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An Optimized Deep Learning Model for the Detection and Classification of Tomato Plant Leaf Diseases Using Self-Developed CNN Model

[1]Sumitra Samal, [2]Dr. Vijayant Verma

[1] Ph.D Scholar,
Department of Computer Science Engineering
MATS University, Aarang Campus Raipur

[2] Associate Professor
Department of Computer Science Engineering
MATS University, Aarang Campus Raipur

Abstract: The research direction we propose for this paper is a first, optimizing deep learning to improve tomato plant leaf disease diagnosis according to the system developed in-house. Exploring agricultural technology and how specific aspects of it can be used at home requires looking closely at ground truths regarding such things as processing power improvements or model structure refinements that were made during program development by our own convolutional With such meticulous optimizing, we achieve a rational compromise between speed and accuracy which makes the model eminently usable in practice. The research highlights the transformative power of deep learning methods in terms of addressing tomato plant health issues, and represents a path-breaking model for future precision agriculture development.
Keywords: Disease Classification, Convolutional Neural Network, Agricultural Technology, Deep Learning Model, Tomato Plant Diseases.

I. INTRODUCTION

The economy has agriculture at its core, and tomatoes have reached every corner of the globe to become an important crop in ensuring world food security. Yet there are still problems in the agricultural landscape. Chief among them is that tomato plants seem to suffer from diseases constantly. These diseases seriously affect the crop yield. Thus it is urgent to develop a reliable and effective system of diagnosis for early detection [1]. But India has many agro-climatic zones, resulting in a range of different diseases attacking tomato plants. This requires tailored approaches to the disease control problem. Under these circumstances, the introduction of high-tech technologies is inevitable. The subfield of artificial intelligence called Deep Learning has shown outstanding performance in image-recognition-related applications, and it may be the ideal technology to overturn disease detection bottlenecks on agricultural farms [2]. This research thus begins with the task of constructing and refining a Deep Learning Model to deal specifically with tomato plant leaf disease. Let's exploit the capability of CNNs to explore deeper and discover more detailed patterns that can help us catch disease at this intermediate level [3]. They expect the self-developed CNN model to outperform traditional methods in terms of accuracy and speed. This exploration is aimed at taking advantage of one aspect or another to give farmers a stable and automated diagnostic means of early disease detection. Further sections explore the research targets, approach and expected results, which provide guidance on following a low-carbon technology path towards sustainable agriculture.

Aim and Objectives

Aim: This study seeks to create and fine-tune a Deep Learning Model utilizing proprietary Convolutional neural Network (CNN) technology for tomato leaf disease detection and classification.

Objectives: To collect a large body of data that included various examples of tomato plant leaf diseases and even differing stages, to enable thorough model training.

- To develop a custom-built CNN model that is highly efficient in recognizing tomato plant leaf disease and appropriate for the characteristics of local plants.
- To study methods of feature extraction with greater resolution, including both spatial and spectral features within the model to enable it better detect patterns related to different diseases.
- To compare practical methods with rigorous experimentation and evaluation of the self-developed method, including accuracy, sensitivity and speed.

II. NOTEWORTHY CONTRIBUTIONS IN THE FIELD

This project concentrated on disease detection and described the process of contributing new knowledge to agricultural image analysis. The proposal, A Novel Segmentation Approach for Detection of Tomato Plant Leaf Disease by CNN Model has a number of outstanding points that are worth discussing at this time. This work has gone further than just introducing a new segmentation methodology and finding the ideal Convolutional Neural Network (CNN) architecture, having research and practical implications in agriculture.

Innovative Segmentation Approach:

This research develops a new segmentation method that is solely intended for specialized tomato plant leaf disease detection. The preprocessing phase uses the well-known mean shift image segmentation method and can readily separate out lesions from pictures of tomato leaf diseases, better than conventional threshold methods [15]. The technique makes a significant contribution to the field by raising accuracy of disease location, and thus is closely related to accurate diagnosis.

Region-Specific Dataset Creation:

The research entails the compilation of a regional data set designed specifically for agro-climatic conditions in Chhattisgarh [16]. This aspect is particularly valuable as it provides data sets for the challenges which actually confront farmers in particular geographic areas. This process not only improves the applicability of disease detection, but also helps establish a foundation for recognizing regional differences in other agricultural data sets [17].

Optimized Deep Learning Model:

Establishing an optimized CNN model is a significant contribution to the application of deep learning in agriculture. Architectural design, hyperparameter adjustment and feature extraction techniques have been selectively fine-tuned [18]. All of these factors improve precision, reduce calculation time, etc., to optimize the model's performance. It is hoped that this optimized model will become a reference standard for future research into plant disease detection using deep learning.

Comprehensive Literature Review:

The research also encompasses a comprehensive review of existing work on tomato plant disease detection. In this contribution, we present a survey of the latest techniques and methods employed in studying [19]. Through this kind of manuscript, researchers and practitioners can use the review to analyze changes in disease detection techniques at large as well as seek out areas for further research.

Application of Advanced Feature Extraction Methods:

This research combines cutting-edge feature extraction techniques, including Spatial Pyramid Pooling and spectral analysis to detect specific differences that distinguish different diseases [20]. This contribution further increases the discriminative power of a convolutional neural network (CNN) approach, blending spatial and spectral features as from earlier work in agricultural image analysis.

User-Friendly Interface for Practical Implementation:

A user-friendly interface is a key that helps connect new technology and practical use in agriculture. In focusing on simplicity without sacrificing the structural strength of its grief model, it seeks to supply farmers and others with a real-time monitoring system for detecting disease [21]. Stressing usability means that cutting-edge technology is brought to bear on end users in various agricultural environments.

