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RESEARCH ARTICLE

A Lesion-Based Diabetic Retinopathy Detection Through Hybrid Deep Learning Model

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ABSTRACT Diabetic retinopathy (DR) can be defined as visual impairment caused by prolonged diabetes affecting the blood vessels in the retina. Globally, it stands as the primary contributor to blindness, impacting approximately 191 million individuals. While prior research has addressed DR classification using retinal fundus images, existing methods often focus on isolated lesion detection, lacking a comprehensive framework for the simultaneous identification of all lesions. Previous studies concentrated on early-stage features like exudates, aneurysms, hemorrhages, and blood vessels, sidelining severe-stage lesions such as cotton wool spots, venous beading, very severe intraretinal microvascular abnormalities (IRMA), diffuse intraretinal hemorrhages, capillary degeneration, highly activated microglia, and retinal pigment epithelium (RPE) damage. In this study, a deep learning approach is proposed to classify DR fundus images by severity levels, utilizing GoogleNet and ResNet models based on adaptive particle swarm optimizer (APSO), for enhanced feature extraction. The extracted features from the hybrid model are further used with different machine learning models like random forest, support vector machine, decision tree, and linear regression models. Experimental results showcased the proposed hybrid framework outperforming advanced approaches with a remarkable 94% accuracy on the benchmark dataset. This method demonstrates potential enhancements in precision, recall, accuracy, and F1 score for different DR severity levels.

INDEX TERMS Diabetic retinopathy, fundus images, transfer learning, hybrid learning, machine learning, lesion detection.

I. INTRODUCTION

Diabetic retinopathy is a microvascular consequence of diabetes mellitus that can harm vision. Roughly, one-third of the 463 million people worldwide who have diabetes are affected by it [1]. The International Diabetes Federation (IDF) projects that there will be a significant increase in the global diabetes population from roughly 552 million in 2035 to 642 million in 2040 [2], [3]. Over 158.2 million people already have diabetic retinopathy, and by 2030, that number is expected to rise to over 191 million [4], [5]. Diabetic retinopathy continues to be a prominent contributor to global blindness. Individuals with poorly controlled blood sugar levels face an increased risk of developing this condition. Frequent classifications of diabetic retinopathy progression include normal, non-proliferative diabetic retinopathy (NPDR), and proliferative diabetic retinopathy (PDR) [6]. The main features of non-proliferative diabetic retinopathy (NPDR) include a slowdown in the formation of retinal blood vessels and a gradual degradation of the

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vessel walls. Based on how serious the disease is, NPDR is then divided into three categories: mild, moderate, and severe. However, proliferative diabetic retinopathy (PDR) is characterized by the development of new blood vessels in the retina, which obstructs the retina's normal blood flow [7], [8].

Retinal fundus images of diabetic patients are routinely captured during retinal screenings. However, the analysis of these images demands a thorough examination by trained ophthalmologists, a process that consumes both time and financial resources [9]. In recent years, researchers have proposed various techniques for detecting abnormalities in retinal images. Earlier studies primarily focused on extracting early symptoms like microaneurysms, exudates, hemorrhages, and blood vessels [10]. Activated microglia, capillary degeneration, highly diffused intraretinal hemorrhages, cotton wool spots, venous beading, severe intraretinal microvascular abnormalities (IRMA), and the retinal pigment epithelium (RPE) have all been noticeably neglected, though [9].

Despite the large existing literature on the use of machine learning approaches for diabetic retinopathy detection, feature extraction approaches are not very well studied for this problem. The limited feature extraction has increased the likelihood of the disease being present in features that were not extracted [11]. Without a doubt, enhancing feature extraction is essential to raising detection and classification accuracy. Using retinal fundus images as supporting data, this research proposes a novel method for the automated diagnosis and classification of diabetic retinopathy. The primary objective of this study is to present a novel approach to diabetic retinopathy prediction and classification, which entails the following steps

- Employing data augmentation techniques to ensure an even distribution of images,
- Introducing feature selection and extraction techniques aimed at optimizing the classification performance for each stage of diabetic retinopathy,
- Presenting an efficient method for the diagnosis and classification of diabetic retinopathy, and
- Proposing a hybrid features-based approach in conjunction with various models for enhanced performance of machine learning models for diabetic retinopathy detection.

The manuscript is organized into four primary sections. Section II delves into the literature review. Following that, Section III details the methodologies developed. Section IV discusses the outcomes and results of the proposed technique. Lastly, in Section V, the conclusion of the proposed system is presented.

II. LITERATURE REVIEW

A large body of literature is available on detecting diabetic retinopathy. These works are divided into machine learning, deep learning, and transfer learning-based approaches and are discussed separately in the subsequent sections.

A. MACHINE LEARNING APPROACHES

Worldwide, diabetic retinopathy stands as the predominant cause of visual impairment among the adult population. Recently, artificial intelligence (AI) techniques have been employed to aid in the identification. For example, Ozbay et al. [7] outlined a methodology using a machine learning model to differentiate diabetic retinopathy from vision-threatening diabetic retinopathy (VTDR) by analyzing fundus images of the retina. The algorithm exhibited exceptional accuracy in distinguishing between VTDR and diabetic retinopathy, surpassing the performance of prior approaches.

In a similar vein, Panwar et al. [8] described an alternative methodology involving the application of machine learning to the analysis of retinal fundus images for detecting diabetic retinopathy. After rigorous training on an extensive collection of retinal images, the model demonstrated significant precision and accuracy in categorizing cases of diabetic retinopathy. Similarly, the study [2] employed a machine learning strategy to analyze retinal fundus images for diabetic retinopathy. Following an extensive training period with a diverse set of retinal images, the model exhibited significant accuracy and precision in categorizing instances of diabetic retinopathy.

A recent study by Yang et al. [12] discovered that a hybrid architecture consisting of support vector machines (SVM) and convolutional neural networks (CNNs) yielded the most accurate identification of diabetic retinopathy. Saranya et al. [13] presented a technique to establish a system utilizing retinal images for the detection and early diagnosis of diabetic retinopathy. The model demonstrated exceptional accuracy after rigorous training on a substantial dataset of retinal images. Machine learning algorithms have displayed remarkable precision in detecting diabetic retinopathy through the analysis of retinal images. These methodologies hold the potential to improve the timely identification of diabetic retinopathy, ultimately reducing the risk of visual impairment in individuals with diabetes [14].

B. DEEP LEARNING APPROACHES

Deep learning-based algorithms are commonly utilized for addressing the various medical image analysis challenges, circumventing the limitations of traditional machine learning methods [15], [16], [17]. Unlike their machine learning counterparts, deep learning models can rapidly discern enhanced features in retinal images with minimal human intervention. Several studies have explored the utilization of deep learning-based algorithms for detecting and diagnosing diabetic retinopathy. These algorithms have shown promising outcomes in automating the diabetic retinopathy detection process, providing potential support for timely diagnosis and intervention.

