Towards an effective tomato leaf disease classification using modified transfer learning algorithm based on resnet50

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This Report Presented in Partial Fulfillment of the Requirements for the Degree of Bachelor of Science in Computer Science and Engineering

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APPROVAL

This Project/internship titled **“Towards an effective tomato leaf disease classification using modified transfer learning algorithm based on resnet50”**, submitted by Md Ashikur Rahman, ID No: 181-15-11093 to the Department of Computer Science and Engineering, Daffodil International University has been accepted as satisfactory for the partial fulfilment of the requirements for the degree of B.Sc. in Computer Science and Engineering and approved as to its style and contents. The presentation has been held on *January 26, 2023*.

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DECLARATION

We hereby declare that; this project has been done by us under the supervision of **Mst. Eshita Khatun, Lecturer (Senior Scale), Department, of CSE** Daffodil International University. We also declare that neither this project nor any part of this project has been submitted elsewhere for award of any degree or diploma.

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ABSTRACT

To increase agricultural productivity, plant diseases must be detected early and accurately. The deep learning approach based on artificial intelligence is critical in detecting illnesses utilizing a large volume of plant leaf photos. However, utilizing deep learning algorithms to identify illness with little datasets is a difficult challenge. One of the most prominent deep learning algorithms for reliably detecting plant disease with minimum plant picture data is transfer learning. This study suggests a transfer learning-based strategy for identifying tomato leaf disease. The model detects illness by combining real-time and archived photos of tomato plants. Adam, SGD, and RMSprop optimizers are also used to assess the performance of the suggested model. The experimental results show that the suggested model, which employs a transfer learning technique, is successful in classifying tomato leaf diseases automatically. When compared to SGD and RMSprop optimizers, the Adam optimizer delivers higher accuracy.

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CHAPTER 1
INTRODUCTION

1.1 Introduction

Climate change, pollinator decline, plant diseases, and other factors all pose a danger to food security. Plant diseases pose a threat to food safety and have severe repercussions for farmers. Farmers spend their money and other resources to avoid plant diseases. We must detect these illnesses in this changing environment. Some illnesses are difficult to diagnose because their symptoms are not evident to the naked eye. We must employ technology to identify these illnesses in this circumstance. Otherwise, they would have to rely on imported food, which will increase costs and put people's health at danger. We can reduce infections and increase production by utilizing these technologies.

Tomatoes are a widely produced commodity in many parts of the globe, and because of their high nutritional value, distinct flavor, and health benefits, they play an essential role in agricultural production and commerce. Given the economic importance of tomatoes, it is vital to use strategies to increase production and product quality. Tomato disease such as early blight, corynespora leaf spot, late blight, septoria leaf spot, leaf mold disease, yellow leaf curl, viral disease, and spider mite disease are quite widespread, thus an actual time and precise detection system is required.

We examined the performance of SGD, RMSprop, and Adam in detecting leaf disease in this study. These kind of optimization techniques are totally based on ResNet50, a set of pre-trained networks. The highest-performing network architecture was then chosen, and tests on the effect of two different hyperparameters on accuracy were conducted.

1.2 Motivation

South Asian farmers' economic conditions are not as excellent as those in other nations. Agriculture is their sole source of income. Bangladeshi farmers, like those in other nations in the area, plant tomato throughout the year. For cultivation, they take out a high-interest loan. The profitability of tomato farming is determined on the quality of the tomato. Tomato leaf diseases pose a significant hazard to growers. Farmers make a profit by selling bad-quality tomatoes at a low price. Occasionally, illness wipes off all tomato plants. As a result, farmers suffer financial losses, making life difficult for them. They can save financial damage if they can identify tomato leaf diseases early on. This will also assist them in improving their financial situation. Calcium, nicotinic acid, vitamin A, fiber, vitamin C, protein, fiber, chlorophyll, minerals, and carbohydrates are all found in tomatoes. Recognizing tomato infections has become a critical responsibility in ensuring greater tomato quality. Because there has not been much research done in this field, we'll utilize deep learning to identify diseases in tomato plants from their leaves.

1.3 Rational of the Study

Tomato disease detection and recognition utilizing deep learning for how to identify and recognize tomato illnesses in plants and leaves by using a camera to record pictures as the foundation for distinguishing different sorts of ailments Deep learning is a more sophisticated image processing technique. People all around the world rely on agriculture as one of the most significant sectors, with vegetables being a basic requirement for survival. Tomatoes are a common vegetable in everyday life. Preventing these illnesses is critical. Deep learning can detect all illnesses. Deep learning diagnoses illnesses from captured photos and determines the precision with which they are recognized. Deep learning is also used to classify illnesses.

1.4 Research Questions

- Is it possible for this study to provide reliable illness predictions?
- Is it possible to improve the size of tomato using technology?
- How useful would it be if I could use this technology to recognize tomato diseases?
- What are the symptoms of Tomato Leaf Disease?

1.5 Expected Outcome

One of the planned outcomes of this study is defined during this session. Technology is rapidly improving nowadays. This study emphasized the use of technology to enhance agriculture. The research strives to give a very effective answer on how to recognize tomato infections and how to prevent them using deep learning technologies. It was trying to give exceptional precision for which it would most likely be a very nice option on a regular basis. In the future, the researchers want to build cellular software that would allow farmers to comprehend the afflicted area and how to remind themselves of the illness. This mobile program is really simple and easy to use for everyone.

1.6 Report Layout

We suggested a CNN model to identify tomato leaf disease in this study, which contains six parts:

- Chapter one: Introduction
- Chapter two: Background Study
- Chapter three: Research Methodology
- Chapter four: Experimental Results and Discussion
- Chapter five: Impact on Society, Environment, and Sustainability
- Chapter six: Conclusion

CHAPTER 2
BACKGROUND STUDY

2.1 Preliminaries

Several experiments of computer instruction for prediction were done. One of Deep Learning's most common applications is prediction. Extensive research has been conducted to predict the occurrence of leaf disease in various trees and to find a remedy. This research focused on challenges and employed a variety of deep learning techniques to address them. This chapter gives an overview of the relevant work that is being done effectively by several experts in the aforementioned field.

2.2 Related Works

Agriculture, employing contemporary technology, generates enough food to fulfill people's needs in today's globe, and India's economy is also reliant on its production [1]. However, environmental changes [2], a drop in pollinators [3], plant diseases [4], and other factors continue to pose a threat to food safety. Tomato cultivation is widely practiced over the world, and because of its high nutritional value, it plays an important part in agricultural production and commerce [5]. Tomatoes are a popular vegetable crop all across the world, and their output has expanded significantly over time, according to data from the United Nations' Food and Agriculture Organization [6].

Smallholder farmers account for more than 80% of agricultural production in India [7], with disease causing 50% of crop yield loss [8]. Plant diseases have been spotted by professionals with the naked eye for decades. This method demonstrates a lack of precision and the scarcity of professionals in rural regions [9]. Early discovery of infections permits pathogens to be combated with preventative measures. Despite the fact that automation in classification, that is one of the most accurate ways for classifying the illness, there are a few issues that emerge owing to interclass plant similarities and extrinsic variables such as picture backdrop, lighting, color, position, and occlusion [10].

Computer vision, DL, ML, and image processing approaches have proven to be effective in detecting plant illness early on and monitoring plant health conditions on a continuous basis. DL has been popular in the latest years and has had great success in a variety of agricultural fields, including plant increase prediction, categorization and disease diagnosis. TL is the most widely used ML approach in deep learning to save computing resources and model construction time [11].

