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Ontology Based Classification Method Using Statistical and Symbolic Approaches for Plant Disease Detection in Agriculture

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Abstract: Agriculturalists spend the majority of their financial resources managing and diagnosing plant diseases. Manually identifying plant diseases requires a lot of time and effort. This study recommends deep neural networks to automatically detect and identify plant diseases. The datasets are trained using a Random Forest technique to classify images of diseased and healthy leaves. The suggested ontology is modelled based on the Web Ontology Language (OWL). Support vector machines, convolution neural networks, and artificial neural networks are just a few of the classifiers utilized to extract features. A dataset that was self-gathered during the augmentation phase is used to validate the augmented method as part of the validation process. The majority of machine-learning methods for identifying plant diseases rely on custom criteria and rarely handle enormous amounts of data. To address this problem, this paper offers an ontology-based method for modelling plant diseases. According to the suggested method, pre-trained architectures include Alex Net and VGG19 CNNs. In order to extract the most useful features from a dataset, the algorithm modifies the details. Based on the correlation coefficient for each characteristic, the right subset of features is selected Convolutional neural networks, artificial neural networks, deep learning, and other artificial intelligence techniques have made it possible to detect diseases in crops like rice, wheat, maize, cotton, tomatoes, peas, potatoes, cucumbers, cassava, berries, peaches, grapes, apples, sweet paper, tea, and others. This study established that training large, publicly available data sets with machine learning algorithms is an effective method for diagnosing plant diseases.

Keywords: Plants diseases; Ontology; Ontology management system; deep learning; feature extraction; classification

1. Introduction

The agricultural sector is the main source of income for many nations around the world. A farmer selects crops, paddies, and pesticides to enhance plant growth in a limited amount of time. Most countries produce most of their food from plants. However, plants are suffering serious problems in the agricultural industry due to illnesses that reduce the quality and quantity of the plants fruits the farming industry also faces problems with shortages of professionals, poor fertilizer management, and a lack of disease and pest awareness. there are many other explanations for the reduced output rate [1]. It can be a supervised or unsupervised learning method for machine learning. In order to learn and train the system, the researcher analyzed a dataset of labelled images of pairs of diseased leaves. These images are used in supervised learning. Using the dataset, the data appear to have been classified correctly. As the dataset size increases, the machine learns to be more accurate and efficient. This study uses an ontology to construct a structured knowledge base on plant diseases. Ontologies are hierarchically structured collections of terminology, statistics, and symbolic techniques for a particular application area. Plant disease taxonomies can be modelled using an ontology [2]. In order to create an ontology for disease detection, this paper aims to enlarge the notions and symptoms of plant diseases by utilizing current ontologies.

The study presents many ontology-based and simulation-based strategies for managing soil, water, and nutrients. Ontology is a method of defining ideas and their relationships. It comprises biological, physical, hydrologic, and transportation-related systems. Ontologies include concepts such as plants, soil profiles, soil layers, water content, and nitrogen concentration [3]. Machine learning approaches include support vector machines, fuzzy logic, fuzzy logic, random forests, K-means

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algorithms, convolutional neural networks, and artificial neural networks [4]. DL classifiers can automatically train thousands of global feature representations from a whole plant leaf. Using artificial intelligence to assist in the early detection and control of plant diseases may be an effective tool for both early detection and early control.

Continuous supply of agronomic inputs, such as water, nutrients, and fertilizers, is essential for maintaining plants' health, growth, and productivity. Without any of these inputs, biotic and abiotic stress may occur. Artificial intelligence is considered the only entity that can decide the number of resources to apply at the right times. This is while also considering the current situation and future predictions at the time of application [5]. The Plant Disease Ontology (PDO) and the Plant Classes Ontology (PCO) are the most relevant ontologies. Ontologies can be categorized and arranged in hierarchies, as shown in (Figure 1) [6]. In "deep learning", neurons are modelled according to their structure in the human brain. Artificial neural networks (ANNs) are used in these methods, as well as convolutional neural networks (CNNs) and recurrent neural networks. A novel hybrid model for automated illness identification is developed. Using Deep Learning algorithms to make image dimensionality more manageable to shorten the processing time for huge datasets with several dimensions [7]. There are various types of machine learning approaches methods that can be used to recognize and detect plant leaf diseases.

There are seven sections in the paper. The first gives a brief introduction, section 2 describes related work, section 3 presents the problem statement, and section 4 explains the detailed architecture of the proposed model, its layers, and hyperparameters. In the last section of the paper, we present the training of the model, the results and discussions, and the future scope of the paper.

