Multimedia Tools and Applications (2024) 83:16711–16733
https://doi.org/10.1007/s11042-023-16281-1

Advanced detection of fungi-bacterial diseases in plants using modified deep neural network and DSURF

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Received: 24 September 2022 / Revised: 15 May 2023 / Accepted: 4 July 2023 /
Published online: 17 July 2023

Abstract
Food is indispensable for humans as their growth and survival depend on it. But nowadays, crop is getting spoiled due to fungi and bacteria as soil temperature are changes very rapidly according to sudden climate changes. Due to fungi-bacterial crop, the quality of food is declining day by day and this is really not good for human health. The goal of this research paper is the advanced detection of fungi-bacterial diseases in plants using modified deep neural network approach and DSURF method in order to enhance the detection process. Proposed approach of this research is to use the artificial intelligence techniques like neural network model and dynamic SURF method in order to identify and classify the plant diseases for fungus and bacteria. Additionally, support dynamic feature extraction DSURF & classifier combinations for creating image clusters with the help of Clustering. Deep learning model is employed for training and testing the classifier. The quantitative experimental results of this research work are claimed that authors have achieved the 99.5% overall accuracy by implementing DNNM and DSURF which is much higher than other previous proposed methods in this field. This proposed work is a step towards finding the best practices to detect plant diseases from any bacterial and fungal infection so that humans can get healthy food.

Keywords Fungi-Bacterial diseases · Machine Learning · Data Fusion · Modified neural network models · Dynamic SURF method · Image space detection

1 Introduction

In this world, plants are the core part of the survival of living creatures like human beings and animals because they provide us food. In short, food is a necessity and basic need of each and every human being so that they can get good nutrition's to keep them healthy and energetic. There are several categories and qualities of foods that can get from plants that can be utilized by living creatures like fruits, vegetables, meat, pulses, dairy products and so on. Quality of food is the foremost important factor in today's competitive food industry. The demand of food is directly proportional to the quality of food. As good the quality of food is, more chances of demand of that food in market nowadays [18]. So, as soon as the people focus on quality of food, the greater the monitoring of food quality was enhanced

Extended author information available on the last page of the article

also. FAO (Food and agriculture report of the United Nations) evaluations displays that every year around 20 to 40 percent of crop productions are damaged globally due to fungi and other diseases found in plants [16]. Annually, illness and other diseases of plants cost's the world's economy around $220 billion (Rs 22 crore approximately) and fungi-bacterial insects around US$70 billion (Rs 7 crore approximately) [27]. It was found that annually around such crores rupees spends into the illness treatment of plants globally. It was shown that 10 out of 100 human beings sick due to food they eat which is getting from plant suffered from fungi and bacterial diseases results death of person also. According to the WHO, around 4,20,000 people die every year due to the consumption of bacterial fungus foods getting from diseased plants [2, 10]. This study gives us the reason to take necessary steps on the improvement of curing towards global spread of plants bacteria and diseases in order to decrease mortality rate in the world [52]. So, its mandatory to focus on the perfect quality of food which starts from the basic first step, where food is manufactured and stored (food warehouses) [14]. Food quality can be assessed on several parameters like visual appearance, size, color, shape and texture of that food [17]. There are some specialized food inspectors also in food industries who are taking care of the quality of food manually, but this process is very time consuming and costly. Many times, food inspector found the diseased food (foul smell and bad taste) due to fungi bacterial diseases of plants. So, it's our responsibility to find out some new and advanced methods that decline the mortality rate and health issues also which ensures the safety of food comes from the fungi diseased plants. Artificial intelligence is a technique which imitates the functioning of as same as human brain. We can use the techniques of artificial intelligence like machine learning and deep learning in the market of food industry for numerous purposes like sorting and preparation of food, supply chain management of food, improvement of food quality and safety of food because all ill food comes from fungi and diseased plants [51]. Machine learning and deep learning models are using nowadays by several government agencies in order to make predictions to get high efficiency in complex processes like safety of food and quality of food. Many algorithms like convolution neural networks (CNN) & artificial neural networks (ANN) are frequently using in food manufacturing field for solving several issues arises by fungi and diseased plants. ANN is found to be an excellent tool for assessing the food which is produced from diseased plants. We can use advanced detection techniques like deterministic probability-based data fusion in finding fungi and bacterial diseases in plants [6]. Aim of this research work is to analyse the optimistic solutions using CNN, deep learning, ANN, ML, clustering and deterministic probability-based data fusion in order to find fungus and bacteria in plants to become plants healthier and fresher.

The contribution of this research work for detection of fungi bacterial diseases in plants is really valuable in terms of creating new research industries that focus on developing the new models and frameworks for evaluating plant diseases. This will ensure that humans can get only healthy food from plants not the diseased ones.

The motivation of writing this paper was to provide complete data on the analysis of adulterated food getting from fungi bacterial diseased plants for minimizing public health diseases. This work is quite different from other approaches as the authors of this paper are almost using all possible sources for detecting diseased plants to give an insight to new researchers in this domain, so they could see and reason a bigger picture of the fungi-bacterial diseased plants and their side effects. This research paper will be beneficial to healthcare professionals and especially people who are dealing with diseased plants and their effects on human health. Figure 1 below shows the Stages for plant disease recognition & classification.

