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RESEARCH ARTICLE

Randomization-Driven Hybrid Deep Learning for Diabetic Retinopathy Detection

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ABSTRACT Diabetic retinopathy (DR), a severe consequence of diabetes, dramatically enhances the likelihood of experiencing vision impairment. Timely identification is crucial for efficient intervention, as untreated diabetic retinopathy can progress to irreversible vision loss. Despite advances, existing diagnostic methods face challenges such as resource dependency, variability in accuracy, and limited accessibility, especially in underserved regions. This study pioneers an innovative framework, using Multi-Scale Discriminative Robust Local Binary Pattern (MS-DRLBP) features, combined with a hybrid Convolutional Neural Network-Radial Basis Function (CNN-RBF) classifier, to enhance the detection of DR. Inspired by principles of randomization-based learning, our approach incorporates elements of stochastic modeling within the CNN-RBF architecture to optimize feature extraction and classification, mirroring the efficiency of non-iterative training processes. We enhance the model's diagnostic capability through complex image preprocessing techniques, such as improved noise reduction and morphological approaches. Additionally, we use Otsu's thresholding method to segment blood vessels accurately. Our methodology demonstrates superior performance in DR screening, significantly exceeding traditional diagnostic methods. Specifically, our precision reached 96.10%, sensitivity was 95.35%, specificity achieved 97.06%, and accuracy was 96.10%. This research enhances the precision of DR diagnosis by applying it to different publicly accessible datasets. It contributes to the broader discourse on the potential of hybrid, randomization-inspired neural networks in medical imaging. This fusion of deep learning innovation with the principles of randomization-based algorithms opens new avenues for developing accessible, accurate diagnostic tools, potentially alleviating the global impact of diabetic vision loss.

INDEX TERMS Diabetic retinopathy detection, fundus image, hybrid CNN-RBF, MS-DRLBP, Otsu's thresholding, randomization-inspired methods, retinal vessels.

I. INTRODUCTION

According to the World Health Organization (WHO), diabetic retinopathy (DR), glaucoma, and age-related macular degeneration are significant contributors to visual impairment [1]. These disorders can be detected and tracked using a non-invasive technique known as retinal fundus imaging. The primary anatomical features visible in color fundus images are the retina's blood vessels, which have a critical role in detecting these diseases, particularly in individuals with diabetes who are at an increased risk of DR owing to damage to the retinal blood vessels. Timely identification, therapy, and recognition can reduce the severity of the illness and impede its advancement [2]. Artificial

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intelligence utilizes image processing and advanced machine learning models to accurately identify and categorize cases of DR [3]. The integration of artificial intelligence techniques into retinal vascular segmentation has emerged because of this field's progressive advancement and expansion [4]. However, traditional methods for diagnosing DR, primarily involving manual segmentation by ophthalmologists, are labor-intensive, time-consuming, and subject to variability in results [5].

Diabetic patients are predominantly impacted by DR, which is the primary factor behind vision loss. Patients with diabetes are more likely to experience DR due to retinal blood vessel damage. Therefore, identifying and isolating the blood vessels in the retina is crucial for diagnosing DR, helping to prevent early vision loss in diabetic patients [6]. A precise segmented image is essential to screening fundus diseases, their subsequent diagnosis, and their treatment. In addition to being time-consuming, arduous, and requiring expert techniques, manual segmentation is also labor-intensive. Variating the segmentation results between different ophthalmologists will result in inaccurate final segmentation results [7], [8]. Automated retinal vessel segmentation alleviates the diagnostic burden for ophthalmologists, and those with limited experience can effectively address issues. Automated methods for identifying and segmenting the blood vessels in the retina are essential for detecting DR [9]. Nevertheless, the accuracy of blood vessel detection and the selection of abnormal features play a significant role in detecting retinal disease DR, which still offers researchers the opportunity to investigate this condition. Therefore, the programmed division of retinal vessels is essential for diagnosing and treating ophthalmic infections.

The quest for more efficient, accurate, and automated diagnostic methods is unending in medical imaging, particularly in diagnosing retinal diseases such as DR. Herein lies the innovation of our approach: We introduce a groundbreaking hybrid methodology that combines a CNN-RBF-based classifier with features from Multi-Scale Discriminative Robust Local Binary Pattern (MS-DRLBP). This technique is designed to automate retinal blood vessel segmentation, address manual segmentation's inherent limitations, and significantly enhance the precision and efficiency of DR diagnosis. Our approach uniquely combines the strengths of deep learning and pattern recognition algorithms, thereby achieving a more accurate and reliable DR diagnosis. This advancement represents a significant leap forward in retinal disease screening.

In this paper, we elaborate on developing and implementing this novel methodology, showcasing its superior performance in classifying retinal diseases compared to conventional methods. Our approach not only sets a new benchmark for accurate and efficient DR detection but also lays the groundwork for its application to a broader spectrum of retinal diseases, potentially transforming the landscape of ophthalmic diagnostics.

Numerous studies have explored the application of artificial intelligence (AI) in diagnosing retinal conditions such as diabetic retinopathy (DR), glaucoma, and age-related macular degeneration. Previous studies have used local binary pattern (LBP)-based feature extraction alongside traditional machine learning algorithms—such as Support Vector Machines (SVM), Decision Trees (DT), K Nearest Neighbors (KNN), and Random Forests (RF)—as well as deep learning architectures like convolutional neural networks (CNNs) to classify retinal diseases. Although LBP offers a cost-effective and straightforward method for feature extraction, its locally extracted features may lack the robustness needed for effective class discrimination. Furthermore, CNNs typically require extensive annotated datasets and significant computational resources for efficient classification. There is a critical need for enhanced diagnostic algorithms that improve accuracy in detecting and classifying retinal diseases, thereby enabling researchers to advance in this specialized field. Our proposed research introduces an automated threshold algorithm for DR diagnosis based on blood vessel segmentation. Furthermore, we utilize MS-DRLBP, in conjunction with a CNN-RBF classifier to address the limitations identified in previous studies.

