Research Article

IOT-Based Pest Classification And Automatic Irrigation For Precision Agriculture Using Wireless Sensor Networks

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Abstract: Automatic pest classification is a very important step to protect the agricultural crops against the attack of pest. This helps to increase the crop yield by reducing the pests that affect agricultural productivity. In addition, automatic irrigation systems aid in the enhancement of agricultural land productivity by computing optimal amount of water required by the plants. In this research, we proposed a new technique called IoT-based pest classification and automatic irrigation algorithm (IPCAI) using wireless sensor networks. In this technique, sensors like moisture sensor, temperature sensor and camera sensors are integrated to Arduino Microcontroller module. The data acquired by these sensors are processed using Raspberry Pi module that is connected to the cloud. The proposed IPCAI machine learning algorithm is embedded into the Raspberry Pi module that classifies the type of pest and also computes the optimal amount of water required by the crops. Based on the type of pest being detected, suitable pesticide is sprayed to the crops to improve the crop yield. This helps in the prevention of spreading of pests. It was found that the proposed algorithm classifies 40 different type of pest with very high accuracy. In addition, the proposed automatic irrigation system helps to conserve enormous quantities of water. The IoT-module connected to the Raspberry Pi helps to upload the data collected by the sensors, pest classification result, and water requirement result to the cloud. From the cloud, the data is transmitted to the farmer's mobile, using which the famers can continuously monitor the crop land from remote locations. The proposed pest classification algorithm achieved high specificity of 95.86% with a precision rate of 96.69%.

Keywords: Wireless sensor networks, machine learning, pest classification, automatic irrigation, cloud.

1. Introduction

Precision agriculture is a concept used for implementing latest tools and techniques to improve the productivity of agricultural land. Precision agriculture is integrated with the Internet of Things (IoT) to provide remote control over the agricultural land by the famers. Further various wireless sensor networks are implemented for monitoring the physical parameter [1]. These physical parameters include temperature, pressure, moisture content, soil pH, texture, climatic conditions, fertilizer content, mineral content etc [2]. Based on the values of these parameters, various processing is done to make decisions that helps to improve the productivity. Further, it has been estimated that by the year 2025, the agricultural IoT market will further expand to around 16-17% [3]. Another main goal of precision agriculture is to reduce the environmental impacts. The impacts due to over irrigation, excessive usage of pesticides and fertilizers, etc., can be reduced by precision agricultural techniques [4]. The data captured using the wireless sensor network are analysed using various techniques like artificial intelligence, machine learning, deep learning etc [5]. With the rapid increase in the population there is a huge necessity for the increase in agricultural produce [6]. This is essential to satisfy the growing needs of the human population. It has been estimated that by the year 2050, the agricultural produce must increase by around 70%. Thus, there is a great necessary for the implementation of precision agriculture [7]. Today, with the rapid development of internet technology, there is greater connectivity to all parts of the world even to the rural areas. Thus, precision agriculture combined with IoT systems can be easily implemented in all the rural regions where there is cultivation [8]. Techniques like fog computing, cloud computing are used for the computation of various parameters necessary for enhancing the quality of agriculture [9]. Scalability and security are the main advantages of using wireless sensor networks for the precision agriculture. In addition, these devices provide long range transmission and low power consumption [10]. Cloud computing is actively used for various processing of the data acquired by sensors and is performed in the cloud. Since the cloud has high storage capabilities, huge amount of big data can be easily stored and processed using the cloud [11]. The farm lands are also monitored using drone cameras and Raspberry Pi cameras. The images and videos captured by these devices can be used for various applications like finding the presence of animals, pests etc. Based on these findings alert signal is sent to the farmers so that immediate action can be taken [12]. The storage and processing capabilities of sensor nodes are increasing rapidly with the advancement in the MEMS technology. Thus these sensors are actively deployed in the precision agricultural systems [13]. Precision agriculture helps the farmers to increase their profit and simultaneously helps to increase the sustainability of agriculture. This helps to increase the reliability and quality of the crops as well. Further, the techniques employed in precision agriculture helps in automating various activities that reduces the workload of the farmers [14].

