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The integration of machine learning and IoT for the early detection of tomato leaf disease in real-time

H. N. Naveen Kumar *
Department of Electronics & Communication Engineering
Vidyavardhaka College of Engineering
Mysuru
Karnataka
India

M. S. Guru Prasad †
Department of Computer Science & Engineering
Graphic Era (Deemed to be University)
Dehradun
Uttarakhand
India

J. Praveen Gujjar §
Faculty of Management Studies
Jain (Deemed to be University)
Bengaluru
Karnataka
India

K. R. Sharath ‡
Department of MCA
NMAM Institute of technology (Deemed to be University)
Nitte
Karnataka
India

* *E-mail:* naveen.vvce@gmail.com (Corresponding Author)
† *E-mail:* guru0927@gmail.com
§ *E-mail:* dr.praveengujjar@cms.ac.in
‡ *E-mail:* sharath.kr@nitte.edu.in

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H. Manoj T. Gadiyar [@]
Department of Computer Science and Business Systems
Canara Engineering College
Mangalore
Karnataka
India

Arun Kumar Dubey [#]
Department of Information Technology
Bharati Vidyapeeth's College of Engineering
New Delhi
India

Abstract

The impact of climate change, pests, and inadequate agricultural practices on crop health is becoming a growing concern. It is estimated that 20-40% of global crop yield is adversely affected by pests and diseases. This has a direct negative impact on food security and nutritional well-being, as staple cereal crops (such as rice, maize, and wheat) and tuber crops (like potato, onion, and tomato) are affected. Advancements in Artificial Intelligence (AI), Computer Vision (CV), and IoT have a significant influence on reducing crop losses by detecting crop diseases at early stages. The primary focus of this research is to develop a real-time system that can detect tomato crop diseases at an early stage by integrating Machine Learning (ML) algorithms and IoT. The most common tomato leaf diseases, such as Tomato Mosaic Virus (TMV), Tomato Bacterial Leaf Spot (TBLS), Tomato Early Blight (TEB), and Tomato Late Blight (TLB), are considered in this work. The hybrid discriminative feature space is derived from the integration of low- and high-level features via Convolution Neural Network (CNN) Layers. The 3-stage Stacked Deep Convolutional Autoencoder is used to optimize the CNN performance by reducing computation complexity. The proposed model is implemented on the Plantvillage benchmark dataset and achieves the highest recognition accuracy of 95.6% for the 5-class problem using 5-fold cross-validation.

Subject Classification: *Primary 62H30, Secondary 62H99.*

Keywords: *Convolutional neural network (CNN), Stacked deep convolutional autoencoder (SDCA), Optimization in CNN model, Low- and high-level features, Plantvillage dataset.*

1. Introduction

Agriculture is one of the prime human occupations that contributes to the development of nations. It is crucial for a country's economy as it

[@] *E-mail:* **hmanojtgadiyar@gmail.com**
[#] *E-mail:* **arun.dubey@bharatividyapeeth.edu**

not only produces food and raw materials but also creates job opportunities [1, 2]. The health of plants plays a crucial role in various aspects of human life, the environment, and the global economy. On a global level, the production of food supplements decreases by an average of 20-40% each year due to plant diseases and insect attacks. Insects, bacteria, fungi, viruses, and other pathogens all contribute to plant leaf diseases, which are the main cause of reduced agricultural yields. Some symptoms of diseased plants include leaf blight, leaf spots, root rots, fruit rots, fruit spots, wilting, dieback, and decline [2].

Tomato farming is of great importance in global agricultural trade due to its abundant nutritional value. Leaf infections are regarded one of the main causes of productivity loss, resulting in major economic losses. Early diagnosis is essential to prevent serious damage from crop diseases. The most common way to identify plant illnesses is by examining the leaves, as various diseases have distinct variations in their appearance. Detecting the disease with the naked eye of a specialist requires significant professional expertise and a comprehensive understanding of the etiology of crop diseases. Although manual inspection is still practiced in rural farms, it fails to precisely recognize the disease or its classes. For larger farms, manual inspection is a labor-intensive and time-consuming process. Since farming is a continuous process, crops must be regularly monitored to detect illness. A new method for detecting and localizing leaf disease is crucial.