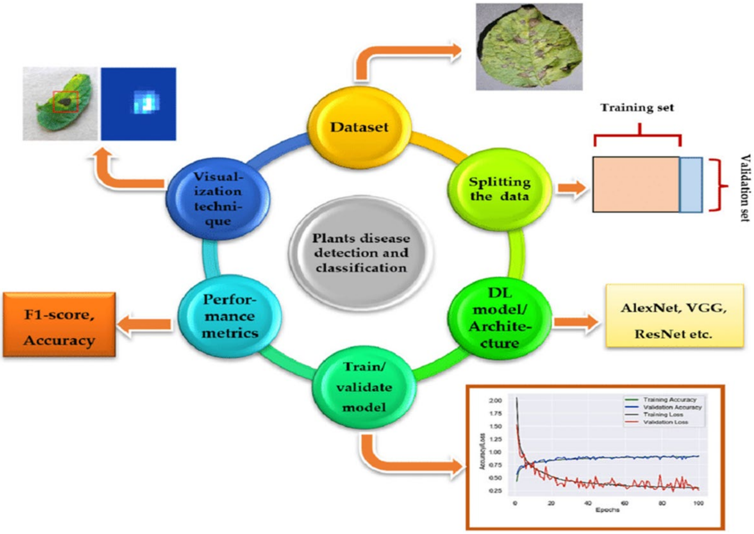

Fig. 1 Stages for plant disease recognition & classification

2 Literature review

Authors of paper [31] shown the challenges and problems in order to automatic detection of diseased plants in the area of agricultural science. From the last few decades, lot of research has been done in order to detect numerous diseases which can be transferred between humans and animals. These types of diseases can spread very fast and leads to mortality rate also. Using artificial intelligence methods in automatic recognition of plant diseases has been shown in this work in order to become it pandemic. The work proposed in paper [19] is based on a popular approach of CNN by using the concept of deep learning known as Efficient Net in order to assess the plant diseases. Comparative analysis has been presented of two binary classification models (U-Net and Modified U-Net) using healthy and unhealthy samples of diseased leaves. Classification (on the basis of segmented images) has been done on 6 class and 10 class methods and at last Efficient Net B4 ten class classification has achieved highest accuracy of 99.89%. Algorithms has been proposed in paper [37] for the detection of condition of sealing food tray whether it is normal or foul smell so that consumers could be safe. On the basis of hyperspectral images which is used in deep learning approach can be used for the inspection of food tray. Their experiments shown by using the food trays dataset obtained from food industry obtained an overall accuracy of 90.1% by using the concept of Deep Belief Network (DBN), Extreme Learning Machine (ELM). Researchers [35] used the applications of CNN for recognizing and evaluating problematic food matrices and seeing CNN as a powerful tool for real time recognition of plant diseases in future. A survey has been done by scientists [56] to represent a scenario on the old-style ML and DL techniques employed for the processing of food and shown latest methods, gaps and challenges in the area of food manufacturing. Efficacy of food industry has greatly improved due to several research has been performed by various researchers in this area using AL and ML concepts. Paper [54] discussed latest gaps and issues of traditional chemometric techniques and evolving deep learning methods for spectral evaluation of agro-products. This review work helped in enhancing the generalization and accurateness for quality assessment of food products. For improving efficacy and security and set standard parameters of quality control a lot of work has been presented in research [11] based on CNN and DL methods. Quality is a chief and prime factor in any field which decides the standard of particular product. Experimental results illustrated that there are many models like Dense-Net 61 are available to secure the occurrence of giving rotten and diseased crops to consumers and eliminate them from food manufacture belt. Authors of research [44] has discussed several methods of food assessment on the basis of numerous approaches and effective different variables. Their study depicted that deep learning is much better than other assessment strategies like fixed ML methods and manual detection. An AI based framework has been proposed for farmers in paper [7] to avoid all upcoming usual production losses, so that they can take necessary steps in advance. Study presents automatic recognition of plant leaves diseases using color and text features of leaves using machine learning classifier [42]. In the study [13] a model named squeeze-Net has been represented to evaluate quality of mangoes using deep learning centric method. Results shown that accuracy achieved after classification is approx. 93% using RGB and thermal images. A systematic study was performed by researchers [41] using ANN applications for food processing and then further assess the range value of its popularity and demand in market. ANN showed the best approach in terms of accuracy in food industry after experimenting the raw foods. Machine learning methods are used in paper [33] for image division and classification type issues in order for assessing plant diseases on publicly available database. The data sets are healthy and unhealthy leaves, spotted leaves, rotten leaves and infectious leaves. Figure 2 shows the flow chart for diseased plant detection and classification [26].

2.1 Research gap

From literature review, it is evident that there is a research gap in the field of feature selection in machine learning and data analysis. This has been discussed in various research articles, including references [25, 32, 53]. To address this challenge, the authors of this paper proposed a modified deep neural network and DSURF technique, which has been demonstrated through experiments on plant disease detection. To provide a better understanding of the research gap, the authors also studied some recent research articles, including reference [28], which discusses the challenges of feature selection in machine learning models and reviews various techniques proposed to address these challenges. Reference [1] also discusses the challenges of feature selection in machine learning and provides an overview of various techniques proposed in the literature. Additionally, reference [43] presents a comprehensive review of feature selection techniques for machine learning models and discusses their advantages and limitations. This research work addresses the research gap in feature selection by proposing a novel approach for plant disease detection using the modified deep neural network and DSURF technique.