2. RELATED WORK

The identification of plant diseases has been attempted with a number of techniques [8, 9, 10]. Methods can generally be classified as direct or indirect. The direct method of detection entails experts performing experiments on collected samples in a laboratory. In [11], the authors reviewed a variety of techniques related to direct methods, including: the Polymerase chain reaction (PCR) technique for finding microorganism counts in samples. Detecting plant diseases through laboratory-based methods is highly accurate, but it is time consuming, requires specialized equipment, and requires expertise [12]. A biomarker-based disease detection method and a property-based disease detection method are indirect methods for detecting diseases. Biomarker-based methods measure volatile organic compounds (VOCs) released by plants and use biosensors to detect causative fungi. A lot of research is being conducted on these techniques, particularly biosensors. According to [13], They discussed the advantages and challenges of developing a portable point-of-care tool for detecting plant diseases in the field using various types of sensors. The vast majority of methods proposed for the detection of plant diseases based on plant property-based methods rely upon images instead. The authors of the study reported in [14] that they reviewed more than a hundred studies dealing with analyzing leaf images for the purpose of detecting plant diseases. An image is acquired, pre-processed, segmented, features are extracted, and classification is performed. Image-based methods, however, face several challenges [15], These include images with backgrounds, photos taken in poor lighting or during a downpour, photos of diseases that are hard to identify, and photos with several diseases.

The method we propose gets around these problems by requiring the user to manually input the features that should be displayed on the screen. These traits can be seen visually as symptoms and indicators [16]. In the conventional method, farmers notice symptoms and indicators before posing questions to professionals to obtain pertinent information. Our method uses an ontology to represent domain knowledge, and queries and reasoning are utilized to find solutions to farmers' queries.