2. Literature survey

Garcia et al. [15] presented a survey on IoT-based smart irrigation framework in which irrigation system was automated for efficient water conservation. Wireless sensor networks that are employed for the acquisition of physical parameters were discussed. Further, the usage of internet technology for the remote monitoring by the farmers was also discussed. Sanjeevi et al. [16] proposed a new scheme for precision agriculture and farming using IoT and wireless sensor network systems. The main aim was the maximization of throughput and minimization of latency. Further, the proposed scheme achieved increased coverage area along with least mean square error and enhanced signal to noise ratio. Torky et al. [17] presented a technique for precision agriculture in which blockchain was integrated with the precision agricultural discipline. Here, IoT systems were integrated with the blockchain to provide immutable and decentralized architecture. This scheme provided transparent and more reliable solutions for implementing precision agriculture. Enhanced agricultural productivity was observed in this study. Lin et al. [18] proposed a new scheme for fertigation management using IoT. The main objective was to optimise the amount of fertilizer to be used in the agricultural land. This scheme attained long term management of fertilizer usage to ensure sustainability. The optimization was achieved using a novel genetic hybrid algorithm. This algorithm was used to estimate the accurate amount of fertilizer necessary for agriculture. Zervopoulos et al. [19] presented a scheme for the synchronization of wireless sensor networks used for precision agriculture. Synchronization is used for achieving time correlated measurements. The accuracy of time correlation helped to achieved improved precision agriculture results. The clock of the sink node was used in synchronization to achieve effective, low-cost synchronized measurements. Popescu et al. [20] designed a scheme for intelligent monitoring to improve crop productivity in precision agriculture. Two objectives were focussed namely, the design of unmanned aerial vehicles and the implementation of effective algorithms that can be used for the processing of the acquired sensor data. Based on these objectives a new model for improving the performance of ecological agriculture was designed and implemented. Keswani et al. [21] proposed an irrigation control system using self-driven precision agriculture. This system was based on the analysis of big data generated using IoT systems. The scheme was designed such that it was weather dependant and zone specific. The moisture content of the soil was detected and based on the content of moisture the control system was automated. Singh et al. [22] designed an architecture for precision agriculture based on wireless sensor networks in greenhouses. The architecture was designed for enabling the transmission of data at low cost over long distances. It was found that physical parameters like temperature and humidity have a greater effect over the performance of the wireless sensors. Khanna et al. [23] presented a survey on the impact of IoT on precision agriculture. The authors presented the evolution history of IoT, how it can be integrated with the precision agricultural systems and its implications over the farmers. The remote control of the agricultural land through the smartphones were discussed in detail along with the drawback of the automation systems. Sureephong et al. [24] presented a comparison of different types of soil sensors used for the automation of irrigation in precision agriculture. Two types of sensors were considered for the analysis that included the frequency domain sensors and the resistor-based sensors. The advantages along with the power requirements, range, and endurance of these sensors was evaluated and compared.

3. Objective

The main objective of the proposed system is to classify the type of pest that attacks the crops. This is used for the selection of suitable pesticide to destroy the pest variety. The second objective is to identify the exact amount of water required by the crops to avoid over irrigation and also for conservation of water.

4. Proposed Methodology

The proposed methodology includes two main objectives namely, the classification of pest category and the adaptive irrigation system. Pest classification aids in the selection of suitable pesticide to kill the pests that improves the productivity. Adaptive irrigation helps to select suitable amount of water to water the crops based on the temperature and moisture level of the soil.

4.1. IoT-based Pest Classification and Automatic Irrigation System

The Internet of Things (IoT) is used popularly as a base for the precision agriculture as it helps in remote monitoring by the farmers. IoT helps in the data collection and storage at the cloud. From the cloud this data can be accessed from any part of the world. This is shown in Figure 1.

