A Novel Segmentation Approach to Detect Tomato Plant Leaf Diseases Using CNN Model

Sumitra Samal, Dr.Vijayant Verma

Ph.D Scholar, Associate Professor

Department of Computer Science Engineering

MATS University, Aarang Campus Raipur

samal.sumitra07@gmail.com, drvijyantverma@matsuniversity.ac.in

Abstract: The crops 'disease detection lies at the heart of agricultural sustainability, and tomatoes-one of humanity's most precious resources-are afflicted by many leaf diseases. The idea of this research is the presentation of a new method based on Convolutional Neural Networks (CNN) for detecting tomato plant leaf disease. Its objective is to improve accuracy by utilizing a segmentation strategy and feature extraction models. This methodology includes the collection of a number of public and private data sets as well as the development of an additional regional-specific dataset for Chhattisgarh in India. This segmentation uses the mean-shift image segmentation strategy which more effectively isolates lesions than traditional techniques. Extraction of shape, texture and colour features used Principal Component Analysis (PCA) to reduce the dimensionality. Pretrained functions, such as VGG-16 go one step further in selecting which features will be used for classification. Phase three is classification. Usually, the classifier goes through machine learning, which allows the selection of models such as SVMs (support vector machines) or decision trees. The results should be a region-specific set of parameters, segmentation which is most suitable for the task and an accurate classifier model. This research builds on past work involving tomato disease detection and extends those advances by uniting segmentation, feature extraction, and classification in a single CNN. Its importance lies in giving farmers an automatic disease alarm system that is also economical, promoting sustainable agriculture.

Keywords: Feature extraction, Convolutional Neural Networks (CNNs), Agricultural sustainability, Tomato leaf diseases, Segmentation.

I. INTRODUCTION

As a staple crop, tomatoes are an indispensable link in the global chain of vegetable production. India is the world's second-largest tomato grower after China, and its agricultural environment is closely interwoven with that of tomatoes. Nevertheless, problems have remained in the agricultural sector. A recent threat to tomato yields comes from disease among crop plants.

Prompt and precise diagnosis of these diseases is crucial to overall crop health, as well as the highest possible productivity [1]. A Novel Segmentation Approach to Leaf Disease Detection Using the CNN Model This research will attempt to answer this question by using a convolutional neural network (CNN) model in an effort to develop a computer vision system that can precisely determine and classify tomato plant leaf diseases [2]. The new approach is outstanding for impelling the creation of a division that can very clearly distinguish diseased portions of tomato leaves. This research looks to break through the impediments of these strategies by consolidating CNN models. The author accepts that by misusing the qualities of both nearby and global characteristics including extraction, his demonstrate ought to be able to make strides in classification accuracy [3]. This component can serve as a premise for more productive computerization of disease discovery forms. This inquiry about has the potential to bring around major progressions in disease determination procedures for tomatoes, in this way giving a much-needed modern pathway toward securing crops and raising rural effectiveness.

Aim and Objectives

Aim:

This study looks to make a new computer vision-based innovation for early discovery and categorization of maladies in tomato plants cleared out by Crowdsor user Novel Segmentation Approach combined with Convolutional Neural Network (CNN) models.

Objectives:

- To collect various different sets of data, such as public repositories and a set specific to the area containing all common leaf diseases afflicting tomato plants.
- To design a Novel Segmentation Technique to accurately pick out diseased areas of tomato leaves in order to optimize detection.
- To design a characterization model to capture both local and global features, improving disease classification accuracy.
- To construct an optimized model of a convolutional neural network, which achieved higher accuracy and speed than traditional methods aimed at the automatic detection and classification of tomato leaf diseased shoots.

II. NOTEWORTHY CONTRIBUTIONS IN THE FIELD

These studies also make a substantial contribution to the most important block in automated agricultural disease detection-adjustment systems [15] [16] [17] and [20]. Saeed et al. (15), for example, demonstrate that transfer learning is well suited to CNNs used in smart tomato growing conditions detection systems of plant disease on leaf surfaces by selecting deeply learned features from a pre-trained channel neural network and combining these with similar-looking channels selected from the device's own camera image. The paper that Sundararaman et al. cite

(16) is a thorough survey of how AI can facilitate sustainable tomato disease management; in fact, its impact has been nothing short of revolutionary across the board. EffiMob-Net Ullah et al. (17) point out that their proposed design is a two-way model with high detection and recognition precision while using less data, called efficient mobile Net — Obviously the first term in our title refers to this device for tomato disease diagnosis which uses leaf images as input! Ulutaş & Aslantaş' study 18 on disease detection research applies ensemble CNN models to create efficient methods of using images for medical checks. Saeed et al. are so far presenting a pioneering work that utilizes the potential of transfer learning to eventuate intelligent monitoring of tomato leaf diseases using Convolutional Neural Networks (CNN). However, taking pre-trained models as objectives for improvement makes the researchers more accurate in their identification of diseases. Transfer learning turns out to be a crucial technique, allowing the sharing of knowledge over domains and helping our model come up with more finely-grained patterns for disease detection.