Our adaptation of discriminative robust local binary patterns (DRLBP) allows for the effective extraction of edges and textures from images, emphasizing pixel contrasts to improve image brightness and contrast. The proposed method retains contrast information, incorporating edge and texture data for object recognition. DRLBP distinguishes objects based on texture and shape, defined by their boundaries. The radial basis function (RBF), known for its efficacy in pattern classification and regression, is extensively utilized in traditional machine learning applications. Our study uses CNN-RBF classifiers for deep learning applications, demonstrating their superior performance over contemporary techniques. By employing segmented features of fundus images, our approach innovates the training process for RBFs, allowing for the use of labeled and unlabeled data for enhanced classification accuracy.

Emerging in the field of explainable artificial intelligence (XAI), it aims to improve the transparency and interpretation of AI systems so that people may grasp the machine learning model decision-making procedures. In high-stakes fields like healthcare, where the consequences of AI choices may greatly affect personal life, this is especially important. Local Interpretable Model-Agnostics (LIME) is one well-known technique in XAI that offers understanding of individual predictions produced by intricate models [10], [11]. LIME is a method for locally explaining machine learning model individual predictions instead of the model taken as whole. Its goal is to offer understanding of the reasons behind a model's unique forecast for a given instance.

Contributions of this paper include:

- We combine three distinct public datasets (STARE, HRF, FFA), which present challenges in dataset complexity and generalizability that are not commonly addressed in DR detection.

- Using a multi-scale discriminative feature extraction approach, we employ an enhanced version of LBP, MS-DRLBP, to extract highly discriminative features for classifying retinal diseases.
- We have developed a novel classifier that employs deep learning techniques to integrate CNNs' capabilities with RBFs.
- Our study integrates XAI approaches, notably LIME, to improve the interpretability of machine learning models in clinical contexts.
- Our approach surpasses current leading techniques for classifying retinal diseases, as demonstrated by our comparative analysis.

Despite their advantages, integrating RBFs into modern CNN architectures presents challenges due to their nonlinear activations, which can impede efficient gradient flow, and the assumption of fixed MS-DRLBP features with predetermined cluster centers at the outset.

The remaining sections are structured as follows: In Section II, we review previous research, while Section III details the dataset and methods used, including our proposed approach. Section IV showcases the experimental outcomes, illustrating the effectiveness of our CNN-RBF architecture on different datasets. Section V serves as the concluding section of the paper.

II. RELATED WORKS

CNN models have been extensively applied to image classification and segmentation tasks in various domains, including diabetic retinopathy (DR), plant disease identification, and underwater imaging [6], [12], [13], [14], [15]. The retinal vascular organization reflects the retina's health, a valid analytic sign. As a result, segmenting retinal blood vessels can be a handy tool for diagnosing vascular diseases [16]. A generalized Gauss-Markov random field was utilized for noise reduction, while a combined Markov-Gibbs random field was applied for blood vessel segmentation. In their 2015 study, Hassan and colleagues [17] proposed a method that utilizes mathematical morphology combined with K-means clustering to segment blood vessels. In their study, Fraz et al. [18] emphasized that automating the segmentation process of retinal blood vessels is a crucial component of retinal disease screening tools. It has been examined in two-dimensional retinal images. In a study by Roychowdhury et al. [19], a three-stage segmentation algorithm involving green channel extraction, high pass filtering, and Gaussian mixture models (G.M.M.s) was presented. In their study [20] Barkana et al. segmented retinal vessels and extracted descriptive statistics from images of different retinal diseases. These features are used to diagnose diseases by employing methods like fuzzy logic, artificial neural networks, SVM, and classifier fusion techniques.

Marin et al. proposed an innovative neural network method for the segmentation and classification of retinal vessels. They utilized the DRIVE and STARE datasets, which are collections of retinal images used to extract vessels and analyze the retina. Their method used a seven-dimensional vector that combined features from gray levels and moment invariants. [9]. By preprocessing retinal vessel images with a Gaussian filter and segmenting them through curvelet transform, Kavitha et al. evaluated the method of diagnosing diabetes using retinal vessel images [21]. Liskowski et al. developed a supervised approach using deep neural networks to classify retinal images, utilizing databases such as DRIVE, CHASE, and STARE [22].

Vasanthi and Banu extracted blood vessels from retinal images by combining preprocessing, feature extraction, and classification [23]. Images are classified as normal or abnormal using a combination of an ANFIS and an ELM. Morales et al. examined texture analysis's discrimination capabilities to differentiate pathologic images from healthy images [24], [25]. A texture discriminator called Local Binary Patterns (LBP) distinguishes DR from AMD. An intelligent vessel segmentation model was developed by Sangeethaa and Uma Maheswari [26] utilizing morphological operations, thresholding techniques, edge detection methods, and adaptive equalization of histograms. In a study of mammograms, Alkhaleefah and Wu devised a mixed approach utilizing convolutional neural networks (CNNs) in combination with radial basis function (RBF)-based support vector machines (SVMs) to classify breast cancer [27]. By using transfer learning, knowledge from deep neural networks can be taken and applied to different tasks. In 2020, Park et al. [28] proposed a novel conditional generative adversarial network called M-GAN for accurate retinal blood vessel segmentation. Their approach utilized stacked deep fully convolutional networks to balance losses and achieve robust segmentation performance. The authors emphasized that precise blood vessel segmentation plays a crucial role in the early detection and diagnosis of retinal disorders such as diabetic retinopathy. Regular retinal screenings using advanced segmentation techniques can enable prompt identification of vascular changes associated with diabetic retinopathy, facilitating early intervention.

To streamline the screening procedure, Dai et al. introduced a deep learning framework called DeepDR that is capable of detecting diabetic retinopathy across all stages, from early onset to advanced progression [29]. DeepDR is trained to perform real-time image quality assessments, identify lesions, and grade. Deep learning techniques have significantly improved applications in detection, partitioning, forecasting, and categorization across various medical fields. Nadeem et al. [30] provided an extensive overview of advancements in deep learning for diabetic DR research, including detection, partitioning, forecasting, categorization, and verification.

