Deep Feature Extraction and Classification of Diabetic Retinopathy Images using a Hybrid Approach

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ABSTRACT

Hybrid approaches have improved sensitivity, accuracy, and specificity in Diabetic Retinopathy (DR) classification. Deep feature sets provide a more holistic analysis of the retinal images, resulting in better detection of premature signs of DR. Hybrid strategies for classifying DR images combine the strengths of extracted deep features using pre-trained networks and Machine Learning (ML)-based classifiers to improve classification accuracy, robustness, and efficiency. Perfect pre-trained networks VGG19, ResNet101, and Shuffle Net were considered in this work. The networks were trained using a transfer learning approach, the pre-trained networks were chosen according to their classification accuracy in conjunction with the Softmax layer. Enhanced characteristics were extracted from the pre-trained networks' last layer and were fed to the machine learning-based classifier. The feature reduction and selection methods are essential for accomplishing the desired classification accuracy. ML-based kNN classifier was used to classify DR and a PCA-based feature reduction approach was utilized to obtain optimized deep feature sets. The extensive experiments revealed that ResNet101-based deep feature extraction and the kNN classifier delivered enhanced classification accuracy. It is concluded that combining deep features and the ML-based classifier employing a hybrid method enhances accuracy, robustness, and efficiency. The hybrid approach is a powerful tool for the premature identification of DR abnormalities. The PCA-kNN classification algorithm, which employs features obtained from the ResNet101, attained a peak classification accuracy of 98.9%.

Keywords-kNN; correlation-based feature selection; PCA; deep features; optimal feature set

I. INTRODUCTION

Diabetes has a profound side effect called diabetic retinopathy (DR) [1]. The retina is damaged due to DR and, if not queried, may result in vision impairment or blindness [2-5]. Deep Learning (DL)-based automated detection of DR has gained significant attention, mainly through binary classification models that aim to distinguish between diseased and non-diseased eyes [3]. The binary classification process for DR through DL generally begins with preprocessing the retinal images [4]. VGG19, ResNet101, and Shuffle Net pre-trained networks [4-6] are made up of pooling, convolutional and fully connected layers, designed to autonomously acquire hierarchical characteristics from retinal images, such as the presence of neovascularization microaneurysms or hemorrhages [6-9]. During training, the Adam optimizer was used to optimize the network parameters to lessen the loss function, which computes the discrepancy between the actual labels (diseased or non-diseased) and predicted labels [8]. Batch normalization, dropout, and regularization, are often applied to enhance the models' robustness, and overfitting is prevented [6-7]. In hybrid approaches, features from DL models enhance the discriminative power of the classifier [9-13]. DL-based pre-trained networks automatically learn hierarchical features from retinal images, identifying critical patterns like microaneurysms, hemorrhages, and exudates [12]. The hybrid model captures high-level semantic information through these features, boosting classification performance [12-27].

In the present work, the pre-trained DL models named ResNet101, VGG19, and Shuffle Net were implemented for feature extraction, followed by a traditional Machine Learning (ML) classifier named k-Nearest Neighbors (kNN) for final grouping [27]. In this setup, the deep features from the retinal images are extracted, using the pre-trained network, and arranged in a spreadsheet into the DR or non-DR categories [17-19]. It is concluded that this approach has been shown to outperform end-to-end CNNs alone, mainly when the dataset is small or imbalanced [20-22, 38]. The effectiveness of the DL-based model is determined using the ROC curve, specificity, sensitivity, and accuracy [27]. High sensitivity is crucial to ensure that diseased cases are not missed [27-32]. Transfer learning consists of modifying a pre-trained model on a vast dataset to enhance its effectiveness on DR data, mainly when the available training data are limited [21-32]. DL models for binary DR classification offer promising avenues for early, automated detection [26-32]. They can help reduce the burden of manual screening and, importantly, enable timely patient treatment, providing reassurance about the potential benefits of this technology [26]. Research on DR has a major social impact by reducing blindness, enhancing healthcare accessibility, improving economic productivity, and fostering better quality of life. The social impact of research on DR is profound, affecting individuals, healthcare systems, economies, and societies as a whole [27].