There are also a number of mobile device applications for disease diagnosis, some examples being Yulita et al. (19). In their work, they introduce the use of a DenseNet architecture for detecting leaf diseases on tomato plants deployed to a mobile platform. Deep learning was going 3D They set out intending both to enable more people to access deep-learning applications and make it easier to do so with machine vision data from an increasingly broad range of devices. That is why at first they focused primarily on creating light Furthermore, Zheng and Du's paper on controlling tomato disease (Nature Scientific Report vol. For all the facts, in a special review, Sundararaman et al. analyse how artificial intelligence has helped several tomato diseases escape from conservatism and cruise towards sustainability. The review does indeed offer readers a broad vista of all kinds of AIs being put to various uses, from detecting disease to taxonomy and comprehensive planning for the protection or eradication of diseases. We can only deduce that AI has the ability to revolutionize global food security by providing efficient sustainable agriculture. Featuring a variety of crops, Abisha et al. suggest integrating the discrete shearlet transform with deep CNNs to tackle brinjal leaf disease detection in silico (21). Anbumozhi and Shanthini (22) provide the groundnut crop disease classification with a Progressive Convolutional Neural Network, stressing that if one wants to achieve an efficient outcome accurate data quality is crucial.

The AIxleaf Scientific Improvement initiative with the repeated use of models for particular crops, making continuous improvements to model architecture is obviously important. Indeed in Bi et al.'s work on corn leaf disease classification (23), this author presents a modified MobileNetV3-based convolutional network that improves upon existing studies. To understand how to train deep neural networks so that they perform well at predictions, Bouni et al. 24 evaluate pre-trained models on tomato leaf diseases during this research process.

Likewise, Chen et al. (Scheme 2:) make Innovative model architectures are explored by Chen et al., who introduce LBFNet, a tomato leaf disease identification model that fuses three channels through an attention mechanism with quantitative pruning of the network on its input and output sides. In addition to this, Gao et al. [26] also introduce an improved MobileNet V3-Small model that specifically looks for diseases on maize leaves--in which some of the key approaches to optimizing models deal with improvements in determining class distributions and variations between different crops.

Taken together, these studies show the many ideas and technological techniques being used by people around here (in agriculture) to chase a dream-rapidly accurate automated disease detection. The addition of deep learning, transfer learning and even attention mechanisms (which rule in) as well as hybrid models represents an increasingly vibrant environment for the use of artificial intelligence to assist farmers in managing their crops.

Transfer Learning-Based Convolutional Neural Networks

This method uses knowledge acquired on a model that is learned from large amounts of pre-labelled data (let's say, apples) and applies it to the problem domain in which there is not much-labeled data--tomato leaf diseases. A CNN is a type of deep learning with grid data, and the most common structure represents images in grids.

$$\text{Loss}_{\text{total}} = \text{Loss}_{\text{pre-trained}} + \text{Loss}_{\text{task-specific}} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(1)$$

Convolutional layers allow them to automatically and adaptively learn such hierarchical input data representations. Through a trained model and the general knowledge contained within it, this kind of algorithm can describe subtle patterns in tomato leaf diseases relatively accurately. Through transfer learning, the model is able to learn these important features from the source domain and apply them in judging diseases on target samples so as to obtain higher accuracy.

$$(I * K)(i, j)) \quad = \sum_m \sum_n I(i + m, j + n). K(m, n) \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(2)$$

Dense Convolutional Network (DenseNet) Architecture

The dense net is a feed-forward neural network with all layers linked to each other. This promotes feature reuse across the entire network. This study uses the mobile equivalent of DenseNet, enabling deep learning on a phone.

$$X_1 = H_1([x_0, x_1, \ldots x_{l-1}]) \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(3)$$

Bringing deep learning to the mobile platform gives farmers what they need--accessibility and usability, right on-location disease detection.

III. PROPOSED METHODOLOGY

This project attempts to design a systemic approach that provides an integrated framework for the recognition and typing of diseases affecting tomato plant leaves, using advanced methods such as the Novel Segmentation Approach coupled with several Convolutional Neural Networks (CNN) models. The approach is programmed in stages, which include the gathering of data sets,

ISSN PRINT 2319 1775 Online 2320 7876
 UGC CARE Listed (Group -I) Journal Volume 11, Iss 12, 2022

preprocessing (cleaning up errors), feature extraction and features reduction, deep feature extraction and classification.

A. Dataset Collection

The first stage requires the collection of data on which to train and test one's model. The strategy will be two-pronged, relying on well-known public data sets as the first prong and creating a second one suited to specific tomato leaf diseases in that area's geography. We will also combine several diverse diseases, such as Tomato mosaic virus; Target Spot Disease; Bacterial spot; Tomato Yellow Leaf Curl Virus Early blight scabbly tomatoes Tosity consists of Plain This large-scale database, which comprises 1 picture for every class (making a total of 110,00 pictures), will undergo stricter control as they are manually balanced proportionally to be used in testing the trigger model [4].

B. Preprocessing

The preprocessing stage uses the mean shift image segmentation technique, a key technology that allows for the accurate identification of lesions and disease locations in tomato leaf images. Departing from traditional threshold segmentation, the mean shift algorithm automatically determines cluster numbers based on variations in pixel distribution [5]. Clusters are discovered in this way by repeatedly shifting the means and labelling corresponding pairs of pixels. This approach makes it easier to extract disease-related features by taking into account the distribution of pixels. The output serves as input for further analysis and feature extraction.

