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Advancement of agro-economy and synthetic agro-data generation using creative AI and drone technology

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Abstract

The applications of drones for smart farming are well accepted nowadays. It also results in huge fiscal losses to the agricultural economy. In conventional agriculture, resources are wasted due to the constant and uniform use of pesticides, fertilizers, and pharmaceuticals. Nevertheless, within the existing literature, no comprehensive approach to these difficulties has been discovered. The current research uses drones to irrigate and distribute insecticides, fertilizers, and medicine to necessary crops in sufficient quantities. By understanding current needs, it generates and stores enough synthetic data. Through optimal resource usage and synthetic data production and analysis, it boosts agro-profit.

Keywords

agricultural economy, irrigation using drones, synthetic data, optimal resource usage, boosts agro-profit

I. Introduction

Agriculture is one of the key sectors that propels the Indian economy. The majority of the agricultural area is dependent on rainfall, with about 45% of it being irrigated. Because of this, over 55% of Indian farmers depend on agriculture that is aided by rainfall [1–4]. Numerous problems make it difficult for people to obtain wholesome food, such as severe labor shortages and high labor costs, shifting weather patterns, pest-related crop losses, a lack of funding and agricultural supplies, wasteful input use, and a poor support pricing structure. Agriculture is the largest industry in India, but it has not kept up with other Western countries in terms of implementing new technologies to boost productivity [5–7]. If Indians want to meet these challenges, they will need to employ more sophisticated technologies to find ways to improve the farming methods and practices that are already employed. Agricultural drones help modern farmers overcome these problems. They help to increase production at lower costs by needing less labor from humans and other inputs [7].

Among the most promising industries is agriculture, where drones have the ability to address significant issues. A high-tech makeover is being given to agriculture by drone technology. By delivering accurate 3-D maps for early soil analysis, drones can help with seed planting planning and data collection for managing irrigation and nitrogen levels.

Drone planting technology from startups reduces planting expenses by 85% [8]. These devices inject fertilizer and seed pods into the soil, giving crops all the nutrients they need to thrive. While spraying to ensure uniform coverage, drones can evaluate the landscape. Thus, aerial spraying can be completed five times faster when using drones rather than more conventional technology. One of the main obstacles is inefficient crop monitoring. Drones can be used to create time-series animations that illustrate crop progress and draw attention to production inefficiencies for improved management. Drone sensors are able to identify dryness or the requirement for field maintenance [8, 9]. Drone-borne technology that uses visible and near-infrared light to scan crops can provide health information, alert farmers to disease, and assist farmers in monitoring plant changes. Future unmanned aerial vehicles (UAVs) might be composed of self-governing drones that gather information and perform missions. The biggest obstacles to its implementation are high-quality data collection devices and data-crunching software that can turn that high-tech dream into reality [10]. An agricultural drone is shown in Figure 1.

Most farms worldwide currently lack experience with advanced machine learning technologies, even though artificial intelligence (AI) has many potential applications in agriculture. Weather, soil, and insect activity are just a few of the environmental variables that farming is very susceptible to. For computers to be trained and generate correct predictions, AI systems need a large amount of data [11, 12]. In the case of a big agricultural region, obtaining temporal data is more challenging than obtaining geographical data. For example, most crop-specific data is only available once a year, during the growing season. Since the construction of the data infrastructure takes time, building a reliable machine learning model is a time-consuming process. Because of this, AI typically uses agronomic products—seeds, fertilizer, pesticides, and the like—instead of exact on-the-ground solutions [12].

Figure 1: Agro-attainable drone.

a. Problem statement

Traditional agricultural practices involve the uniform application of water, pesticides, fertilizers, and pharmaceuticals across the entire harvesting zone. It wastes resources during harvesting and causes large financial losses. Even with today's drone-based smart farming, the founder drone handles each distinct component on its own [13, 14]. Thus, another major issue is obtaining adequate agro-data and enhancing the agroeconomic by analysis of such data. As a result, many drones are needed to cover all of these aspects simultaneously. This raises the cost of harvesting and damages the agro-economy [15]. Moreover, one of the main worries is how much storage space the collected data is taking up. All of the modern methods, though, were unable to solve this problem.

b. Motivation

Providing enough water, fertilizers, herbicides, and medications to plants in need are further components of contemporary farming [15, 16]. Rather than spreading these resources evenly throughout the entire farming area, provide the necessary inputs—water, pesticide, fertilizers, medication, or their combinations—in sufficient amounts after identifying a particular plant that requires them. There is little doubt that using this strategy increases earnings while lowering agricultural expenses. It is not easy to integrate these components into a single platform, though [17]. Nonetheless, the current body of study is likewise inadequate in bringing these issues into harmony. This research offers a drone-based solution that can achieve all of these objectives on a single podium as a result.

c. Objectives

This study introduces a cost-effective integrated method for smart firming to close the present research gap. The additional goals of this study are as follows:

1. Expanding this study effort and looking more closely at the current research gaps in the drone-based agile firming strategy to increase the performance of the predicted integrated technique's efficacies in numerous areas by analyzing the agro-data.
2. Introducing a clever farming and gardening method based on drones to cut down on water,

pesticide, fertilizer, and medication waste with the help of AI.

3. Maximize the utilization of space during the storing of the input and output data with the help of a unique data compression technique.

d. Paper organization

This paper is categorized as follows: In order to identify the current and comparable research gaps, Section I gives a general overview of the various drone-based agricultural issues. Section II offers a compelling review that analyzes the advantages and disadvantages of such existing security approaches. Section III illustrates the development of the suggested integrated technique to close the current research gap. In order to implement the suggested technique, Section IV details the Experimental Setup and specifies the parameters needed for result analysis. In order to determine whether this technique is appropriate for smart drone-based agriculture, Section V looks at how well it performs both overall and in each of its component elements. The research is concluded in Section VI, which also foresees the need for additional research to improve this study in the future.

II. Background study

One farming technique that needs a lot of intensive labor is irrigation. Irrigation automation can increase overall production when machines are taught on past weather patterns, soil types, and crop varieties to be farmed. Automation can assist farmers in better managing their water concerns, as irrigation accounts for about 70% of global freshwater consumption. Most farms worldwide currently lack experience with advanced machine learning technologies, even though AI has many potential applications in agriculture [16–18]. Farming involves a great deal of exposure to environmental factors, such as soil, weather, and insect population. India is mostly dependent on agriculture, but it has not done a very good job of implementing modern technology to build high-quality farms. Drones can be used in agriculture to monitor crop productivity, weather patterns, and the communication range between the monitoring regions. They can also be equipped with a wide range of payloads as delivery vehicles, such as sensors, infrared and high-resolution cameras, tracking, and a global positioning system (GPS). High-energy batteries like lithium batteries allow these drones to fly for up to 40 min at a time. Nevertheless, battery life is a problem for drone systems, particularly when a standalone drone maneuver is required [19]. Furthermore, the drone's battery charging problem has not received much notice yet, which could be due to a comprehensive examination. Numerous studies on drone-based agriculture have been carried out. As a result, this part provided a thorough review of drone-based cultivations in order to identify the current research gap and offer a special integrated solution to address this discrepancy [19, 20]. Figure 2 illustrates many components of the agro drone as well as other facets of drone-based agriculture.

