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SMARF: Smart Farming Framework Based on Big Data, IoT and Deep Learning Model for Plant Disease Detection and Prevention

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Abstract. Plant disease can become a serious threat toward food production and security since the demand for food increased significantly over the year. The big data and deep learning have been discussed and explored highly in recent years due to its capability to detect certain features in smart ways. Whilst, crop disease that attack leaves can be cured if farmer detects the early symptoms and avoid the spreading of the disease. This paper presents the capability of big data and deep learning to give predictive analytic toward the plant crop disease. Some features such as leaves, weather, soil and other landscapes condition are taken as an input for the system. Smart farming will utilize IoT technology on capturing the data and localize the position of the infected plant. The combination of computer vision and GPS technology will be able to pinpoint the disease location in efficient ways. The experimental result has shown that deep learning is superior compare to logistic regression with 72% accuracy of identification of an infected leaf. Of course, this result can be augmented further by involving the extra of the leaf. Overall, the Smart Farming framework is able to give a better solution for plant disease spreading prevention by early detection and localization of the disease. A farmer might get advantage by this notification, especially for wide-scale farming. The future work might involve real-time data from the drone or CCTV camera in the real farming field.

Keywords: Plant disease · Big data · Disease localization · IoT

1 Introduction

Smart farming has been initiated for the past few years. More machine and sensor have been involved in the process of farming plant or processing. It concerned high-end technology that can be controlled and supervised easily by a human through data-driven of the farming plant. Farmer is currently moved toward sensor and wireless control of IoT technology to observe their farming plant from anywhere and anytime, this kind of trend known as smart farming [1].

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Furthermore, the researcher focused on augmenting the meticulousness of agriculture that will stimulate smart farming to do a more advanced task that covers context-awareness in the daily situation [2]. It covers the real-time response toward an event that occurs unexpectedly such as disaster due to weather or another natural disaster. It should able to trigger the warning alert for the disease or disaster that will occur in the upcoming future. The artificial intelligence may help a farmer to predict and anticipate based on the availability of data that previously-stored and processed for a certain purpose. Even though the human has used advanced technology to boost food production to keep up of demand for around seven billion people on the earth. This still barely enough if facing climate factor such as natural disaster or plant disease [3]. This paper consists of several sections which are started by the introduction of the research followed by related works. Afterwards, the proposed framework is discussed and continued by deep learning analysis for the crop disease. Finally, it is closed by a conclusion.

2 Related Works

Therefore the involvement of Artificial intelligent and big data analysis is very important to make prediction and estimation with several factors such as plant growth timeline, disaster, plant disease, water supply, etc. Plant disease detection and diagnosis through computer vision and image processing are very crucial for the early prevention toward spreading of plant disease [4, 5]. Mohanty et al. Did a comparison among two convolutional neural networks (CNN) to identify 26 diseases on a plant based on leave images database of fourteen different plants.

The convolutional neural network in deep learning also used widely to do automatic recognition for plant-based on their leaves features [6]. The other researcher present more powerful network based on the leaves vein pattern to identify the plant [7, 8]. While Big data also play an important role to give deep learning algorithm a better training data set and made them smarter to identify any plant disease spreading in the future [9, 10]. The previous work can be summarized as described in Table 1.

Table 1. Research comparison of Big data and deep learning utilization for farming.

Authors	Research finding
Wolfert et al. [2]	Utilizing the internet as a collaborative platform in providing healthy food
Mohanty et al. [4]	They used a deep learning algorithm to identify plant disease based on an image of the leaves
Konstantinos [5]	Using deep learning detect and analyze the plant disease in agriculture
Pantazy et al. [12]	They are using Local Binary Patterns (LBPs) to extract the features and classify based on One-class classification. Their method is applied for crop disease identification automatically
Singh and Misra [13]	They proposed an approach based on image segmentation for classification and identification of plant disease

(*continued*)

Table 1. (*continued*)

Authors	Research finding
Bhange and Hingoliwala [14]	The proposed Smart Farming for pomegranate disease based on image processing. Its initiated by resizing the image and all its features such as colour, shape are used for clustering and classification input using K-means and SVM to determine either the plant infected or not
Proposed framework	A combination of Big data, IoT technology and deep learning that can help the farmer to study the behaviour of plant disease from previous data and collect data simultaneously through IoT and identify the plant disease by analyzing through a deep learning algorithm. The synergy between these three main elements will help farmers to produce better plan and prevention toward plant disease spreading and boost the productivity of the plant

3 Proposed Framework

The proposed framework is suggesting the combination of big data and deep learning algorithm for analyzing the data from the farm. The artificial neural network consists of several components such as activation function, weights, cost function, learning algorithm. Basically, a neural network mainly consists of input, hidden layers, and output. The complex network comprised of input, three hidden layers and output. The more hidden layer means greater processed are conducted and of course more computational cost. Additionally, deep learning as a special form of machine learning used a convolutional neural network that consists of more complicated layers of a network as shown in Fig. 1.

