A Smart Agriculturing IoT System for Banana Plants Disease Detection through Inbuilt Compressed Sensing Devices

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A Smart Agriculturing IoT System for Banana Plants Disease Detection through Inbuilt Compressed Sensing Devices

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Abstract

The Internet of Things (IoT) solutions for agriculture are rapidly growing and have the potential to transform agriculture in many aspects. In particular, the plant disease detection devices play a vital role in improving the agriculture. The visual monitoring of plants for the onset of diseases is a tedious and time-consuming task for farmers and at the same time it is less accurate. Hence an automated system with environmental data and camera sensors can serve as an alternative and effective solution for manual monitoring of plants. In this paper, a novel and efficient compressed sensing inbuilt plant disease detection device is developed which uses a foreground-based segmentation method and two step feature extraction technique to detect and classify two of the major banana diseases. A database is created for banana bunchy top and sigatokaleaf spot diseases by collecting images in real time from the fields of southern parts of Tamilnadu namely Thadiyankudisai and Thandikudi of Dindigul district, KC Patti, Muthalapuram, Suruli Patti and Kambam of Theni district and ICAR NRCB, Tiruchirapalli. The suggested device's effectiveness has been assessed in terms of the proportion of infected areas, detection accuracy, percentage of feature reduction, and classification accuracy. The prototype of the proposed device is developed and validated using the Raspberry pi board. The findings demonstrate that the suggested device achieves classification accuracy of 97.33% and detection accuracy of 96.75%.

Keywords: Banana, Compressed sensing, plant diseases, detections, ORB features, Support Vector Machine, bunchy top disease, sigatoka leaf spotdisease.

1. Introduction

The Internet of Things (IoT) solutions for agriculture are rapidly growing and have the potential to transform agriculture in many aspects [1,2,3,4]. There are different types of IoT sensors that can be used in smart agriculture applications [5,6,7] such as Monitoring of Environmental Conditions [8], Greenhouse Automation [9], crop disease and management [10], Cattle Monitoring and Management [11], and End-to-End Farm Management Systems [12]. In precision agriculture applications, accurate detection of pest and diseases plays a major role as they cause significant economic loss to farmers. The visual identification of plant diseases is a less accurate and tedious task; hence the machine learning can automate the process of classifying the diseases based on the features extracted from the images. Recently, the identification and monitoring of the agricultural field has been carried out using various imaging sensors such as RGB, multispectral, hyper spectral, thermal, fluorescence based and 3D sensors[13]. The advancement in these sensors has augmented the demand for cost effective precision agriculture. Moreover, the IoT enabled solutions are proliferating due to the ease of implementation and timely diagnosis of the diseases in the plants. The disease infected leaves of strawberry plants are identified using a fuzzy decision maker and achieved a detection accuracy of 97% [14]. A web-based tool is developed in [15] to identify fruit diseases by extracting the features using color, morphology and color coherence vector. The K-Means solution is used for segmentation and the Support Vector Machine (SVM) for classification in [15]. The procedure achieved an accuracy of 82% to identify the pomegranate diseases. Though these solutions achieve reasonable detection accuracy, they lack in real time monitoring and actual identification of diseases.

A compressed sensing (CS) based disease detection system is proposed in [16]. The CS measurements of the thresholded images are acquired and transmitted to the monitoring site in order to classify the diseases. The SVM classifier is used for the analysis and classification. Another CS based system for disease detection in paddy plants is proposed in [17]. The statistical texture features are obtained using the Gray level Co-occurrence matrix (GLCM), and the threshold is calculated K-means clustering. Both methods utilizing the CS process achieve a detection accuracy of nearly 98.4%. Moreover, the features are extracted from the recovered segmented images at the monitoring site. The feature and the training set required are larger in size to achieve the requisite detection accuracy.

A disease detection framework is proposed in [18] where the image segmentation is done by using a genetic algorithm and classification using SVM. The proposed system's detection accuracy was found to be 95.71 percent, and its classification accuracy to be 97.6 percent. Neural networks are used in [19] to detect and classify the diseases in pomegranate plants. The Fruit Spot, Bacterial Blight, and Leaf Spot are the diseases in pomegranate that are considered for implementation. The proposed approach showed an accuracy of around 90% which was found to be satisfactory. The authors have developed a system in [20] that uses heterogeneous sensor nodes that are used for collecting data such as acoustic, light, temperature, rain, wind and PH levels of the cornfield. These data are collected by the coordinator nodes which is then forwarded to the drones. From the drones the data is sent to the base stations for monitoring on farmers device.

The image processing features that capture the color information or local descriptor are considered for the analysis of diseases in corn fields [21]. The feature extraction methods used are Red Green Blue (RGB) [21], the scale-invariant feature transform (SIFT) [22], the speeded up robust features (SURF) [23], the oriented FAST and rotated BRIEF (ORB) [24], and histogram of oriented gradients (HOG) [25]. Thus, considering hybrid features for the analysis, it is essential to extract the features with invariance for rotation and transmitting the same to the monitoring site with minimal complexity which can be achieved with the appropriate usage of compressed sensing (CS). The key idea is to develop an Internet of Things (IOT) based compressive sensing inbuilt banana plant disease detection system (CS-BPDDS) for monitoring the diseases such as bunchy top and sigatoka leaf spot in banana plants. The main functionality of Compressed Sensing Inbuilt Banana Plant Disease Detection System (CS-BPDDS) is real time in-situ sensing using temperature/humidity sensors and soil moisture sensors which are interfaced with the device. The environmental sensors can sense parameters from the fields and once the measurements cross the ideal conditions the camera is triggered to check for onset of diseases. On the other hand, the camera can also be triggered automatically or manually at regular intervals which can be programmed in the device. However, this paper discusses only the processing of image sensor connected to the device for classification of diseases.

