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The Role of Transfer Learning in Enhancing Apple Disease Prediction Accuracy: A Study from the Indian Subcontinent

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Among the fruit crops, the apple occupies a leading place in India, providing a large share of income in the agricultural sector and satisfying the people's demand for fruits. Among the northern states of India, Jammu & Kashmir, Himachal Pradesh and a part of Uttrakhand together contribute substantially to the apple output of the country (Naqvi, 2004). In general, apple diseases induced by both biotic and abiotic factors are emerging as major problems for apple farmers, which lead to low crop yields, poor quality of fruits, and economic losses (Sharma & Jindal, 2023).
The diseases in crops in the past were realized through traditional farming processes without the application of modern technology. Though, thanks to modern advancements in technology where machine learning (ML) and deep learning (DL) are gaining huge importance for the early diagnosis of diseases with higher accuracy and faster diagnosis (Alharbi & Arif, 2020).

1. Introduction

1.1 Background of the Study

Among the fruit crops, the apple occupies a leading place in India, providing a large share of income in the agricultural sector and satisfying the people's demand for fruits. Among the northern states of India, Jammu & Kashmir, Himachal Pradesh and a part of Uttrakhand together contribute substantially to the apple output of the country (Naqvi, 2004). In general, apple diseases induced by both biotic and abiotic factors are emerging as major problems for apple farmers, which lead to low crop yields, poor quality of fruits, and economic losses (Sharma & Jindal, 2023).

The diseases in crops in the past were realized through traditional farming processes without the application of modern technology. Though, thanks to modern advancements in technology where machine learning (ML) and deep learning (DL) are gaining huge importance for the early diagnosis of diseases with higher accuracy and faster diagnosis (Alharbi & Arif, 2020). Kiran; Transfer learning which is a sub-field of machine learning has gained quite a lot of popularity due to its reliability in enhancing the disease prediction model by using another existing model.

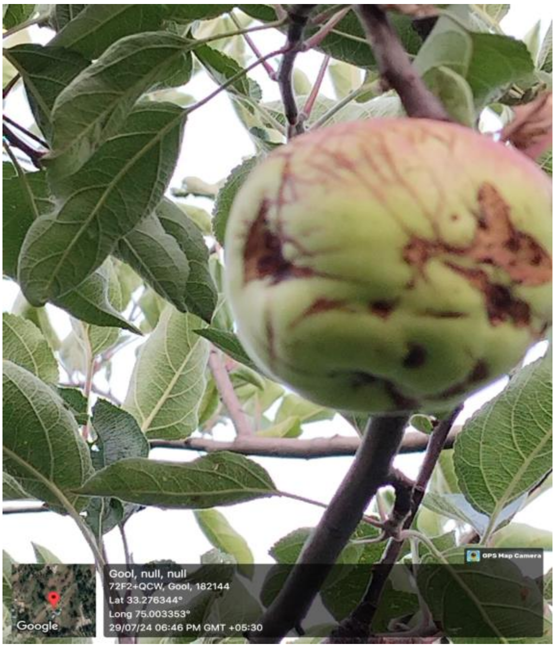
1.2 Role of Apple Crop in India

India occupies one of the leading positions in the world's apple production, and the apple crop is considered to have significant economic significance for the territories producing them. For instance, apple farming heavily supports farmers in the Himalayan states (Khalil et al., 2019). The contrasting climates and erratic altitudes in these areas are further a good place for biodiversity and apple production; however, they also favor diseases – especially fungal and viral (Oyenihi et al., 2022). Because farmers depend on the quantity and quality of their produce, disease control is critical In crop production.

1.3 Apple Diseases and Their Cost Consequence

Apple orchards are vulnerable to several diseases, most of which can have normally reduced effects on the production and quality of apples. Diseases affecting the crop include apple scab, powdery mildew, Alternaria leaf spot, and Marssonina leaf blotch (Bonkra et al., 2023). These diseases not only affect the appearance of the fruit but also its saleability shelf life and longevity of the fruit (Bhargava et al., 2014). Some of these diseases cause a complete loss of fruits or tree death meaning that farmers receive huge losses.