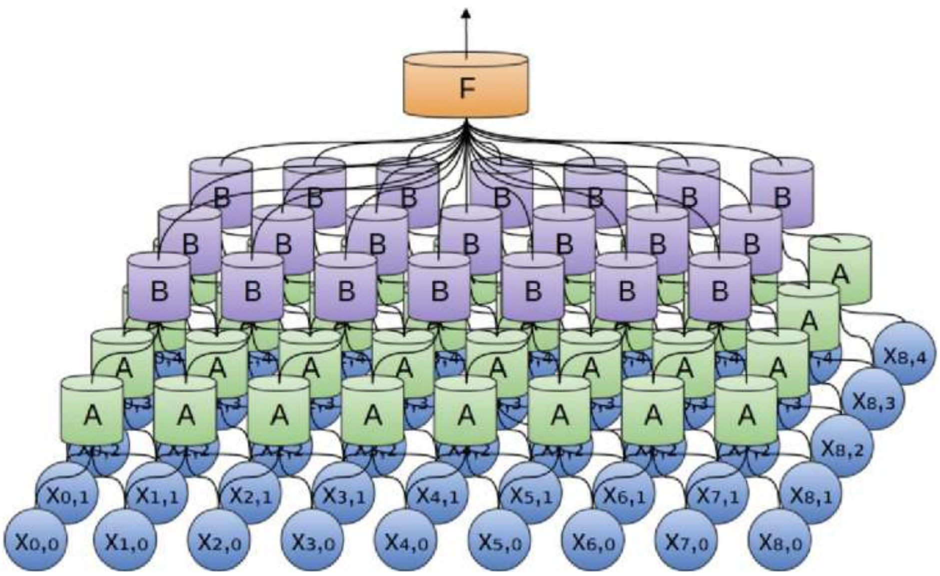

Fig. 1. Convolutional network [8]

Whilst in the Fig. 2, the CNN is described by numerous convolution tagged by pooling process that will continue until the feature map size lessens to one.

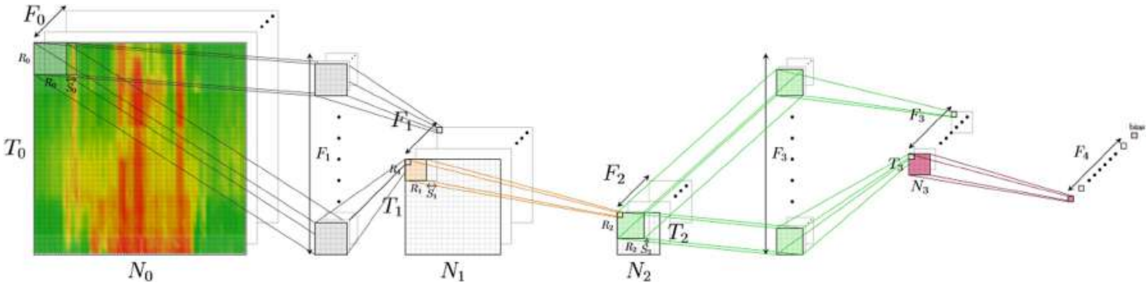

Fig. 2. Typical convolutional neural network architecture

The discrete convolution of functions f and g is labelled as Eq. 1:

$$(f * g)(x) = \sum_t f(t)g(x + t) \tag{1}$$

Whilst two dimensional signal (images) can be computed as two-dimensional convolutions.

$$(K * I)(i, j) = \sum_{m,n} K(m, n)I(i + n, j + m) \tag{2}$$

K: convolution kernel for images

Based on the initial observation, it is found that smart farming requires an integration framework since planting the seed process until the crop period. At the beginning of the planting process, some variable such as temperature, humidity, soil water composure, fertilizer composition, air quality, wind and other climate factor affect the seed plant. All these elements can be captured through the planted sensor, while the picture and video can be detected through the installed camera in the field. The plant leaves, a stem will be monitored and all data will be sent through the server for further analysis. The data will be processed to identify the plant disease in the early stage, so the farmer may take action immediately.

