Advance CNN methods applied to the classification of diseases in sunflower

Afsana Kabir Sinthia[1], Nisat Islam Mozumder[1], Md. Tariqul Islam Islam[1]
[1]Department of Computer Science and Engineering, Brac University of Bangladesh, Dhaka, Bangladesh
Email: afsana.kabir.sinthia@g.bracu.ac.bd, nisat.islam.mozumder@g.bracu.ac.bd, md.tariqul.islam5@g.bracu.ac.bd

***Abstract*—Sunflowers are a well-established and successful oil seed crop in Bangladesh. It is the second-largest oil crop after soybeans and a potential source of high-quality edible oil. However, they are vulnerable to parasites, insects, and illnesses, which can lead to output losses. Digital image processing and computer vision methods have been used to classify and identify plant diseases in leaves, fruits, and flowers, allowing for early detection of diseases and minimizing farmers' financial losses. The sunflower leaf disease that exists in Bangladesh has yet to be extensively studied. This information has yet to be used in any research to determine the types of sunflower leaf diseases that have been reported in Bangladesh. In addition, seven machine learning models were developed, of which three are based on advanced versions of the Vision transformers BERT, DeiT, and Swin transformers. In contrast, the remaining three are based on well-known deep learning models Resnet, VGG16, DesNet, and Inception v3. Although the Resnet and Inception v3 models did a great job, the swin transformer performed better than all of them in terms of accuracy, with an accuracy of 96.50 percent. The Swin transformer beats all other models and is the quickest to train, according to the comparison of precision and recall and the F1 score. The study also made public the black box of the VGG16, Resnet, DesNet, and Inception models, proving that Resnet is more accurate than the others. We anticipate that our Swin transformer-based and the Resnet-based models can be effective in identifying sunflower disease due to their higher accuracy.**

***Index Terms*—Sunflower disease detection, Convolutional Neural Network, VGG, ResNet, InceptionV3, DensNet121, DeiT .**

I. INTRODUCTION

Sunflower is a crop that thrives in Bangladesh's natural agricultural system and throughout the majority of the nation. It is recognized as a cash crop with a high return on investment. Sunflower cultivation is a great substitute for growing other crops due to climate hazards like unpredictable rainfall or flooding. Sunflowers are more suitable for growing in coastal regions due to their high output and wide range of adaptability [1]. Due to its numerous applications and advantages, sunflower is a crucial crop in agriculture such as oil Production, animal Feed. Moreover, it is a crucial crop that is important to the agricultural sector. Nonetheless, it is vulnerable to a number of diseases that might cause large financial losses. Effective disease control and prevention depend on early diagnosis and accurate analysis of these disorders. Early detection of infections in sunflowers enables farmers to lessen financial losses by preventing them from spreading across the farm. [2].

Agricultural science is a rapidly growing discipline since it has a significant impact on the global agricultural industry. A new dimension has been added to this sector by technology. To increase agricultural yield overall, researchers are using various approaches and creating new kinds of seeds, treatments, and weeds. Recent advances in deep learning-based image processing techniques have considerably increased the accuracy of disease categorization. There are at least 30 diseases that affect wild or domesticated sunflowers that are brought on by different fungus, bacteria, and viruses. However, only a tiny number are significant economically in terms of reducing yields [3], [4]. Verticillium wilt, leaf blight, and sunflower phoma blight are a few diseases that can seriously harm sunflower field. Such diseases can occur, and if the essential measurements are not made in a timely manner, they might be fatal. Throughout the years, researchers have developed a wide range of approaches and models for the identification of diseases in plants. Many feature extraction and segmentation techniques have been used [3]–[5]. They proceed by categorizing illnesses using a dataset composed of field images representing four foliar diseases of sunflowers using the ResNet neural network (Helianthus) [6]. To categorize or predict outcomes, deep learning techniques are commonly utilized [7]. Convolutional neural network is the primary classifier employed in deep learning approaches for the active categorization of plant diseases [8]. Whether we have a large or small data collection, the CNN is one of the most suggested models for classification or recognition using pictures [9]. There is no need to manually build the feature extraction function and classifier since deep learning dynamically analyzes structural properties. As image classifiers, deep learning techniques outperform machine learning, with CNN being the best.

