

Towards Sustainable Agriculture: A Hybrid Deep Learning with Super Resolution for Grape Leaf Disease Detection from Low Resolution Image

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Abstract- Grapes are small, sweet, and versatile fruits that come in various colors and are not only enjoyed fresh but also used for making wine, raisins, and a variety of culinary products. A healthy grape harvest requires prompt identification of grape disease and taking appropriate measures to stop it from spreading. Accurate disease identification is now possible with the help of recent research advancements. However, these techniques yield low accuracy and perform poorly with low-resolution images. A novel framework incorporating TSRNet model based super resolution followed by DataLiteViT classification model is suggested as a solution to this problem. For scale factors of $\times 2$, $\times 4$, and $\times 6$, respectively, the utilised lightweight TSRNet model with 2.25 M parameters can reach 30.12, 28.38, and 27.57dB Peak Signal Noise Ratio (PSNR) values and Structural Similarity Index Measure (SSIM) value of 0.913, 0.841, and 0.756. The proposed DataLiteViT model achieved accuracies of 97.90%, 97.12%, and 96.69% for low resolution images with scale factors of $\times 2$, $\times 4$, and $\times 6$, respectively. Furthermore, the employed method utilizing TSRNet model for super-resolution improved DataLiteViT's classification accuracies of 99%, 98.71%, and 98.28% for LR images with scale factors of $\times 2$, $\times 4$, and $\times 6$, demonstrating an efficient and highly effective solution.

Keywords: Ai in agriculture, image super resolution, transformer, interpolation, grape leaf disease detection, accuracv parameters

I. INTRODUCTION

Indian Council for Agricultural Research (ICAR) states that India is the sixth largest producer of grapes worldwide. About 53,000 tonnes of grapes are exported from India annually, making up 1.5% of all grape exports worldwide [1]. As such, they are an important crop for expanding the nation's economy. The prompt identification of crop diseases is essential for a healthy harvest, limiting yield losses, and minimizing the necessity for pesticides[2]. Conventional disease diagnosis techniques depend on grower expertise or professional advice, which is a tedious and inefficient procedure.

Recent digitization of agricultural images [3] has significantly advanced semi-automatic [4], [5] and completely automatic [6], [7], [8] disease diagnosis in agriculture. Various deep learning models based on CNNs [9] can automatically extract key features like color, texture etc. to efficiently detect diseases. Recent research investigations show that ViT-based networks outperform CNN on categorization tasks. Unfortunately, they encounter challenges with

capturing local dependencies on limited datasets often used in agricultural domain and require extensive datasets [10] such as JFT-300M [11] to achieve optimal performance. Various attempts have been made to overcome these limitations by merging ViTs with CNNs [12], [13], [14] and adapting the self-attention process [15], [16], [17], [18], [19] to cope with medium-sized datasets like ImageNet[20]. However, their performance on smaller dataset remains a challenge. The proposed methodology addresses this issue by improving receptive fields of DataLiteViT based on a novel Displaced Patch Embedding technique.

Furthermore, despite achieving remarkable classification accuracy on high-resolution input images, the performance of the various deep learning approaches significantly declined for small target detection [21], lower resolution images [22] and environmental imaging constraints [23]. Early research in smart farming using UAVs to identify plant diseases through images [24], [25] has shown that, although increasing altitude expands field coverage, it also makes it more challenging to

identify different plant characteristics (such as lesions, etc.). Furthermore, drone propeller motion, climatic conditions, and low light levels can all contribute to image deterioration, including low resolution [26], blurring, etc. In order to resolve such issues, a pioneering technique [27] employing SR model to improve the disease detection by enhancing the features in LR images for subsequent processing. Similar approaches employing SR models have been adopted in contemporary research [27], [28] to identify diseases such as wheat yellow rust [29], potato late blight [30], [31], and tea leaf blight [26] in order to boost the predictive capacity of the model.

The primary contributions of the suggested research are:

A novel ViT-based backbone architecture termed DataLiteViT which employs Displaced Patch Embedding to enhance receptive fields and learn low range dependency in the small sized dataset and capture more spatial information to accurately detect disease.

The demonstration that the proposed integrated framework outperforms state-of-the-art methods in identifying diseases from deteriorated images.