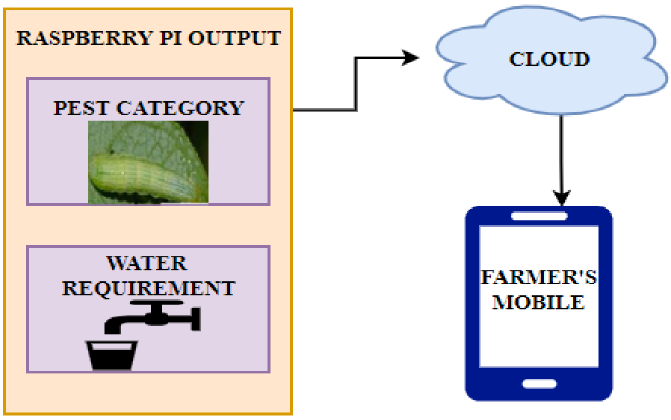

Figure 1. IoT-based Pest Classification and Automatic Irrigation System

Figure 1 illustrates the IoT-based pest classification and automatic irrigation system. In this system, two main components are transferred to the cloud. These components include, pest classification result and the water requirement level. The pest classification result is obtained using a new Minkowsky Distance based Pest Classification (MDBPC) algorithm and the water requirement level is obtained using Temperature and Moisture based Adaptive Irrigation (TMBAI) algorithm. These two results are then transmitted to the cloud. The cloud transfers these values to the mobile phone of the farmers. Using the mobile phone, the farmers can monitor and identify the correct pesticide and water quantity required for irrigation. That is the farmer can decide when to start and stop the irrigation process.

4.2. Proposed architecture of IoT-based Pest Classification and Automatic Irrigation System

The proposed architecture is based on Arduino microcontroller module. This module is used for acquiring the input from the sensors. Three sensors are used namely, the moisture sensor, temperature sensor and the Raspberry Pi camera sensor. The microcontroller is activated using a power supply module.

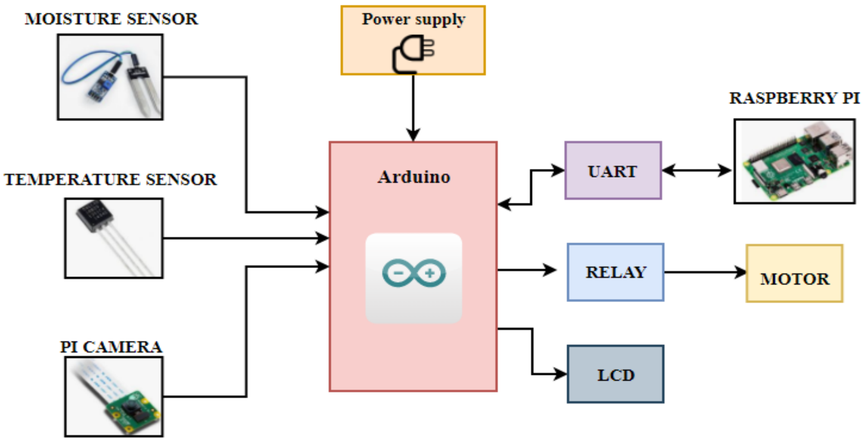

Figure 2. Architecture of IoT-based Pest Classification and Automatic Irrigation System

Figure 2 depicts the architecture of IoT-based Pest Classification and Automatic Irrigation System. The moisture sensor is used for identifying the moisture level of the soil. If this level is high, irrigation is not needed. However, of it is low, then the soil required water. Similarly, temperature sensor is used for identifying the temperature of the soil. If its high, then the soil must be irrigated. The Raspberry Pi camera module is used for capturing photos of the plants. The pictures of the pests are also captured by this module. The values of these three sensors are acquired by the microcontroller unit. These values are transmitted to the Raspberry Pi unit through UART module. This unit is used for processing the data using two novel algorithms. The output of these algorithms is used for the activation of motor and selection of pesticide. In addition, the output of these algorithms is also displayed in the LCD screen.