Bhattacharjee et al. [21] and Norrman and Johansen [22] claimed that as drones are essential at the start of a crop cycle, the agricultural industry would benefit greatly from their use as the population grows. Data study indicates that it would result in better outcomes and time savings. Crop management will be more successful with systematic monitoring. With the new technology, production will increase faster while consuming less energy. Drones can be used for more than only field and soil research; they can also be used for seeding and fertilizing plants. Problems with agricultural monitoring could also be solved by using drones. To improve current agronomy, the most sophisticated data analysis algorithm and data collection method are still lacking [23]. According to several studies, adding hyperspectral, thermal-spectral, or multispectral sensors facilitates the evaluation of irrigation strategies and helps identify dry spots in the landscape. In order to assess the health of crops, drones can also be used to scan them for visible and near-infrared light. As a result, improved data quality and sophisticated data processing techniques are required to further develop the modern agro-economy.

According to Younes et al. [24], drones can be utilized in agricultural applications to track crop productivity, weather patterns, and the range of wireless sensor networks in monitoring areas. However, researchers note that factors including drone flight duration, power consumption, and communication distance present challenges and limitations to climate monitoring in agricultural applications. The use of magnetic resonant coupling (MRC) for Wireless Power Transfer (WPT) was taken into consideration in this study due to its ability to transfer power and efficiency over tens of centimeters, transfer power in misalignment situations, charge multiple devices simultaneously, and be weather-unresponsive [24–26]. In order

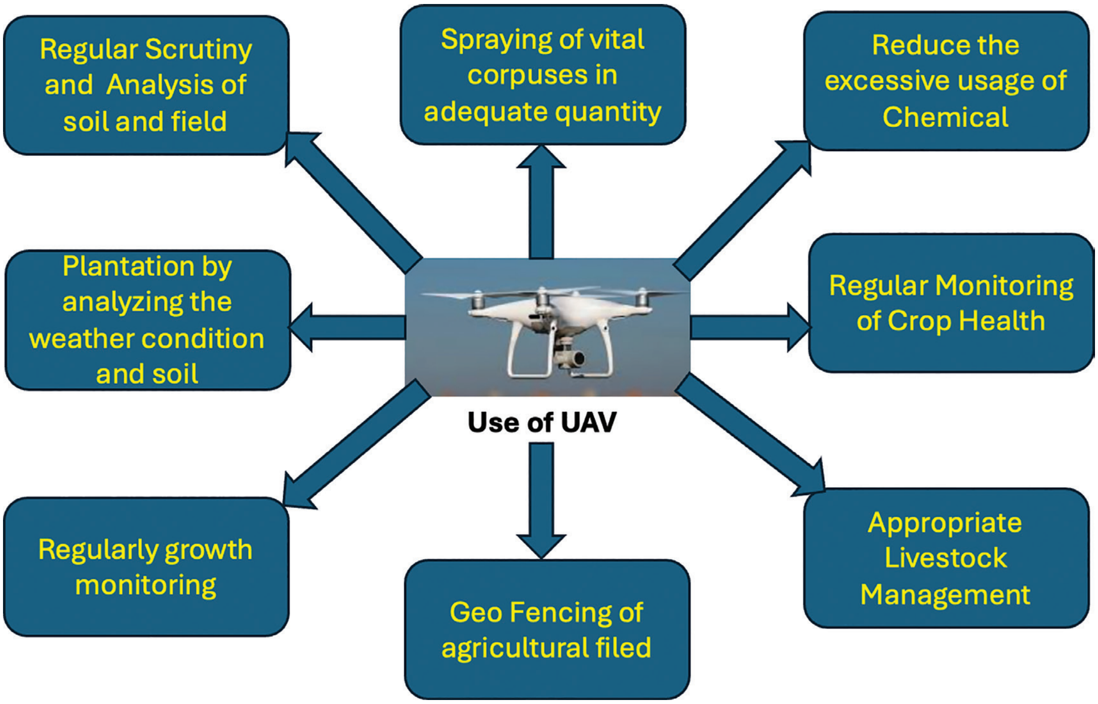

Figure 2: Distinct features and aspects of drone-based agriculture. UAV, unmanned aerial vehicle.

to account for the alignment and misalignment of two coils at different distances, the authors proposed a flat spiral coil (FSC) in the transmitter circuit and a multi-turn coil (MTC) in the reception circuit (drone). WPT was subsequently practically implemented using a solar cell. However, the pertinent agricultural sensors and wireless internet of things (IoT) technologies such as Long Range Wireless Modulation Technique (LoRA) and SigFox for tracking wind direction and speed, soil temperature, CO_2 concentrations, light intensity, barometric pressure, and rainfall are not integrated in this study [27].

Pests are one of the most major factors affecting crops, as they drastically reduce food output [28, 29]. Furthermore, early and accurate detection of pests can reduce losses and improve food quality by allowing farmers to take the necessary preventive measures. The apparent similarities among various insect species make hand investigation a challenging and time-consuming process. As a result, a straightforward drone-based approach was suggested, utilizing a custom CornerNet technique with the DenseNet-100 foundation net. There are three stages to the suggested framework. Sample annotations are created during the initial acquisition of the region of interest and are subsequently used to train the model. The next step involves computing deep key points with the DenseNet-100, which leads to the suggestion of a custom CornerNet [30]. The final step of the one-stage detector CornerNet is to recognize and classify various insect pests. The DenseNet network improves the ability of feature representation and assists the CornerNet model in identifying insect pests as paired key places by incorporating the feature maps from all of its prior layers. But in order to be more effective, this method must produce a more appropriate feature fusion and boost fine-grained pest classification.

To increase agricultural productivity and food management, larger-scale precision agriculture monitoring is desperately needed [31]. While satellite data has been used for land cover classification and farm monitoring on a broader scale during the past few decades, drones are now used for smaller-scale precision agriculture monitoring. It is challenging to track agriculture accurately on a large scale. In this study, a strategy for precision agricultural monitoring—the classification of sparse and dense fields using publicly available satellite data (Landsat 8) and drone data—is given by Alec et al. [32]. In order to minimize the use of drones, an adaptive categorization system that takes into account the picture statistics of the selected area has been developed. Nevertheless, this method falls short in terms of accuracy when it comes to testing and validating data. Table 1 provides