A study by Radha et al. [31] explicitly mentions that DR can arise from harm to the blood vessels in the retina. Ophthalmologists can identify and annotate these vessels manually using certain clinical and geometric characteristics, though this process is labor-intensive. Extracting and segmenting the anatomy of a vessel is essential for differentiating a normal vessel from one with recent abnormal developments. Detecting, isolating, and analyzing the blood vessels in the retina is a complex procedure. Prabha and colleagues studied diabetic retinopathy, a condition where elevated glucose levels in the body start impacting the vessels in the retina [32]. An adaptive histogram equalization method with contrast limitations has been employed to improve baseline contrasts and reduce noise. Segmentation is further divided into two steps. The initial step involves utilizing Fuzzy C-Means clustering to identify the primary retinal vessels. Subsequently, a region-based active contour method emphasizes the blood vessels within the targeted area.

In the study by Sivapriya et al. [33], a ResEAD2Net design was proposed, potentially separating imperceptible micro-vessels accurately. A self-attention approach is applied during the network's subsequent decoding phase to capture higher-level semantic features, improving its capacity to differentiate between classes and consolidate information within a single class. The network is tested on publicly available datasets such as CHASE_DB1, DRIVE, and STARE. Jaspreet and Prabhpreet [34] employed image preprocessing to eliminate blood vessels, the optic disc, and undesirable pixels from the retinal images. They also used the KNN classifier on the Diabetic Retinopathy Database (DIARETDB1) dataset. In 2021, Li et al. [35] introduced a network architecture combining U-Net with the DenseNet model to improve microvessel segmentation accuracy and completeness. Retinal vascular segmentation was done on the public DRIVE dataset.

Distinctive features of microaneurysm and hemorrhage (area, major and minor axis, perimeter, etc.) are extracted after removing morphological features from the fundus images by the study done by Kumar et al. [36]. They stated that their technique has improved sensitivity and specificity for detecting DR based on DIARETDB1 data. Kamran et al. [37] asserted that segmentation techniques based on autoencoding cannot restore retinal microvascular structure due to the loss of resolution during encoding and the subsequent inability to recover it during decoding. They introduced a generative architecture called RV-GAN to address this issue by segmenting retinal vascular tissue at many scales. Their model was based on the same datasets used by Sivapriya et al. Similarly, Zhendi et al. [38] employed a U-Net model with a decoder fusion module (DFM) and context squeeze and excitation (CSE) module to successfully blend multi-scale elements on the same datasets. They gathered information from multiple levels, thus improving the segmentation of the fundus images.

Numerous eye health problems can be identified using retinal blood vessels. Yubo et al. [39] focus on visual cortex cells and orientation selection processes. They utilized DRIVE, CHASE, High-Resolution Fundus (HRF), and STARE datasets for the model analysis based on W-shaped Deep Matched Filtering (WS-DMF). The study by Xialan et al. [40] presents a revised technique for segmenting retinal blood vessels using a network-based approach utilizing the CHASE, DRIVE, and STARE datasets. This method extracts various features of the blood vessels at different scales and continuously segments them. Low contrasts in retinal fundus images hinder segmentation. Soomro et al. [41] accessed independent component analysis (ICA) structures using STARE and DRIVE datasets to fix image segmentation issues caused by uneven contrast.

The LBP is emphasized as a nonparametric descriptor that effectively encapsulates local features in pictures, rendering it very proficient for tasks including image identification, and recognition [42]. The benefits of LBP encompass its computing efficiency and resilience to monotonic illumination variations, which are essential considerations in medical imaging because of the large fluctuations in lighting conditions [43].

Berbar [44] utilizes Uniform Local Binary Patterns Encoded Zeroes for feature extraction in the classification and grading of DR, without necessitating lesion segmentation. This strategy mitigates a notable constraint in conventional image processing techniques, which frequently depend on segmentation that may introduce inaccuracies and compromise the overall precision of DR identification. In a study, Pan et al. [45] a technique for pixel selection that modifies the sampling radius according to local gray-value distributions, thereby improving the LBP approach to image classification is suggested. It overcomes a significant shortcoming of conventional LBP techniques, therefore overlooking the intrinsic diversity in specific texture features.

The study by Wang et al. [46] utilized separate datasets for image segmentation using the U-net architecture, which demonstrated superior performance. Despite the exceptional performance of their approach, achieving generalizability inside the model remains a difficulty. Most image segmentation studies with public data employ a single dataset for evaluation [47], [48]. By incorporating LBP-based methodologies into hybrid deep learning frameworks, the proposed study can utilize the advantages of both conventional feature extraction methods and contemporary deep learning approaches, thereby tackling the intricacies of retinal image analysis and enhancing detection accuracy.

III. MATERIALS AND METHODS

Our study focuses on advancing diagnostic methods for retinal diseases, particularly diabetic retinopathy (DR), by applying sophisticated image preprocessing techniques and a novel classification approach. Our objective is to leverage randomization-inspired techniques within a combined framework of Convolutional Neural Network and Radial Basis Function (CNN-RBF), enhanced by features derived from Multi-Scale Discriminative Robust Local Binary Pattern (MS-DRLBP). The selection of MS-DRLBP features and the initialization process within the CNN-RBF classifier are guided by principles of randomness. This randomness is not arbitrary but is strategically applied to enhance model performance and generalizability.

A. PROPOSED APPROACH

We introduce a detailed approach incorporating advanced image preprocessing to improve vessel segmentation, essential for precise DR detection. This method includes reducing noise, applying morphological techniques, performing background subtraction, and using Otsu's method for optimal image binarization [49]. After preprocessing, the features were extracted using a Multi-Scale Discriminative Robust Local Binary Pattern (MS-DRLBP). Meanwhile, we also utilized the CNN (VGG16) model to extract instant features from the input images. Both features are combined and given to the classifier layer to classify the images into DR and normal. This classifier embodies the constructive collaboration of deep learning and traditional pattern recognition, offering a robust framework for retinal disease screening. The full process of the suggested approach is illustrated in Figure 1.