The most common diseases that significantly reduce tomato yield are Tomato Mosaic Virus (TMV), Tomato Bacterial Leaf Spot (TBLS), Tomato Early Blight (TEB), and Tomato Late Blight (TLB) [3]. Tomato plants can be affected by various diseases. Here are some common diseases and their symptoms:

Tomato Mosaic Virus (TMV): Infected leaves may show a dark green mosaic pattern or yellow mottling. The young foliage could appear deformed or stunted, and there may be elevated green regions on leaves with severe infection. The leaves of the petioles may develop dark necrotic streaks.

Tomato Bacterial Leaf Spot (TBLS): Bacterial diseases are characterised by lesions that initially appear as tiny, water-soaked patches. Over time, these lesions multiply and combine to form mortification zones on the leaves, which give the leaves a blemished appearance.

Tomato Early Blight (TEB): It is a fungal infection that causes yellow chlorotic areas over oval lesions. Infected leaves may also show concentric lesions.

Tomato Late Blight (TLB): The entire aerial portion of the tomato plant is susceptible to late blight, another fungal infection. The disease first manifests as water-soaked green to black patches on leaves, which quickly turn into brown lesions. Infected areas and the undersides of leaves may develop fluffy white fungal growth during rainy seasons.

The key contributions of the proposed work are:

- The integration of low- and high- level features derived from Convolutional Neural Network (CNN) layers to create discriminative hybrid feature space
- The Stacked Deep Convolutional Autoencoder (SDCA) to derive the highly discriminative abstract feature distribution to reduce the computation complexity
- The proposed model is implemented in real-time on Plantvillage benchmark and custom dataset

2. Related Work

Traditional methods for identifying and localizing crop diseases rely on creating a robust and highly discriminative feature distribution, but these methods often have poor generalization capabilities. To address this, a Full Convolutional Network (FCN) algorithm, powered by the VGG-16 model, has been proposed for crop image segmentation [3]. The study presented in [4] introduced two unique Deep Learning (DL) architectures. The initial architecture improved categorization by learning a feature hierarchy through residual learning. The accuracy of DL models in classification is dependent on the volume of the trained data. To enhance the dataset volume, a Conditional Generative Adversarial Network (C-GAN) was proposed [5]. C-GAN generated synthetic leaf images of tomato plants. Tomato leaf images were using a DenseNet121 model that was trained using both artificial and real data via transfer learning.

It is proposed that ResNet-34 be used to classify and localize tomato leaf diseases [6]. By utilizing convolve filters, the Faster-RCNN (region-based CNN) method is capable of analyzing the structure of the alleged sample and extracting a dependable collection of critical points. It has been suggested that the Residual Neural Network (RNN) [7] be used to assign the classification designation for the tomato leaf. The findings indicate that pre-training is effective in establishing a range of suitable learning rates. A new model called Deep Learning enhanced Mask Region

Convolutional Neural Network (Mask R-CNN) has been presented to detect and segment diseases automatically. The recommended method can detect even tiny infected patches of diseased leaves using the annotation tool and multi-class datasets [8].

3. Methodology

The aim of this work is to establish a real-time detection system for early-stage tomato leaf diseases. The proposed model is represented in Figure 1 and involves integrating low- and high-level features from the convolution layers to create a robust and discriminative feature space for tomato leaf classification. The model also utilizes Stacked Deep Convolutional Autoencoders (SDCA) to derive a highly discriminative and abstract bottleneck representation. Finally, the CNN classifier predicts the class label for the leaf based on the trained model.

3.1 *CNN Model to derive low- and high-level features*

Morphological operations are used to preprocess the images in the dataset. Detecting visual signs that suggest early stages of diseases is crucial for classifying leaf diseases. Low-level features such as edge information, color variations, and texture patterns help in distinguishing healthy and diseased leaves. The convolutional layers apply filters that help capture information about edges, contours, and texture features. The Rectified Linear Unit (ReLU) activation function instigates non-linearity, which enables the model to capture complex relation. The spatial dimensions are down-sampled using max-pooling layers, which lowers computing overhead and focuses on discriminative information. Pooling helps retain crucial low-level features while removing redundant details.

