Incremental Learning Approach for Tomato Leaf Disease Detection Without Catastrophic Forgetting Problem

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ABSTRACT

In the agricultural sector, the early detection on the crop disease is one of the major factor to prevent the diseases spread out and counteract the loss. However, in some cases the disease are still detected manually by the expert which is considered time-consuming, cost a lot of money, and somewhat inconsistencies occur. In the last decades, the utilization of machine learning has proven to allow the automation of identifying diseases on the leaf plant quickly and accurately. Nonetheless, the major problem has been faced as the lack of model to recognize the crop leaf diseases on the real condition. Therefore, huge number of various kind of leaf disease sample data is necessary to feed on the model. Incremental leaning is one of the best applicable approach to keep the model up to date by continually learning the new incoming plant leaf dataset. This study aims to classify the disease on the tomato leaves using CNN (Convolutional Neural Network) current state-of-the-art and implement the incremental learning as well as reducing the catastrophic problem by Freezing the last Layer and Rehearsal proposed method. The result shows that the best performance achieved when applying the Dense-Net with 95% accuracy and the proposed method succeed to outperform the highest previous performance on incremental learning which remain on the 94% of accuracy value after conducting incremental process on the base model

INTRODUCTION

In the era of big data, the ability of the machine to update the knowledge from incoming massive new data is significantly important and necessary to keep the model up to date (Hu et al., 2021). The terms of incremental learning, continual learning, online learning, or lifelong learning has been used interchangeably depend on the associated work of the project. It is the counter path from the batch learning approach which the system does not have the capability to learn incrementally. It must be trained using all the available new data along with the old data. When the first training done, the model will be launched into production and the model will run without learning anymore. When the incoming new data is available on the fly, retraining the model from scratch is needed and replacing the existing model in the production is also necessary to keep the model up to date.

On the other hand, incremental learning approach does not require to retrain the existing model using all the old dataset when the new data available. Incremental learning is the continuous training and classification proceed by iterations. The system can be learned incrementally by feeding it with the new data sequentially either with the single data or in the small group of data that often called as *mini-batches*. The incremental learning approach is more efficient to apply for the typical continues data, the huge dataset with the limited memory space, and for the system that need to rapidly adapt and change autonomously. The advantage of incremental learning method which not necessity train the model from scratch could reduce the time consuming.

Moreover, it can be implemented in any kind of modelling both in machine learning and deep learning algorithm including the CNN architecture. Some previous research has studied and applied incremental learning on the image classification (Sirshar, Hassan, Akram, & Khan, 2021) as the existing model required to learn continually when the new data available (Tahir & Loo, 2020) (Masana et al., 2022). However, it is still difficult to find the research and the application of online learning classifier in the field of crop's leaf disease detection. Regardless the researchers have been succeed to reach the model performance accuracy higher than 90% (Albattah, Nawaz, Javed, Masood, & Albahli, 2022) in the case of plant's leaf disease detection, the problem still exist in accordance to the lack of model in recognizing the crop's disease on the real complex natural environment (Liu & Wang, 2021). Those weakness occur because of the some challenges faced on the plant leaf disease detection problem such as small difference between the lesion area and the background of the leaf, low contrast, large variations in the scale of the lesion area and various types, and a lot of noise in the lesion image (Liu & Wang, 2021) as the variety of the leaf is uncountable. Address the obstacle on the most of plant leaf disease detection work, the classifier model need to be on stream ingested with the various crop leaf images exist on the field.

We propose incremental learning approach to continually update the CNN model to tackle the problem exist when applying them in to actual environment. However, the shortcoming faced by the researchers in the last decade when utilizing the incremental learning method has been the major hitch that need to be solved. It is well-known as the *catastrophic forgetting* problem. Therefore, the main focus on this study is to find the best method to both minimize the *forgetting* problem as well as optimize the performance of the baseline classifier when incrementally training in to the new set of data. The best CNN classifier among the current state-of-the-art used as the initial model. Then, the incremental learning modelling will be applied to these model using the combination of three methods. One of them called the *Classification Confidence Threshold* (CCT) approach. This approach has been experimented in the previous study and turn out succeed on NLP and CV classification task (Leo & Kalita, 2021). We try to combine the used of CNN current state-of-the-arts like *Dense-Net, Efficient-Net, or VGG-16* as the baseline classifier with our proposed methods for incremental learning which are the CCT , *Freezing last layer and Rehearsal* approach to keep our classifier up to date whenever the new tomato leaf data is available by applying the incremental learning method.