C. Feature Extraction

A key aspect of the proposed methodology is training a reference model for extracting features from tomato leaf diseases. The process involves extracting shape, texture and colour characteristics with each making a unique contribution to disease diagnosis [6]. Morphological characteristics for the different types of tomato leaf lesions will be determined by such shape features as area, major axis, minor axis perimeter and roundness. Shape complexity is also to be a consideration in data analysis. Also, colour and texture characteristics like correlation morosity), homogeneity (the similarity of the probabilities in a group) and entropy will also be used to fine-tune feature selection so as to get an even more thorough picture of disease attributes [7].

ISSN PRINT 2319 1775 Online 2320 7876
 UGC CARE Listed (Group -I) Journal Volume 11, Iss 12, 2022

Table 1: Layer Types and parameter description

Layer Type	**Output Shape**	**Number of Parameters**	**Hyper parameters**
Input	(Height, Width, Channels)	0	Input size: (256, 256, 3)
Convolution (Conv2D)	(256, 256, 32)	896	Filters: 32, Kernel size: (3, 3), Activation: ReLU
Max Pooling	(128, 128, 32)	0	Pool size: (2, 2)
Convolution (Conv2D)	(128, 128, 64)	18496	Filters: 64, Kernel size: (3, 3), Activation: ReLU
Max Pooling	(64, 64, 64)	0	Pool size: (2, 2)
Flatten	64 * 64 * 64 = 262144	0	-
Fully Connected (Dense)	128	335872	Activation: ReLU

D. Principal component analysis (PCA) reduction of features

To reduce the number of dimensions in the feature set and speed up the calculation, PCA will be used. PCA thus converts the feature space into a low-dimensional representation, while keeping key information and eliminating redundancy [8]. This simplifies the model so that later stages need only consider those characteristics with greater impact on classification, reducing dimensionality. The intent of this proposed methodology is to balance precision, maximizing the retention of important information for accurate disease classification with efficiency and applying PCA.

E. Deep Learning Model for Extracting Deep Features

ISSN PRINT 2319 1775 Online 2320 7876
 UGC CARE Listed (Group -I) Journal Volume 11, Iss 12, 2022

One proposed methodology is to utilize deep feature extraction provided by pre-trained models such as VGG-16. These models represent powerful features extracted, defined by the features they learn from vast quantities of data [9]. These pre-trained models will be matched with new classifier models whose input consists of the output from a layer just before that is used to determine a label. In this way, the deep features extracted from these models include detailed patterns and subtleties related to various tomato plant leaf diseases [10]. By using pre-trained models, the model is better able to target diseases. The specific nature of disease descriptions allows for more detailed characterizations and adds precision to all levels of classification accuracy.

F. Classification:

The last phase of the methodology proposed here consists in classifying these extracted features using a supervised learning model. A set of machine learning classifiers, among them Support Vector Machines (SVM), decision trees and ensemble techniques, will be used to match input data with disease classes. Yet this is one of the phases that must be undergone to achieve the overall objective--building an effective and reliable disease detection network [11]. This trained model will then be able to automatically identify and categorize tomato leaf diseases, which can serve as a great reference for growers and others in the agricultural community.

IV. EXPECTED OUTCOME OF THE PROPOSED WORK

A. Dataset Enrichment:

Another main anticipated result is the production of a richer and regional database. The research hopes to provide the scientific community with a comprehensive resource of diverse data by compiling various different kinds, such as in open repositories or other forms. It also generates its own proprietary database specific for leaf diseases commonly seen in that geographic location where they are photographed and analyzed [12]. This data set, which includes large numbers of images from each class and a wide range of diseases afflicting tomato plants, should become the standard for most future research efforts in agricultural disease detection.

ISSN PRINT 2319 1775 Online 2320 7876
 UGC CARE Listed (Group -I) Journal Volume 11, Iss 12, 2022