The image acquisition and feature extraction are done at the field to be monitored. The classification is done at the monitoring site by the experts. Finally, the solution to the problem is advised to the users through text messages or user friendly mobile app. The camera sensor is placed in the farm to capture the image of the plant leaves. The image is then processed further to detect and segment the affected portion of the leaves. The agricultural specialist extracts features from the segmented image and analyzes them for diseases. The information about the areas where the disease has spread and the exact quantity of pesticides to the affected area would help the farmers in terms of both economic and environmental benefits. The main contributions of the paper are

i) A plant disease detection device for banana.

ii) A novel foreground-based segmentation (FBS) technique and

iii) A novel two-step feature extraction technique comprising of ORB feature detection and compressed sensing (ORB-CS) for accurate classification of diseases. The idea of combining CS with ORB for feature extraction has not been reported in literature so far, and in this work, it has shown to improve the classification accuracy without increasing the complexity.

In real time scenario, for continuous monitoring CS can used in the system as a feature extractor which extracts only useful features by reducing the transmission and storage overhead at the cloud. Initially, the disease affected part is extracted as the foreground from the leaf image and then the features are extracted. The performance of the proposed IOT based Compressed Sensing Inbuilt Banana Plant Disease Detection System (CS-BPDDS) described in section 2 is evaluated in terms of percentage of reduction in features, detection accuracy and classification accuracy.

The rest of the paper is organized as follows. In Section 2 we discuss the proposed framework in detail and the performance evaluation is conducted in Section 3. Finally, Section 4 gives the conclusion and scope for future work.

2. The Proposed Framework of the IoT based Compressed Sensing Inbuilt Banana Plant Disease Detection System (CS-BPDDS)

We introduce a novel and efficient compressed sensing inbuilt plant disease detection system for banana plants. The overall framework of the IOT enabled plant disease detection device and the data flow of the working of the proposed IOT based Compressed Sensing Inbuilt Banana Plant Disease Detection System (CS-BPDDS) explained in this section are shown in Figures 1 and 3, respectively. In this system, data collected in the field can be transferred to the cloud for real-time decision making.

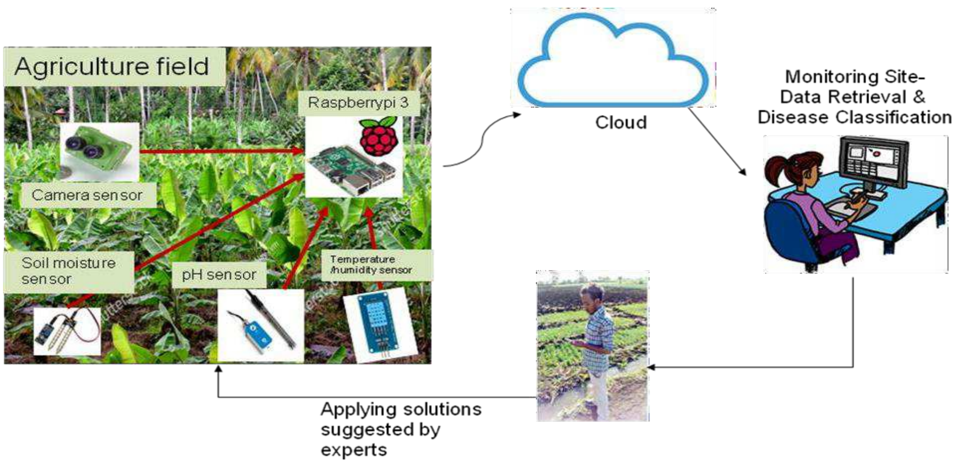


Fig. 1 Overview of the proposed IOT based plant disease detection

The proposed FBS and ORB-CS are the techniques that makes the device efficient by extracting the useful features with minimal complexity which helps in accurate classification. The disease monitoring and detection system collects the temperature, humidity, pH, soil moisture and image details using multiple end nodes which further sends the data to the cloud for further analysis. The mobile app fetches the data, performs the classification and indicates the same to the end users.

The domain model of the system is given in Fig. 2. It has a physical entity which is the agricultural field that is to be monitored. There is an associated virtual entity along with its attributes for the same. The device includes the temperature and humidity sensor, soil moisture sensor, pH sensor, camera and Raspberry Pi. Resources are software components which can be either on-device or network resources. The system has a native controller service that monitors the related parameters and sends the readings to the cloud.

