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CERTIFICATE

This is to certify that Dr. / Mr. / Ms. **G. Prasanna Kumar** has presented paper titled *Plant Leaf Classification through Deep Feature Fusion with Bidirectional Long Short-Term Memory* in the Third International Conference on Innovation in Science and Technology for Sustainable Development organized by the Department of Electrical and Electronics Engineering and Department of Electronics and Communication Engineering, College of Engineering, Perumon, sponsored by TEQIP-II and technically co-sponsored by IEEE Kerala section on 25, 26 August 2022.

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Plant Leaf Classification through Deep Feature Fusion with Bidirectional Long Short-Term Memory

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***Abstract*-Manual plant species classification requires more time, effort, and professional knowledge and also, and they are very costly. At present days, researchers utilized deep learning techniques for the classification of plants over plant images. The deep learning models attain great success, and then, the lack of interpretability set a limit on their application. To overcome these limitations, they utilized measurable, interpretable, and computer-aided features from plant leaf images. Image processing became very complex and crucial at the time of feature extraction. There are nearly 391,000 vascular plant species present in the world widely. So, the classification and identification of plants became complex and impractical for professionals. Most of the plant species have huge similarities and it consumes a huge amount of time for classification. So, it is essential to develop a computerized system for the identification and classification of plants. A great advancement is widely developed in science and technology for the recognition and classification of plant species in biological fields. Thus, the automatic plant leaf detection models are utilized to help professionals and botanists to classify plant species rapidly. This work proposes a novel automatic plant leaf image classification method through a deep learning algorithm. At first, the input images are gathered from the standard dataset, where the deep features from the gathered images are extracted using Resnet and VGG16. The extracted features are fused and fed to the classification stage. The plant leaf image classifications are done through the Bidirectional Long Short-Term Memory (Bi-LSTM). The empirical outcomes of the developed model have achieved better performance regarding precision and accuracy.**

Keywords-Plant Leaf Classification; VGG16; Resnet; Bidirectional Long Short-Term Memory; Artificial Intelligence;

I. INTRODUCTION

A plant variety is generally scattered in the natural environment, presented in the ecosystem material cycle, and also acts as an essential role in the production of Earth's ecosystem. In recent times people can realize climate change very clearly [6]. Day by day, the existing natural environment is demolished by humans for the enlargement of cities and buildings, and it leads to heavy loss in plant and species numbers. So, it is essential to protect plant biodiversity, but the restoration of plant species needs artificial classification to classify the species [7]. The identification of traditional plant species by normal individual become a complex task, even professionals also get confused at the time of classifying similar plant species. Normally, all plants can be classified by processing the plant leaf image over the semi-supervised model in expert systems, but this method requires a huge amount of time to analyze [8][9].

In enhanced image technology, computer technology is utilized for the automatic classification of leaf features [10]. Various types of research are performed over the field, the features of the leaves are acquired manually, and they are classified by shape difference present in leaf edges. Different technologies developed for leaf vein texture and feature detection are "Sparse Representation (SR) and Singular Value Decomposition (SVD)", which are infused to provide minimized plant leaf image, the moment the invariant model is utilized to attain multiple shapes, and "Artificial Neural Network (ANN) along with Support Vector Machine (SVM)" to attain successful extent [11]. Generally, plant leaves are presented in the form two-dimensional in nature, and so it is essential to provide automatic identification in a plant leaf by utilizing image processing approaches.

Recently, deep learning as well as CNN has provided suitable solutions for computer-based vision issues in plant classification. The issues that occurred in the manual processing and feature selection process enhanced the multiscale and advanced features to minimize workload and complexity. The performance rate of deep CNN is comparatively high in the computer vision field and stays a lead role to resolve the issues presented in image recognition, semantic segmentation, and image classification [12]. The deep learning application in plant leaf recognition has attained an effective performance rate and their comprehensive rate is superior to other manual feature extraction models and they offer a very good performance rate in generalization [13]. Deep learning neglects the usage of hard-core and domain expertise feature extraction, and it can be only provided by botanist's experts. Yet, various disadvantages are presented in deep learning, the assumption for high classification accuracy in the network has only enough amount of supervised learning samples, which is more complex to use [14]. So, new samples are initiated, and the individuals can provide an accurate conclusion by contrasting the sample over measurements. The measurement model is developed by utilizing the training

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network to learn from tiny samples and applied in automatic plant leaf classification [15]. The above-mention works mainly based on single classifiers and so it didn't provide better-classified outcomes. Thus, multiple classifiers are designed based on deep learning features.