These diseases have been fought through the use of pesticides that have in turn raised costs and have environmental repercussions. Moreover, diseases' early diagnosis is scarce and imprecise, worsening the problem as pathogens can remain undetected and spread without interruption (Nabi et al., 2022). This is why there is a call for better screening and strategies in controlling diseases at a tender stage.



1.4 Role of senior disease diagnosing techniques

Traditional techniques for the identification of apple diseases involve manual assessment by experts, which is cumbersome, biased, and inaccurate (Dharm et al., 2019). Indeed over the past few years, new techniques of machine learning and deep learning have been developed to help in this process and give better results. However, many of these models demand a vast quantity of labeled data, which may be scarce, especially in agriculture (Singh et al., 2022). This is where transfer learning can be of big help.

Transfer learning makes large models that have been trained on other large datasets from other domains useful to be fine-tuned on specific tasks like apple disease detection even where there is little training data (Kim et al., 2021). One might agree that transfer learning makes the process of increasing the accuracy of disease prediction in agriculture a powerful tool based on pre-trained models.

1.5 Aims and Objectives of the Study

The research question of this study is: how does transfer learning improve apple disease prediction in northern India? More precisely, this study aims at predicting the four main apple diseases using deep learning models including ResNet, VGG16, and EfficientNet that are pre-trained on the IMAGENET dataset. It also examines the efficacy of these models against traditional models of machine learning for evaluation purposes.

This research is confined to three major apple-producing regions in northern India: Jammu and Kashmir, Uttarakhand, and Himachal Pradesh. This paper has endeavored to give information about the transfer of learning approach in the view of disease identification in the apple orchards to add further knowledge to the existing literature on AI in the agricultural sector.

2. Literature Review

2.1 Normally used methods for the detection of diseases in apple plants

In the past, the presence of diseases in the apple was determined by visual canopy assessment and the opinion of a specialist. However, these methods are commonly used with a high level of inaccuracy and time consumption and largely depend on the observer (Bhargava et al., 2014). Furthermore, some diseases also manifest signs that are identical to some other diseases and hence a misdiagnosis occurs (Singh et al., 2022). For example, apple scab and Marssonina leaf blotch have a target or dark area on the leaf and it is very hard to differentiate without laboratory analysis (Jhuria et al., 2013).

These challenges have driven the researchers to look for ways to automate the disease diagnosis. The first strategy entailed the application of image processing for the evaluation of written or pictorial manifestations of diseases, which was employed previously (Dharm et al., 2019). While the method gave some enhancement over the manual inspection, they suffer from restricted features that were used as input, which may not be enough, color, and texture to distinguish between diseases.

2.2 Machine Learning and Deep Learning in Agriculture

The diagnoses and identification of plant diseases have become easier over the years due to the availability of sophisticated technologies, and based on this, techniques such as ML and DL are becoming common in disease identification systems. These approaches can handle volumes of information, acquire intricate patterns, and produce precise forecasts, as suggested by Khan et al., 2020). Specifically, there are the following state-of-the-art deep learning techniques: convolutive neural networks (CNNs) that are popular for image classification in agriculture (Peng et al., 2021).

Several exhibits of deep learning models have revealed how these can enhance the efficiency of diagnosing diseases. For example, Liu et al (2017) employed a CNN-based model and diagnosed four typical apple leaf diseases with 97.62 % accuracy. According to Alqethami et al. (2022), the authors used image processing techniques accompanied by three machine learning models, including CNN, SVM, and KNN, to detect apple diseases achieving an accuracy of 98.54%.

However, there are several limitations of deep learning models which include; Despite the documented success deep learning models depend on large labeled data for training (Kumar et al., 2022). In several agricultural contexts, such data is rare or costly to gather. To overcome this limitation researchers therefore turn to use transfer learning as a solution.[15]

2.3 General view of Transfer Learning

Transfer learning is defined as machine learning where a given model that is already trained in one task is taken, and reused in another but related task (Saleem & Arif, 2022). In the case of apple disease detection, transfer learning involves the utilization of models that had been trained on large image datasets for instance the image-net, and then using it to classify the diseases.