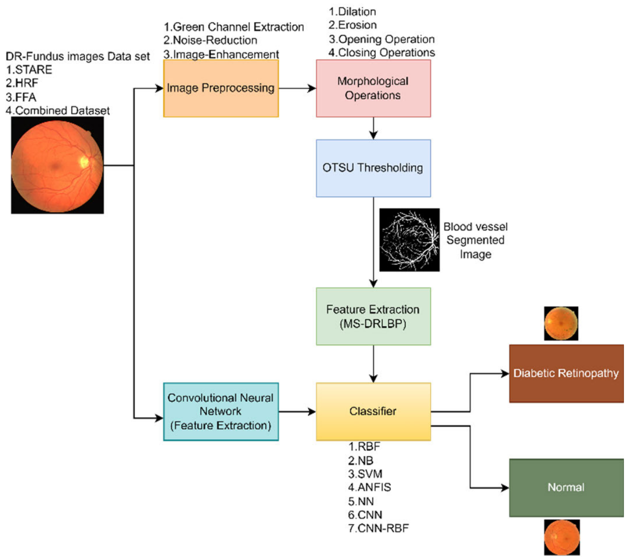

FIGURE 1. Diagrammatic representation of the suggested diabetic retinopathy screening process.

B. DATA ACQUISITION

Our study employs three open-access datasets: HRF (High-Resolution Fundus), STARE (Structured Analysis of the Retina), and FFA (Fundus Fluorescein Angiography) [50], [51], [52], Consisting of 190 images, these datasets include cases of DME (Diabetic Macular Edema), DR (Diabetic Retinopathy), AMD (Age-Related Macular Degeneration), and CNV (Choroidal Neovascularization). Due to the limited number of images per category, we grouped these into 'Normal' and 'Abnormal DR' for analysis.

C. DATASET PREPARATION AND PREPROCESSING

In preparing the datasets for analysis, each image underwent a standardized preprocessing pipeline to maximize the efficacy of subsequent classification stages. This pipeline includes advanced algorithms for noise reduction, utilizing adaptive filtering techniques that mirror the adaptability inherent in randomization-based methods. Morphological operations and background exclusion techniques were meticulously applied to isolate and enhance the retinal blood vessels' structural features, with Otsu's thresholding method employed for optimal segmentation [49]. Otsu's technique determines the threshold that reduces within-class variance in the segmented image, enabling automatic differentiation between the foreground (retinal blood vessels) and the background. This technique is particularly effective due to its non-iterative nature, aligning with the principles of randomization-inspired methods by reducing reliance on parameter tuning and iterative optimization commonly seen in traditional thresholding techniques.

1) PREPROCESSING

Preprocessing is necessary to enhance the image quality. This can lead to an increase in the success rate of the suggested approach. As shown in Figure 1, we used the model developed by Sangeethaa and Uma Maheswari. We performed five steps, including extracting green channels, contrast enhancement, morphological operations, background exclusion, and Otsu's thresholding [49]. The MS-DRLBP features are chosen through a stochastic process that considers a randomized subset of available features at each iteration of the model training. This approach ensures a diverse feature set that can capture a broad spectrum of discriminative characteristics within the retinal images, thereby improving the classifier's generalization ability across various datasets. The processed images are shown in Figure 2. The green channel is extracted from the image to mitigate noise present in the red and blue channels. This extracted green channel is subsequently enhanced using CLAHE (Contrast Limited Adaptive Histogram Equalization), which splits the total area into a small, tiny area, improving the contrast for better blood vessel information.

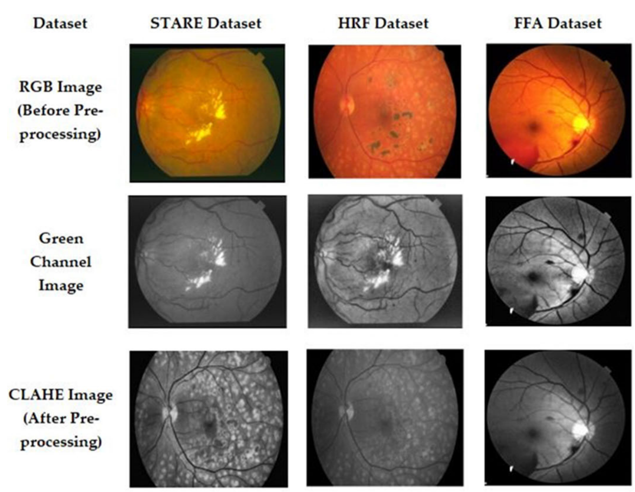

FIGURE 2. Preprocessed images for STARE, HRF, and FFA datasets.

2) MORPHOLOGICAL OPERATIONS

In retinal images, morphological operations brighten small or tortuous blood vessels. A pre-processed image is morphologically opened with a structuring element (Se) using dilation, erosion, opening, and closing operations.

3) BACKGROUND EXCLUSION

Every image captured has a background part, which may replicate some information that leads to incorrect diagnosis. Therefore, removing the background is essential to facilitate the clear analysis of foreground objects. This work uses CLAHE image enhancement to exclude background by subtracting the morphological image.

4) OTSU'S THRESHOLDING

Several global thresholding methods were employed in earlier works for blood vessel segmentation from retinal images. However, Otsu's thresholding gives the most effective segmentation performance due to its ease of implementation and robustness. Throughout the iterative procedure, the algorithm identifies the threshold that reduces within-class variance by computing the combined variances of the background and foreground classes. Greyscale colors range from 0-255 (0-1 if they are floats). If a threshold of 100 is selected, pixels with values below 100 are designated as the background, while those with values equal to or above 100 are classified as the foreground. The equation for calculating within-class variance at a given threshold is provided in Equation (1).

$$\sigma^2(t) = \omega_{bg}(t)\sigma_{bg}^2(t) + \omega_{fg}(t)\sigma_{fg}^2(t) \tag{1}$$

here $\omega_{bg}(t)$ and $\omega_{fg}(t)$ represent the probabilities corresponding to pixels categorized as background and foreground, respectively, based on the threshold t. Similarly, σ_{bg}^2 and σ_{fg}^2 denote the variances of pixel intensities in the background and foreground, respectively. The term $\sigma^2(t)$ embodies the within-class variance, which is the focal point of minimization in Otsu's method for optimal threshold selection.

Figure 3 shows an example of the resultant input and output images for better understanding and clarity. The suggested methodology demonstrates high accuracy in segmenting blood vessels.

D. RELATION TO RANDOMIZATION-INSPIRED METHODS

Using Otsu's thresholding and the proposed hybrid CNN-RBF classification framework fundamentally aligns with the essence of randomization-inspired methods. These approaches prioritize efficiency, robustness, and the ability to operate with minimal assumptions about the data distribution or parameter settings. The non-iterative aspect of Otsu's method and the adaptive nature of our preprocessing and classification strategies embody the core advantages of randomization—speed and generalizability—thereby enhancing the performance and reliability of DR detection.