By building a Modified-ResNet model, we looked at the detection and identification of illnesses from tomato plant leaves in this article. The Xception [12] model is a more advanced variant of the inception network that employs separable convolution layers instead of conventional convolution layers. It is made up of thirty-six convolution layers that are used to select the data features. Classifier is made up of the optional fully connected layers and the logistic regression layer. To get improved accuracy, DL models require a significant amount of data. Because DL needs a large amount of computing resources to train a network from scratch, it is more common to use pre-trained models to complete the task [13][14].

To isolate the diseased region, Sannakki et al. recommended using k-means based clustering done on each picture pixel [15]. They noticed that the Grading System they developed utilizing machine learning and fuzzy logic is quite good at rating diseases in plants. A Researcher proposed a new histogram related method for detecting potato scab diseases and used image segmentation by its color, that technique to detect intensity patterns [16]. With a classification accuracy of 97.5 percent, they came out on top. Another one used fuzzy decision creating and a fuzzy multicriteria decision-making technique to determine weed form, with the accuracy that is 92.9 percent [17]. Cheng used DT, SVM, and NN to distinguish rice and weed, with Decision Tree providing the greatest accuracy of 98.2 percent [18].

Deep learning technologies have recently been widely used in diagnosing plant disease. ResNet and AlexNet were used by Cheng to identify agricultural pests [19]. Simultaneously, they conducted comparison trials using SVM and BP neural networks, with ResNet-101 providing the greatest accuracy of 98.67 percent. ConvNets were used by Ferreiraa et al. [20] to detect weeds in soybean crop photos and categorize them as grass or broadleaf. The highest level of accuracy they were able to obtain was 99.5 percent. Sladojevic developed a CNN model to categorize and identify fifteen varieties of leaf diseases automatically [21]. In the meanwhile, that was capable to tell plants apart from the environment. That were 96.3 percent accurate on average. Mohanty et al. used the pretrained AlexNet and GoogLeNet to build CNN model to recognize fourteen crop types and twenty-six illnesses [22]. They were 99.35 percent accurate. Using CNN, Sa suggested a unique technique to fruit identification [23]. They used transfer learning to modify the Faster R-CNN model. In a field farm dataset, they obtained an F1 score of 0.83.

2.3 Scope of the Problem

We determined that huge images cannot be handled utilizing their suggested technique for tomato disease diagnosis after reviewing numerous relevant scientific papers. We have to train our identification model on a large dataset to enhance it. They just utilized a few photographs for their proposed model. As a consequence, their proposed system will have trouble dealing with new test photographs. A significant chunk of the research group has recently begun employing DL to address identification difficulties and has trained their model using a large dataset. Their notion is technologically compatible, making their discoveries applicable and valuable to the broader population. As a consequence, we planned to construct a model for identifying illnesses using DL. It will work with existing technologies and will benefit ordinary people.

2.4 Challenges

When I was writing this paper or looking for material for it, I had to overcome several obstacles. For example, I looked for the identical paper because I need to know how many papers I've written about my subject before and I need to extract some information from it. I've encountered some difficulties gathering data for my thesis. I had to collect several leaves from various ailments, which was a difficult task for me. I have to extract the data from the photograph after gathering the data. Then I had to use numerous techniques to determine the dataset's correctness, which made my job time harder. However, I was unable to locate any papers that were directly linked to my topic. As a result, I believe it was one of my most difficult assignments. Which I was able to tastefully and thoroughly finish or gather. My next obstacle will begin when I begin my writing by completing a large amount of documentation and delivering information that is superior to theirs. But, in the end, I overcame all of my obstacles and completed my assignment.

CHAPTER 3
RESEARCH METHODOLOGY

3.1 Research Subject and Instrumentation

To recognize Tomato Leaf Disease, this study report uses Deep Learning. Deep Learning is a sophisticated image processing technique. Deep Learning can evaluate photos and videos in real time and provide the required outcome. Deep Learning systems recognize picture attributes and compare them to a profile database. To accomplish illness identification, a large amount of data was needed. I'll need some tools to accomplish this study because they're necessary for the thesis to be completed. First and foremost, I require a critical component: the data collection, which consists of photographs. The platform on which the code is executed is then required. I utilized Google Colab, which is a free online collaboration tool. It can do a lot like, image enhancement, image processing, image segmentation. Furthermore, geometric transformations, noise reduction and 3D image processing can be done by this.

3.2 Data Collection Process

The plantvillage, an open access resource with 54,306 tagged various kind of leafs picture of damaged and healthy plants from fourteen different crop types, was used in this research. The tomato leaves dataset from the plantvillage database, as well as photos from an agricultural area in the western portion of Tamilnadu, India, were utilized to verify the suggested technique. The plantvillage database has 10 separate classifications, nine of which are unhealthy and one of which is healthy.

Sl. No.	Authors name	Model name	Size of Dataset	Total classes	Accuracy (%)
1	Mohammed Brahimi et al	AlexNet GoogLeNet	14,828	9	98.60 99.18
2	Halil Durmuú et al	AlexNet SqeezeNet	19,742	10	95.65 94.30
3	Keke Zhang et al	AlexNet GoogLeNet ResNet	5,550	9	95.83 95.66 97.28
4	Aravind Krishnaswamy Rangarajan et al	AlexNet VGG16	13,262	7	97.49 97.29
5	Rajasekaran Thangaraj	Modifed-Xception	16,578	10	99.55
6	Proposed method	Modifed-ResNet	28019	10	99.75

3.3 Statistical Analysis

There are ten different classifications in the plantvillage database, nine of which are dangerous and one of which is beneficial.

3.4 Proposed Methodology

This research focuses on using deep learning to diagnose tomato leaf disease. The mathematical model for recognizing tomato disease is visualized initially in this section. Meanwhile, the standard CNN method is explained using formulae. The data augmentation is shown in number ten. Finally, we introduced ResNet, one of the strong deep neural networks used in this article. In this study, the primary process of identifying tomato leaf disease may be abstracted as a mathematical model.

3.4.1 Raw Dataset

In its native nature, the dataset. The freely accessible picture archive for plant wellness provided the raw leaf data used in this study. Early blight leaf, two-spotted spider mite, viral, corynespora spot, leaf mold, late blight, septoria spot, and yellow leaf curl these diseases are a few of the illnesses described. The collection has a total of 28019 recordings.

3.4.2 Data Augmentation

Deep CNN requires a significant amount of data because it has millions of boundaries. Otherwise, the network may be unstable or overfit. The most popular method to reduce overfitting involves manually enlarging a collection of images and performing label-preserving modifications. In this study, the initial division of the raw picture dataset into training samples and testing samples as 80% and 20% respectively was followed by the use of the data augmentation technique.

Using this approach, the training dataset's picture count may be increased. Throughout the training process, it helps to prevent the issue of overfitting. Overfitting is the term used to describe a situation when the network learns the data itself rather learning the general pattern of the dataset. Image augmentations were carried out by applying particular alterations to the image, including rotation, horizonal flipping, and share range.

3.4.3 ResNet50

In transfer learning, models like AlexNet, GooLeNet, AlexNetOWTBn, VGG, and Overfeat are increasingly frequent. There were a lot of convolutional layers. Network management and optimization, degradation concerns, and the vanishing gradient problem are among issues that deep CNN networks face. ResNet is a completely new idea. It makes tough jobs easier to complete and enhances recognition rate. Deep CNN training has a number of drawbacks, including saturation and accuracy loss. ResNet seeks to alleviate these issues. In this study, we used the ResNet50 model. ResNet50 consisted of 50 layers of residual networks. ResNet50's architecture is seen in Figure 3.1.

