TTL : Transformer and Transfer Learning Approach To Detect Sunflower Disease

***Abstract*—Sunflowers are a popular oil seed crop in Bangladesh, second only to soybeans. They have the capacity to generate high-quality edible oil, but because of their susceptibility to parasites, insects, and illnesses, crop yields may be reduced. To effectively tackle this problem, the implementation of digital image processing and computer vision techniques is necessary to detect diseases in sunflower leaves, fruits, and flowers. However, the specific sunflower leaf diseases found in Bangladesh have not been extensively studied. To fill the gap in knowledge, we created seven machine learning models, including four popular deep learning models (Resnet, VGG16, DenseNet, and Inception v3), and three advanced Vision Transformers (ViT, DeiT, and Swin). Among them, the Resnet and Inception v3 models showed good performance, but the Swin Transformer surpassed them all with an accuracy score of 96.50%. According to a comparison of precision and recall as well as the F1 score, the Swin transformer outperforms all other models and is the easiest to train. The study analyzed several models, including VGG16, Resnet, DenseNet, and Inception. Our Swin transformer model and Resnet model have a high accuracy rate, which makes them effective in identifying sunflower diseases.**

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

I. INTRODUCTION

Sunflowers are a highly profitable crop that thrives in Bangladesh's natural agricultural system and throughout the majority of the country. They are recognized as cash crops due to their high return on investment and are an excellent substitute for other crops that are vulnerable to climate hazards like unpredictable rainfall or flooding. Sunflowers are especially suitable for growing in coastal regions because of their high output and wide adaptability range [1]. Due to its numerous applications and advantages, sunflower has become a crucial crop in agriculture such as oil Production, Animal Feed. In agriculture, sunflowers are crucial for oil production and animal feed and are considered an essential crop. However, they are vulnerable to diseases that can cause significant financial losses. In order to effectively control and prevent disease, early diagnosis of infections in sunflowers is essential. This allows farmers to stop the spread of these diseases throughout their farms, eventually lowering financial losses. [2].

The field of agricultural science is expanding quickly and plays a crucial role in the global agricultural industry. Technology has brought new advancements to this sector, allowing researchers to develop different methods, seeds, treatments, and weeds to increase overall agricultural yield. Recent improvements in deep learning-based image processing techniques have significantly improved the accuracy of categorizing disease. There are more than 30 different diseases that damage wild or domesticated sunflowers, and they are all brought on by fungi, bacteria, and viruses. Still, only a small number of them have a significant economic impact on reducing yield [3], [4]. Sunflower fields can be seriously affected by diseases such as verticillium wilt, leaf blight, and sunflower phoma blight. These diseases can be fatal if not detected and treated promptly. Over the years, researchers have developed a variety of methods and models to identify diseases in plants, including feature extraction and segmentation techniques. [3]–[5]. Utilizing a dataset consisting of field images showing four foliar diseases that affect sunflowers, the diseases are categorized. The ResNet neural network (Helianthus) is implemented here [6]. To categorize or predict outcomes, deep learning techniques are commonly utilized here [7]. In deep learning methods used for identifying and categorizing plant diseases, a convolutional neural network is the main classifier utilized [8]. Whether we have a large or small data collection, CNN is a more suggested model for classification using pictures [9]. Since deep learning dynamically analyses structural properties, there is no need to manually construct the feature extraction function and classifier. As image classifiers, deep learning techniques outperform machine learning, with CNN being the best.

In the agricultural industry, identifying plant diseases, traditionally requires visual inspections done by professionals, followed by more detailed analyses in labs. However, this process can be time-consuming and not always accessible to small-scale farmers. The researchers have built automated and intelligent disease detection systems deploying machine learning, deep learning, and artificial intelligence methodologies to address this issue. The algorithms extract features from images to classify or regress the purpose. Combining multiple deep learning methods can improve results by providing a larger pool of descriptive data. Quick disease detection is important for crop protection, and reducing the occurrence of plant diseases is critical.

Our strategy is based on an architecture for a convolutional neural network (CNN) that has been designed to identify various sunflower diseases. A real dataset of labeled images of sunflower plants has been used as the training data for the CNN. The following is a summary of this paper's major contributions:

- Various deep-learning models that rely on CNN technology, such as VGG16, Resnet, DensNet, and Inception v3, have been utilized for identifying sunflower diseases. Their effectiveness has been thoroughly assessed.