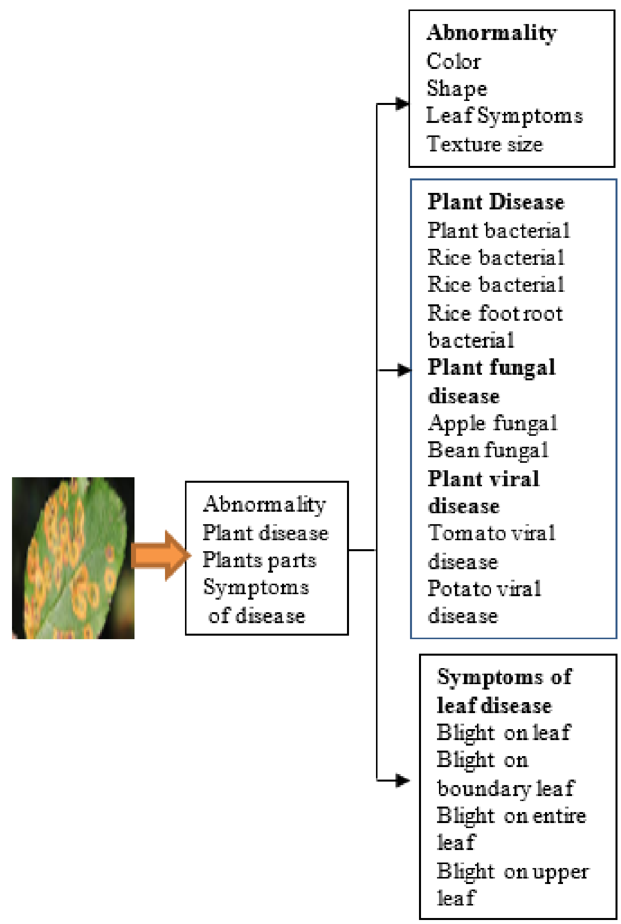

Figure 1. A class hierarchy for plants disease ontology

In the agriculture sector, ontologies have been developed

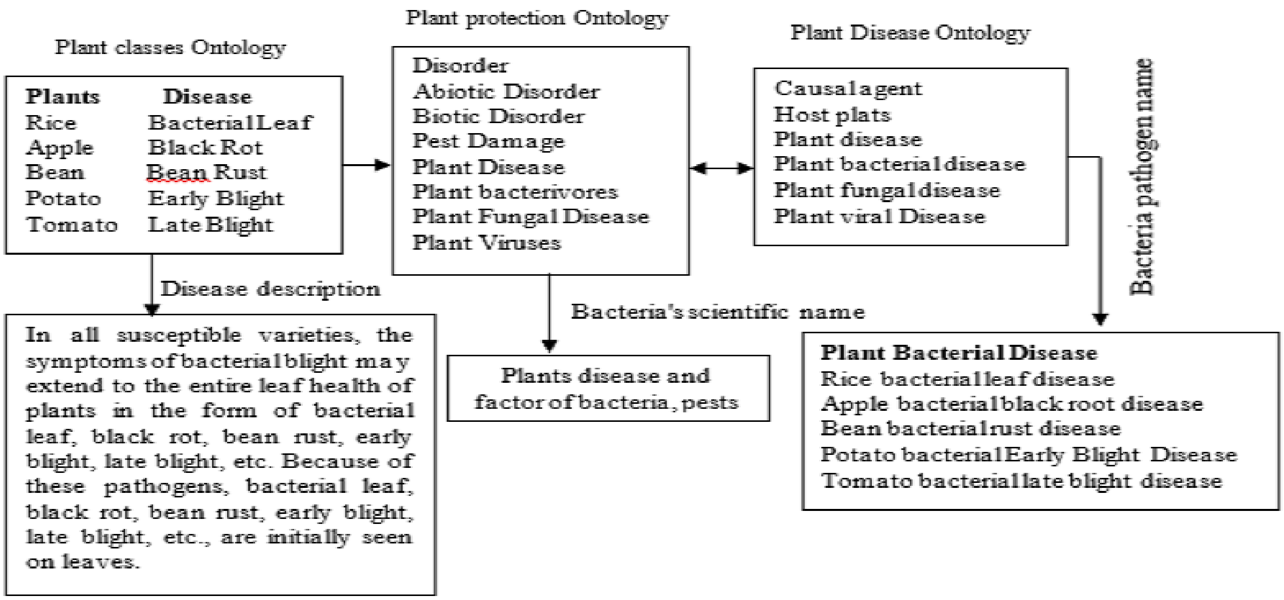

Figure 2. An ontology class hierarchy of plants disease

to model a variety of types There are several sources of information, such as [17,18]. A rice production ontology was created [19] to justify rice production. The key search terms used in this ontology are connected to research publications about rice cultivation in Thailand. Furthermore, according to [20]. The described concepts and qualities do not contain information on specific traits of rice plants. In [21], the crop-pest-environment model is shown. A pesticide ontology for use in Ontology-defined concepts are not taken into account in this work. Instead, it is intended to be used in conjunction with a set of guidelines to give farmers information on rice growth stages and the environment.

A. *Problem Statement*

This study aims to discover a way to effectively represent knowledge from data in plant disease tasks in digital agriculture in an effective manner. Computer science makes use of ontologies and knowledge graphs to show how concepts relate to the knowledge they represent [22]. Knowledge bases and ontologies are becoming more and more well-liked as a result the evolution of linked data and the semantic web. Digital agriculture domain knowledge, whether generic or specific, is included in these methods of knowledge representation. It is necessary to develop a model in order to describe mind knowledge adequately and effectively. Agricultural knowledge encompasses concepts and connections as well as principles, laws, and models. Agriculture is one of India's main economic sectors [23]. The agricultural sector employs more than 60 percent of the Indian workforce. In terms of pulses, rice, wheat, spices, and products derived from spices, India is the world's largest producer. Farmers create quality items, dependent on plant growth and production, that determine their businesses' success. Therefore, spotting plant diseases is imperative in the agricultural sector.

Plants are susceptible to illnesses that stunt their growth, impacting farmer environment. Automated disease detection techniques help spot early phases of plant diseases. In certain areas of a plant, such as the leaves, plant diseases are obvious. It is laborious to diagnose plant illness using leaf photographs manually [24]. Therefore, it is necessary to create computer techniques that automate disease identification and categorization using leaf pictures.Our ontology includes echelon classes to represent the different levels of abstraction required to conform to the ontology specifications (Figure 2). Bedi and Gole devised a three-dimensional system of Style, Shape, and Symptoms to depict plant illnesses' abnormalities [25]. Plant leaf ailment is any condition that develops in plant leaves. Plant Disease divides plant leaf ailments into bacterial, fungal, and viral. Blight on the leaf is an example of a symptom that displays minor appearance differences

3. Proposed Methodology

A. *Dataset Description*

The Plant Village dataset, a collection of photos that is freely available, contains 54,306 pictures of both healthy and damaged plant leaves, stems, and roots as shown in figure 3. The dataset was created to aid in the creation of machine learning algorithms for automatically detecting plant diseases [26]. The images were captured under various environmental conditions and with various camera angles, which makes it more challenging for machine learning algorithms to correctly classify the images [40]. The dataset includes 38 different plant species, with 26 different diseases and pests. Each image in the dataset is labeled with a class indicating the type of plant and the presence or absence of disease or pest [27]. The dataset also includes metadata such as plant species, disease type, and image acquisition details. The Plant Village dataset is a valuable resource for researchers and developers interested in developing automated plant disease detection systems [39]. It can also be used to train machine learning models for other related tasks such as the classification of plant species, pest detection, and crop yield estimation [28].

Figure 3. Shows some examples of the dataset that was used for this research. The pictures, from top to bottom, depict general apple scab, serious apple rust, ring rot, healthy green and red apples, healthy cedar apple rust, serious cedar apple rust, general apple scab, healthy apple leaf, and general and serious apple scab. Other instances are common apple scab, severe apple scab, and widespread cedar apple rust

B. Pre-processing of Input

The input picture is pre-processed before being processed, in which the images are resized of 224*224*3, and the imagery is enhanced using image enhancement techniques such as noise reduction and contrast enhancement using median filters to accomplish the noise removal and contrast enhancement for all the images that are input [29].