The tag of location also plays an important role to notify the exact location of detected plant disease, so the farmer will not find any difficulty to check the infected plant. All the collected data will be sent through a data network. This monitoring process from seed plantation till crop will be continued and make synergy among each part to achieve optimum harvest. The data analysis will act as an observatory and decision support to a farmer to take immediate action toward a certain plant that got infected by disease or destroyed by climate factors as early as possible to maintain the finest harvest (refer to Fig. 3 for SMARF architecture).

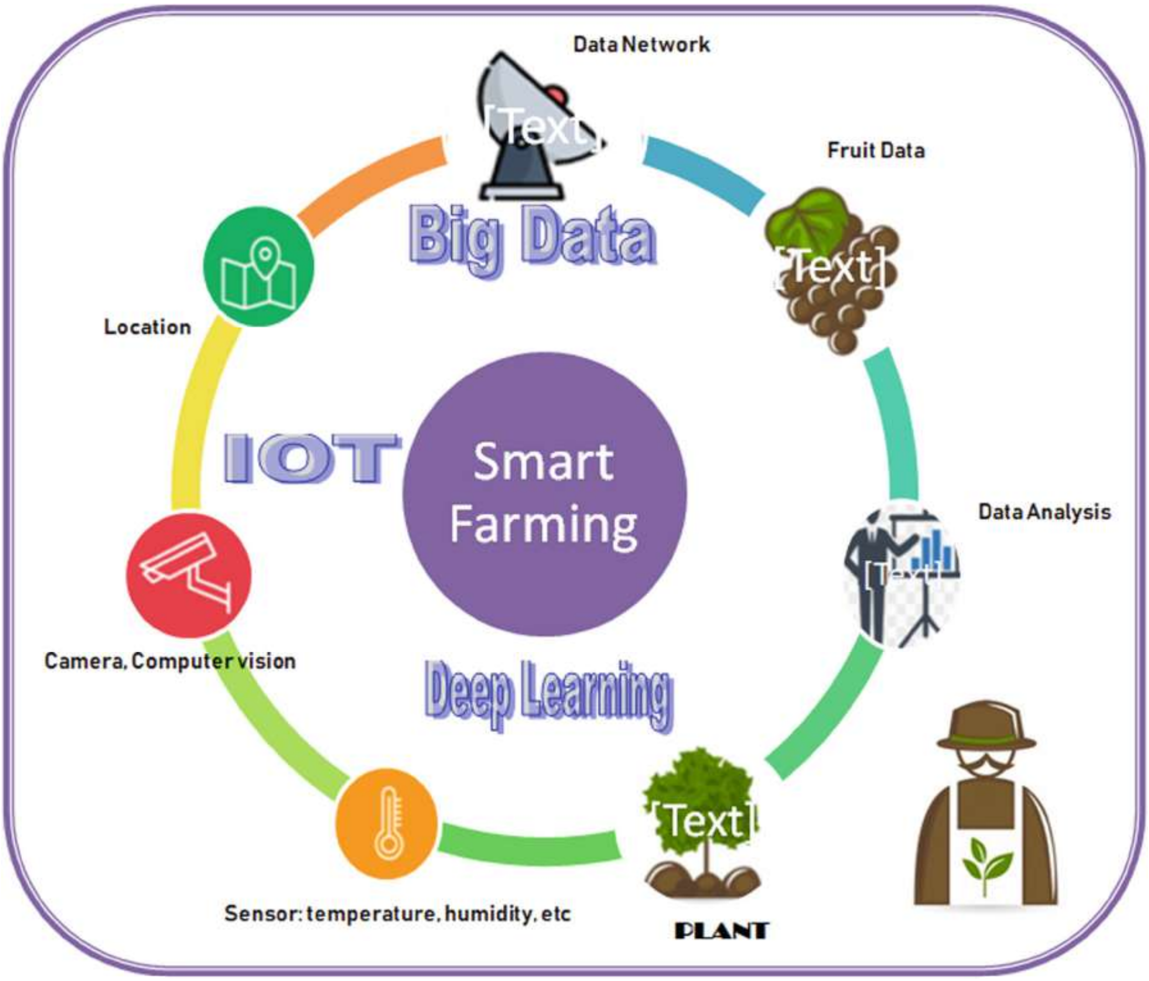

Fig. 3. SMARF: smart farming architecture.