- More accurate classification with a manageable number of parameters.
- Three advanced Vision transformer variants, namely DeiT, ViT, and Swin transformers, were utilized to analyze the sunflower dataset. The models' effectiveness was presented through metrics such as 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, the use of image processing and classification has grown significantly across various applications. Consequently, numerous researchers have developed advanced learning techniques for image detection, classification, and generation. These methods will be utilized in industrial and medical research fields.

A new classification model that incorporates a Deep Neural Network and the JOA optimization algorithm was reportedly proposed in the author's publication to categorize photos of paddy leaves with diseases [10]. The model achieved high accuracy, with 98% for one disease and 94% for another. Pre-processing steps involving hue-based HSV images and K-means clustering were used to improve accuracy, but the authors suggest that applying transformers to more pre-processed data could yield even better results. In a paper [11] the researcher developed a meta-deep learning model that combines multiple models, including CNN, VGG16, and ResNet50, to improve accuracy. The model was trained on a dataset of cotton leaves using custom CNN, VGG16, and ResNet50. The models were then merged using stacked ensemble learning to create a final model. The stacked model achieved an impressive classification accuracy of 98.53%. According to the paper [12] their proposed model extracted deep features from corn leaf images using EfficientNetB0 and DenseNet121 models and combined them to create a comprehensive feature set. Data augmentation techniques were applied for increased image diversity, resulting in a 98.56% accuracy rate. In the paper [13] a deep learning framework for tomato leaf data was developed, including convolution, max-pooling, flatten, and dense layers, as well as dropouts to prevent overfitting. Results showed that using dropouts improved accuracy, making it a recommended technique. A new method [14] for processing and annotating datasets of citrus fruit has been introduced. The method involves the use of an algorithm which rescales, sets bounding boxes, and extracts HSV images to identify different disease locations, affected areas, and the severity level of the disease present in the citrus fruit. The researchers were able to extract information such as diameter, colour features, shape, and surface area of the affected portions of the fruit from the HSV images. To classify the severity of the disease, they used a deep neural network and transfer learning method to create a multi-classification framework. The accuracy levels for low and high severity are 99% and 98%, respectively. The researchers also noted that the quality of the training model is heavily reliant on the precision of the feature labelling.

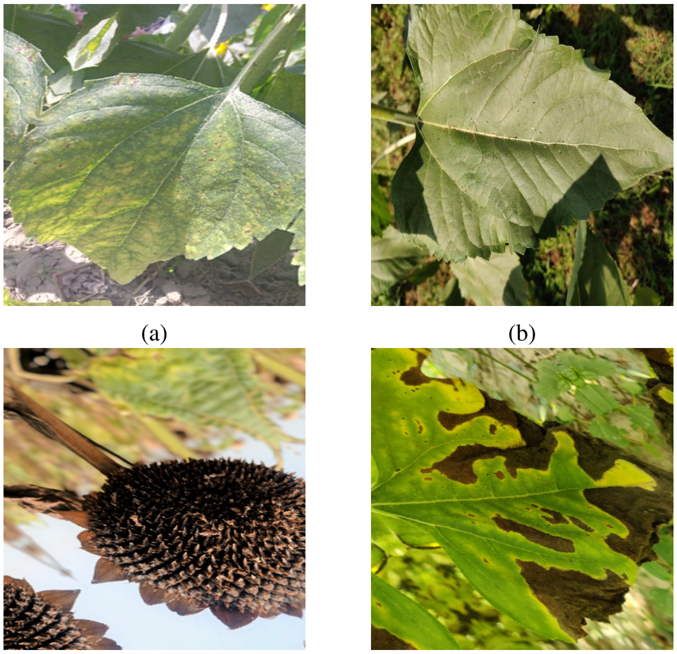
In their research [6], they utilized the RestNet152 model, which had been pre-trained on the ImageNet dataset, and then further trained on a new dataset focused on sunflowers. To prevent any classification errors, they removed the image background. Additionally, they utilized a saliency map to measure the gradient of the loss with input image pixels and converted the RGB into a greyscale image. They also identified the causes of incorrect classification by measuring occlusion sensitivity and correlating disease manifestation with highlighted image regions. Their research revealed that the model differentiated classes primarily based on colour. During their discussion, they [15] shared the outcomes of using a proposed model to classify foliar diseases in sunflowers. The model automatically segmented the leaf lesions using Faster R-CNN and Mask R-CNN. They utilized ResNet50 and ResNet152 to classify diseases based on the lesion. The results were satisfactory for diseases such as Alternaria and rust, where the lesions were well-defined. The research indicates that both the network for segmenting lesions and the network for disease classification are necessary for optimal performance. The research paper [16] presented a hybrid deep learning model that combines Vgg16 and MobileNet for classifying different sunflower diseases such as Alternaria leaf blight, Downy mildew, Phoma blight, and Verticillium wilt. The model was developed using a stacking ensemble learning process. Although the paper is relevant to our research, it requires improvement in accuracy rate.

