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Development of an IoT based smart potato leaf diseases monitoring and controlling system with image processing

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ABSTRACT

Potato (*Solanum tuberosum L.*) is a key crop and a major source of livelihood for a vast population of the world after wheat and rice. However, diseases have diverse effects on potato fields, leading to damage to crops and reducing crop production. The two major diseases that afflict potato plants are referred to as early blight and late blight. Protection of this crop yield from blight diseases is one of the foremost challenges. Therefore, detection of these leaf diseases at appropriate time is very essential to prevent the damage. This study intends an internet of things (IoT)-based smart potato leaf diseases monitoring and control system that combines IoT technology with eco-sensing and image processing to identify and categorize these diseases. Studies have found that blight diseases are directly related to temperature and humidity of the planted area. This study measures environmental information using a sensor network installed in the planted area. After sensing and measuring environmental information, acquired values are displayed and farmers get these acquired values via message notification. The system obtains a 97% accuracy rate in recognizing these diseases by using our fine-tuned model of ResNet-50 for image processing.

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1. INTRODUCTION

Bangladesh's economy is largely shaped by its agricultural sector, which is its main source of income. Agriculture has historically contributed significantly to the gross domestic product (GDP) and made up more than 50% of the country's total economic output. The foundation of this industry lies in the cultivation of various crops, which are generally categorized into food crops and cash crops. The potato is one of these crops that is quite important both in Bangladesh and around the world. Potatoes are fourth in production behind wheat, maize, and rice and are regarded as a staple food in at least 40 countries worldwide.

The seventh-largest producer of this adaptable tuber crop is Bangladesh. For people throughout the world, potatoes are an essential source of nutrition since they are high in fiber, potassium, and vitamins (particularly C and B6). Potato starch, often known as farina, is used in the textile industry to size cotton and worsted textiles in addition to its culinary uses. Diseases pose a significant threat to agriculture and plant life, often caused by genetic issues, microbes, and infectious agents like viruses, bacteria, and fungi. In potato cultivation, fungal infections e.g., early blight due to *Alternaria solani* and late blight due to *Phytophthora infestans*, are particularly detrimental [1]. The globally recognized and destructive disease, late blight, is estimated to cause over $5 billion in damages annually worldwide [2]. Outbreaks of this severe disease cause a large 30 percent drop in Bangladesh's yearly potato yield [3]. Warm temperatures and high humidity are ideal for early blight growth, whereas cool, damp weather is preferred for late blight. The worst potato disease, late blight, can kill plants in two weeks if the weather is cool and damp. Farmers can hardly afford to continuously monitor their potato crops in order to determine the best weather for cultivation or disease control. Manual surveillance is laborious and time-consuming, particularly in light of the difficulty in obtaining agricultural knowledge in remote locations due to the lack of access to such expertise. It is challenging for individual farmers to diagnose and treat illnesses in a timely manner to guarantee the highest and greatest quality. Historically, all illnesses and dangers were detected through visual inspection by knowledgeable individuals who may have used characteristics like color, texture, and shape to aid in their analysis. This approach resulted in high costs and low efficiency. The goal of this study, which views this problem as a challenge, is to technically offer a solution using the IoT technique.

This study develops an IoT-based solution with integrated image processing to monitor the ongoing temperature and humidity of potato farms and detect and classify leaf diseases. Temperature and humidity are two key environmental factors that affect potato cultivation, and they are collected using an IoT based sensor network. Potato leaf diseases are categorized using image processing, which makes early identification possible. The following are the study's main contributions:

- To develop an IoT-based infrastructure that enables real-time monitoring of the potato farm.
- To provide live feedback about temperature, humidity, and disease symptoms.
- To precisely identify and classify blight diseases of potato leaf.
- To decrease the level of decline in potato yield.