C. A description of the proposed model's architecture

A Deep Neural Network, also known as Deep Learning, is a multi-layered artificial neural network consisting of several layers. Due to its proficiency in handling a variety of data sets, it has recently been investigated as a potential additional essential resource [38]. It is highly recognized in the literary community. A convolutional neural network (CNN) is the mathematical dimension, which is produced by matrix convolution. Layers of Convolutional Neural Networks (CNNs) include pooling, nonlinearity, convolutional, and fully connected layers [30]. It has seen that Convolutional Neural Networks are effective in a variety of design recognition applications, including image recognition, speech recognition, and data mining. A primary edge can be identified in an image, followed by less challenging forms in successive layers, and finally, highlights at the highest level [37].
An SVM is a nonlinear classifier that divides highlights into two groups and employs statistical learning frameworks. Component vectors may be separated into several classes using a hyperplane. To prevent vector misclassification, SVM seeks to create a significant separation between the hyperplane and the class limit. In order to identify damaged leaf areas, images are taken with digital cameras or other comparable equipment [31]. After the images have been captured, various leaf types are examined to determine which leaves have been damaged. Next, various image-processing methods are used to process the pictures so that various useful parameters can be obtained for analysis to be performed in the future [36]. The fundamental ideas of Convolutional Neural Networks (CNN) and Support Vector Machines for Feature Extraction of Plant Leaf Disease, which are used to construct the suggested model, will be covered in this study. Figure 4. depicts the suggested CNN and SVM models, whereas the specifics of the suggested models' architecture [32]. Pooling occurs after the convolutional layer to reduce the convolutional feature map size.

The feature map dimension is minimized by a pooling layer, which lowers the computing complexity required to comprehend the input. There are many different pooling strategies, such as maximum, minimum, and average. The convolution or pooling layer, where each input is weighted for each output, converts the output feature maps into a one-dimensional vector. The last completely connected layer may have one or more fully linked layers and the same number of outputs as classes [33].Training a plant leaf disease dataset typically involves using machine learning algorithms to classify leaf images as healthy or diseased. The initial action is to gather a large dataset of images of plant leaves labeled as healthy or diseased. This dataset can be obtained from various sources, such as academic institutions, research labs, or online repositories [34]. A machine learning model learns how to classify images in a training set by adjusting its parameters so that the loss function is minimized. Once the model is trained, it can classify newly discovered, A picture of a plant leaf that has no disease or is healthy [35].

4. Results and discussion

A. Performance evaluation

The system's effectiveness is assessed using fifteen classes from four distinct plant species. The Plant Village Database is the source. The dataset was split into three parts for training, validation, and testing. In the first step, we split the dataset in half, using 85 percent for training and validation and 15 percent for testing and assessing models after training. In the second step, 85 percent of the data were divided into two groups with varying combinations of