The use of CNN in diabetic retinopathy detection has become increasingly prevalent due to their remarkable ability to efficiently extract and learn intricate features from retinal

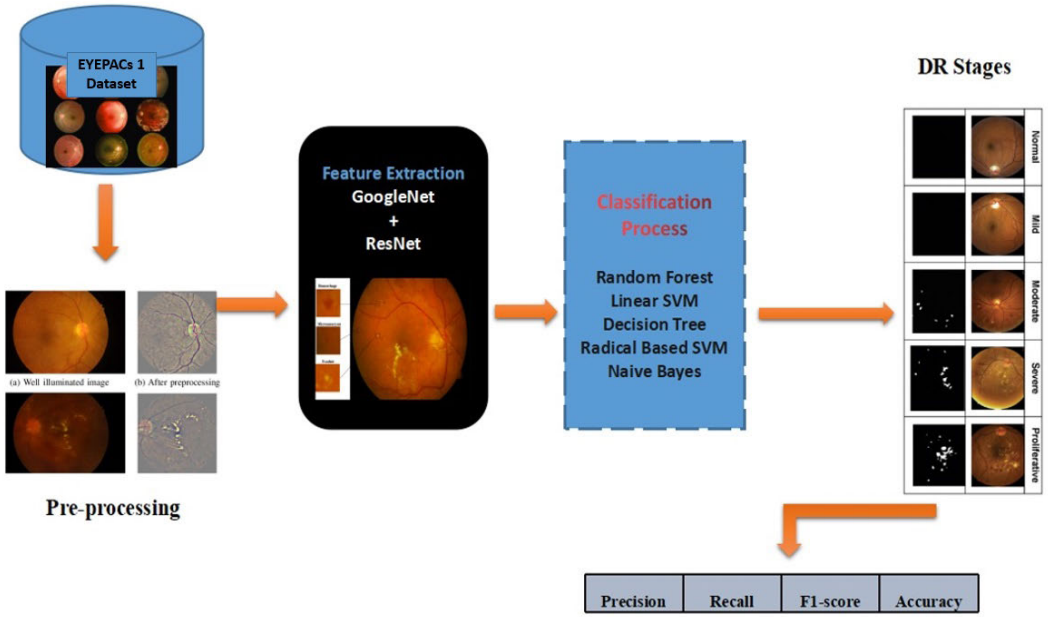

FIGURE 1. Architecture of the proposed methodology for diabetic retinopathy detection.

images. Indeed, the study conducted by Gulshan et al. [18] shows promising results. By employing a CNN-based algorithm to analyze a massive dataset of retinal images, referable diabetic retinopathy was detected with remarkable precision. For diabetic retinopathy detection, alternative deep learning architectures have also been investigated alongside CNN variants. Li et al. [19] implemented a deep fusion network, which integrates several deep learning models for improving the precision of diabetic retinopathy severity level detection. By fusing these models, complementary characteristics can be utilized more efficiently, thereby improving the algorithm's overall performance. Moreover, efforts have been made to investigate preprocessing methods for enhancing the performance of deep learning algorithms in diabetic retinopathy detection. As a solution to the issue of inadequately annotated data, transfer learning has been implemented. Through the application of insights obtained from a more extensive dataset, the proposed algorithm exhibited competitive efficacy despite being trained on a limited quantity of data [20].

C. TRANSFER LEARNING BASED APPROACHES FOR DIABETIC RETINOPATHY DETECTION

Transfer learning-based techniques are emerging successfully in the image-based analysis of different diseases. Past research focused on the detection of diabetic retinopathy through using transfer learning-based models. For instance, Karakaya and Hacisoftaoglu [21] introduced a deep fusion network that integrates multiple deep learning models to enhance the precision of diabetic retinopathy severity level classification. By fusing these models, multiple features can be utilized more efficiently, thus leading to improved performance.

Another important aspect of diabetic retinopathy detection is to investigate preprocessing methods to enhance the accuracy of diabetic retinopathy detection. In response to the challenge of limited annotated data, transfer learning has been employed. By leveraging knowledge acquired from a larger dataset, the algorithms demonstrated competitive performance even with a restricted amount of training data. Saranya and Umamaheswari [20] facilitated the development and evaluation of a transfer learning system intended for the identification of diabetic retinopathy, glaucoma, and age-related macular degeneration (AMD). For experiments, the authors implemented eight CNN designs inspired by VGGNet. Similarly, a CNN model was utilized by Zago et al. [22], to evaluate the severity of diabetic retinopathy. In order to acquire patches, a pre-trained CNN on ImageNet was utilized. The Kaggle dataset was processed using a random forest classifier, which produced a Kappa score (K-Sc) of 0.86.

The above-discussed research works show promising results for diabetic retinopathy, yet, further improvements are needed for timely and accurate diabetic retinopathy detection. Predominantly, these works focus on model optimization, ensemble methods, and preprocessing improvement. The enhancement in feature engineering approaches is rather overlooked or under-investigated. This study proposes a hybrid feature engineering approach for improving the performance of machine learning models in diabetic retinopathy detection and contributes significantly to this important research field.

III. MATERIALS AND METHODS

This study introduces an innovative hybrid approach utilizing transfer learning based on two widely recognized

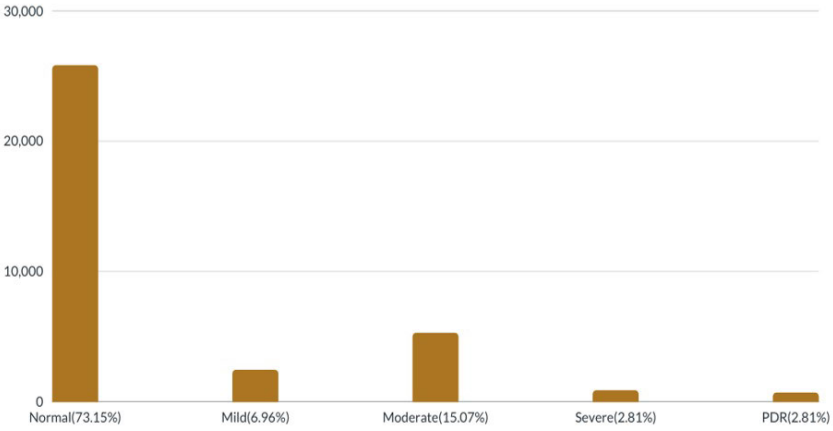

FIGURE 2. Image distribution in the EYEPACs dataset.

architectures, GoogleNet and ResNet-16. To ensure compatibility with these models, fundus images are preprocessed by resizing and normalizing to a standard size of 224 × 224×3 pixels. By freezing the layers of both architectures, fundus images pass through the models, extracting features from a fully connected layer at the end of each architecture. The softmax layer, primarily used for classification, is removed. This preprocessing and feature extraction pipeline involves convolution, normalization, and pooling layers in both models.

GoogleNet employs inception modules to efficiently reduce computational resources while capturing crucial spatial and local features. ResNet-16 incorporates skip connections to mitigate degradation issues and minimize training errors. Feature vectors from both models are combined to create a hybrid feature vector with 2000 features. This hybrid vector serves as input for diverse classifiers, enabling a comparative evaluation of their performance in diabetic retinopathy classification.

For classification, fundus images are categorized into four groups: no signs of diabetic retinopathy (NDR), representing stage 0 on the ICDR severity scale, and mild, moderate, and severe stages of diabetic retinopathy. Multiclass classification divides images into three classes: NDR (stage 0), MDR (stages 1 and 2), and PDR (stages 3 and 4) on the ICDR severity scale.