METHOD

The base model used in this work is the existing model which has the best performance when training with the tomato leaf disease dataset. This initial model is trained using the conventional group batch training. This training process which aims to produce the baseline model is the first phase of training. The total class of tomato trained to the default classifier is 10 classes including the healthy tomato. The figure 1 shows the flow of the proposed method of this work.

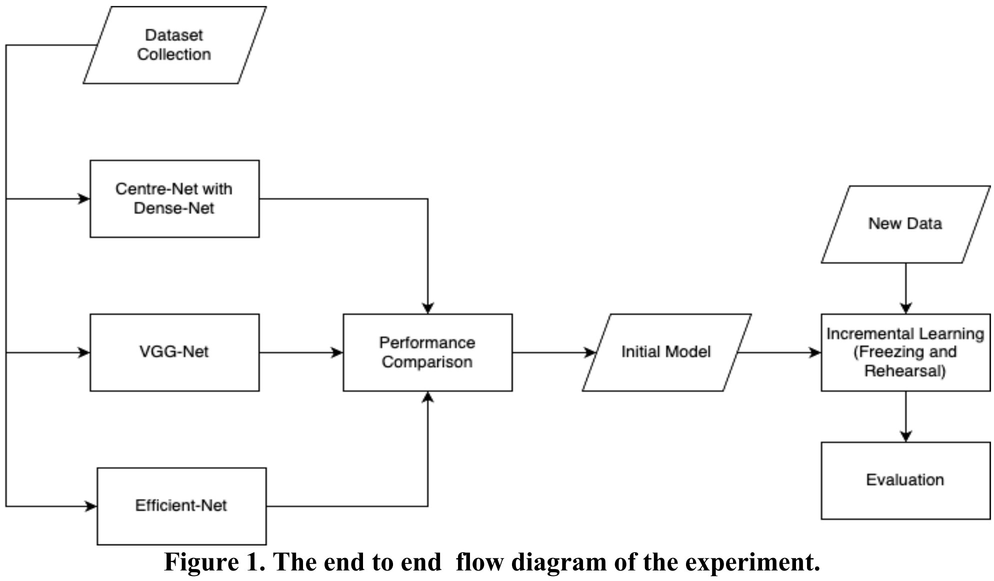

Figure 1. The end to end flow diagram of the experiment.

Dataset. In this study, the open dataset of tomato leaf disease from open source *Kaggle* used which consists of 10 classes of images. Those 10 classes are the tomato leaf images with contain diseases and 1 class is the healthy leaf images. The dataset are the coloured images with the various size of pictures. The total number of images on the dataset is 18315. The dataset used in this study categorized as the imbalanced dataset. Figure 2 shows the random sample of different classes on the dataset. The dataset divides into 3 category with the ratio of 70% for training on the base model, 20% for training on the incremental process and 10% for testing. Each data training split into 0.8 training and 0.2 validation. The incremental training dataset combine with 30 subset of old images to feed into the baseline model. This process is *Rehearsal* step of this study.

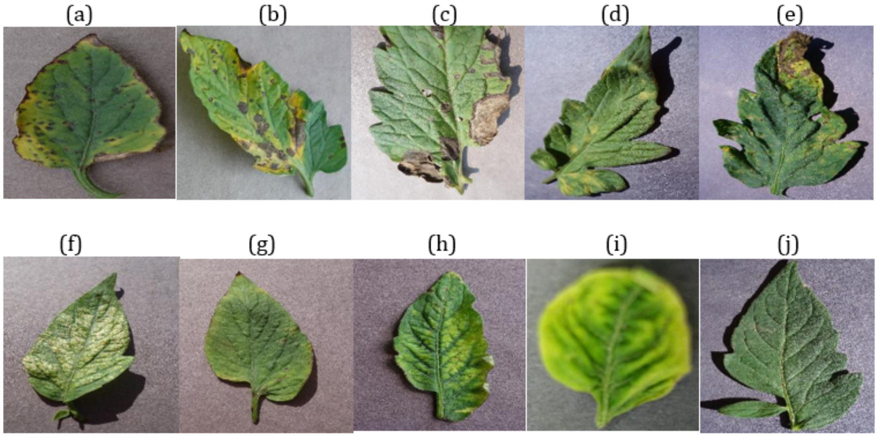

Figure 2. Sample tomato leaf disease dataset: a) bacterial spot b) early blight c) late blight d) leaf mold e) Septoria leaf spot f) spotted spider mites g) target spot h) mosaic virus i) yellow leaf curl virus j) healthy

