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Encouraging hygiene permanence in tomato leaf and applying machine learning techniques

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ABSTRACT

Tomatoes are the major ingredient in food preparation, which leads to a huge food production rate. Most countries cultivate huge tomatoes at the same time that crop diseases affect the production rate due to many different types of diseases. The various types of diseases are bacterial spots, septoria leaf spot, left mold, late blight, early blight, arget and spot. Many research studies review these tomato leaf diseases with various statistics. The survey on disease will give a clear idea of reasons and prevention methods, also presenting how to reduce it in the early stages. In another study, tomato leaf images were taken to classify the diseased and non-diseased varieties. Few studies compare the standard model of disease prediction with the machine learning models. Therefore, this research study discusses tomato leaf disease detection and prevention methods used by various researchers in their studies and finally consolidate the observations. This study also deals with encouraging hygiene permanence in tomato leaf using machine learning algorithms. The convolutional neural network (CNN) was used to predict the early nature of the hygiene nature of leafy vegetable plants for the benefit of agriculture people and concluded with better future suggestions.

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1. INTRODUCTION

Plant growth depends on factors like water, light, temperature, nutrients and plant hormones. A drastic change in these factors leads to plant diseases. However, these are natural factors that cause diseases. But plant diseases are also majorly caused by the pathogenic organisms such as fungi, bacteria, viruses, protozoa, insects and parasitic plants which are termed as infectious plant diseases. These diseases may affect various parts of the plant which include leaf, root, and stem [1]. When leaves get affected by pests or pathogens or environmental stress, they end up getting affected. These effects include brown spots, white spots, holes, leaf discoloration, leaf deterioration, leaf softening, yellowing of leaves and sticky leaves. Nowadays, the majority of plants are affected by leaf spots and other leaf diseases. These can be prevented by proper crop management techniques [2]. Various disease resistant plants are being produced and cultivated by biotechnological research techniques to encourage hygiene permanence in leafy vegetable plants [3].

Tomato cultivation is done with three types of methods, they are Beta-carotene, vitamin C and vitamin E. When the disease affects tomato leaf, it mostly affects the leaf and stem. India is third in position for tomato production among various counties in the world, in India forty thousand hectares of tomato planted for every year [4]. Therefore, India needs emergency precaution to increase the production rate of tomato by reducing the disease on tomato leaf [5]. Therefore, research gap identified from various research studies are used to encourage the hygiene permanence on vegetable leaves, for this convolutional neural network (CNN) machine learning algorithm applied on tomato leaf dataset to predict various diseases at the early stage in order to give input for future research to apply many contributions with respect to machine learning techniques.

2. RESEARCH METHOD

Explaining in Ferentinos [6], predicting the leaves, which is affecting the tomato leaves and harming the crops with large amounts of production and affecting the quality of the production, this will be avoided by early prediction. For this 8,567 images were taken and started with pre-processing and used the CNN machine learning algorithm with ResNet50 a pre-trained model and predicted the result. The result of this experiment shows that the CNN algorithms have acceptable accuracy [6]. This research study conducted at machine learning lab at Saveetha School of Engineering, Chennai, India.

Bensaadi and Louchene [7], a k-means machine learning algorithm for recognizing and grouping distinctive foliage disorders affecting tomato plantations. Additionally, it took into consideration structural traits of the vegetation. Like hue, consistency, and edge characteristics [8]. Within this study, typical deep artificial intelligence (AI) models featuring changes were showcased. Also covered were biotic illnesses brought on by bacterial and fungal infections, specifically tomato leaf blight, blast, and browning. The precision of the recommended model's identification rate is 98.49% [9]. The recommended model was evaluated against variants of visual geometry group (VGG) and ResNet with the identical dataset. The suggested model achieved better results than alternative models when the data was examined [10]. The recommended technique for detecting tomato sickness is a revolutionary thought. Subsequently suggested, the current study aims to expand the framework to include particular non-living illnesses caused by lack of nutrients within plant foliage [11]. Our objective is to gain a deeper understanding of the influence of these weaknesses on the condition of crops and create plans for avoiding and addressing them [12], [13]. The research further indicates that an objective in the long run ought to be to enhance the accumulation of individualized data and acquire a noteworthy volume of information related to various plant maladies [14].