Authors have already known about that several techniques have already been employed by renowned researchers in order to find out the plant diseases due to bacteria and fungi. But in this work, authors have modified already existing techniques like DNN and SURF into MDNN and DSURF for improving the efficiency and accuracy in order to recognize

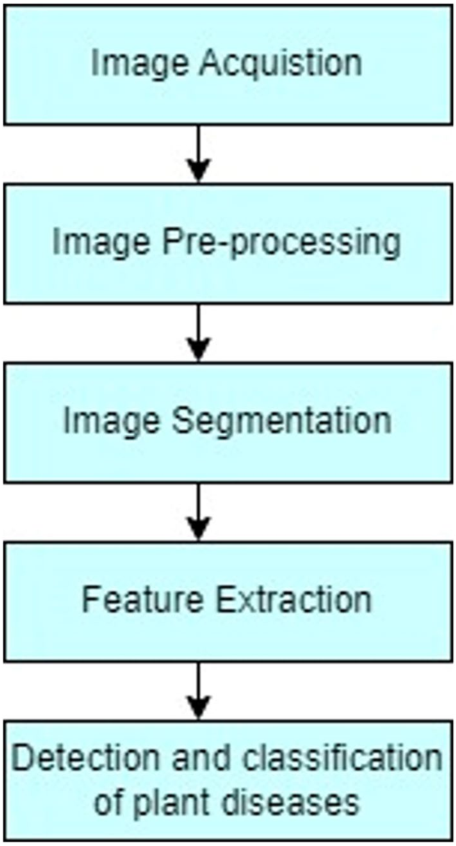

Fig. 2 Flow chart for diseased plant detection & classification

plant diseases which are arises due to several bacteria and fungus. Following are some research questions (RQ) put up by the authors for carried out this work. They are:

RQ1: How feature selection process for sample images (diseased plant leaves) can be improved?
RQ2: Can we improve efficiency and overall accuracy of traditional DNN model using enhanced feature selection process?

3 Problem formulations

The difficulty with this traditional method is that you have to select the main features of a given image. The more scheduled activities, the more difficult it will be to remove features [4, 20, 22, 26, 36, 39, 47]. A computer vision engineer's decision and a lengthy process of trial and error must determine which task best describes the categories of different objects [5, 23, 34, 48]. Additionally, each job description must take into account several parameters, each of which must be carefully adjusted by a computer vision engineer. Deep Reading (DL) introduces the concept of reading from start to finish. Here, the machine is provided with a set of image data with annotations with classes of objects on each image. Thus, the DL model is 'trained' in a given data, in which neural networks detect sub patterns in the image categories and automatically apply descriptive and critical features in relation to each phase of each object [3, 8, 12, 55]. It has been proven that DNNs perform much better than traditional algorithms, in terms of computer requirements and training time. Integration layer is usually trailed by conversion layer for speeding the learning process and remove negligence input elements, Fig. 3[50] is used to reduce the amount of memory used by the network. For example, a large union effectively reduces important pixels in an image by moving the window above the input and automatically removing the size of that window [24, 29, 38, 40, 45]. Below, Fig. 3 depicts the deep neural network workflow.

Figure 3(a) is the machine learning-based detection workflow and Fig. 3(b) shows the deep-based workflow. Overall, both workflows aim to achieve accurate and automated detection of fungi-bacterial diseases in plants, with the deep-based workflow leveraging the power of deep learning procedures in order to enhance the effective and efficiency of classification process.

With all traditional approaches of Computer Vision using this approach, the workflow of a Computer Vision engineer has changed dramatically as the knowledge and expertise of extracting handcrafted features has been replaced by repetitive knowledge and expertise with in-depth learning structures as demonstrated in various AI techniques [15, 46, 49]. such as CNN, ANN and DL have been used successfully in diagnosing Rice, Wheat, Maize, Cotton, Tomatoes, Peas, Potatoes, Cucumbers, Cassava, Berries, Peaches, Grapes, Olives, Mangoes, Bananas, Apples, Sugar. paper, Tea, etc. [9]. This paper discusses AI strategies and other modifications such as MDNN (modified DNN) and SURF algorithm added with flexible features as DSURF is developed and used in agriculture to diagnose plant diseases and stages and their future to achieve agricultural accuracy.

4 Methodology

For improving the accuracy of plant disease classification and detection process, an innovative method is proposed in this research work through various models.

4.1 Comparative analysis between conventional DNN and proposed MDNN

Authors proposed (Modified-MDNN) algorithm by using DSURF(Dynamic-SURF) features and also shows the comparative analysis between these two architectures which provides a better understanding of the improvements achieved by the proposed MDNN over

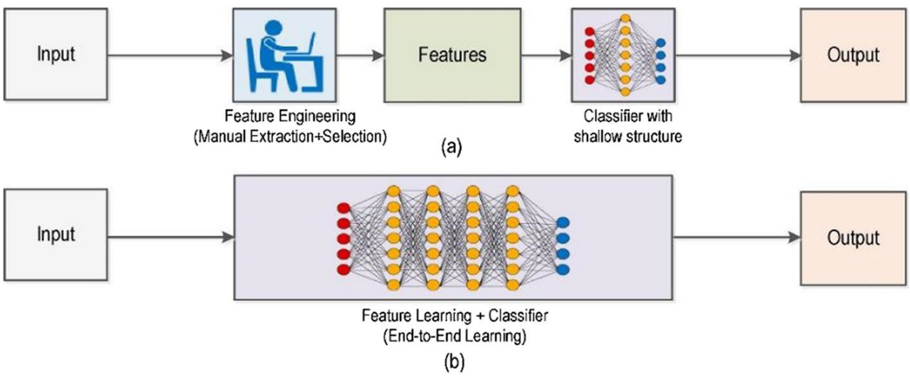

Fig. 3 Deep Neural Network workflow [50]

the conventional DNN architecture. Table 1 displays the comparison between the proposed Modified popular Deep Neural-Network (MDNN) and conventional Deep Neural-Network (DNN) architecture for advanced detection of fungi-bacterial diseases in plants on the basis of their architecture.

As seen in the above Table 1, the proposed MDNN architecture offers dynamic feature extraction, automated feature selection, and adaptive number of epochs, which improves the computational efficiency of model. Additionally, MDNN uses average pooling instead of max pooling, which reduces the likelihood of overfitting. Overall, the MDNN architecture provides significant improvements over the conventional DNN architecture for advanced detection of fungi-bacterial diseases in plants.