The proposed methodology, depicted in Figure 1, outlines the hybrid feature extraction and classification process for fundus images. Following the preliminary preprocessing stage, images are inputted into the transfer learning models like GoogleNet and ResNet-16, which independently perform feature extraction. The obtained features are utilized as input for various classifiers, such as the radial SVM (RSVM), the decision tree (DT), Naïve Bayes (NB), and the random forest (RF). In order to assess the performance of these classifiers, metrics such as the F1-score, precision, accuracy, as well as, recall are utilized. Results are compared with existing literature, providing insights into the advancement of diabetic retinopathy classification techniques.

A. EXPERIMENTAL DATASET

The present investigation utilized the Kaggle EyePACS1 dataset [23], which comprised retina fundus images of high resolution. The dataset came from the California Healthcare Foundation's Diabetic Retinopathy Detection competition. With great care, ophthalmologists labeled the pictures, classifying them into five distinct groups: 'normal', 'mild', 'moderate', 'severe', and 'proliferative' diabetic retinopathy. The dataset includes 35,126 fundus photos in total. Four percent of the fundus images in the training set were set aside for validation, leaving the remaining ninety-six percent of the photos for training and assessment of our suggested model. Figure 2 provides a visual representation of the dataset for easy understanding.

B. DATASET PREPROCESSING

The EyePACS dataset includes a wide variety of retinal images taken with cameras of different sizes and different lighting conditions. In order to reduce the resulting differences, the images were normalized through a number of preprocessing steps. The fundus images of the eye are shown in Figure 3 in their original state prior to the application of these preprocessing steps.

1) IMAGE RESIZING

The resizing technique is a critical aspect of preprocessing diabetic retinopathy fundus images. Bicubic interpolation stands out as a commonly employed method for resizing, involving the computation of the weighted average of neighboring pixels. Its preference lies in the capacity to yield smooth and visually pleasing results, effectively minimizing artifacts and distortions in the resized images. Preferentially, this method produces aesthetically appealing and seamless outcomes by reducing the presence of artifacts as well as distortions in the resized images.

2) GREEN CHANNEL EXTRACTION

The dataset images of the retina exhibit a variety of large, yellowish tones against a dark background. To reduce

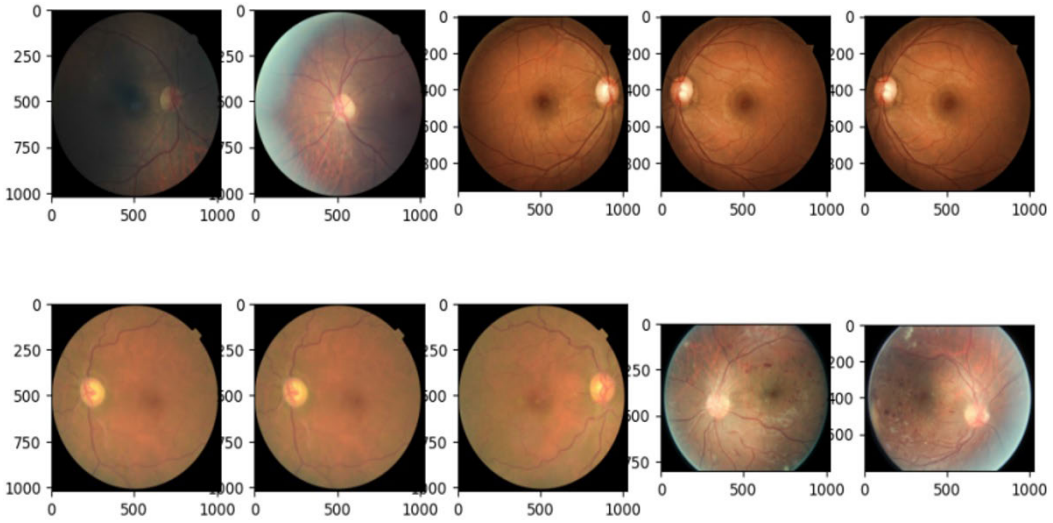

FIGURE 3. The retinal fundus images of the eye prior to undergoing preprocessing.

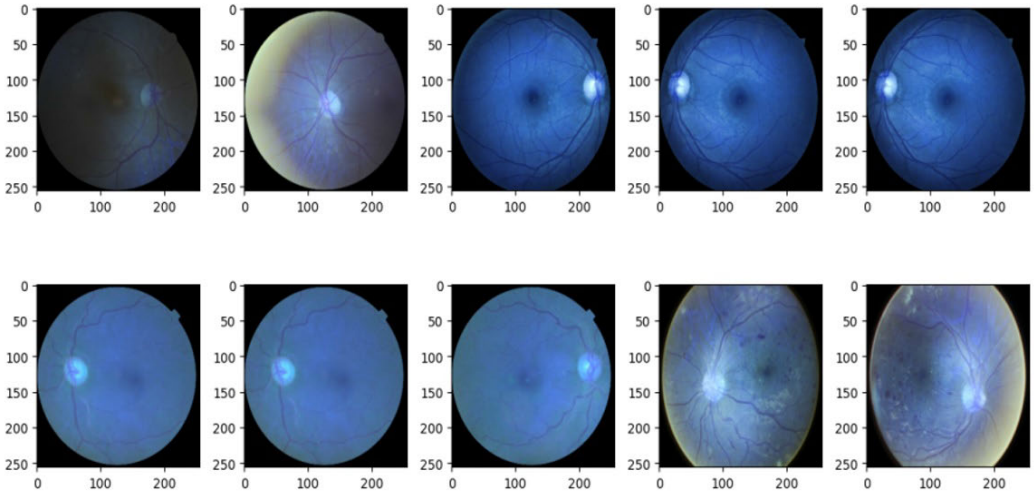

FIGURE 4. The retinal fundus images of the eye after image resizing.

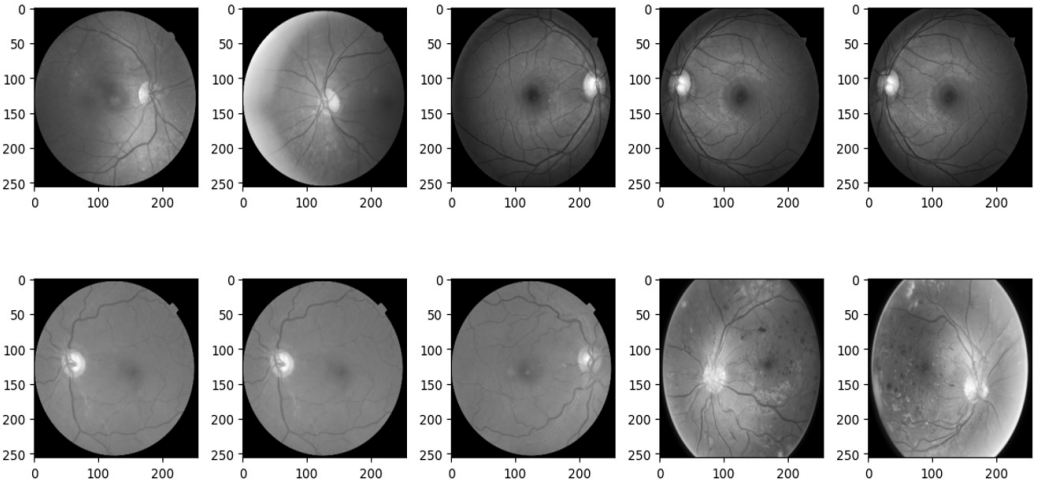

FIGURE 5. The retinal fundus images of the eye after the extraction of the green channel.