Table 1: Comparison of various drone-based agricultural strategies

Sl. No.	Addressed shortcomings and applied technique	Prevailing limitations
1.	In Refs [28–30], the authors presented the UAV thermal imaging applications in precision agriculture to determine the type of thermal radiation needed for the use and interpretation of thermal data.	Still, the extensive agricultural regions can benefit from cutting-edge technology, including the usage of UAVs.
2.	A technique based on modules for Just-In-Time Specifications of client orders in the aviation manufacturing sector was introduced in Refs [31–32] to provide the freedom to choose a product's modules precisely when needed depending on the lead times of each module.	However, it needs to be expanded by including *ad hoc* and short lead time choices as well as by carrying out the planning in accordance with the presented planning processes.
3.	Drone with IoT for agricultural fields to improve crop quality by combining drones with other machine learning and IoT ideas, the potential for future advancement is increased [33].	The drone can charge while it is functioning on the pitch throughout the day by placing solar panels, which eliminates the requirement for external charging. The categorization of crops and plants based on yield may be another potential use for the SVM.
4.	A compact drone-based strategy, namely, a unique CornerNet strategy using DenseNet-100 as the network's foundation was introduced in Refs [24–35]. Creating sample annotations that will subsequently be utilized for model training and allow for the initial acquisition of the region of interest.	However, to enhance the efficacy of our system for fine-grained pest classification, it must create a more potent feature fusion strategy.
5.	Inexpensive remote sensing instruments and techniques were developed in Ref. [36] to aid smallholder farmers with the study of vegetation factors like NDVI or cropping areas.	Making the system more user-friendly, however, will enable consumers to collect reliable data without paying extra, which will take a lot of work. More education and lobbying efforts are required to make UAV-based remote sensing a common method of acquiring agricultural data.
6.	Adaptive precision agriculture monitoring method development using drone and satellite data for employing drone data and openly accessible satellite data (Landsat 8), the categorization of sparse and dense fields was carried out [37].	The suggested technique's accuracy is decreased by certain misclassified dense pixels that are created near the boundary of the sparse class or the field. To address this weakness, the suggested approach must be enhanced further.
7.	A cutting-edge drone-based remote sensing system, integrated data processing, algorithms, and applications to smart farming were introduced in Ref. [38]. Three imaging modules—multispectral, thermal, and visible video imagers—as well as a high-performance drone are included in the system.	The systematic integration of drone-based remote sensing with drone-based management practices, such as site-specific application of agrochemicals, will be realized further given the rapid advancements in drone technology (payload, flight time, etc.).

IoT, internet of things; NDVI, normalized difference vegetation index; SVM, support vector machine; UAVs, unmanned aerial vehicles.

a more thorough comparison of the numerous drone-based agriculture strategies now in use.

a. Research gap analysis

We have learned from recent literature that drone-based agriculture is not without its share of problems. The absence of appropriate resource management and data processing strategies hinders the development of unique ways for smart agriculture, drone technology, and sophisticated AI-based data processing techniques. Another crucial issue in drone-based smart firming is the employment of sophisticated cameras and sensors [22, 23]. The agro-economy and data analysis may suffer if insufficient and erroneous images and data are captured using used cameras and sensors. Another major challenge with drone-based agriculture is the proper management of space for storing the data and images obtained by sensors and the input camera. As a result, the management of data storage for analysis in order to make precise forecasts from them and take appropriate action has a significant impact on improving the agro-economy [14–16]. However, none of these problems are well addressed in the literature that is currently in publication. Consequently, more research is needed to fill up these gaps in a combinatorial manner.

III. Proposed technique

The proposed architecture consists of the following: (i) marking or guiding the drone to fly over designated agricultural fields; (ii) taking pictures of each plant using a camera (video) installed in the drone and/or sensors installed for monitoring; (iii) analyzing the taken pictures (video) to determine what needs to be done for action; (iv) causing the drone's associated dissemination system to start spreading the necessary appliance in sufficient amounts; and (v) compressing the input image or video for later usage or storage. Figure 3 shows a representative structure of the projected technique.

Figure 3 shows that the proposed integrated technique comprises a few individual components. The first part includes regulating or navigating the drone from a laptop or mobile device using a navigating software application. This step further helps the input drone cover all corners of a specific agro-field and maintain the gap between the plants and the begetter drone. The second step includes capturing a high-resolution image of each plant from a certain height and collecting important information with the attached depth sensor data using the second step. The third step analyzes captured images and collected data from the sensor depending on the various parameters such as color, the shape of the leaves, stems, and Red, Green, Blue (RGB) values, and collected pulses from the depth sensors. It further investigates whether the surroundings of a particular plant are dry or wet from the captured image. It analyzes the collected images and data to determine which substances and in what quantity (such as water, pesticide, fertilizer, medicine, or a combination of these) a particular plant needs. It further decides the adequate quantity of any substance or combination. This phase analyzes the images and makes decisions using advanced image processing techniques and supervised learning. In the final phase, the drone distributes the required substance in an adequate quantity based on the contrived decision from step 4. The final step compressed the captured image and data using

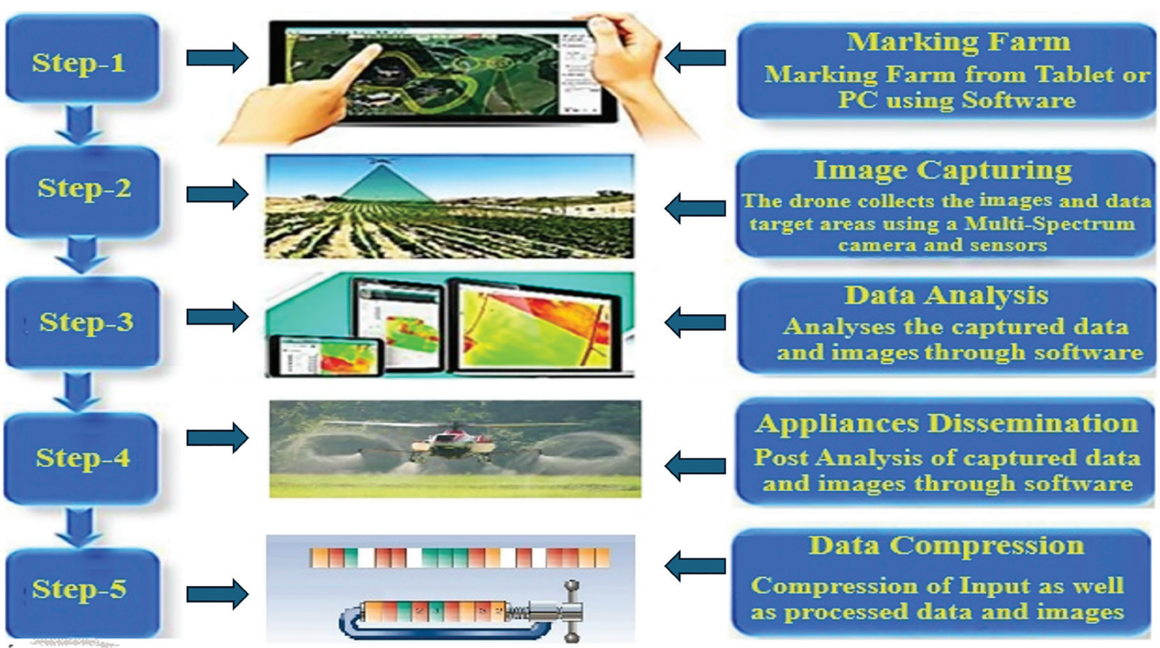

Figure 3: Workings of the proposed technique.

the proposed data compression technique. Each of the steps is described precisely in the following.

a. Marking farm area, capturing images, and collecting data

In the proposed architecture, the IoT sensors are deployed at various farming areas according to their length and width. These IoT sensors collect the information related to the temperature and wetness of their surrounding areas and send it to the antecedent drone. Any smart device such as a mobile or laptop is used to control the begetter drone by adopting any Android/web-based application. At the same time, whenever this begetter drone travels over a specific area along with the instruction of the controlling device, it captures images of the shrubs of that region. After collecting the information from the IoT sensors and the captured images, the artifice drone transmits all the information to the cloud with the help of IoT using an IoT-based transmitter. After collecting the transmitted data and the captured image, they are processed in the next phase of this proposed technique.