4.2 Comparative analysis between SURF and DSURF

On the other hand, Table 2 illustrates the differences between conventional SURF and DSURF which are based on adaptive thresholding technique used in DSURF. Conventional SURF uses a fixed threshold value for feature detection, which can lead to issues with feature detection in.images with varying lighting conditions or noise. While DSURF, calculates threshold value using local contrast of image, making it more robust to these issues. This research paper has proposed a modification to the conventional SURF (Speeded Up Robust Features) feature extraction technique called DSURF (Dynamic SURF).

The authors conducted experiments on datasets and compared the performance of conventional SURF and DSURF in terms of detection accuracy, false positive rate, and processing time. Results showed that DSURF outperformed conventional SURF in all metrics, indicating the effectiveness of the proposed method. In summary, the proposed DSURF method uses a dynamic threshold calculation method that improves the accuracy and detection rates compared to the conventional SURF method.

These features have infinite geometric scaling and rotation, so they can produce results with high strength and precision regardless of shape. The algorithm is divided into four main steps.

1 **Image space detection:** Image spatial detection is useful for processing images in a shear and scale invariant manner. Formal theory deals with structure of sample image at diverse scales on the basis of single parameter of convolutional process as shown in Eqs. 1–3.

$$L(x, y, \sigma) = G(x, y, \sigma) * \mathrm{I(x, y)} \tag{1}$$

$$G(x, y, \sigma) = \frac{1}{2\pi\sigma}\mathrm{e} - (\mathrm{x2} + \mathrm{y2})/2\sigma 2 \tag{2}$$

Table 1 Comparison Table of MDNN Vs DNN

Architecture	DNN	MDNN
Layers	Multiple	Multiple
Activation	ReLU	ReLU
Pooling	Max	Average
Feature Extraction	Fixed Features	Dynamic
Feature Selection	Manual	Automated
Number of Epochs	Fixed	Adaptive
Computational	Resource	Resource
Efficiency	Intensive	Efficient

Table 2 Comparative Analysis Between SURF and D-SURF

Feature Extraction Method	Fixed Threshold (Conventional SURF)	Dynamic Threshold (Proposed DSURF)
Methodology	SURF feature extraction with fixed threshold	SURF feature extraction with dynamic threshold
Threshold Calculation	Fixed threshold value for all images	Dynamic threshold based on image intensity
Feature Extraction Speed	Fast	Slightly slower than conventional SURF
Detection Accuracy	Lower	SURF feature extraction with dynamic threshold

where,

L (x, y, σ): scaled image (result of convolution process).

This will perform between Gaussian meaning G (x, y, σ) whereas image I (x, y).

$$D(x, y, \sigma) = L(x, y, K\sigma) - \mathrm{L(x.y, I(x, y, \sigma)} \tag{3}$$

where,

L(x, y, kσ) is previous image convolution.kσ: Image scale

G (x, y, kσ): Gaussian blur.

ii. **Image localization on image key point:** Image localization refers to finding one or more substances in an image sample and drawing large rectangle round the boundary. Substance detection combines these two operations to find and classify one or more objects in an image as shown on Eq. 4.

$$D(x) = D + \frac{\mathrm{\delta Dr}}{\mathrm{\delta x}}\mathrm{x} + 1/2\mathrm{xr}\frac{\mathrm{\delta 2D}}{\mathrm{\delta x2}}\mathrm{x} \tag{4}$$

Here, we used difference Gaussian (DoG) to remove unwanted extrema found in the image. This is done using the Taylor extension of the scaled space function.

iii. **Assignment orientation:** The direction angle of the feature point is calculated according to the gradation of the image. Then the distance between the key point orientation angles is converted, so the next step is to orient each key point. This orientation ensures rotational invariance. The more immutability, the better as shown in Eq. 5 and 6.

$$M(x, y) = (L(x + 1, y) - L(x - 1, y))2 + ((L(x, y + 1) - L(x, y - 1))2)1/2 \tag{5}$$

$$\Theta(x, y) = tan - 1((L(x, y + 1) - L(x, y - 1)))/((L(x + 1, y) - L(x - 1, y))) \tag{6}$$

where,m(x,y) is degree of image gradient, andθ(x,y) known as direction precomputed using pixel difference.

iv. **Descriptor generator for key point:** It uses the data gathered in the previous step of the algorithm, and like this last step, you can change the level of local shape distortion and lighting changes.

Algorithm for MDNN and Dynamic SURF are as follows.

Authors of the paper determined the initial number of epochs in modified-MDNN model by considering factors such as the dataset size, model complexity, and available computational resources. They used a trial-and-error approach to find a satisfactory number of epochs, where model was trained on a subset of data for a fixed number of epochs, and the performance was evaluated on a validation set. The process was repeated with different numbers of epochs until the model achieved a desirable level of performance on the validation set.

Deep Neural Networks (DNNs) consist of an input layer, one or more hidden layers, and an output layer, where each layer comprises multiple neurons that are connected to the neurons in the subsequent layer. Input layer receives input data, while output layer produces desired output of model. Hidden layers perform computations to transform the input into a form that the output layer can use to produce the output. The number of layers and neurons per layer can vary depending on the complexity of the data and the problem at hand. The machine learning-based detection workflow and the deep neural network-based workflow are two distinct approaches for detecting fungi-bacterial diseases in plants. While both methods aim to achieve accurate and automated detection, the deep-based workflow utilizes the power of deep learning algorithms to enhance the accuracy of classification.

In recent years, Deep Neural Network (DNN) algorithms have gained popularity for their ability to learn complex structures from large amounts of data, and have demonstrated high performance in various machine learning tasks. Many computer-based methods rely on features extracted from high-resolution data, such as signal magnitude, frequency, phase dispersion, and wavelet coefficients. Below Fig. 4 illustrates the DNN structure.