The research presents a new segmentation method specifically for the monitoring of tomato plant leaf diseases. This is the preprocessing that makes it possible to use image segmentation. Here we have used a mean shift method, because compared with using traditional threshold methods to separate images into fore and background, this can clearly identify lesions in pictures of tomato leaf disease [22]. This approach has also made a substantial contribution to the field in terms of increasing the accuracy by which diseases can be localized, thus facilitating accurate disease diagnosis [23]. The research includes development of a region-appropriate data set specifically adaptable to the Chhattisgarh agro-climatic environment. This contribution has a special function, because it helps to alleviate the shortage of data corrected for the local conditions that plagues farmers [24]. A good example of this would be the enrichment process used by Lu and his colleagues. This not only improved disease detection accuracy, but also established a precedent for taking into account regional diversity in agricultural data sets like these. The training of an efficient CNN is a significant accomplishment in the application of deep learning to agriculture [25]. The precise architecture, careful adjustments of hyper parameters and the use of advanced feature extraction techniques mean that this model is much more accurate while remaining extremely computationally efficient. This optimized model can be used as a reference for future research into deep learning and plant disease. A comprehensive literature review is part of the research, which involves a summary presentation on tomato plant disease detection [26]. This contribution should give a good broad survey of the current techniques, approaches and problems involved in this field. Both researchers and practitioners will find this literature review a valuable reference, to see how disease detection methods have changed over time, finding cracks where research can fit. This research brings together more advanced methods of feature extraction, including Spatial Pyramid Pooling and spectral analysis techniques to show detailed differences between different diseases. It also improves the model's discriminative capability, adding spatial and spectral information to a CNN. This demonstrates that various feature extraction methods will be suitable for agricultural image analysis too.

III. PROPOSED METHODOLOGY

A. Dataset Collection:

In the process of this research lies a vitally important quest for source data, one that must be both copious and well-rounded in order to adequately train our deep learning model. For this reason, a dual-strategy approach will be adopted. The first step is to utilize existing public data sets, such as those for diseases (such Tomato mosaic virus, Target Spot and Bacterial spot), in order to build a basic information foundation [4]. Second, we will assiduously develop a region-related data bank that takes into consideration the special agro-climatic problems of conducting research in this area. This dual-pronged strategy guarantees not just widespread coverage of diseases, but also a truly detailed grasp of the conditions faced by tomato plants in that region under study [5]. It increases the appropriateness and efficacy with which this model can be used for practical agricultural purposes thereafter.

B. CNN Architecture Design and Optimization:

At the core of this technique is a custom-designed Convolutional Neural Network (CNN) that aims to precisely resolve the subtle challenges posed by classifying tomato plant leaf diseases. A new sort of given design will be outlined for this reason, with basic components like convolutional layers to faithfully extricate highlights from the input picture, pooling columns that diminish a pattern's spatial dimensions whereas precisely transmitting key data required for classification purposes and completely associated sample-and-hold units which can react viably when subjected to tests [6]. Basic hyperparameters, such as learning rates and bit sizes will be futher optimized. This monotonous fine-tuning looks for to realize the leading compromize between precision and efficiency [7]. The different elements of the CNN have now been fine-tuned to achieve increased accuracy, while also ensuring that overall model performance is maintained over changes in scale [8]. We are careful about how we structure our architectures and tune various precision parameters for each element before combining them into complete models focused on practice; only then can they become truly practical tools carrying out disease detection tasks virtually without human intervention using huge