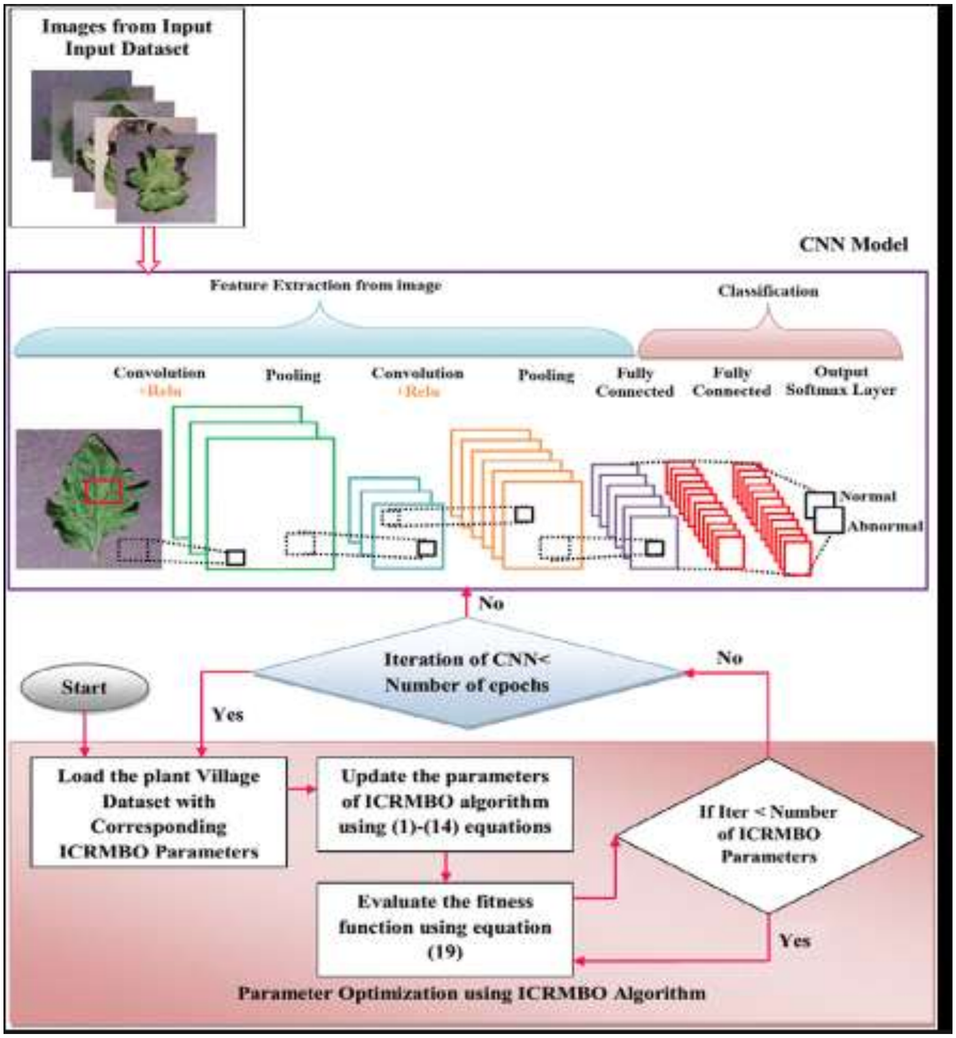

Figure 1: CNN architecture for tomato leaf disease

B. Improved Segmentation Accuracy:

It is hoped that the new Novel Segmentation Approach will increase accuracy in targeting diseased parts of tomato leaves. However, in contrast to traditional approaches, with mean shift image segmentation, the number of clusters is adjusted according to pixel distribution within an image so lesions can be exactly located [13]. The hope is that the result will be a segmentation model capable of distinguishing place spots from healthy tissue and formulating a basis for subsequent analysis.

C. Enhanced Feature Extraction:

The research believes the feature extraction model will capture local and global characteristics of tomato leaf diseases with greater accuracy than ever before. The extraction of shape, texture and colour attributes will provide a feature set that should enable the different features associated with various diseases to be distinguished [14]. This improved feature selection is essential to developing a strong model that can identify fainter patterns associated with certain diseases and help in the overall mechanism of classification.