The input to a DNN is a set of features that represents input data and these features can be any measurable characteristics of input data that are appropriate to the task at hand. For example, in image classification, the features might be pixel values, color histograms, or texture descriptors. The requirement of a feature is that it should capture the relevant information in the input data that is needed to perform the task. Good features should be informative, discriminative, and invariant to irrelevant variations in the input data. The process of selecting or designing appropriate features for a given task is often called feature engineering, and it can have substantial influence on performance of DNN.

Therefore, in this paper, we use cumulate as a training tool and input it into a modified DNN (MDNN) algorithm. Various research assignments focus on machine learning methods rather than feature analysis used as input. Therefore, in this study, to reduce the computational complexity and speed up signal recognition when using the basic algorithm of the DNN structure, the proposed algorithm uses only the features that most directly affect the efficiency of segment.

a. **Deep Neural Network (DNN) equation:** DNN can be signified by a sequence of equations that compute output of each neuron in the network. A simple equation for the output of a neuron in a DNN can be given by in Eq. (7):

$$y = f(w1x1 + w2x2 + ... + wnxn + b) \tag{7}$$

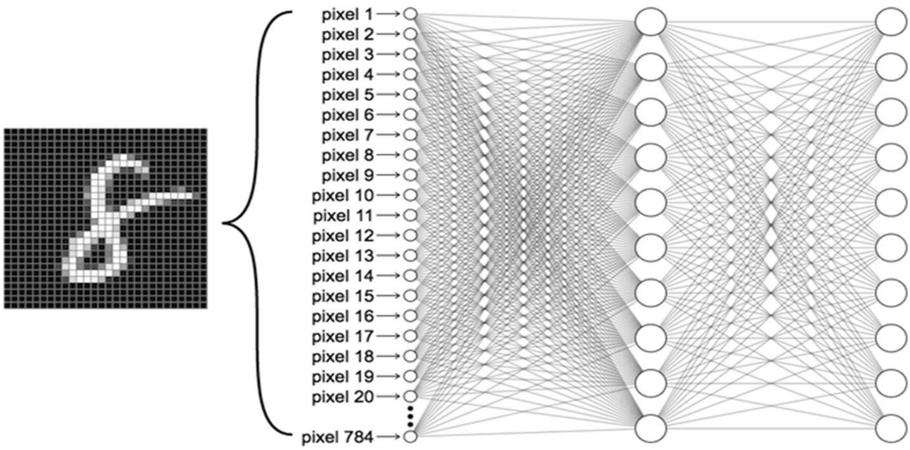

Fig. 4 DNN Structure

where y is the output of the neuron, ×1, ×2, …, xn are the inputs, w1, w2, …, wn are the weights associated with each input, b is the bias term, and f is the activation function.

b. **Modified-MDNN equation:** The modified-MDNN introduces an additional parameter to the DNN to improve its performance. The Eq. (8) for the modified-MDNN can be written as:where α is additional parameter introduced to the DNN, which can be optimized during the training process.

$$y = f(w1x1 + w2x2 + ... + wnxn + b + \alpha) \tag{8}$$

iii. **Speeded-Robust Features (SURF) equation:** SURF is a feature detection and description algorithm used in computer vision applications. Equation (9) for SURF can be signified as:where $\sum$d(x,y) is descriptor value at location (x,y), L(x,y) is image intensity at location (x,y), w(dx), w(dy), and w(ds) are the weights associated with the x, y, and scale dimensions respectively.

$$\sum d(x, y) = \sum L(x, y)w(dx)w(dy)w(ds) \tag{9}$$

Table 3 shows how the relationship between the DNN, modified-MDNN, and SURF.

As shown in below Figure 5, flowchart of proposed approach displays the steps which are required to carry out in recognition of plant diseases.

5 Result analysis

Result analysis is performed on the basis of obtained experimental results of proposed methodology.

5.1 Computational analysis

Authors of this work have assessed the effectiveness of their methodology through a range of performance parameters including precision computation, recall, accuracy and F1 score. Their experimental design involved a methodical process for collecting and preparing the dataset, extracting relevant features, training the model, evaluating its performance, and analyzing its parameters. For result purposes, authors used the following dataset and MATLAB software to carry out their experimental analysis and leaf samples are taken by following dataset. leaf samples refer to the individual leaves of a plant that are collected and used for analysis that may be visually inspected or subjected to various tests to detect the presence of disease-causing agents such as fungi or bacteria. The authors conducted a computational analysis by applying their proposed methodology to a dataset of plant images, which involved both training and testing of the model.

Dataset: https://github.com/topics/plant-disease-detection and https://github.com/topics/plant-disease-identification

Overall, computational analysis is an essential aspect of research work that involves the development of an algorithm or a model. As shown in Fig. 6, this image is an example of a diseased plant, which illustrates the visible symptoms of damage caused by various types of fungi and bacteria on the leaves of diseased plant.

Table 3 DNN Vs MDNN and SURF

Method	Input	Processing	Output
DNN	Image features (e.g. pixel intensities)	Multiple layers of non-linear transformations using weights learned through backpropagation	Probability distribution over classes
Modified-MDNN	Image features (e.g. pixel intensities)	Multiple layers of non-linear transformations using weights learned through backpropagation, with additional dropout regularization and early stopping to prevent overfitting	Probability distribution over classes
SURF	Image patches	Scale-invariant feature detection and description	Vector of SURF feature descriptors