Many researchers have focused on deep learning-based IoT systems to perform automation in the agriculture sector, such as field monitoring, plant disease diagnosis, and prediction to ensure respectable crop production. The study [4] summed up the latest innovative IoT approaches to support sustainable crop production and highlighted the advantages of establishing smart efficient farming systems with the help of these sophisticated strategies. In order to monitor hydroponics farming with accuracy (99.29%) and F-measure (99.23%), Raju *et al.* [5] developed a smartphone app that combines an artificial intelligence-powered smart hydroponics expert system with IoT devices. The system includes a number of real-time sensors, a convolutional neural network (CNN) for predicting nutrient levels and plant conditions, and an android-based mobile application system. Singh *et al.* [6] developed a pest monitoring and control system by utilizing a variety of wireless sensors to identify and classify the behaviors of insects, to detect early bug infestations and to alert about their location for plants like carnation, gerberas, anthodium, tomato, and roses. This paper [7] presented a mobile-based system that was implemented using CNN to automatically diagnose and classify plant leaf diseases. The study revealed that the classification accuracy was 94% using a dataset consisting of 96,206 photos categorized into 38 different disease types. Ali *et al.* [8] proposed a unique combination of feature fusion, principal component analysis reduction, and linear discriminant analysis classification (FF-PCA-LDA) system to detect crop leaf diseases, where the features were extracted using a modified ResNet-50 model. Kang *et al.* [9] developed a potato leaf disease detection system based on the Django framework and trained a lightweight CNN model to reduce the parameters and achieved over 93% top-1 accuracy.

Alatawi *et al.* [10] classified 19 different plant diseases using a plant village dataset. They applied VGG-16 model and attained 95.2% accuracy with a 0.4418 loss. Authors used CNN model to predict various plant diseases at early stages with 85% optimal accuracy in terms of poly-house farming which is a huge breeding ground for various insects [11]. Gao *et al.* [12] designed a framework for pest occurrence with regard to weather patterns using IoT and unmanned aerial vehicles (UAV) captured images collected from cloud data centers for remote locations in China. Algani *et al.* [13] proposed an ant colony optimization (ACO) method merged with CNN to diagnose diseases in plant leaves. A thorough review of the deployment of machine learning, IoT, computer vision and deep learning for plant disease diagnosis has been found in the references [14]-[17]. Frikha *et al.* [18] demonstrated an intricate greenhouse platform for observing potato growth using deep learning frameworks and blockchain technology to safely handle and monitor greenhouse data. In order to monitor and manage cattle, crops, greenhouse automation, and climate conditions, Sen *et al.* [19] have presented an integrated Agro-IoT system. For identifying potato leaf diseases, a multi-level deep learning framework has been created by Rashid *et al.* [20]. Features were extracted from the data using the YOLOv5 picture segmentation approach, and diseases were identified using CNN.

It has been found through an analysis of previous studies that utilizing IoT technology for smart farming significantly enhances agricultural practices via various means, including smart sensor-enabled large-scale data collection and improved monitoring and control of internal agricultural processes. Benefits from IoT integration in agriculture include improved cost control, decreased waste, process automation, and increases in the number and quality of produced goods. Notably, one of the biggest issues is preventing infections from degrading crop quality. Thus, initial detection of such diseases is a decisive strategy for lowering agricultural losses. Neural network algorithms and image processing approaches have been investigated recently for the purpose of identifying and categorizing plant leaf diseases. Plant disease diagnosis using CNNs is growing in popularity, and research has produced encouraging results. Creating an architecture that integrates IoT tactics with image processing concepts in order to identify and classify potato leaf diseases is the intent of this study.

2. METHOD

2.1. Proposed system

Creating a distinctive system for monitoring and recognizing various leaf diseases affecting potato plants is the aim of this study. The experiment of the study is divided into three tasks: implementation of temperature and humidity measurement and display system, implementation of short message service (SMS) alert system and potato leaf diseases detection as well as classification. The proposed system's schematic view is depicted in Figure 1. Figure 2 shows an architectural model of the proposed system. The system utilizes a temperature and humidity sensor (DHT22) to measure ambient temperature and humidity, and an ESP32-CAM module to take images of leaves. The sensor transmits its collected data to the Arduino UNO. A liquid crystal display (LCD) panel shows the data about temperature and humidity that has been gathered. The Arduino UNO is linked to a global system for mobile communications/general packet radio service (GSM/GPRS) module (SIM900A), which transmits a message to the farmer regarding the state of the farm every 12 hours when the temperature and humidity exceed their ideal range (temperature 15-20 °C and humidity ≤90%). Every half an hour, the camera is used to take pictures of potato leaves in order to check for disease symptoms. A fine-tuned deep CNN model of ResNet-50 is used to detect and classify diseases of leaves. A user interface is also designed in this study through which farmers can get live feedback about temperature, humidity, and disease symptoms when the internet is available.

