artificial Intelligence" AND "Coffee" | 96 |
| "Smart Agriculture" AND "Coffee" | 2 | "Electronic " AND "Coffee" | 92 |
| "IoT" AND "Coffee" | 34 | "Microcontroller" AND "Coffee" | 11 |
| "Internet of Things" AND "Coffee" | 43 | "Microprocessor" AND "Coffee" | 8 |
| "Big Data" AND "Coffee" | 9 | “Network” AND “Coffee” | 148 |
| "Deep Learning" AND "Coffee" | 27 | “Drone” AND “Coffee” | 1 |
| "ML" AND "Coffee" | 10 | “Robot” AND “Coffee” | 68 |
| "Machine Learning" AND "Coffee" | 46 | “5G” AND “Coffee” | 1 |
| "AI" AND "Coffee" | 10 | | |

### *3.3. Appraisal*

After obtaining the relevant articles, the following step is to evaluate them. This step is necessary to make the article selection criteria transparent. Below is a table including the considered appraisal rule or quality criteria. Whether the articles are included or eliminated as relevant articles for the next phase is the final outcome of this step (Table 2).

### *3.4. Synthesis*

In this stage, the selected articles were iteratively classified for use in subsequent rounds. The papers were classified according to their applicability to coffee farming. Additionally, the employed or deployed technology is recognized and assessed. Table 3 displays the classification findings.

### 3.5. Analysis

In the analysis step, the categorized articles was deep-analyzed, and the result of the analysis can be in the form of narrative paragraphs or a table. Trend analysis and technology gap was analyzed as well in this step. The analysis result of this paper is in narrative paragraphs and can be found in part 3.

**Table 2.** Appraisal rule.

| Selection Criteria | Decision |
|---|---|
| When the predefined keyword exists in the article's title, keywords, or abstract | Inclusion |
| The article is written in English or Bahasa (Indonesian language) | Inclusion |
| The article is a review paper, or the article cannot be accessed | Exclusion |
| The article is duplicated | Exclusion |
| The article was published before 2017 | Exclusion |

### 3.6. Report

In this step, the analysis result was concluded, and the report can be a recommendation article to the broader readers. This study report was described in this article and the conclusion.

## 4. Results and Discussion

From the search results in the IEEE database and using the search string setup shown in Table 1, 607 article titles were found. The evaluation is conducted with the aid of Rayyan's application [27]. The duplicate check was aided by Rayyan's features, which yielded 377 articles for additional examination. Following the appraisal step are the appraisal rule, abstract, title, keyword, and relevance check phases. This stage is further aided by the information management component of Rayyan, which enables the collection of 48 article titles that are ready to be categorised, analyzed, and reported. This procedure is depicted in Figure 1.

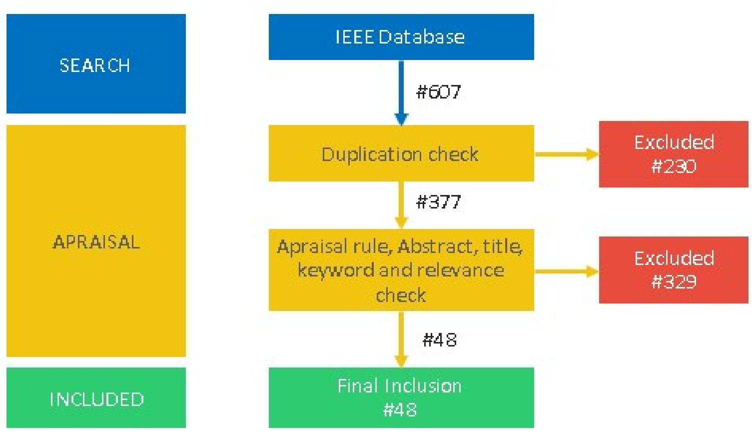


**Figure 1.** Search and appraisal process.

### 4.1. Classification results

After 48 articles were incorporated, the categorization phase followed. Relevance, AI-ML-DL, and the research phase are used to classify information. Observations of the technological clusters that lead to AI classification define its AI and non-AI classification. Aside from this, the dissemination of AI technology into other industries is currently quite intense, and the development of AI-based technologies necessitates the assignment of specialized personnel. In the meanwhile, the classification of articles is based on the research phase, as this defines which innovations may be deployed immediately and which still require development time. Table 3 provides a summary of the findings of the classification.