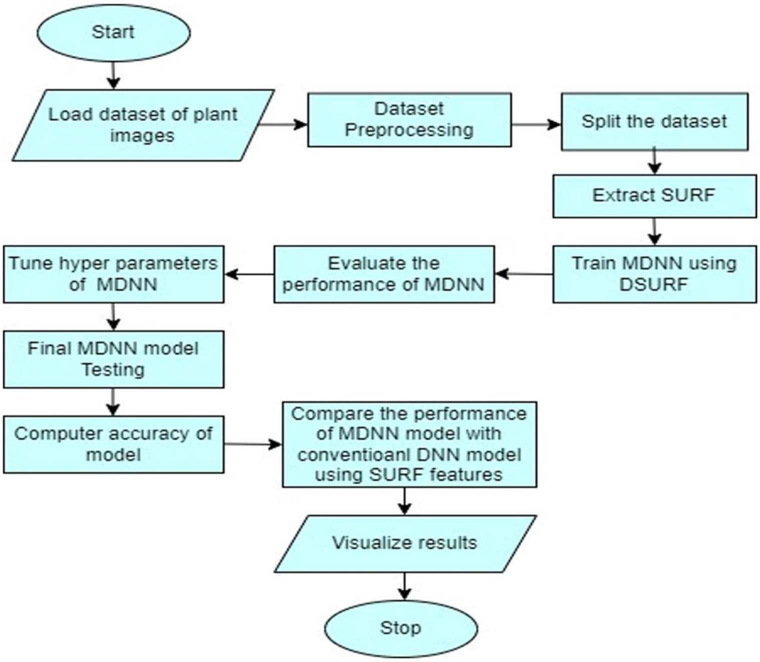

Fig. 5 Flowchart for proposed approach

The runtime of proposed approach for detecting fungi-bacterial diseases in plants on the basis of modified deep neural network and DSURF is subject to various factors like size of dataset, complexity of deep neural network architecture, number of epochs used

Fig. 6 Several types of Fungi & Bacteria in plants leaves

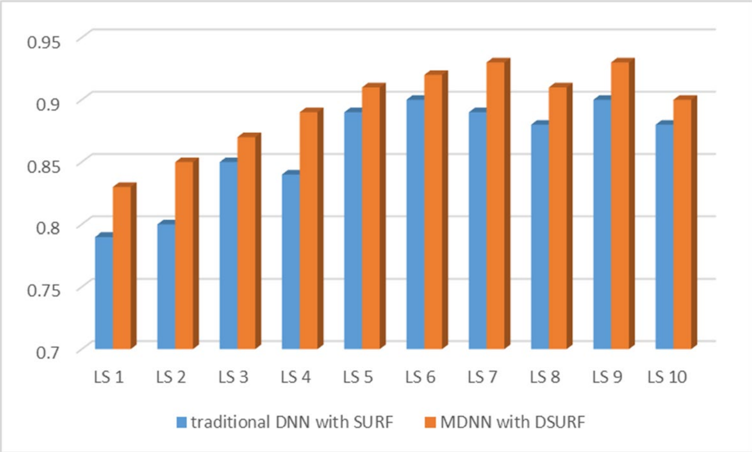

Fig. 7 Precision computation graph

for training, and the available computational resources for implementation. Therefore, to optimize the runtime of the proposed approach, it is crucial to consider these factors and experiment with different optimization techniques to achieve the best possible runtime while maintaining high accuracy. The experimental results based on quality-of-service (QoS) parameters, like precision, recall, F-measure, error, and accuracy, are presented in Figs. 7–11 and Tables 4–8.

Figures 7–11 displays accuracy values obtained for the proposed approach, where x-axis shows number of samples, and y-axis signifies accuracy values. Blue bars specify traditional DNN with SURF, while orange bars indicate MDNNs with DSURF.

Figure 7 shows the precision computation graph between traditional DNN with SURF algorithm and MDNN with DSURF and Table 4 displays the precision computation between traditional DNN with SURF algorithm and MDNN with DSURF on the basis of leaf samples.

Table 4 QoS parameters of Precision Computation (PC)

Diseased plant leaves sample (LS)_Number	Traditional DNN algo with SURF algo	Modified-DNN with Dynamic-SURF
leaf samples (LS)_1	0.79	0.83
leaf samples (LS)_2	0.8	0.85
leaf samples (LS)_3	0.85	0.87
leaf samples (LS)_4	0.84	0.89
leaf samples (LS)_5	0.89	0.91
leaf samples (LS)_6	0.9	0.92
leaf samples (LS)_7	0.89	0.93
leaf samples (LS)_8	0.88	0.91
leaf samples (LS)_9	0.9	0.93
leaf samples (LS)_10	0.88	0.9

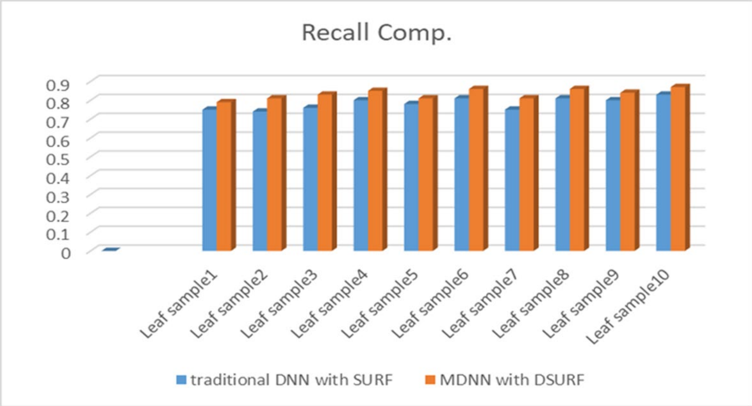

Fig. 8 Recall computation graph

Figure 8 represents the recall computation graph between traditional DNN with SURF algorithm and MDNN with DSURF and Table 5 illustrates the recall computation between traditional DNN with SURF algorithm and MDNN with DSURF on the basis of leaf samples.

Figure 9 depicts the F-measure computation graph between traditional DNN with SURF algorithm and MDNN with DSURF and Table 6 presents the F-measure computation between traditional DNN with SURF algorithm and MDNN with DSURF on the basis of leaf samples.