interference, especially since fundus details do not overlap with the background, the background was removed. After image resizing, a green channel is obtained from the images. The retinal images are traditionally low resolution and low

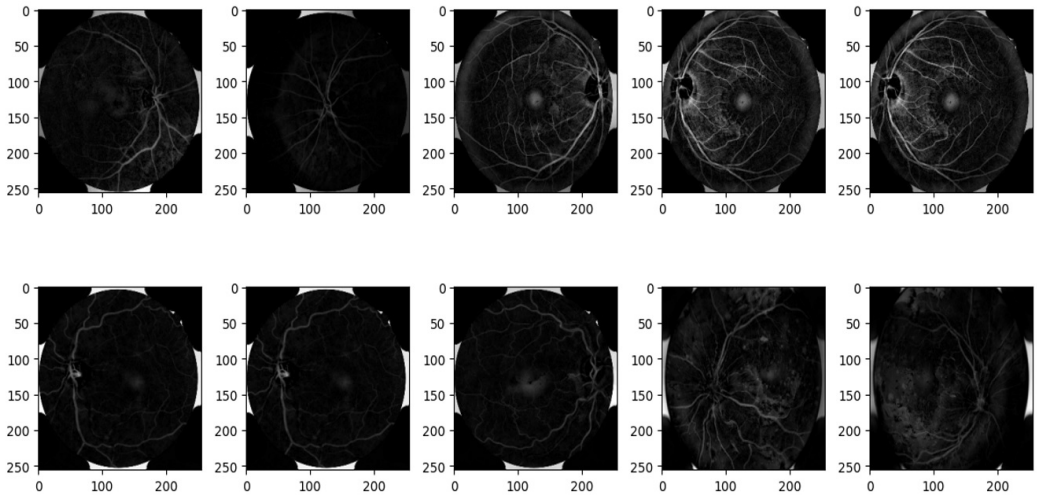

FIGURE 6. Images of the retinal fundus of the eye subsequent to morphological transformations.

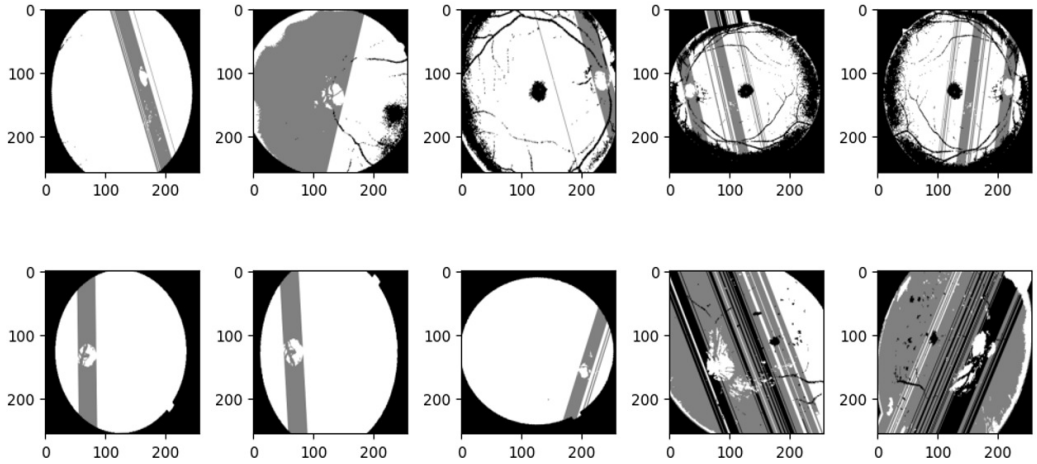

FIGURE 7. The fundus images after applying different data augmentation techniques.

contrast and various types of diabetic retinopathy are visible in the green channel. It is easy to detect diabetic retinopathy in green channel images due to high contrast. The green channel extraction step of preprocessing aims to enhance the image contrast. Figure 5 shows the output of green channel extraction of retinal images.

3) TOPHAT AND BOTTOMHAT TRANSFORMATIONS

Morphological operations are like the unsung heroes of image processing, right? Opening and closing, in particular, are like the dynamic duo in pre-processing diabetic retinopathy fundus images. They can really help fine-tune the details and enhance the features in the images, contributing to a more effective analysis. These operations are instrumental in noise reduction, contrast enhancement, and highlighting specific image features. Tophat and bottom hat transformations are commonly employed morphological changes in this context. Figure 6 provides a visual representation of the fundus images after undergoing these morphological operations.

C. DATA AUGMENTATION

Certainly, the effectiveness of models is significantly influenced by the size and diversity of the dataset. It is crucial to have a substantial and varied training dataset to prevent overfitting and facilitate robust generalization. Figure 7 visually demonstrates the implementation of various techniques, including flipping, cropping, rotating, and zooming, to enhance the visual appeal of augmented images. These augmentation techniques contribute to a more robust and varied training dataset, ultimately improving the performance and generalization ability of DL models.

Figure 8 displays the impact of applying augmentation operations to the training dataset. Techniques like flipping, rotating, cropping, and shearing are instrumental in this process. An increase of 3.6 times in the extent of the dataset resulted in a fair allocation of all grades of diabetic retinopathy in a 1:1 proportion. This augmentation strategy significantly bolsters the comprehensiveness and representativeness of the training dataset, laying a solid foundation for the model.

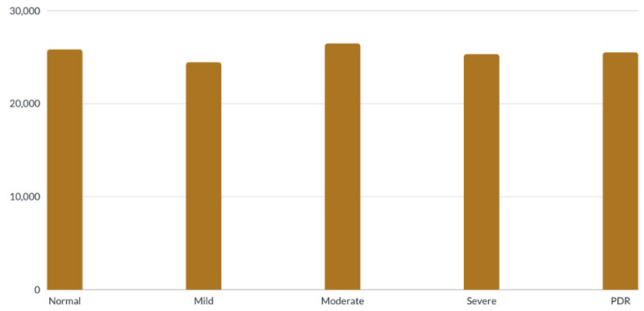

FIGURE 8. The dataset representation after applying different data augmentation techniques.

D. APSO-GRESNET-BASED FEATURE EXTRACTION MODEL

Large-scale fundus image datasets are used to train deep learning models, specifically the APSO-GRESNET hybrid technique, in order to facilitate the extraction of characteristics associated with diabetic retinopathy (DR) lesions. Carefully labelled to provide the specific location and classification of every DR lesion, these datasets offer a strong basis for training and assessment.

The hybrid learning models make use of this abundant information to identify complex structures and patterns that correspond to different types of DR lesions. For example, the models are trained to identify ovoid or circular morphologies that show a marginally increased brightness in relation to their surrounding areas in order to detect microaneurysms. The models use yellow or white regions which are often found in the macular region to identify exudates. On the other hand, bleeding appears in the pictures as red dots that fluctuate in size and prominence. By fusing the advantages of Google's ResNet with Adaptive Particle Swarm Optimizer (APSO), the APSO-GRESNET hybrid model goes beyond conventional feature extraction techniques. The model's capacity to identify subtle characteristics linked to DR lesions is strengthened by this integration, which raises the accuracy of diagnosis. ResNet and GoogleNet two essential parts of the hybrid model—both demonstrate competence in identifying anomalies in fundus images that go beyond those associated with DR alone. Figure 9 shows the visual representation of the feature extraction method, which consists of sequential phases to emphasize and capture unique features associated with lesions connected to diabetic retinopathy. This novel method not only improves the identification of recognized lesions but also expands the scope to include a greater variety of anomalies shown in fundus pictures.