**Table 3.** Results of inclusion and classification.

| No | Relevance | AI-ML-DL application* | Research phase** | Ref |
|---|---|---|---|---|
| 1 | Maintaining the health of the coffee plant, Detecting the health of the coffee plant through the leaves | A | AR | [9] |
| 2 | Handling coffee plant pests with image processing and mechatronics technology | A | AR | [10] |
| 3 | Coffee quality control, pest anticipation, detection of biological characteristics of coffee plants, a study of tissue characteristics of coffee plants | N | AR | [11] |
| 4 | Detect the quality of coffee beans, and maintain the quality. | A | AR | [12] |
| 5 | Coffee bean quality control, Detect the number of coffee beans from the image, classify the object of coffee beans | A | AR | [14] |
| 6 | Coffee bean quality control, processing coffee beans, maintaining coffee bean quality, monitoring coffee pH | N | AR | [15] |
| 7 | Coffee bean quality control, optimizing coffee production, improving the quality of production operations with IoT | N | AR | [16] |
| 8 | Coffee bean quality control, monitoring of soil and environmental parameters | N | AR | [17] |
| 9 | Coffee bean quality control, taste quality detection | A | AR | [28] |
| 10 | Utilization of coffee waste for energy. | A | BR | [29] |
| 11 | Coffee bean quality control, taste quality detection | A | AR | [30] |
| 12 | Coffee bean quality control | A | AR | [31] |
| 13 | Anticipation of coffee pests, detection of coffee pests | A | AR | [32] |
| 14 | Quality Control of coffee quality, processing, maintaining the quality of coffee beans | N | AR | [33] |
| 15 | Quality Control coffee quality, coffee moisture content detection | N | AR | [34] |
| 16 | Anticipation of OPT Coffee, detection of coffee leaf disease | A | AR | [35] |
| 17 | Quality Control coffee quality, maintain coffee bean quality, detect soil quality | A | AR | [36] |
| 18 | Quality Control of coffee quality, maintaining the quality of coffee beans, selection of ripe and unripe coffee beans | A | AR | [37] |
| 19 | Quality control of coffee quality, maintaining coffee quality, classification of coffee bean species | A | AR | [38] |
| 20 | Monitoring the climate and environment of coffee plantations, applying technology to integrate agricultural monitoring systems (one of which is coffee), increasing farmer productivity | N | AR | [39] |
| 21 | Quality Control of coffee quality, maintaining the quality of coffee beans, identification of defects in coffee beans | A | BR | [40] |
| 22 | Quality Control of coffee quality, maintaining the quality of coffee beans, identifying the nutritional content of coffee leaves | A | AR | [41] |
| 23 | Quality Control of coffee quality, classification of coffee quality levels | A | AR | [42] |
| 24 | Quality Control of coffee quality, classification of coffee quality levels | A | AR | [43] |
| 25 | Quality control of coffee bean quality, Maintaining the quality of coffee beans, detection of defects in coffee beans | A | AR | [44] |

(continued on next page)