Different sets of identical layers make up the ResNet50 structure. The first layer in Figure 3.1 comprises 64 filters with a kernal size of 77%, followed by a maxpooling layer with a size of 33%. The initial tier is made up of three identical blocks. On the other hand, groups two, three, and four each feature four separate blocks, four exact blocks, and three specific blocks, respectively. The identification block that connects two layers of differing sizes is shown by the blue-colored arcs linking particular groups. Following these blocks, a total of 38 totally connected layers do the categorization task. We didn't employ these completely linked layers in our suggested model.

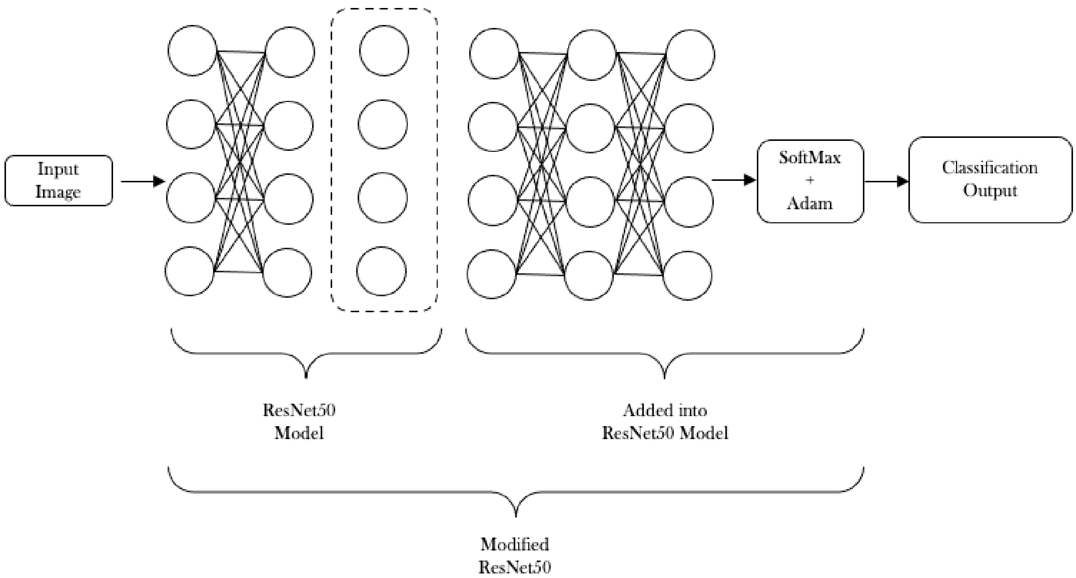

Figure 3.4.1 ResNet50 architecture

3.4.4 Adam

Adaptive Moment Estimation is simple to build, computationallly efficient, requires minimal memory, is insensitive to diagonally resizing of the gradients, and it is well suited for problems with a large number of dataset and/or parameters. The AdaGrad and RMSProp advantages are combined in the Adam optimizer. This implies it doesn't require a stationary objective and can function with both sparse and continuous gradients. Data subsampling might result in noisy goals. Dropout regularization in deep neural network training can also result in noisy objectives. In such instances, effective stochastic optimization approaches are required. In such circumstances of stochastic outcomes with high-dimensional factor spaces, Adam performs well.

3.4.5 RMSprop

Root Mean Square Propagation, or RMSProp, is a gradient descent optimization approach. The RMSProp algorithm was created to address the shortcomings of the AdaGrad algorithm. That is, RMSProp prevents convergence by not decaying the learning rate too rapidly. In the sense that both employ the square of the gradient to scale coefficients, RMSProp is quite similar to Adagrad. The leaky averaging is shared by RMSProp and momentum. RMSProp, on the other hand, use the approach to fine-tune the coefficient-wise necessary task. In practice, the experimenter must arrange the learning rate.

3.4.6 Stochastic gradient descent

SGD is a known and widely used approach in many ML algorithms, and it is the foundation of Neural Networks. After calculating the cost function for each item in the data set, a stochastic gradient descent method modifies the weights of each neuron's input signals. This indicates that a stochastic gradient descent method will go

through n iterations before traversing through the complete data set in a data set with n observations. On each run of a traditional gradient descent method, the complete data set is used.

3.4.7 Performance evaluation metrics

Performance measures including precision, recall, accuracy, and F1 score are used to evaluate the model's predictive power. The accuracy is the percentage of correctly predicted photographs among all guesses. The accuracy is expressed in the following equation.

$$Accuracy = \frac{\text{Number of correct predictions}}{\text{Total number of predictions}} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\text{i}$$

The ratio of accurately predicted truly positive results (TP) to the summation of the number of positive values (TP+FP) anticipated by the model is the accuracy metric. Because of the significant numbers of FP, the precision value is reduced. The precise bound is 0 to 1 and is calculated as follows:

$$Precision = \frac{TP}{TP + FP} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots ii$$

The recall is used to calculate the number of right positive forecast by comparing the number of true posetive results (TP) to the total numbers of sample (TP+FN). The recall is determined by applying the following formula:

$$Recall = \frac{TP}{TP + FN} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots iii$$

The harmonic means of the precisiion and recall is used to compute the F1-score, which is one of metric used to jusify the model's accuracy. It is defined as follows:

$$F1\ score = 2\ \times \frac{Recall \times Precision}{Recall + Precision} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots iv$$

where TP, FP, TN, FN, and FN, respectively, stand for True Positive, False Positive, True Negative, and False Negative.

3.5 Implementation Requirements

The experiment is carried out on a system with

1. An Intel Core i5 3.5 GHz CPU
2. 8 GB RAM
3. A 2 GB integrated NVIDIA graphics card.

Python-based deep learning frameworks like TensorFlow and Keras are utilized to implement the model.

CHAPTER 4

EXPERIMENTAL RESULTS AND DISCUSSION

4.1 Experimental Setup

The dataset contains 28019 photos that have been worked on. There were nine disorders of tomato leaves found here, with one being healthy leaves. The suggested model was trained using a cloud-based notebook. In this study, we built the CNN algorithm to produce a model that can recognize diseases affecting tomato leaves. Using our suggested model, we were capable to get a great degree of precision.

4.2 Experimental Results & Analysis

The experiment initially runs for a maximum of 50 epochs, with each epoch chosen to test the model's accuracy on validation and training datasets. Figure 3.2 displays the loss variations and accuracy of the method that Adam optimizer was used to train. According to that graph, training and validation accuracy increases quickly up to 10 epochs before waning in later epochs. The training and validation loss is also shown in Figure 3.2, showing how the loss increases initially but gradually lowers as the number of epochs grows during network finetuning.

Similarly, RMSprop and SGD optimizers are used to train the suggested model. Figures 3.3 and 3.4 show the changes in validation accuracies, training, and losses employing both optimizers. Figures 3.3 and 3.4 illustrate that as the number of epochs rises, accuracy improves and loss decreases.