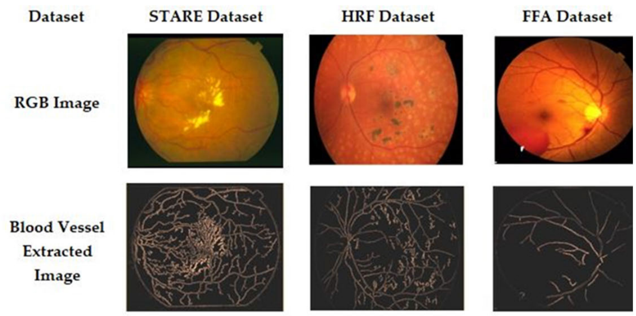

FIGURE 3. Input RGB image and blood vessel segmented image for STARE, HRF, and FFA datasets.

E. MS-DRLBP FEATURE EXTRACTION

MS-DRLBP is an enhanced form of the LBP feature descriptor extensively applied in image processing. The traditional LBP operator interprets the result as a binary number by comparing each pixel's neighborhood with the center value through thresholding. MS-DRLBP improves this by examining patterns at several orientations and scales, strengthening its robustness and discriminative power. It is accomplished by altering the radius of the neighborhood that is considered surrounding each pixel. The inclusion of multi-scale features is advantageous since they can capture and represent both intricate and broad aspects of the image. MS-DRLBP algorithm specifically targets prominent patterns that have statistical significance within the image. By reducing the dimensionality of the feature space, this approach prioritizes the most valuable characteristics, resulting in improved efficiency and efficacy in classification. Figure 4 represents the MS-DRLBP feature extraction step.

```
Input    : Blood vessel extracted image
Output   : The MS-DRLBP extracted features
begin
   ⇒ Step 1 : initialize a list of radii to define the scale of LBP
   ⇒ Step 2 : initialize an empty list
   ⇒ Step 3 : for each radii
                do
   ⇒ Step 4:  extract LBP features from the images
   ⇒ Step 5:  determine the histogram parameters to compute how the distribution of the
              binary patterns is aggregated over the image
   ⇒ Step 6:  normalize the histogram
   ⇒ Step 7:  append the normalized histogram to the list
              End for
   ⇒ Step 8:Concatenate all histograms to form a multi-scale feature vector of the image
end
```

FIGURE 4. Pseudo-code for the MS-DRLBP feature extraction.

F. CLASSIFICATION METHODOLOGY

Our classification strategy harnesses the power of the high-level feature extraction capabilities of CNNs with the conventional features extracted through MS-DRLBP for DR classification. To thoroughly evaluate classification performance and enhance the DR detection rate, we employed various classifiers, including NB (Naïve Bayes), RBF, ANFIS, NN (Neural Network), and SVM (Support Vector Machine).

benchmark the performance of nuanced pattern recognition strength of RBF networks. This combination is particularly effective for analyzing the complex textures and patterns in retinal images. The CNN-RBF classifier benefits from random initialization of network weights and RBF centers. This process incorporates a controlled level of randomness, optimizing the diversity of the neural network's internal representations and enhancing its capacity to learn complex patterns. Such initialization mimics the essence of non-iterative randomization-based methods, facilitating a more efficient solution for space exploration. Integrating MS-DRLBP features further enriches this model, enabling the discrimination of subtle variances between normal and DR-affected retinal images. This method marks a significant breakthrough in medical analysis, emphasizing the capability of hybrid models to attain high precision in disease classification tasks.

G. NETWORK MODEL AND TRAINING

The training of our network model involves a careful process to enhance performance, utilizing a momentum-based stochastic gradient descent optimizer alongside a cross-entropy loss function. The model parameters, including learning rate and batch size, were carefully selected to achieve high accuracy in disease classification, demonstrating the potential of hybrid models in medical image analysis.

CNN is a deep-learning algorithm. It is where individual neurons are arranged in tiles to relate to a given area in a visual field. Our work also leverages randomization-based learning principles, which form the foundation of the hybrid CNN-RBF architecture. Randomization-based learning employs stochastic processes during model training or architecture design, simplifying learning and reducing computational complexity. Unlike traditional iterative optimization methods like backpropagation, randomization-based approaches focus on non-iterative processes or stochastic initialization to efficiently learn decision boundaries. In our model, the RBF layers integrate stochastic modeling to enhance feature extraction and classification without the need for extensive iterative tuning. This results in faster training and improved efficiency, which is especially important for applications requiring scalable and accessible solutions.

In the proposed approach, the segmented RBV is evaluated by computing the proportion of RBV pixels correctly identified as RBV (P), the proportion of background pixels accurately detected as background (N), and the overall proportion of correctly classified pixels (T). A segmented blood vessel image is subsequently processed by MS-DRLBP for feature extraction and CNN-RBF for additional feature analysis and classification as either normal or DR.

The proposed study employed different preprocessing methods and used CNN-RBF as a feature extractor and classifier. The MS-DRLBP features are integrated with the features extracted by CNN-RBF in this study. Figure 5 shows the CNN-RBF classifier network model of the proposed study.

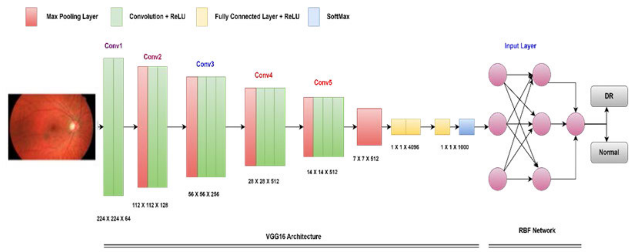

FIGURE 5. Proposed CNN-based retinal image classification.

The present work utilizes a DNN model (VGG16) with hyperparameter settings including a maximum of 100 epochs, a learning rate of 0.001, and a momentum factor of 0.9, with batch sizes tested at 8, 16, and 32. Finally, batch size 32 is selected to achieve higher accuracy in retinal image classification. Based on the training, the tested optimizers include Adaptive Moment Estimation (ADAM), Root Mean Square Propagation (RMSPROP), and Momentum-based Stochastic Gradient Descent (SGDM), with SGDM ultimately yielding superior results, as presented in Table 1.