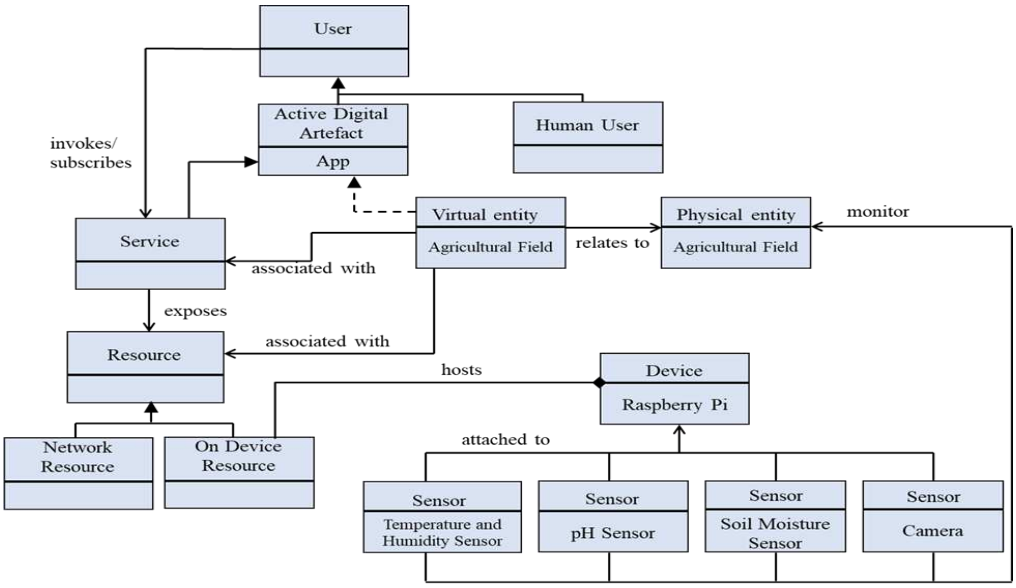


Fig.2 Domain Model of the System

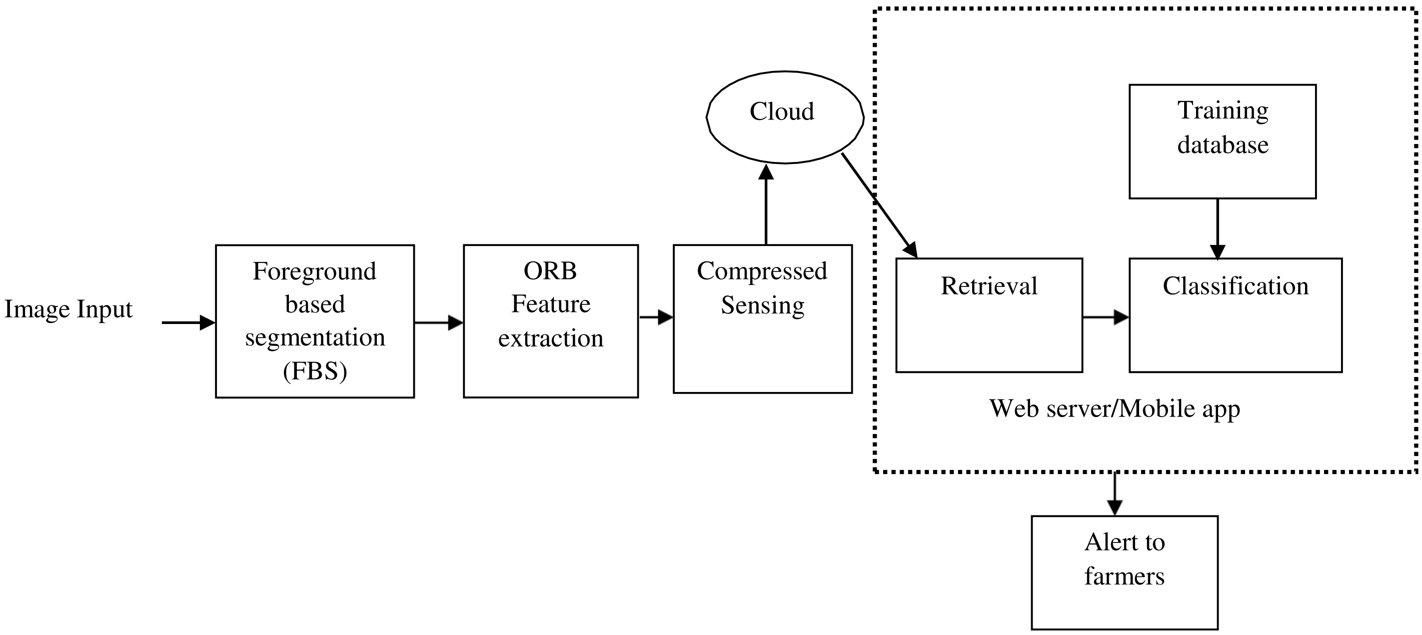


Fig. 3 Overall dataflow of the proposed FBS and ORB-CS process

The analysis is done in the cloud-based App and is used for visualizing the data and the decisions made. The centralized controller can also send commands to the end nodes to configure the monitoring interval on the nodes. The image sensor captures the image and then the FBS is applied out on the pre-processed image to extract the infected part of the leaf. The ORB-CS technique is used to extract the significant features from the segmented diseased image. These compressed features are alone transmitted to the cloud for storage. From the cloud the features are retrieved and original features are recovered and classified at the web server and mobile app. The SVMis used for classification purpose. Once the classification is done the farmers will be alerted through text messages. The bunchy top disease and sigatoka leaf spot disease are the two most commonly occurring diseases in banana plants which contribute to major loss hence the database is created for these two diseases by collecting images from the fields at southern parts of Tamilnadu namely Thadiyankudisai and Thandikudi of Dindigul district, KC Patti, Muthalapuram, Suruli Patti and Kambam of Theni district and ICAR NRCB, Tiruchirapalli. Each process in the CS-BPDDS is explained below:

a) The Image Acquisition

The image camera sensor in the device is used to acquire the leaf images in the field to which the pre-processing techniques such as contrast enhancement and Red Green Blue (RGB) color space to L*a*b* color space (where L denotes for Lightness, a* denotes for Red/Green value, b* denotes for Blue/Yellow value) transformation is carried out. The color transformation is done to enhance segmentation process.

b) The Foreground based Segmentation (FBS)Technique

The diseased area in the leaf image is extracted through a novel FBS technique where the foreground is extracted by using the thresholding strategy which gives the disease affected area. The threshold is designed by using a simpleblock change method. The L* component of the (L*a*b*) transformed image is divided into n x n blocks. Each block is compared with the previous block in a pixel-by-pixel manner and if the difference in the pixel is greater than the mean of the current block then that block contributes to the foreground. With this method the disease affected area is extracted efficiently.

c) The novel two-step feature extraction process:

Once the image is segmented the features of the image is extracted by using the ORB feature detector. ORB detects the features from Accelerated and Segments Test (FAST) and Binary Robust Independent Elementary Feature (BRIEF) techniques [24]. The FAST is used to find the edges in an image in the form of key points. The ORB assigns orientation to each key point depending on how the levels of intensity change around it. The Brief approach turns each key point to a binary feature vector, allowing all of the vectors to represent an object when combined. The binary feature vector is represented by 1's and 0's.