In a research paper [17], it was found that the transformer model can work well with CNN in image classification. The authors built a deep ensemble learning system by combining CNN and vision transformer model to classify olive leaf disease. The study showed promising results indicating the effectiveness of using CNN and vision transformer models together. The model achieved high accuracy rates of around 96 %in multiclass classification and 97 %in binary classification [18].

Many studies have overlooked the various leaf diseases that affect the growth of sunflowers, which are crucial to the production of sunflower cash crops. These crops are in high demand in our country for cooking purposes, and this demand has increased due to the ongoing Ukraine-Russia conflict. Our team was inspired to create a practical system that can aid in sunflower growth research projects within our country.

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) (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

A. Dataset

We conducted a study on the classification of diseases in sunflowers using a dataset of images featuring sunflower leaves affected by various diseases. We obtained this data from Mendeley Data, a publicly available online repository. The dataset was sourced from the Bangladesh Agricultural Research Institute (BARI) in Gazipur. The data was collected in November 2021 from the farm. There are a total of 1892 augmented image data in the dataset, with 398 images of Gray mold, 509 images of Leaf scars, 470 images of Downy mildew, and 515 images of Fresh Leaves. 1. Sunflowers are susceptible to various diseases, including Gray mold, leaf scars, and downy mildew. Gray mold is a fungal disease that can create brownish-gray lesions on the plant's leaves, flowers and stems. Leaf scars are another typical symptom of sunflower rust and downy mildew, appearing as sunken, brownish-black areas on the leaves with a yellow halo. Downy mildew is also a fungal disease that can cause yellow or brown patches on the leaves, usually with a fuzzy, greyish-white growth on the underside of the leaves.

B. Image Processing

Images were captured using a digital camera [19]. Each raw picture has a consistent size of 512 x 512 pixels and is in jpg format. To prepare the data for analysis, we resized all images to 224 x 224 pixels and augmented the image data. The dataset we used contained a total of 1,892 augmented images created from the original images of healthy and disease-affected sunflower leaves and blooms. The dataset was divided into a training set (80%) and a testing set (20%).

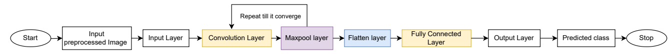


Fig. 2: CNN Architecture

C. Conceptual Background

Some of the key ideas and techniques employed in the suggested model are described in this section. **Convolutional Neural Networks(CNNs)** a type of deep learning algorithm that is commonly used for analyzing visual data. Images undergo the convolution process to extract different details and convert them into a smaller form that can be processed quickly while retaining essential information. The initial layers of a CNN are responsible for learning low-level spatial information, such as an object's borders, boundaries, or essential qualities. The deeper layers are capable of picking up on more intricate and complex information, such as object orientations and sophisticated forms. A Convolutional Neural Network (CNN) has two primary parts: feature extraction and classification. To extract features from an image and create a feature map for classification, the CNN uses multiple convolutional and activation layers, followed by a pooling layer. This process enables the network to learn low/mid/high-level traits from the picture, such as edges, patterns, and textures. A mathematical tensor with the dimensions as in can be used to represent a picture as in 2.

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

To perform the convolutional operation, we need to know the height and width sizes of the input image (n_h and n_w) as well as the number of channels (n_c). Filters are tensors with odd dimensions that are multiplied by the window they sit on during the convolutional operation, which is applied in a sliding-window manner over the input.