TABLE 1. Hyperparameters of CNN architecture.

CNN Architecture	Min-Batch Size	Learning Rate	Training Optimizers
VGG16	32	0.0001	SGDM

IV. RESULTS AND DISCUSSION

This part outlines the experimental findings of retinal image classification and compares them with state-of-the-art detection methods for DR, highlighting their strengths and limitations. The simulation was performed on a computer equipped with an Intel i7 processor, operating on Windows 11, running at 3.20 GHz with 16 GB of RAM. We developed and tested the code for the proposed retinal image classification algorithm in MATLAB software. We use 90 images from the STARE database, 30 from the HRF database, and 70 from the FFA database to assess the effectiveness of the proposed system. Table 2 shows descriptions of the datasets. Table 3 shows images separated into training and testing types based on their classes. The dataset is divided into 60% for training and 40% for testing.

TABLE 2. Description of STARE, HRF, and FFA datasets.

Dataset	Normal Image	DR image
STARE	38	52
HRF	15	15
FFA	30	40
Total	83	107

In this evaluation, the performance metrics—recall, precision, sensitivity, accuracy, specificity, and F-score—of the proposed CNN-RBF model are compared with those of SVM, RBF, Naive Bayes (NB), ANFIS (Adaptive Neuro Fuzzy

TABLE 3. Training and testing images for STARE, HRF, and FFA datasets.

Dataset	STARE		HRF		FFA		ALL	
	Normal	DR	Normal	DR	Normal	DR	Normal	DR
Training	22	31	9	9	18	24	49	64
Testing	16	21	6	6	12	16	34	43
Total	38	52	15	15	30	40	83	107

Inference System), CNN, and Nearest Neighbor (NN) classifiers. Sensitivity, specificity, precision, accuracy, and F-score were computed using TN (True Negative), TP (True Positive), FN (False Negative), and FP (False Positive) values, as described in the Equations 2–6.

- True positive (TP): The DR image is appropriately classified as a DR image.
- False positive (FP): This occurs when a non-DR image is incorrectly categorized as a DR image.
- True negative (TN): A non-DR image that is correctly identified as a normal image.
- False negative (FN): DR image mistakenly recognized as Normal image (NR).

$$Precision = \frac{T_P}{T_P + F_P} \quad (2)$$

$$Sensitivity = \frac{T_P}{T_P + F_N} \quad (3)$$

$$Specificity = \frac{T_N}{T_N + F_P} \quad (4)$$

$$F - Score = \frac{2T_P}{2T_P + F_P + F_N} \quad (5)$$

$$Acc. = \frac{T_P + T_N}{T_P + T_N + F_P + F_N} \quad (6)$$

The validation split is 10% of the training data. The validation patience is set to 8, and the objective metric is loss. So if the loss has not decreased for eight iterations, then the training stops. Hence, the overfitting can be evaluated.

Table 4 shows the performance of the proposed and the conventional classifiers on three publicly available datasets, namely, STARE, HRF, FFA, and ALL (combining all three datasets).

The derived Friedman test statistic and its accompanying p-value are essential for evaluating the outcomes of the proposed study, which involves comparing many models across various metrics. The test's null hypothesis states that there isn't a discernible variation in the algorithms' performance. The null hypothesis is considered valid if the p-value is greater than 0.05 (the significance threshold). However, with a Friedman test statistic of 21.8108 and a p-value of 0.0013, the null hypothesis is rejected in favor of the alternative hypothesis. Table 5 and Table 6 shows that CNN-RBF outperforms other models based on the average rank obtained on accuracy and precision measure.

Across the three individual datasets as well as the combined dataset, the proposed CNN-RBF classifier outperformed traditional machine learning and deep learning algorithms. Also, the maximum accuracy of 97.30%, 91.67%, 96.43%, and 96.10% is achieved in DR classification using STARE, HRF, FFA, and ALL datasets, respectively. In addition, the deep learning algorithms (CNN-RBF and CNN) reported higher accuracy than machine learning algorithms such as Naïve Bayes, Nearest Neighbour, Support Vector Machine, and ANFIS. It shows that deep learning algorithms extract more meaningful and valuable information from the retinal image and accurately identify the retinal diseases from the input fundus image. Among the different machine learning algorithms, NB reported a lower accuracy in retinal image classification. The confusion matrix of CNN-RBF for individual and combined datasets is depicted in Figure 6.

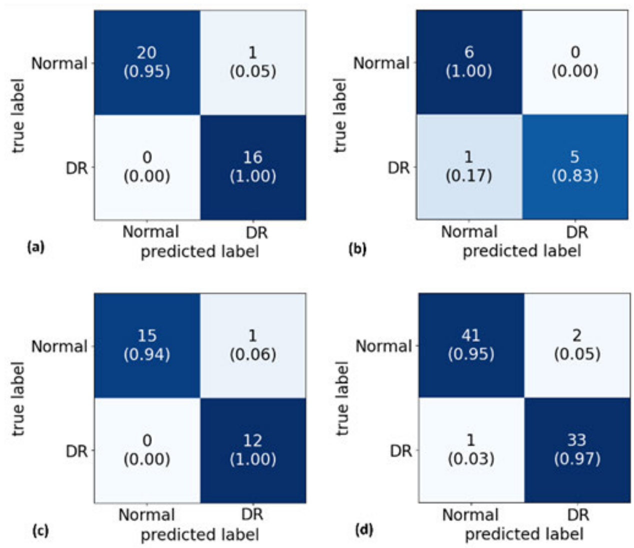

FIGURE 6. Confusion matrix of the test data with CNN-RBF model. (a) STARE, (b) HRF, (c) FFA, and (d) ALL datasets.

Figure 7 summarizes the maximum performance achieved in retinal image classification across different datasets. All performance measures, such as precision, sensitivity, specificity, and accuracy, showed that the proposed CNN-RBF classifier performed at least 90% better than the baseline classifier. Compared to other advanced methods for retinal image classification, the proposed classifier stands out for its simplicity and efficiency, delivering top performance across all three datasets.