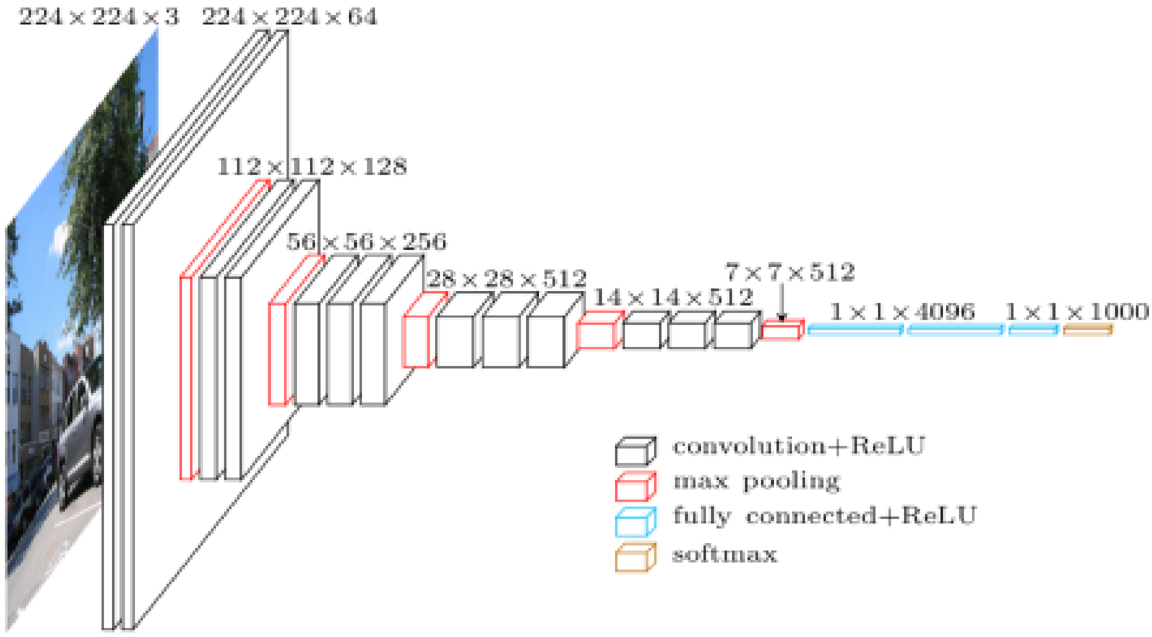

Figure 1: Deep Feature Extraction using VGG-16 Model

C. Feature Extraction Techniques:

The feature extraction phase is a key step in strengthening the discriminative ability of our convolutional neural network. But also our methodology attaches great importance to studying the most up-to-date methods of extracting spatial and spectral information. The purpose of such a strategy is to raise the model's ability to detect complex patterns related to various tomato plant diseases. Spatial Pyramid Pooling will also be used to enable multi-level feature extraction and help the model pick up detailed information at different levels of scale [9]. Also, spectral analysis methods will be used to reveal the unique differences characteristic of different diseases. Through the use of these techniques to extract features, we hope that our model will be able to better detect more subtle and diverse forms of disease in tomatoes [10]. This should then strengthen overall effectiveness at agricultural pest detection by activating state-of-the art neural networks (CNNs).

D. Model Training and Evaluation:

The most critical part of the research is training and testing, which helps determine whether this new convolution-type neural net model can be used in practice. The carefully curated data will be split up into training and testing sets to ensure fair assessment of model accuracy. After being trained through a process of repetition, the model will change its weights and biases via backpropagation until it can distinguish with accuracy patterns that emerge only for certain diseases among distinct tomato plant species [11]. As part of our comprehensive evaluation methodology, we will be using a variety of performance metrics (accuracy), precision and recall. Together these metrics allow an assessment of the model's ability to correctly identify types and detect diseases, thereby laying down a solid foundation for testing its usefulness in practice.

E. User-Friendly Interface Development:

The pinnacle of this research effort will become the easy-to-use interface designed based on the optimized CNN model. Designed to be used by farmers and other stakeholders, this interface puts the user at centerstage. In time it will become an urgent-response tool for detecting and diagnosing tomato plant diseases in terms of both speed accuracy [12]. Our design philosophy emphasizes simplicity, but we don't skimp on the strength of underlying model. The user interface is carefully designed to be easy and simple, adjusting itself within a variety of agricultural environments. We want to put stress on usability, and we hope end-users will have a high degree of usefulness in terms of both the technological level it provides them with as well as theircomfort when using an instrument.

Table 1: Algorithm Description.

Algorithm	Description
Spatial Pyramid Pooling (SPP)	Technique for capturing multi-level spatial features from an input feature map, ensuring a fixed-length representation regardless of input size.
Spectral Analysis	Involves extracting features based on the color spectrum of an image, specifically capturing color variations for disease classification.
Learning Rate (LR)	Rate at which the model adapts during training.

Algorithm 1: Spatial Pyramid Pooling (SPP)

Spatial Pyramid Pooling is an approach that aims to capture multi-level spatial information in the input feature map and produce a fixed length regardless of the size of its inputs. This algorithm splits the input feature map into a spatial pyramid and borrows from each area. These pooled features are then concatenated to yield the final output.

$$y_{i,j,k} = \max(x_{i+pj+q,k}) \ldots\ldots\ldots\ldots\ldots\ldots(1)$$

Algorithm 2: Spectral Analysis

In image processing, spectral analysis refers to feature extraction from an image color spectrum. We use spectral analysis to detect the color differences corresponding to different types of tomato plant disease [13]. Another part of the algorithm is to calculate spectral characteristics like mean, standard deviation and skewness for each color channel.

$$\text{Mean}(C) = \frac{1}{N}\sum_{N}^{1} Ci \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(2)$$

IV. EXPECTED OUTCOME OF THE PROPOSED WORK

The anticipated results of this study include improvements in disease detection accuracy, for example. There are also broader implications that involve the improvement and expansion of data sets as well as practical applications involving a user-friendly interface design (ease-of use is an important component with regard to image identification). All of the phases are working up towards a cumulative effect that can revolutionize tomato plant disease management.