4 Deep Learning Analysis on the Plant Crop Disease

In order to prove our hypothesis regarding the machine learning process to identify the crop disease, there are several steps of image processing that need to be performed before determining whether the crop infected or not. We did use deep learning in this case convolutional neural network (CNN) to identify the crop disease. CNN is given by Eqs. 1 and 2 in Sect. 2. In order to prove our hypothesis of a smart framework, the collection of image dataset of crop disease from Sharma [11] is analyzed and evaluated. Figure 4 is representing the original image of a leaf with crop disease then it will be processed further by image segmentation using mean shift. The mean shift responsible for finding the maxima of density function or also known as mode-seeking approach (refer to Fig. 5).

Fig. 4. The original sample of leaf image with crop disease

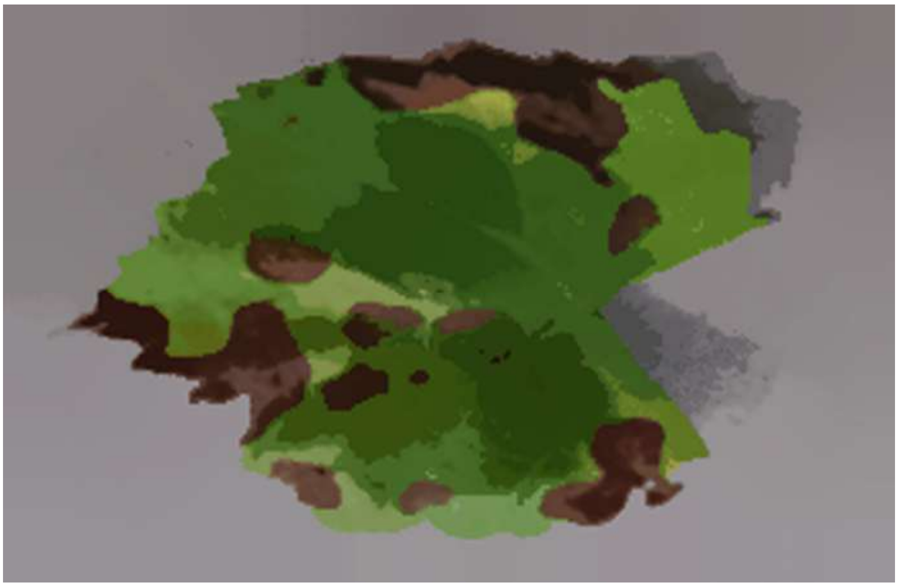

Fig. 5. Mean shift segmentation

This image segmentation will localize the image based on their density and it will be useful for further processes such as edge detection and contour observation. Figure 6 is the result of canny edge detection of the leaf image, it will show the boundary of the leaf. It will give a clear picture of object shape by removing the noise and give a black and white pattern. Edge detection is capable to detect discontinuity of brightness in the image. The shape of the object will be revealed and it will help us to identify the object properties.

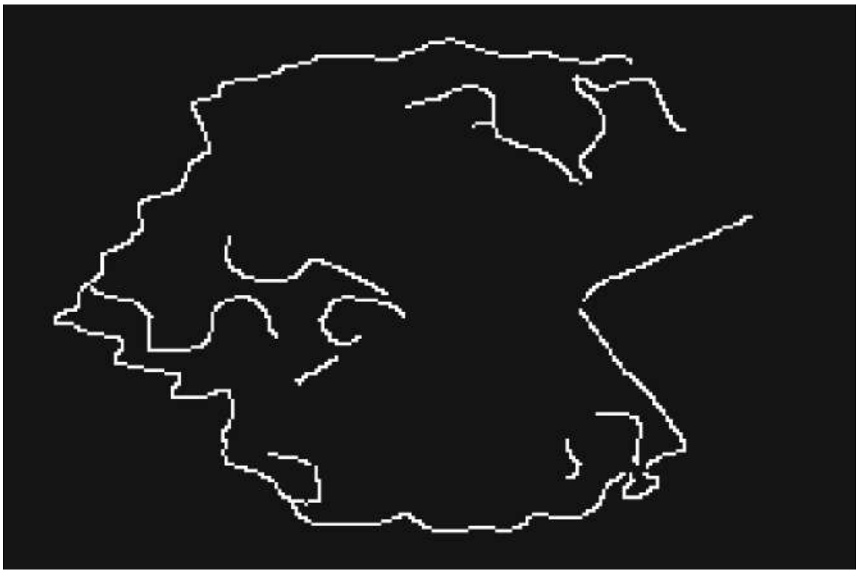

Fig. 6. Canny edge detection

The further process is contour segmentation, its different with edge detection because contour may contain hierarchy that may be valuable for an object inside object localization (Fig. 7). Contour segmentation focused on the edges with the same colour or intensity value that grouped together around the boundary. It is stored as a hierarchy to be used further.