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

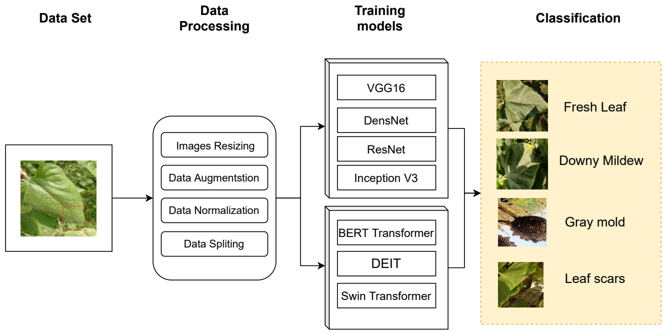


Fig. 3: System Architecture of the proposed CNN

using a mix of the horizontal flip, rotation, shearing, and zooming procedures to prevent over-fitting.

B. Training Phase

The CNN architecture used in the experiment is illustrated in 3. We trained all CNN models on Google Colab Pro Edition using Cuda version 11.2, which has 26.3 GB of GEN RAM and 16160 MB of GPU RAM. To train each model, we used a batch size of 32 and up to 50 epochs.

1) Transfer Learning Based Neural Network Models: **ResNet-152** is a widely used convolutional neural network design for image classification, including identifying diseases in sunflowers. The ResNet-152 model uses skip connections to prevent deep neural networks from experiencing performance decline due to the vanishing gradient problem. We utilized a modified version of ResNet-152 with 152 layers and made adjustments to the final levels for the classification task. Our version has a total of 58,733,060 parameters, with 401,412 being trainable and 58,331,648 being non-trainable 4.

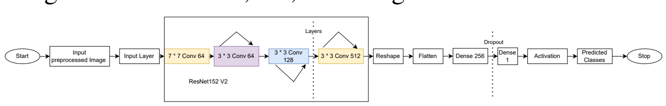


Fig. 4: Resnet Architecture

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 employed 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 is a type of Convolution Neural Network developed by Google. It has multiple levels of convolutional and pooling operations, along with fully connected layers. We made modifications to the model's final layers, flattening one dense layer and adding another to improve its classification abilities. Our modified InceptionV3 has a total of 22,007,588 parameters, with 204,804 being trainable and 21,802,784 being non-trainable. By using this method, the model can effectively categorize complex images by capturing features at different levels of abstraction and resolution. See Table 1 for the number of parameters in other models used in our study.

Densenet is a convolutional neural network that uses Dense Blocks to connect all layers directly. This maintains the feed-forward nature of the system, with each layer receiving extra inputs from earlier levels and transmitting its own feature maps to later layers. The DenseNet-121 model has 120 convolutions and four average pools. Our modified DenseNet-121 has a total of 7,238,212 parameters, with 200,708 being trainable and 7,037,504 being non-trainable. You can refer to Table 1 for the number of parameters for the different models in our study.

2) Transformer Based Models: **ViT Transformer** The Vision Transformers (ViT) 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 is a type of transformer that utilizes a shifted window scheme to create hierarchical feature maps using input image patches. These merged patches are processed through a linear embedding layer, and the Swin transformer block multiple times in each stage. This transformer features a modified self-attention, a block of multi-head self-attention, layer normalization (LN), and a two-layer MLP (multi-layer perception). With the shifted windowing scheme, self-attention computation is limited to non-overlapping local windows while still allowing for cross-window connections, resulting in significant efficiency improvements. The hierarchical architecture can model at different scales and has a linear computational complexity based on the image size, making it flexible [20].

DeiT Transformer 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. To determine the accuracy, precision, and sensitivity of a model, we use equations labelled Eq. 2, Eq. 3, and Eq. 4. These equations are based on the true positive (TP), false positive (FP), true negative (TN), and false negative (FN) samples. Recall, which is also referred to as sensitivity, measures a model's ability to identify all relevant examples within a dataset. 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 is Downy Mildew or Gray Mold or Leaf Scars or Fresh Leaf class for the classification scheme. TP is represent True Positive, FN represents False Negative and TN represents True Negative.