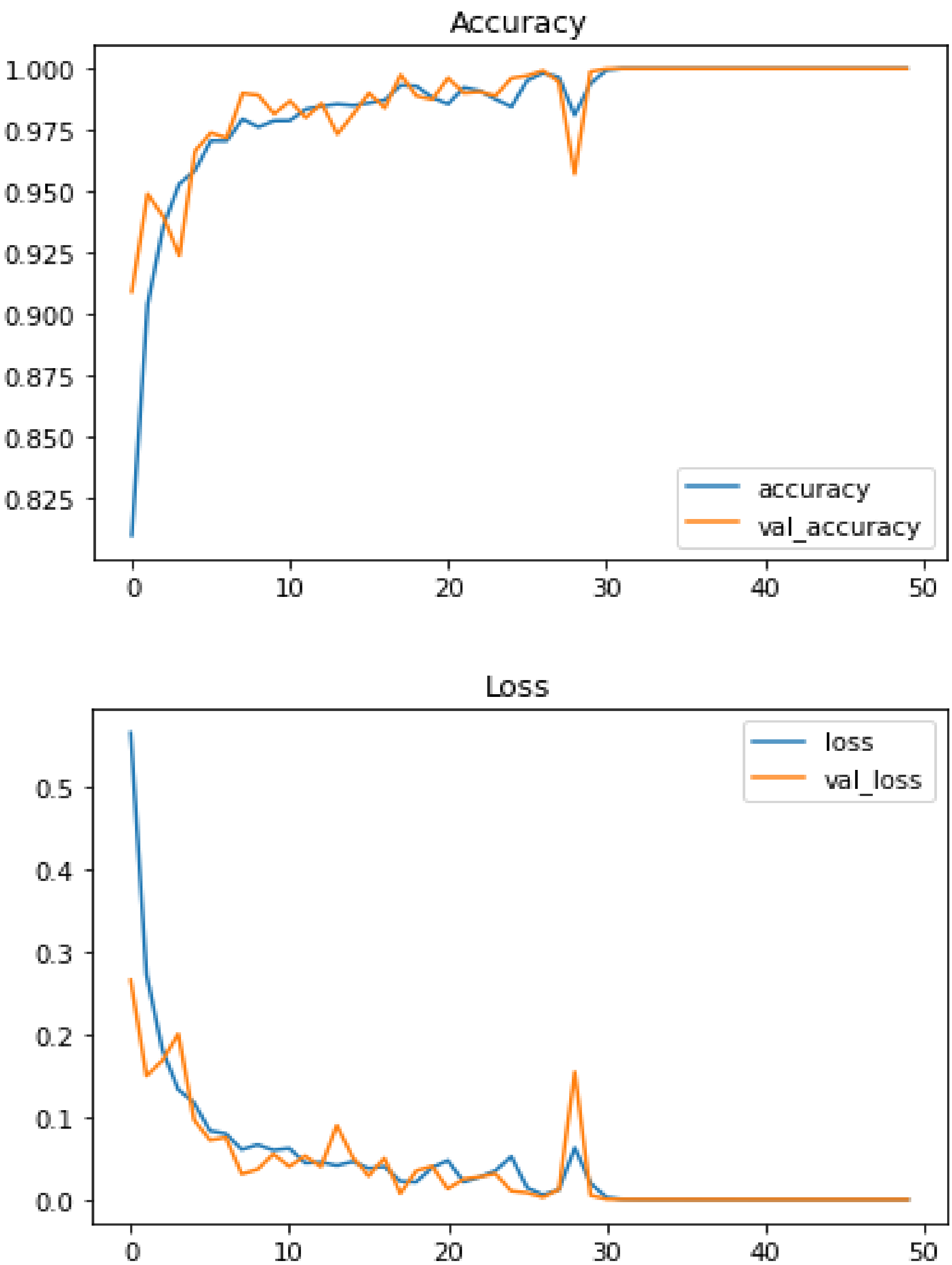

Figure 4.2.1 The model which proposed trained on the validation and training sets, collecting efficiency and loss variations using the Adam optimizer

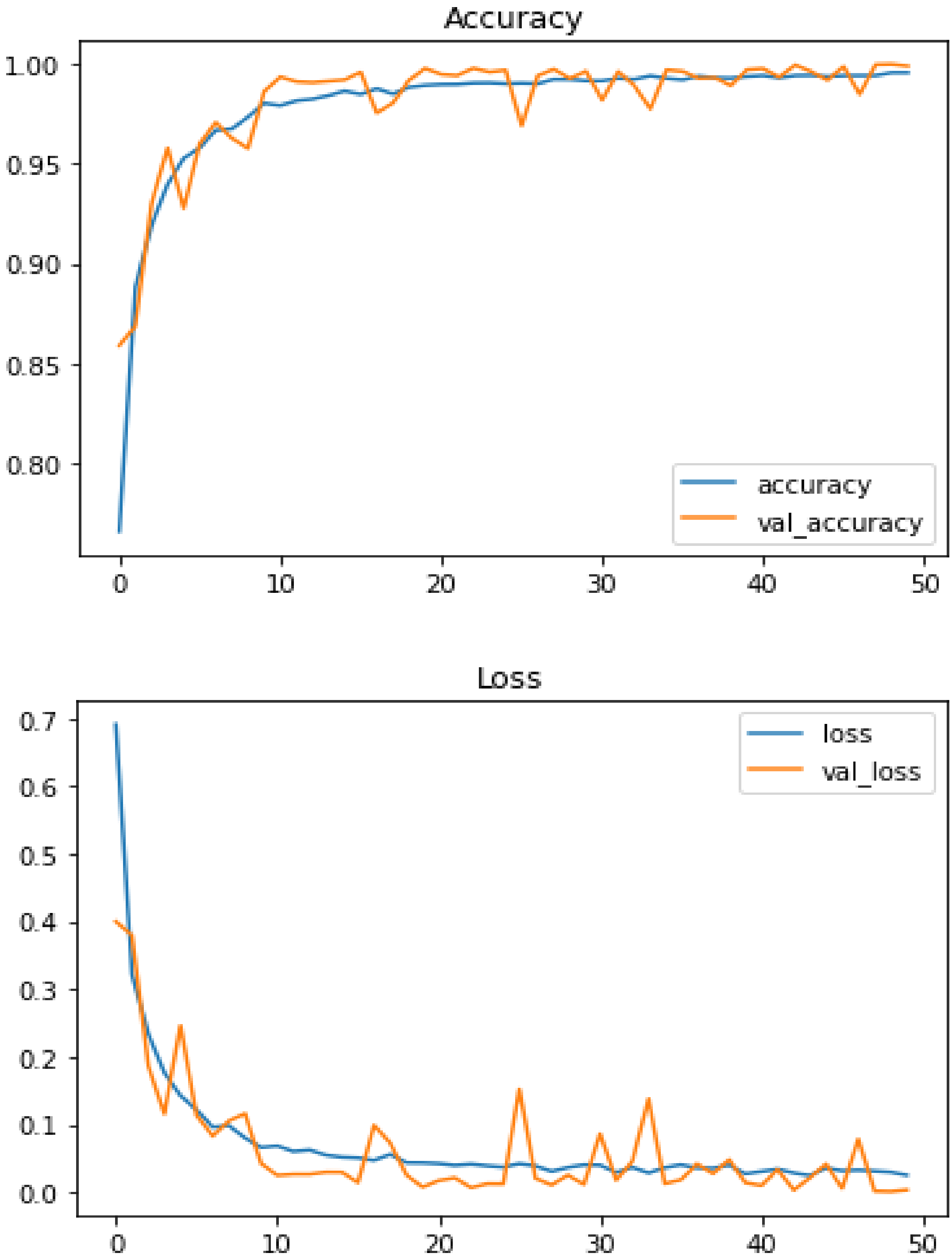

Figure 4.2.2 The model which proposed trained on the validation and training sets, collecting efficiency and loss variations using the RMSprop optimizer