II. METHODOLOGY

The methodology for binary classification of DR using DL and ML-based classifiers follows a structured pipeline encompassing data collection, pre-processing, model selection, Training, and evaluation. This process ensures accurate classification of images into either "diseased" (DR detected) or "non-diseased" (no DR) [1-23]. Various researchers have used different pre-trained networks in their studies. Also, it is noted that most studies utilizing modified pre-trained networks with transfer learning for binary and multi-class classification used the Diabetic Retinopathy Dataset as APTOS 2019, IDRiD, and EyePACS [1-23]. Authors in [23] attained maximum accuracy of 98.36%. Remarkably, only 10 out of 63 considered studies (15.87%) employed pre-trained networks as classifiers and feature extractors. Gaussian filters are also mentioned extensively as a denoising approach [27]. According to the literature review, a Gaussian kernel convolves the image to reduce noise while preserving the underlying structure [27]. It is a simple method of lowering Gaussian noise without compromising performance [27]. Most researchers have employed benchmark datasets APTOS2019, IDRiD, and EyePACS in their studies.

A. *Benchmark Dataset of Diabetic Retinopathy*

High-quality, labeled retinal images consist the foundation of DL and ML approaches [27]. Data are typically sourced from publicly available datasets.

The Diabetic Retinopathy Dataset (DRD-EyePACS), is a dataset publicly accessible on Kaggle [33], comprises 2750 images, 1000 of which belong to the healthy class and 1750 in the unhealthy class. Each image is 256×256 pixels in size. IDRiD (Indian Diabetic Retinopathy Image Dataset) [34], has 516 total images, divided in 103 unhealthy and 413 healthy images, all 4288×2848 in size. The third dataset, APTOS - 2019, contains 3662 images [35], gathered from several participants in rural India. A hybrid technique has been employed in this work to classify diabetes imaging utilizing all three datasets. Data preprocessing is critical in building an adequate DL or ML model for classifying DR images [27]. Since retinal images have variations in quality, size, and illumination, preprocessing helps standardize the input data and enhances the model's ability to detect relevant pathological features [27]. The data initial processing and preparation modules in this work are: (a) dataset resizing, (b) image normalization, (c) denoising, (d) data bifurcation for training and testing, (e) data augmentation, and (f) data bifurcation for training and validation after data augmentation [27]. Figure 1 illustrates the procedure for preparing the DR image dataset for classification.

1. Resizing the Dataset

Retinal images from different sources can vary significantly in size. To ensure uniformity, images are rescaled to a standard pixel size (227×227 or 224×224), allowing efficient batch processing and compatibility with pre-trained deep-learning models [27].

2. Image Normalization

Normalization is essential to reduce illumination variations across different images, which can lead to misinterpretation by the model. Techniques such as histogram equalization are often applied to adjust the contrast of retinal images, emphasizing key features like blood vessels, microaneurysms, and hemorrhages [23-27].

3. Denoising

Retinal images may contain noise due to imaging [27]. This work uses a Gaussian filter to reduce noise, improve image quality without losing important pathological information, and apply contrast enhancement or filtering to emphasize retinal features such as microaneurysms and hemorrhages [27].

4. Data Bifurcation for Training and Evaluation

DR classification entails splitting the available dataset into subsets used for training and testing to ensure that the model generalizes effectively and eliminates overfitting [27]. This division is critical for evaluating model performance, particularly in medical imaging tasks requiring high accuracy and robustness. Proper data bifurcation and careful management of class distributions are essential in DR classification [27-35]. These practices ensure that the model performs well on unseen data and provides reliable diagnostic support in real-world scenarios. In the present work, the testing dataset contains 450 healthy and 450 unhealthy DR images. The remaining set belongs to the training dataset containing 6028 DR images [27].