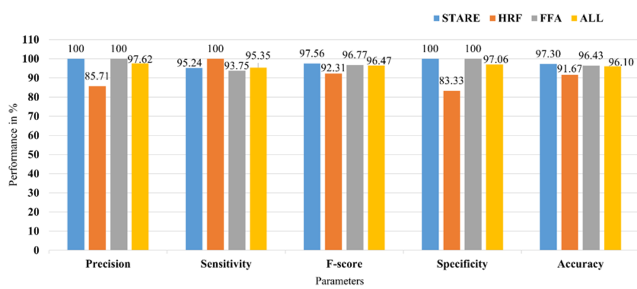

FIGURE 7. Evaluation metrics of the proposed method in DR screening.

TABLE 4. Performance based on test set with all models.

Techniques	True Positive	True Negative	False Positive	False Negative	Precision (%)	Sensitivity (%)	Specificity (%)	F-score (%)	Accuracy (%)	Dataset
CNN-RBF	20	16	0	1	100.00	95.24	100.00	97.56	97.30	STARE
CNN	19	15	1	2	95.00	90.48	93.75	92.68	91.89	
RBF	18	15	1	3	94.74	85.71	93.75	90.00	89.19	
ANFIS	18	14	2	3	90.00	85.71	87.50	87.80	86.49	
NN	17	14	2	4	89.47	80.95	87.50	85.00	83.78	
NB	16	13	3	5	84.21	76.19	81.25	80.00	78.38	
SVM	18	13	3	3	85.71	85.71	81.25	85.71	83.78	
CNN-RBF	6	5	1	0	85.71	100.00	83.33	92.31	91.67	HRF
CNN	5	5	1	1	83.33	83.33	83.33	83.33	83.33	
RBF	4	5	1	2	80.00	66.67	83.33	72.73	75.00	
ANFIS	5	3	3	1	62.50	83.33	50.00	71.43	66.67	
NN	3	4	2	3	60.00	50.00	66.67	54.55	58.33	
NB	3	3	3	3	50.00	50.00	50.00	50.00	50.00	
SVM	4	5	1	2	80.00	66.67	83.33	72.73	75.00	
CNN-RBF	15	12	0	1	100.00	93.75	100.00	96.77	96.43	FFA
CNN	14	12	0	2	100.00	87.50	100.00	93.33	92.86	
RBF	14	11	1	2	93.33	87.50	91.67	90.32	89.29	
ANFIS	13	11	1	3	92.86	81.25	91.67	86.67	85.71	
NN	12	10	2	4	85.71	75.00	83.33	80.00	78.57	
NB	13	10	2	3	86.67	81.25	83.33	83.87	82.14	
SVM	15	12	0	1	100.00	93.75	100.00	96.77	96.43	
CNN-RBF	41	33	1	2	97.62	95.35	97.06	96.47	96.10	ALL (STARE, HRF, FFA)
CNN	38	32	2	5	95.00	88.37	94.12	91.57	90.91	
RBF	36	31	3	7	92.31	83.72	91.18	87.80	87.01	
ANFIS	36	28	6	7	85.71	83.72	82.35	84.71	83.12	
NN	32	28	6	11	84.21	74.42	82.35	79.01	77.92	
NB	32	26	8	11	80.00	74.42	76.47	77.11	75.32	
SVM	37	30	4	6	90.24	86.05	88.24	88.10	87.01	

TABLE 5. Rank based on accuracy metric.

Dataset	CNN-RBF	CNN	RBF	ANFIS	NN	NB	SVM
STARE	1	2	3	4	5.5	7	5.5
HRF	1	2	3.5	5	6	7	3.5
FFA	1.5	3	4	5	7	6	1.5
ALL	1	2	3.5	5	6	7	3.5
Average Rank	1.125	2.25	3.5	4.75	6.125	6.75	3.5

TABLE 6. Rank based on precision metric.

Dataset	CNN-RBF	CNN	RBF	ANFIS	NN	NB	SVM
STARE	1	2	3	4	5	7	6
HRF	1	2	3.5	5	6	7	3.5
FFA	2	2	4	5	7	6	2
ALL	1	2	3	5	6	7	4
Average Rank	1.25	2	3.375	4.75	6	6.75	3.875

Since VGG16 forms the framework for the CNN-RBF, its computational cost will be comparable to that of a regular VGG16 model, with extra estimations needed for the RBF layer. Both CNN and NN algorithms have time complexity that is associated with matrix multiplications. However, CNNs often incur larger computational costs due to the convolutional operations they perform. RBF requires a lot of computing power because it calculates distance. ANFIS is commonly regarded as computationally intensive since it involves the integration of fuzzy logic with neural networks. NB is extremely efficient because of its straightforwardness and lack of dependency on feature computations. SVM can incur significant computational costs, particularly when dealing with huge datasets and intricate kernels.

Our study stands out by utilizing three distinct public datasets, which present challenges in dataset complexity and generalizability that are not commonly addressed in DR detection. This element of our research highlights the capacity of our technique to adjust and excel in diverse datasets, a substantial obstacle in medical image analysis that is essential for practical applications. The primary contribution of our work is in the innovative methodology that integrates several preprocessing approaches. The CNN-RBF is employed as both a feature extractor and a classifier.

CNNs are very good at automatically deriving hierarchical feature representations from unprocessed input, such as photographs. The network can further hone these acquired properties by including RBF layers in CNN designs, possibly enhancing class discrimination. The capacity of RBF networks to simulate intricate, nonlinear interactions between inputs and outputs is well established. Adding RBF layers to CNNs can improve the network's ability to model non-linearly and identify more complex patterns in the data. RBF networks and CNNs use distinct learning processes and capacities. Their integration makes Complementary learning possible, allowing each network node to concentrate on a distinct part of the input. Compared to using either architecture alone, this may increase overall performance. Since RBF networks identify nonlinear correlations and CNNs learn the

TABLE 7. Comparison of the proposed study with previous research based on retina segmentation.