| No | Relevance | AI-ML-DL application* | Research phase** | Ref |
|---|---|---|---|---|
| 26 | Quality control, the anticipation of OPT, Maintaining the health of coffee plants, Detecting the health of coffee plants through the leaves | A | AR | [45] |
| 27 | Quality control, the anticipation of OPT, Maintaining the health of coffee plants, Detecting the health of coffee plants through the leaves | A | AR | [46] |
| 28 | Quality control, the anticipation of OPT, Maintaining the health of coffee plants, Detecting the health of coffee plants through the leaves | A | AR | [47] |
| 29 | Quality control, the anticipation of OPT, Maintaining the health of coffee plants, classification of coffee diseases through leaf detection | A | AR | [48] |
| 30 | Quality control of coffee bean quality, classification of coffee bean quality levels | A | AR | [49] |
| 31 | Quality control, the anticipation of OPT, Maintaining the health of coffee plants, Detecting the health of coffee plants through the leaves | A | AR | [50] |
| 32 | Coffee bean quality control, coffee bean type classification | A | AR | [51] |
| 33 | Quality control of coffee beans, Control of the coffee bean process to produce the desired taste | N | AR | [52] |
| 34 | Quality control, the anticipation of OPT, Maintaining the health of coffee plants, Detecting the health of coffee plants through the leaves | A | AR | [53] |
| 35 | Quality control, the anticipation of OPT, Maintaining the health of coffee plants, Detecting the health of coffee plants through the leaves | A | AR | [54] |
| 36 | Coffee quality control, coffee bean defect detection | A | BR | [55] |
| 37 | Quality control of coffee beans, Detect the number of coffee beans from the image, classification of ripe and unripe coffee beans | A | BR | [56] |
| 38 | Coffee production planning, remote sensing coffee plantation imagery. | A | BR | [57] |
| 39 | Coffee production planning, remote sensing coffee plantation imagery. | A | BR | [58] |
| 40 | Coffee bean quality control, coffee bean defect classification | A | AR | [59] |
| 41 | Coffee bean quality control, coffee bean quality classification | A | AR | [60] |
| 42 | Coffee bean quality control, coffee bean quality classification | A | BR | [61] |
| 43 | Quality Control coffee quality, taste quality detection | A | AR | [62] |
| 44 | Coffee production planning, remote sensing coffee plantation imagery. | A | BR | [63] |
| 45 | Quality Control coffee quality, classification of coffee types | A | AR | [64] |
| 46 | Coffee bean quality control, coffee bean type classification | A | AR | [65] |
| 47 | Coffee bean quality control, coffee bean type classification | A | BR | [66] |
| 48 | Quality control of coffee beans, Control of the coffee bean process to produce the desired taste | A | AR | [67] |

* “A” for AI-ML-DL application and “N” for non-AI-ML-DL application
** “AR” for applied research and “BR” for basic research

Table 4 shows the classification results of Scope and Application. The coffee quality control (Quality Control) scope concerns many researchers, around 91%. Technology application solutions to coffee detection problems are a sub-section of the dominant QC solution sought, with a percentage is 46%. There is one discussion about the coffee waste that can be reused as raw material for batteries, and the percentage is 2%.

**Table 4.** Classification of scope and application.

| Scope | Application | Total | Percentage (%) | References |
|---|---|---|---|---|
| Quality Control | OPT Anticipation | 13 | 27 | [9–11,32,35,41,45–48,50, [53], [54] |
| | Coffee Detection | 22 | 46 | [24,26,42,44,45,51,52,54,56–58,63,65,69,70,73–76, 78–80] |
| | Coffee Processing | 6 | 13 | [27,28,47,48,66,81] |
| | Environment and Climate Monitoring | 3 | 6 | [29,50,53] |
| Production Planning | Remote Sensing | 3 | 3 | [71,72,77] |
| Waste Utilization | Waste for Energy | 1 | 2 | [29] |

The findings in this study are almost in line with another study [68]. Many studies discussing and using AI, ML, and DL for coffee detection were also found by [68], although not as dominant as the results of this study. The same applies to IoT applications for climate and environmental monitoring and coffee processing and management monitoring applications. Remote sensing applications also appear in both the results of this study and the research results [68]. However, the case of the use of coffee waste for energy only appears in this study because the point of view of the classification is different. This paper's classification is based on the potential utilization of all aspects of coffee farming, while [68] bases its classification on the technology relevant to coffee farming problems.

**Table 5**. Classification based on AI-ML-DL application and non-AI-ML-DL.

| Scope | Application | Subtotal | Total | Percentage (%) | References |
|---|---|---|---|---|---|
| AI-ML-DL | OPT Anticipation | 12 | 40 | 83.333 | [20,21,46,49,55, 59,62,64,67,68] |
| | Coffee Detection | 22 | | | [24,26,42,44,45,51,52 ,54,56–58,63,65,69,70, 73–76,78–80] |
| | Coffee Processing | 1 | | | [67] |
| | Environment and Climate Monitoring | 1 | | | [36] |
| | Remote Sensing | 3 | | | [71,72,77] |
| | Waste for Energy | 1 | | | [29] |
| Non-AI-ML-DL | OPT Anticipation | 1 | 8 | 16.667 | [11] |
| | Coffee Detection | 0 | | | - |
| | Coffee Processing | 5 | | | [27,28,47,48,66] |
| | Environment and Climate Monitoring | 2 | | | [29,53] |
| | Remote Sensing | 0 | | | - |
| | Waste for Energy | 0 | | | - |