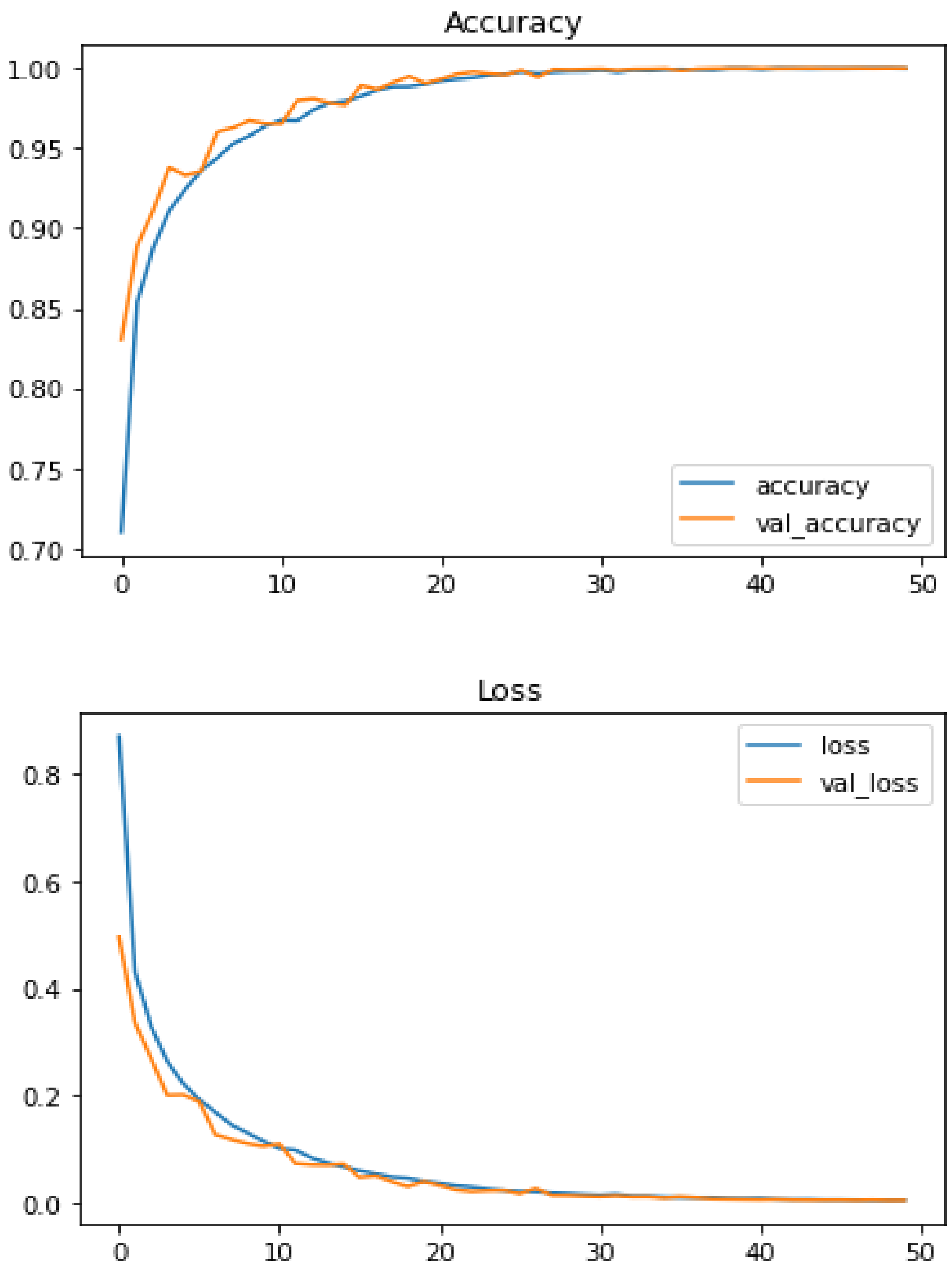

Figure 4.2.3 The model which proposed trained on the validation and training sets, collecting efficiency and loss variations using the SGD optimizer

4.3 Comparative Analysis

Figure 3.5 shows that the proposed model's Adam optimizer obtains the greatest Top testing accuracy of 98.30 percent, followed by RMSprop of 93.48 percent, SGD of 97.47 percent, and so on. Finally, the results show that the suggested model's Adam optimizer outperforms the above-mentioned optimizers.

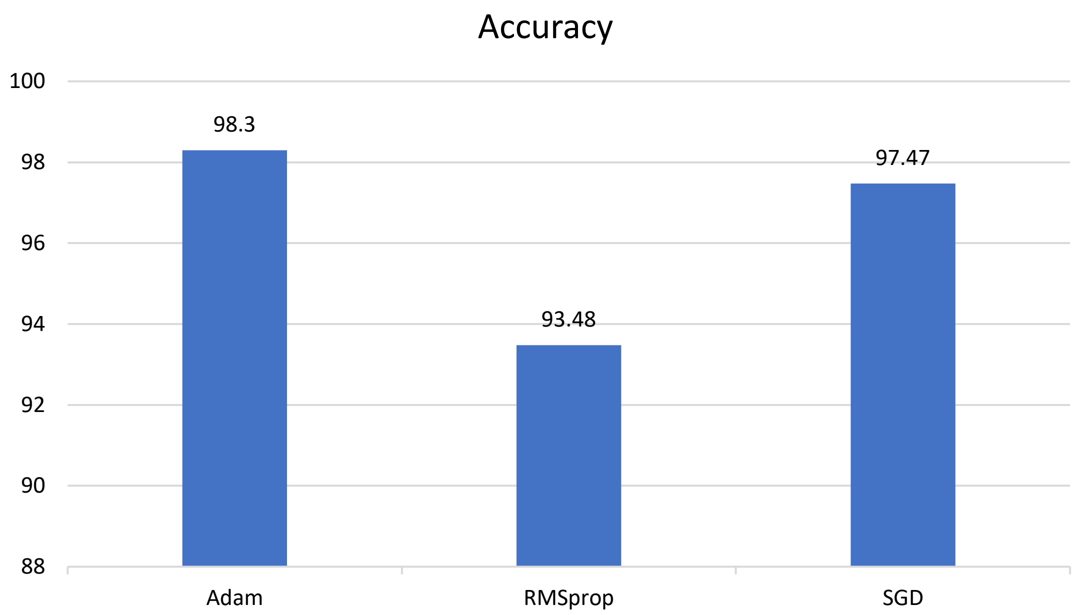

Figure 4.3.1 Comparative evaluation of the test accuracy of the proposed model using SGD optimizers, Adam, and RMSprop

The accuracy value derived on the testing dataset for several optimizers of the proposed model is shown in Figure 4.3.2. The results demonstrate that the suggested model for Adam optimizer outperformed RMSprop and SGD in terms of accuracy.