With the help of the ORB 'f' number of features or key point descriptors can be extracted from the input image out of which first 'f1' number of key point descriptors or features are considered in this work. The first 'f1' (f1 < f) number of features are alone selected instead of all the key points for reducing the complexity without compromising the accuracy.

Compressed sensing is applied on the extracted ORB features for extracting only useful features from the images in the sparse domain[26],[27]. With this novel strategy, the accuracy of the classification process can be improved with less transmission complexity. The features are compressed by using measurement matrix and the compressed measurements are alone transmitted to the cloud. Initially the ORB features are transformed to a sparse feature vector using transform basis such as discrete cosine transform (DCT) and then hybrid measurement matrix reported in [28] is applied to obtain the compressed feature vector. The input feature vector of size $f_1 \times 1$ is transformed to sparse feature vector of size $f_1 \times 1$ using DCT, where f_1 represents the number of features extracted using ORB. The input feature vector is then multiplied with a measurements matrix to obtain the measurement vector. In this framework hybrid measurement matrix is used. The Hybrid matrix is designed by combining the Toeplitz matrix of size $M \times f_1/2$ and the Binary matrix of size $M \times f_1/2$, where 'M' represents the number of measurements. The Toeplitz matrix contains -1 and +1 entries, while the Binary matrix contains 0 and 1 values. The Toeplitz matrix and Binary matrix are used as its generation is simpler and also satisfies the properties such as restricted isometry property and incoherence property of ideal measurement matrix. The M compressed features are extracted for processing instead of the entire f_1 features. This reduces the storage, processing and transmission energy complexity. The hybrid matrix of size $M \times f_1$ is applied to the sparse feature vector $f_1 \times 1$ to obtain the compressed feature vector of size $M \times 1$. The sparse feature vector and compressed feature vector are shown in equation (1) and (2).

$$s_f = \Psi I_f \quad (1)$$

$$y_f = \phi s_f \quad (2)$$

where s_f represents the sparse feature vector of the image, ψ represents the basis matrix, y_f represents the compressed feature vector of size $M \times 1$ of the image block and Φ represents the hybrid measurement matrix of size $M \times f_1$. The concept of CS applied to ORB features is depicted in Figure.4. The compressed feature vector is uploaded to the cloud for subsequent recovery and categorization.

d) The CS Recovery and Classification

At the monitoring end, the compressed feature vector is retrieved from the cloud and the original ORB features are recovered using a simple and effective orthogonal matching pursuit (OMP) algorithm [27],[29]. Further, with the help of SVM the diseases can be classified from the ORB features. The SVM is a supervised machine learning algorithm used for classification problems. Each feature is plotted in f1 dimensional space, where f1 is the number of features and the value of each feature is the coordinate value. [30],[31].SVM works well for linear data and classification is done by finding the hyperplane differentiating the two classes. Once the disease classification is carried out at the web server/mobile app level an alert message of the disease along with the solutions for the diseases by agricultural experts are sent to the farmers through text message.

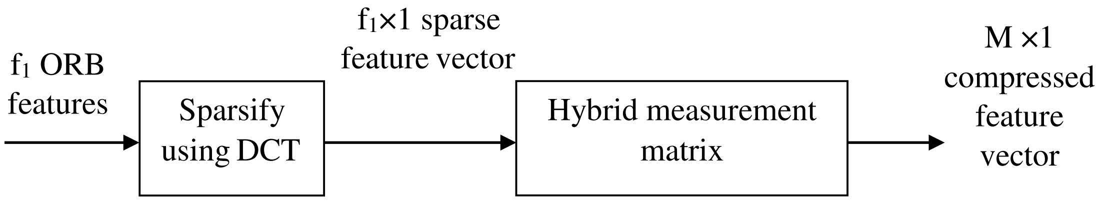


Fig. 4 Compressed sensing process

e) The Mobile App Development

The android app is developed using Google's Android studio. It is an open source software. The programming language is Java. The developed app contains 8 activities. It has a splash screen and it pops on the screen when the app icon is pressed. The home page contains different icons with their own functionality as shown in Fig.5. When user clicks the ‘instructions’ button in home activity, this activity pops up as shown in Fig. 6. This activity contains instructions about how to use this app. This provides user a better understanding about the app. After extracting the features from the capture image, the device sends it to the server unlike the state-of-the-art Tumaini mobile app which requires manual intervention for capturing the images using the mobile [32]. The feature is sent as a byte stream to the server and there the python script makes use of the received feature as input to the model. The python script returns a JSON object(number)to the app and depending on the value the disease is displayed on the mobile screen. The server part code is built using flask (Python web framework). The app supports 3 languages with the help of strings.xml file as shown in Fig. 7. The language supported are Tamil, English, Hindi. Thereby this app can cover large users. The user can navigate to settings activity to change language by clicking the settings button in home screen. The history activity page shown in Fig.8 becomes visible when the user clicks the history button in home screen. This activity displays all the images that are uploaded from the device. The images uploaded are stored in the firebase storage and retrieved by the app when user enters this activity. Each image contains attributes like date, time, disease detected which are displayed in the screen. The user can also delete the images from firebase storage through the app if not needed.