Reference and Models	Dataset	F-score (%)	Sensitivity (%)	Specificity (%)	Accuracy (%)
[20] Fuzzy+ANN+SVM	STARE	-	70.14	98.46	95.53
[42] ICA	STARE	-	78.60	98.20	96.70
[37] RBFNN	DIARETDB1	-	87.00	93.00	-
[38] RV-GAN	STARE	83.23	83.56	98.64	97.54
[36] Dense-U-Net	DRIVE	-	79.31	98.96	96.98
[35] KNN	DIARETDB1	-	92.60	87.56	95.00
[49] Attention+U-Net	STARE	83.94	80.06	98.66	97.96
[34] ResEAD2Net	STARE	-	90.24	99.01	98.07
[39] U-Net	STARE	82.98	78.11	98.80	96.60
[40] WS-DMF	STARE	-	84.48	98.54	96.13
	HRF	-	83.78	99.75	95.71
[41] MU-Net	STARE	-	82.64	98.21	96.93
Our Proposed study, CNN-RBF	STARE	97.56	95.24	100.00	97.30
	HRF	92.31	100.00	83.33	91.37
	FFA	96.77	93.75	100.00	96.43
	ALL	96.47	95.35	97.06	96.10

spatial hierarchies of features, their combination can generalize well to previously unknown data. This generalization capacity is essential for real-world scenarios where the model must function well on fresh, untested data. The comparison of previous studies is represented in Table 7.

Figure 8 represents the LIME explanations of the image classification model, explaining the model's decision-making process based on attributes from fundus images. The image illustrates the beneficial outcomes derived from the prediction. The crucial characteristics affecting the categorization are readily indicated by the yellow outlines.

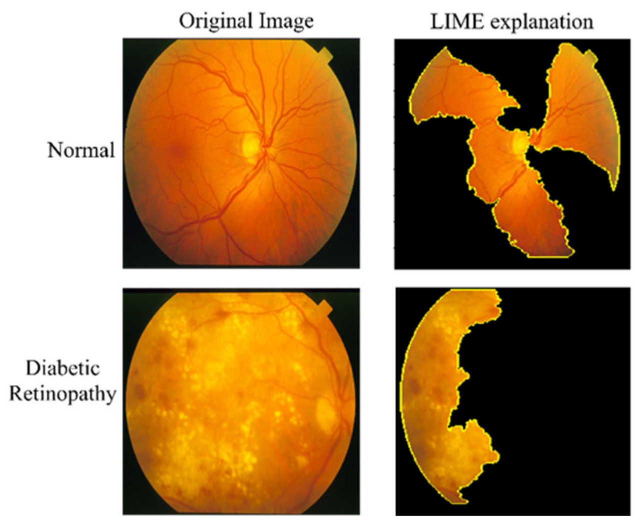

FIGURE 8. The LIME explanation for the normal and diabetic retinopathy images.

A. LIMITATIONS AND FUTURE WORKS

The proposed methodology performed well in retinal image classification with a limited number of features and with less computational complexity, but it has a few significant limitations:

- The proposed methodology has been designed and evaluated using only three publicly available datasets with a relatively small number of images. As a result, its robustness may be limited when applied to unseen datasets. Testing with a broader range of datasets is necessary to validate and generalize the proposed approach. Additionally, augmentation techniques could be employed to generate more samples, enhancing the training and testing of the DR detection model.
- Future studies might focus on hybrid models combining the effective learning processes of random vector functional link networks with CNNs.
- A future approach involves employing advanced optimization techniques like Particle Swarm Optimization or Bayesian Optimization for hyperparameter tuning to enhance the model's performance and generalizability. These methodologies offer a more systematic and cost-effective approach for determining ideal hyperparameter combinations compared to traditional grid or random search methods.
- Another improvement is the integration of diverse medical data, such as fundus pictures, clinical information,

and temporal health records, using multi-modal transformer networks. This method facilitates thorough, contextually enriched learning that integrates cross-modal interactions within a single framework.

V. CONCLUSION

This study introduces an innovative hybrid classifier that combines Convolutional Neural Network and Radial Basis Function (CNN-RBF) models, integrated with Multi-Scale Discriminative Robust Local Binary Pattern (MS-DRLBP) features, to improve the detection of diabetic retinopathy in retinal images. A key aspect of our approach is the deliberate integration of randomization-inspired techniques, which greatly improve the model's efficiency, robustness, and flexibility. Our methodology highlights the potential of combining deep learning with elements of randomness to achieve superior performance in medical image analysis, particularly in the challenging domain of retinal disease detection.

Our work contributes to the burgeoning field of randomization-based learning algorithms by demonstrating the practical advantages of integrating randomization principles within deep learning frameworks. Our approach's efficiency gains, and improved generalizability underscore the value of randomization-inspired methods in addressing complex biomedical imaging tasks. Furthermore, our comparative analysis with traditional and randomization-based methods highlights the efficacy of our model, marking a significant step forward in applying randomization principles to enhance diagnostic accuracy and computational efficiency.

Looking ahead, we envision several promising directions for future research. First, exploring the application of our methodology to other medical imaging modalities and disease detection tasks could further validate its versatility and impact. Also, investigating deeper integrations of randomization within the architecture of CNNs and RBF networks can unlock new levels of performance and efficiency. Finally, developing theoretical models to understand better the interaction between randomization and deep learning could provide valuable insights into the design of future randomization-based learning algorithms.

In conclusion, our study not only contributes a novel and effective tool for diabetic retinopathy detection but also opens new avenues for research in randomization-based deep and shallow learning algorithms. By bridging the gap between traditional deep learning methods and randomization-based approaches, we pave the way for the next generation of efficient, robust, and adaptable models for medical image analysis and beyond.

AUTHOR CONTRIBUTIONS

Conceptualization, G. R. Hemalakshmi, A. M. Mutawa, and M. Murugappan; methodology, G. R. Hemalakshmi and N. B. Prakash; software, G. R. Hemalakshmi and M. Murugappan; validation, A. M. Mutawa; resources, G. R. Hemalakshmi; data curation, N. B. Prakash; writing—original draft preparation, M. Murugappan; writing—review and editing, A. M. Mutawa and M. Murugappan; project administration, A. M. Mutawa; and funding acquisition, A. M. Mutawa. All authors have read and agreed to the published version of the manuscript.

ETHICAL STATEMENT

The authors declare that the study was conducted with publicly available datasets, and therefore, there is no violation of ethics toward the publication of this manuscript.

DATA AVAILABILITY STATEMENT

The authors declare that the study was conducted with publicly available datasets.

CONFLICTS OF INTEREST

The authors declare no conflicts of interest.

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