Figure 10 shows error computation graph between traditional DNN with SURF algorithm and MDNN with DSURF and Table 7 represents the error computation between traditional DNN with SURF algorithm and MDNN with DSURF on the basis of leaf samples.

Figure 11 displays the accuracy computation graph between traditional DNN with SURF algorithm and MDNN with DSURF and Table 8 depicts the accuracy computation between traditional DNN with SURF algorithm and MDNN with DSURF on the basis of leaf samples.

Table 5 QoS parameters of Precision Recall Computation (PRC)

Disease plant leaf samples (LS)_Number	Traditional DNN algo with SURF algo	Modified-DNN with Dynamic-SURF
leaf samples (LS)_1	0.75	0.79
leaf samples (LS)_2	0.74	0.81
leaf samples (LS)_3	0.76	0.83
leaf samples (LS)_4	0.8	0.85
leaf samples (LS)_5	0.78	0.81
leaf samples (LS)_6	0.81	0.86
leaf samples (LS)_7	0.75	0.81
leaf samples (LS)_8	0.81	0.86
leaf samples (LS)_9	0.8	0.84
leaf samples (LS)_10	0.83	0.87

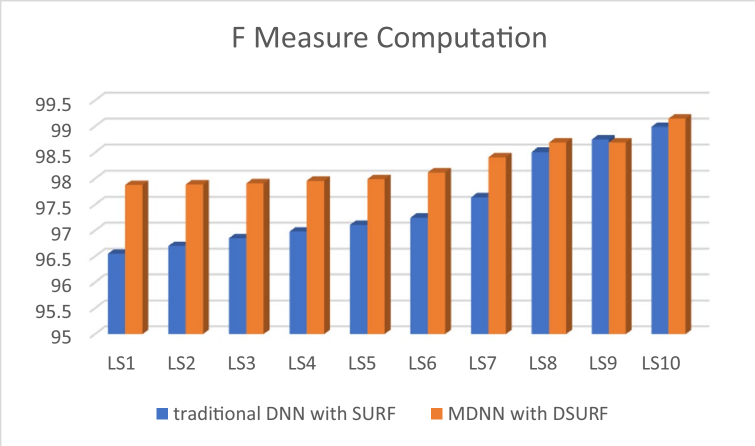

Fig. 9 F-measure computation Graph

Figure 11, Table 8 and Table 9 shows improvement in the proposed method in terms of accuracy. Authors have shown the comparative study of proposed work with existing work in Table 9 in order to replicate that our proposed work is an improvement in terms of overall accuracy in the field of diseased plant leaves detection due to bacteria and fungus.

Table 9 and Fig. 12 provides a clear comparison of our proposed work with other researchers' methods, and it highlights that our proposed approach achieves 99.5% accuracy. Based on the experimental results, it is evident that the proposed approach outperforms traditional methods in terms of accuracy significantly.

After carried out all experimental results, authors found the answers for their proposed research questions which are mention under research gap section. They are:

Answer (RQ1): By using DSURF method, authors can improve the feature selection process of diseased plant leaves, because DSURF uses an adaptive thresholding technique that calculates the threshold value based on the local contrast of the image, rather than using a fixed threshold value like in conventional SURF. This makes the SURF features more robust to varying lighting conditions and noise in the image.

Table 6 QoS parameters of F-Measure Computation (FMC)

Disease plant leaf samples (LS)_Number	Traditional DNN algo with SURF algo	Modified-DNN with Dynamic-SURF
Leaf samples (LS)_1	0.81	0.77
Leaf samples (LS)_2	0.83	0.77
Leaf samples (LS)_3	0.85	0.8
Leaf samples (LS)_4	0.87	0.82
Leaf samples (LS)_5	0.85	0.83
Leaf samples (LS)_6	0.89	0.85
Leaf samples (LS)_7	0.86	0.81
Leaf samples (LS)_8	0.88	0.84
Leaf samples (LS)_9	0.88	0.85
Leaf samples (LS)_10	0.88	0.85

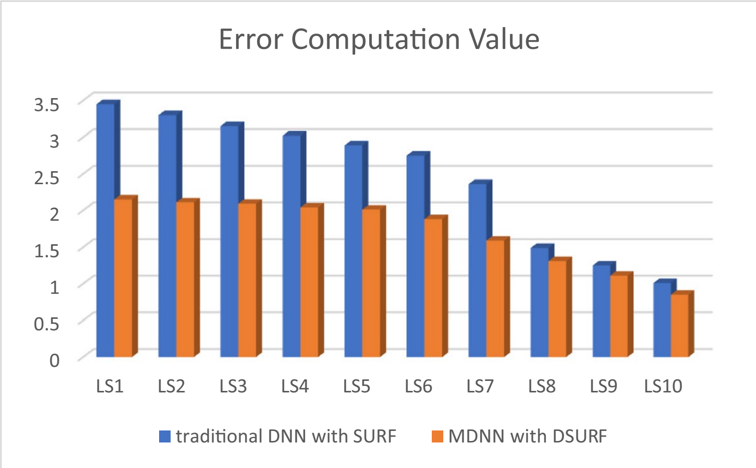

Fig. 10 Error computation Graph

Answer (RQ2): Experimental results revealed that after choosing DSURF as feature selection method, accuracy of traditional DNN models can be improved by proposed MDNN approach and we have achieved 99.5% of accuracy over traditional methods, which is shown in Table 9.