Luaibi *et al.* [15], according to his survey, the agricultural industry has experienced many difficulties. In fact, timely and accurate detection of leaf diseases could help to fulfill the growing need for food supply [16]. Approaches based on deep learning (DL) have shown promise in detecting plant diseases. The study proposed a dependable and precise neural network pipeline for the computerized recognition and classification of tomato diseases [17]. In this aspect, the researchers suggested an innovative method that blends machine learning algorithms employing visual processing methods. The suggested pipeline used three small CNN architectures with reduced deep layer count and scan parameters as opposed to a sole CNN framework [18]. This one model requires high processing power and computing resources and has been utilized in much of earlier research. Moreover, it employed a combination of feature selection (FS) strategy to select a vast array of attributes with fewer dimensions [19]. It was not true for most of previous research that hinged on large characteristics. The proposed pipeline first combined high-level features from each CNN's final fully connected (FC) layer. The hybrid FS was then used to choose the most important features. To classify images of tomato leaves, six machine learning classifiers were used [20]. The suggested pipeline's results showed that mixing features from CNNs with various structural configurations enhanced performance. Additionally, the given hybrid FS technique was successful in choosing a smaller number of important deep features [21]. These selected features made the training models less difficult while achieving accuracy that was at least on par with the complete set of combined features, if not somewhat better. Additionally, when compared to past studies for tomato leaf diseases, the results demonstrated the superiority of the experimental performance of the proposed pipeline [8].

Luna *et al.* [22], has put out the model that is both the most effective and accurate for identifying diseases that affect tomato crops. The production of tomatoes is drastically reduced as a result of tomato leaf diseases. The suggested strategy divides tomato crop diseases into nine categories and a healthier one to increase tomato crop quality and output. Due to its ability to automatically extract features from photos, the DL-based approach has recently gained popularity for the categorization of plant diseases. In order to identify tomato crop illnesses, the deep convolutional network model has been suggested in this study. The typical deep convolutional network-based models ResNet50, DenseNet121, DenseNet201, MobileNet, and Xception are also applied in this analysis. It is accomplished for the purpose of assess the efficiency of the suggested method. Pictures of robust and infected foliage from tomato harvests were acquired from the botanical collection. The objective was to evaluate the efficiency of the recommended framework. 18,160 red-green-blue photos overall are included in the data set. The data has been processed and split into a ratio of 75 to 25 train and test dataset for this research. Ultimately, the algorithms' effectiveness is measured with trial data. After it was tested using training data, for comparing the efficiency of these models, two measures-accuracy and loss-have been employed. The results of the experiment reveal that the proposed deep CNN exceeded the performance of all pre-trained models and the advanced identification model. It reached a recognition accuracy at 99.71% and a decrease of 0.05%. Furthermore, a setback and precision graph is exhibited. This demonstrates the decline and exactness of all the models as time passes. The research additionally contains a misclassification table that facilitates the visualization of the model's effectiveness for all disease classes. The recommended model's effectiveness is furthermore analyzed with a cross-validation method. Following 100 epochs during the training process, the model reaches an identification precision with a precision of 99.42%. In conclusion, our suggested approach results in this research is evaluated through partitioning the dataset into the train, validation, and test partitions. The algorithm's accuracy is measured on every group individually. The accuracy for validation and test of the trained model are 99.23% and 99.12% each [9].

Trivedi *et al.* [10], reviews the farming sector as a significant crucial industry where a large portion of the Indian population relies. Illness identification within these plants is therefore vital for the growth of the economy. Tomato plants are an essential produce that is produced in large quantities. Consequently, the objective of this study is to locate and pinpoint ten separate ailments in the tomato harvest. In order to classify tomato foliage diseases utilizing the Plant Village dataset. The recommended strategy utilizes a CNN structure. In order to classify diseases affecting tomato leaves into ten distinct categories, a minimalistic CNN with the minimum number of layers was employed. In the context of further research, different learning rates and optimization algorithms may be implemented to explore the recommended model. Additionally, it involves testing using more recent structures to boost the performance of the model on the training dataset. Consequently, the model mentioned above is utilized as a tool for making decisions to help and aid farmers to acknowledge diseases that can be detected in the tomato cultivation. Using a precision around 94-95%, the proposed technology is capable of detecting plant diseases using limited computing power.