Fig.5 Home Page

Fig.6 Instructions Page

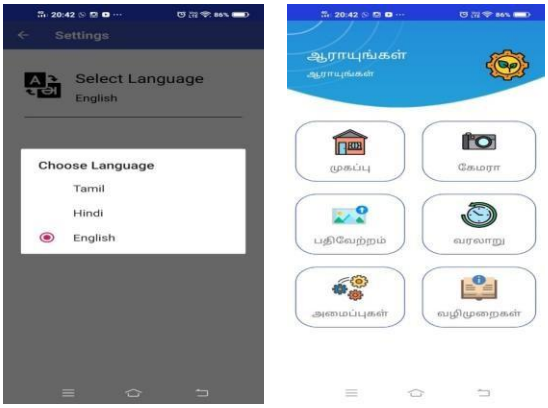


Fig. 7 Language Selection Page

Fig. 8 History Page

3.Performance Evaluation

The prototype of the IoT based proposed plant disease detection device was implemented and validated experimentally using Raspberry pi 3 model b board [33] with Raspbian jessie OS [34] and Python software. Figures 9, 10and 11 show the design of the plant disease detection device and prototype developed using Raspberry Pi 3 board and node MCU, respectively. The design layout in Fig. 9 shows that the environmental sensors are interfaced with the nodeMCU [35] which in turn is serially connected to the Raspberry pi board. The image sensor is interfaced with the Raspberry pi board directly and the device has three power options such as battery, USB and AC mains to work as a standalone device in real fields. The whole is system is enclosed inside an industrial grade box for real time deployment.

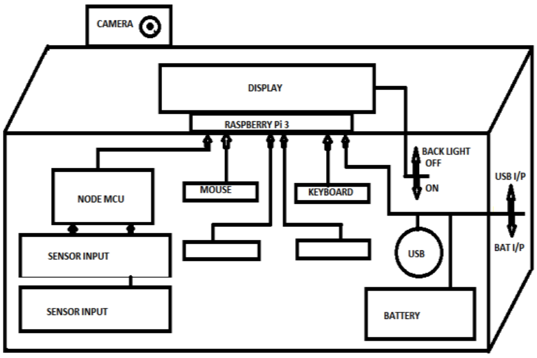


Fig.9 Design Layout

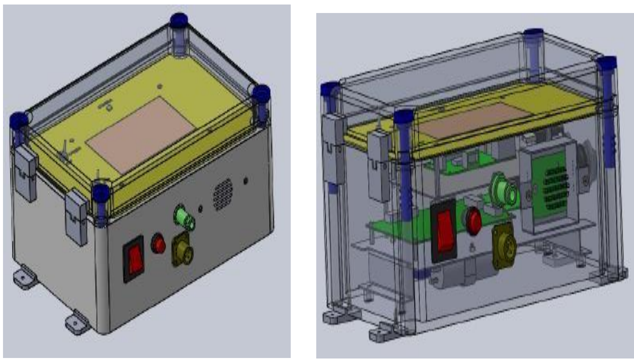


Fig.10 3D views of the design

3.1 Testing:

The prototype developed has been tested in real fields at southern parts of Tamilnadu namely Thadiyankudisai and Thandikudi of Dindigul district, KC Patti, Muthalapuram, Suruli Patti and Kambam of Theni district and ICAR NRCB, Tiruchirapalli. where the banana is cultivated as the major crop. The algorithm developed for monitoring the environmental parameters and detecting diseases has been validated at the fields of above mentioned locations. Sufficient number of images at different stages of diseases (Bunchy top and sigatoka leaf spot) has been captured to generate the database and train the system. Figure 12 shows the image of the prototype tested in real field.

Fig.11 Prototype developed

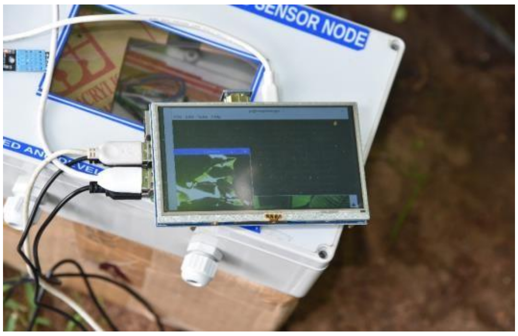
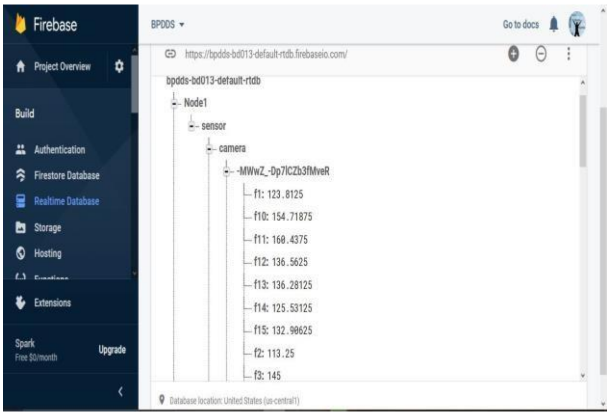