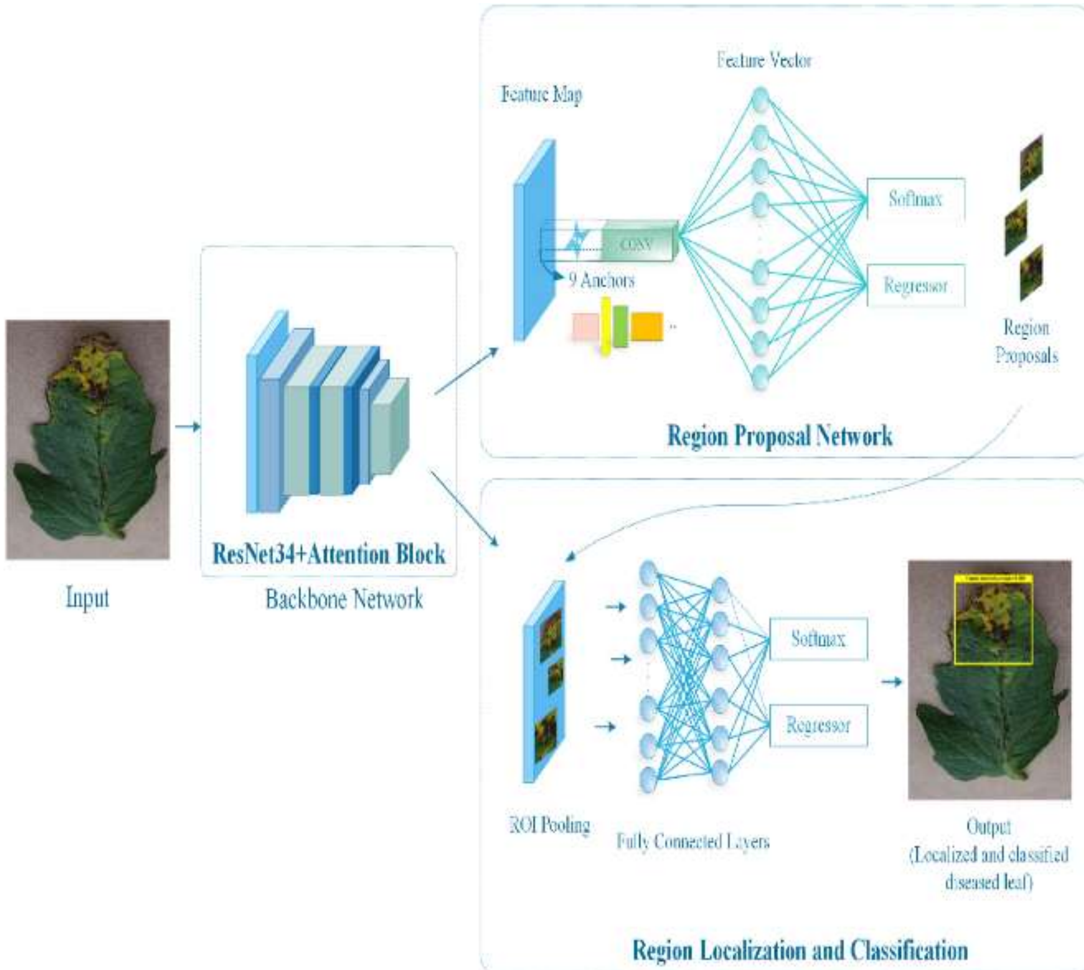

Figure 2: deep learning approach for tomato plant leaf disease localization and classification

D. Dimensionality Reduction with PCA:

It is hoped that the use of PCA to reduce features will allow some simplification in model calculations while minimizing the loss of information. The result is a pared-down component list that selects the most important components, to ensure even more effective downstream classification [27]. In this way, the difficulties of high-dimensional data can also be overcome. This is why PCA will play a role in accelerating and resource-conserving modelling to form an even more solid model.

E. Deep Feature Extraction and Generalization:

Based on the experiments with pre-trained models such as VGG-16, he believes that using existing deep feature extraction models will improve the generalizability of his model. It's hoped that these extracted deep features, trained on large volumes of data, will capture the complex patterns and subtleties specific to various tomato plant leaf diseases [28]. This result enables the model to generalize well and can be applied in environments with many different paths of disease manifestation.

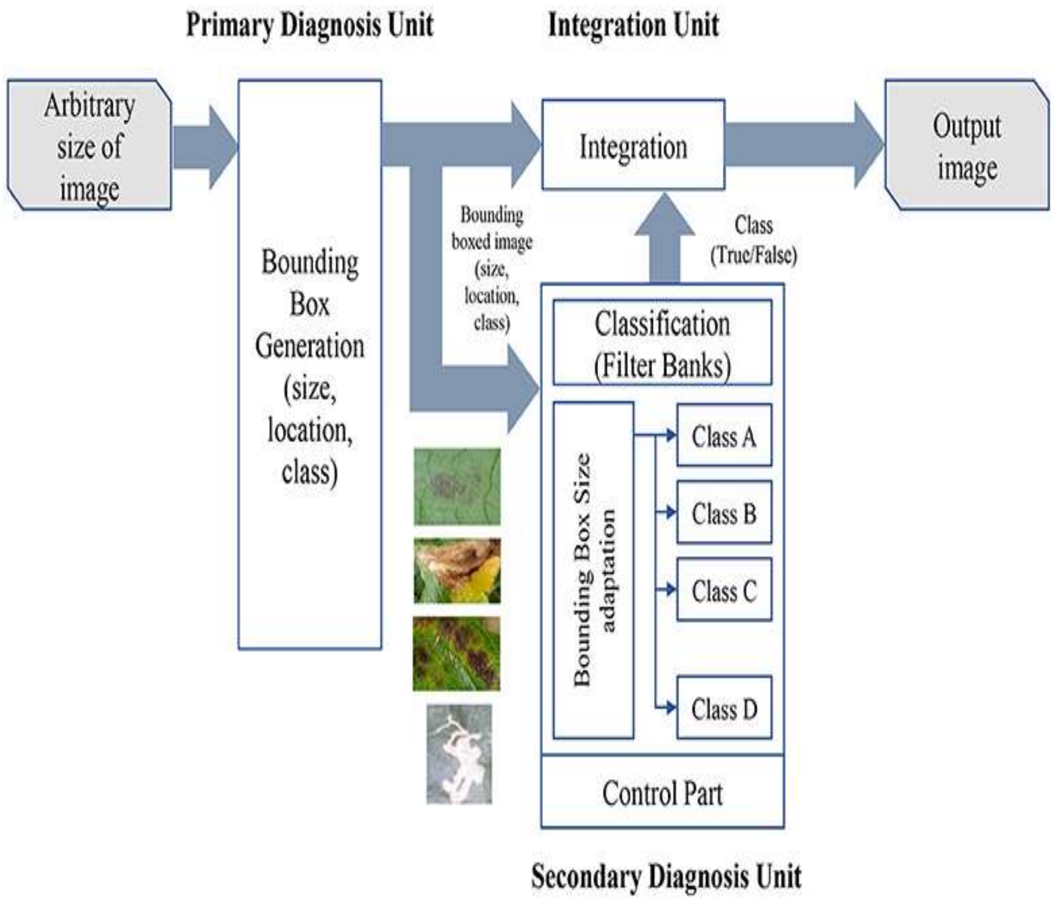

Figure 3: Deep Neural Network-Based Tomato Plant Diseases and Pests Diagnosis System

F. Optimized Classification Model:

The goal is to eventually produce an optimized classifying model based on a convolutional neural network. After training on the expanded data and equipped with more precise segmentation, improved feature extraction, and reduction of dimensions to improve efficiency (i.e., have fewer features that are easier to interpret), it is hoped that the classification model will be able to classify tomato-plant leaf diseases even better than human experts can see them in person [29]. Exploiting machine learning classification techniques, such as Support Vector Machines (SVM) and decision trees, the model should eventually provide a convenient automated mechanism of detecting disease with real-world application.