The rest of the article is structured as follows. Section 2 presents literature survey. Section 3, explicates the proposed methodology. Details of the image dataset analyzed and outline of experimental implementation are presented in Sections 4 and 5. This is followed by evaluation & analyses of the experimental performance with state-of-the-art models in Section 6. Section 7 outlines ablation study and finally, section 8 offers conclusions and suggestions for future work.

II. RELATED WORK

In recent years, an enormous amount of research has been done on the automatic classification and high-accuracy detection of plant diseases. Due to the rapid evolution of deep learning, machine learning, and image processing methods, considerable advancements have been made demonstrating promising results for disease identification

Literature Review of SR

Single Image Super-Resolution (SISR) is a prominent topic within computer vision research with wide-ranging applications. A pioneering deep learning approach [32] for super-resolution (SR) reconstruction was developed by employing a three-layer convolutional neural network (CNN) surpassing traditional methods. Subsequent research achieved remarkable results in its representational capability, with emphasis on innovative model designs, such as dense blocks [33] and residual blocks [34], [35], [36].

In order to manage the increasing amount of parameters and processing power in such larger networks, recursive learning has been utilized to reduce the number of parameters by overlapping weights and using skip connections, as in DRCN [37]. Recursive learning methods require a lot of processing power as they perpetually employ the same set of parameters to get superior performance. Several attention mechanisms have also been integrated into the model as an alternative way to effectively improve restoration performance, as shown by RCAN [38] with channel attention and PAN [39] with pixel attention. However these networks have inherently complex architecture and a large number of trainable parameters.

Simultaneously, significant research has been done on developing lightweight CNN models to optimize the balance between complexity and performance in super-resolution (SR). Although SRCNN[32] was a pioneer in the CNN-based super-resolution method, it was computationally expensive. For instance, FSRCNN [40] improved upon the initial SRCNN model by substituting a highly efficient transposed convolution layer with smaller kernels for pre-upsampling. CARN-M and CARN [41] utilize both local and global cascading architectures to improve performance through effective parameter usage. IMDB [42] employed contrast-aware channel attention at the end of the block to highlight key channel features produced by successive filtering for efficient utilization of resources. The subsequent study, RFDN [43], enhances network performance by incorporating selective fusion [35] module and a feature extraction mechanism. These studies collectively underscore the substantial scope for

improving the balance between model complexity and performance

Literature Review of grape leaf disease detection

Numerous studies on grape leaf disease detection have examined recent developments in deep learning techniques in an attempt to improve disease detection accuracy and efficiency. A deep learning algorithm [44] based on YOLOv3 which employs spatial pyramid pooling, with super-resolution image enhancement as a preprocessing step, has detected black rot in grape leaves with 95.79% accuracy. Another approach[45] outperformed conventional techniques by creating a precise black rot spot detection method utilizing DeepLab V3+ and a ResNet 101 backbone. Dataset enhancement using deep learning approaches and CNN-based VGG architecture [46] enabled precise grape leaf disease identification, attaining an astounding accuracy of 98.40% with hyper-parameter modification.

In another method [47], utilising CNN-SVM classifier identified five grapevine leaf species attaining 97.60% classification accuracy. This was achieved by combining feature extraction from MobileNetv2's logits layer with SVM classification utilizing various kernels and Chi-squares feature selection. Additionally, the diagnosis of Grape black measles disease was investigated [48] by using fuzzy logic with a DeepLabV3+ segmentation model based on ResNet-50.

Based on extracted attributes and the number of infections linked to the measles illness, the method divides disease severity into healthy, mild, medium, and severe categories. These studies collectively underscore a clear trend toward the adoption of advanced deep learning models to enhance the accuracy and efficacy of grape disease detection methods.

III. METHODOLOGY

The novel method employs the TSRNet[49] based Super Resolution (SR) technology to enhance a low-resolution, degraded grape leaf image into a super-resolution image. Subsequently, a DataLiteViT based

classification model is utilized to identify diseases inside these improved images. This integrated TSRNet & DataLiteViT based model offers significantly superior classification performance for disease diagnosis from LR images.