b. Analyses of captured images and collected data

Initially, the captured images of crops and vegetables using the high-resolution cameras of used done are taken as inputs from any field area. After that, these images are quantized and calibrated digital numbers (d_n) where n is the number of images. The Spectral Reflectance (Sr_n) from each d_n with the following equation is:

$$Sr_n = Mf_n \times P_n + Ar_n \tag{1}$$

where, reflectance with multiplicative factor is represented as Mf_n, adaptive reflectance factor is represented as Ar_n, and P_n is the pixel values corresponding to each image. At the same time, an adaptive thresholding technique is used to determine the quality of each pixel value with the following equation:

$$T = \mu_n + \sigma_n \tag{2}$$

Here, T_n represents the threshold value determined by calculating the mean and standard deviation images and n is the number of captured images. Depending upon the calculated threshold values, the accuracy rate of selected pixels and the rate of false alarm rate are further calculated with the following formulas to determine the quality of the captured images:

$$Ar = \left(\frac{P_C}{P_T}\right) \tag{3}$$

In Eq. (3), Ar is the overall accuracy rate, P_C is the total number of correctly detected pixels, whereas P_T is the total number of pixels:

$$F_R = \left(\frac{P_c}{P_T - P_I}\right) \tag{4}$$

Equation 4 calculates the rate of false alarms (F_R), which is basically the ratio of ta total number of correctly detected pixels (P_c) and the pixel differences. This pixel difference is further calculated by subtracting the total number of ignored pixels (P_I) from the total pixels (P_T). Then these correctly detected pixels (P_c) are taken and formed the corresponding three-dimensional matrices depending upon the height, width, and dimensions of the corresponding images. The goal of pixel-wise decomposition is to comprehend the contribution of each individual pixel to a classifier's prediction $(f(x))$ during an image classification job. Here, a deep convolutional neural network (CNN) with a wealth of features has been utilized to analyze pixel information. Input, output, many intermediate hidden layers that are convolutional in form, pooling layers, and a fully connected layer are just a few of the layers that make up the building blocks of CNN. The benefit of CNN is underlined by its shared weights, fewer nominal neurons, lack of preprocessing requirements, and ability to accept input images in their raw form. Multiple hidden layers combine to form one layer by multiplication. A CNN model only has two convolutional layers, two pooling layers, and one fully connected layer that assigns the picture to one of the classes in the final layer. By using a multi-layer perceptron, CNN minimizes processing needs step by step. In addition, image processing efficiency is improved when the process is carried out at the resolution level. Additionally, CNN effectively extracts the spatial and temporal information from the input matrices by utilizing the appropriate analyses.

The multilayer perceptron (MLP) model has been used here for processing the collected sensor data. The MLP model is made up of an input layer, many hidden layers, and a classification layer. Here, we build a three-hidden-layer MLP with distinct units such as 10, 20, and 10 units in each hidden layer, respectively. A cross-entropy loss function also serves as its cost function. Additionally, all models are tested on 10% of the data after being trained on 80% of the data. A validation set is utilized with the remaining 10%. In this research, each model has been trained over 1000 epochs using the adaptive gradient technique (Adagrad). The complexity has been minimized for these models using regularization methods and dropout to avoid over-fitting. Additionally, we choose the hyperparameters for these models using fivefold cross-validation. Three types of real-world data, power, loop, and land sensor data, have been considered in this research.

c. Dissemination of appliance

The Cloud application server immediately processes this received sensor information and the images using the proposed integrated machine learning technique [16, 17]. The cloud application server further sends the instruction after processing the input data to a drone for conducting the adjacent action. Such analogous actions could be the circulation of pesticides, water, fertilizer, medicine, or a combination. As soon as the begetter drone receives the information from the cloud application server for sprinkling any innards, it disseminates the required substance in adequate quantity as per the instruction. The proposed framework thus helps optimize the use of agro-utilities within the framework of Industrial Revolution 4.0 (IR4.0) [18].

d. Data compression and storage

Each of the matrices, formed from the input images and drone data sets after processing are taken as input, and the proposed compression technique is applied to them. The proposed compression method operated in two stages: the first stage constructed the character table to be used as a reference throughout the decompression process, and the second stage produced the final compressed codes. At the first stage, redundant elements from the input string array are removed to create the character table (*Text′*). As a result, a second integer array called the frequency table (*Ferq*) is created and contains the frequencies of the matching irredundant items from the character table (*Text′*). Construct the character table by the following equation:

$$CharTab = \binom{Text'_n}{m} \quad (5)$$

In Eq. (5), n is the total number of characters and m is the total number of irredundant characters. Calculate the frequencies of each redundant characters in the character table (*CharTab*) and create a corresponding frequency table (*Ferq*). Sort the frequency table and corresponding character table according to the decreasing order of frequencies. Create the code table with Algorithm 1 using the frequency table (*Ferq*), code table $\langle Code_m \rangle$, and after creation of the code table replace all the characters with the corresponding compressed code from the code table and store the resultant compressed file in the cloud for future reference.

Steps b1 and b2 of Algorithm 1 declare the different variables that are utilized to calculate the compressed codes inside the algorithm description. The compressed codes that match the decimal values of the associated characters are created using the remaining steps, b3 through b45. Here, the ranges of related decimal values are separated into groups during the creation of the compressed code. The relative position values of every character in the character table are used to construct the compressed code. The final code table is created by concatenating the compressed codes. Following generation of the code table, replace each character with the appropriate compressed code and save the resulting compressed file in the cloud for later use.

e. Retrieval of data

In this phase the encoded data is initially retrieved from the cloud and stored temporarily in the primary memory of the drone processing unit. The decompression technique (it comprises the reverse operation of the proposed compression technique) is applied to decompress the compressed data in the input drone. In this phase of decompression, the character table is $(CharTab)$ separated based on the separator (Sep') from the compressed string *CompStr*. Each 8 bits symbol is generated from the *CharStr*. Form the character table from the *CharStr*. Construct the code table from the symbol table by the previously described technique. Similarly, separate each code substring from *CodeStr*. Replace each code substring by the corresponding symbol from the character table comparing from the code table. Finally concatenate all the symbol string into single string and convert it into its original from the binary string to get the original file. After decompression of the compressed data the processed data are sent to the decision-making unit of the input drone for further processing them.