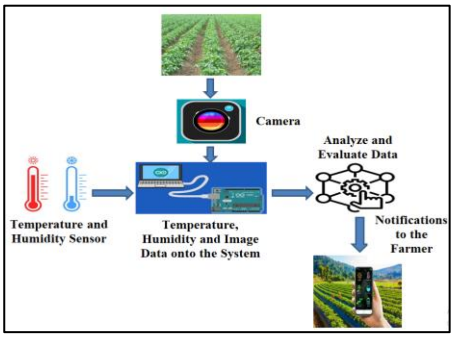

Figure 1. Schematic view of proposed system

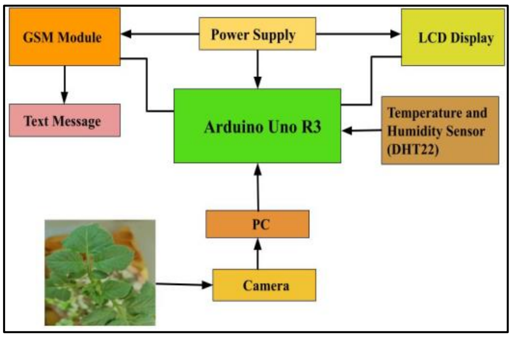

Figure 2. Architectural model of proposed system

2.1.1. Procedure to measure and display temperature and humidity

The ecological information of the potato growing area, such as temperature and humidity are measured by a DHT22 sensor. The sensor data is processed by the Arduino UNO and displayed on a 16×2 LCD. A light-dependent resistor (LDR) model RBD-2093 is used for daytime and nighttime measurements. Algorithm 1 shows the process of measuring temperature and humidity.

Algorithm 1. Measurement of temperature and humidity

1. The DHT22 temperature and humidity sensor has three pins: positive, output, and negative.
   - The DHT22's positive pin is linked to the Arduino UNO's 5 V power source.
   - The Arduino UNO's D7 pin is connected to the output pin of the DHT22.
   - The negative pin of the DHT22 is connected to the GND pin of the Arduino UNO.

2. Compile the code and verify that there are no errors.
3. Transfer the code to the Arduino UNO device.
4. To view the humidity and temperature, click Tools> Serial monitor.

2.1.2. Execution procedure of SMS alert system

The Arduino UNO is connected to a GSM/GPRS module, which allows the farmer to receive messages on temperature and humidity. Utilizing an Arduino UNO and a GSM/GPRS module, this system enables real-time monitoring and immediate notifications. The SMS alert system enhances safety and responsiveness by providing timely alerts. Algorithm 2 shows the basic steps of SMS alert system.

Algorithm 2. SMS alert system
1. Collect temperature and humidity data from DHT22.
2. Send temperature and humidity data to Arduino UNO.
3. Analyze temperature and humidity data.
4. **If** Temperature and humidity cross threshold value **then**
   send a message to farmer's mobile device via GSM/GPRS module with safety notification.
   End

2.1.3. Procedure to detect and classify potato leaf diseases

Two image datasets are initially acquired during the image processing stage. The first dataset is prepared from the data collected directly from the potato field using ESP32-CAM and the other is the plant village dataset [21] collected from Kaggle. We augmented our dataset by integrating it with the existing plant village dataset creating a consolidated dataset for analysis. A training set and a testing set are the two separate portions of the dataset that are separated upon acquisition. Subsequently, data pre-processing steps, including resizing the training and test images, are performed before feature extraction and classification. Then extract an image's features, followed by the identification of diseases and categorization. Figure 3 shows the flow of the experiment.