Figure 3. Pest image cropping

Figure 3 shows the first step used in the processing of pest image. The first step is the cropping of the pest image. The image is cropped such that the background leaf portion is removed and only the pest region is focussed. This helps in accurate recognition of the type of pest.

4.3. Proposed Minkowsky Distance based Pest Classification (MDBPC) Algorithm.

The proposed MDBPC algorithm uses pest image training dataset belonging to *C* classes as the input. Further, the test pest image $T(m,n)$ is used during the classification. Initially, consider each training pest image $I(m,n)$. First crop the pest region and consider the cropped image $I^c(m',n')$ and resize the cropped image to form $I^R(s,s)$. Then, partition the resized image to form blocks $b(r,r)$. Using the resized partitioned image, for each block calculate *p* HOG features. Later, form feature matrix (*FM*) using the computed features of all blocks as $FM(p \times R)$, where *R* is the total number of blocks. Using all images of each class, form dictionary represented as $D(p \times NR)$, where *N* is the number of images in each training class. Using the dictionary compute the pest vector $PV \in R^{p \times 1}$. Similarly, compute the pest vector for the test image as $TV \in R^{p \times 1}$. Then compute the Minkowsky Distance for each class to identify the test class.

Algorithm 1: Proposed Minkowsky Distance based Pest Classification (MDBPC) Algorithm.

Input:

Pest image training dataset belonging to *C* classes.
The size to image cropping *s*.
The size for creation of blocks *r*.
The number of HOG features *p*.
Test pest image $T(m,n)$.

Output:

Pest image class *c*.

Algorithmic Steps:

1. Consider each training pest image $I(m,n)$.
2. Crop the pest region and consider the cropped image $I^c(m',n')$.
3. Resize the cropped image to form $I^R(s,s)$.
4. Partition the resized image to form blocks $b(r,r)$.
5. For each block calculate *p* HOG features.
6. Form feature matrix (*FM*) using the computed features of all blocks as $FM(p \times R)$, where *R* is the total number of blocks.
7. Using all images of each class, form dictionary represented as $D(p \times NR)$, where *N* is the number of images in each training class.
8. Represent the dictionary as

$$D(p \times NR) = D(p \times Q) \quad (1)$$

9. Compute pest vector $PV \in R^{p \times 1}$ as

$$PV = \sum_{j=1}^{Q} D(i, j) \quad (2)$$

10. Compute the pest vector of each class as

$$PV_k; \quad j \in 1, 2, \ldots, 40. \quad (3)$$

11. Calculate test pest vector for test pest image $T(m,n)$ as $TV \in R^{p \times 1}$.
12. Compute Minkowsky Distance for each class as

$$MD_k = \left(\sum_{i=1}^{p} \left| PV_k(i) - TV(i) \right|^t \right)^{1/t} \tag{4}$$

13. Test pest class is computes as

$$c = \arg\min_k MD_k \tag{5}$$

4.4. Proposed Temperature and Moisture based Adaptive Irrigation (TMBAI) Algorithm.

The proposed TMBAI algorithm used four sets of training values namely, the temperature sensor training values in C to start irrigation $[Ts_1, Ts_2, \ldots, Ts_n]$, the temperature sensor training values in C to stop irrigation $[Ts_1^{'}, Ts_2^{'}, \ldots, Ts_n^{'}]$, the moisture sensor training values in VWC to start irrigation $[Ms_1, Ms_2, \ldots, Ms_n]$ and the moisture sensor training values in VWC to stop irrigation $[Ms_1^{'}, Ms_2^{'}, \ldots, Ms_n^{'}]$. For testing, it uses temperature sensor test value Ts_t and moisture sensor test value Ms_t. Initially, average temperature sensor for normal range, average temperature sensor for abnormal range, average moisture sensor for normal range and average moisture sensor for abnormal range are computed. Using the computed values, temperature and moisture threshold are calculated. Finally, irrigation is done when the condition $Ts_t > \zeta_1 \; || \; Ms_t < \zeta_2$ is satisfied.