G. Practical Application and Agricultural Impact:

These anticipated effects bring the research to a natural conclusion that it may have practical applications for agriculture. It is hoped that the developed model with its greater segmentation accuracy, feature extraction and classification abilities can be used as a reference for farmers and practitioners in agriculture [30. This automated system that detects disease could greatly lessen the problems of manual inspection, allowing timely treatments and creating healthier tomatoes. Such results fit with the larger objective of increasing agricultural efficiency and maintaining food security.

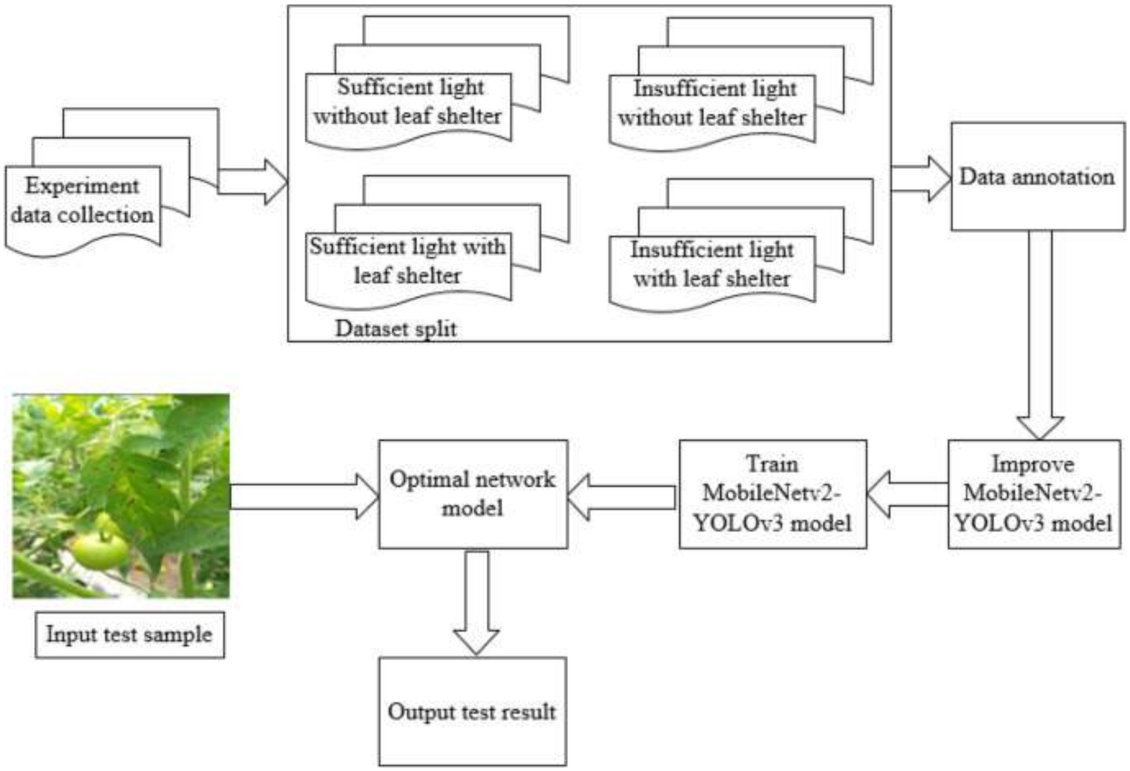

Figure 4: Early recognition of tomato gray leaf spot disease based on MobileNetv2-YOLOv3 model

V. CONCLUSION AND FUTURE WORK

To sum up, the suggested research outlined a coherent approach to the employment of novel segmentation approaches and convolution neural network (CNN) models as solutions for the early detection and classification of tomato plant leaf diseases. What is envisioned comprises many aspects, including adding value to the databases; accuracy in dividing up segmentations and feature detection; as well as designing a good classification model. The holistic approach seeks to overcome the limiting factors that currently hamper the detection of agricultural diseases, offering an important contribution. By combining public databases and region-based information to create a single large data set, we will have a repository for evaluating future research results. The large number of photos in this set and the diversity of tomato plant leaf diseases present a valuable resource for scientists to reference. This promises an improvement in segmentation accuracy when the mean shift image segmentation technique is used, the first step on a road to more accurate discovery of portions of tomato leaves suffering from the disease. The feature extraction model that incorporates local and global features is innovative, and will surely be able to improve the performance of disease classification. By extracting features like shape, texture and colour from the images, that model should be able to detect subtle patterns reflective of certain diseases. Furthermore, it is hoped that feature reduction via Principal Component Analysis (PCA) will make calculation faster and save resources without information loss--a more efficient model. Incorporating pre-trained models for deep feature extraction (such as VGG-16) would certainly improve the generalization ability of the proposed model. From their training on vast quantities of data, the deep features that emerge from these models are predicted to include patterns representative of all sorts of tomato leaf disease, aiding generalization in this area.