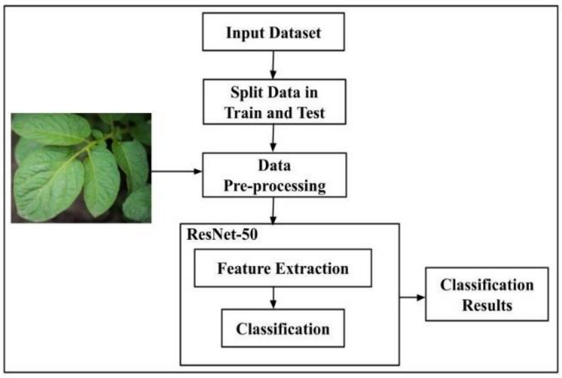

Figure 3. Potato leaf diseases detection and classification procedure

Splitting data: there are 2,152 photos of potato leaves in the dataset, both healthy and diseased. Seventy percent is used for training and thirty percent for testing. Following splitting, the training set has 1,506 images, whereas the testing set contains 646 images. Table 1 displays the data for the train-test-split.

Table 1. Train-test-split data

Label	Type	Amount	Training instance	Test instance
1	Early blight	1,000	700	300
2	Late blight	1,000	700	300
3	Healthy	152	106	46
Aggregate		2,152	1,506	646

Data pre-processing: an input image having 224 pixels in width and 224 pixels in height and three RGB color channels is required to be fed into ResNet-50. The sizes of training and test images vary, so all images are resized to the target size of 224*224*3. The RGB pixel value of each image is normalized as (1):

$$x(c,k) = \frac{x(c,k)}{127.5 - 1} \quad (1)$$

where, $x(c,k)$ is a vector that has RGB pixel values at the coordinate of (c,k) [22].

Working model of ResNet-50 for classification of potato leaf diseases: ResNet-50 uses 7*7 convolutions with stride 2 at the first layer. Three obstructions follow before it is down-sampled by 2. The down-sampling layer also has a convolution layer; however, it does not account for personality connection. That is how it goes for a couple of deeper layers. The last layer, called "normal pooling," takes the ImageNet data and produces a normal distribution along with 1,000 element maps for every feature map. The outcome would be a vector with 1,000 dimensions, which would be passed straight into the softmax layer to create a fully convolutional image. Ultimately, we would obtain the categorization of the image according to its class. At each preparation put together, lone focus focuses either exit the net with likelihood p, so a decreased system is left; moving ever closer edges to an exited focus point are besides exhausted. The dropout regard is set to 0.5, which suggests those center points that have regard under 0.5 are blocked from the planning orchestrate. Finally, the softmax layer is used for the last assumption for the yield class. The softmax capacity is used to discover the probabilities of each target class. When choosing the target class for the specified data sources, the prepared probabilities are later employed. It goes from 0 to 1 and the completeness of the broad number of probabilities is relative to one. For the purpose of detecting and classifying potato leaf diseases, Figure 4 depicts the step-by-step model of ResNet-50.

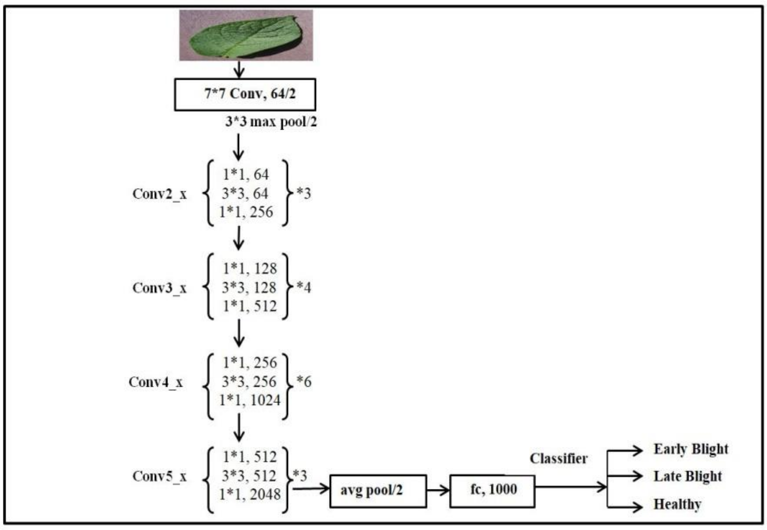

Figure 4. Working model of ResNet-50 for detection and classification of potato leaf diseases