Super Resolution based on TSRNet

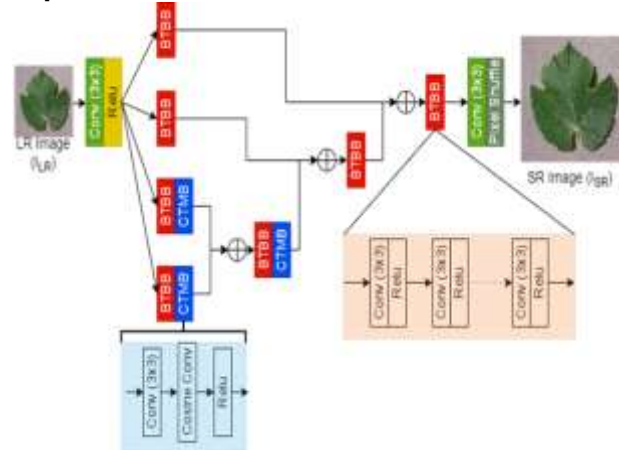


Fig. 1. Architecture of TSRNet Super Resolution method

Figure 1 shows the proposed TSRNet super-resolution (SR) architecture by integrating a tree-based backbone with cross-domain feature extraction to refine structural details.

- **Tree-Guided Backbone:** The network features four distinct branches composed of Binary Tree Branch Blocks (BTBB). These branches are fused sequentially to amplify the relationship between key nodes and recover complex textures.
- **Cosine Transform Mechanism Block (CTMB):** To prevent information loss, CTMBs use Sharpened Cosine Similarity (SCS) instead of standard dot products. This allows the model to focus on directional feature orientation rather than absolute pixel scale, improving local saliency.
- **Reconstruction:** A final Pixel-Shuffle layer transforms low-frequency features into high-resolution outputs.

By combining recursive tree fusion with frequency-domain insights, TSRNet achieves a superior balance between restoration accuracy and computational efficiency, consistently delivering high-fidelity results.

Classification of disease based on DataLiteViT

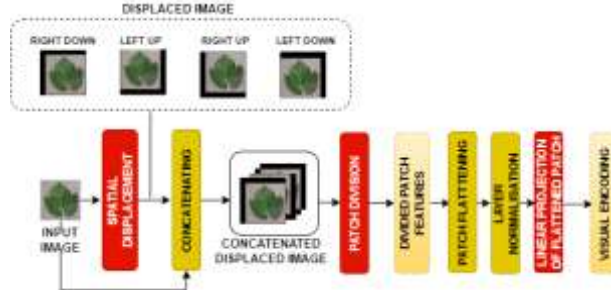


Fig. 2. Network architecture of Displaced Patch embedding mechanism

The proposed method is based on a key mechanism of Displaced Patch Embedding for improved receptive fields as depicted in figure 2. DPE leverages data augmentation by spatially displacing input image by half patch size in diagonal directions. These shifted images are then cropped to original image dimension and concatenated with the original input image. This enhances the capability of model to learn low range dependency within the data and capture more spatial information in the output embeddings. This enriched input representation is then divided into non-overlapping patches, flattened, and converted into a 1D vector series ($S(i)$) representation, as shown in equation 1:

$$S(i) = [i_p^1; i_p^2; i_p^3; \dots; i_p^N]$$

Where, i represents the input image with dimension $h \times w \times c$, i_p^j is the 1D representation of j th flattened concatenated patch features of displaced image i , & N indicates total number of patches ($N = hw/p^2$), where p is patch size

These vectors series are subsequently processed by the neural network using the layer normalisation and linear projection as shown in the equation 2.

$$E(i) = LN([v_p^1; v_p^2; v_p^3; \dots; v_p^N]) * LP$$

Where, $E(i)$ is the visual embedding output of image i , LN is the Linear normalization function and LP is the learnable linear projection used for transformation.

These encoded visual embeddings ($E(i)$) are then concatenated with class token and added to learnable positional embedding to incorporate

positional information in the Visual Encoding layer. In the absence of a class token, the input encoded vectors are augmented solely with learnable positional embeddings.

$$\begin{aligned} \text{if } v_{cls} \text{ is not null, } E_{pe} &= [v_{cls}; E(i)] + PE \\ \text{elseif } v_{cls} \text{ is null, } E_{pe} &= [E(i)] + PE \end{aligned}$$

Where, v_{cls} is the class token, PE is the positional embedding & $[E]_{pe}$ is the final output from the visual encoding layer.

These visual embeddings ($[E]_{pe}$) are subsequently processed with a Vision Transformer (ViT) [50] like-architecture comprising of few stages of various multihead attention, layer normalization, dense, dropout, add modules in order to achieve high disease detection accuracy.