5. Data Augmentation

Augmentation techniques expand the dataset artificially to address overfitting and enhance model generalization. In this work, rotation, flipping, and translation data augmentation techniques were used [27]. They rotate images by 90^o and 180^o to simulate different viewing perspectives. Horizontal and vertical flipping were performed in the rotated images [27-28]. Various translations were used to increase the samples' overall quantity. In the present work, the training dataset contained 6028 images artificially enlarged with data augmentation techniques. After the augmentation, the training set contained 24053 DR images [27].

6. Data Bifurcation for training and validation after augmentation.

Data bifurcation for training and validation in DR classification is an essential procedure that ensures the ML or DL generalizes well to unknown data and avoids overfitting. The dataset is typically divided into test, validation, and training sets.

In [27],we described data bifurcation for training and validation sets after augmentation. A total of 24053 DR images were separated into training set containing 21000 DR images (healthy -10500, unhealthy -10500) and a validation set containing 3053 images (1524 healthy and 1529 unhealthy images).

B. Pre-trained Network Selection

VGG19, ResNet101, and Shufflenet have distinct strengths [27]. VGG19 excels in feature extraction but is resource-intensive, ResNet101 handles deep networks effectively with high accuracy, and Shufflenet balances accuracy and computational efficiency for mobile applications. The choice of DL architectures depends on the conclusions of our previous work on classification accuracy based on the softmax layer [27].

C. Selection of Machine Learning-based Classification Module

Selecting an appropriate ML algorithm for classifying DR images involves considering the nature of the data, the problem complexity, and the desired performance metrics [28-32]. DR image classification typically distinguishes between diseased and non-diseased retinas, making it a binary classification task [25]. Numerous ML algorithms can be implemented depending on the feature extraction techniques and dataset size [35]. The DR image kNN classification is an uncomplicated and interpretable algorithm. The images are classified based on their similarity to other images in the dataset. However, it is sensitive to the dimensionality of the data and performs efficiently if the dataset is large or if irrelevant features are not removed.

D. Feature Reduction Module for DR Image Classification using the kNN Classifier

Feature reduction is essential in DR image classification, especially when using algorithms like kNN, which can be sensitive to high-dimensional data [25]. High-dimensional feature spaces can lead to poor performance due to the "curse of dimensionality," in which, with the increase in the dimensions, the distance among the points gets less informative [28-30]. To address this issue, feature reduction techniques are applied to select or transform the most relevant features, improving classification accuracy and computational efficiency [31-33]. Principal Component Analysis (PCA) is a commonly employed dimensionality reduction technique that retains the most significant variation while transforming high-dimensional data into a lower-dimensional space [28-33]. In DR image classification, PCA can reduce redundant extracted features from the images, such as color, texture, or shape descriptors. It projects the features onto new axes (principal components) that identify the most significant variation in the data. Keeping only the top principal components allows kNN to operate more effectively in a lower-dimensional space, improving speed and accuracy [33]. kNN classifier is utilized effectively in medical image analysis, including classification and detection of DR images [28]. Diabetes-related illness impacts the retina's blood vessels, and initial identification is essential to avoid visual loss. kNN can be very beneficial to categorize these images according to their degree of severity (e.g. proliferative DR, severe, mild, or moderate) [27]. In the case of DR images, preprocessing steps like image resizing, contrast enhancement, and noise reduction are typically utilized to improve image quality [28]. Features extracted from retinal images may include blood vessel patterns, microaneurysms, hemorrhages, and exudates indicative of DR [28-33]. These features are represented in numerical form, and kNN uses them to find the closest matching images based on distance measures like the Euclidean distance [28].

In a standard application, after extracting features from standard and DR-affected images, a new retinal image is classified employing the kNN algorithm by identifying its k-nearest neighbors in the feature space [27-29]. The class of the majority among these neighbors (e.g. DR-positive or DR-negative) is assigned to the new image [28]. The advantages of kNN for DR classification include its simplicity and intuitive nature, making it easy for medical professionals and researchers to implement [28]. Additionally, it requires no complex training phase, which is useful when dealing with evolving datasets in medical research [28]. However, the algorithm's performance can be hampered by the curse of dimensionality, especially since retinal images are high-dimensional [28]. Optimizing performance necessitates dimensionality reduction techniques or feature selection techniques like PCA [32].