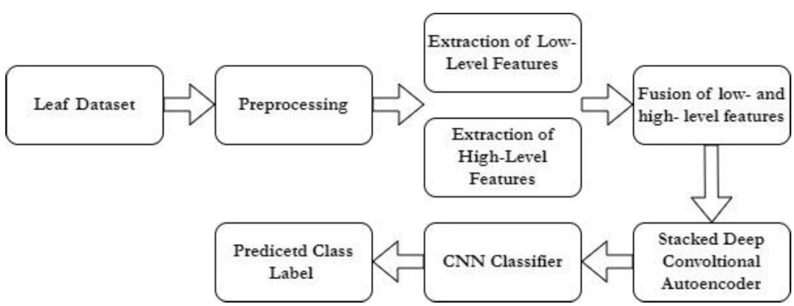

Figure 1

Proposed methodology

Batch normalization and dropout techniques are performed to enhance the model's generalization and reduce overfitting. Pretrained models can also be used to extract low-level features.

CNNs are a class of ML algorithms capable of autonomously learning intricate patterns from data. This makes them useful for identifying both basic and advanced features in an image. The deeper layers of a CNN can identify more abstract and complicated features. The Dense layer helps to identify the more important features. The feature vectors, which capture both low-level and high-level details, are combined and then passed through the SDCA network. This helps us to identify the most important features and classify the image using a hybrid and latent representation.

3.2 *Stacked Deep Convolutional Autoencoder (SDCA)*

The work is focused to solve the problem of tomato leaf classification in real-time. To achieve this, we need to reduce the computation complexity and represent the feature space in an abstract manner. In the proposed work a neural network design called an autoencoder for dimensionality reduction and feature learning. A convolutional autoencoder uses convolutional layers to process image input, and it can become a deep autoencoder by stacking several layers. The bottleneck layer of the SDCA will provide us with highly discriminative latent representations. The mathematical modelling for the SDCA is presented in the following section [9].

F : Feature distribution derived from CNN

F_i : Input to the i^{th} layer ,

H_i : Output to the i^{th} layer

W_i : Weight vector of i^{th} layer,

B_i : Bias vector of i^{th} layer

σ_i : ReLU activation function of i^{th} layer,

$\hat{F}_i$: Reconstructed output of the i^{th} layer

ρ : Weighting factor to address the reconstruction loss

M : Mean square error & N: Numbers of layers in SDCA

$$\text{Encoder (Forward path)}: F_i = \sigma_i(W_i F_{i-1} + B_i) \tag{1}$$

$$\text{Decoder (Forward path)}: \hat{F}_i = \sigma_i(W_i^T F_i + B_i) \tag{2}$$

$$\text{Loss function for each layer } \varepsilon_i = \rho \ \mu(F_i, \hat{F}_i) \tag{3}$$

$$\text{Total loss function of SDCA } \varepsilon = \sum_{i=1}^{N} \varepsilon_i \tag{4}$$

The training objective of SDCA is to minimize the total loss function:

$$\min_{W_1, B_1 \ldots\ldots W_N,\ B_N} \varepsilon \tag{5}$$

The gradient descent optimization algorithm is employed to update the weights and biases during training.

$$Weights: \frac{\partial \varepsilon}{\partial W_i} = \frac{\partial \varepsilon_i}{\partial W_i} \qquad Biases: \frac{\partial \varepsilon}{\partial B_i} = \frac{\partial \varepsilon_i}{\partial B_i} \tag{7}$$

The output layer of the model employs softmax activation function to perform multiclass classification.

4. Results and Discussion

The proposed work is implemented on Plantvillage benchmark dataset [10]. The number of samples in each class are represented as follows. Healthy (1591), TMV (373), TEB (1000), TLB (1909), & TBLS (2127). The image samples from the Plantvillage Dataset are depicted in Figure 2.