Fig. 7. Contour edge detection of the crop disease

Figure 8 represents the region of interest (ROI), it focused on an area that will be processed with various filtering techniques or other operation. The process is started by initiating the mask in a binary form where the mask size must have had the same size as the image that will be processed. The ROI pixels will be created with 1 value for all the ROI while other pixels will be adjusted to 0.

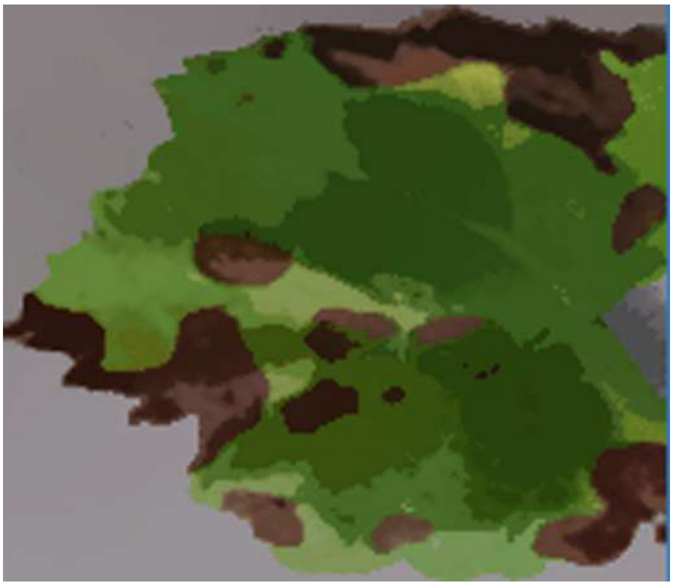

Fig. 8. Region of Interest (ROI) of the crop disease

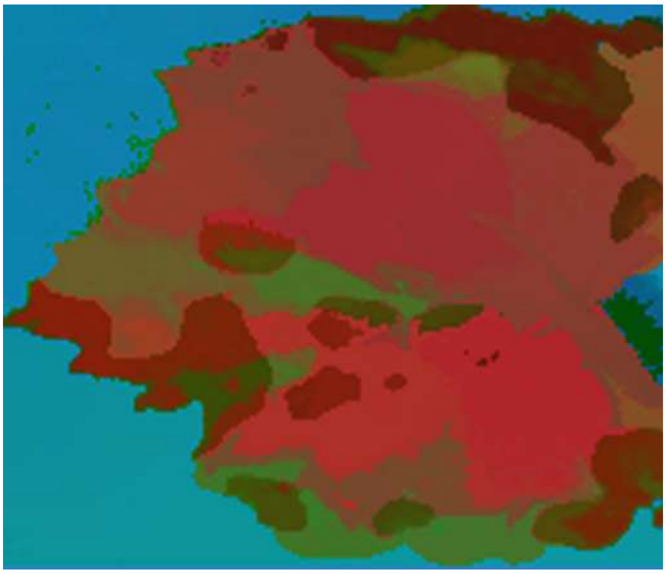

Fig. 9. HLS of the crop disease

Figure 9 represents the high-level synthesis (HLS) of the image that potential for features extraction. HLS will be useful for graphic acceleration since the image processing process required a high amount of resources for the graphic card and processors.

While Fig. 10 is masked out of the crop disease that clearly reveals some region which is identified as a region of disease. The masking process is a non-destructive procedure to highlight certain region with a particular purpose, as mentioned before to identify the region of the disease.