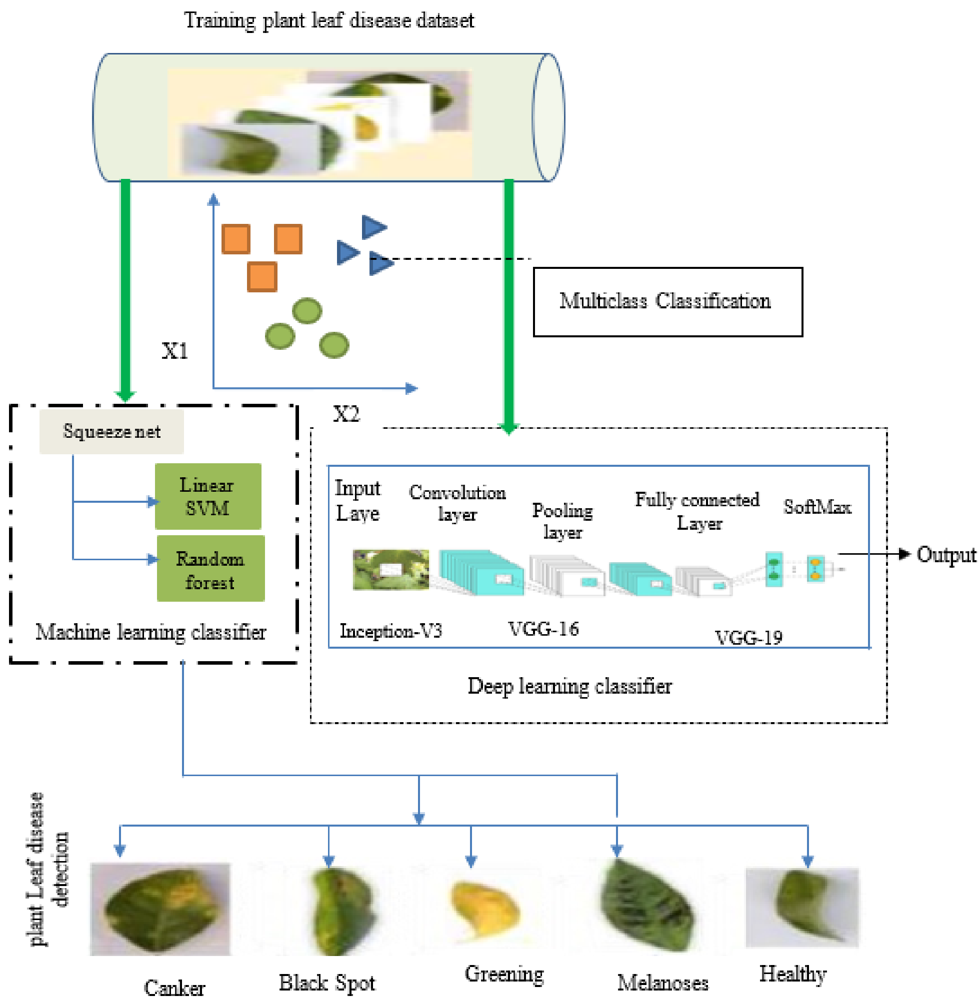

Figure 4. A workflow for detecting plant leaf diseases

training and validation tasks.

In order to ensure that each division had both the original and enhanced images, we partitioned the original and enhanced data independently before combining them. A Python program handled the data splitting, and after training and validation, all studies evaluated the models on a 15 percent test dataset. Original and enhanced datasets of plant leaf images are used to evaluate each model. Finally, we constructed confusion matrices to determine how accurate the models were at classifying diseases. A confusion matrix provides the following variables. The confusion matrix provides valuable information about the model's performance. From the matrix, we can calculate various metrics like accuracy, precision, recall, F1-score, etc., to assess how well the model is classifying the different diseases. These metrics help author to understand the strengths and weaknesses of the model for each class and overall.The confusion matrix is typically a square matrix where rows represent the true classes and columns represent the predicted classes.

Confusion matrix	Actually Positive (1)	Actually Negative (0)
Predicted Positive (1)	*True Positive (TPs)*	*False Positive (FPs)*
Predicted Negative (0)	*False Negative (FNs)*	*True Negative (TNs)*

Figure 5. Confusion matrix

The next method was to calculate the true positive (TP), false positive (FP), true negative (TN), and false negative (FN) values of the model. Some performance metrics were collected in these studies: precision, recall, accuracy, and

F1 scores.

Precision: Precision refers to the percentage of data items our model has determined to be relevant based on the available data.

$$Precision = \frac{True\ Positive}{True\ Positive + False\ Positive}$$

Recall: A model's recall is the percentage of relevant results identified and categorized correctly by the model based on their nature.

$$Recall = \frac{True\ Posituve}{True\ Positive + False\ Negative}$$

F1-Score: Based on the accuracy and recall of the test, the F1 score is a weighted average, where 1 means the best and 0 means the worst.

$$F_1 = 2 \times \frac{precision \times recall}{precision + recall}$$

Accuracy: The model's overall performance should be measured to ensure it performs as expected.

$$Accuracy = \frac{TP + TN}{TP + FN + TN + FN}$$

Figure 6. A sample of leaf images from distinct categories

The research is performed using real-time data collection, and the proposed algorithm is tested on the plant datasets given in this research. The performance of the suggested approach is determined by experimenting with different values for quantitative parameters like the size of the kernel, the size of the neighborhood pixel, and the size of agricultural land. This research aims to determine the extent to which the recommended parameters affect classification accuracy and the error rate analysis. Therefore, it is necessary to demonstrate the consistency of the suggested algorithms for both diseased and healthy datasets. The figure 3 to displays some samples. When choosing the optimal kernel size, the temporal complexity parameter is also important. Although 11x11 generates better results than 5x5, the amount of time required to extract features is longer for 11x11 than for 5x5. However, filtering with 5x5 produces only a slightly better result (a minor fractional improvement). Therefore, a kernel size of 11x11 produces the greatest results.

As demonstrated in Figure 7, of a confusion matrix of class six with predicted labels of classifier of a degree of accuracy has been achieved in identifying each of the six classes, in general, based on the data provided. The results of this study show that the strategy that has been proposed has a high degree of discriminatory power. that the Improved Sparse Representation Classifier achieves maximum classification accuracy when applied to a kernel of size 11x11. Based on the findings presented in I.

TABLE I. An examination of classification accuracy

Kernel	**Pathogens**	**Germs**	**Microbes**
3x3	0.9101	0.921	0.9104
5x5	0.921	0.9312	0.9231
7x7	0.9318	0.9371	0.932
9x9	0.9412	0.9518	0.9584
11x11	0.9567	0.9527	0.9672
15x15	0.9682	0.9559	0.9875

TABLE II. Performance Metrics Determined Using a Real-Time Dataset

Time-series data	Performance Metrics				
Classes	Precision	Recall	F1-Score	Error Rate	Acc.
Apple black rot	0.986	0.9152	0.930	0.021	0.953
Bean Rust	0.960	0.9751	0.931	0.037	0.968
Tomato late blight	0.9871	0.9627	0.945	0.010	0.989
Rice bacterial leaf	0.9253	0.9854	0.987	0.027	0.987
Tomato bacterial spot	0.9153	0.9852	0.9854	0.018	0.989
Banana's rust	0.9025	0.9381	0.9746	0.016	0.991

Figure 8 compares the classification accuracy values provided by the 3x3 technique and the 15x15-kernel size approach. The 15x15-kernel size approach has a higher value than the 3x3 approach. When these two figures are compared, in light of this, the 15x15-kernel size technique is preferable to other kernel size approaches.