Noola and Basavaraju [11], The objective of the study was intended to allow AI models to operate on the mechanical device in real-time. Consequently, it will have the capability to identify plant diseases when moving the agricultural area or hothouse using human effort or with independent control. Illnesses are also able to be identified using detailed images of vegetation captured by probes placed inside man-made greenhouses. Nevertheless, it should be emphasized that this strategy might not be as efficient for finding ailments in outdoor conditions. The conditions examined in this research cause visible changes within the foliage of the tomato plant. RGB cameras can detect these changes in the leaves. In previous investigations, typical feature extraction algorithms on plant leaf photos were employed to detect illnesses. DL approaches were employed to detect disorders in this study. The choice of DL architecture was critical for implementation. As a result, two distinct DL network topologies, AlexNet and SqueezeNet, were tried. All of these machine learning networks underwent training and validation on the Nvidia Jetson TX1 device. In order to train, images of tomato leaves from the PlantVillage database were utilized. Ten various categories are engaged, including well images. Pictures from online sources are additionally utilized to evaluate educated networks.

Badiger and Mathew [12], observes that an automated image capturing device was created to photograph all angles of every tomato plant with the aim to determine and acknowledge plant diseases. Diamond max, a distinct tomato breed, was selected as the experimental subject. This innovation was developed for identifying diseases like phoma rot, leaf miner, or target spot conditions. We educate a complex CNN to identify three ailments or the lack thereof utilizing a dataset of 4,923 pictures of sick and healthy tomato plant leaves captured under controlled conditions. This system employed a ConvNet to detect if there were any tomato plant diseases on the monitored tomato plants. This faster region convolutional neural network (F-RCNN) developed anomaly detection model obtained an accuracy with 95.75%. In the meantime, the pre-trained disease detection model obtained a certainty score with a score of 80%. The automatic image capture technology underwent testing on-site and determined to be 91.67% precise in recognizing ailments of tomato plant foliage.

Vasavi *et al.* [13], explains how India remains a rural nation with a majorly agricultural output. Consequently, from this study, farming can to serve as the main support for every industry for our country. Choosing for every cultivation is vital for farm planning. Selection of crops is affected by different factors like market value, output rate, and governmental regulations. Several modifications within the farming sector are crucial to boost transformations in the economic conditions in India. It is possible for us to advance farming methods by employing computational intelligence methods [22]. These strategies are conveniently applied in the agricultural sector. In addition to progress within agricultural equipment and advancements, important and trustworthy information regarding various subjects is also crucial [23]. The following section has the proposed CNN algorithm application on tomato leaf dataset and related results for future directions.

3. RESULTS AND DISCUSSION

This research study presents the state of the art of tomato leaf disease prediction at an earlier state of the art and its related issues, also the tomato dataset used for predicting the early-stage hygiene permanence on tomato leaves, for this tomato dataset taken from the Thirumullaivoyal, Chennai Garden with 1,510 images with resolution 720×400 pixels. These images were applied for image data retrieving machine learning algorithm called CNN algorithm with OpenCV library of Python programming. In Figure 1, different tomato leaf disease symptoms are shown with healthy leaf.

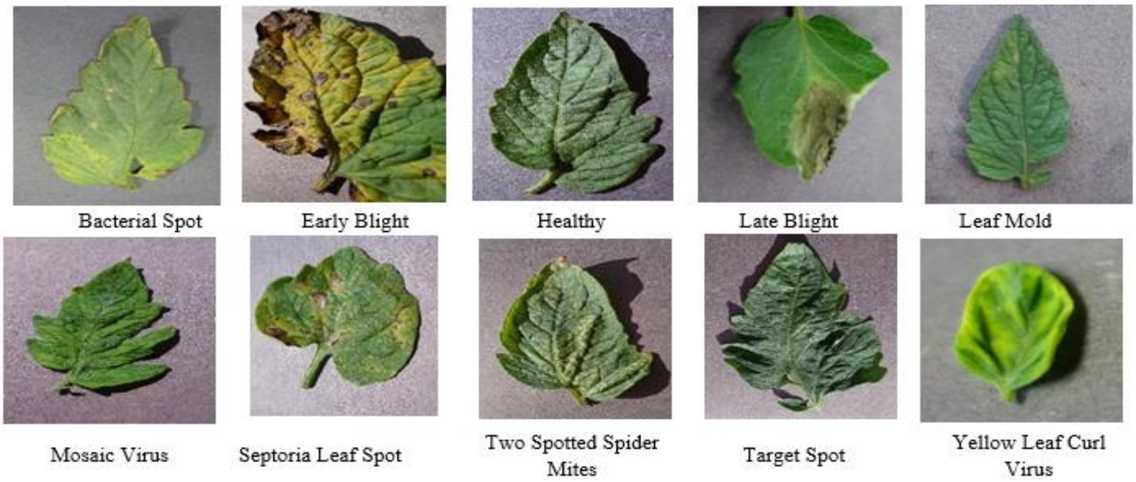

Figure 1. Tomato leaf images of thirumullaivoyal dataset

3.1. Dataset

The dataset taken for this study has 9 different tomato leaf disease categories with one healthy leaf type. The dataset has 1,510 images each with 9 types as shown in Table 1. In each case has a disease with training and testing dataset as shown in Table 2.