E. Steps Involved in the kNN Classifier

The first stage is selecting the number of closest neighbors to account for classification. In the second stage, the Euclidean distance is calculated for each neighbor. The k nearest neighbors are computed in the third stage by computing and comparing their Euclidean distances. In the fourth stage, the number of data points belonging to each category among the k nearest neighbors is calculated. In the next stage, the neighbor count is at its topmost, and new data points are placed in that category. In the last stage, the model is finished. Figure 1 shows the procedure adopted for preparing the DR image dataset for classification. The adopted workflow for DR image classification is shown in Figure 2.

F. Selection of Evaluation Criteria for DR Image Classification

In [27], classification accuracy, precision, F1-score, specificity, and sensitivity were employed to evaluate the classifiers [27]. The same assessment parameter has been employed in the current work for comparison.

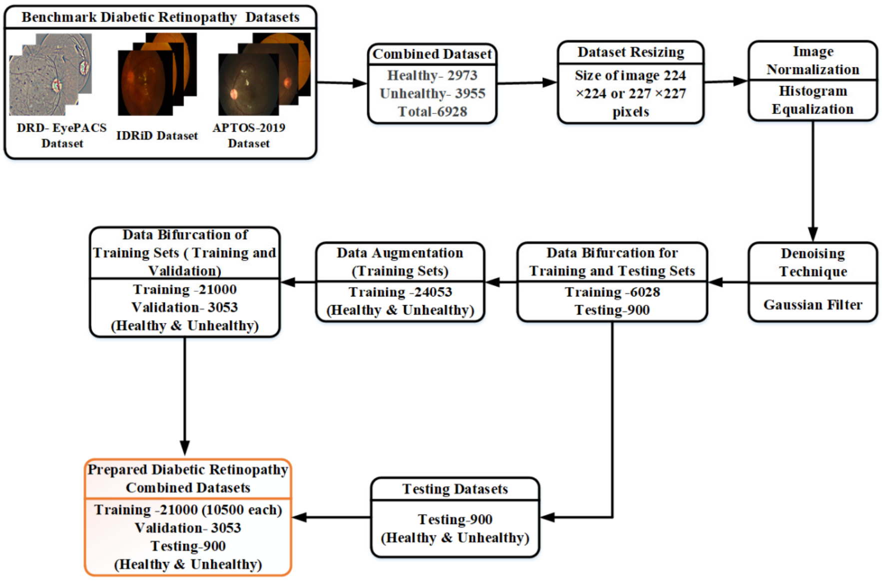

Fig. 1. Procedure adopted for preparing the DR image dataset for classification.

III. RESULTS

Pre-trained networks VGG19, ResNet101, and Shuffle Net are frequently employed for identifying DR images due to their outstanding feature extraction capabilities. Pre-trained on extensive datasets like ImageNet, these networks offer a strong foundation for transfer learning, allowing models to adapt quickly to the specific task of DR classification.

TABLE I. CLASSIFICATION RESULTS OF DR IMAGES USING DEEP FEATURES DERIVED FROM PRE-TRAINED NETWORKS USING TRANSFER LEARNING AND SOFTMAX LAYER

Category	Network	Confusion Matrix		ACC %	Sen.	Sp.	Pr.	F1
Series	VGG 19	435	15	96.22	0.96	0.97	0.97	0.96
		19	431					
DAG	ResNet 101	440	10	97.33	0.97	0.98	0.98	0.97
		14	436					
Lightweight	Shuffle net	439	11	96.66	0.98	0.98	0.98	0.98
		19	431					

As can be seen in Table I and II ResNet101 offers the highest classification accuracy with the PCA-KNN classifier. It is computationally expensive but requires less memory and training time. VGG19 similarly demands significant computational resources, making it less practical for real-time applications. ShuffleNet shows comparably higher classification accuracy than VGG19 but less than ResNet101. The ROC curve using PCA-kNN is shown in Figure 3.