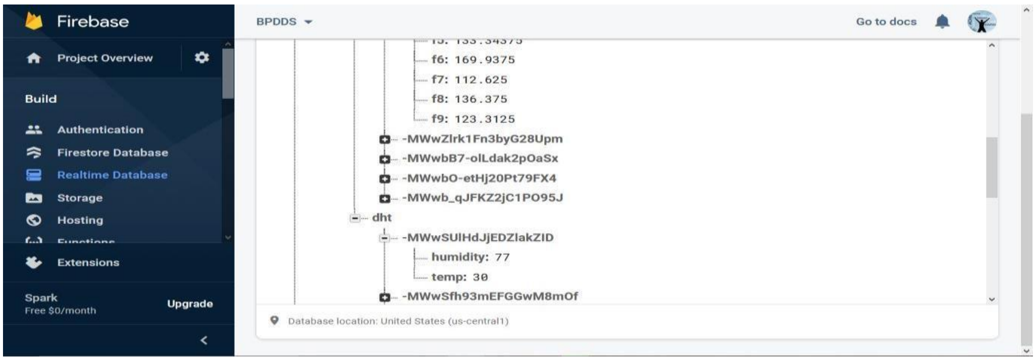
Fig. 12 Prototype tested in real field

Figure. 13 shows the deployment of prototype at ICAR-NRCB Trichy for testing by mounting it on a pole. The data from the device are sent to firebase and Fig. 14 shows the screenshots of the data received on firebase platform.

Fig.13 Prototype mounted on pole in field at ICAR-NRCB Trichy



(a)

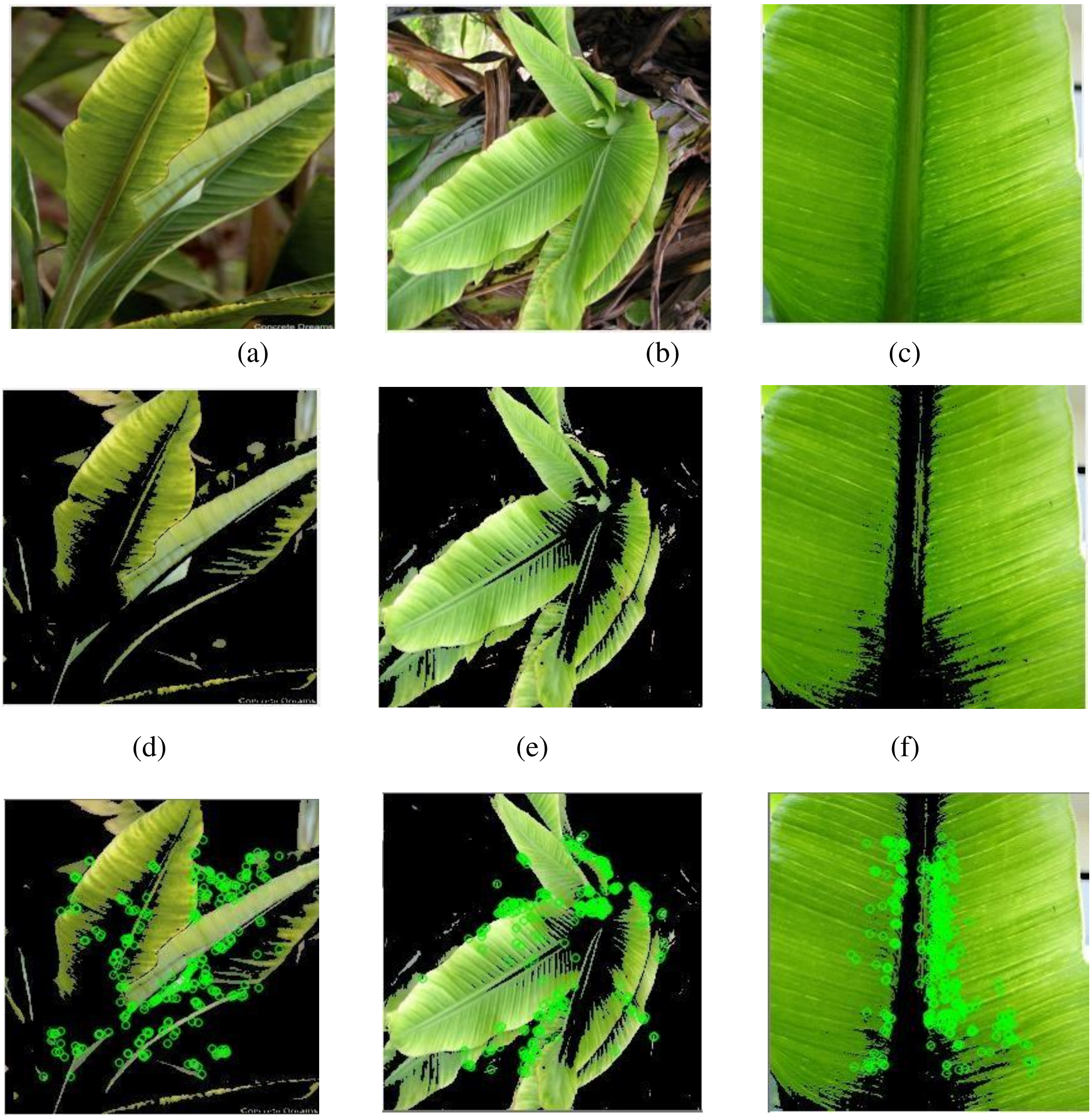


(b)

Fig.14 Screenshots of camera sensor data and temperate/humidity data received from the device to firebase

3.2 Analysis and Discussions:

For demonstration 5000 training images and 500 test images are considered for each category such as bunchy top disease, sigatoka disease and healthy leaves of banana plants, respectively. The system is trained with the ORB features of the training database and the performance of the system is evaluated by using the test images. The images are read from the database of size 256×256 and pre-processed to enhance the image for efficient processing. The FBS technique is applied to the enhanced image to segment the disease affected area. The enhanced image is divided into blocks of size 8×8 and the pixels of each block is compared with the previous block to detect major changes in any particular block. When the difference between two pixels is greater than the mean of the pixels in the block, then that particular block corresponds to the foreground. After the foreground extraction ORB-CS technique is applied to the segmented image. Firstly, the ORB feature detector is used to extract the ORB features from the segmented image. The maximum of 50 features are chosen for analysis and CS is applied to the feature set to obtain the compressed feature vector. Figure 15 and 16 show the original image, segmented image and ORB features in the image for bunchy top and sigatoka leaf spot respectively.