Traditional techniques for manually identifying plant diseases in the agricultural industry need professionals to conduct visual inspections, followed by more thorough detection in labs, which takes time and is not always available to smallholder farmers. As a result, researchers investigated the use of automated and intelligent illness detection systems by creating such systems utilizing artificial intelligence, machine learning, and deep learning approaches. The primary objective of deep learning algorithms is to extract features from pictures and use these characteristics to do either classification or regression, depending on the purpose. While each deep learning algorithm has a particular way of extracting features, combining the retrieved characteristics of several deep learning methods might produce superior results since the classifier will have a larger pool of descriptive data to draw from. To protect the crop, a quick disease detection system is also necessary. Hence, lowering the incidence of plant diseases is a crucial step in improving crop quality in general. Every stage of the sunflower's growth is affected by diseases.

Our approach is based on a convolutional neural network (CNN) architecture that is specifically designed to recognize different types of sunflower diseases. The CNN is trained on a real dataset of labeled images of sunflower plants. The key contributions of this paper are summarized as follows:

- Several CNN-based deep learning models, including VGG16, Resnet, DensNet, and Inception v3, are used to detect sunflower disease, and their performance is extensively evaluated.
- Increased classification accuracy with a reasonable number of parameters.
- On the sunflower dataset, three modern, state-of-the-art Vision transformer variants—namely, the DeiT, BERT, and Swin transformers—are applied. The performances of the models are shown using the confusion matrix, accuracy, sensitivity, specificity, and F1 score.

The rest of the paper is organized as follows. Section II describes relevant existing work in disease detection. Section III describes the system framework and assumption. Algorithms and methods for classifications are presented in Section IV. Section V demonstrates the comparative performance evaluation of the experimental results. Finally, we conclude the whole paper in Section VI.

II. Related Work

In recent years and with the rapid utilization of image processing and classification in various applications, many researchers have proposed various learnig methods for image detection and classification. To increase accuracy for the classification if object classes is a crucial issue in the research field image processing.

According to paper [10] the author proposed a classification model combining Deep neural Network and JOA optimization algorithm to classify disease paddy leaves images. Here they got an accuracy of 98 percent on one disease prediction and at 94 percent in other disease prediction from leaves images. Moreover, the two hidden layer concept became useful in fast processing of the dataset. Their significant improvement in the field of accuracy also depends on their pre processing step where they converted the RGB image into Hue based HSV image and segmented the image portions into disease and normal part with K mean clustering method.However, it could be better if they applied deep CNN with the same preprocessed dataset but in greater amount. In the paper [11] the researcher proposed a meta deep learn model which learns from multiple models such as CNN, VGG16 and ResNet50.It learns from different models using the ensemble method to combine all models and produce a final model.Here, first of all, they trained multiple models like custom CNN, VGG16, and ResNet50 their cotton leaves dataset. After training different models, the models were combined together using stacked ensemble learning and a final model was implemented. The stacked model improved the classification accuracy about 98.53 percent. According to the paper [12] their proposed model utilizes two pretrained CNN model, EfficientNetB0, and DenseNet121 for extracting the deep features of corn leaves images.The deep features are fused and concatenated to produce a more complex feature set.data augmentation techniques were used on the dataset to add variations to the images.Through this it increased the varietyof the images and enabled the model to learn more complex cases of the data which helps to gain a higher accuracy rate of 98.56 percent. In the paper [13] the author tries to implement a deep learning framework consists of convolution layers, max-pooling layers, a flatten layer, dense layers, and a special part called dropouts on their tomato leaves dataset.Dropout helps the model to prevent over fitting.Here they used Leaky ReLU as their activation function.They compared the validation accuracy after using and not using dropouts which encouraged the dropout technique to be performed for better validation accuracy. The authors in [14] has introduced a new idea of annotating and pre processing the dataset of citrus fruit where they implemented an algorithm with rescaling, establishing bounding box, extracting HSV image etc to pre process different disease location, affected portion and identify the severity level of the disease present in the citrus fruit.They identified and extracted the diameter, color features, shape and the surface area of the affected portion of the disease portion of the fruit HSV images. Moreover, they used deep neural network and transfer learning method to implement a multi-classification framework for severity classes of fruit.The accuracy level for low severity is 99 percent and for the high level severity is 98 percent.moreover they believes that,the quality of the training model is strongly influenced by the precision of the feature labeling.