Algorithm 2: Proposed Temperature and Moisture based Adaptive Irrigation (TMBAI) Algorithm.

Input:

Temperature sensor training values in C to start irrigation $[Ts_1, Ts_2, \ldots, Ts_n]$.

Temperature sensor training values in C to stop irrigation $[Ts_1^{'}, Ts_2^{'}, \ldots, Ts_n^{'}]$.

Moisture sensor training values in VWC to start irrigation $[Ms_1, Ms_2, \ldots, Ms_n]$.

Moisture sensor training values in VWC to stop irrigation $[Ms_1^{'}, Ms_2^{'}, \ldots, Ms_n^{'}]$.

Temperature sensor test value Ts_t .

Moisture sensor test value Ms_t .

Output:

Start/stop Irrigation

Algorithmic Steps:

1. Compute average temperature sensor for normal range as

$$Ts_{avg} = \frac{Ts_1, Ts_2, \ldots, Ts_n}{n} \tag{6}$$

2. Compute average temperature sensor for abnormal range as

$$Ts^{'}_{avg} = \frac{Ts_1^{'}, Ts_2^{'}, \ldots, Ts_n^{'}}{n} \tag{7}$$

3. Compute average moisture sensor for normal range as

$$Ms_{avg} = \frac{Ms_1, Ms_2, \ldots, Ms_n}{n} \tag{8}$$

4. Compute average moisture sensor for abnormal range as

$$Ms^{'}_{avg} = \frac{Ms_1^{'}, Ms_2^{'}, \ldots, Ms_n^{'}}{n} \tag{9}$$

5. Calculate the temperature threshold as

$$\zeta_1 = \sqrt{\frac{(Ts_{avg})^2 + (Ts_{avg}^{'})^2}{2}} \tag{10}$$

6. Calculate the moisture threshold as

$$\zeta_2 = \sqrt{\frac{(Ms_{avg})^2 + (Ms_{avg}^{'})^2}{2}} \tag{11}$$

7. Using the test values Ts_t and Ms_t check

if $Ts_t > \zeta_1 \parallel Ms_t < \zeta_2$ (12)
Start Irrigation
else
Stop Irrigation
end
end

5. Results and Discussion

5.1. Dataset Used

To verify the accuracy of the proposed MDBPC algorithm, we have used the NBAIR insect dataset [25] This dataset comprises of 40 different pest image classes. These include the common type of pests that affects the agricultural yield like sugarcane, cotton, rice maize etc.

Figure 4. Sample images from NBAIR insect dataset

5.2. Parameter Settings

In our research we have used, the value of resized image $s \times s$ as 128×128. The size of block was considered to be $r \times r$ which 12×12 was. The total number of classes C was chosen to be 40. The number of HOG features p was found to be 120.

5.3. Simulation results

Figure 4 shows some sample images from the NBAIR insect dataset. This shows different categories of pests that affects the crop productivity. To verify the excellence of the proposed algorithm, various metrics like precision, F-score, time taken, etc., were used in our research. For comparison we have used machine learning algorithms like k-nearest neighbour (k-NN), Naïve Bayes (NB), support vector machine (SVM) and sparse representation-based classification (SRC) algorithm.

Table 1. Variation of classification accuracy

Classification algorithm	Accuracy (%)
k-NN	77.56
NB	81.48
SVM	85.96
SRC	89.74

MDBPC	95.86

Table 1 shows the comparison of classification accuracy. The k-NN achieves the least accuracy of 77.56%. The next highest was achieved by NB that attained 81.48%. The next highest was attained by SVM with a rate of 85.96%. Then, the SRC attained 89.74%. The proposed MDBPC achieved highest accuracy of 95.86%.