IV. DATASET

In proposed methodology widely recognised open-access PlantVillage dataset [50] comprising of greater than 54,000 sample images of plant leaves was employed. This freely accessible resource has gained popularity in recent years for exploring distinct diseases affecting diverse leaf crops. This dataset encompasses images depicting both healthy and diseased leaves, categorized into 38 categories spanning across 14 different plant crop species. Furthermore, a consistent background and homogeneous illumination were ensured when taking these images in controlled lab environments. However, the dataset is also imbalanced with varying quantities of images for various disease classes. It includes 4,062 images of grape leaves exhibiting typical symptoms.

Among these images, 1,180 were identified as having Black Rot, 1,383 as having Esca measles, 1,076 as having Leaf spot, and 423 as representing healthy leaves, all with a consistent resolution of 256×256 pixels. Additionally, the ground truth and its equivalent Low-Resolution (LR) grape leaf image can be observed at different scale factors ($\times 2$, $\times 4$, and $\times 6$) in Figure 3.

Table 1. PlantVillage grape leaf description

Type of leaf	No of scans
Black Rot	1180
Esca measles	1383
Leaf spot	1076
Healthy leaves	423
Total grape leaf images	4062



Fig. 3. Grape leaf images for scale factor $\times 2$, $\times 4$, and $\times 6$

V. EXPERIMENTATION

High resolution images(IHR), or the ground truth, are downsampled by a variety of scale factors to produce LR images (ILR), which are subsequently utilized as input by the super resolution model named TSRNet. Next, using a classification model termed DataLiteViT, on these enhanced SR pictures, the disease is identified as depicted in Figure 4.

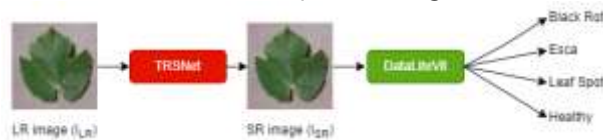


Fig. 4. Suggested approach implementing TSRNet with DataLiteViT for precise disease detection

The proposed methodology involves allocating 10% of dataset for testing, 20% for validation, and the remaining 70% for training the model. To assess the quality of the generated SR images, the loss function employed is MSE (Mean Square Error), and effectiveness of super resolution technique is measured using metrics such as SSIM (Structural Similarity Index) and PSNR (Peak Signal to Noise Ratio). Figure 5 visualizes the performance of TSRNet model and the integrated TSRNet–DataLiteViT framework by plotting training and validation curves across epochs.

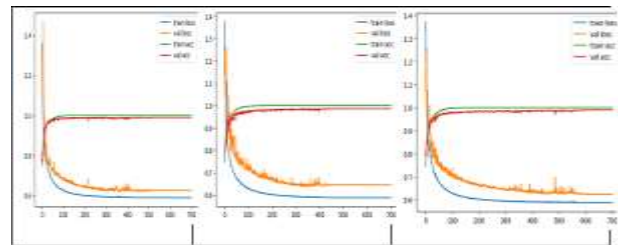


Fig. 5 Loss and accuracy curve for x2, x4, and x6 for DataLiteViT

VI. RESULTS

In this assessment, a thorough analysis is employed and the results are presented using both qualitative and quantitative methods. To effectively assess the quantitative performance of the model, a comparative analysis is conducted using two key metrics: PSNR (Peak Signal-to-Noise Ratio) and SSIM (Structural Similarity Index) as shown in Table 2.

Table 2. Comparison table (PSNR/SSIM) for various models

Model	No. of parameters (in Millions)	$\times 2$ input size (PSNR/ SSIM)	$\times 4$ input size (PSNR/ SSIM)	$\times 6$ input size (PSNR/ SSIM)
TSRNet (2022)	2.25	30.12/0.9134	28.38/0.8416	27.89/0.756
EWSCNN(2023)[51]	0.15	30.1785/0.9042	28.446/0.8474	27.158/0.7315
SRResCGAN (2020) [52]	1.16	29.2416/0.8913	28.695/0.8346	27.0761/0.7541
DBPN(2018) [53]	4.97	29.1849/0.8826	28.328/0.8309	26.5835/0.7227
CARN(2018) [41]	1.6	28.802/0.8927	27.006/0.8230	25.2061/0.7369
SRCNN(2014) [32]	0.057	26.8513/0.8231	25.151/0.7607	23.7014/0.7021