1) GOOGLENET ARCHITECTURE

GoogleNet is renowned for its deep architecture comprising 22 layers. Noteworthy for its efficient utilization of computational resources, GoogleNet incorporates repeated inception modules. These modules play a pivotal role in expanding the network's width and depth, allowing for the capture of features at various scales. Each inception module within the network employs convolutional layers of diverse sizes to detect different local and spatial characteristics of the input. Figure 9 represents the structure of the inception module utilized in the GoogleNet model. The 1×1 convolutional layers are responsible for reducing input dimensions while extracting local cross-channel features. Conversely, the 3×3 and 5×5 convolutional layers contribute to capturing spatial attributes of input. Additionally, a pooling layer is added in the inception module to further reduce input dimensions. This intricate design enables GoogleNet to effectively extract and process features from complex images.

2) RESNET-16 ARCHITECTURE

A residual neural network (ResNet) is a type of CNN, which is created to address the vanishing gradient problem by incorporating skip connections. These skip connections allow for the omission of specific layers within the network, mitigating the vanishing gradients issue and contributing to a reduction in training time. Non-linear activation functions are applied between the skipped layers to enhance the accuracy of the network. Batch normalization is also utilized in the shortcut connections to ensure stable training. A weight matrix calculates the weights associated with these skip connections. As the network learns input features, expansion is applied in subsequent stages to refine the model further.

The fundamental unit of a ResNet, illustrated in Figure 10, serves as the foundational building block repeated multiple times within the network. The mapping of input x to output $f(x)$ is learned in a CNN. This mapping is accomplished in the fundamental ResNet block by a feed-forward neural network that incorporates shortcut connections denoted by $x + g(x)$. When the dimensions of the input and output are the same, the function $g(x)$ acts as an identity connection. Zero padding is used when there are differences in measurements. ResNet can effectively train deep networks and produce remarkable results in image classification applications because of the integration of these skip connections.

Equation 1 provides the expression for the resulting residual block obtained when stacking layers with matching dimensions within the network.

$$y = f(x, Wi) + x \tag{1}$$

In the ResNet architecture, the function $f(x, Wi)$ represents the learned mapping of the convolutional layer, which evolves during the training process. Additionally, the architecture includes an average pooling layer that employs a 1×1 filter, and a single fully connected layer is utilized for the final assessment of the network. These components contribute to the overall structure of ResNet, allowing it to effectively learn and map features during the training process.

The two main phases of the suggested framework for identifying and describing diabetic retinopathy are feature extraction and disease classification. During the feature extraction stage, GoogleNet and ResNet models are employed to extract high-level features from fundus images. Pre-trained on extensive datasets, these models are able to recognize a wide range of characteristics associated with diabetic retinopathy lesions.

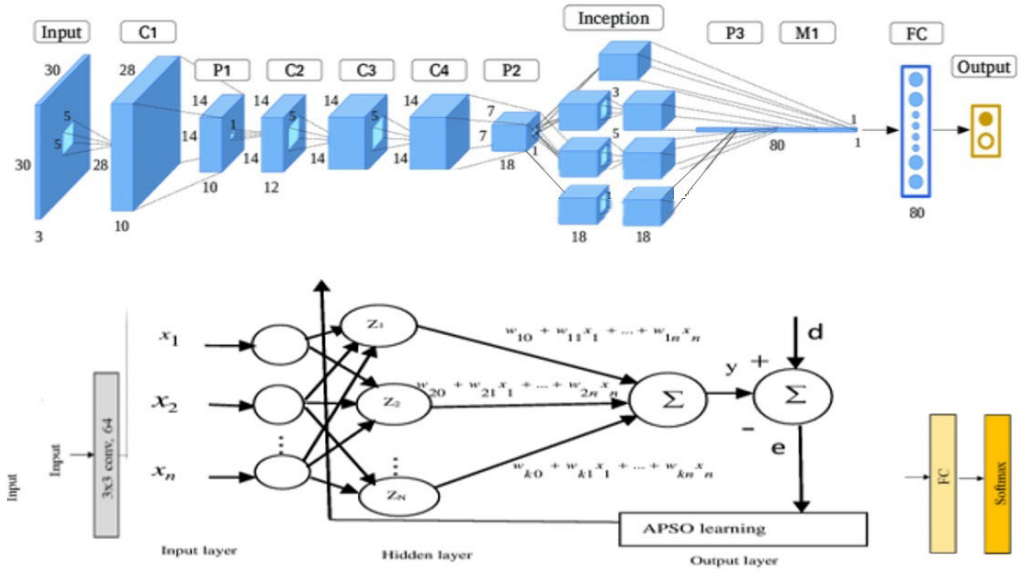

FIGURE 9. Hybrid feature extraction model.

The second step is classifying diseases using the features that were extracted. Different classifiers are employed for the categorization of fundus images following the various phases of DR. These classifiers are trained on labeled data to identify patterns that distinguish between different phases of diabetic retinopathy and distinguish between healthy fundus images and those that are sick. Using a dataset of diabetic patient fundus images, the suggested approach is assessed. F1-score, precision, accuracy, and recall, alongside recall are utilized to approach the high performance of the system and offer a comprehensive evaluation of its ability to detect and categorize diabetic retinopathy.

IV. EXPERIMENTAL RESULTS

Several classifiers are used in this study with the hybrid feature vector, which was produced by integrating the retrieved feature vectors from GoogleNet and ResNet-16. Based on the image data, the features were taken out of the GoogleNet and ResNet-16 architectures that have already been trained. The multiclass classification of the input image is done using a variety of classifiers. To evaluate the effectiveness of classifiers, we employed performance indicators such as F measure, accuracy, precision, and recall. Precision calculates the percentage of positive predictions in a given class that are truly correct, whereas accuracy shows the percentage of correctly classified predictions out of the total.

A. SYSTEM CONFIGURATION

A framework with the accompanying particulars was utilized for the strategy. It has Windows 10 as the operating system with an Intel 8th Generation Core i5 processor running on 16 GB RAM. A graphics card with 12 GB RAM is used. The models are implemented using Python language on GoogleCollab.

B. PERFORMANCE METRICS

To assess the general working of the introduced plot, we dissected the presentation of unusual human movement acknowledgment from a disarray matrix and afterward figured out the accompanying execution measurements [20].