In this paper [6], they worked on RestNet152 model which was pre-trained on ImageNet dataset and then trained on the new sunflower dataset.They removed the background of the image to prevent classification error.Next, they used saliency map to measure gradient of loss with input image pixel and it converts the RGB into greyscale image.Moreover they measure the occlusion sensitivity by correlating disease manifestation with highlighted image region which find out the causes of wrong classification. Through this research, they observed color to be the first element to differentiate classes in the model. The paper [15] talked about the results obtained from classifying foliar diseases in sunflower implementing proposed model which automatically segments the leaf lesions.They segmented the lesions with Faster R-CNN and Mask R-CNN.They implemented residual neural networks ResNet50 and ResNet152 to classify the diseases based on lesion.For the diseases such as Alternaria and rust the segmentation result was satisfactory where the lesions are well-outlined.The research shows that the system network that segments lesions along with the network for disease classification both needed for a better performance experience. The research paper [16] showed a hybrid deep learning model combining Vgg16 and MobileNet through stacking ensemble learning process to classify the sunflower diseases, i.e. Alternaria leaf blight, Downy mildew, Phoma blight, and Verticillium wilt.This paper widely related to our research though however it needs much improvement in their accuracy rate.

According to a paper [17] transformer model effectively works with CNN in image classification. The authors developed a deep ensemble learning system combining CNN and vision transformer model to categorize olive leaf disease. The results are encouraging and show how effectively CNN and vision transformer models can be used together. The model had significant accuracy of about 96 percent in multiclass classification and 97 percent in binary classification. [18]

However, most of the existing works have not focused on the several leaf diseases of sunflowers that are a significant aspect of the growth of Sunflower cash crop production. This crop oil has a major demand in our country for cooking purposes and the demand is getting higher because of the recent Ukrain-Russia war has being conducted. These observations have motivated us to design a fruitful system that can successfully be used in our country for sunflower growth research projects.

III. System Framework and Assumptions

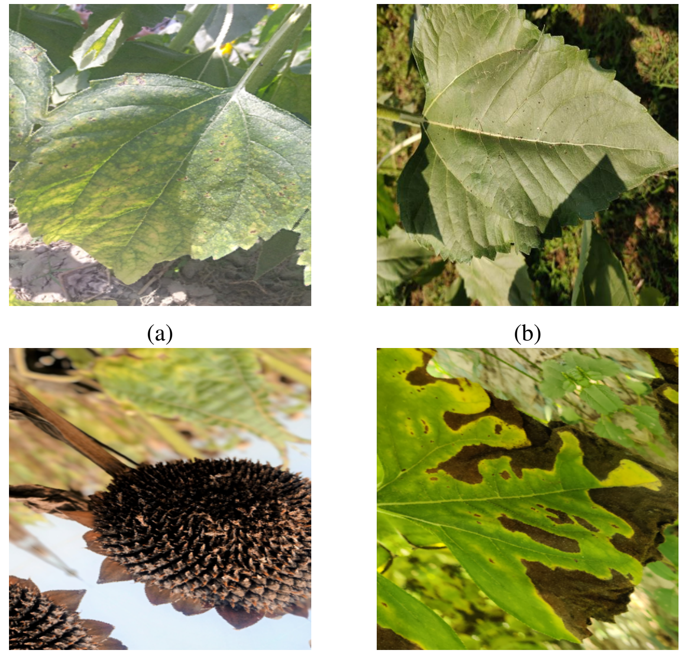
In this section, relevant subheadings are used to describe the specifics of the dataset-gathering procedure and suggested models. Also, here we explain the model hyperparameters.

A. Dataset

In this paper, classification of diseases in sunflowers, the dataset we employed consists of images of sunflower leaves that have been affected by different diseases. For sunflower diseases classification we use data from online repositories which is Mendeley Data (Repository name) and that dataset is publicly available. They collect the data from Bangladesh Agricultural Research Institute (BARI) at Gazipur. For data collection, they go to the farm from November (25th to 29th), 2021. The dataset contains 1892 augmented image data within it in which the Gray mold contains 398, Leaf scars 509, Downy mildew 470, and Fresh Leaves 515 1. Sunflowers usually have many diseases from among many diseases we working with Gray mold, leaf scars, and downy mildew which are three common diseases that can affect plants like sunflowers. Gray mold is a type of fungal disease that can cause brownish-gray lesions on the leaves, flowers, and stems of the plant. Leaf scars are another common symptom of several plant diseases, including sunflower rust and downy mildew. These appear as sunken, brownish-black areas on the leaves, often with a yellow halo around them. Downy mildew is also a fungal disease that can cause yellow or brown patches on the leaves, often with a fuzzy, grayish-white growth on the underside of the leaves.