The main objectives of this work are depicted here.

- To develop a plant leaf classification model by using deep learning techniques for the identification of respective plant leaves.
- To identify different plant species as the outcome with the concatenated features using the Bi-LSTM classifier.
- To validate the developed plant leaf classification model using comparative analysis with different classifiers.

The residual of these sections is depicted here. Part II explains various related works based on plant leaf classification. Part III elaborates on the developed plant leaf classification model using deep learning. Part IV describes the Bi-LSTM implementation. Part V discusses the result and part VI concludes the work.

II. Literature Survey

A. Related Works

In 2020, Tan *et al.* [1] have advanced a CNN-aided method D-leaf. The collected leaf images were pre-processed, and their characteristics were acquired by utilizing three multiple CNN models such as fine-tuned AlexNet, D-leaf, and pre-trained AlexNet. The acquired features were classified with the help of five different machine learning techniques like Naïve-Bayes (NB), k-Nearest-Neighbor (k-NN), Artificial Neural Network (ANN), CNN, and SVM". A conventional morphometric model was utilized to validate the morphological measurement based on Sobel segmented vines for standard intention. The developed D-leaf model attained a comparatively high accuracy rate than fine-tuned AlexNet and AlexNet models. In 2021, Kanda *et al.* [2] have presented three different technologies to attain a high accuracy rate in plant classification. A Conditional Generative Adversarial Network (CGAN) was utilized to produce synthetic data, and CNN was employed to perform feature extraction. The acquired rich extracted features were provided to Logistic Regression (LR) classifier to attain effective classification in plant species. The outcomes of the developed model over the LR classifier as well as deep learning have efficiently classified the plants based on their leaves with a high accuracy rate.

In 2019, B. Wang and D. Wang [3] have initiated a few-shot learning model related to Siamese network structure to resolve the classification issues presented in plant leaves with a small number of samples. Initially, two various image characteristics were acquired by parallel two ways CNN model overweight sharing. The loss function was used to study the metric space because all the leaf samples were different. The spatial Structure Optimizer (SSO) model was utilized to improve the accuracy rate in leaf classification. The attained average accuracy rate was utilized in different measures and the developed model attained a high classification rate with small samples. In 2020, Su *et al.* [4] have suggested multi-scale representations such as Triangle Vertex Angle representation (TVA), Triangle Unsigned Area representation (TUA), and new representations on a triangle like Gray Average (TGA), Side Length Integral (TSLI) and Gray Standard Deviation (TGSD). The multiscale leaf features were attained by contour curvature features, shape area features, and textural features. The new adaptive KNN was utilized for optimization to enhance the retrieval rate in the leaf dataset. Various validation over the proposed model achieved a high accuracy rate in Swedish and Flavia plant leaf datasets.

In 2021, Tavakoli *et al.* [5] have recommended a discriminative model based on CNN to recognize 12 various cultivars in beans. The advanced loss functions like "Large Margin Cosine Loss (LMCL) and Additive Angular Margin Loss (AAML)" were utilized by neglecting the standard softmax loss function to perform classification to achieve high discrimination rates in different classes. Validation was performed over level 1 (spices classification), level 2 (cultivators from the same species), and level 3 (cultivators from different species). The maximum mean classification accuracy rate was achieved in all three stages.

B. Problem statement

With a huge amount of plant species and leaves presented worldwide, it became a complex task for expects to classify leaves according to their variety. Most of the plant leaf looks similar to each other and need a huge amount of time to classify the plant variety. The present state of the art and gap in the literature are discussed below.

- Ensemble learning [1] has high robustness and also provides deep information about the image. But it requires more pre-processing techniques to extract the features. In this present work, the pre-processing is done using improved deep learning strategies.
- CGAN and CNN [2] utilized rich data to provide an effective classification rate. Still, it didn't have an adequate amount of training data to resolve the issues. In the present work, the data are split into training and testing phase which is utilized to resolve the various issues.
- KNN [3] utilized the loss function to analyze the metric space and it use a very small sample set to resolve the classification issues. Yet, it has very less generalization efficiency and the performance rate is decreased gradually. In this present work, the experimental results are revealed that the suggested method attains more advanced performance.
- Adaptive KNN [4] effectively enhances the retrieval rate in the dataset. However, it took a huge amount of time to classify the leaf. In this present work, the empirical outcomes yield maximum classification accuracy which improves

the system performance and the computation time is low.