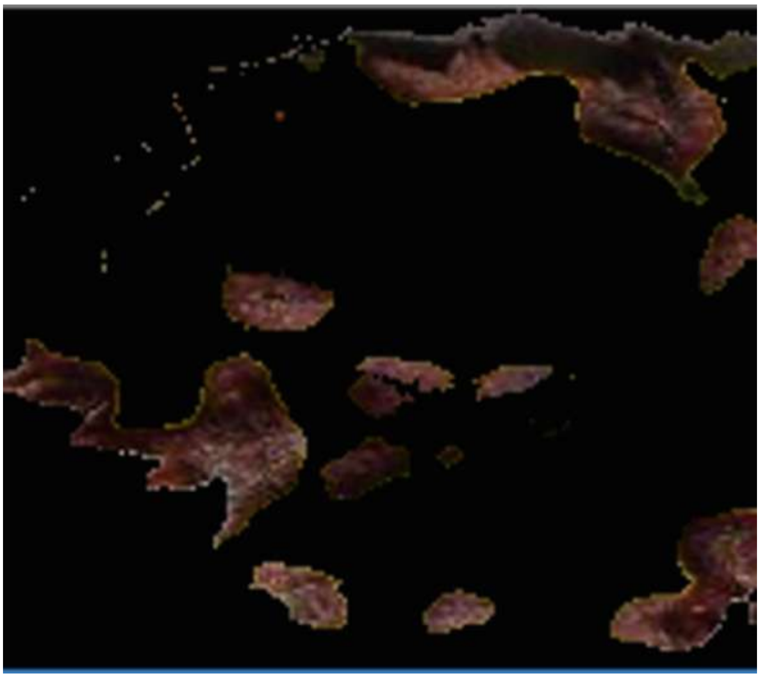

Fig. 10. Masked out of the crop disease

Fig. 11. Contour Masked of the crop disease

Figure 11 is a sample of contour masked for the infected leaf. Contour masked focused on enhancing the detected region by giving a clear boundary around. The combination of contour and masked out will bring a good combination to augment the identified region.

Evaluation Results

Model	AUC	CA	F1	Precision	Recall
Neural Network	0.844	0.719	0.719	0.722	0.719
Logistic Regression	0.615	0.702	0.699	0.708	0.702

Fig. 12. Test and score result for deep learning neural network and logistic regression

Figure 12 shows the evaluation result which demonstrates the superiority of deep learning neural network compares with logistic regression with accuracy 72%. While Figs. 13, 14 and 15 show the density of each feature: feature 1 (are of the leaf), feature 2 (the percentage % of the infected leaf and feature 3 is the perimeter of the leaf.