State of the art CNN based models. The base model used is the chosen best performance of the 3 available popular algorithm used on some previous research in classifying the plant leaf's diseases which are Dense-Net, VGG-Net, and Efficient-Net (Mohameth, Bingcai, & Sada, 2020) (Kaur & Sharma, 2022) (Trivedi, Shukla, & Pandey, 2021). The model performed excellent with the accuracy up to 98% on the open dataset like ImageNet, CIFAR-100, and Crop Images open dataset. We conduct some experiment and pick the model with the highest accuracy score when training those algorithm to find the most suitable model for our tomato dataset.

Dense-Net. DenseNet architecture proposed by (Albattah et al., 2022) has two major improvement from the Dense-Net. It has fewer parameters and the dense block (DB) layers are attuned which can minimize the cost. The 7x7 convolution layer with stride 2 implements on the first layer followed by 3x3 pooling layer. The 3 major DB layer of this architecture is utilized before it's fully connected layer. While the conventional Centre-Net utilize ResNet-101 as the feature calculator, in this study they propose DenseNet-77 instead. The DenseNet-77 apply for feature extraction and as the key point for advance performance by Center-Net. The flow of the proposed method shows on the figure 3 below.

The dataset used in this study is the PlantVillage dataset (Hughes & Salathé, 2015) which comprises 38 types of crop leaf disease. The main goal is to tackle the problem of low intensity of image background and foreground, the huge colour resemblance in the healthy and plant areas, the occurrence of noise in the image, the changes in position structure and size on plant leaves, which becomes the obstacle of precise classification on plant disease detection. The result of the research classified into the perfect result with the 99.52%, 99.92%, 99.982% for precision, recall, and accuracy metric respectively. In this research the basic Dense-Net applied to classify tomato leaf disease.

VGG-Net-19. VGGNet-19 is the improvement of VGG-Net architecture which first introduced by Karen Simonyan and Andrew Zisserman in 2014 (Simonyan & Zisserman, 2014). The VGG-Net consists of 2 typical model of VGGNet-16 and VGGNet-19 which available as pretrained model. The VGGNet-19 implement by (Kaur & Sharma, 2022) to perform plant leaf disease detection using PlantVillage dataset (Hughes & Salathé, 2015). This architecture has total of 19 layers which 16 layers of convolutional layer and 3 fully connected layers with 5 max pooling layers inside as better explain on the figure 4. As pre-trained model, the default dataset was train on the VGGNet-19 is the ImageNet which consists 14197122 images with the input size 224x224 on RGB images. The result shows the excellent model performance at the epoch 20^{th} with the evaluation metric using accuracy with the value of 93% on training and 93% for validation accuracy.

Figure 3. The architecture of VGGNet-19

Efficient-Net. The research conducted by Mingxing Tan and Quoc V.Le on 2019 (Tan & Le, 2019) is the study which initially suggest Efficient-Net as the scaling up of Mobile-Net and Res-Net. They success achieve state-of-the-art 97.1% accuracy on ImageNet and it is 6.1x faster on inference compare to the best existing Conv-Net at that time. The Efficient-Net consists of 8 models (B0,B1,B2,B3,B4,B5,B6,B7). The main technique used in this study to build the Efficient-Net is called compounding coefficient. The researcher figure out that scaling single dimension, balancing all three dimension of width, depth, and image resolution can help improve the overall model performance. The balancing dimension conducted by scaling with a constant ratio. The following equation shows how to achieve the goal mathematically:

Depth $d = a^{\emptyset}$
Width $w = \beta^{\emptyset}$
Resolution $r = \gamma^{\emptyset}$
$a \geq 1, \beta \geq 1, \gamma \geq 1$

where α, β, γ are constant value that can be found using the grid search. This architecture has applied on 2021 by (Atila, Uçar, Akyol, & Uçar, 2021) for the particular case to examine the effectiveness of Efficient-Net for plant leaf disease classification and detection comparing to other state-of-the-art in deep learning. The Plant-Village dataset with 54305 number of images from 14 different type of plant and 38 total of classes comprises the disease and the healthy leaf. They implement Efficient-Net both in the original and the augmented data. The result shows that B4 and B5 has achieved the highest value with 99.91% and 99.97% respectively for accuracy. The main building block of the Efficient-Net is the MBConv which consist of the expand layer at first then compress the channels. The detail architecture shows on the figure 5 below.