Algorithm 1: Creation of code table

(b1) *a, b, c, d, e* are the ordinary variables where;
(b2) *str*, *str*1, *str*2 are string variables;
(b3) if $m \geq 0$ and $m \text{″} 2^7$
(b4) $a = a + 5$; // if $m \text{″} 40$ put $a = 4$
(b5) if $m \geq 0$ and $m \leq \left(2^a - a\right)$
(b6) for $b = 0$ to a
(b7) $c = m \div 2^b$;
(b8) $d = c\, modulo\, 2^b$;
(b9) Concatenate (str, d); //concatenation of strings
(b10) end for
(b11) $Code_m = str$;
(b12) end if
(b13) if $m > \left(2^a - a\right)$ and $m \leq \left(2^{(a+1)} - (2 \times a)\right)$
(b14) $e = \left(2^a - 4\right)$; //prefix code generation for second level
(b15) for $b = 0$ to a
(b16) $c = e \div 2^b$;
(b17) $d = c\, modulo\, 2^b$;
(b18) Concatenate $(str1, d)$; //concatenation of strings
(b19) end for
(b20) Repeat step (b6) to (b10);
(b21) Concatenate $(str2, str1, str)$ //concatenation of strings
(b22) $Code_m = str2$;
(b23) end if
(b24) if $m > (2^{(a+1)} - (2 \times a)$ and $m \leq \left(\left(3 \times 2^a\right) - (3 \times a)\right)$
(b25) $e = \left(2^a - 3\right)$ //prefix code generation for third level
(b26) Repeat step (b15) to (b22);
(b27) end if
(b28) if $m > \left(\left(3 \times 2^a\right) - (3 \times a)\right)$ and $m \leq \left(2^{(a+2)} - (4 \times a)\right)$
(b29) $e = \left(2^a - 2\right)$;
(b30) Repeat step (b15) to (b22);
(b31) end if
(b32) if $m > \left(2^{(a+2)} - (4 \times a)\right)$ and $m \leq 2^{(a+2)}$
(b33) $e = \left(2^a - 1\right)$; // prefix code generation for 4th level
(b34) Repeat step (b15) to (b22);
(b35) end if
(b36) $e = 2^a$; //prefix code generation for 5th level
(b37) for $b = 0$ to a
(b38) Repeat step (b16) to (b17);
(b39) Concatenate (d, Sep); // concatenation of strings
(b40) end for
(b41) end if
(b42) if $m \geq 0$ and $m \text{″} 2^8$
(b43) $a = a + 6$;
(b44) Repeat step (b5) to (b40)
(b45) end if

IV. Assessment platform

The performance assessment of the proposed technique on different aspects can be counseled along with the few important and concerned parameters related to it. Therefore, this part contains all necessary information pertaining to our experiment, such as the experimental setup, information on the kind and quantity of inputs, key definitions that will be utilized in the result analysis section, and so on.

a. Experimental setup

The Hexa and Agro Drones, GPS positioning multifunction cameras are taken for the experimental setup. Consequently, the multifunctioning sensors for smart agriculture are deployed to collect different data. At the same time, android-based drone applications are used to control and handle the drone. A private cloud is set up to store the process data collected by the deployed sensors and captured image by the input high-resolution camera from a different angle after compressing them. The proposed data analyses and compression technique is developed in Python with the Ubuntu 16.04 LTS platform. For the performance evaluation of the proposed compression technique, Standard calligraphic text files have been downloaded and tested its performance using them in different aspects.

b. Some important definition:

This section provides numerous definitions that will be used in the section on result analysis. The proposed data analyses can be measured in terms of Accuracy Percentage. Time complexity of the proposed integrated technique can be measured by measuring Cyclomatic Complexity. Time efficiency can be measured by measuring the throughput offered by the entire system, and finally the efficiency of the proposed compression technique can be calculated by measuring bits per code (BPC) and compression percentage (CP). Each of the parameters is addressed in further detail in the following subsections.

a.i. Accuracy percentage

The accuracy percentage measures the number of right answers in relation to the number of questions in a certain situation [14]. The acceptability of the chosen approach in the case base management system is determined by its ability to deliver a higher accuracy percentage. It can be expressed as follows:

$$\text{Accuray Percentage} = \frac{\text{Total correct decisions}}{\text{Total number of instances}} \times 100$$

A system is stated to be efficient if it generates a larger proportion of accuracy or vice versa, according to the definition. The performance of entire system is dependent on the suggested analytical technique. Therefore, the correctness of the appropriately chosen judgment is critical in our suggested system.

a.ii. BPC

After compression, the compressed code is formed out of certain binary bits. The average amount of bits required to specify a compressed code in any compression technique is known as BPC [15]. The following formula is used to determine the BPC:

$$BPC = \left(\frac{\text{File Size after compression}}{\text{Size of input file}} \times 8 \right) \tag{7}$$

According to Eq. (6) and convention, if any data compression technique offers lower BPC, the used compression technique is said to be efficient or vice versa.

a.iii. CP

The CP is the measurement of compression that we obtained in relation to the input file size after applying a compression method to that input file [16]. The CP can be expressed as follows:

$$CP = \left(\frac{\text{Input File Size} - \text{Output File Size}}{\text{Input File size}} \times 100 \right) \tag{8}$$

According to the definition, if any compression technique offers higher CP, it is said to be efficient or vice versa.

a.iv. Cyclomatic complexity

The Cyclomatic Complexity measures the effectiveness of the employed system and source program in solving any specified job. It is often measured by creating a Control Flow Graph of the program module, which counts the total number of linearly independent pathways through a utilized program module [12, 20]. It may be computed as follows:

$$M = \left(E - N + \left(2 \times P \right) \right) \tag{9}$$

Table 2: Significance for various ranges of Cyclomatic Complexities

Cyclomatic complexity	Evolution
1–10	A simple program, highly efficient, and low risk
11–20	More complex, moderate inefficiency, and risk
21–50	Highly complex, less efficient, and high risk
>50	Unstable, inefficient, and unreliable

In Eq. (8), M stands for Cyclomatic Complexity, E stands for the number of edges on the control flow graph, N stands for the number of nodes in the graph, and P stands for the number of connected components at the graph. Table 2 defines the significances for various ranges of Cyclomatic Complexities.

One of the essential factors for measuring the time efficiency of any strategy, according to the definition, is the Cyclomatic Complexity generated by that technique. Therefore, the performance of the proposed technique, as well as the reasoning system and other important machine learning systems, has been evaluated and shown in the results section. In the next section, they are compared to illustrate the superiority of the proposed technique over them.

a.v. Throughput (TP)

TP is the quantity of work completed in a given length of time. It is used to calculate the effectiveness of a specific procedure [10, 21]. We have calculated the TP for compression using the following formula:

$$TP(\text{Compression}) = \left(\frac{\text{Compressed File Size}}{\text{Compression Time}}\right) \quad (10)$$

When a data compression approach provides a better throughput for any data set, it is considered to be time efficient, or vice versa. As a result, the suggested technique's time efficiency may be judged by its capacity to provide higher throughput.

V. Result analysis

This part measures the performance of the proposed integrated technique as well as the many parameters described in the Assessment Platform section. Furthermore, the suggested approach's performance in several aspects is compared with the comparable current technique in this part to demonstrate its superiority over them. In this part, the performance of the suggested integrated technique is divided into three categories to meet the numerous stated objectives. The first component of this section examines the accuracy rate provided by the suggested approach to analyze the input data and pictures to validate its decision-making capabilities. The second half of this section examines the suggested compression technique's ability to reduce file size. Finally, the final section demonstrates its time efficiency and analyses the time complexity.

a. Analysis of capacity to offer accuracy percentage

The ability of the suggested integrated approach and a few contemporary similar procedures to supply a accuracy percentage is estimated and shown in Figure 4 based on Eq. (6). It further validates the proposed approach's superiority over the other existing techniques to provide a larger accuracy percentage and decide.