Accuracy shows the proportion of a few parts true positive (TP) and true negative (TN) to the complete number of TP, TN, false positive (FP), and false negative (FN). It can be determined using

$$Accuracy = \frac{TP + FN}{TP + FN + TN + FP} \tag{2}$$

Precision is communicated as the proportion of the total number of TPs concerning all positive predicted labels (i.e., the amount of TP and FP). Precision can be determined using

$$Precision = \frac{TP}{TP + FP} \tag{3}$$

Recall is a performance metric used in statistics and machine learning to measure the effectiveness of a classification model in identifying positive instances correctly. It is the ratio of the TP instances to the total number of actual positive instances in the dataset. It can be determined using

$$Recall = \frac{TP}{TP + FN} \tag{4}$$

F1 score is the arithmetic mean of precision and recall and is considered a better choice to evaluate the model's performance, especially for imbalanced datasets. It can be determined using

$$F1 \ - score = 2 * \frac{Precision * Recall}{Precision + Recall} \tag{5}$$

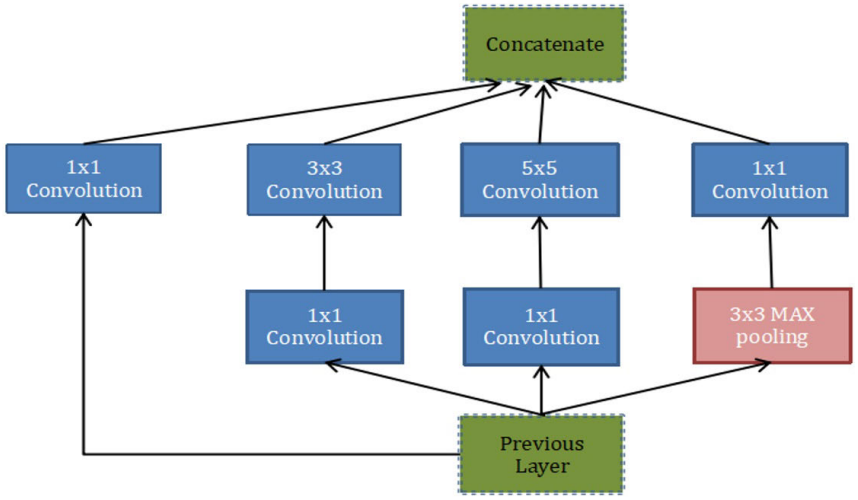

FIGURE 10. Inception module for the GoogleNet model.

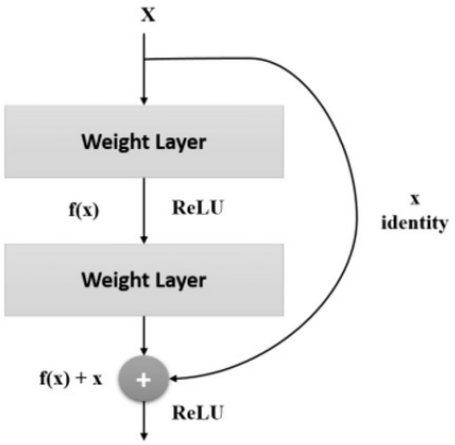

FIGURE 11. Building block of residual network.

TABLE 1. Classification results using RF model.

Class	Precision	Recall	F1-score	Accuracy
0	0.88	0.96	0.92	0.90
1	0.89	0.75	0.81	0.91
2	0.96	0.92	0.94	0.91
3	0.94	0.91	0.92	0.91
4	0.90	0.93	0.92	0.91

C. RESULTS OF MACHINE LEARNING MODELS

1) RANDOM FOREST RESULTS

Table 1 shows the assessment results of the random forest classification. The model exhibits impressive overall performance when utilizing the random forest classifier, achieving an accuracy of 0.91. Furthermore, the comprehensive metrics of accuracy, precision, and F1-score stand quite high at 0.91, 0.90, and 0.90, respectively, indicating a strong and effective model performance.

Figure 11 illustrates the assessment of the RF classification for each diabetic retinopathy class, including the F1 score, accuracy, precision, along recall.

TABLE 2. Classification results using DT model.

Class	Precision	Recall	F1-score	Accuracy
0	0.89	0.85	0.87	0.87
1	0.68	0.81	0.74	0.86
2	0.98	0.87	0.92	0.87
3	0.88	0.90	0.89	0.87
4	0.88	0.87	0.88	0.86

The confusion matrix sheds light on how well the RF classifier predicts the grades of diabetic retinopathy. The anticipated grades are shown in the columns, and the actual grades are shown in the rows. Correct predictions are indicated by diagonal entries, and incorrect predictions are shown by off-diagonal entries.

Figure 12 depicts the confusion matrix for the RF model. The confusion matrix showed that the model performed exceptionally well in terms of accuracy, recall, and F1 score when it came to predicting classes 0, 1, 2, and 4. By obtaining an F1 score of 0.92, a recall of 0.96, and an accuracy of 0.88, the model successfully identified 214 out of 222 cases for class 0. In the same way, the model achieved an accuracy of 0.89, a recall of 0.75, and an F1 score of 0.81 for class 1. The model achieved a 0.96 F1 score, 0.92 recall, and 0.96 accuracy in the case of class 2. Last but not least, the model yielded an accuracy of 0.90, a recall of 0.93, and an F1 score of 0.92 for class 4.

2) DECISION TREE RESULTS

Table 2 shows a detailed evaluation of the decision tree classification, providing a comprehensive breakdown of performance metrics across different classes. With an overall accuracy of 0.86, the model can correctly predict 86% of the observations. Interestingly, each class has varied recall, accuracy, precision, and F1 scores, indicating unique performance in each class. The highest accuracy is observed for class 2, reaching 0.98, suggesting that the model accurately predicts class 2 in 98% of instances.

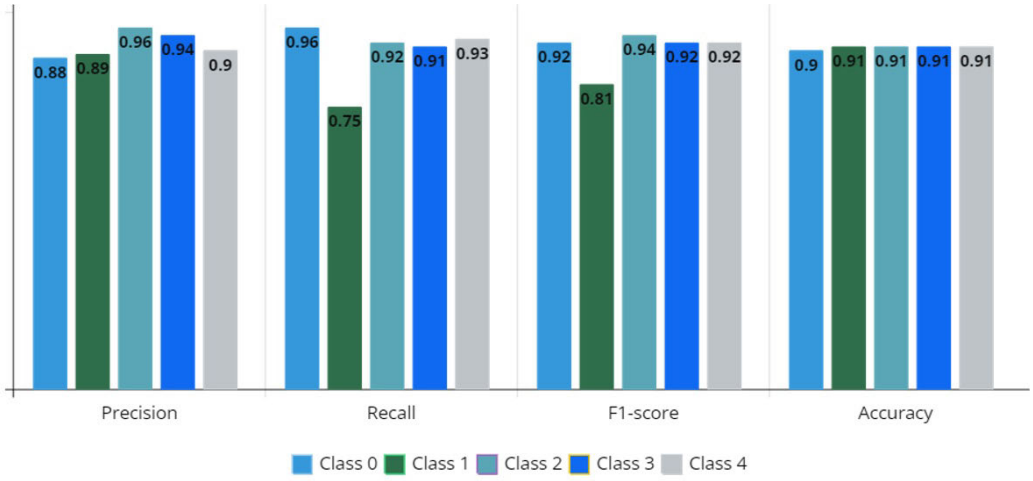

FIGURE 12. An evaluation of the RF classification algorithm for every diabetic retinopathy class.