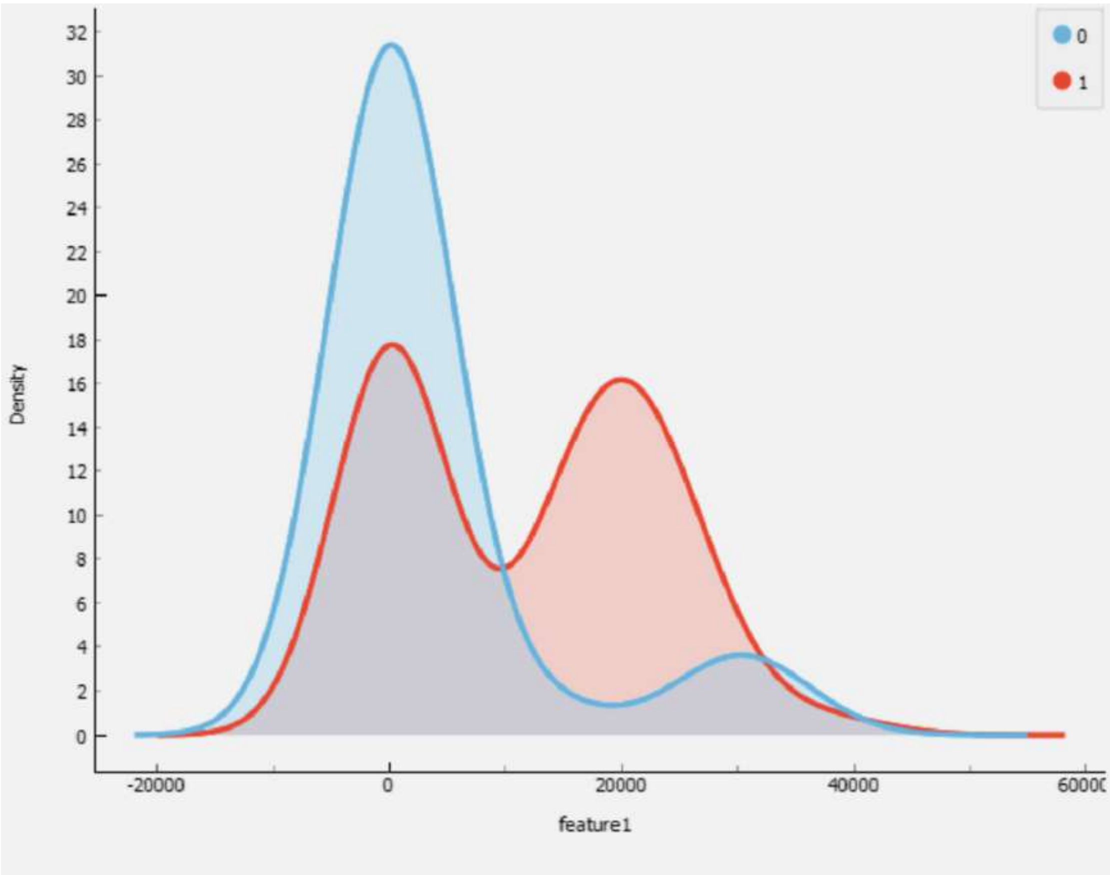

Fig. 13. Density distribution graph for feature 1 (Color figure online)

The blue curve in Fig. 13 describes the density of uninfected leaf. In the beginning, the density of image rise significantly, then its drop in 0 of the x-axis. The infected leaf that shown by the red curve is lower than the blue curve which means infected area still not as dense as an uninfected blue curve.

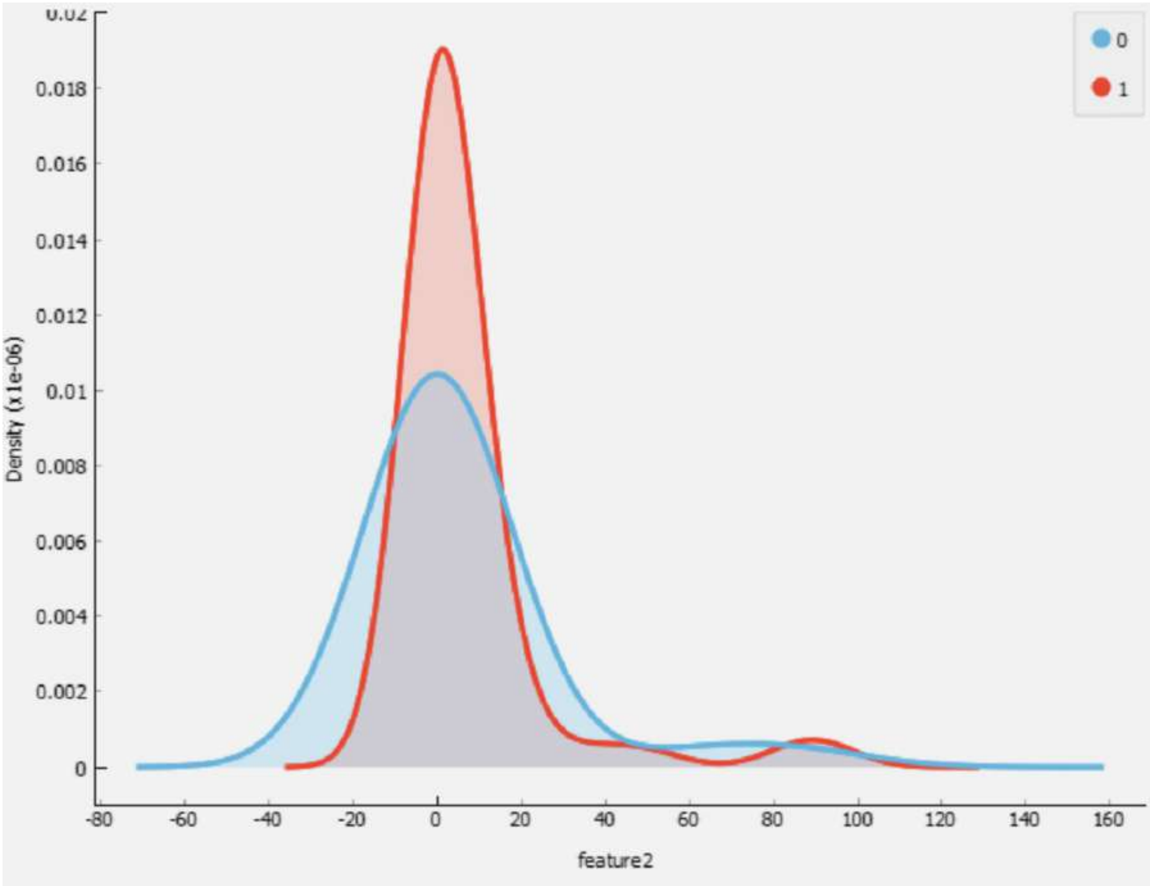

Fig. 14. Density distribution graph for feature 2 (Color figure online)

Figure 14 describe the feature 2 and Fig. 15 illustrate the feature 3 which is the perimeter of a leaf. The read curve reaches its peak on 600 while the blue curve reaches a peak in 1000. This means the infected leaf has more infected region compare to the uninfected one at the beginning of feature extraction.