Figure 4 shows that the proposed integrated technique outperforms other existing data analysis techniques such as weighting, clustering, outliers, and internal case detection (WCOID), clustering, outliers, and internal case detection (COID), condensed nearest neighbor (CNN) Rule, recurrent neural network (RNN), and instance-based learning (IBL). The results reveal that the proposed approach has the greatest Accuracy Percentage among the well-known data analysis techniques provided. As a result, we may infer that the suggested approach can make more correct judgments than the others, which supports our first and second aims.

b. Analysis of capacity to reduce file size and offer space efficiency

Space efficiency is one of the most important aspects for large data processing. Therefore, the used compression technique to reduce file size plays an important role in this aspect. This section therefore inspects the capacity of the proposed compression technique to minimize the file size in terms of BPC and CP. With the help of Eqs (7) and (8), the corresponding BPC and CP are calculated for the proposed compression technique and other related existing data

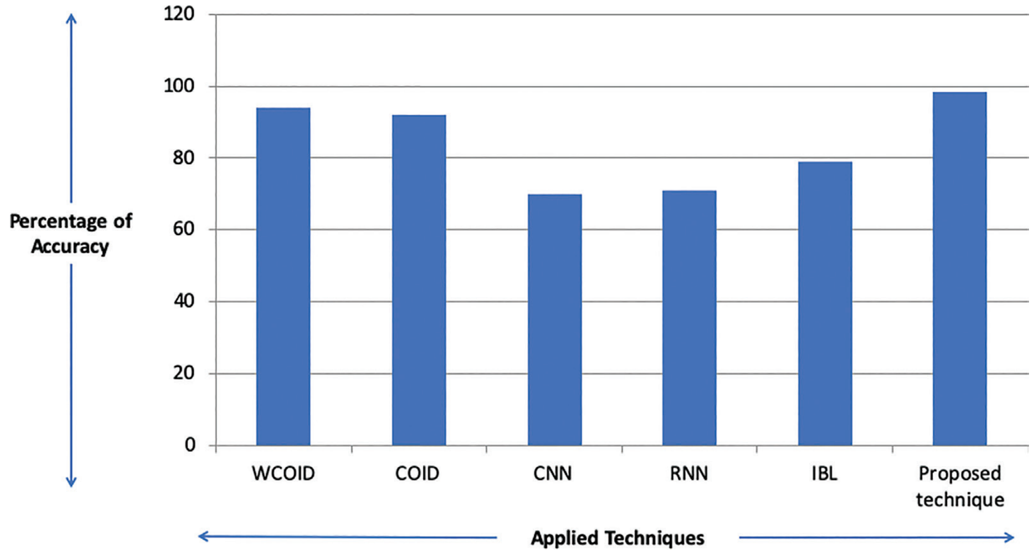

Figure 4: Accuracy percentage offered by various techniques. CNN, convolutional neural network; COIDs, clustering, outliers, and internal case detection; IBL, instance-based learning; RNN, recurrent neural network; WCOID, weighting, clustering, outliers, and internal case detection.

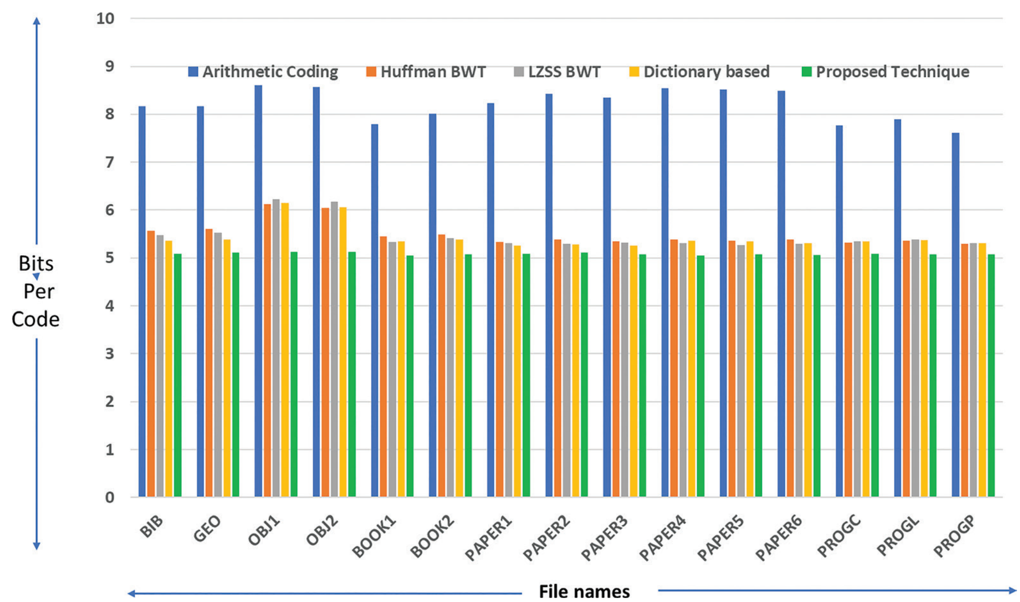

Figure 5: BPC offered by different compression technique. BPC, bits per code.

compression techniques. The corresponding results are further plotted in Figures 5 and 6.

Various Standard calligraphic texts are used as input files to test the performance of the suggested and their associated data compression algorithms in terms of BPC. Figure 5 demonstrates that the suggested approach has the lowest BPC than the other similar compression techniques, demonstrating its superiority in terms of file size reduction and space efficiency over the other stated strategies. In Figure 6, the efficiency of the proposed approach and other comparable compression techniques is computed and shown.

CPs for several compression algorithms have been computed here, with input sizes ranging from 50 GB to 1 TB. Figure 6 further demonstrates that the

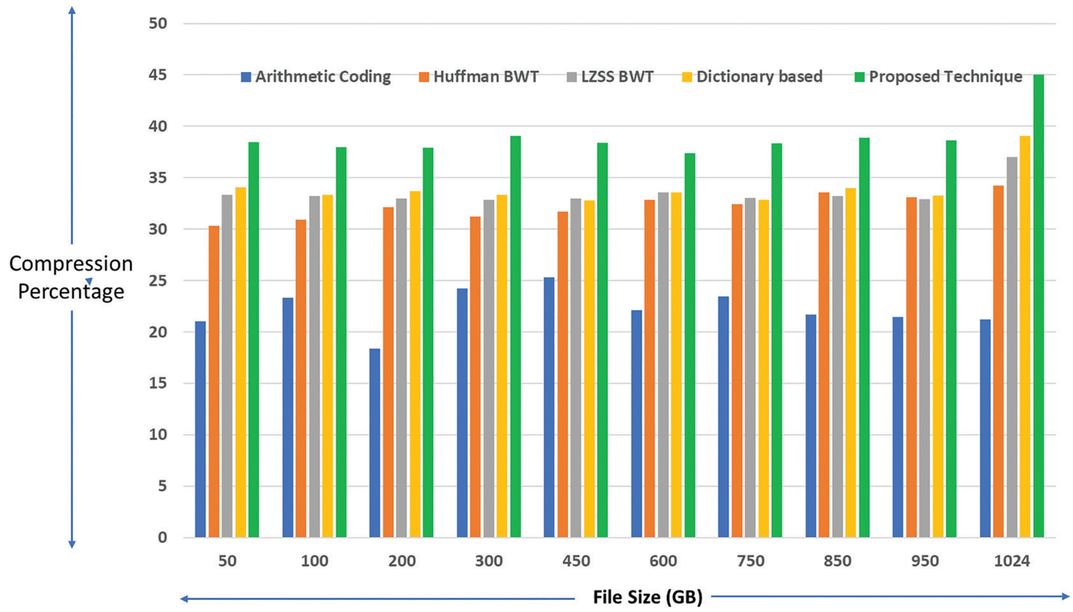

Figure 6: Compression percentage.

proposed approach consistently provides the highest CP. As a result, according to the definition, the suggested approach is more efficient than the other stated data compression strategies in reducing file size. As a result, Figures 5 and 6 support the third goal of this study.

c. Analysis of time complexities and time efficiencies

According to the definition of Cyclomatic Complexity, it aids in determining the temporal complexity of any algorithm. The Cyclomatic Complexities of various data analyses have been determined using Eq. (9) and Table 2 and are displayed in Table 3.