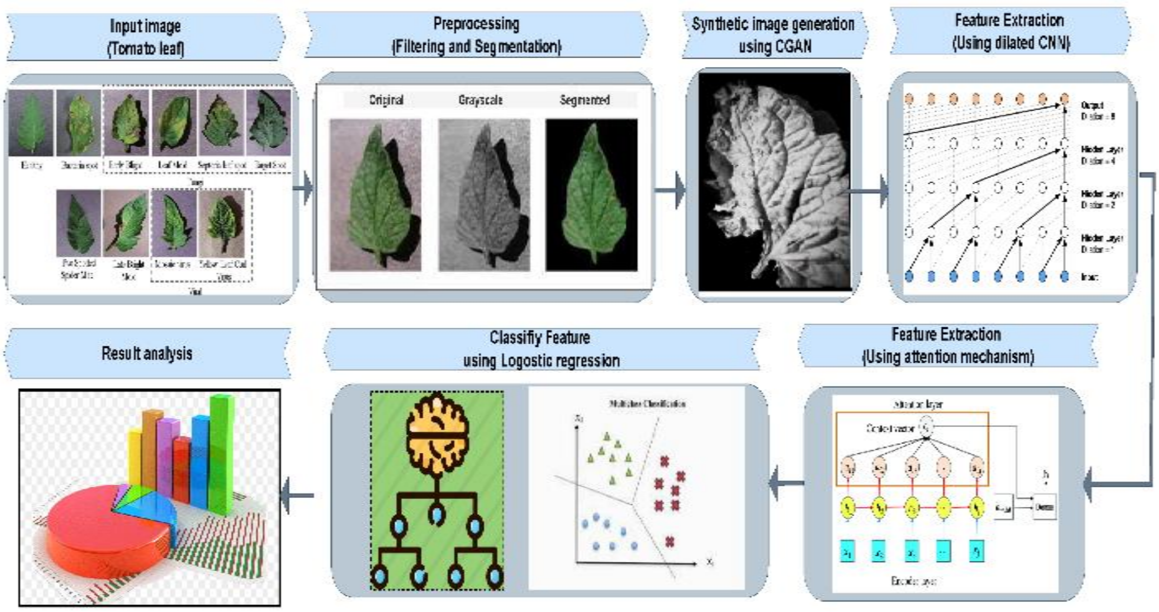

Figure 2: Deep Learning Approach to Detect Tomato Leaf Disease Using Attention Based Dilated Convolution Feature Extractor

A. Enriched Dataset and Improved Classification:

Another important result of this research has been the development of a data bank specifically suited to the agro-climatic factors in Chhattisgarh. In addition to providing the local yet necessary base of reference for image-based disease detection, this dataset would become a powerful asset which can be referred back to by future research projects [14]. They hope that integrating this data set will improve the model's performance, so it can spot minor differences in ways disease manifests itself which are particular to Chhattisgarh.

- The dataset contains 11,000 images (7000 images from different areas of Raipur, Bhilai and 4000 from online platform) of each class (10 different types of diseases classes for tomato leaves such as: Tomato mosaic virus, Target Spot, Bacterial spot, Tomato Yellow Leaf Curl Virus, Late blight, Leaf Mold, Early blight, Spider mites Two-spotted spider mite, Tomato healthy, Septoria leaf spot).
- From this, we selected 7,700 images from each class for training purposes, and keep 3,300 images of each class for testing purpose. Since we are focusing on diseases in a specific location, it will be more beneficial for us to generate our own dataset that would highlight the region's significant diseases. The dataset must contain images of major leaf diseases of tomato plants in our region.
- Link: kaggle kernels output kaustubhb999/tomato-leaf-disease-detection-using-cnn-p/path/to/dest

Figure 3: Data Collection

B. Optimized Deep Learning Model:

The key to the research is developing an ideal CNN model. It is hoped that such a model can perform better than traditional methods in terms of accuracy and efficiency. In this way the CNN model would be finely tuned, making it more precise and effective in terms of recall rate (accuracy) and F1-score [27]. The logic behind the process of optimizing finds a middle path that is as accurate yet time saving, in order to cultivate a model capable of being used in actual disease detection conditions.

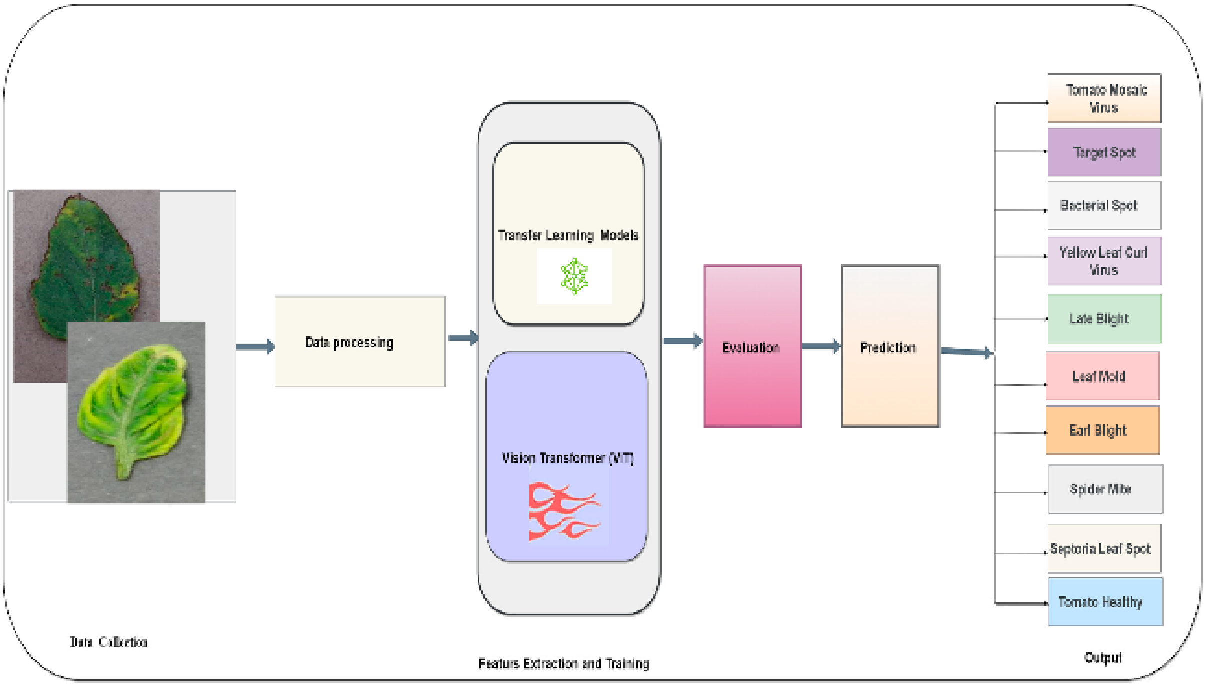

Figure 4: transform and Deep Learning Algorithms for the Early Detection and Recognition of Tomato Leaf Disease

C. Segmentation Approach for Disease Localization:

It is hoped that the segmentation approach will prove a breakthrough for disease localization. The segmentation model attempts to increase the accuracy of disease diagnosis by precisely identifying which parts of a tomato plant are infected. This is significant for farmers because apart from testing whether the insects are a carrier of disease, it can locate exact whereabouts in an area that was infected.