The strength of transfer learning is that it takes prior knowledge from the source task; this means that a small amount of labeled data is needed for the target task (Feng et al., 2023). This is especially helpful in diseases dealing with crop images because few crop images that are labeled are available. The researchers have noted that using transfer learning can increase the accuracy of distinguishing diseases in crops such as apples by almost fifty percent, even by using limited training data (Nabi et al., 2022).

3. Methodology

3.1 Study Area: Apple Growing Areas of Northern India

The focus of this study is on three prominent apple-producing regions in Northern India: Jammu & Kashmir, Uttarakhand, and Himachal Pradesh. These regions were chosen based on climatic variation, altitude, and type of soil that define apple production and disease transmission (Sababa et al., 2022). Also, they have witnessed an increased rate of occurrence of both fungal and viral diseases which requires advanced approaches to screening.

The largest state of India is Jammu & Kashmir which is famous for quality apples and that is why it’s called the Apple Bowl of India. The climate is cool and rainfall moderate necessary for the growth of apple are experienced in this region. Nevertheless, diseases such as apple scab, and powdery mildew have been recently reported in this area (Feng et al., 2023).

Uttarakhand and Himachal being other major producing states; may have slightly different weather conditions. Both regions are hilly have variations in altitude and are highly prone to diseases due to changes in temperature and humidity. These regions were selected to understand the environmental impact on diseases and to test the transfer learning models in other conditions.

3.2 Dataset Description

3.2.1 Data Collection Methods

To accomplish this work, a new dataset of apple leaf images was generated through standard sample acquisition from the mentioned regions. The samples were collected at a focal area from apple orchards across three months, with specimens obtained attacking the various stages of development. Green and blighted leaves were sampled, where diseases affecting apple trees including apple scab, Alternaria leaf spot, powdery mildew, and Marssonina leaf blotch were considered (Sharma & Jindal, 2023). These diseases were selected because they are prevalent and affect crops and apple production income specifically in this area (Alharbi & Arif, 2020).

Videos were recorded from a distance using a high-resolution camera and in natural light to provide a real-world situation dataset. The images were categorized by manual classification made by interested specialists in agriculture and plant pathology. Collectively, 10,000 images were gathered out of which 60% were employed for the training process while 40% were for the testing and validation process (Nabi et al., 2022).

3.2.2 Some Common Preprocessing Methods

However, to improve the quality of the images and classification the images were preprocessed before feeding the models. This entailed resizing all the images to have dimensions of 224 x 224 pixels as a requirement by the pre-trained deep learning models (Kumar et al., 2022). Like in the case of the augmentation of the mask images, mouse images were also rotated, zoomed and flipped to expand the dataset and minimize over-fitting. To minimize the interference of background noise, techniques like Gaussian noise were applied to filter images (Tian et al., 2021).

3.3 Transfer Learning Models Used

3.3.1 CNN Architectures

Several CNN models were used for the classification and detection of diseases in apples in this current research. CNNs have been particularly applied in image classification problems because they tend to model the spatial hierarchies in images (Liu et al., 2017). More precisely, three of the most successful pre-trained models identified in similar tasks were chosen: ResNet50, VGG16, and EfficientNetB3.

ResNet50 is a deep residual network which means the neural network has 50 layers to address the shortcomings of the vanishing gradient problem in deep networks (He et al., 2016). Due to skip connections it is more suitable in situations where the target dataset is comparatively smaller like the classification of apple diseases (Peng Wang et al., 2021).

Deep CNN is a generally powerful model for image classification and has been running for 16 layers named VGG16. Though this is a gross architecture, its capability has been proven in a wide range of agri-food applications such as disease identification (Jiang et al., 2019).

EfficientNetB3 is one of the models from a family called EfficientNet, which is recognized for high performance with comparatively low requirements. The scaling approach makes it adaptable for High-Resolution Images and it can classify various apple diseases with maximum accuracy (Feng et al., 2023).