Table 3 shows the proposed technique has the lowest Cyclomatic Complexity compared with alternative data analytical systems. At the same time, according to definition and Table 2, a source program is deemed to be time-efficient if it has a reduced Cyclomatic Complexity in any case. Table 3 shows that the proposed technique is more time-efficient than other existing data analysis techniques for feeding the large data set. Along with these realities, the suggested integrated approach supports the first and second goal of this research, respectively. The time efficiency of the proposed technique is further investigated by calculating the TPs offered during encoding and decoding with the help of Eq. (10). The examined results are further plotted in Figure 7.

Table 3: Cyclomatic Complexities, offered by various data analysis techniques

Applied technique	Cyclomatic complexity
WCOID	6
COID	7
CNN rule	5
RNN technique	5
IBL	8
Proposed integrated technique	3

CNN, condensed nearest neighbor; COID, clustering, outliers, and internal detection; IBL, instance-based learning; RNN, recurrent neural network; WCOID, weighting, clustering, outliers, and internal cases detection.

According to Figure 7, as file sizes increase, so do the throughputs for both encoding and decoding. Therefore, we can see that both encoding and decoding yield higher throughputs on all occasions. Consequently, Table 3 and Figure 7 show that the proposed integrated strategy has less time complexity and better time efficiencies than other similar current data analysis approaches, which satisfies our first and second objectives.

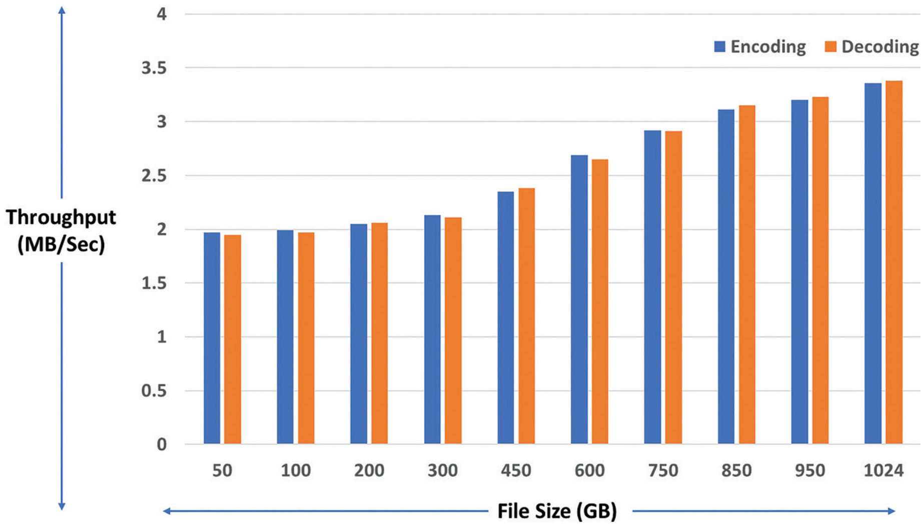

Figure 7: TPs, offered during encoding and decoding. TPs, throughputs.

VI. Conclusion and future work

The collection of information in the form of images and sensory data about the conditions of crops, health of the crops and so on, are very crucial information in modern agriculture. Other components of sophisticated farming include the proper distribution of pesticides, fertilizer, water, and medication to necessary plants. Instead of distributing such resources equally throughout the whole farming area, distribute enough vital inputs such as water, insecticide, fertilizer, medication, or their combinations after identifying a specific undernourished plant. Apart from that, storage space consumption to store the collected data and captured images are also a very serious concern. However, the current literature fails to address all these aspects of smart agriculture in an integrated way. Therefore, drones are being used in a novel way to irrigate and the provision of insecticides, fertilizers, and medication to needed crops. As a result, it generates and stores sufficient synthetic data by analyzing current requirements. As the drone travels around the field, the high-resolution camera connected to it records the images of each plant and its surroundings. The drone analyzes the collected image using powerful image processing and supervised learning techniques to determine the needs of each plant. Simultaneously, it applies pesticides, fertilizers, water, or medication to each shrub in the proper amount after analyzing the stored synthetic data. Aside from that, it makes better use of storage space by introducing a new data compression approach that improves data integrity even more. In Result Analysis Figure 4, Table 3 and Figure 7 justify that the proposed integrated technique is efficient to analyze the captured image and collected data and taking efficient decisions with adequate time efficiency. Consequently, Figures 5 and 6 justify its space efficiency. However, this study effort will need to expand in the future to cover more agricultural difficulties as well as data security concerns.

References

[1] G.-J. Higinio, J. Martínez-Sánchez, M.Bueno, and P. Arias. “Unmanned aerial systems for civil applications: A review.” Drones 1, no. 1 (2017): 2.

[2] M. Gaetano, and G. Modica. “Applications of UAV thermal imagery in precision agriculture: State of the art and future research outlook.” Remote Sensing 12, no. 9 (2020): 1491.

[3] A. D. Boursian, M. S. Papadopoulou, P. Diamantoulakis, L.-T. Aglaia, P. Barouchas, G. Salahas, G. Karagiannidis, S. Wan, and S. K. Goudos. “Internet of things (IoT) and agricultural unmanned aerial vehicles (UAVs) in smart farming: A comprehensive review.” Internet of Things 18 (2022): 100187.

[4] Y. Zhao, “Key technology research on decentralized Internet-based smart agriculture platform,” Applied Mathematics and Nonlinear Sciences (2024).

[5] S. C. Hassler and B.-G., Fulya “Unmanned aircraft system (UAS) technology and applications in agriculture.” Agronomy 9, no. 10 (2019): 618.

[6] B. J. G. Arnal. “A review on the use of unmanned aerial vehicles and imaging sensors for

monitoring and assessing plant stresses." Drones 3, no. 2 (2019): 40.

[7] B. Cui, L. Liang, B. Ji, L. Zhang, L. Zhao, K. Zhang, F. Shi, and J. C. Créput, "Exploring the YOLO-FT Deep Learning Algorithm for UAV-Based Smart Agriculture Detection in Communication Networks." IEEE Transactions on Network and Service Management (2024).

[8] B., Jens, F. Belkadi, C. Hupays, R. K. Gupta, F. Bitte, G. Lanza, and A. Bernard. "A modularbased approach for Just-In-Time Specification of customer orders in the aircraft manufacturing industry." CIRP Journal of Manufacturing Science and Technology 21 (2018): 61-74.

[9] S. Bhattacharjee, L. B. A. Rahim, J. Watada, and A. Roy. "Unified GPU technique to boost confidentiality, integrity and trim data loss in big data transmission." IEEE Access 8 (2020): 45477-45495.

[10] I. M. Kulmány, A. Bede-Fazekas, A. Beslin, Z. Giczi, G. Milics, B. Kovács, M. Kovács, B. Ambrus, L. Bede, and V. Vona. "Calibration of an Arduino-based low-cost capacitive soil moisture sensor for smart agriculture", Journal of Hydrology and Hydromechanics (2022):70(3):330-40.