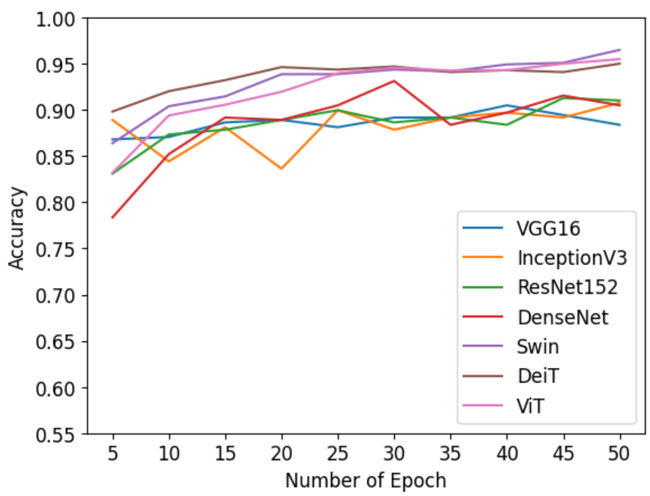


Fig. 5: Accuracy of all the models

V. Performance Evaluation

In this section, we evaluate our trained models and compare their performance with each other. We reviewed the outcomes of seven models that were developed and tested by calculating their accuracy, recall, F1 score, positive predictive value and using unknown data. The results of the seven models examined in this paper are summarized in Table I.

TABLE I: Performance Measures

Models	Accuracy	Precision	sensitivity	F1
ResNet-152	91.03%	0.89	0.92	0.88
VGG16	88.39%	0.84	0.81	0.79
InceptionV3	90.77%	0.88	0.89	0.89
Densenet	90.50%	0.92	0.90	0.91
ViT Transformer	95.50%	0.94	0.89	0.92
Swin Transformer	96.51%	0.96	0.98	0.97
DeiT Transformer	95.01%	0.93	0.96	0.94

In Fig. 5, the VGG16 model fared poorly with our dataset and provided an accuracy of 88.39%. With accuracy scores of 90.77%, 91.03%, and 90.50%, InceptionV3, ResNet, and DenseNet fared average. ViT, Deit, and Swin Transformers offered accuracy of 95.50%, 95.01%, and 96.51%, respectively. The Swin transformer, which is a model based on transformers, has been found to have superior accuracy compared to other models. With a recall of 0.98 and class image detection, the Swin Transformer offers a respectable recall. A higher recall indicates that the probability of misdiagnosing class images is lower. However, the Swin transformer model had a slightly greater recall than the other models. The statistical data in Table I shows that the Swin transformer model has the highest precision, scoring 0.96 for images in the Downy Mildew, Gray Mold, Leaf Scars, and Fresh Leaf categories. Based on the transfer-based approach, it is clear that DenseNet offers higher precision in comparison to Inception V3, VGG16, and Resnet152. For the Downy Mildew, Gray Mold, Leaf Scars, and Fresh Leaf classes, the highest F1 score is provided by the swin transformer also, and the number is 0.97. Based on the information presented, it can be concluded that the Swin transformer model is the most effective and outperforms all other models. It can be beneficial in identifying sunflower diseases. When it comes to transfer-based learning, Resnet outperforms other models in terms of accuracy. On the other hand, when using transformers-based learning, the swin transformer may be the most effective in identifying sunflower diseases due to its high level of accuracy.

VI. Conclusion

In our Sunflower Leaves classification scheme, we gathered and processed a total of 1892 augmented images. These images contained Gray Mold, Leaf Scars, Downy Mildew, and Fresh Leaves. We preprocessed the images to be used in our classification models. We extensively evaluated three natural language processing models - ViT, Swin, and Deit transformers - along with other popular deep learning models such as Custom CNN, DenseNet121, Resnet, Vgg16, and Inception v3. We displayed the performance evaluation using accuracy, F1 score, confusion matrix, specificity, precision, etc. We also compared the models and found that ResNet and InceptionV3 performed well in accuracy measurement, but the Swin transformer outperformed every other model used in this sunflower data so far, achieving around 96.5% accuracy, which is the highest in the field of Sunflower Leaves classification. Additionally, the Swin transformer took less time to generate epochs in the validation section compared to other 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

[20] M. N. Islam, M. Hasan, M. K. Hossain, M. G. R. Alam, M. Z. Uddin, and A. Soylu, “Vision transformer and explainable transfer learning models for auto detection of kidney cyst, stone and tumor from ct-radiography,” *Scientific Reports*, vol. 12, no. 1, p. 11440, Jul 2022. [Online]. Available: https://doi.org/10.1038/s41598-022-15634-4