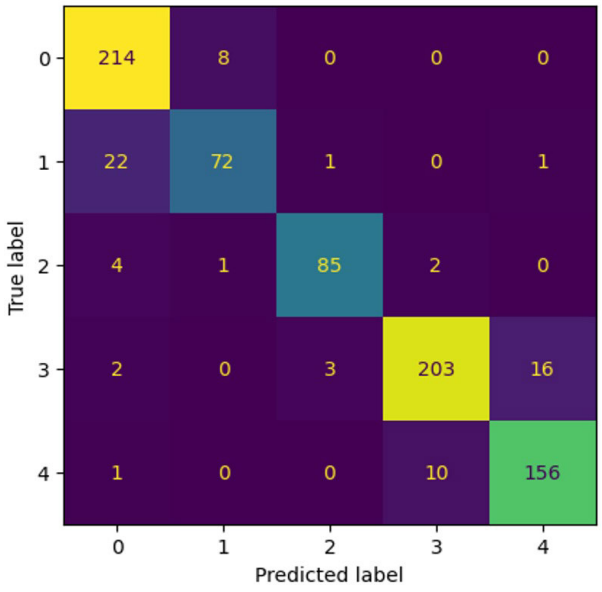

FIGURE 13. Confusion matrix based on the random forest classification.

Figure 13 displays the evaluation results for DT for each class of diabetic retinopathy. Results demonstrate that the performance of DT is not as good as that of RF for diabetic retinopathy classification. Results are good in terms of precision for classes 0 and 2, however, for other classes, especially class 1, the results are poor. For example, scores for precision, recall, F1 score, and accuracy for class 1 are 0.68, 0.81, 0.74, and 0.86, respectively.

For the DT classifier, the confusion matrix given in Figure 14, delineates the quantity associated with each distinct form of diabetic retinopathy. Actual labels are represented in the rows, whereas the columns contain the anticipated labels. The depicted figure offers a lucid illustration of the label distribution, both predicted and actual, as it pertains to the classification of diabetic retinopathy. Confusion matrix results also indicate a comparatively lower performance from the DT classifier. For example, it has 188, 78, 80, 201, and 145 true positives compared to 214, 72, 85, 203, and 156 true positives from the RF model, for classes 0, 1, 2, 3, and 4, respectively.

TABLE 3. Classification results using linear SVM model.

Class	Precision	Recall	F1-score	Accuracy
0	0.90	0.94	0.92	0.92
1	0.85	0.81	0.83	0.91
2	0.94	0.91	0.93	0.92
3	0.98	0.91	0.94	0.92

3) LINEAR SUPPORT VECTOR MACHINE RESULTS

Across several classes, the SVM model produced an overall accuracy score of 0.92, recall values ranged from 0.81 to 0.94, precision values from 0.85 to 0.98, and F1 score values from 0.83 to 0.94. The aforementioned discovery indicates that the SVM model demonstrated remarkable precision when it came to categorizing cases of diabetic retinopathy. For a detailed breakdown of the assessment metrics, refer to Table 3, which presents the evaluation results of the linear SVM model. If there are specific aspects you'd like to delve into or discuss regarding the SVM model's effectiveness.

The evaluation of the F1 score, recall, accuracy, and precision of the linear SVM for each class level of diabetic retinopathy is shown in Figure 15. The figure indicates better results for classes 0, 1, 2, 3, and 4, however, the precision, recall, F1 score, and accuracy are low for class 1 of diabetic retinopathy.

Figure 16 presents a graphical representation of the confusion matrix for a linear SVM classifier. As per the confusion matrix results, the SVM model produced 801 predictions in total. A total of 164 true positives, 203 true positives, 84 true positives, 78 true positives, and 203 true positives for classes 4, 3, 2, 1 and 0, respectively. The model produced 15 erroneous predictions for the first class, 4 false predictions for the second class, 3 deceptive predictions for the third class, and 2 errors in predicting the fourth class.

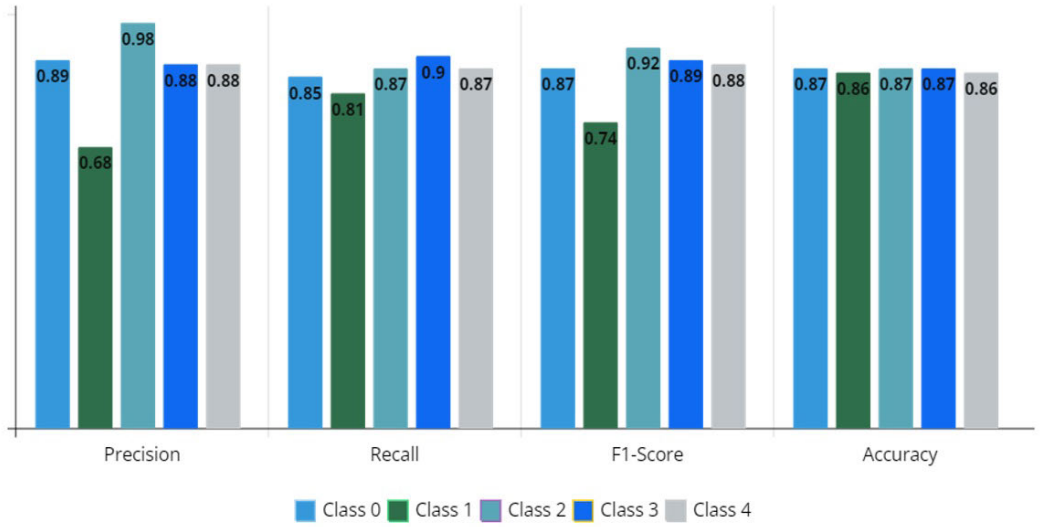

FIGURE 14. The evaluation of DT classifier.

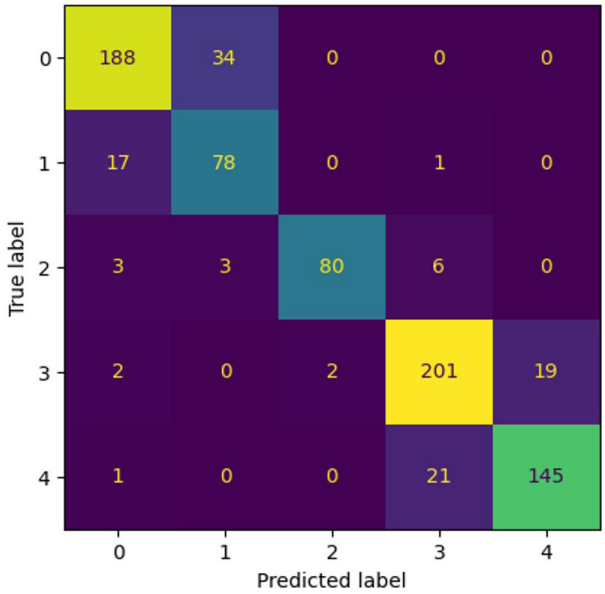

FIGURE 15. The confusion matrix for DT classifier.

In addition to overall metrics weighted by the total number of samples in each class, class-specific model performance metrics like accuracy, recall, and F1 score are included in the classification report.

4) RADIAL SUPPORT VECTOR MACHINE RESULTS

A thorough assessment of the radial-based SVM can be found in Table 4. Reslts indicate that it obtains the best accuracy score of 0.94 for class 4; however, for other classes, its accuracy varies between 0.71 to 0.83. The best precision of 0.95 is obtained for class 3 while the best recall and F1 scores of 0.94 and 0.92 are obtained for class 4 and classes 2,3 and 4 each, respectively.