B. Image Processing

Raw images are capture using a Digital camera [19]. Sequentially, each raw picture maintains a 512 x 512 pixel width



(a) (b) (c) (d)

Fig. 1: Sample images from Wheat Rust Classification Dataset: a) Downy Mildew b)Fresh Leaf c) Gray Mold and d) Leaf Scars

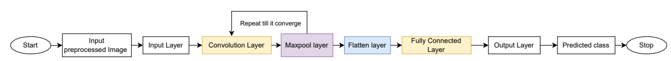


Fig. 2: CNN Architecture

and height also contain jpg format.For data pre-processing steps we do resize all image into 224*224 size and also augmented the image data.The dataset we used that total containing eighteen hundred and ninety-two augmented images created from the original images of healthy and disease affected sunflower leaves and blooms. The dataset was split into the training set(80

C. Conceptual Background

Some of the key ideas and techniques employed in the suggested model are described in this section. **Convolutional Neural Networks(CNNs)** are a kind of deep learning algorithms that are frequently used to analyze visual data.The convolution process is used to extract various information from the pictures.The picture is then translated into a smaller form that can be processed quickly without losing many of the image's properties.The earliest layers of a CNN are responsible for learning low-level spatial information, which often correlate to an object's borders, boundaries, or basic qualities.The deep layers also pick up on additional high-level, sophisticated data, such as complex forms and object orientations. The two basic components of a CNN are feature extraction and classification.Several convolutional and activation layers, followed by a pooling layer, are often used to extract features from an image. This step creates a feature map that is delivered to the classification section using the image's pixel values as input. In order to learn low/mid/high level characteristics from the picture, such as edges, patterns, and textures, convolutional layers are made up of filters that are applied to the layer's input. A mathematical tensor with the dimensions as in can be used to represent a picture as in 2.

$$dim(image) = (n_h, n_w, n_c) \tag{1}$$

Where n_h is the size of the height, n_w is the size of the width, and n_c is the number of channels. By conducting the convolutional operation of multiplying the filter values by the window on which they sit, afilter is a tensor that typically has an odd dimension and is applied to the input in a sliding-window fashion.

IV. Methodology

In this section, we discuss our methodology of CNN classification for sunflower disease detection. We begin this section by introducing our methods. Subsequently, the proposed classification is being performed into three sub-phase, that is image processing, training phrase and evaluation phrase.

A. Data processing

The dataset was split into an 80% training split and a 20% test split in order to facilitate training and evaluation of the model. 20% of the training samples were taken to create a validation split from the training subgroup. To teach the model the intricate aspects of the photos, the training subset is used. The validation subset, in contrast, is maintained apart from the training subset. Information is fed to the model after each epoch and the model's performance is assessed in order to track how well it is doing. When the training is complete, the model's performance on data that it has never seen before is evaluated using the test subset. The dataset was expanded using a mix of the horizontal flip, rotation, shearing, and zooming procedures to prevent over-fitting.

B. Training Phase

The architecture of the CNN used in the experiment can be demonstrated as in 3. All CNN models were trained using Cuda version 11.2 on Google Colab Pro Edition with 26.3 GB of GEN RAM and 16160 MB of GPU RAM. A batch size of 32 and up to 50 epochs were used to train each model.