- CNN [5] classification rate is enhanced by utilizing the discriminative loss function. At the same time, it becomes very complex when the inter-class variability is low. In this present work, the simulation findings confirmed the better inter-class variability.

The above challenges are considered and motivated to develop a new plant leaf classification method regarding the deep learning mechanism.

III. Development of Novel Plant Leaf Classification Using Deep Structured Architectures

A. Proposed Methodology

Leaves are widely utilized for the recognition of plant species because of their presence throughout the year, especially, in the tropical region. Most of the helpful characteristics like color, texture, venation pattern, and shape are attained from a single leaf. Automatic leaf identification technology performs classification as well as retrieval in leaf images, but most researchers are fascinated to acquire multi-scale contour characters from leaf images. These researchers trusted that counter characteristics can explain local information as well as the overall layout of the leaf world widely. At the same time, a different set of researchers are fascinated by shape area characteristics, which are validated in the form of shapes fitted by contour points in plant leaf images and consider the parameters like area, eccentricity, aspect ratio, and centroid. Leaf recognition, as well as retrieval technology related to texture characters, acquire a different set of features such as “Gabor characters, local binary patterns and gray-level co-occurrence matrix” of leaf image. The above-listed method is related to the characteristics of leaf shape, leaf textural features, or leaf contour features, and they provide high preference in leaf classification as well as in leaf retrieval. In present days, integrating the above three features provide efficient leaf classification and retrieval rate, and so it is considered a very effective method and attained high accuracy rate by utilizing ELM classifier. The traditional artificial plant leaf recognition model needs operators to attain several professional knowledge as well as to identify the plant variety. But, this type of traditional plant identification model attained several issues like low work efficiency, and heavy workload, and the operators are easily affected by those factors. To overcome all those issues, it is essential to suggest a novel classification method with deep learning which is given in Fig 1.

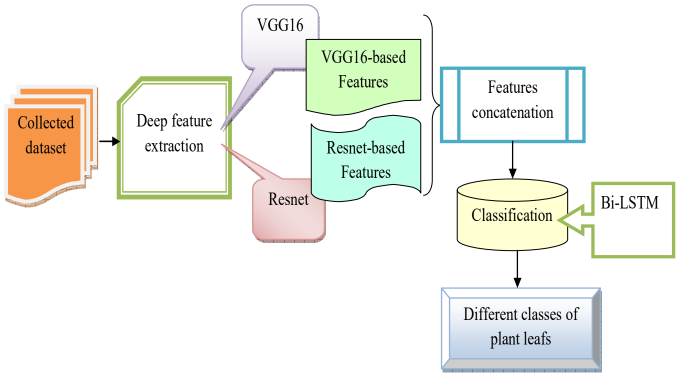


Fig. 1. A new plant leaf classification architecture based on deep learning

A novel plant leaf classification method is initiated with the help of the features of deep learning. Different plant leaf-related dataset is collected from standard sources. The acquired dataset is subjected to the deep feature extraction stage. Here, deep features are collected with the VGG16 and Resnet. Further, the acquired VGG16 features, as well as Resnet features, are provided to the feature concatenation phase for attaining concatenated features. Then, the concatenated features are provided to the classification stage, where the features are classified with the help of Bi-LSTM. Thus, the developed model classifies different classes of plant leaves.

B. Datasets and Sample Images

The suggested plant leaf classification model gathered two various datasets from benchmark resources.

Dataset 1: Different types of leaf images are acquired from the dataset named Mendeley data, and the data are acquired from “https://data.mendeley.com/datasets/hb74ynkjcn/1: access date 2022-06-13”. For the analysis process, twelve different plant leaf images are utilized, and also their advantages are validated in terms of economic and ecological factors. The acquired leaf images from dataset 1 are presented in Fig.2.