Table 2. Variation of specificity

Classification algorithm	Specificity (%)
k-NN	78.52
NB	81.58
SVM	85.46
SRC	91.49
MDBPC	95.86

Table 2 shows the variation of specificity. The proposed scheme achieves highest specificity of 95.86%. The next highest was achieved by SRC at a rate of 91.49%. The next highest was attained by SVM with a value of 85.46%. The least specificity was attained by k-NN with a rate of 78.52% followed by NB at a rate of 81.56%.

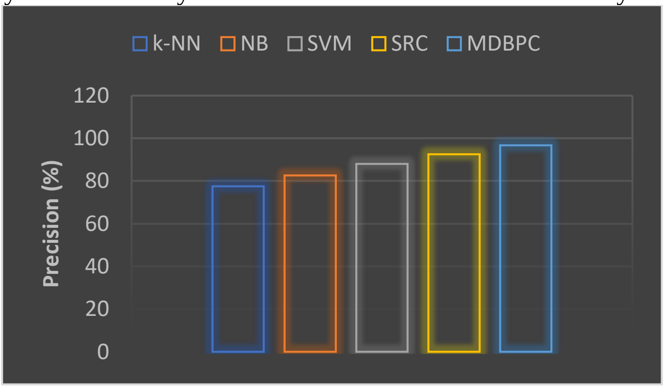

Figure 5. Variation of precision

Figure 5 shows the variation of precision. It is evident that the precision achieved by the proposed MDBPC scheme is maximum with a rate of 96.69%. The least precision is attained by the k-NN algorithm with a rate of 77.52. Next to the proposed scheme, the highest precision is achieved by the SRC scheme with a rate of 92.56%.

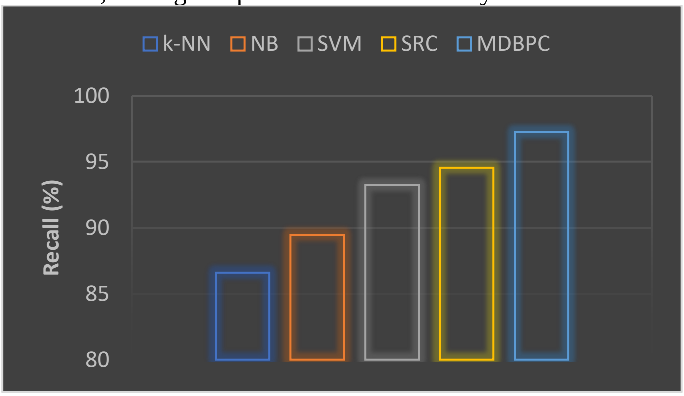

Figure 6. Variation of recall

Figure 6 shows the variation of recall. The proposed scheme achieves highest recall of 97.24%. The next highest recall was achieved by SRC at a rate of 94.56%. The next highest recall was attained by SVM with a value of 93.25%. The least recall was attained by k-NN with a rate of 86.58% followed by NB at a rate of 89.45%.

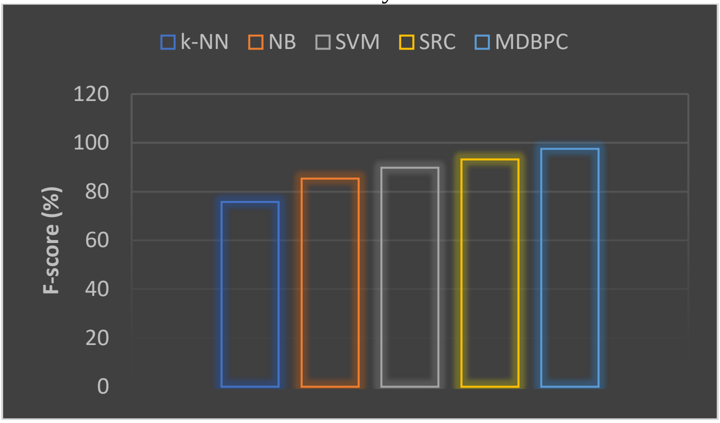

Figure 7. Variation of F-score

Figure 7 shows the comparison of classification F-score. The k-NN achieves the least F-score of 75.69%. The next highest F-score was achieved by NB that attained 85.36%. The next highest F-score was attained by SVM with a rate of 89.74%. Then, the SRC attained 93.25%. The proposed MDBPC achieved highest F-score of 97.58%.