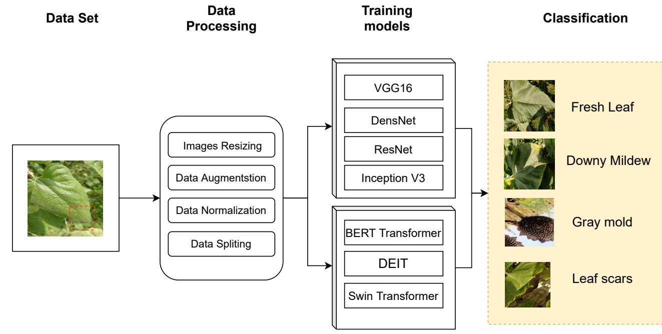


Fig. 3: System Architecture of the proposed CNN

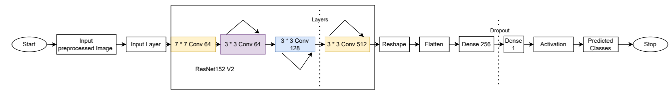


Fig. 4: Resnet Architecture

1) Transfer Learning Based Neural Network Models: **ResNet-152** is a popular convolutional neural network design called ResNet-152 that is used to classify images, including in the setting of classifying sunflower diseases. The original Resent model makes use of skip connections to prevent the vanishing gradient problem and performance deterioration of deep neural networks. For the classification job, we applied 152-layer resnet152 models and tweaked them in the final few levels. In our modified Resnet152, there are 58,733,060 parameters in total, 401,412 of which are trainable and 58,331,648 of which are not 5.

VGG16 is a pre-trained transfer learning model that is mostly used to classify a large number of data sets. The performance of a ConvNet Model can be improved by increasing the depth of the layers. To improve performance in our experiment we employing the first 13 layers of the original VGG16 model, the final few layers have been modified where we added flattening, and a dense layer with a softmax activation function.In our modified VGG16, there are a total of 14,815,044 parameters, 100,356 of which are trainable, and 14,714,688 of which are not.

InceptionV3 which is consists of several levels of convolutional and pooling operations, followed by several completely linked layers, and is the third iteration of the Convolution Neural Network created by Google. In a manner similar to VGG 16, we made changes to the Inception v3 model's final few layers, flattening one dense layer, and then adding another dense layer to complete the classification assignment. The total number of parameters in our modified InceptionV3 is 22,007,588, out of which 204,804 are the trainable parameters and 21,802,784 are the non-trainable parameters. Table 1 shows the number of parameters of the different models used in our study. This method enhances the model's capacity to categorize complicated images by enabling it to record characteristics at various degrees of abstraction and resolution.

Desnet Using Dense Blocks, a type of convolutional neural network called DenseNet uses dense connections between layers to connect all layers (with matching feature-map sizes) to one another directly. Each layer receives extra inputs from all earlier levels and transmits its own feature maps to all later layers in order to maintain the feed-forward character of the system.DenseNet-121 features four average pools and 120 convolutions. The total number of parameters in our modified DenseNet121 is 7,238,212, out of which 200,708 are the trainable parameters and 7,037,504 are the non-trainable parameters. Table 1 shows the number of parameters of the different models used in our study.

2) Transformer Based Models: **BERT Transformer** The Transformers Bidirectional Encoder Representations (BERT) are used for feature encoding. A position encoding vector is also appended to each patch installation, creating a token inserted for the transformer encoder's primary layer. The image is divided into smaller, proportionately sized patches and masked in between. The most crucial elements are encoded into the Masked Image Modelling Head by the Encoder, which uses attention processes.

Swin Transformer Swin transformer is a variant of transformer which uses shifted window scheme and make hierarchical feature maps with input image patches. The merged patches pass through linear embedding layer and win transformer block multiple times in each stages.The Swin transformer has a modified self attention,a block of multi head self attention,a layer normalization (LN) and a two-Layer MLP or multi layer perception. The shifted windowing scheme limits self-attention computation to non-overlapping local windows and at the same time allows cross-window connection which give significant efficiency . This hierarchical architecture has the flexibility to model at various scales and has linear computational complexity with respect to image size.

DeiT Transformer DeiT or data-efficient image transformers is used in computer vision , image classification for efficient processing of image with less data and less complexity and without requiring any external data and also in a single computer in short time comparing to other transformer models.This model doesnt require convolution steps rather it uses a teacher student technic where a distillation token is required to ensure students learn from teacher through back propagation and interacting with class and patch tokens through self-attention layers.

C. Evalution Phase

The accuracy, sensitivity or recall, precision, or positive predictive value (PPV) metrics are used to produce the quantitative evaluation of all six models. The accuracy Eq. 2, precision Eq. 3, and sensitivity Eq. 4 are determined using the true positive (TP), false positive (FP), true negative (TN), and false negative (FN) samples. The model's capacity to find all pertinent examples within a data set is known as recall, often referred to as sensitivity. The sum of the true positives and false negatives is divided by the number of true positives. It speaks to the ability of the study to correctly identify ill patients who have the disease. In medical diagnosis, diseases are commonly classified as a positive category.