D. User-Friendly Interface for Real-Time Disease Detection:

One of the main results of this research is providing a user-friendly interface that natively includes an improved CNN model. The interface has been developed with the target end-users, mainly farmers and stakeholders, in mind. The expected result will be a real-time platform that gives users an easy but powerful tool to diagnosis and categorize tomato plant diseases [28]. It is the stress on user-friendliness which makes it possible to apply these techniques in various different levels of agricultural operation and bridge the gap between sophisticated technology and practicability.

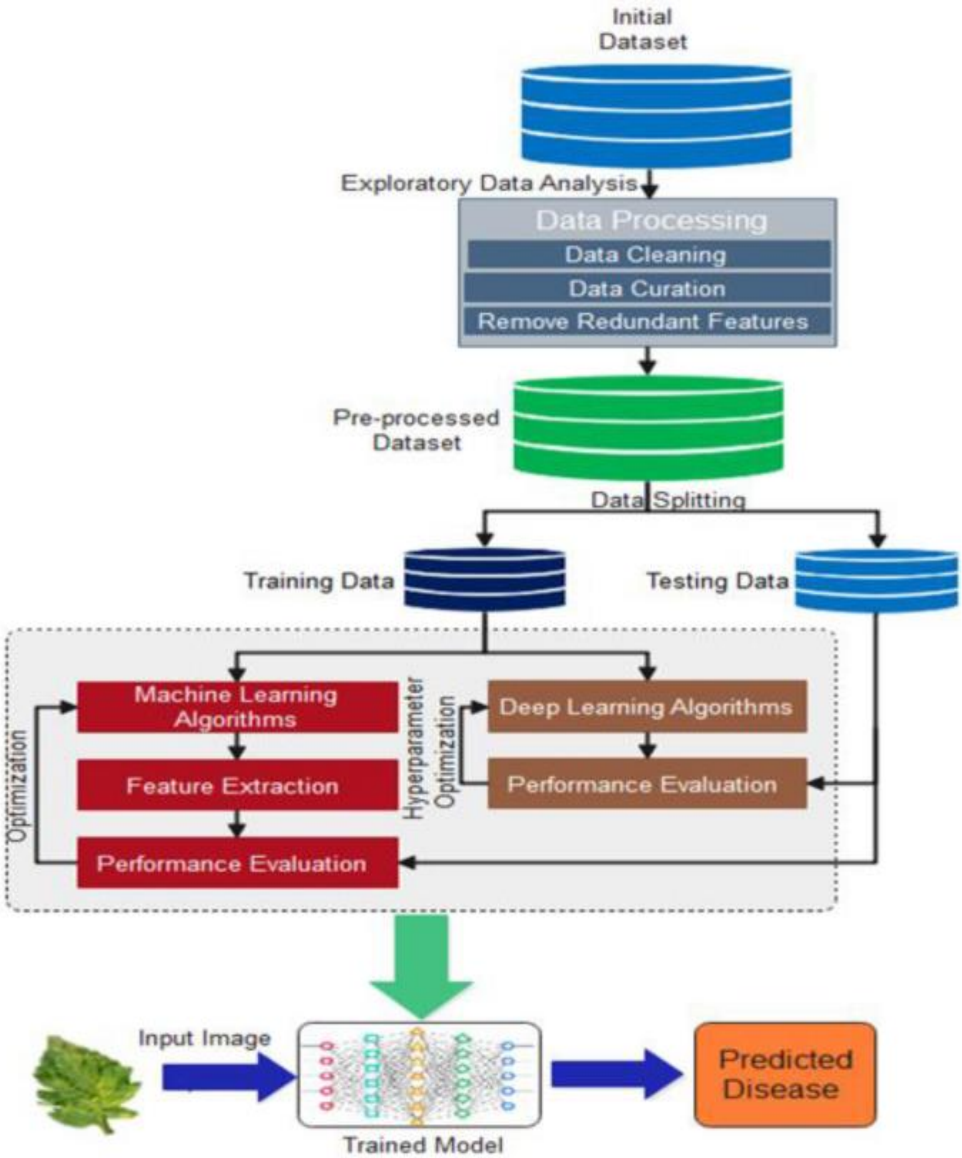

Figure 5: Artificial intelligence in tomato leaf disease detection

E. Noteworthy Contributions to the Research Community:

Literature review, methodology and initial dataset location all indicate that the discipline is making a significant contribution to our knowledge. Through a comprehensive survey of related research, suggesting that the procedure be segmented in accordance with specific needs and industrial requirements, then using advanced feature extraction techniques to provide reference materials for researchers as well as practitioners involved in agricultural image analysis [29].

F. Implications for Agricultural Practices:

The results expected from this research have all original applications with definite and effective consequences for agricultural work, especially in the Chhattisgarh region. Taking a data set that is tailored to the region and an optimized CNN model would seem well suited to local practical realities. Widespread detection and localization of tomato plant diseases, for instance, could go a long way to helping with crop management measures that aim at keeping losses as low as possible [30]. This is sure to be helpful in promoting sustainable agricultural methods going forward.