Table 1. Tomato leaf disease name with training and testing data taken for machine learning

Disease name	Total number of images	Training dataset size	Testing dataset size
Bacterial spot	154	123	31
Early blight	129	103	26
Healthy	164	131	33
Late blight	135	108	27
Leaf mold	145	116	29
Mosaic virus	178	142	36
Septoria leaf spot	162	130	32
Two spotted spider mites	114	91	23
Target spot	157	126	31
Yellow leaf curl virus	172	138	34

In Table 2, it has training and testing dataset with different disease names were given to apply the CNN algorithm and it retrieves attributes such as corners, edges, and colors from a photograph. This operation is carried out by ongoing sliding of a filter (kernel) on the pixels of the image. This operation performs the scalar product of the corresponding element of filter and pixel of the input image. The prediction model for tomato leaf disease consists of six convolution layers using a kernel size of 3×3.

Table 2. Tomato leaf disease name and number of images taken for machine learning

Disease name	Number of images
Bacterial spot	154
Early blight	129
Healthy	164
Late blight	135
Leaf mold	145
Mosaic virus	178
Septoria leaf spot	162
Two spotted spider mites	114
Target spot	157
Yellow leaf curl virus	172

3.2. CNN algorithm activation function

Every single layer is succeeded by a rectified linear unit (ReLu) activation function [24]. The sigmoid activation function is commonly employed to empower the input neuron competent at acquiring advanced and intricate features. The ReLU activation function also fixes the challenge of gradient vanishing [25]. Because of the rise in convolution stages, the parameter of the network grows exponentially. Thus, pooling takes place to diminish the extent of the feature grid. This process extracts important characteristics from the map of features through the removal of irrelevant attributes.

3.3. CNN algorithm experimentation on dataset

The Google Cloud platform was utilized to apply the dataset. Google Colab is known for offering free graphics processing unit (GPU) resources to AI developers. Jupyter notebooks are used in Google Colab. The following describes Google Colab's hardware requirements: utilizes 33 GB of storage space, 13 GB of GDDR5 VRam, and a single Tesla K80 GPU. The Tensorflow framework and Keras library are used to implement the models, 1,510 photos of nine common tomato leaf illnesses as well as a healthy tomato leaf are included in the dataset used for this research project. The dataset is divided into a training sample and a validation sample with an 80:20 percentage split, 100 epochs are used to train the model.

The confusion matrix as shown in the Figure 2, where the rows correspond to the anticipated class label and the rows to the true class labels. Therefore, the confusion matrix aids in visualizing the system's identification accuracy. The confusion matrix's diagonal elements display the proportion of samples that were properly identified in a particular batch of samples, while the remaining elements display the proportion of wrongly classified samples. The CNN's confusion matrix for a set of test picture samples is shown in Figure 2. There are 10 rows and 10 columns in the matrix of confusion. The class label for tomato crop diseases is shown by each row.