$$Acc_i = \frac{TP_i \times TN_i}{TP_i + TN_i + FP_i + FN_i} \times 100\% \tag{2}$$

$$Precision_i = \frac{TP_i}{TP_i + FP_i} \tag{3}$$

$$Sensitivity_i = \frac{TP_i}{TP_i + FN_i} \tag{4}$$

$$F_1 = 2 \times \frac{Precision_i + Sensitivity_i}{Precision_i + Sensitivity_i} \tag{5}$$

Where, i=Downy Mildew or Gray Mold or Leaf Scars or Fresh Lea class for the classification task. TP= True Positive FN= False Negative. TN=True Negative

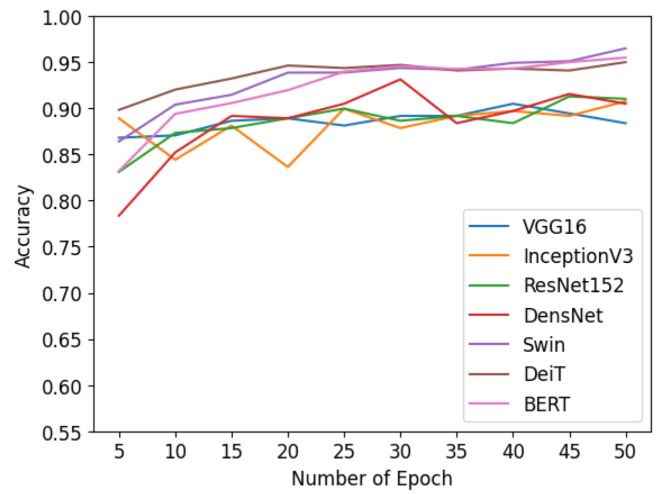


Fig. 5: Accuracy of all the models

TABLE I: MEASURES OF PERFORMANCE FOR THE SEVEN MODELS STUDIED IN THE RESEARCH

V. Performance Evaluation

In this section, we evaluate our trained models and compare their performance with each other. By calculating the accuracy, recall, F1 score (F1), accuracy (Acc), and positive predictive value (PPV) and using unknown data, the outcomes of the seven models that have been developed and tested are reviewed. The results of the seven models examined in this paper are summarized in Table **??**.

VI. Conclusion

In our Sunflower leaves claassification we collected and processed a total of 1892 augmented images which contains Gray mold, Leaf scars,Downy mildww and Fresh leaves.The images are then preprocessed to be fed into the classification models. Three natural language processing models Bert, Swin, Deit transformers are extensively evaluated along with the other popularly known deep learning models Custom CNN, DenseNet121, Resnet, Vgg16, and Inception v3 and performance evaluation has been displayed using accuracy, F1 score, confusion matrix, specificity ,precision etc. Furthermore, a comparison assessment has been performed among the models where ResNet and InceptionV3 performed well in accuracy measurement but the transformer Swin model outperformed every other model used in this sunflower data so far till now achieving around 96.5 percent accuracy which is the highest in the field of Sunflower leaves classification. Moreover, Swin transformer has taken quite less time for generating epochs in validation section compared to other models.in conclusion, leaves images can be effectively processed and classified with transformer models.

References

[1] A. J. Mila, R. W. Bell, E. G. Barrett-Lennard, and E. Kabir, "More strategic use of fresh water can produce a four to eight-fold increase

in fresh water productivity in irrigated sunflower on saline soils in the ganges delta," *Available at SSRN 4062892*.

[2] S. H. Habib, A. L. Akanda, P. Roy, U. Kulsum, M. Rohman, and M. M. Rahman, "Mutant divergence in sunflower induced through gamma radiation," *Journal of Crop Science and Biotechnology*, Dec 2022. [Online]. Available: https://doi.org/10.1007/s12892-022-00186-w

[3] A. H, Y. B. H, and Y. N, "Leaf disease detection and prevention using deep learning," in *2022 International Conference on Artificial Intelligence and Data Engineering (AIDE)*, 2022, pp. 223–229.