Table 3. Comparison of classification accuracy for various scale factors

Model	No. of parameters (in Million)	Classification Accuracy in % for scale factor $\times 2$	Classification Accuracy in % for scale factor $\times 4$	Classification Accuracy in % for scale factor $\times 6$
DataLiteViT	7.1	97.90	97.12	96.69
DLVTNet(2025)[54]	1.05	96.83	94.12	91.24
MobileNetv4(2024) [55]	9.2	96.83	94.85	92.28
Eanet(2022) [56]	6.1	96.98	94.36	93.01
Gmlp(2021) [57]	19	97.29	96.57	93.63
ViT (2020) [58]	86	94.71	94.74	93.93
VGG16(2015) [59]	14	95.54	90.99	89.28

Table 3 provides a comprehensive assessment of the classification accuracy, offering a detailed comparison between the proposed DataLiteViT classification model and other state-of-the-art (SOTA) models. As observed in Table 4, the recommended approach employing TSRNet with only 2.25M additional parameters, consistently improved DataLiteViT's accuracy by more than 1% across a range of scale factors.

Table 4: Performance improvement of the proposed DataLiteViT model by using the SR images (ISR) from TSRNet as input for various scale factors

Model	No. of parameters (in Million)	Classification Accuracy in % for scale factor $\times 2$	Classification Accuracy in % for scale factor $\times 4$	Classification Accuracy in % for scale factor $\times 6$
Proposed methodology	9.35	99	98.71	98.28
DataLiteViT	7.1	97.90	97.12	96.69

Table 5 reveals a comprehensive analysis where multiple performance evaluation metrics are employed to assess the effectiveness of various classification models specifically for a scale factor of 2. These metrics encompass a range of statistical measures, including specificity, F1 score, recall, accuracy, Matthews Correlation Coefficient (MCC) and precision [60].

Table 5: Performance comparison of the various classification models

Model	Accuracy (%)	Specificity	Recall	Precision	F1score	MCC
Proposed methodology	99	0.9990	0.9854	0.9879	0.9866	0.987
DataLiteViT	97.90	0.9960	0.9511	0.9700	0.9590	0.963
DLVTNet(2025) [54]	96.83	0.9914	0.9382	0.9476	0.9424	0.947
MobileNetv4(2024) [55]	96.83	0.9928	0.9444	0.9549	0.9484	0.952
Eanet(2022) [56]	96.98	0.9921	0.9556	0.9649	0.9597	0.959
Gmlp(2021) [57]	97.29	0.9942	0.9557	0.9645	0.9593	0.959
ViT (2020) [58]	94.71	0.9891	0.9225	0.9327	0.9252	0.930
VGG16(2015) [59]	95.54	0.9918	0.9308	0.9406	0.934	0.913

It is clearly evident that the recommended approach employing TSRNet substantially improved the DataLiteViT model's disease detection competence. As indicated in Table 4 the DataLiteViT model managed to identify disease on LR images($\times 2$) with 97.90% accuracy. However with the introduction of TSRNet, the accuracy increased to 99%. This demonstrates an approximately one percent improvement in classification performance with an evident increase in all key metrics like recall, F1 score etc. This implies that the suggested approach not only raised overall accuracy but also preserved an excellent balance between precision and recall.

Figure 6 illustrates the corresponding confusion matrix, which offers a graphical depiction of how the model correctly and incorrectly classifies data, aiding in a more intuitive understanding of the model's classification outcomes. This combined use of above mentioned quantitative metrics and visual representation enhances the depth of evaluation, making it more comprehensive and informative.