[11] S. Bhattacharjee, M. Chakkaravarthy, and D. M. Chakkaravarthy. "GPU-based integrated security system for minimizing data loss in big data transmission." In Data Management, Analytics, and Innovation: Proceedings of ICDMAI, Springer Singapore (2019):2:421-435.

[12] B. Farouk, J. Buergin, R. K. Gupta, Y. Zhang, A. Bernard, G. Lanza, M. Colledani, and M. Urgo. "Co-definition of product structure and production network for frugal innovation perspectives: towards a modular-based approach." Procedia Cirp, (2016): 50 :589-594.

[13] M. U.M. Rao, and B. B. V. L. Deepak. "Review on application of drone systems in precision agriculture." Procedia computer science 133 (2018): 502-509.

[14] R. Abderahman, A. Abdollahi, K. Rejeb, and H. Treiblmaier. "Drones in agriculture: A review and bibliometric analysis." Computers and electronics in agriculture 198 (2022): 107017.

[15] V. Choudhary, P. Guha, S. Mishra, A. Singh, V. Sharma, and R. K. Dhanaraj, Smart production monitoring using drones in cyber-physical agricultural systems." InAgri 4.0 and the Future of Cyber-Physical Agricultural Systems, (2024):pp. 197-218, Academic Press.

[16] S. A. Kumar, J. Saha, R. Ray, S. Sircar, S. Dutta, S. P. Chattopadhyay, and H. N. Saha. "IOT-based drone for improvement of crop quality in agricultural field." In 2018 IEEE 8th Annual Computing and Communication Workshop and Conference (CCWC), pp. 612-615. IEEE, 2018.

[17] J. A. Mahmood, H. M. Jawad, R. Nordin, S. K. Gharghan, N. F. Abdullah, and M. J. Abu-Alshaeer. "Wireless power transfer with magnetic resonator coupling and sleep/active strategy for a drone charging station in smart agriculture." IEEE Access 7 (2019): 139839-139851.

[18] L. B. A. Rahim, K. M. Kudiri, and S. Bhattacharjee. "Framework for parallelisation on big data." PloS one 14, no. 5 (2019): e0214044.

[19] S. Bhattacharjee, L. B. A. Rahim, and I. B. A. Aziz. "Hiding of compressed bit stream into audio file to enhance the confidentiality and portability of a data transmission system." In 2015 International Symposium on Mathematical Sciences and Computing Research (iSMSC), pp. 196201. IEEE, 2015.

[20] C. A. Toledo, A. M. Villegas, L. A. Muñoz, "Model based on the principles of smart agriculture to mitigate the effects of frost and improve agricultural production in the Cundiboyacense plateau", International Journal on Smart Sensing and Intelligent Systems, (2022).

[21] S. Bhattacharjee, L. B. A. Rahim, A. W. Ramadhani, M. Chakkaravarthy, and D. M. Chakkravarthy. "A study on seismic big data handling at seismic exploration industry." In Intelligent Computing and Innovation on Data Science: Proceedings of ICTIDS 2019, pp. 421429. Singapore: Springer Singapore, 2021.

[22] F. P. C. Norrman, and K. Johansen. "Agricultural innovation and the role of institutions: lessons from the game of drones." Journal of Agricultural and Environmental Ethics 32 (2019): 681-707.

[23] V. Kaliannan, and F. K. A. Saidi, "Intelligent Computing with Drones and Robotics for Precision Agriculture." InIntelligent Robots and Drones for Precision Agriculture 2024:pp.1-17. Cham: Springer Nature Switzerland.

[24] A. Younes, N. Almaadeed, S. Al-Maadeed, and O. Elharrouss. "Applications, databases and open computer vision research from drone videos and images: a survey." Artificial Intelligence Review 54 (2021): 3887-3938.

[25] A. M. W. Li, M. M. Cheema, S. Hussain, A. Shaheen, B. Aslam, C. Liu, and A. Ali. "Assessment of optimal flying height and timing using high-resolution unmanned aerial vehicle images in precision agriculture." International Journal of Environmental Science and Technology (2021): 118.

[26] F. Ahmad, A. Farooq, L. Goparaju, J. Rizvi, "The Geospatial Understanding of Climate-Smart Agriculture and REDD+ Implementation: Indian Perspective," Ekológia (Bratislava), (2020): 39:1: 72-87.

[27] S. Bhattacharjee, L. B. A. Rahim, and I. B. A. Aziz. "A security scheme to minimize information loss during big data transmission over the internet." In 2016 3rd International Conference on Computer and Information Sciences (ICCOINS), pp. 215-220. IEEE, 2016.

[28] S. Bhattacharjee, L. B. A. Rahim, and I. B. A. Aziz. "A Lossless compression technique to increase robustness in big data transmission system." International Journal in Advances in Soft Computing and Its Application (2015).

[29] S. Meivel, and S. Maheswari. "Remote sensing analysis of agricultural drone." Journal of the Indian Society of Remote Sensing 49 (2021): 689-701.

[30] S. Vishnoi, and R. K. Goel, " Climate smart agriculture for sustainable productivity and healthy landscapes". Environmental Science & Policy. (2024)151:103600.

[31] A. Waleed, M. Masood, A. Javed, M. Nawaz, and S. Albahli. "Custom CornerNet: a drone-based improved deep learning technique for large-scale multiclass pest localization and classification." Complex & Intelligent Systems 9, no. 2 (2023): 1299-1316.

[32] Z. Alec, S. A. Wheeler, and H. Sun. "Flying over the farm: Understanding drone adoption by Australian irrigators." Precision agriculture 22, no. 6 (2021): 1973-1991.

[33] C.-P. Gonzalo, H. Loayza, S. Palacios, M. Balcazar, M. Carbajal, and R. Quiroz. "Development of low-cost remote sensing tools and methods for supporting smallholder agriculture." Applied Geomatics 12 (2020): 247-263.

[34] D. Murugan, A. Garg, and D. Singh. "Development of an adaptive approach for precision agriculture monitoring with drone and satellite data." IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing 10, no. 12 (2017): 5322-5328.

[35] C. Ching-Ju, Y.-Y. Huang, Y.-S. Li, Y.-C. Chen, C.-Y. Chang, and Y.-M. Huang. "Identification of fruit tree pests with deep learning on embedded drone to achieve accurate pesticide spraying." IEEE Access 9 (2021): 21986-21997.

[36] D. Huo, A. W. Malik, S. D. Ravana, A. U. Rahman, and I. Ahmedy, " Mapping smart farming: Addressing agricultural challenges in data-driven era". Renewable and Sustainable Energy Reviews. (2024)189:113858.

[37] P. K. R. Maddikunta, S. Hakak, M. Alazab, S. Bhattacharya, T. R. Gadekallu, W. Z. Khan, and Q.V. Pham. "Unmanned aerial vehicles in smart agriculture: Applications, requirements, and challenges." IEEE Sensors Journal 21, no. 16 (2021): 17608-17619.

[38] I, Yoshio, and M. Yokoyama. "Drone-Based Optical, Thermal, and 3d Sensing for Diagnostic Information in Smart Farming–Systems and Algorithms–." In IGARSS 2019-2019 IEEE International Geoscience and Remote Sensing Symposium, pp. 7266-7269. IEEE, 2019.