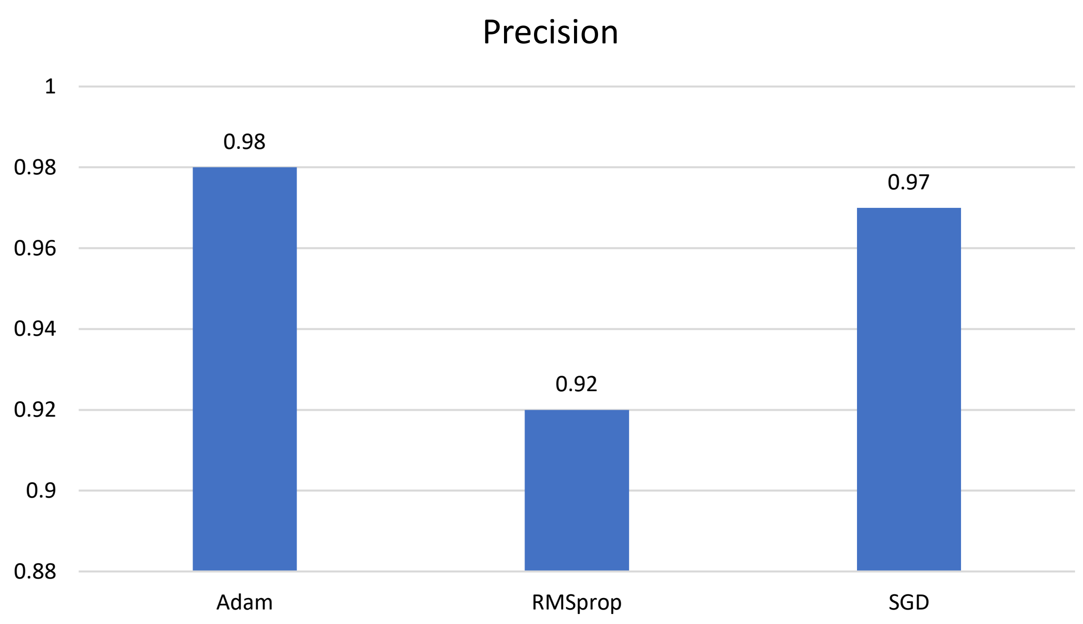

Figure 4.3.2 Comparative evaluation of the test precision value of the proposed model using SGD optimizers, Adam, and RMSprop

The recall values of the proposed model for the various optimizers are shown in Figure 4.3.3. The suggested model for Adam optimizer has a greater recall value than the other optimizers.

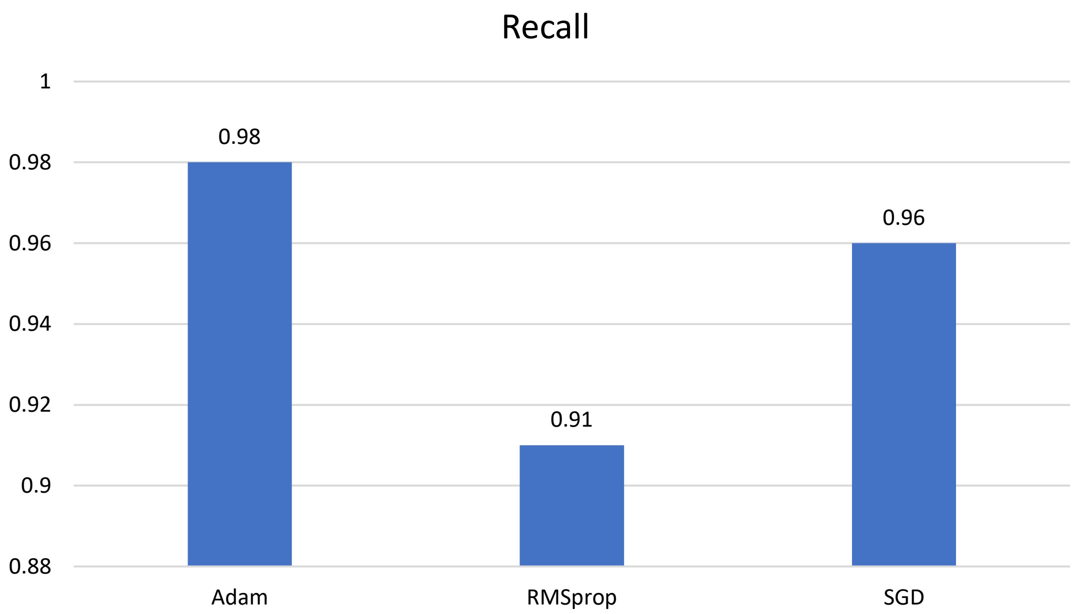

Figure 4.3.3 Comparative evaluation of the test recall value of the proposed model using SGD optimizers, Adam, and RMSprop

Figure 4.3.4 shows the f1-score for multiple optimizers of the proposed model based on the testing dataset. In terms of f1-score, the findings show that the recommended model for Adam optimizer beat RMSprop and SGD.

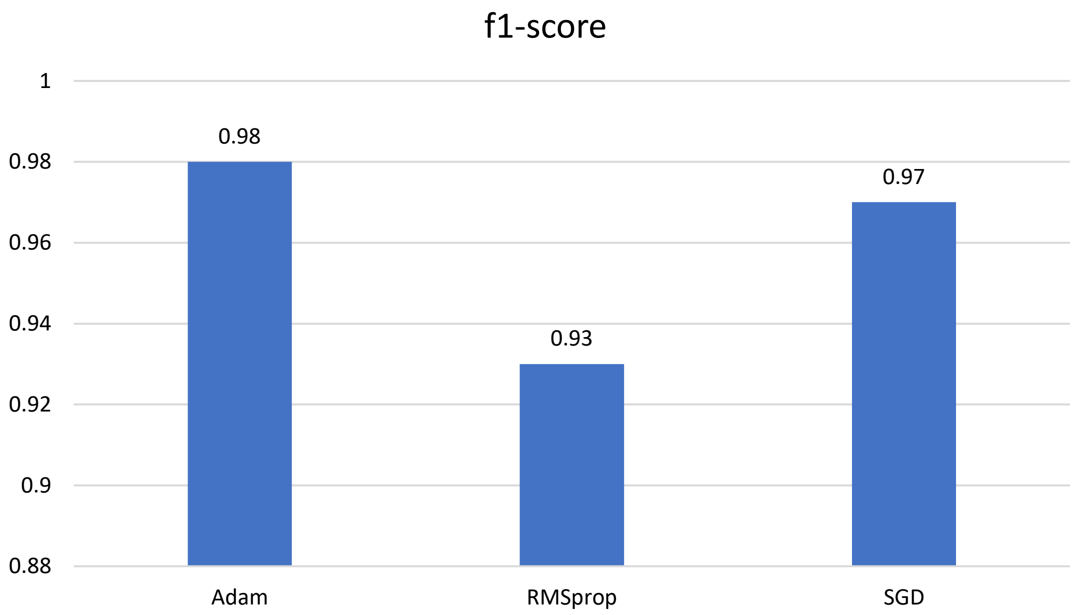

Figure 4.3.4 Comparative evaluation of the test f1-score value of the proposed model using SGD optimizers, Adam, and RMSprop

Finally, when evaluating the accuracy, recall, precision and F1 score of the proposed model, the Adam optimizer outperformed the RMSprop and SGD optimizers in diagnosing tomato disease using leaf pictures which is shown in table 4.3.1. Our proposed model outperformed compare to others, that is shown in figure 4.3.5.