(a) (b) (c)

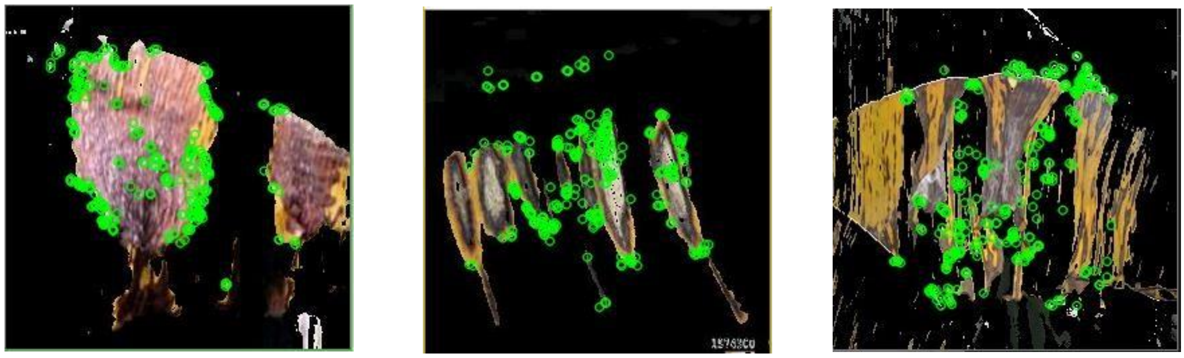
(d) (e) (f)

(g) (h) (i)

Fig. 15Bunchy top disease (a),(b) and (c) input images, (d),(e) and (f) foreground segmented images, (g), (h) and (i) ORB features

(a) (b) (c)

(d) (e) (f)



(g) (h) (i)

Fig. 16 Sigatoka disease (a),(b) and (c) input images, (d),(e) and (f) foreground segmented images, (g),(h) and (i) ORB features

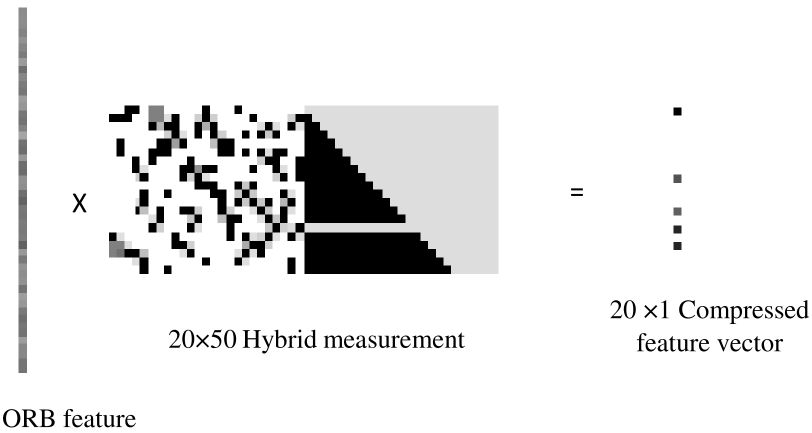


Fig.17 ORB-CS process

The CS process on the ORB features is shown in Figure 17 where the input ORB feature vector is sparsified using DCT to obtain the sparse feature vector of size 50 × 1. Hybrid measurement matrix of size 20 × 50 is generated and applied to the sparse vector to obtain the compressed feature vector of size 20 × 1. These 20 features are sent to the cloud, where they are retrieved and the original 50 ORB features are reconstructed using the OMP method.

These 50 ORB features of the test image along with the training dataset are given as input to the SVM classifier to classify the disease as shown in Figure 18.

a) The Detection Accuracy

The detection accuracy is calculated using metrics such as recall, precision and f measure [34],[35] as shown in equation (3), (4) and (5).

$$Recall = \frac{T_p}{T_p + F_n} \quad (3)$$

$$Precision = \frac{T_p}{T_p + F_p} \quad (4)$$

$$acc = 2 \times \frac{Recall \times Precision}{Recall + Precision} \quad (5)$$

where T_p represents the number of pixels correctly detected as belonging to diseased region, F_p represents the number of background pixels incorrectly detected as belonging to diseased region, F_n represents the pixels belonging to diseased region incorrectly detected as background pixels. Table. 1 shows the efficiency of the FBS technique in terms of detection accuracy.

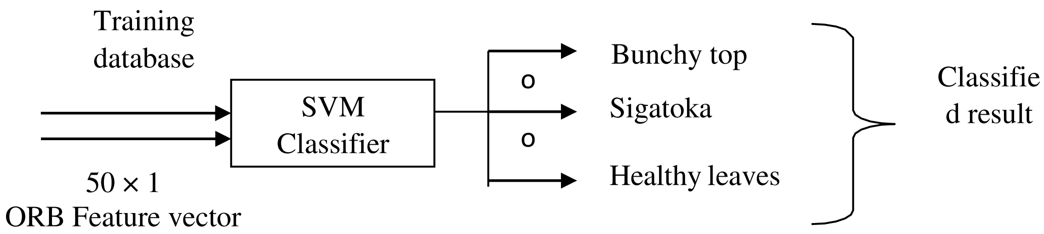


Fig.18 Classification process

Table. 1: Detection accuracy of bunchy top and sigatoka diseases

Diseases	Recall	Precision	Detection accuracy (%)
Bunchy top	0.95	0.96	94.5
Sigatoka leaf spot	0.97	0.98	97.5
Overall Detection Accuracy (%)			96