Fig. 2. Sample images of different plant leave from dataset 1

Dataset 2: Here, images are acquired from the dataset named “Swedish Leaf Dataset” and images are acquired from the dataset link "http://www.cvl.isy.liu.se/en/research/datasets/swedish-leaf/: access date: 2022-06-14". The dataset holds 15 types of species and 75 pictures of all varieties. The dataset is mainly utilized to estimate the shape matching algorithm, and also the leaves are aligned manually with the help of small rotation. This dataset contains a huge number of distinct characteristics. The image sample attained from dataset 2 is shown in Fig.3. The collected plant leaf images are given Ig_v^{inp} and they are integrated into the deep feature extraction stage. Here, $v = 1,2,\ldots,V$ and V indicated the acquired image for plant leaf classification.

Fig. 3. Sample images of different plant leave from dataset 2

IV. Implementing BiLSTM with Deep Features for Enhanced Plant Leaf Classification

A. VGG16 and Resnet-based Deep Feature Extraction

The collected leaf image Ig_v^{inp} provided as the input to the deep feature extraction phase using VGG16 and ResNet.

VGG16 [16] is a network trained by utilizing imageNet database. The VGG16 network has the efficiency to train the large-scale network, thus it provides an efficient accuracy rate when a tiny quantity of image datasets is provided. This VGG16 network model consists of a small receptive field in the size of 3×3 as well as 16 conventional layers. The VGG16 network attain the max pooling layer in 2×2 size and occurred with five max pooling layers. The attained layers are followed up with three fully connected layers and also utilized a classifier named softmax in the final layer. The acquired features from the VGG16 are termed as Ds_q^{vgg}.

ResNet [18] is the most widely used deep learning structure with different modification numbers in each layer like 101, 50, 150, etc. Different analysis on ResNet is performed over residual representation of the structure. Here, the network collects the outcomes of prior layers and provides them as the input to the current layer without any modification. Some of the features of Resnet are recognition and localization, which starts to split the images into the tiny portion to perform segmentation in the leaf for further observation. Resnet is the combination of two blocks like a conventional block and an identification block. A set of residual structures has the efficiency to enlarge the building block to initiate the network. The residual layers are classified into "conventional layer, batch normalization layer, and pooling layer" and their unit is presented in Eq. (1) and Eq. (2).

$$S_v = z\left(Ig_v^{inp}\right) + f\left(Ig_v^{inp}, m_v\right) \tag{1}$$

$$H_{v+1} = f\left(S_v\right) \tag{2}$$

Here network input is denoted by Ig_v^{inp}, the function of residual in v^{th} the unit is indicated by f and finally, the outcome of v^{th} the unit is presented as H_{v+1}. The network Identity mapping is given in Eq. (3).

$$z\left(H_v\right) = H_v \tag{3}$$

The identity mapping of ReLu is represented by $z\left(H_v\right)$. To design a Resnet network, the entire parameterized layer is used with recurrent connection and they performed as a rest block in relocating learning. The acquired attributes from Resnet are denoted by Ds_p^{rsnt} and given to the concatenation stage.

The attained features from VGG16 Ds_q^{vgg} and Resnet Ds_p^{rsnt} are then subjected to the concatenation stage and attained the concatenated features, it is represented by Ds_r^{Cff} respectively. The concatenated features are provided in the classification phase.

B. Bi-LSTM-based Plant Leaf Classification

The concatenated features Ds_r^{Cff} are provided as the input for classification. Bi-LSTM [17] is obtained from a network called Bidirectional RNN (BRNN). The sequences of input data get processed in reverse as well as forward directions by installing hidden layers in two different types. The major goal of Bi-LSTM is to integrate a whole number of suitable hidden layers in the resultant layer. The established RNN can utilize only the prior context presented in the input data sequence. Thus, the Bi-LSTM affixes the issues by assigning multiple types of data in both backward direction and forward direction. The term $\vec{b}$ denotes the onward hidden layer and $\overleftarrow{b}$ denotes the rearward hidden layers. The output layer is represented as N that starts to replicate the onward layer from $b = 1$ to X. The rearward hidden layer travels from $b = X$ to 1. In the end, the outcome was improved by Eq. (4), Eq. (5), and Eq. (6).