**Table 6**. Classification based on basic research and applied research.

| Scope | Application | Subtotal | Total | Percentage (%) | References |
|---|---|---|---|---|---|
| Basic Research | OPT Anticipation | 0 | 9 | 18.75 | - |
| | Coffee Detection | 5 | | | [54,69,70,75,80] |
| | Coffee Processing | 0 | | | - |
| | Environment and Climate Monitoring | 0 | | | - |
| | Remote Sensing | 3 | | | [71,72,77] |
| | Waste for Energy | 1 | | | [29] |
| Applied Research | OPT Anticipation | 13 | 39 | 81.25 | [20–22,46,49,55,59–62,64,67,68] |
| | Coffee Detection | 17 | | | [24,26,42,44,45,51, 52, 56–58,63,65,73,74, 76,78,79] |
| | Coffee Processing | 6 | | | [27,28,47,48,6],81] |
| | Environment and Climate Monitoring | 3 | | | [29,50,53] |
| | Remote Sensing | 0 | | | - |
| | Waste for Energy | 0 | | | - |

Table 5 shows the classification of AI, ML, and DL roles in each application. It can be seen in the table that the roles of AI, ML, and DL are very dominant in solving smart farming problems in coffee farming, which is 83.333%. This condition is in line with the increasing popularity of AI, ML, and DL topics from 2017 onwards (years > 2017 is the year limit used for appraisal) [69,70]. From the potential application point of view, research can be classified according to its status, whether it is basic research or applied research. If referring to the Technology Readiness Level (TRL) table from the Ministry of Research, Technology, and

Higher Education, basic research is in TRL 1-3 while applied research is in TRL 4-9. From Table 6, applied research is very dominant (81.25%) compared to basic research (18.75%). This is good for people involved in smart farming because research that has already been done can be used to solve real problems in the field, especially in coffee farming.

### *4.2. IoT smart farming technology solution for coffee farming*

One of the problems in coffee agriculture is the presence of OPT. It is necessary to detect their presence as soon as possible to prevent pests from destroying all existing plants. Almost all of the filtered articles discussed the detection of diseases or the health level of coffee plants through their leaves [9,10,35,41,45–48,50,53,54]. The rest detected insect pests based on sound [32] and detected tissue characteristics using ultrasonic waves [11]. Detection of coffee disease through the leaves is done by combining image processing with ML or DL.

Detection of coffee quality and quantity is important in the classification of coffee production, both in harvesting coffee cherries and coffee products ready to be sold. Coffee detection can be divided into several types of detection, namely detection of coffee bean quality [12,30,31,42,43], coffee fruit quality [37,49], coffee fruit quantity [14,56], coffee bean defects [40,44,55,60], coffee taste quality [28,62], and coffee type [38,51,59,61,64–66]. The input from the detection system can be divided into four categories, namely detection based on images [12,14,30,31,37,38,40,42–44,49], gas [51,59,62,64–66], light (spectrometry) [61], and expert opinion (humans) [28]. Coffee detection is the most dominant in terms of coffee detection types. At the same time, many other researchers use image input most often to find coffee from a system input point of view.

For coffee processing applications, the main focus is how to control coffee quality by monitoring and controlling the processing. Research [15] detects coffee's pH to control the coffee maturity level. Research [16] demonstrates that coffee handling can be transformed from a manual method to a fully automatic method to maintain the hygiene of the coffee. Research [33] designed a coffee sorter system based on a capacitive sensor detecting coffee moisture. Research [34] is almost the same as research [33]. However, the development focus is on simulation and software design that is more user-friendly, while research [34] focuses on portable hardware design. Research [52] and [67] has designed coffee roaster systems that parameters can control. Both use a microphone, a temperature sensor, and a gas sensor to monitor the cracking of the roasted coffee beans. Then the signal is used to regulate the temperature in the chamber of the coffee roaster. The strength of the research [67] lies in the use of fuzzy logic and NN in monitoring the ripeness of the coffee. The advantage of research [52] compared to [67] is integrating smartphone technology into a modified coffee roaster machine.