Table.2 Comparison of the proposed work with existing literature

Technique	Accuracy in (%)
[13]	82
[15]	95.4
[16]	95.71
[17]	90
Proposed work	96

From the table.1 it is observed that the detection accuracy is found to be 94.5% for bunchy top disease and 97.5% for sigatoka disease. On the average the detection accuracy of the proposed device is found to be 96%. Table.2 shows the comparison of the proposed technique with the existing works reported in literature. From the table.2 it is clear that the proposed technique yields similar or better accuracy compared with existing works reported in [15],[17],[18] and [19].

b) The Percentage of Reduction in Samples and Features

The percentage of reduction in features after applying CS is calculated using equation (6)

$$P_f = (1 - \frac{M}{f_1}) \times 100\% \qquad (6)$$

Where M represents the number of compressed features per image and $f1$ represents the number of ORB features per image. Table. 3 shows the analysis of percentage of reduction in features to be transmitted for different banana diseases.

Table. 3: Percentage of reduction features to be transmitted to the cloud

Diseases	Samples	ORB features	Compressed features	Percentage of reduction in samples (%)	Percentage of feature reduction (%)
Bunchy top /Sigatoka leaf spot	65536	50	20	99.97	60
			30	99.95	40
			40	99.94	20
Overall Percentage of Reduction (%)				99.95	40

From table 3 it is inferred that the overall percentage of reduction in samples is around 99.95% and features is 40% thereby reducing the storage and transmission complexity.

c) The Classification Accuracy

The classification accuracy of the system (C_{acc}) is calculated using (7).

$$C_{acc} = \frac{C_c}{T_i} \times 100\% \qquad (7)$$

where C_c denotes the number of correct classifications and Ti denotes the total number of test images [38],[39]. Table 4 shows the classification accuracy of the proposed device. Out of 500 bunchy top images, 448 images are correctly classified as bunchy top, 23 are incorrectly classified as sigatoka and 29 are incorrectly classified as healthy. Out of 500 sigatoka images,25 images are incorrectly classified as bunchy top and 468 images are correctly classified as sigatoka. Out of 500 healthy images, 496 images are correctly classified and 4 images are incorrectly classified as bunchy top. The average accuracy achieved is 94.13 % and is similar or better compared to the work reported in [15],[17],[18] and [19].

Table. 4 Overall classification accuracy

	Bunchy top	Sigatoka	Healthy	Accuracy (%)
Bunchy top (500)	448	23	29	89.6
Sigatoka leaf spot (500)	25	468	7	93.6
Healthy (500)	4	0	496	99.2
Total Accuracy (%)				94.13

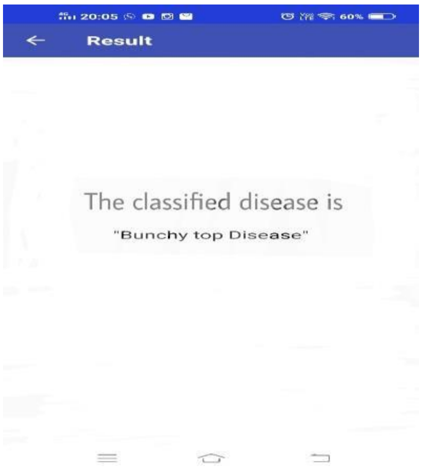


Fig. 19 Classified result in Mobile app

The accuracy is slightly less with high reduction in transmission complexity compared to the work reported in [16]. The accuracy can be improved by optimizing the classifier and increasing the training dataset images.

d) The Mobile App

The extracted features from the device are uploaded to the python server where the python script for the SVM is running. The python script takes the features as input and returns the classified result which is displayed in the android device for user acknowledgement. The screenshots of the classified result in mobile app are shown in Figure 19.

4. Conclusion and Scope for Future Work

A novel and efficient compressed sensing inbuilt banana plant disease detection system (CS-BPPDS) is developed. This system makes use of the proposed FBS technique for extraction of infected portions in the leaves and ORB-CS techniquefor efficient extraction of significant features which contributes to accurate classification. The prototype of the device developed has been tested and validated with the images captured in real field from Thadiyankudisai and Thandikudi of Dindigul district, KC Patti, Muthalapuram, Suruli Patti and Kambam of Theni district and ICAR NRCB, Tiruchirapalli. The device processes the image with FBS and ORB-CS and transmits the compressed features to the cloud with minimal storage and transmission complexity. The features are retrieved and ORB features are recovered using OMP algorithm after which the classification is done using SVM at web server/ mobile app level. The proposed CS-BPDDS has been validated in terms of detection accuracy, percentage of reduction of samples and features and classification accuracy. The results show that the proposed CS-BPDDS outperforms the existing techniques in terms of accuracy and complexity. The suggested device has an overall detection accuracy of roughly 96%, a classification accuracy of around 94.13% with a 40% reduction in features, and a sample reduction of 99.9%.

The developed prototype will be deployed and tested in the field in the future. The measurements of other environmental sensors can be considered along with image sensor for more accurate prediction and classification of diseases. Other soil related sensors can also be deployed underground and connected with the proposed IOT system for monitoring the soil health which in turn can predict the plant health. Ideal conditions for the banana growth at various regions will be collected and maintained for reference.

Declarations:

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Data Availability

The datasets generated during and analysed during the current study are available from the corresponding author on reasonable request.

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