[4] S. Pirsa, E. Banafshechin, S. Amiri, A. Rahimirad, and J. Ghafarzadeh, "Detection of fraud of palm, sunflower, and corn oil in butter using hplc profile of tocopherols and tocotrienols by response surface method," *Journal of the Iranian Chemical Society*, vol. 18, no. 5, pp. 1167–1177, May 2021. [Online]. Available: https://doi.org/10.1007/s13738-020-02100-z

[5] A. Malik, G. Vaidya, V. Jagota, S. Eswaran, A. Sirohi, I. Batra, M. Rakhra, and E. Asenso, "Design and evaluation of a hybrid technique for detecting sunflower leaf disease using deep learning approach," *Journal of Food Quality*, vol. 2022, p. 9211700, Apr 2022. [Online]. Available: https://doi.org/10.1155/2022/9211700

[6] R. G. Dawod and C. Dobre, "Resnet interpretation methods applied to the classification of foliar diseases in sunflower," *Journal of Agriculture and Food Research*, vol. 9, p. 100323, 2022. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S2666154322000564

[7] G. Park, K. Sim, M. Kyeon, S. Lee, J. Baek, and J.-I. Park, "Detection of leaf diseases using color and shape models," in *International Workshop on Advanced Imaging Technology (IWAIT) 2023*, vol. 12592. SPIE, 2023, pp. 267–272.

[8] Suresh and K. Seetharaman, "Real-time automatic detection and classification of groundnut leaf disease using hybrid machine learning techniques," *Multimedia Tools and Applications*, vol. 82, no. 2, pp. 1935–1963, Jan 2023. [Online]. Available: https://doi.org/10.1007/s11042-022-12893-1

[9] N. Mahesh Kumar, K. Premalatha, and S. Suvitha, "Lung disease detection using self-attention generative adversarial capsule network optimized with sun flower optimization algorithm," *Biomedical Signal Processing and Control*, vol. 79, p. 104241, 2023. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S1746809422006954

[10] S. Ramesh and D. Vydeki, "Recognition and classification of paddy leaf diseases using optimized deep neural network with jaya algorithm," *Information Processing in Agriculture*, vol. 7, no. 2, pp. 249–260, 2020. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S2214317319300769

[11] M. S. Memon, P. Kumar, and R. Iqbal, "Meta deep learn leaf disease identification model for cotton crop," *Computers*, vol. 11, no. 7, 2022. [Online]. Available: https://www.mdpi.com/2073-431X/11/7/102

[12] H. Amin, A. Darwish, A. E. Hassanien, and M. Soliman, "End-to-end deep learning model for corn leaf disease classification," *IEEE Access*, vol. 10, pp. 31 103–31 115, 2022.

[13] A. K. Aggarwal, "Biological tomato leaf disease classification using deep learning framework," *Int. J. Biol. Biomed. Eng.*, vol. 16, pp. 241–244, Mar. 2022.

[14] P. Dhiman, V. Kukreja, P. Manoharan, A. Kaur, M. M. Kamruzzaman, I. B. Dhaou, and C. Iwendi, "A novel deep learning model for detection of severity level of the disease in citrus fruits," *Electronics*, vol. 11, no. 3, 2022. [Online]. Available: https://www.mdpi.com/2079-9292/11/3/495

[15] R. G. Dawod and C. Dobre, "Automatic segmentation and classification system for foliar diseases in sunflower," *Sustainability*, vol. 14, no. 18, 2022. [Online]. Available: https://www.mdpi.com/2071-1050/14/18/11312

[16] A. Malik, G. Vaidya, V. Jagota, S. Eswaran, A. Sirohi, I. Batra, M. Rakhra, and E. Asenso, "Design and evaluation of a hybrid technique for detecting sunflower leaf disease using deep learning approach," *Journal of Food Quality*, vol. 2022, p. 9211700, Apr. 2022.

[17] H. Alshammari, K. Gasmi, I. Ben Ltaifa, M. Krichen, L. Ben Ammar, and M. A. Mahmood, "Olive disease classification based on vision transformer and CNN models," *Comput. Intell. Neurosci.*, vol. 2022, p. 3998193, Jul. 2022.

[18] F. Wang, Y. Rao, Q. Luo, X. Jin, Z. Jiang, W. Zhang, and S. Li, "Practical cucumber leaf disease recognition using improved swin transformer and small sample size," *Computers and Electronics in Agriculture*, vol. 199, p. 107163, 2022. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S016816992200480X

[19] U. Sara, A. Rajbongshi, R. Shakil, B. Akter, S. Sazzad, and M. S. Uddin, "An extensive sunflower dataset representation for successful identification and classification of sunflower diseases," *Data in Brief*, vol. 42, p. 108043, 2022. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S2352340922002542