Figure 4. The architecture of Efficient-Net

Incremental Learning Approach. The main core of this study is to implement incremental learning for the particular cases of tomato leaf disease classification which aim to reduce the forgetting problem. We proposed to combine 3 main methods on the incremental learning approach. They are Classification Confidence Threshold (CCT), Freezing layer and Rehearsal as shown in the figure 5. The CCT approach has been previously studied . In this research, we offer Freezing layer and Rehearsal method combine with existing method of CCT.

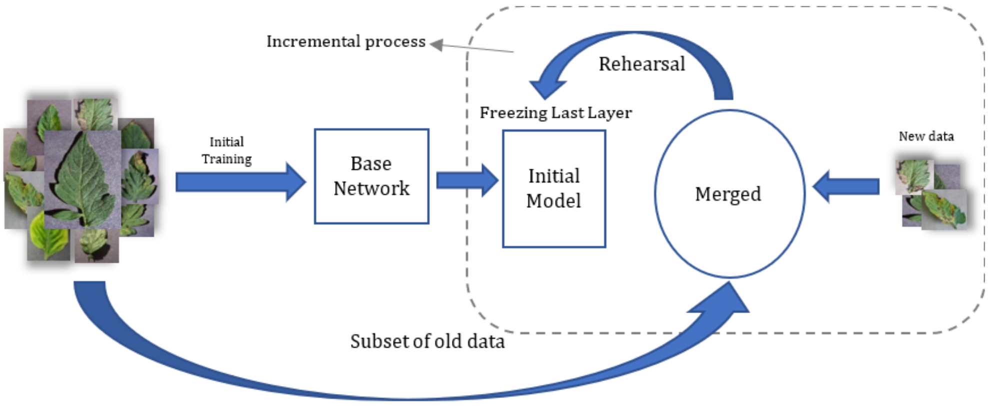

Figure 5. The diagram of incremental learning proposed method started from the initial training using Efficient-Net architecture by freezing and train the last layer then continually applied rehearsal using the merged subset of old data with and the incoming new data.

The idea of CCT method is to have the base classifier with the highest accuracy performance before feeding them with the new set of data. The define threshold should be higher or equal to 90% when training with the state-of-the-art CNN model as the output of the previous phase of this research. As in the previous study conducted by (Castro, Marín-Jiménez, Guil, Schmid, & Alahari, 2018) using *cross-distilled loss*, *loss function balancing* by (Shmelkov, Schmid, & Alahari, 2017), and *pre-trained truncated gradient confidence weight* approach by (Sirshar et al., 2021) it shows the decreasing value of the final accuracy to 70% as the highest from 80% of the initial model performance accuracy which indicates the shrink value 20% at least when the existing model feed with the new incoming data. By setting and keeping the threshold for the initial classifier to be in the highest performance they have which is 90%, the classifier model even loss 20% accuracy after implementing incremental learning still in the number of 70% in performance.

Implement these method on the primary trained model along with *Freezing* its last layer when training the model incrementally with the unknow set of data will help to reduce the forgetting problem occurred during the incremental learning task. Moreover, the combination of the *Rehearsal* approach throughout the continual task preserve the base model to lose its memory of the previous knowledge. The *Rehearsal* allow the model to periodically expose the previously learned data while training new data. In *Rehearsal*, a subset of the fixed size number of old data stored in a fixed-size-buffer and the model will train with both old and new data. Furthermore, the metrics used in this paper to evaluate and compare the proposed method with the current state-of-the-art is the standard classification metrics such as accuracy, F1 score, Precision, and Recall on the testing dataset

RESULTS AND DISCUSSION

We carried out the experiment by first obtaining the best algorithm for the leaf disease collection of data. As the rules of CCT method, the initial model must achieve above the 90% of the accuracy score to move in the next phase of incremental learning process. The most suitable state-of-the-art model for this tomato leaf dataset has been proof in the evaluation of metric accuracy which shows that all network trained has met the requirement for the *CCT.* However, the best CNN method among the training network using the tomato leaf disease set of data is Dense-Net architecture. The comparison between the amount of time needed to reach the state of convergence in the training process as well as the best accuracy among the methods trained lead us to choose the Efficient-Net as the best model baseline in this case. The following table 1 shows the comparison between 3 current state-of-the-art of the CNN network using the tomato leaf diseases dataset.