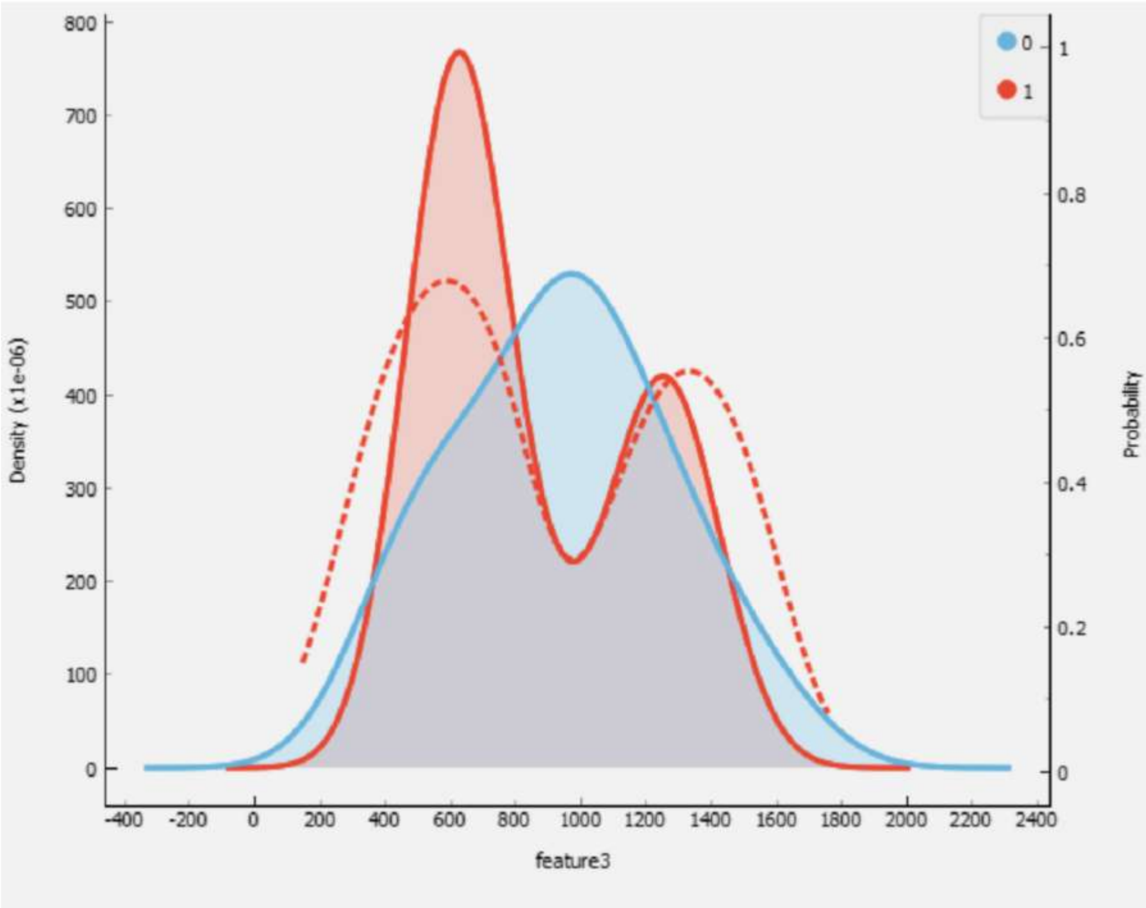

Fig. 15. Density distribution graph for feature 3 (Color figure online)

5 Conclusion

The proposed framework that presented in this paper is a result of an observation of the previous system. It offered an integration of Big data analytics, IoT technology for data communication and deep learning algorithm for further analysis. This synergy of three main elements is very crucial for preliminary plant disease detection so the farmer can take necessary action to keep harvest optimum and reduce plant disease as low as possible. The further analysis with deep learning and logistic regression has shown that deep learning neural network was able to perform good identification of the infected leaf with 72% accuracy, this result still able to be enhanced further by giving more features to be analyzed. This result is a little bit better than logistic regression. The experimental result and evaluation have shown the prospective of smart farming to boost up the crop harvest. Early identification of crop leaf disease may prevent the spreading of disease and make the handling easier.

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