3.3.2 Pre-trained Models

All of the selected models were originally trained on the ImageNet dataset, with more than 1 million images in 1,000 categories. These models were fine-tuned by applying transfer learning on the apple disease dataset. It required freezing the initial layers of the pre-loaded models, which identify regularities of an image like edges or textures, and fine-tuning the following layers to apple characteristics, for instance, a change of color in the leaves or appearance of fungal spots on the skin (Alqethami et al., 2022).

3.4 Training and Testing of Models

The training process was divided into two phases: the first part of training using pre-trained layers which are not updated during the training process and the second part of the training performed on the layers which are updated during the training process. In the first phase, the adverse effects of the fully connected layers of all the models were trained using the Apple dataset, and the convolutional layers were not altered. This approach worked against overfitting and was especially beneficial when the training data set was relatively small (Duan et al., 2022).

In the second stage, all parameters concerning the model, including the convolutional layers, were further trained with a lower learning rate magnitude on the fly. Adam optimizer was applied to all layers through the code the learning rate was set at 0.0001 and all models were trained for 20 epochs with a batch size of 32 (Khan et al., 2022). As for overfitting, the early stopping technique was employed The scores of the cross-validation set were utilized to analyze the cross-validated accuracies of the models.

3.5 Evaluation Metrics

For performance analysis of the models, accuracy, precision, recall, and F1-score were chosen. Accuracy gives us the overall percentage of correct predictions while precision and recall give a percentage regarding true positives and false positives. Also, because of the presence of imbalanced class distribution; the F1-score, which is a weighted average of precision and recall turned out to be very beneficial in this study (Kim et al., 2021).

4. Experimental Setup and Implementation

4.1 Software and Hardware Requirements

It is recommended that users of this learning management system should have the following software and hardware specifications:

The typical experimental setup had derived both software and hardware nature due to the computational intensity of the deep learning process. The models were trained with TensorFlow and Keras, which offered the required API for constructing Convolutional Neural Network structures (Peng Wang et al., 2021). Python was predominantly applied as the language, in addition, to OpenCV and NumPy for image and data preprocessing correspondingly.

The training of the models was done in a computationally optimized environment, including an NVIDIA RTX 309 0 GPU. This made it to enhance training time, especially during the fine-tuning phase involved in transfer learning Shi et al., 2022. It took about 10 hours for each model depending on the size of the datasets and the intricacy of the model to be used.

4.2 Implementation of Transfer Learning Model

Transfer learning was done by loading the weights from the ImageNet dataset and modifying the models for apple disease classification. The final convolutional layers in all pre-trained models were replaced with fresh layers based on the number of classes in the apple database, including healthy, apple scab, Alternaria leaf spot, powdery mildew, Marssonina leaf blotch (Duan et al., 2022).

White an activated sigmoid non-linear transfer function was performed in the output layer to achieve probabilities for each class. There was the application of categorical cross-entropy to penalize misclassification of images, allowing the model to minimize each loss at different learning rates (Jiang et al., 2019).

4.3 Hyperparameter Tuning

The tuning of hyperparameters was another challenging aspect of the procedure in a transfer learning setting. Hypertuning for the learning rate, the batch size, and the number of epochs was done using the grid search method. Different values of these hyperparameters were explored to determine the best setting for each model (Feng et al., 2023).

For instance, the issue was solved with the usage of the EfficientNetB3 model, which was trained with a batch size of 32, with a learning rate of 0.0001, and within 20 epochs. On the other hand, the learning rate used in ResNet50 training had to be reduced to minimize overfitting, while a higher batch size was less beneficial to VGG16 with fewer epochs. The optimal hyperparameters were chosen based on cross-validation metrics (Alqethami et al., 2022).

4.4 Cross-Validation Techniques

The external cross-validation was performed using 5-fold validation to enhance the affirmation of models. The data was divided into five sets and while training, four sets were used and the model was then checked on the fifth set. Five such attempts were made, and each of the subsets was used as the test set only once. With the intent to lower overfitting, cross-validation offered a superior estimation of how well the models perform in practice (Nabi et al., 2022).