The proposed work is implemented in Python. In each class 80% of the images were considered for training and remaining 20% were used for testing. K-fold cross validation (CV) is employed, wherein the optimum value of K is determined by conducting set of experiments. The confusion matrix for the 2, 3 and 5-fold cross validation approaches are shown in Table 1, 2, and 3 respectively. The results are obtained for 25 epochs and 32 batch sizes.

Table 1

Confusion matrix for the 2-fold CV

2-fold	Healthy	TMV	TEB	TLB	TBS
Healthy	1495	77	19	0	0
TMV	25	337	8	0	3
TEB	14	0	915	40	31
TLB	0	8	76	1784	41
TBLS	24	0	39	56	2008

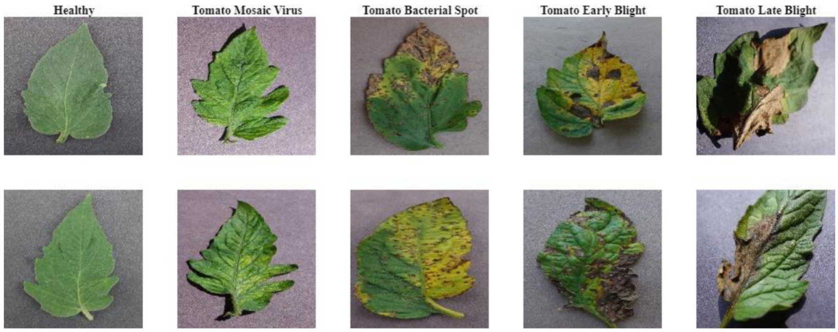

Figure 2

Image samples from the Plantvillage Dataset

Table 2

Confusion matrix for the 3-fold CV

3-fold	Healthy	TMV	TEB	TLB	TBS
Healthy	1516	66	9	0	0
TMV	21	342	7	0	3
TEB	11	0	932	34	23
TLB	0	4	59	1809	37
TBLS	18	0	32	44	2033

Table 3

Confusion matrix for the 5-fold CV

5-fold	Healthy	TMV	TEB	TLB	TBS
Healthy	1535	51	5	0	0
TMV	16	351	4	0	2
TEB	8	0	947	27	18
TLB	0	2	43	1835	29
TBLS	12	0	23	29	2063

The confusion matrix has diagonal entries that represent correct classifications and off-diagonal entries that represent the misclassification rate. In comparison to 2- and 3-folds, 5-fold cross-validation reduces the misclassification rate. Among all the classes taken into consideration, the 5-fold method has displayed superior performance. Table 4 presents the recognition accuracy of the 2-, 3-, and 5-fold cross-validation schemes, and it reveals that the 5-fold approach achieves better recognition rates.

Table 4

The recognition accuracy of the proposed model

	2-fold	3-fold	5-fold
Recognition Accuracy	92.7	94.1	95.6

The proposed model has been implemented in real-time for image samples from Plantvillage and a custom dataset. To test the model in real-time, a Raspberry Pi 4 Model B was used. The Pi camera captures the leaf image of the plant, which is then pre-processed and applied to the proposed model. The model has demonstrated good performance in real-time, although some of the state-of-the-art pre-trained models have shown better recognition accuracy than our model. The main focus of the proposed work is to optimize the model architecture for real-time implementation and testing.

5. Discussion and Conclusion

The proposed work aims to implement a tomato leaf disease detection model that is accurate and robust, and can be used in precision agriculture. The proposed model uses a combination of low- and high-level features to classify five types of tomato leaf diseases, namely healthy, TEB, TLB, TMV, and TBS. The model uses a 3-stage SDCA to derive a bottleneck representation from the hybrid space, which is then used to train and test a CNN classifier. The model is tested on the Plantvillage benchmark dataset and achieves an accuracy of 95.6% for 5-fold cross validation. The integration of low- and high-level features in the proposed model facilitates the development of a more effective and efficient detection system that can identify tomato leaf diseases in real-time. However, to test the model's generalization capability, it needs to be implemented on additional datasets.

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