Future Work:

This study sets the stage for later investigations and improvements with reference to automated diagnosis of diseases in agricultural plants, especially as applied to tomato leaf disease problems. Several avenues for future work emerge from the anticipated outcomes and the evolving landscape of technology and agriculture:

Extension to Other Crops: The methodology thus established in tomato plants can be applied to other crops, increasing its range. It can be seen that adapting and customizing for various crops is an important part of a comprehensive solution to differing agricultural problems.

Integration of Advanced Deep Learning Architectures: Exploring these kinds of high-end neural network architectures, besides the current models based on CNNs, might be a worthwhile direction. Using architectures such as recurrent neural networks (RNNs) or attention mechanisms may allow for a better ability to capture the temporal and contextual nature of disease.

Real-Time Implementation: The next steps include investigating the possibility of applying such a model in real-time to agricultural environments. What this means is making the model suitable for implementation on edge computers so that farmers can enjoy early detection and treatment of diseases.

Continuous Dataset Enrichment: Due to their comprehensive nature, the data set also can be continuously expanded with photographs of new diseases and variations. Continued enrichment will guarantee that the model hereafter remains current and is able to weather changing disease profiles.

Collaboration with Agricultural Experts: It is even more important to cooperate with agricultural scholars and practitioners in order for the model's efficacy to be recognized. Through this cooperation, it is possible to gain an understanding of ensuring the newly developed technology meets real agricultural requirements.

Exploration of Explainable AI: As the model grows more mature, how to weave in explainable AI techniques is inevitable. Results and explanations that are easy to understand increase the trust users have in using such technologies, and understanding how these models make their decisions.

REFERENCE

[1] ALRUWAILI, M., MUHAMMAD, H.S., KHAN, A., AZAD, M., KHAN, A. and ALANAZI, S., 2022. RTF-RCNN: An Architecture for Real-Time Tomato Plant Leaf Diseases Detection in Video Streaming Using Faster-RCNN. Bioengineering, 9(10), pp. 565.

[2] ATTALLAH, O., 2023. Tomato Leaf Disease Classification via Compact Convolutional Neural Networks with Transfer Learning and Feature Selection. Horticulturae, 9(2), pp. 149.

[3] BALJON, M., 2023. A Framework for Agriculture Plant Disease Prediction using Deep Learning Classifier. International Journal of Advanced Computer Science and Applications, 14(8),.

[4] BHANDARI, M., SHAHI, T.B., NEUPANE, A. and WALSH, K.B., 2023. BotanicX-AI: Identification of Tomato Leaf Diseases Using an Explanation-Driven Deep-Learning Model. Journal of Imaging, 9(2), pp. 53.

[5] DEBNATH, A., HASAN, M.M., RAIHAN, M., SAMRAT, N., ALSULAMI, M.M., MASUD, M. and BAIRAGI, A.K., 2023. A Smartphone-Based Detection System for Tomato Leaf Disease Using EfficientNetV2B2 and Its Explainability with Artificial Intelligence (AI). Sensors, 23(21), pp. 8685.

[6] GONG, X. and ZHANG, S., 2023. A High-Precision Detection Method of Apple Leaf Diseases Using Improved Faster R-CNN. Agriculture, 13(2), pp. 240.

[7] GUERRERO-IBAÑEZ, A. and REYES-MUÑOZ, A., 2023. Monitoring Tomato Leaf Disease through Convolutional Neural Networks. Electronics, 12(1), pp. 229.

[8] HOANG-TU VO, NHON, N.T. and KHEO, C.M., 2023. Tomato Disease Recognition: Advancing Accuracy Through Xception and Bilinear Pooling Fusion. International Journal of Advanced Computer Science and Applications, 14(8),.

[9] HOSSAIN, S., REZA, M.T., CHAKRABARTY, A. and JUNG, Y.J., 2023. Aggregating Different Scales of Attention on Feature Variants for Tomato Leaf Disease Diagnosis from Image Data: A Transformer Driven Study. Sensors, 23(7), pp. 3751.

[10] JUNG, M., SONG, J.S., SHIN, A., CHOI, B., GO, S., KWON, S., PARK, J., PARK, S.G. and KIM, Y., 2023. Construction of deep learning-based disease detection model in plants. Scientific Reports (Nature Publisher Group), 13(1), pp. 7331.

[11] MARIA, V.S., SANIDA, T., SIDERIS, A. and DASYGENIS, M., 2023. An Efficient Hybrid CNN Classification Model for Tomato Crop Disease. Technologies, 11(1), pp. 10.

[12] NAGAMANI, H.S. and SAROJADEVI, H., 2022. Tomato Leaf Disease Detection using Deep Learning Techniques. International Journal of Advanced Computer Science and Applications, 13(1),.