This paper will test and analyses the ontology classifiers to disease detection of leaves taken from the plant using real-time data collection. The work ultimately facilitates the development of databases with information on pathogens, germs, and microorganisms. Table II, and Figure 7 both present the results of the computations used to get the performance values. This was done so that we could evaluate how well the suggested classifier worked with real-time data by utilizing performance metrics.

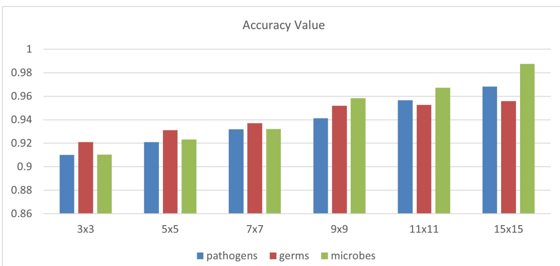

Figure 8. Classification accuracy analysis based on the data collected

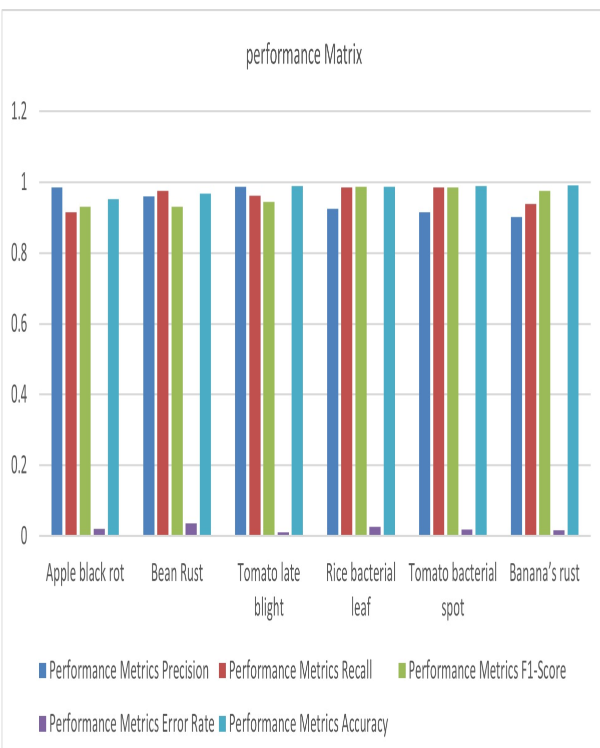

Figure 9. Metrics for measuring performance based on real-time data

B. Classifier Performance Analysis

In this experiment, five types of classifiers are evaluated and compared for identifying disease-afflicted parts in leaves: KNN, Naive Bayes, ANN, SVM, and CNN. Table III shows the detection accuracy of each classifier for fruit crops, vegetable crops, commercial crops, and cereal crops.

TABLE III. A comparison of classification methods based on accuracy

Testing data	GLCM	SVM	ANN	KNN	Naive Bayes
Apple black rot	0.824	0.918	0.931	0.94	0.984
Bean Rust	0.889	0.911	0.945	0.924	0.962
Tomato late blight	0.845	0.93	0.892	0.954	0.943
Rice bacterial leaf	0.859	0.912	0.95	0.964	0.927
Tomato bacterial spot	0.899	0.945	0.86	0.923	0.938
Banana's rust	0.875	0.955	0.981	0.941	0.953
Apple black rot	0.913	0.941	0.931	0.964	0.95

It can be seen in graph 10 that the ML technique has a detection accuracy value that is much enhancing than that of the other methods currently in use. Therefore, compared to other approaches of categorization, the ML method is superior. A KNN, Naive Bayes, ANN, SVM, and ML method for error rate value is the best alternative to the current methods. ANN method gets the second-best result.

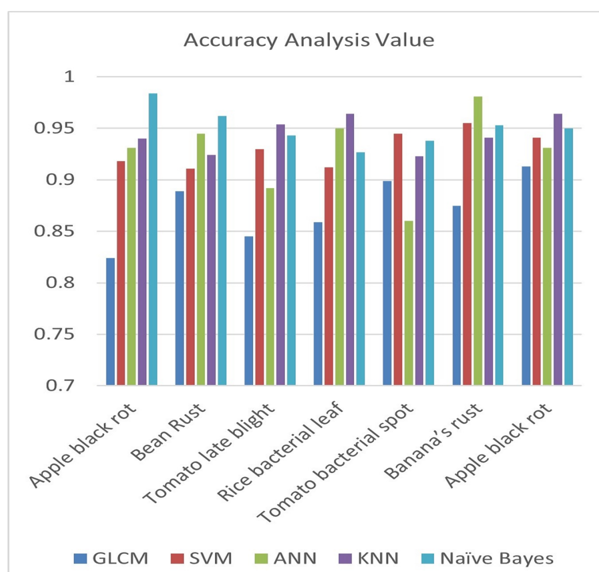

Figure 10. Explanation and Evaluation of the Accuracy of the Classification Method