In the case of environmental and climate monitoring, all the technology used is based on IoT technology. Research [17] applied LoRa technology and sensors such as humidity, temperature, soil moisture, and light intensity sensors to monitor important parameters in coffee plantations. Research [36] focuses on the problem of identifying soil quality to be used in coffee plantations or other plantations. Research [39] focuses on offering an IoT monitoring platform to monitor potatoes, corn, cocoa, lettuce, cabbage, and coffee plantations.

In the case of remote sensing, the considered technologies are image processing technology combined with deep learning. The three pieces of research are basic research that offers new methods in image processing from remote sensing results. The three articles discuss remote sensing for mapping coffee plantations, which is used for production planning. The only article that was filtered and discussed the use of coffee waste was researched in reference [29]. Coffee waste is used as a raw material for activated carbon in metal-air batteries. Battery design optimization is done using a Genetic Algorithm (GA). From this research, it can also be concluded that coffee waste processing has new economic potential, which simultaneously supports the world agenda of using biomass energy as a renewable energy source. Of the various applications described above, there are two dominant ones: detecting coffee diseases based on images of leaves and detecting coffee types. Detection of coffee disease from dominant coffee leaves is done using image processing technology and AI-ML-DL. Detection of the type of coffee can be done in various ways, either through the image, the aroma, or the light spectrum. The sensing signal from the image, gas (aroma), or light spectrum must be reprocessed using the AI-ML-DL algorithm. Therefore, the key technology that must be mastered if we want to detect coffee diseases and detect coffee types is AI-ML-DL technology.

### *4.3. Potential implementation and challenges*

Table 6 indicates many technologies are ready to be adapted to solve coffee agriculture problems, especially in Indonesia. To apply this technology in Indonesia, other factors that can support the successful application of the technology must be considered, one of which is the readiness of telecommunications network technology. Table 5 indicates that AI, ML, and DL applications for coffee agriculture technology solutions are very dominant, especially for applications for pest anticipation, coffee detection, and remote sensing. Good computing resources are needed to perform complex calculations. For the case of anticipating pests, for example, calculations are performed on a high-specification microcontroller [9], on a mini-computer [10], or in the cloud [35]. If we want to do computing in the cloud, the connection between devices in the field and the cloud must be stable and reliable. In this case, telecommunications technology is an important determining factor for applying AI, ML, and DL technologies whose computing is done in the cloud. IoT is a key technology for processing applications and monitoring climate and environmental conditions. IoT technology, of course, is very dependent on the existing telecommunications infrastructure. Again, telecommunication technology is a determining factor in whether or not technology can be applied.

Table 7 shows coffee production, land area, density, and Base Transceiver Station (BTS) numbers for each province. The effectiveness of land use is represented by density, which depends on the amount of production divided by land area. For a rough idea, it is assumed that the number of BTS per unit of effectiveness, namely density, represents the level of adequacy of telecommunications infrastructure in an area for smart farming and IoT coffee farming. Table 7 shows the distribution of the telecommunications infrastructure's adequacy for smart IoT coffee farming needs. The figures and tables indicate that most Java telecommunications infrastructure is sufficient to meet the needs of smart farming. But in other areas, the distribution still needs to be increased. Although further identification is still needed for data per region (village, district, or city), this information shows how much telecommunications infrastructure is needed to be improved in some areas in Indonesia. especially for technology that requires high telecommunication needs, such as image and video streaming data for pattern identification.