Table 3. Variation of classification time

Classification algorithm	Time for classification (ms)
k-NN	5.69
NB	4.86
SVM	4.19
SRC	3.35
MDBPC	1.49

Table 3 shows the variation of classification time. The proposed scheme achieves least classification time of 1.49ms. The next least classification time was achieved by SRC at a time of 3.35ms. The next least classification time was attained by SVM with a value of 4.19ms. The highest classification time was attained by k-NN with a classification time of 5.69ms followed by NB with a classification time of 4.86ms.

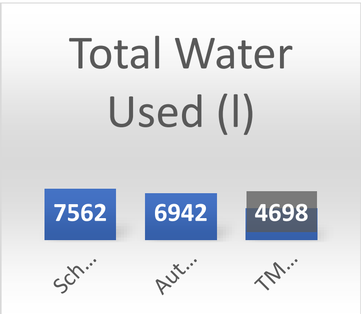

Figure 8. Variation of water consumption

Figure 8 shows the variation of water consumption for three different cases, namely, the scheduled irrigation system, automatic irrigation system and the proposed TMBAI scheme. It can be seen that the scheduled irrigation consumes 7563l of water over a period of 1 week. For the same duration, the automatic irrigation used 6942l of water. Whereas, the proposed TMBAI scheme uses just 469l of water for irrigation. Thus, enormous amount of water is conserved using the proposed irrigation scheme, compared to the scheduled and automatic irrigation. The reduction in the amount of water helps to reduce huge volume of water when used for a long period of time. In this way, the proposed system produces increased agricultural productivity since excessive water more than the requirement also causes water clogging.

6. Advantages of the proposed methodology

The main advantage of the proposed Minkowsky Distance based Pest Classification algorithm is the accurate classification of pest category with very high accuracy. The second advantage is the excellent water level requirement prediction performance by the proposed Temperature and Moisture based Adaptive Irrigation algorithm that uses the temperature and moisture levels to detect water level.

7. Disadvantages of the proposed methodology

The main disadvantage of the proposed scheme is the computational complexity of the proposed algorithms. Further, another drawback is the collection of training data for training the systems. For instance, in pest classification enormous amount of pest images are required for training the system prior to pest identification

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8. Conclusion

A new scheme for precision agriculture is proposed in this research. The proposed scheme uses the data from three sensors namely, Raspberry Pi module, temperature and pressure sensor to identify the water requirement and the pest category. The pest classification result is obtained using a new Minkowsky Distance based Pest Classification (MDBPC) algorithm and the water requirement level is obtained using Temperature and Moisture based Adaptive Irrigation (TMBAI) algorithm. These two results are then transmitted to the cloud. The cloud transfers these values to the mobile phone of the farmers, using which the farmers can monitor and identify the correct pesticide and water quantity required for irrigation.

To verify the performance of the proposed pest classification algorithm we have used the pest images from the NBAIR insect dataset. The proposed Minkowsky Distance based Pest Classification algorithm was validated using various classification metrics and it attained a high recall of 97.24%, F-score of 97.58 and accuracy of 95.86%. In addition, the classification time is very minimum around 1.49ms. Further, the proposed Temperature and Moisture based Adaptive Irrigation algorithm attained minimum water requirement of 4698l for irrigation over a period of 1 week. Thus, the credibility of the proposed algorithms was proved using quantitative analysis.

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