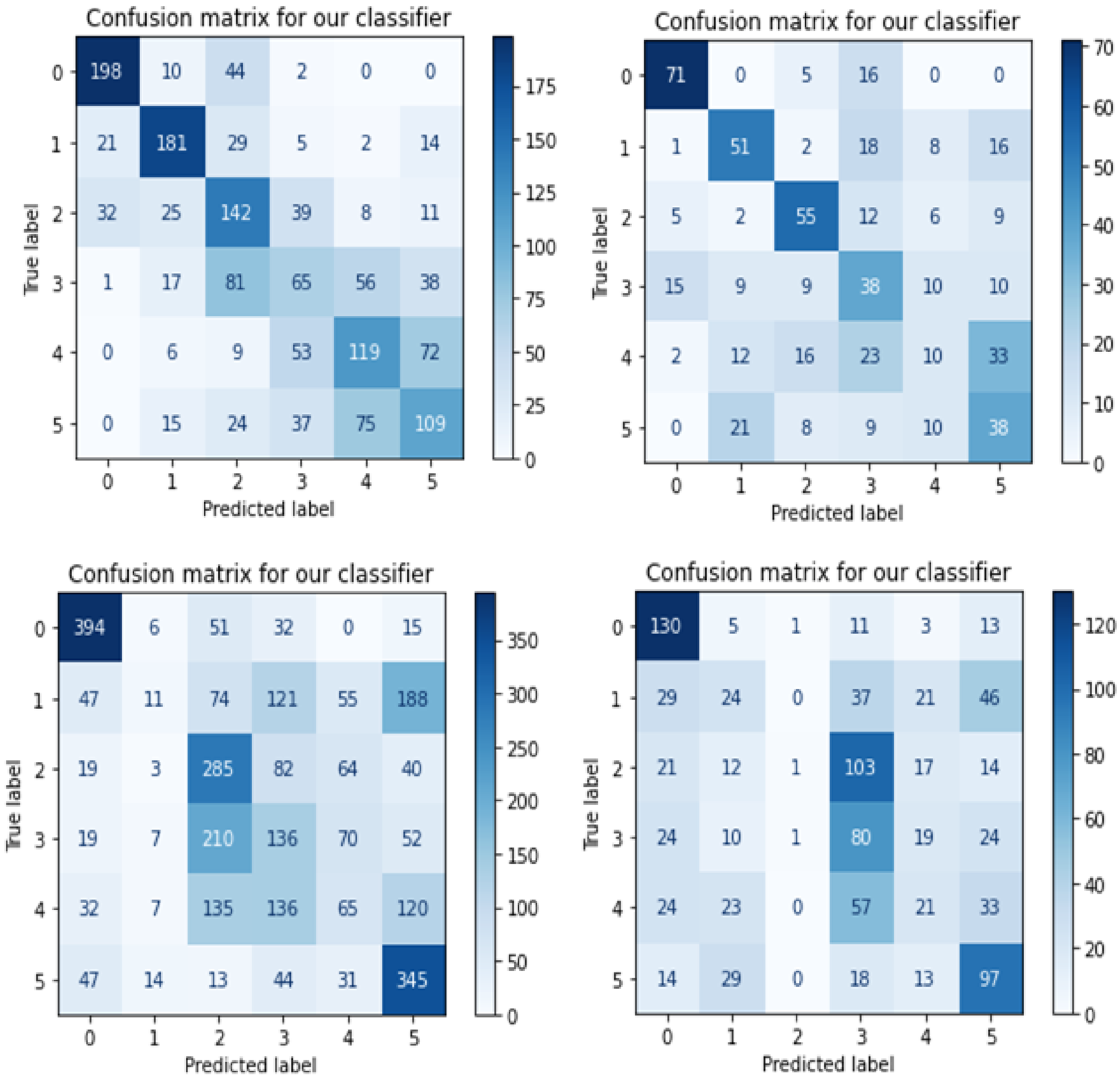

Figure 7. Shows a confusion matrix that was obtained the application of to identify plant diseases proposed method

C. Classification of the Disease

In CNN-based models, we also used sigmoid models. Compared to K-NN and SVM, detection accuracy is satisfactory. Models were edge-detected before feature learning and classification. Detection accuracy for all leaf species is plotted against the probability of detection accuracy. This is to validate predictions made during each epoch.Diseases can also be grouped according to the organ systems they affect. Examples include cardiovascular diseases, respiratory diseases, neurological diseases, and gastrointestinal diseases.Edge detection before feature learning can enhance the model's ability to focus on important features in the images. It's a pre-processing step that highlights edges, which are often crucial in distinguishing different disease patterns on plant leaves.