Accuracy Obtained

In my research work I consider SGDM, RMSPROP and ADAM solver for analysing the performance in various learning rates. When comparing optimizer in terms of accuracy performance is essential to conduct a reasonable comparison.

This optimizer includes hyperparameters tuning, algorithm suitability, benchmarking etc. Moreover, these factors are selected reasonably and the model where trained particular training criteria for experimental purpose. Besides, statistical significance where helps to ensure effectiveness of the comparison outcomes.

Figure 6: Accuracy obtained from RMSPROP with 20 epochs

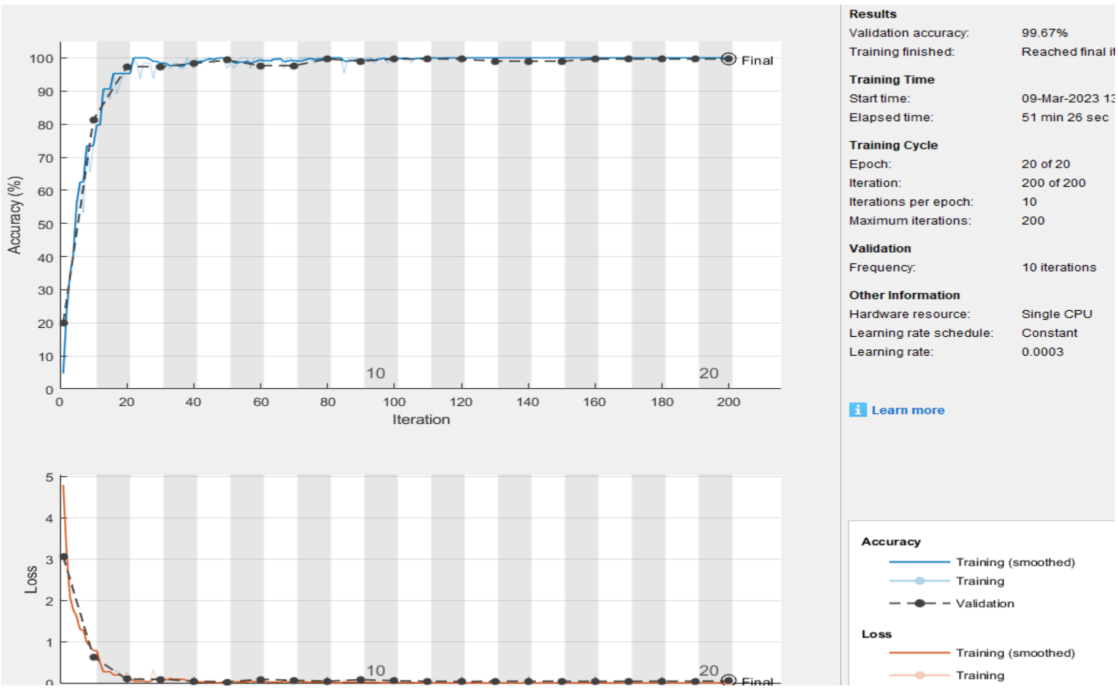

Figure 7: Accuracy obtained from Adam solver with 20 epochs

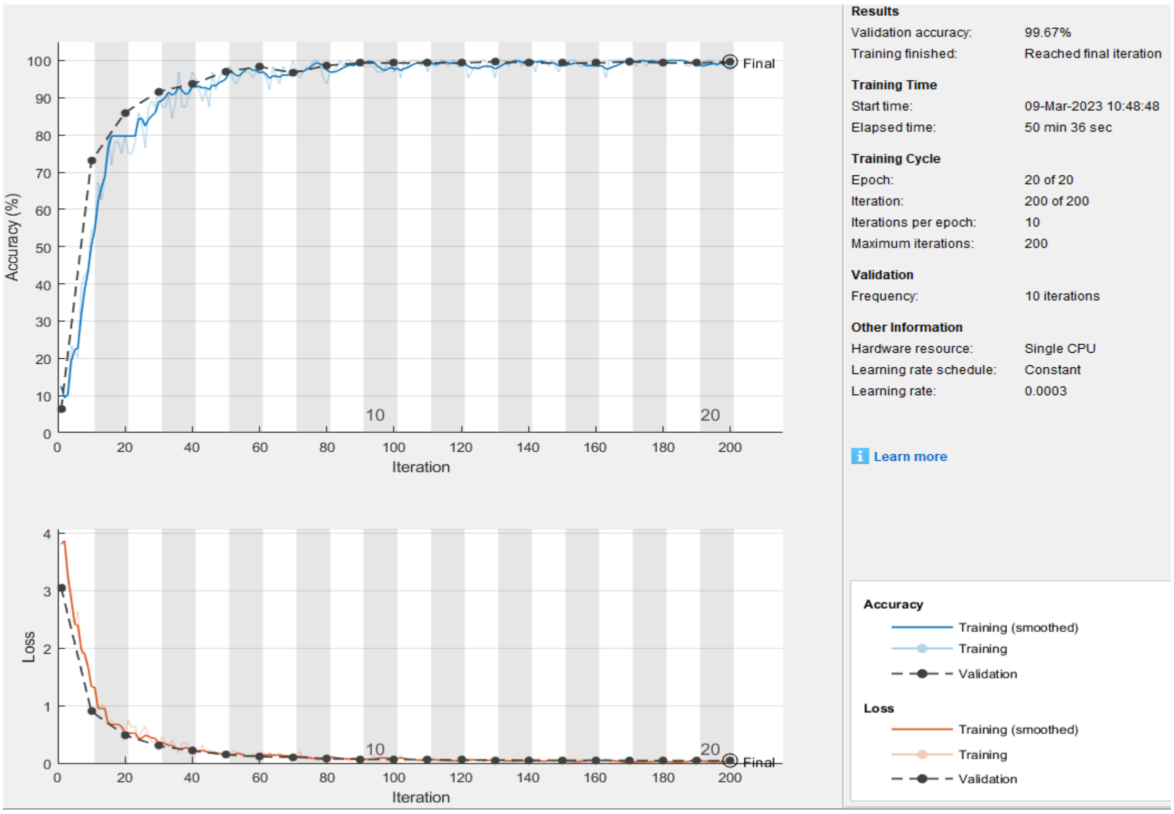

Figure 8: Accuracy obtained from "SGDM" solver with 20 epochs

Target class Confusion Matrix