3. RESULTS AND DISCUSSION

3.1. Evaluation of classification model's performance

A CNN model of ResNet-50 has been utilized in this study to recognize potato leaf diseases, whereas the model's performance is manipulated using four types of evaluation metrics, namely precision (PRS), recall (RC), F1-score (FS), and accuracy (ACR). These four metrics are determined by (2)-(5):

$$PRS = \frac{TP}{FP + TP} \quad (2)$$

$$RC = \frac{TP}{FN + TP} \quad (3)$$

$$FS = \frac{2TP}{FN + FP + 2TP} \quad (4)$$

$$ACR = \frac{TN + TP}{FP + TP + FN + TN} \quad (5)$$

where, the viewpoint for false positives is symbolized by FP, true positives by TP, false negatives by FN, and true negatives by TN.

The confusion matrix is given in Figure 5 for measuring FP, TP, FN, and TN. The precision (PRS) values for early blight, late blight diseases and healthy are 0.99, 1, and 0.92, respectively, while the recall (RC) values are 1, 0.91, and 1, respectively. Additionally, the F1-scores (FS) for both diseases and healthy are 0.99, 0.95, and 0.96, respectively, with corresponding accuracies (ACR) of 0.99, 0.97, and 0.97. The average precision (PRS), recall (RC), F1-score (FS), and accuracy (ACR) are 0.97. The classification model's performance is illustrated in Table 2.

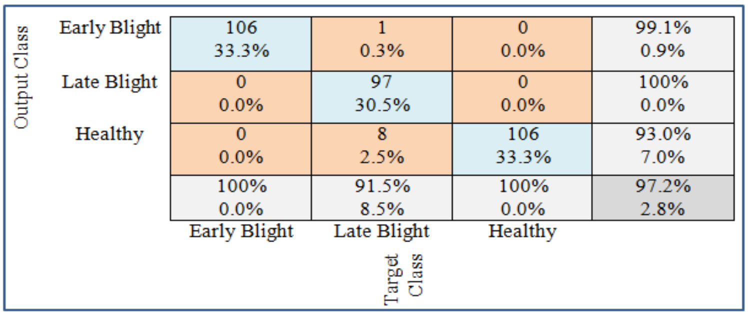

Figure 5. Confusion matrix

Table 2. Classification model's performance

Category	PRS	RC	FS	ACR
Early blight	0.99	1	0.99	0.99
Late blight	1	0.91	0.95	0.97
Healthy	0.92	1	0.96	0.97
Average	0.97	0.97	0.97	0.97

Through the use of image processing, a number of researchers have already made contributions to the field of plant disease identification. As shown in Table 3, we performed a comparative analysis with other relevant research publications to demonstrate the efficacy of our study. With a 93% accuracy rate, Gavhale *et al.* [23] detected leaf diseases of citrus by applying support vector machine (SVM) technique. AlexNet was used by Shrivastava *et al.* [24] to detect diseases in rice leaves. With a 95% classification accuracy, Islam *et al.* [25] identified potato leaf diseases using the SVM technique. VGG-16 was used by Ghosal and Sarkar [26] to identify diseases in rice leaves. Our applied model, ResNet-50, outperformed other studies by achieving the highest accuracy rate of 97%.