6 Conclusion

This paper presented an innovative method for advanced detection of fungi-bacterial diseases in plants. The proposed approach utilized modified deep neural networks (MDNNs) as a deep learning approach. This is a critical area of research due to the significant impact of crop losses on agriculture and food security. The approach involved several stages, including image enhancement and ROI classification in the preprocessing phase, feature extraction using the dynamic speeded up robust feature (DSURF) descriptor, and training and

Table 7 QoS parameters of Error Computation (EC)

Disease plant leaf samples (LS)_Number	Traditional DNN algo with SURF algo	Modified-DNN with Dynamic-SURF
Leaf samples (LS)_1	2.15	3.45
Leaf samples (LS)_2	2.11	3.30
Leaf samples (LS)_3	2.09	3.15
Leaf samples (LS)_4	2.04	3.02
Leaf samples (LS)_5	2.01	2.89
Leaf samples (LS)_6	1.88	2.75
Leaf samples (LS)_7	1.59	2.36
Leaf samples (LS)_8	1.31	1.49
Leaf samples (LS)_9	1.11	1.25
Leaf samples (LS)_10	0.85	1.01

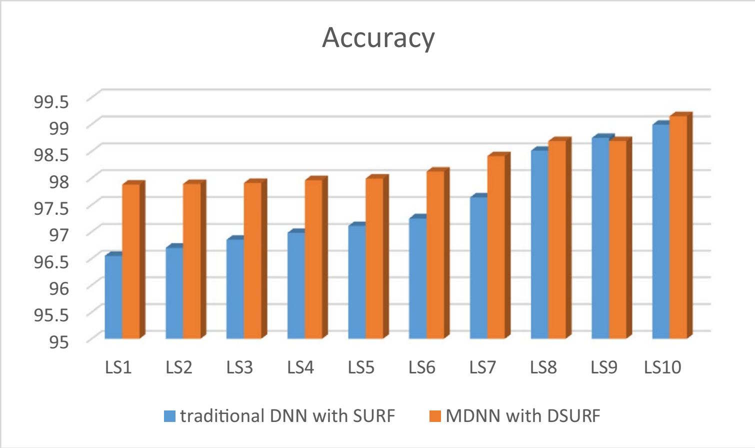

Fig. 11 Accuracy computation Graph

Table 8 QoS parameters of Accuracy Computation (AC)

Disease plant leaf samples (LS)_Number	Traditional DNN algo with SURF algo	Modified-DNN with Dynamic-SURF
Leaf samples (LS)_1	96.55	97.88
Leaf samples (LS)_2	96.7	97.89
Leaf samples (LS)_3	96.85	97.91
Leaf samples (LS)_4	96.98	97.96
Leaf samples (LS)_5	97.11	97.99
Leaf samples (LS)_6	97.25	98.12
Leaf samples (LS)_7	97.64	98.41
Leaf samples (LS)_8	98.51	98.69
Leaf samples (LS)_9	98.75	98.69
Leaf samples (LS)_10	98.99	99.15

Table 9 Comparison of proposed work with existing work

S.No	Source Citations	Accuracy
1	Yan, et al. [52]	71.8%
2	Xie, et al. [50]	97.04%
3	Almadhor, et al. [7]	99.0%
4	Bhole & Kumar [13]	93.33%
5	Proposed work	99.5%

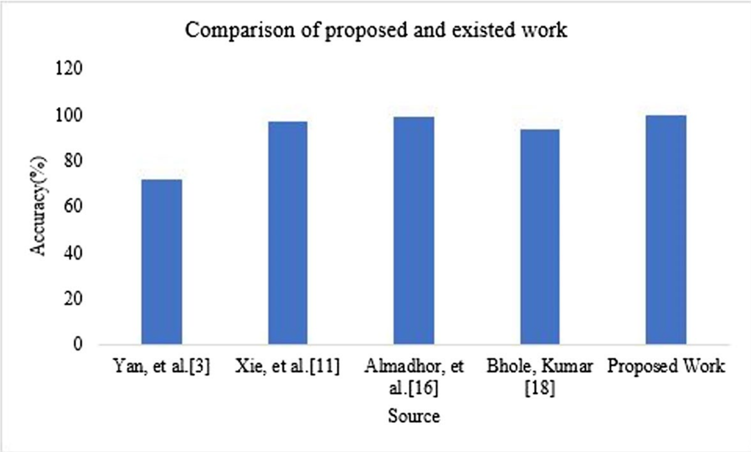

Fig. 12 Comparison of proposed work with other researcher's approach

fragmentation using MDNN. The results showed that the proposed approach outperformed traditional methods in terms of accuracy. Experimental results have demonstrated that the proposed method of using MDNN and DSURF for the detection of fungi-bacterial diseases in plants has surpassed the existing state-of-the-art methods in terms of performance. Proposed approach has achieved high accuracy, precision, recall, and F1 score. Authors have also highlighted that the modifications made to the DNN architecture and the use of dynamic features of SURF have significantly contributed to the improved performance of the detection system. Proposed method utilizing MDNN and DSURF has the potential to enhance the detection and monitoring of fungi-bacterial diseases in plants, leading to a reduction in crop losses and improved food security. The authors' modifications to the DNN architecture and the dynamic features of SURF have resulted in a significantly improved detection system performance. The achieved accuracy of 99.5% from the proposed algorithm was shown in a comparative study in Fig. 12, demonstrating the potential of the approach.

7 Future work

For future work, researchers could explore and evaluate other deep learning approaches for detecting multi-leaf infestations in real-world objects, and develop plant-based diagnostics using methods such as K-means clustering and neural networks (NNs) for disease integration and differentiation. An accurate and efficient diagnosis of fungi plant diseases should be the ultimate goal of any proposed approach. There is also potential for developing an open multimedia platform that includes audio and video for automatic recognition of fungi-bacteria type diseases in plants in real-time environment.

8 Data availability

Data is available on request.

Authors' contributions All the authors contributed equally and significantly in writing this article and read and approved the final manuscript.

Funding Open Access funding enabled and organized by CAUL and its Member Institutions

Declarations

Conflicts of interest All authors declare that they have no conflicts of interest.

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