For the implementation smaller learning rate is very important to attain the better validation accuracy and by varying the number of epochs. Moreover, larger learning rate can create training accuracy more accurate. Furthermore, confusion matrix is used to compute the classification module performance.

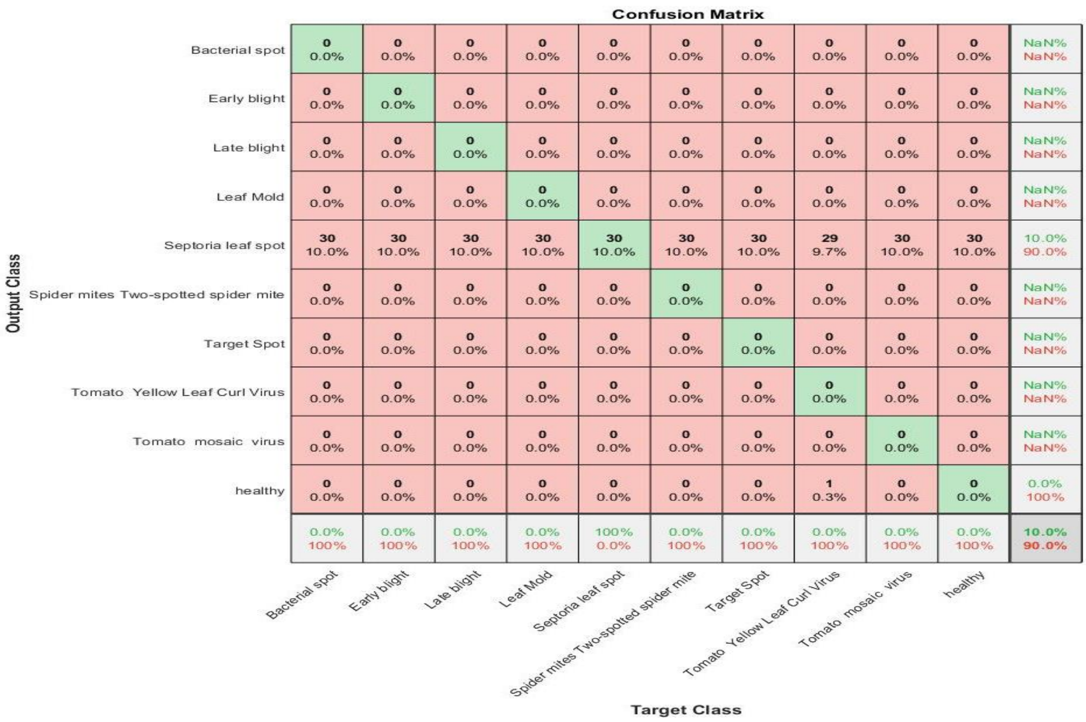

Figure 9: Confusion Matrix

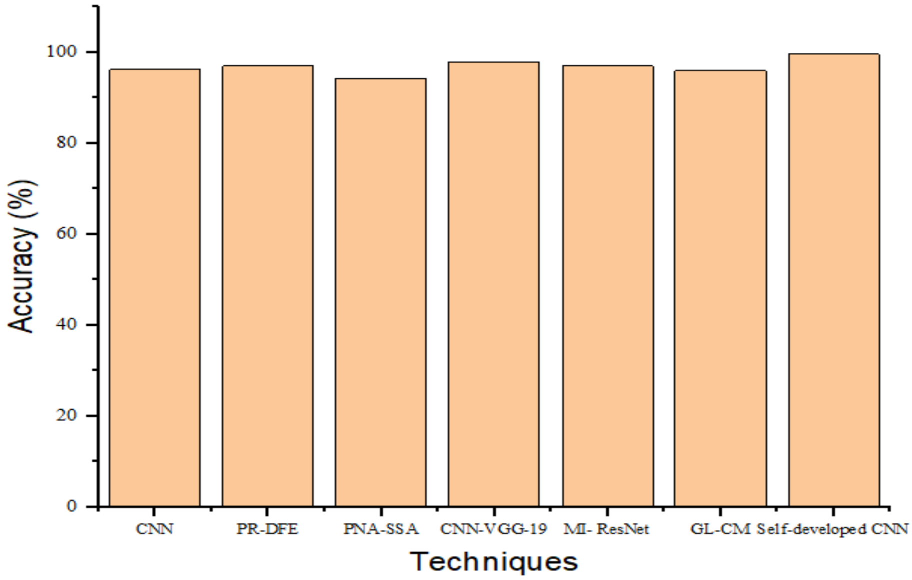

Figure10: Accuracy Comparison

From the comparison, the CNN framework has archives 96.25% of accuracy, PR-DFE method has attained 97% of accuracy which is higher than the CNN framework. Moreover, PNA-SSA replica has achieves 94.35% of accuracy and CNN-VGG-19 model attains 98% accuracy which is higher compared to PNA-SSA replica. Consequently, MI-ResNet model and GL-CM algorithm has attained 97 % and 96% accuracy respectively. But, the proposed advanced self-developed CNN model can attained 99.667% of accuracy while comparing to existing four methods.