Table 4.3.1 Comparison of Adam, RMSprop, and SGD

	Accuracy	**Precision**	**Recall**	**F1-score**
RMSprop	0.93	0.92	0.91	0.93
Adam	**0.98**	**0.98**	**0.98**	**0.98**
SGD	0.97	0.97	0.96	0.97

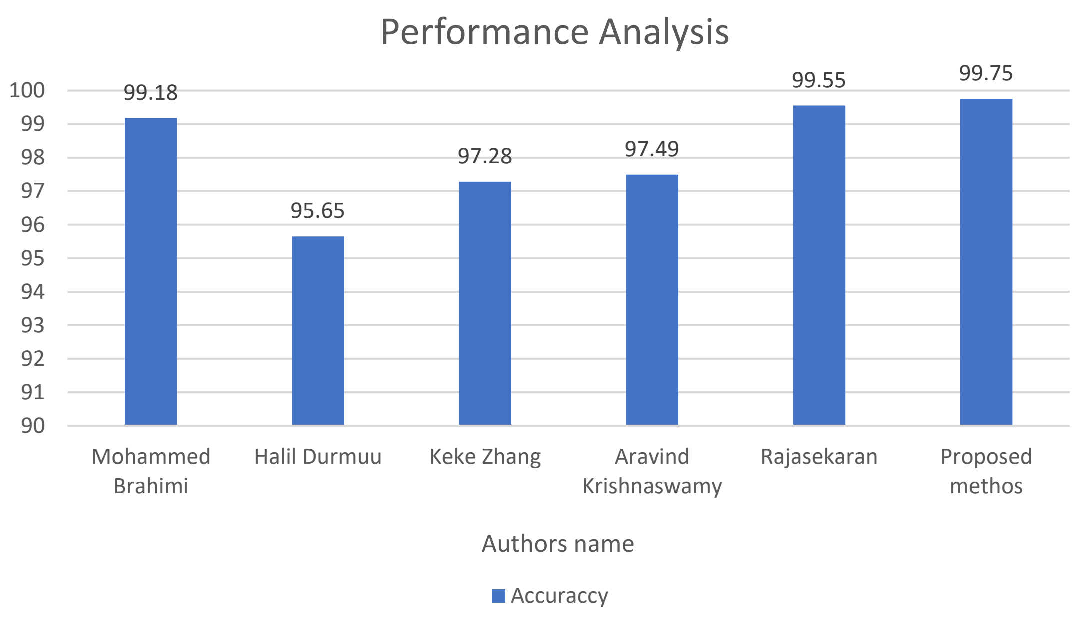

Figure 4.3.5 Compare the proposed model's accuracy with different existing works

4.4 Discussion

We run the model so that it could learn about the attributes and discriminate between different classes, as well as its health status. We used 22415 training photos and 5604 validation images of diseased and healthy plants to develop our algorithm (partitioning into 80:20). In figure 4.4.1, certain statistics have been shown.

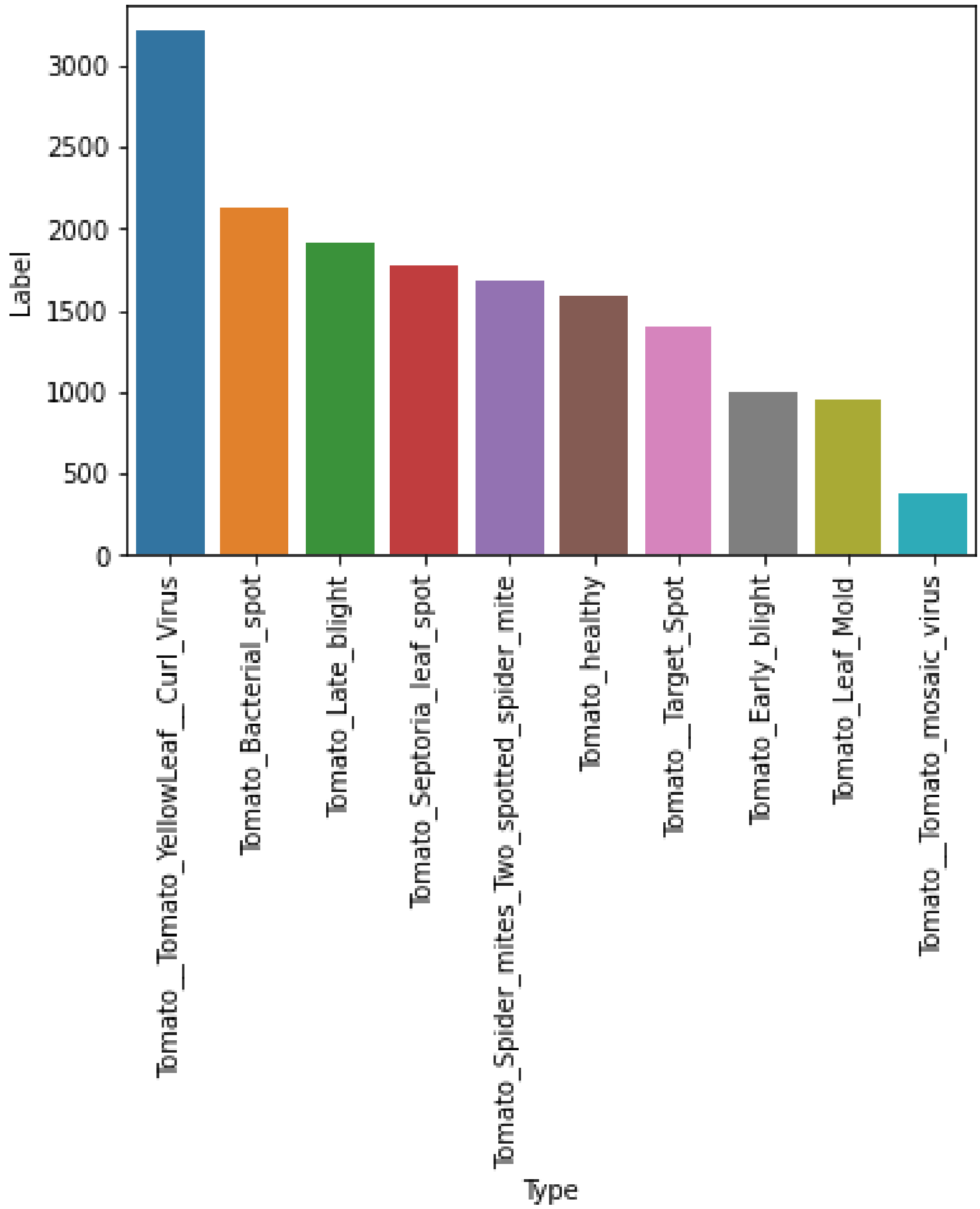

Figure 4.4.1 Distribution of images among its different classes

Figure 4.4.2 depicts some of the expected visuals.