[13] PADAMATA, R.B. and ATLURI, S.K., 2023. Deep Learning-Assisted SVMs for Efficacious Diagnosis of Tomato Leaf Diseases: A Comparative Study of GoogleNet, AlexNet, and ResNet-50. Ingenierie des Systemes d'Information, 28(3), pp. 639-645.

[14] RAJASREE, R. and C BEULAH, C.L., 2023. Improved YOLO-X Model for Tomato Disease Severity Detection using Field Dataset. International Journal of Advanced Computer Science and Applications, 14(9),.

[15] SAEED, A., ABDEL-AZIZ, A., MOSSAD, A., ABDELHAMID, M.A., ALKHALED, A.Y. and MAYHOUB, M., 2023. Smart Detection of Tomato Leaf Diseases Using Transfer Learning-Based Convolutional Neural Networks. Agriculture, 13(1), pp. 139.

[16] SUNDARARAMAN, B., JAGDEV, S. and KHATRI, N., 2023. Transformative Role of Artificial Intelligence in Advancing Sustainable Tomato (Solanum lycopersicum) Disease Management for Global Food Security: A Comprehensive Review. Sustainability, 15(15), pp. 11681.

[17] ULLAH, Z., ALSUBAIE, N., JAMJOOM, M., ALAJMANI, S.H. and SALEEM, F., 2023. EffiMob-Net: A Deep Learning-Based Hybrid Model for Detection and Identification of Tomato Diseases Using Leaf Images. Agriculture, 13(3), pp. 737.

[18] ULUTAŞ, H. and ASLANTAŞ, V., 2023. Design of Efficient Methods for the Detection of Tomato Leaf Disease Utilizing Proposed Ensemble CNN Model. Electronics, 12(4), pp. 827.

[19] YULITA, I.N., AMRI, N.A. and HIDAYAT, A., 2023. Mobile Application for Tomato Plant Leaf Disease Detection Using a Dense Convolutional Network Architecture. Computation, 11(2), pp. 20.

[20] ZHENG, J. and DU, M., 2023. Study on Tomato Disease Classification based on Leaf Image Recognition based on Deep Learning Technology. International Journal of Advanced Computer Science and Applications, 14(4),.

[21] ABISHA, S., MUTAWA, A.M., MURUGAPPAN, M. and KRISHNAN, S., 2023. Brinjal leaf diseases detection based on discrete Shearlet transform and Deep Convolutional Neural Network. PLoS One, 18(4),.

[22] ANBUMOZHI, A. and SHANTHINI, A., 2023. Leaf Diseases Identification and Classification of Self-Collected Dataset on Groundnut Crop using Progressive Convolutional Neural Network (PGCNN). International Journal of Advanced Computer Science and Applications, 14(2),.

[23] BI, C., XU, S., HU, N., ZHANG, S., ZHU, Z. and YU, H., 2023. Identification Method of Corn Leaf Disease Based on Improved Mobilenetv3 Model. Agronomy, 13(2), pp. 300.

[24] BOUNI, M., HSSINA, B., DOUZI, K. and DOUZI, S., 2023. Impact of Pretrained Deep Neural Networks for Tomato Leaf Disease Prediction. Journal of Electrical and Computer Engineering, 2023.

[25] CHEN, H., WANG, Y., JIANG, P., ZHANG, R. and PENG, J., 2023. LBFNet: A Tomato Leaf Disease Identification Model Based on Three-Channel Attention Mechanism and Quantitative Pruning. Applied Sciences, 13(9), pp. 5589.

[26] [26] GAO, A., GENG, A., SONG, Y., REN, L., ZHANG, Y. and HAN, X., 2023. Detection of maize leaf diseases using improved MobileNet V3-small. International Journal of Agricultural and Biological Engineering, 16(3), pp. 225-232.

ISSN PRINT 2319 1775 Online 2320 7876
 UGC CARE Listed (Group -I) Journal Volume 11, Iss 12, 2022

[27] GHOSH, P., MONDAL, A.K., CHATTERJEE, S., MASUD, M., MESHREF, H. and BAIRAGI, A.K., 2023. Recognition of Sunflower Diseases Using Hybrid Deep Learning and Its Explainability with AI. Mathematics, 11(10), pp. 2241.

[28] IPARRAGUIRRE-VILLANUEVA, O., GUEVARA-PONCE, V., TORRES-CECLÉN, C., RUIZ-ALVARADO, J., CASTRO-LEON, G., ROQUE-PAREDES, O., ZAPATA-PAULINI, J. and CABANILLAS-CARBONELL, M., 2023. Disease Identification in Crop Plants based on Convolutional Neural Networks. International Journal of Advanced Computer Science and Applications, 14(3),.

[29] ISLAM, M.S., SULTANA, S., FARID, F.A., ISLAM, M.N., RASHID, M., BIFTA, S.B., HASHIM, N. and HUSEN, M.N., 2022. Multimodal Hybrid Deep Learning Approach to Detect Tomato Leaf Disease Using Attention Based Dilated Convolution Feature Extractor with Logistic Regression Classification. Sensors, 22(16), pp. 6079.

[30] JEONG, S., JEONG, S. and BONG, J., 2022. Detection of Tomato Leaf Miner Using Deep Neural Network. Sensors, 22(24), pp. 9959.