**Table 7.** Statistic data of coffee production and BTS density in Indonesia 2020*.

| No | Province | Area (Ha) | Production (Ton) | Density (Ton/Ha) | BTS (unit) | BTS/Density |
|---|---|---|---|---|---|---|
| 1 | ACEH | 126289 | 73419 | 0.581357046 | 1586 | 2728.099729 |
| 2 | NORTH SUMATERA | 95477 | 76597 | 0.802256041 | 2567 | 3199.726608 |
| 3 | WEST SUMATERA | 25358 | 12528 | 0.494045272 | 912 | 1845.984674 |
| 4 | RIAU | 4213 | 2423 | 0.575124614 | 1220 | 2121.279406 |
| 5 | JAMBI | 30603 | 18613 | 0.608208346 | 727 | 1195.314082 |
| 6 | SOUTH SUMATERA | 250305 | 198945 | 0.794810331 | 1449 | 1823.076453 |
| 7 | BENGKULU | 85703 | 62279 | 0.726684013 | 439 | 604.1140192 |
| 8 | LAMPUNG | 156460 | 117311 | 0.749782692 | 1350 | 1800.52169 |
| 9 | BANGKA BELITUNG ISLAND | 111 | 21 | 0.189189189 | 339 | 1791.857143 |
| 10 | RIAU ISLAND | 19 | 0 | 0 | 299 | N.A |
| 11 | DKI JAKARTA | 0 | 0 | N.A | 239 | N.A |
| 12 | WEST JAVA | 49825 | 22980 | 0.46121425 | 4476 | 9704.817232 |
| 13 | CENTRAL JAVA | 47757 | 26179 | 0.548170949 | 4377 | 7984.735437 |
| 14 | DI YOGYAKARTA | 1728 | 514 | 0.297453704 | 337 | 1132.949416 |
| 15 | EAST JAVA | 90735 | 45278 | 0.499013611 | 4621 | 9260.268453 |
| 16 | BANTEN | 6233 | 1978 | 0.317343173 | 1085 | 3419.011628 |
| 17 | BALI | 34746 | 15740 | 0.453001784 | 557 | 1229.575731 |
| 18 | WEST NUSA TENGGARA | 13365 | 5625 | 0.420875421 | 892 | 2119.392 |
| 19 | EAST NUSA TENGGARA | 72919 | 23930 | 0.328172356 | 1031 | 3141.64183 |
| 20 | WEST KALIMANTAN | 11904 | 3700 | 0.310819892 | 922 | 2966.348108 |
| 21 | CENTRAL KALIMANTAN | 2490 | 405 | 0.162650602 | 542 | 3332.296296 |
| 22 | SOUTH KALIMANTAN | 2928 | 1204 | 0.411202186 | 827 | 2011.17608 |
| 23 | EAST KALIMANTAN | 2088 | 210 | 0.100574713 | 621 | 6174.514286 |
| 24 | NORTH KALIMANTAN | 1293 | 64 | 0.049497293 | 210 | 4242.65625 |
| 25 | NORTH SULAWESI | 7834 | 3705 | 0.472938473 | 673 | 1423.018084 |
| 26 | CENTRAL SULAWESI | 10191 | 2741 | 0.26896281 | 681 | 2531.948559 |
| 27 | SOUTH SULAWESI | 79394 | 35573 | 0.448056528 | 1616 | 3606.687769 |
| 28 | SOUTHEAST SULAWESI | 8521 | 2676 | 0.314047647 | 612 | 1948.748879 |
| 29 | GORONTALO | 1437 | 144 | 0.100208768 | 293 | 2923.895833 |
| 30 | WEST SULAWESI | 16272 | 4396 | 0.270157325 | 220 | 814.3403094 |
| 31 | MALUKU | 1262 | 441 | 0.349445325 | 527 | 1508.104308 |
| 32 | NORTH MALUKU | 414 | 14 | 0.033816425 | 392 | 11592 |
| 33 | WEST PAPUA | 206 | 73 | 0.354368932 | 396 | 1117.479452 |
| 34 | PAPUA | 12375 | 2673 | 0.216 | 535 | 2476.851852 |

* Data from Central Bureau of Statistics of the Republic of Indonesia

Based on data from the Global Competitiveness Index 4.0 (GCI 4.0) 2019, in which there are 12 pillars and 103 indicators, Indonesia is ranked 50th with 64.6 points (0-to-100 scale). In the report, several indicators are considered relevant to applying smart farming technology. The pillars and indicators and their scores can be seen in Table 8. Table 8 shows several indicators that are already good and must be maintained or maximized again (green); some indicators need to be improved again (yellow-orange); and some need special attention (red). Because smart farming technology is dominated by AI-ML-DL and IoT technology, the electricity infrastructure, telecommunications, and ICT adoption in the community are the absolute foundations that must exist. In the future, there will be human resources to implement it. Therefore, the quality of human resources needs to be considered, starting from the vocational aspect, digital skills, and critical thinking. In the future, it is hoped that more private sectors will be interested in and dare to take a role in implementing smart farming. Therefore, the entrepreneurial culture factor is relevant to be considered. Finally, in order not only to apply smart farming technology but also to become a pioneer country in smart farming technology, the innovation capability factor needs to be really improved, especially related to patents, funding, and the structuring of research institutions.