$$\vec{b}_x = W(E_{n\vec{b}}F_x + E_{\vec{b}\vec{b}}\vec{b}_x + 1 + g_{\vec{b}}) \tag{4}$$

$$\overleftarrow{b}_x = W(E_{n\overleftarrow{b}}F_x + E_{\overleftarrow{b}\overleftarrow{b}}\overleftarrow{b}_x + 1 + g_{\overleftarrow{b}}) \tag{5}$$

$$V_x = E_{\bar{b}t}\vec{b}_x + E_{\bar{b}t}\vec{b} + g_t \quad (6)$$

The term V_x indicates the outcome matrix and it is achieved by utilizing Eq. (7).

$$V_x = \sigma(\vec{b}_x, \bar{b}_x) \quad (7)$$

The output series attained from several suitable neurons in the hidden layer is indicated by σ and it holds four functions summation, multiplication, concatenation, and averaging. The outcomes attained from Bi-LSTM are referred to as different classes of a plant leaf. The structural view of Bi-LSTM is shown in Fig.4.

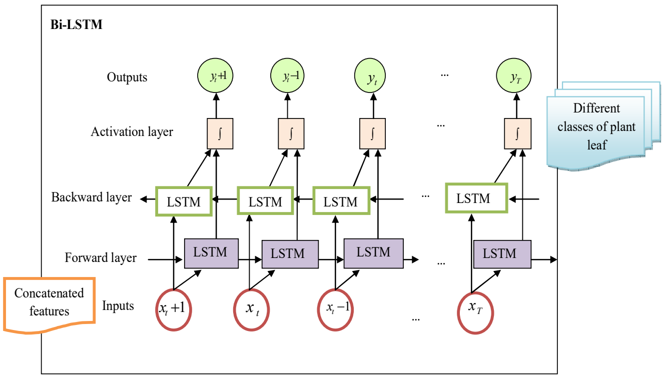


Fig. 4. Structural view of Bi-LSTM-based plant leaf classification

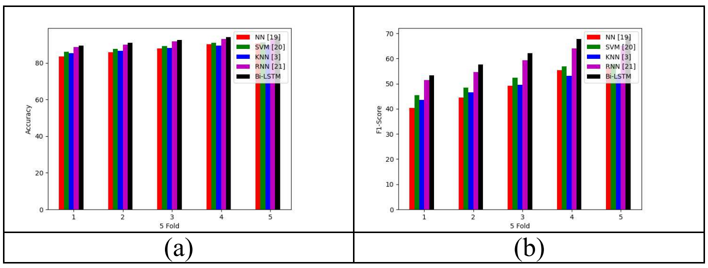
V. RESULTS

A. *Simulation setup*

The experimental analyses on the developed plant leaf classification were executed in python, and also the efficacy of the classification method was computed over multiple baseline approaches. Different comparative classifiers utilized for the analyses were "Neural Network (NN) [19], SVM [20], KNN [3], and Recurrent Neural Network (RNN) [21]".

B. *Evaluation of 5-fold on developed method over various classifiers*

Evaluation of 5-fold performed over developed Bi-LSTM-based plant leaf classification method with multiple classifiers are shown in Fig.5. The enhanced plant leaf classification model with recommended Bi-LSTM has attained the accuracy rate 10.34% higher than NN, 7.86% better than SVM, 9.09% progressed than KNN and 3.32% above than RNN. Thus, the developed Bi-LSTM has a good efficiency in classifying the respective plant leaf.