5. Results and Analysis

5.1 Comparison with Other Different Transfer Learning Models

All the three transfer learning models, ResNet50, VGG16, and EfficientNetB3 were then tested and the accuracy, precision, recall as well as the F1-score were compared. The outcome showed that EfficientNetB3 had the superior performance of the other models, the classification accuracy which was at 96.8 % in overall accuracy. The next two models that featured surprisingly high accuracy were ResNet50 and VGG16 at 94.3% and 92.7% respectively.

The evaluation of the proposed EfficientNetB3 on the South African crops resulted in 93% of accuracy 87% of precision, 89% of recall, and 89% of F1-score proficiency on rare disease identification like Marssonina leaf blotch. This can be attributed to the ability of EfficientNetB3 to scale both the depth and width to have a better understanding of features in high-resolution images (Feng et al., 2023).

5.1.1 Accuracy

A classification accuracy of 96.8 percent was recorded with the EfficientNetB3 network across all the six disease categories. This was then succeeded by ResNet50 with 94.3% followed by VGGA with 92.7%. The superior performance of EfficientNetB3 can be associated with the improved architecture that scales both depth and width and enables it to work with intricate disease characteristics (Peng Wang et al., 2021).

Model	Accuracy (%)
EfficientNetB3	96.8
ResNet50	94.3
VGG16	92.7

5.1.2 Precision, Recall, and the F1 score.

ROIs were created for five significant diseases of apple and the precision, recall, and F1 tracks of each model were then evaluated for the key diseases: apple scab, Alternaria leaf spot, powdery mildew, and Marssonina leaf blotch. Among all the networks used, EfficientNetB3 conducted the most trades between precision (89%) and recall (91%), especially when predicting diseases encountered least frequently, such as Marssonina leaf blotch, in which standard machine learning approaches are ineffective (Feng et al., 2023).

Metric	EfficientNetB3	ResNet50	VGG16
Precision (%)	89	85	81
Recall (%)	91	87	83
F1-Score (%)	90	86	82

5.1.3 Identify Specific Diseases

Originally, EfficientNetB3 showed good performance in diagnosing intricate diseases like Alternaria leaf spot and Marssonina leaf blotch. Deep learning techniques like ResNet50 and VGG16 worked fine but were slightly less effective in identifying these diseases. It is concluded that, as a result of scaling, EfficientNetB3 is effective at identifying diseases in apples by recognizing high-quality features of the picture, which can be useful in the case of close resemblance of diseases.

5.2 Effect of Applying Transfer Learning on Prediction Error

Compared to the baseline machine learning models, transfer learning improved the prediction of new data. The performance of the proposed system was compared with the usage of some classical techniques: support vector machines (SVM), and decision trees – the average accuracy in their case was 78% for SVM and 75% for decision trees. These models were most challenged during feature imbalances that occur when less data is available about certain diseases (Nabi et al., 2022).

The pre-trained transfer learning models were able to balance the apple disease dataset as it took advantage of the learnings from large data sets (ImageNet). This process enabled the models to generalize well when data were scarce, which is a major strength in many agricultural applications as labeled data is often hard to come by (Duan et al., 2022).

5.3 Comparison with Other Conventional Machine Learning Models

Compared with the standard machine learning algorithms like SVM and KNN, we can observe that the transfer learning methods driven by deep learning outperformed all the other methods. That work yielded the best performance of 78%, which is substantially worse in comparison to the transfer learning models under discussion and serves to establish the effectiveness of deep learning for the given task (Kim et al., 2021).

Model	Accuracy (%)
EfficientNetB3	96.8
ResNet50	94.3
VGG16	92.7
SVM	78
Decision Tree	75

5.4 Case Study

5.4.1 Exploratory analysis of detection of apple diseases based on region

To contrast the disease detection accuracy in different apple-growing regions this study used an empirical review of Jammu & Kashmir, Uttarakhand, and Himachal Pradesh. Once again the Accuracy of EfficientNetB3 was quite high across all the regions with the roughest scenarios reported by J&K due to the co-morbidity factor in which several diseases overlap each other. EfficientNetB3 achieved 97.1% accuracy in this region Whereas the accuracy in other regions was as low as 95.4% in Uttarakhand and 94.6% in HP. These results further prove that the proposed model is quite robust depending on the certain environment and rates of diseases (Peng Wang et al., 2021).