Table 3. Comparison of various plant disease classification techniques

References	Applied technique	Plant disease	Classification accuracy (%)
Gavhale *et al.* [23]	SVM	Citrus	93
Shrivastava *et al.* [24]	Alexnet	Rice	91.37
Islam *et al.* [25]	SVM	Potato	95
Ghosal and Sarkar [26]	VGG-16	Rice	92.46
This Study	ResNet-50	Potato	97

In this study, high PRS, RC, FS, and ACR are achieved by utilizing ResNet-50 for potato leaf disease detection and classification. These findings point to the possibility of using the created system in agricultural contexts to monitor and detect diseases early on. This study's limitation is that it merely alerts farmers to disease symptoms; it doesn't offer guidance on what precautions to take in the event that a disease is found.

3.2. User interface and message alert

The user interface represents a dashboard that is composed of three parts. The first section displays the evolution and real-time changes in the various environmental parameter values such as temperature and humidity. The image of a potato leaf is represented in the second section. The message notification is shown in the third section. With the help of this intuitive interface, a farmer can understand the condition of the potato field, as depicted in Figure 6, even with minimal knowledge of information and communication technology.

The farmer is also able to remain updated without requiring an internet connection as they receive notifications on their mobile device through SMS. Figure 7 shows the message alert that is sent to the farmer. Almost every mobile phone, from entry-level feature phones to smartphones, can send and receive SMS messages. SMS enables instant communication since messages are typically delivered just seconds after being sent. When there is an urgent notification or emergency and real-time communication is required, this quick transmission is vital.

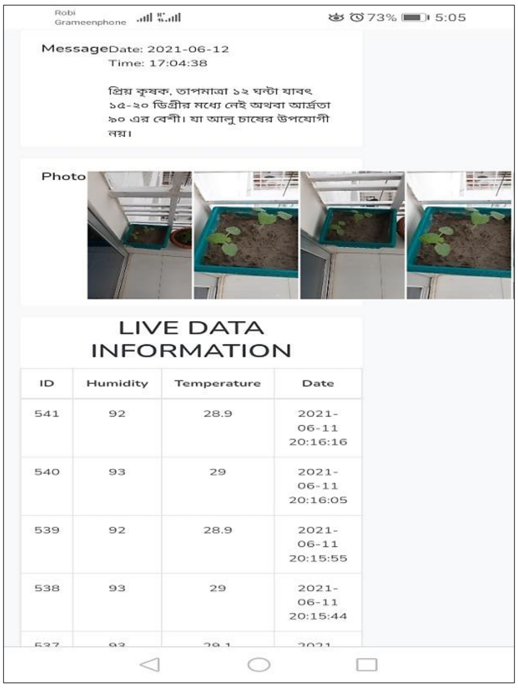

Figure 6. User interface

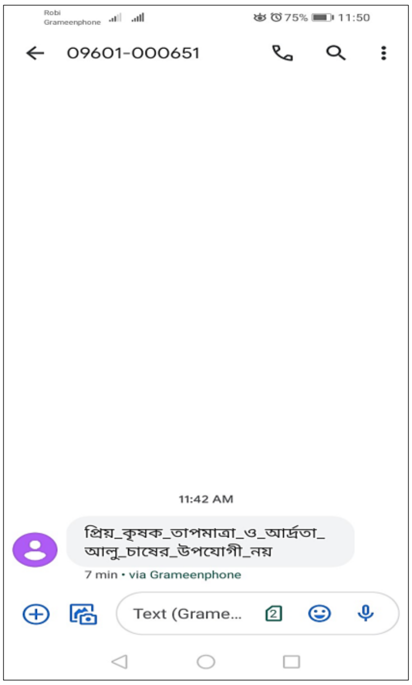

Figure 7. Message alert

4. CONCLUSION

In this study, we presented a novel IoT system that is combined with image processing methods to continually monitor environmental factors in order to protect potato farms from diseases. We developed a robust automated system by merging IoT sensors for temperature and humidity monitoring with image processing algorithms to diagnose potato leaf diseases. Our study shows an impressive 97% accuracy rate in disease classification, indicating that our method is useful for detecting and classifying a wide range of diseases that impact potato crops. Large-scale potato production stands to gain greatly from the deployment of this automated method. Farmers may actively control crop health and reduce the risk of output losses by enabling real-time monitoring and early disease diagnosis. In the future, a cross-validation method will be introduced to image processing to validate classification results.

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