TARGET OUTPUT	Class0	Class1	Class2	Class3	Class4	Class5	Class6	Class7	Class8	Class9	SUM
Class0	30.8 9.74%	0 0.00%	0 0.00%	0 0.00%	0 0.00%	0 0.00%	0 0.00%	0 0.00%	0 0.00%	0 0.00%	30 100% 0.00%
Class1	0 0.00%	25.8 8.12%	0 0.00%	0 0.00%	0 0.00%	0 0.00%	0 0.00%	0 0.00%	0 0.00%	0 0.00%	25 100% 0.00%
Class2	0 0.00%	0 0.00%	32.8 10.39%	0 0.00%	0 0.00%	0 0.00%	0 0.00%	0 0.00%	0 0.00%	0 0.00%	32 100% 0.00%
Class3	0 0.00%	0 0.00%	0 0.00%	27 8.77%	0 0.00%	0 0.00%	0 0.00%	0 0.00%	0 0.00%	0 0.00%	27 100% 0.00%
Class4	0 0.00%	0 0.00%	0 0.00%	0 0.00%	28 9.09%	0 0.00%	11 3.57%	0 0.00%	0 0.00%	0 0.00%	39 100% 0.00%
Class5	0 0.00%	0 0.00%	0 0.00%	0 0.00%	0 0.00%	34 11.04%	0 0.00%	0 0.00%	0 0.00%	0 0.00%	34 100% 0.00%
Class6	0 0.00%	0 0.00%	0 0.00%	0 0.00%	0 0.00%	0 0.00%	32 10.39%	2 0.65%	0 0.00%	0 0.00%	34 100% 0.00%
Class7	0 0.00%	0 0.00%	0 0.00%	0 0.00%	0 0.00%	0 0.00%	0 0.00%	22.8 7.14%	0 0.00%	0 0.00%	22 100% 0.00%
Class8	0 0.00%	0 0.00%	0 0.00%	0 0.00%	0 0.00%	0 0.00%	0 0.00%	0 0.00%	31.4 10.06%	0 0.00%	31 100% 0.00%
Class9	0 0.00%	0 0.00%	0 0.00%	0 0.00%	0 0.00%	0 0.00%	0 0.00%	0 0.00%	0 0.00%	34.4 11.04%	34 100% 0.00%
SUM	30 100% 0.00%	25 100% 0.00%	32 100% 0.00%	27 100% 0.00%	28 100% 0.00%	34 100% 0.00%	43 100% 0.00%	24 100% 0.00%	31 100% 0.00%	34 100% 0.00%	295 / 308 95.78 4.22%

Figure 2. Confusion matrix results of the tomato leaf dataset using CNN algorithm

The performance results of the tomato leaf shown in Figure 3 and the confusion matrix shows that the model correctly classifies 1,498 out of the 1,510 test images from the ten classes, while classifying 12 wrongly. We may visually calculate the model's performance using this result. For each class label, we can additionally determine the recognition accuracy. The CNN has 100% recognition accuracy for the disease's bacterial spot (A), leaf mold (D), leaf curl virus (H), and mosaic virus (I) based on the confusion matrix results. The confusion matrix on test samples is displayed in Figure 2. The model showed 100% accuracy in identifying the disease-causing agents leaf mold (D), leaf curl virus (H), and mosaic virus (I) in test samples. The Figure 3 has the accuracy of 0.9578 (i.e, 95.78%), it shows higher rate of prediction for early stage of disease prediction on tomato leaves, comparing with other research studies.

Class name	Precision	1-precision	Recall	1-recall	f1-score
Class0	1.0000	0.0000	1.0000	0.0000	0.0000
Class1	1.0000	0.0000	1.0000	0.0000	0.0000
Class2	1.0000	0.0000	1.0000	0.0000	0.0000
Class3	1.0000	1.0000	1.0000	1.0000	1.0000
Class4	0.7179	0.2821	1.0000	1.0000	0.8358
Class5	1.0000	0.0000	1.0000	0.0000	1.0000
Clas6	0.9412	0.0588	0.7442	0.2558	0.8312
Class7	1.0000	0.0000	0.9167	0.0833	0.9565
Class8	1.0000	0.0000	1.0000	0.0000	1.0000
Class9	1.0000	0.0000	1.0000	0.0000	1.0000
Accuracy			0.9578		
Misclassification Rate			0.0422		
Macro-F1			0.9624		
Weighted-F1			0.9581		

Figure 3. Performance results of the tomato leaf dataset using CNN algorithm

4. CONCLUSION

This research paper reviewed many states of the art discussion from various research papers including our Saveetha University research and development team. The contribution of this paper related to various types of diseases. This review process has many findings on bacterial spot septoria leaf spot, left mold, late blight, early blight and arget spot. Also, many research studies review these tomato leaf diseases with various statistics and survey on disease will give clear idea for reason and prevention methods at the same presenting how to reduce in early stage were discussed. In another study discussing the accuracy comparison on disease prediction at early stage, few studies discussed with tomato leaf dataset experimentation conducted to predict earlier disease prediction. In another study tomato leaf images were taken to classify the diseased and non-diseased for generalization. The CNN machine learning algorithm resulting 95.78% of accuracy to predict early-stage disease on tomato leaves and presented the results, but the standard model of disease prediction on tomato leaves was not compared with existing models, this accuracy is significant for future research studies. Therefore, this research study is limited and applied only CNN machine learning algorithm. These reviews and experimentation were useful for future research studies to apply many machine learning algorithms to predict the early hygiene nature of leafy vegetable plants for agricultural peoples.

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