TABLE II. CLASSIFICATION RESULTS OF DR IMAGES USING DEEP FEATURES DERIVED FROM PRE-TRAINED NETWORKS. AND PCA-KNN CLASSIFIER

Category	Network	Confusion Matrix		ACC %	Sen.	Sp.	Pr.	F1
Series	VGG 19	440	10	97.67	0.98	0.98	0.98	0.98
		11	439					
DAG	ResNet 101	446	04	98.89	0.99	0.99	0.99	0.99
		06	444					
Lightweight	Shuffle net	441	09	97.89	0.98	0.98	0.98	0.98
		10	440					

IV. CONCLUSION

ShuffleNet offers a lightweight architecture and achieves competitive performance with significantly reduced computational demands, making it ideal for mobile or embedded applications with limited computational resources. However, the trade-off slightly reduces accuracy compared to ResNet101 and VGG19. VGG19, despite being a simpler architecture, performs well, although it requires more computational resources due to its large number of parameters.

VGG19 effectively captures fine-grained details but may suffer from overfitting on smaller datasets due to its complexity. Research on (DR) has a major social impact by reducing blindness, enhancing healthcare accessibility, improving economic productivity, and fostering a better quality of life. Advances in retinal imaging techniques, including Optical Coherence Tomography (OCT), fluorescein angiography, and AI-powered fundus imaging, have significantly improved early detection, diagnosis, and disease monitoring. These imaging technologies help detect microaneurysms, hemorrhages, and neovascularization, allowing for timely intervention and reducing the risk of severe vision impairment. Continued advancements in imaging and treatment strategies will further benefit individuals, families, and societies worldwide. ResNet101 achieves the highest performance among the tried networks due to its more profound architecture and residual connections, circumventing the vanishing gradient problem and allowing for better feature representation. ResNet101 consistently reaches high accuracy levels with excellent sensitivity and specificity in detecting an early indication of DR.