**Table 8.** GCI 4.0 selected pillars and indicators for Indonesia 2019*

| Pillars | Indicators | Score |
|---|---|---|
| Utility Infrastructure | Electricity Access | 94.8 |
| | Electricity supply quality | 94.7 |
| ICT Adoption | Mobile-cellular telephone subscriptions per 100 pop | 99.9 |
| | Fixed-broadband Internet subscriptions per 100 pop. | 6.6 |
| | Internet users % of the adult population | 39.8 |
| Skills | Quality of vocational training | 60.1 |
| | Skillset of graduates | 59 |
| | Digital skills among the active population | 58.5 |
| | Critical thinking in teaching | 53.7 |
| Entrepreneurial culture | Attitudes towards entrepreneurial risk | 58.4 |
| | Growth of innovative companies | 63.8 |
| | Companies embracing disruptive ideas | 55.5 |
| Innovation capability | Multi-stakeholder collaboration | 59.7 |
| | Scientific publications score | 78.2 |
| | Patent applications per million pop. | 1.3 |
| | R&D expenditures % GDP | 2.8 |
| | Research institutions prominence | 10.6 |

* Data from The Global Competitiveness Report 2019, World Economic Forum

In addition to the importance of technological factors, other factors need to be considered if we want to apply IoT smart farming technology to coffee farming. Factors other than technology are actually outside the scope of this research. Still, this information needs to be conveyed as input for future research and as an illustration of the potential for real application. Another important factor in question is the social factor [71-72] and ethics [73], [74]. From the social aspect, research [71] concludes that the involvement of agricultural leaders and the existence of a clear organization are the dominant factors in the real adoption of smart farming technology. Research [72] classifies social problems related to the implementation of smart farming into several classes, including those related to technical adaptation issues, the effects of digitalization on farmers (identity, skills, and livelihood availability), ethical and legal system ownership, the potential for innovation, and business problems (aspects of business), economics, and management. In terms of ethics, research [73] views ethical issues in the application of smart farming can be divided into three: namely, those related to data ownership and access; distribution of power; and impact on human life and society. Research [74] emphasizes the importance of legal aspects of data ownership, clear data regulations, and integrity in data quality to avoid data misuse and the full effectiveness and usability of smart farming.

## 5. Conclusion

This study concludes the list of smart farming technologies for coffee that have the potential to be applied in Indonesia. Those technologies are classified based on their application scope: quality control (including subtopics like coffee quality control), climate monitoring, the anticipation of pest organisms, and coffee processing), coffee production planning, and coffee waste utilization. Quality control in coffee production has become a widely discussed publication topic (91%), of which 45% of it discusses coffee detection quality control. Most of the articles use AI, ML, and DL technology to solve problems in coffee farming. Calculations for AI, ML, and DL can be performed using a cloud platform service on embedded devices. However, doing calculations using cloud platform services needs to consider the availability of telecommunications infrastructure, especially in Indonesia. Regarding infrastructure readiness and the need for smart farming technology for coffee, the island of Java has the most potential for implementing smart farming for coffee as soon as possible. The high potential for application in Java is because the telecommunications technology infrastructure is ready, and the land area and coffee production are large. Regarding human resources and entrepreneurial culture, globally, Indonesia is already at the middle level, so it allows the application of new technology but requires intensive education and training efforts. To become a pioneer in coffee farming and smart farming technology, Indonesia needs to increase its patents nationally, increase research funding and further optimize existing research institutions, especially in AI and IoT. This study can be re-done using the search query and broader database resources. To deepen and understand more about the topic of IoT smart farming in coffee farming, Moreover, to implement IoT smart farming in coffee farming in Indonesia, the Indonesian government needs to ensure the availability and readiness of the Indonesian telecommunication infrastructure. Another important thing is a further study about the communication data needed for IoT smart farming devices to implement AI, ML, and DL technology with appropriate capacity in Indonesia. The two non-technical aspects that need to be considered if we want to implement smart farming in Indonesia are social and ethical.

## Competing Interest

The authors declare no financial or non-financial competing interest.

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