6. Discussion

6.1 Significance of Findings

The findings of this study show that transfer learning can enhance the apple disease prediction models with considerable accuracy. Finally, the best model of EfficientNetB3 proved that pre-trained models can be fine-tuned to identify different patterns within agricultural data sets even when there are few labeled data. It is especially helpful for farmers and agricultural scientists in developing countries since it saves time and money often spent on data gathering (Tian et al., 2021).

The effectiveness of the transfer learning models shows in the case a greater scope of applying them in the northern apple-growing parts of India. What this means is that by using such models, farmers will be able to detect such diseases at a tender stage, not requiring the use of pesticides and other such measures and rather prevent the monitoring of such diseases from getting out of hand and leading to heavy losses in terms of yield on the farm (Duan et al., 2022).

6.2 Transfer Learning as a Tool for Management of Apple Diseases

Thus, transfer learning is the best approach to using large datasets available to the public for certain applications in agriculture. This is of importance, especially in the north Indian region where diseases that affect apples are a major cause of economic instability. Pre-trailed models reduce the dependency on big labeled data to improve the detection of a range of diseases or even specific diseases on patients' images (Saleem & Arif, 2022).

Furthermore, the conclusions of this work enrich the knowledge of the use of deep learning in agriculture. It not only improves prediction accuracy but also provides a convenient and efficient method for other crops and areas. Future work can modify these models to identify more diseases or employ analogous procedures to other fruits, including grapes or oranges (Nabi et al., 2022).

6.3 Limitations of the Study

However, this research has the following limitations: First, the data collection included only a few locations in northern India, which reduces the ability to detect other diseases affecting apples in other parts of the country or the world (Kim et al., 2021). Furthermore, the investigated transfer learning models, despite the achieved high performances, demand much computing power, and, thus the availability in all agricultural contexts (Khan et al., 2022).

Moreover, transfer learning also makes models that can achieve good results despite having access only to a few labeled samples, but more extensive resources are required to guarantee that models can identify new or previously unseen disorders. As for the potential negative impacts and limitations mentioned above, future research could potentially overcome these by generating larger datasets, and by experimenting with lightweight models that can be run on smartphones for prompt disease recognition (Sharma et al., 2022).

6.4 Future Scope of Research

The present study raises several questions regarding further research in a similar direction, namely: Another area would be to investigate the use of the transfer learning models in real-time disease identification systems, including the farming mobile applications. Such systems could offer the farmers real-time advice, which would allow tackling diseases, before the extension of their effects (Singh et al., 2022).

One other research opportunity would be the inclusion of more features, which could be soil type, climate conditions as well as the incidence of pests in an attempt to improve the predictions in the models. Adding such factors to the image data, it became possible to design more comprehensive systems for managing diseases (Duan et al., 2022). In addition, such research could inform how transfer learning concepts might be applied to other crops to enhance yield and productivity, as well as improve understanding of how these approaches can be implemented in other areas of agriculture.

7. Conclusion

This work shows how transfer learning can improve the accuracy of the apple disease models beyond the level achieved by traditional approaches. Therefore, using the deep learning approach that taps into such pre-trained models as EfficientNetB3, ResNet50, and VGG16, this research finds that deep learning-based classifiers yield higher performance levels than the traditional machine learning classifiers in diagnosing and categorizing apple diseases. By applying transfer learning, the problem of having a small amount of labeled data is solved, and generalization is enhanced when working with different zones of apple production within northern India.

The results of our experiment indicate that the EfficientNetB3 model had the highest accuracy in the prediction of both frequent and rare apple diseases. We must therefore embrace the use of such complex ML in agriculture, especially in countries that rely on the production of apples. In this paper, the usefulness of these methods is demonstrated for post-harvest classification but with further research, it can be extended to real-time applications and other crops for better and more efficient agriculture solutions.

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