Table 1. The evaluation comparison between the 3 current state-of-the-art CNN base network for average accuracy score, f1-score, precision, and recall respectively

CNN method	Accuracy	F1-Score	Precision	Recall
Dense-Net	95%	95%	95%	95%
VGGNet-19	87%	87%	88%	87%
Efficient-Net	94%	94%	95%	95%

Furthermore, the selected network as the output result from the previous stage has been trained incrementally with the set of new unknowing data of tomato diseases using the proposed method of *Freezing* its last layer along with doing *Rehearsal* during the tasks. The goal of these suggested approach to minimize the existing model of losing the knowledge from the previous task while learning different kinds of tomato leaf diseases has evidently shown the improvement result compare to other previous study. The comparison between the evaluation result before and after conducting incremental process learning shown in the table 2 and table 3 below which represent the evaluation result respectively.

Table 2. The obtained performance of precision, recall, and f1-score respectively on 10 classes before incremental learning being process

Class_Name	Precision	Recall	F1-Score
Tomato__Bacterial_spot	0.95	0.94	0.95
Tomato__Early_blight	0.88	0.94	0.91
Tomato__Late_blight	0.98	0.92	0.95
Tomato__Leaf_mold	0.94	0.97	0.96
Tomato__Septoria_leaf_spot	0.97	0.90	0.93
Tomato__Spotted_spider_mites	0.97	0.94	0.95
Tomato__Target_spot	0.88	0.92	0.90
Tomato__Mosaic_virus	0.96	1	0.98
Tomato__Yellow_leaf_curl_virus	1	0.99	0.99
Tomato__Healthy	0.97	0.97	0.97

Table 3. The obtained performance of precision, recall, and f1-score respectively on 10 classes after incremental learning being process

Class_Name	Precision	Recall	F1-Score
Tomato__Bacterial_spot	0.96	0.96	0.96
Tomato__Early_blight	0.86	0.88	0.87
Tomato__Late_blight	0.93	0.90	0.91
Tomato__Leaf_mold	0.94	0.88	0.91
Tomato__Septoria_leaf_spot	0.85	0.87	0.86
Tomato__Spotted_spider_mites	0.92	0.99	0.95
Tomato__Target_spot	0.94	0.89	0.91
Tomato__Mosaic_virus	0.95	0.99	0.97
Tomato__Yellow_leaf_curl_virus	1	0.98	0.99
Tomato__Healthy	0.95	0.99	0.97

As in the some previous research, most of the performance of the classification model has decreased more than 20% in the accuracy after doing the incremental tasks. In this study, we has compared the model performance before and after applied our proposed method in the continual process in order to figure out the vanishing accuracy while conducting the incremental learning on each class. And the result has surpassed the other previous research regarding the image classification work which success to reduce the forgetting problem. The performance of the model obtained after incremental learning process conducted is 94% for accuracy, precision, and recall value. The final result indicate that our proposed method success to tackle the forgetting problem in the case of tomato leaf disease detection using Dense-Net model as the initial classifier

CONCLUSION

The presented approach introduced an incremental learning scheme for detection and categorization of plant diseases on the tomato leaf. We have compared 3 existing current state-of-the-art network that has proven as the best network to do the task in classifying disease on the plant village dataset. In this work, the pre-trained Dense-Net as a base network has been selected as the best algorithm to apply, as the evident from the table 3. The classification network is continually trained with the new incoming set of data via *Freezing layer and Rehearsal* along with *Classification Confidence Threshold (CCT)* approach that only retrained the model when achieve the confidence level accuracy threshold combining with freezing the last layer of the network and conduct rehearsal on the subset of the sample previous data to reduce the forgetting problem in the incremental learning process. Compared to the state-of-the-art incremental learning approaches like *cross-distilled loss*, *loss function balancing* by, and *pre-trained truncated gradient confidence weight*, the proposed method show high improvement to resist the catastrophic forgetting phenomena on the tomato leaf disease detection. The proposed method also result in the performance of the classification network after incremental learning task did not decrease drastically like what have been experienced by some of the previous researchers in other work of image classification. According to the inference result, we can indicate that the plant leaf disease classifier model produced from the proposed method in this study is relevant to be implemented by the end user to predict these leaf diseases on the real case scenario. In the future study, the ability for the base network to learn both set of new data and incoming new classes incrementally need to be consider. Furthermore, instead of training with only tomato crop, we plan to conduct experiment using the same method with the variety number of plant and their diseases with respect to expand the model ability to predict most of the crops diseases.

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