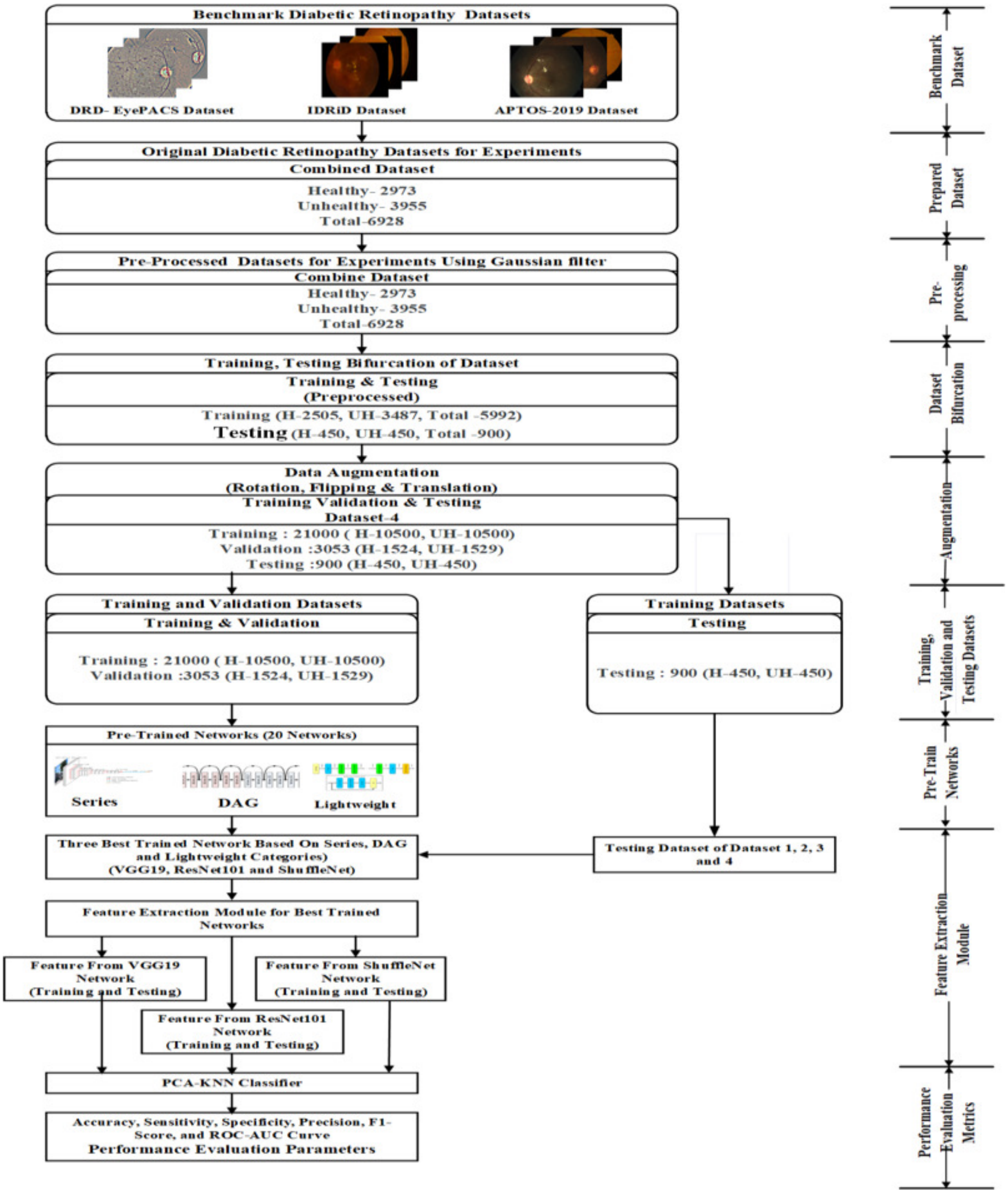

Fig. 2. The adopted workflow for DR image classification applying a hybrid approach.

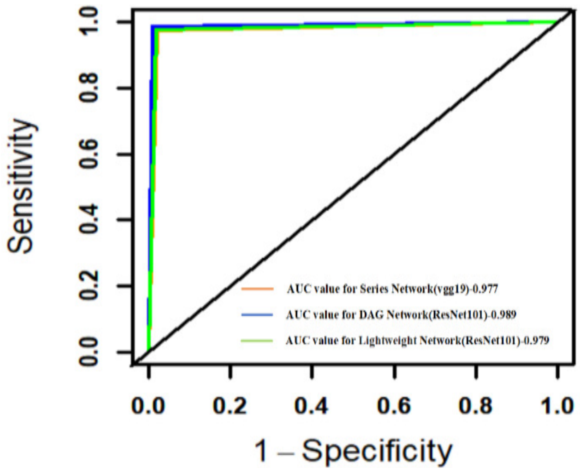

Fig. 3. ROC curve of the obtained classification accuracy using Pre-trained networks and PCA – kNN classifier.

Despite the high accuracy, several challenges still need to be solved. Imbalanced datasets, where non-DR images dominate, can lead to model bias. Techniques like data augmentation, oversampling, or weighted loss functions can mitigate this. Additionally, small datasets can limit the model's ability for generalization, emphasizing the significance of transfer learning and fine-tuning pre-trained networks to perform DR tasks. Overall, pre-trained networks like ResNet101, VGG19, and ShuffleNet deliver high performance in DR classification. ResNet101 provides the best accuracy, VGG19 effectively captures detailed features, and efficiency and accuracy are balanced by ShuffleNet for real-time applications. These models offer promising solutions for early DR detection, which is imperative for avoiding vision loss in diabetic patients.

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