TABLE IV. Losses and Accuracy of Binary CNN for All Epochs Before Pretraining

Number of Epoch	Loss	Accuracy
01	1.203	0.0159
02	5.410	0.0321
03	7.634	0.0451
04	3.742	0.0325
05	7.501	0.0359
06	9.104	0.0875
07	10.567	0.0962
08	10.874	0.0980
09	9.351	0.0320
10	8.638	0.0985

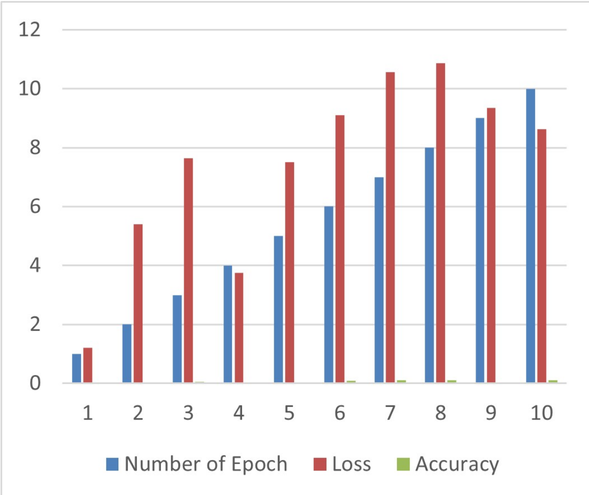

Figure 11. Accuracy of validation - Epoch 1

TABLE V. Validation and training of the binary CNN

Number of Epoch	Training loss	Training Accuracy	Validation Loss	Validation Accuracy
01	3.426	0.0381	9.358	0.089
02	1.351	0.0842	1.254	0.087
03	4.367	0.0951	6.521	0.087
04	6.325	0.0758	7.365	0.245
05	4.120	0.0361	9.235	0.985
06	2.256	0.0124	0.851	0.930
07	4.873	0.0210	0.364	0.851
08	9.253	0.0758	0.875	0.087
09	6.349	0.0140	1.701	0.843
10	1.150	0.0135	7.506	0.851
11	4.326	0.0187	9.890	0.098
12	7.015	0.0192	7.802	0.085
13	0.032	0.0370	5.632	0.987
14	6.520	0.0320	8.951	0.831
15	8.497	0.0347	4.983	0.843
16	9.580	0.0385	8.961	0.951
17	0.965	0.0101	6.270	0.078
18	0.354	0.0186	8.340	0.031
19	0.962	0.0873	9.510	0.250
20	1.367	0.0985	2.980	0.952
21	1.875	0.0781	1.983	0.025
22	1.851	0.0934	7.651	0.910

The process of training and validating a binary CNN involves preparing the data, choosing an appropriate architecture, training the model, validating its performance, tuning it, and testing it. In order to optimize the network weights, a training set of data has to be used. The network learns to classify input images into one of several classes during training. A network's weights are updated through iterative forward and backward propagation of errors. The aim of training is to reduce the discrepancy between expected and actual results.

Validation involves evaluating the trained model's performance using a dataset that was not used during training. In this way, it is possible to check if the model has overfitted (that is, if it has memorized the training data instead of generalizing from it) or underfitted (that is, it has not learned enough from it). By validating the model, we can assess whether it is capable of generalizing to new data as well as improving its performance.

Validation of a binary CNN involves determining whether the model can accurately predict whether an input image belongs to a particular class. Validating the network helps identify optimal hyperparameters and architecture for achieving better performance with new data.

D. Limitation

As a result of a comparison with the previous paper, our proposed techniques do a much better job of classifying data than any existing classification technique. Although the proposed techniques are quite time-consuming in comparison with other existing models, they can be further optimized using advanced optimization techniques in the future.

5. Conclusion and future Scope

The development of plant disease identification systems has been suggested using a variety of different methodologies. They often concentrate on evaluating leaf images as well as specialized data like as VOCs, but they do not take into consideration the everyday observations made by a farmer. Our research focuses on developing an ontology and system architecture for diagnosing plants illnesses through human observation. The modelled ontology builds on the concepts presented in PDO and PPOntology, two other existing ontologies. We developed other key ideas and traits to describe rice anomalies seen during observation. Many concepts and characteristics are used to describe plants. These studies led to the development of an ontology that represents irregularities in plants illness in terms of signs, colors, forms, and affected plant parts. plants illnesses and anomalies are linked by subclass relationships. Rice disease is identified using DL queries and reasoners to locate subclasses of farmer observation data expressed in terms of symptoms, colors, forms, and affected plant portions. This is necessary for an accurate diagnosis of a disease. To evaluate the modelled ontology's efficiency, dependability, and accuracy. Based on their observations of the disease symptoms, rice farmers and specialists would utilize it to pinpoint rice diseases.

Future work: Future work will focus on creating deeper networks, and augmentation of plant leaf images will be integrated throughout all network levels. Training times will be shortened and accuracy rates will be higher. The use of parallelism can also be used to create various accelerating and optimizing techniques, such as Fourier-based rapid convolution methods for training. III.

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