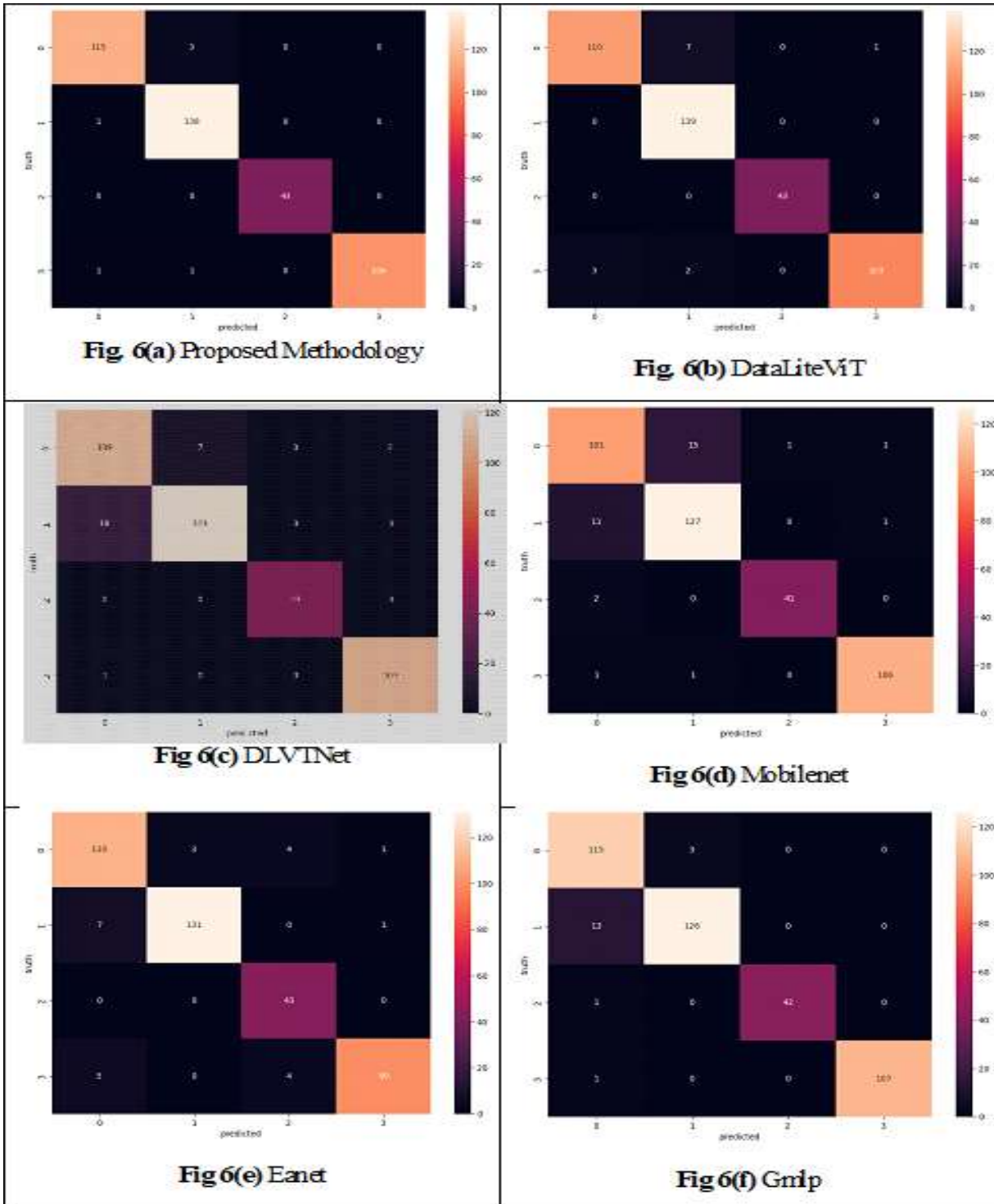


Fig.6 (a-h). Confusion matrix of the proposed methodology and various state-of-the-art models for classification of the grape plant leaf for $\times 2$ low-resolution images.

VII. ABLATION STUDY

Table 6 Ablation experiment results for ILR ($\times 2$)

TSRNet	DPE	ViT backbone	Accuracy (%)	Specificity	Recall	Precision	F1score	MCC
✓	✓	✓	99	0.9990	0.9854	0.9879	0.9866	0.987
✓		✓	98.28	0.9894	0.9632	0.9680	0.9716	0.956
	✓	✓	97.90	0.9960	0.9511	0.9700	0.9590	0.963
		✓	97.06	0.9896	0.9732	0.9724	0.9727	0.954

Ablation study verified that the disease detection efficiency of ViT backbone was considerably enhanced by employing the proposed TSRNet and DPE modules. The quantitative results shown in Table 6 & 7 demonstrate the progressive performance increase achieved through the sequential integration of these components and also confirm their complimentary contributions to the overall architecture. The model represents the regular ViT architecture when the ViT backbone is exclusively used for classification.