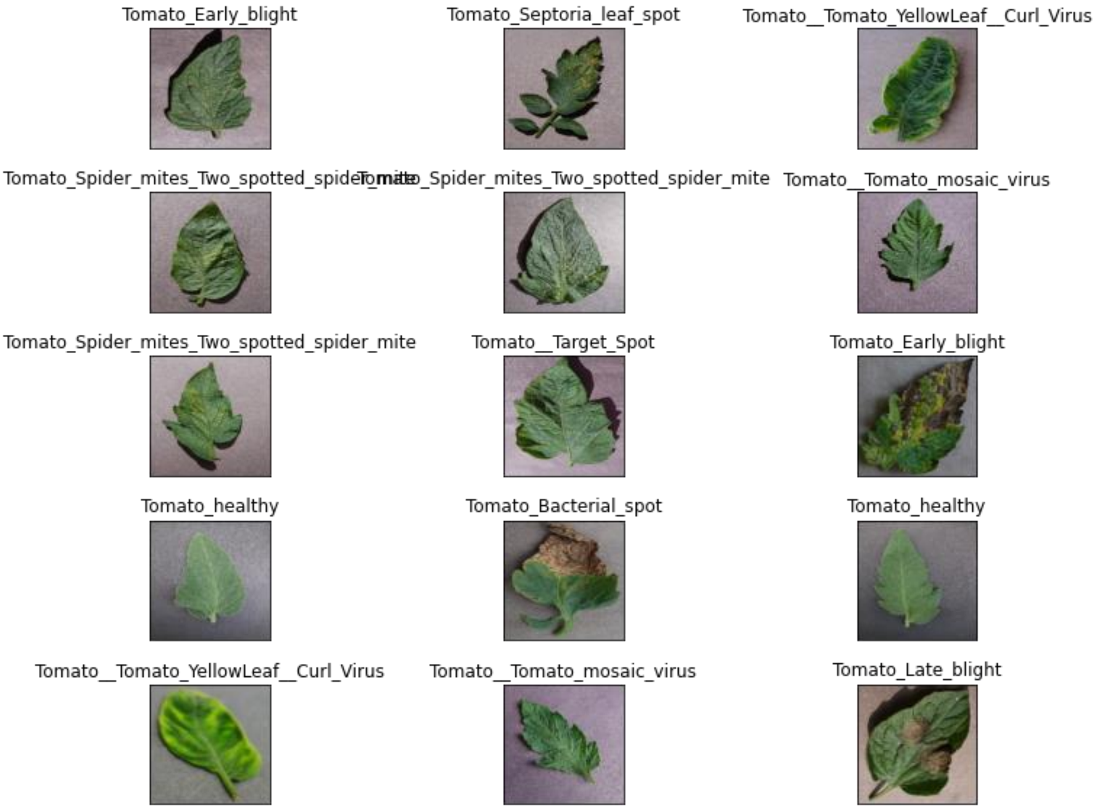

Figure 4.4.2 Some predicted images with the proposed model

With 10 classes of tomato dataset, ResNet50 with the SGD has the greatest test accuracy of 97.47 percent, but the suggested model achieves a test accuracy of 98.3 percent, which is 0.87 percent higher than ResNet50 with the SGD. Our suggested model ResNet50 with Adam optimizer, on the other hand, obtains a training accuracy of 99.75 percent. Finally, the Adam optimizer beat the RMSprop and SGD optimizers in detecting tomato illness using leaf photos when the accuracy, recall, and F1 score of the proposed model were evaluated.

CHAPTER 5

IMPACT ON SOCIETY, ENVIRONMENT, AND SUSTAINABILITY

5.1 Impact on Society

One of the major goals of this study is to improve the financial situation of persons who work in the tomato industry. Farmers in Bangladesh, as well as other South Asian nations, are inexperienced with contemporary agricultural methods. As a result, they are frequently financially disadvantaged. Because tomato plants are extremely delicate, growing tomatoes is a difficult undertaking. Farmers must rely on their luck in order to make a profit. Tomato disease makes things difficult for farmers. Our findings will aid farmers in detecting tomato leaf infections early on. They will then be able to take steps to reduce sickness while also ensuring their profit. Our findings will benefit farmers financially in this way. This disease detection equipment will also assist in the manufacturing of high-quality items. We were ready to teach the CNN models and get great accuracy using a larger image dataset. CNN is suitable with current technologies, and it can be easily implemented on any platform. As a result, our research will aid farmers and ordinary people who are unfamiliar with tomato leaf diseases. As a result, this study has a significant societal influence.

5.2 Impact on Environment

Different types of fertilizers are used by tomato producers to combat disease. Fertilizers pose a significant environmental risk. These fertilizers pollute adjacent regions' water, air, and solids. Tomato gardening provides a living for a large number of farmers. As a result, the usage of fertilizers in this type of agriculture is increasing every day. Fertilizers, on the other hand, are unable to completely suppress disease outbreaks. The expense of cultivation rises as a result of this. To address this issue, farmers must first detect illnesses and then take appropriate efforts to manage them.

This will reduce fertilizer consumption while increasing the profitability of tomato farming. Resultantly, our research has a big influence on the environment. The CNN models we propose are able to respond accordingly diagnosing tomato diseases. These models can be used in any intelligent software program. People would be able to detect illnesses at an early stage using smart software based on this concept. This will reduce fertilizer consumption and protect our civilization from pollution.

5.3 Ethical Aspects

Every year, there is a great demand for tomatoes in our nation that is not satisfied since there are many tomato illnesses in our country, and our farmers are unable to cure the disease in this manner. However, if we can quickly diagnose the illness using this way, we will have no trouble growing tomatoes. Farmers who can simply implement it will be able to satisfy our country's need by planting a large number of tomatoes and earning a lot of money.

5.4 Sustainability Plan

Our study intends to aid farmers in early disease detection in tomato leaves. This approach may be used by the Ministry of Agriculture and other organizations whose are worked for agriculture to expedite their procedures. Given that the tomato industry is increasing quickly in domestic and international markets, our study will give farmers financial advantages, which will have an effect on economies.

CHAPTER 6

SUMMARY, CONCLUSION, RECOMMENDATION AND FUTURE WORKS

6.1 Summary of the Study

We employed DL to recognize tomato leaf diseases in our research. This work is decrepit into numerous sections, like disease research, image gathering, techniqque implementation, and experment evaluation. We opted to employ ResNet50 in our research after examining other similar research papers. One of key advantages of using ResNet50 is like that it is adaptable with latest technology. We used Google Colab to teach our ResNet50 models. Without employing a pretrained model, we were capable to obtain a high-level accuracy with our suggested model. We also employed three optimization models to boost the identification capabilities. The Adam model has outperformed the competition. We discovered that our ResNet50 models with Adam optimization are more efficient than others after comparing them to similar studies. With new photos, these ResNet50 models have performed admirably.

6.2 Conclusion

Using Adam optimization, we construct an effective ResNet50 model to identify tomato leaf diseases in this study. This model is capable of properly identifying tomato leaf diseases. We suggested a new technique for identifying illnesses of tomato leaves using ResNet50 in this work. ResNet50 is broadly applied across a wide range of disciplines. Our ResNet50 devices have been thoroughly tested and proved to operate admirably. The ResNet50 model works brilliantly in recent test photographs. This approach also exhibits its ability to recognize every category on its own. Farmers who work with tomatoes will benefit from our study. It would improve their financial situation by assuring tomato quality. Tomato demand is skyrocketing in both domestic and international markets for a variety of applications. This research has broad societal and environmental ramifications. This study might be used by the Ministry of Agriculture and other organizations to enhance farmer economic conditions and ensure greater tomato production.

6.3 Implication for Further study

Artificial intelligence-based technology simplifies our daily lives. AI has the power to transform anything, just like electricity does. To disseminate our ResNet50 models, we would want to utilize an Android mobile application. Day after day, the number of individuals who use cellphones and the internet increases. The general public and farmers would greatly benefit from a user-friendly smartphone app with attractive user interfaces. Now, 10 diseases in photographs may be identified by our RenNet50 models. The number of ailments will rise in the next years. A more reliable dataset will be created for next studies. We'll focus on enhancing our ResNet50 model's accuracy going forward. We would like to make a model available that has already been pre-trained for several leaf diseases. The Ministry of Agriculture's assistance might help the model grow and progress.

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