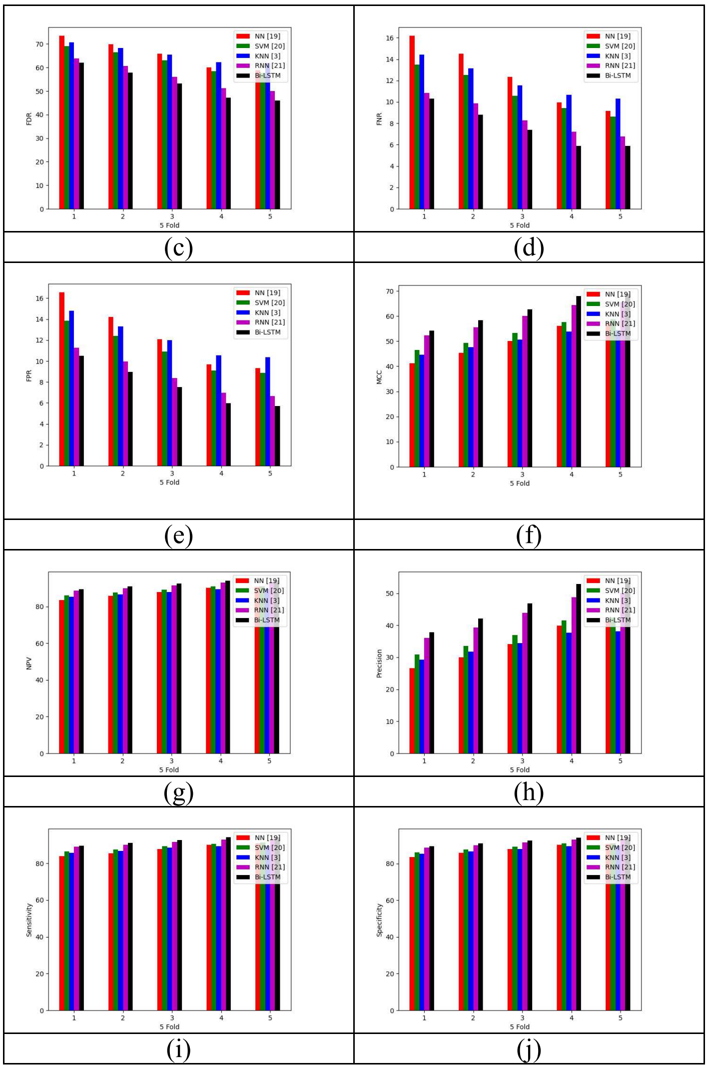


Fig. 5. Evaluation of designed plant leaf classification model over "(a) accuracy, (b) F1-score and (c) FDR, (d) FNR, (e) FPR, (f) MCC, (g)NPV, (h) precision, (i) sensitivity and (j) specificity ".

C. *Estimation of the developed model*

The computation of the developed plant leaf classification method over Bi-LSTM is weighted with diverse classifiers presented in Table I. The accuracy rate of the plant leaf classification model with the proposed Bi-LSTM has secured 3.9%, 3.4%, 5.1%, and 0.9% higher than NN, SVM, KNN, and RNN, respectively. Hence, the designed method has attained better plant leaf classification ability.

TABLE I. ESTIMATION OF SUGGESTED PLANT LEAF CLASSIFICATION METHOD WITH DIVERSE CLASSIFIER

Measures	NN [19]	SVM [20]	KNN [3]	RNN [21]	BI-LSTM
"Accuracy"	0.907	0.911	0.896	0.933	0.942
"Sensitivity"	0.908	0.913	0.896	0.932	0.941
"Specificity"	0.906	0.911	0.896	0.933	0.942
"Precision"	0.410	0.423	0.381	0.500	0.540
"FPR"	0.093	0.088	0.103	0.066	0.057
"FNR"	0.091	0.086	0.103	0.067	0.058
"NPV"	0.906	0.911	0.894	0.933	0.942

“FDR”	0.589	0.576	0.618	0.499	0.459
“F1-score”	0.565	0.578	0.535	0.651	0.686
“MCC”	0.573	0.586	0.544	0.654	0.688

VI. Conclusion

A new plant leaf classification method was designed to give efficient classification outcomes for plant researchers. Different standard images were collected and provided for deep feature extraction from VGG16 and Resnet and, further concatenation was performed with extracted features. Later, the attained concatenated features were provided for classification, and the developed Bi-LSTM to provide a better classification rate. Finally, the plant leaf classification was performed using Bi-LSTM. The developed plant leaf classification model with recommended Bi-LSTM has attained an accuracy rate of 10.34% higher than NN, 7.86% better than SVM, 9.09% greater than KNN, and 3.32% better than RNN. Hence, the designed plant leaf classification model achieved more advanced performance. The limitations of this work are depicted here. Here, the training of a leaf classifier using deep learning strategies wants a more number of samples for supervised training. Moreover, dealing with difficult features and multi-scale features radically enlarged the difficulty and workload, which generates a generalizability problem. In the future, try to improve the generalization ability of the designed method and also add more standard data to improve the efficiency of the suggested method.

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