Table 7 Ablation experiment results across various scale factors

TSRNet	DPE	ViT backbone	Classification Accuracy in % for scale factor $\times 2$	Classification Accuracy in % for scale factor $\times 4$	Classification Accuracy in % for scale factor $\times 6$
✓	✓	✓	99	98.71	98.28
✓		✓	98.28	98.53	97.30
	✓	✓	97.90	97.92	96.69
		✓	97.06	97.55	96.32

Influence of DPE on model's efficiency

Table 7 describes that the ability to identify objects of the ViT model increased by 0.5% across various scale factors, when DPE was used in place of the original patch partitioning approach, demonstrating that DPE successfully improves recognition performance. Additional investigation reveals that increasing the patch size in DPE from 8 to 16 and 32, gradually increases the accuracy. Patches with smaller sizes result in more patches, splitting features that ought to be processed together and jeopardize feature integrity. On the other hand, larger patches retain more comprehensive attributes, which improves identification accuracy. The DPE method in the DataLiteViT outperformed

the standard patch partitioning method when used for feature extraction.

Influence of TSRNet on model's efficiency

Table 7 demonstrates that the accuracy of DataLiteViT and the standard ViT for grape leaf images improved significantly, when TSRNet was deployed to assess classification performance on ISR across various scaling factors.

Assessment of generalisation performance

The pre-trained model's generalization ability outside of its training distribution on the PlantVillage dataset was tested using 100 grape leaf images from each of the four classes from the Grape400 dataset independently.

Grape400 dataset

Table 8 Comparison of classification accuracy for various scale factors

Model	Classification Accuracy in % for scale factor $\times 2$	Classification Accuracy in % for scale factor $\times 4$	Classification Accuracy in % for scale factor $\times 6$
Proposed methodology	99.62	99.50	99.02
DataLiteViT	98.50	98.62	98.35

Table 9 Performance comparison for scale factor of $\times 2$

Model	Accuracy (%)	Specificity	Recall	Precision	F1score	MCC
Proposed methodology	99.62	0.9983	0.9900	0.9950	0.9925	0.991
DataLiteViT	98.50	0.9908	0.9675	0.9724	0.9702	0.961

The dataset [61] of 1,600 RGB images of grape plant leaves have been separated into four classes: Healthy-leaf, Black-rot, Leaf-blight, and Black-measles. There are 400 images dedicated to each class. Table 8 and 9 compares the proposed DataLiteViT classification models on ILR and ISR across various scale factors on Grape400 dataset.

parameters by utilizing SR images (ISR) as input. As a result, the classification process outperforms existing state-of-the-art (SOTA) models, yielding classification accuracies of 99.3%, 98.71% and 98.28% for scale factors of $\times 2$, $\times 4$, and $\times 6$, respectively.

VIII. DISCUSSION

The proposed DataLiteViT model outperforms existing state-of-the-art (SOTA) models achieving accuracies of 97.90, 97.12, and 96.69 for scale factors of $\times 2$, $\times 4$, and $\times 6$, respectively. The TSRNet model demonstrates impressive performance, achieving PSNR values of 30.12 dB, 28.38 dB, and 27.57dB, along with SSIM values of 0.913, 0.841, and 0.756 for scale factors of $\times 2$, $\times 4$, and $\times 6$, respectively. This enhancement provided the DataLiteViT classification model with more detailed and reliable information, enabling it to produce more accurate predictions. The results demonstrate that the recommended approach employing TSRNet super-resolution with DataLiteViT classification method significantly improves overall classification performance by successfully overcoming the drawbacks of low-resolution images. DataLiteViT's accuracy progressively increased by over 1% across a variety of scale factors with just 2.25M additional

IX. CONCLUSION

The novel methodology presented here demonstrates its effectiveness in resolving a problem that is frequently encountered in prevalent technique by precise detection of illnesses from low-resolution images. It utilizes an innovative TSRNet-based super-resolution (SR) approach to generate enhanced resolution (ISR) images from low-resolution (ILR) images with different scaling factors, specifically $\times 2$, $\times 4$, and $\times 6$. These SR images (ISR) are subsequently employed for disease detection through classification.

The study can easily be extended to encompass various other crop disease detection at different stages. Hence, it is imperative for fostering sustainable ecological development. Subsequent research endeavors can focus on the acquisition of images under varying environmental conditions and the inclusion of a broader range of leaf disease categories to enhance the accuracy of disease

detection in real-world scenarios. Future research work should focus on the development of automated drones capable of swiftly assessing field conditions, thereby empowering farmers and mitigating agricultural losses.

Conflicts of Interest: The authors certify that they have NO Conflicts of Interest. Data Availability Statement: No external dataset is created and the dataset used in this research is available online for research purposes.

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