Precision comparison with other models

From the comparison, the CNN framework has archives 97% of precision, PR-DFE method has attained 98% of precision which is higher than the CNN framework. Moreover, PNA-SSA replica has achieves 97.71% of precision and CNN-VGG-19 model attains 98% precision which is higher compared to PNA-SSA replica. Consequently, MI-ResNet model and GL-CM algorithm has attained 97.4% and 96.4% precision respectively. But, the proposed advanced self-developed CNN model can attained 99.667% of precision while comparing to existing four methods.

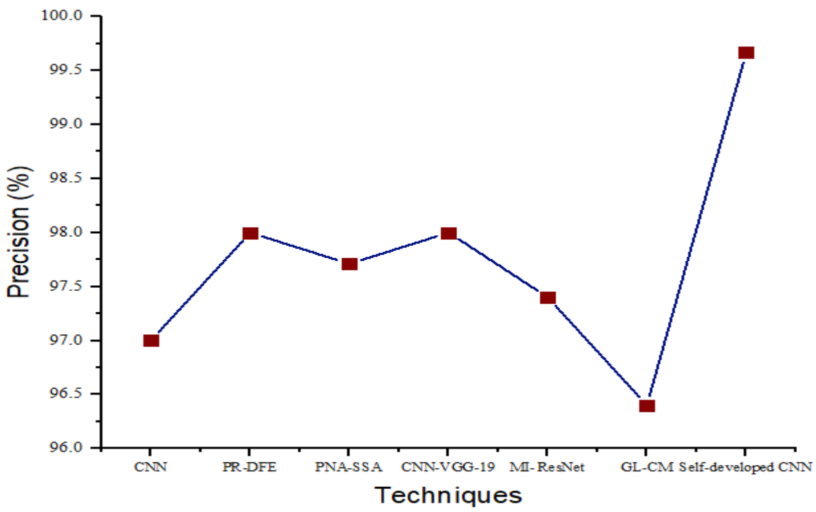

Figure 11: Precision Comparison

Computation time is defined as total time taken to complete the entire process based on the disease detection and classification. Moreover, the proposed method requires less time to classify the disease based on the detection process.

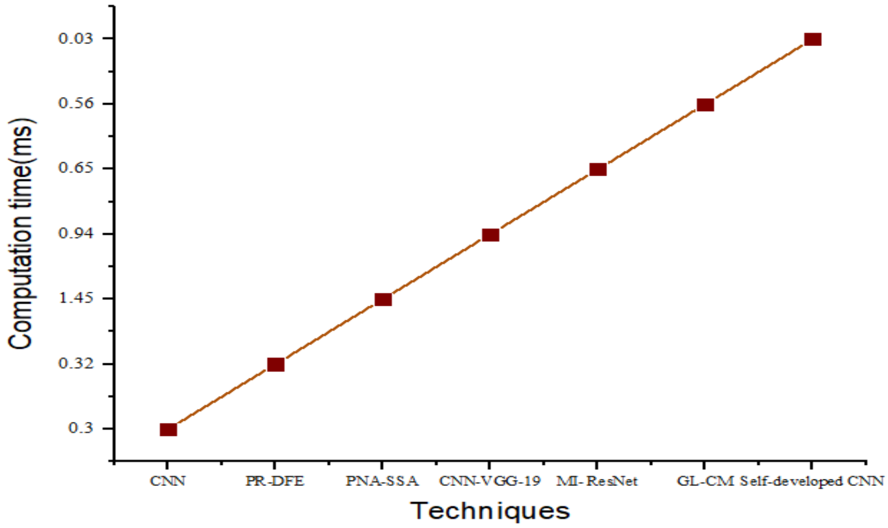

Figure 12: Computation Time

From the comparison, the CNN framework has archives 0.3ms of execution time, PR-DFE method has attained 96.7% of f-measure which is slightly higher than the CNN framework. Moreover, PNA-SSA replica has achieves 1.45ms of f-measure and CNN-VGG-19 model attains 0.94ms execution time which is higher compared to PNA-SSA replica. Consequently, MI-ResNet model and GL-CM algorithm has attained 0.65ms and 0.56ms execution time respectively. But, the proposed advanced self-developed CNN model can attained 99.667% of execution time while comparing to existing four methods,

V. CONCLUSION AND FUTURE WORK

To sum up, work on a Deep Learning-based Approach to Develop a Computer Vision Model for Predicting and classifying Tomato Illnesses of the Takes by Self Developed Convolutional Neural Systems has made an imperative commitment in terms of agrarian innovation investigation. Formulating and fine-tuning a Convolutional Neural Network (CNN) which is particularly outlined for the tomato plant disease location arrangement is genuinely a critical breakthrough. This model's precision at distinguishing and classifying diseases on tomato clears out has set the arrange for a progressive impact upon rural strategies. The precision of the self-developed CNN model, combined with refined highlight extraction methods, makes illness discovery more exact and compelling. An broad handle of reoptimization is utilized in fine-tuning basic parameters, accomplishing a adjust between precision and speed that produces a demonstration comprehensible sufficient to apply for genuine world conditions. The research also highlights the need for tapping into deep learning methods to solve such problems in agriculture--in this case, that of tomato plant disease.

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