The efficiency, accuracy, precision, F1 score, recall, and accuracy of the radial-based SVM model for each class of diabetic retinopathy are graphically represented in Figure 17. Results indicate that the radial SVM shows superior performance compared to other performances and obtains very good precision, recall, F1 score, and accuracy for classes 2, 3, and 4.

Figure 18 displays the confusion matrix, which serves as the graphical representation of the radial-based SVM. It indicates the number of correct and wrong predictions for each class. For example, radial-based SVM has 222, 93, 85, 199, and 157 correct predictions for classes 0, 1, 2, 3, and 4 which is better than other models.

TABLE 4. Classification results using radial SVM model.

Class	Precision	Recall	F1-score	Accuracy
0	0.69	0.91	0.81	0.83
1	0.70	0.79	0.80	0.75
2	0.92	0.92	0.92	0.71
3	0.95	0.89	0.92	0.78
4	0.89	0.94	0.92	0.94

TABLE 5. Classification results using NB model.

Class	Precision	Recall	F1-score	Accuracy
0	0.87	0.47	0.61	0.80
1	0.40	0.84	0.54	0.84
2	0.86	0.92	0.89	0.78
3	0.97	0.82	0.89	0.84
4	0.85	0.97	0.91	0.84

5) NAIVE BAYES RESULTS

Table 5 provides a comprehensive analysis of the Naive Bayes classifier evaluation findings. The overall accuracy score of the Naive Bayes model is 0.77. For every class, the F1 score, recall, accuracy, and precision are also given. For classes 2, 3, and 4, the model showed good accuracy, recall, and F1 score; however, classes 0 and 1 showed lower scores.

Figure 19 illustrates the performance of the NB classifier for classifying various classes of diabetic retinopathy. Although the performance of other classes is satisfactory,

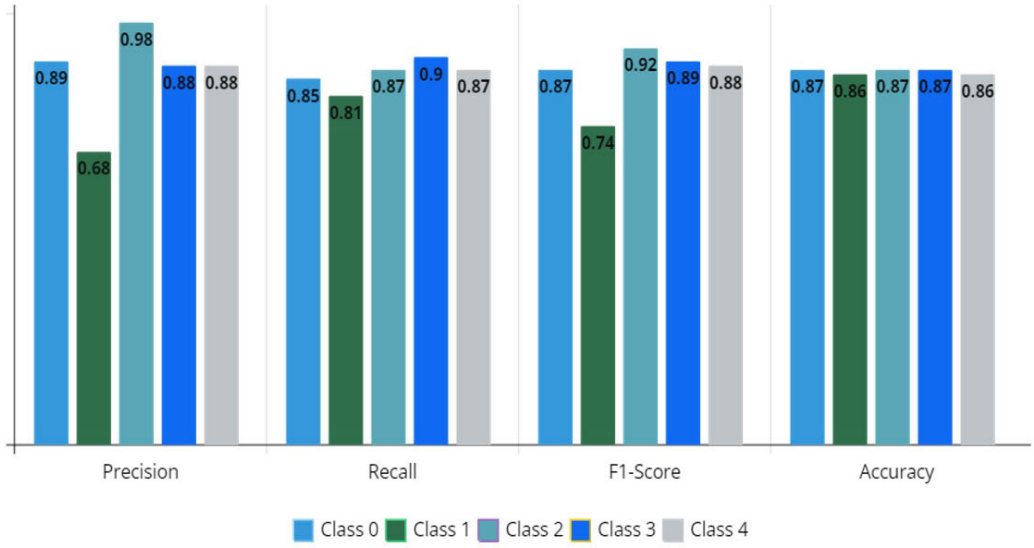

FIGURE 16. The evaluation of linear SVM classifier.

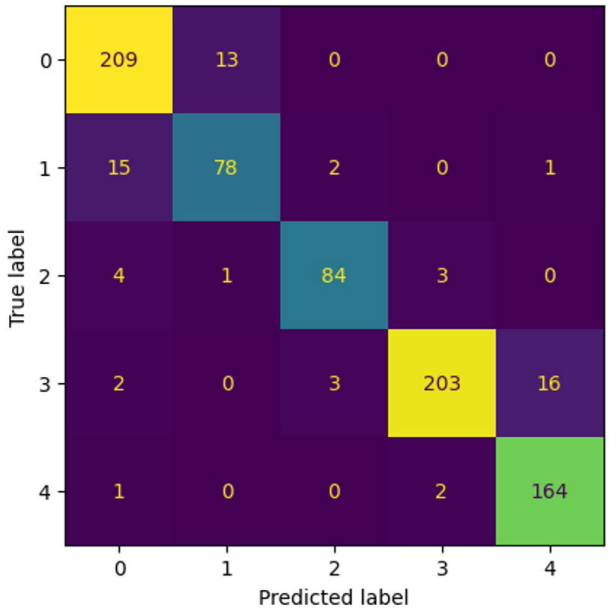

FIGURE 17. Confusion matrix based on the linear SVM classification.

class 0 of diabetic retinopathy shows poor results using NB indicating scores of 0.4, and 0.54 for precision and F1 score. Similarly, recall and F1 scores for class 0 are also low.

The confusion matrix for the NB classifier is shown in Figure 20. Each of the five classes (0 to 4) is represented in the matrix, showcasing the true and predicted values for a comprehensive evaluation of the model's diagnostic accuracy. The model shows poor performance for class 0, especially indicating only 104 true positives. Similarly, only 81 cases of class 1 are correctly classified by the model.

D. DISCUSSION

Table 6 presents performance evaluation measures for six different models employed in this study. The performance

TABLE 6. Experimental results of various machine learning models.

Model	Accuracy	Precision	Recall	F1-score
Random Forest	0.93	0.93	0.88	0.91
Linear SVM	0.92	0.91	**0.89**	0.94
Decision Tree	0.89	0.88	0.87	0.86
Naive Bayes	0.89	0.88	0.77	0.77
Radial SVM	**0.94**	**0.97**	**0.89**	**0.96**

is evaluated in terms of recall, accuracy, precision, and F1 score. The models with the highest precision values are SVM and RF with 97% and 93% precision. Conversely, the NB and DT classifiers exhibit the lowest accuracy of 88% each. Results reported in Table 6 indicate the averaged results for five classes of diabetic retinopathy used for experiments.

Radial-based SVM model is regarded as the most accurate with a 94% accuracy score, followed closely by RF and linear SVM with 93% and 92% accuracy, respectively. RF model shows an average accuracy of 91% for five classes. Regarding recall score, both linear and radial-based SVM obtained the same 0.89 score, followed by a 0.88 recall score by the RF model. F1 score is regarded as one of the most commonly employed metrics for performance evaluation, especially when the class distribution is not equal. F1 scores for all models indicate that the best F1 score of 0.96 is obtained by radial-based SVM, followed by linear SVM and RF with 0.94 and 0.91 F1 scores, respectively.

Results demonstrate that the support vector machine model distinguishes itself with impressive performance across recall, accuracy, precision, and F1-score. Still, other models show encouraging results as well, especially when it comes to accuracy and F1-score. Among the models that were assessed, it is interesting that the models with the highest recall rates were the SVM and RF. A visual presentation of performance comparison of all models is given in Figure 21.

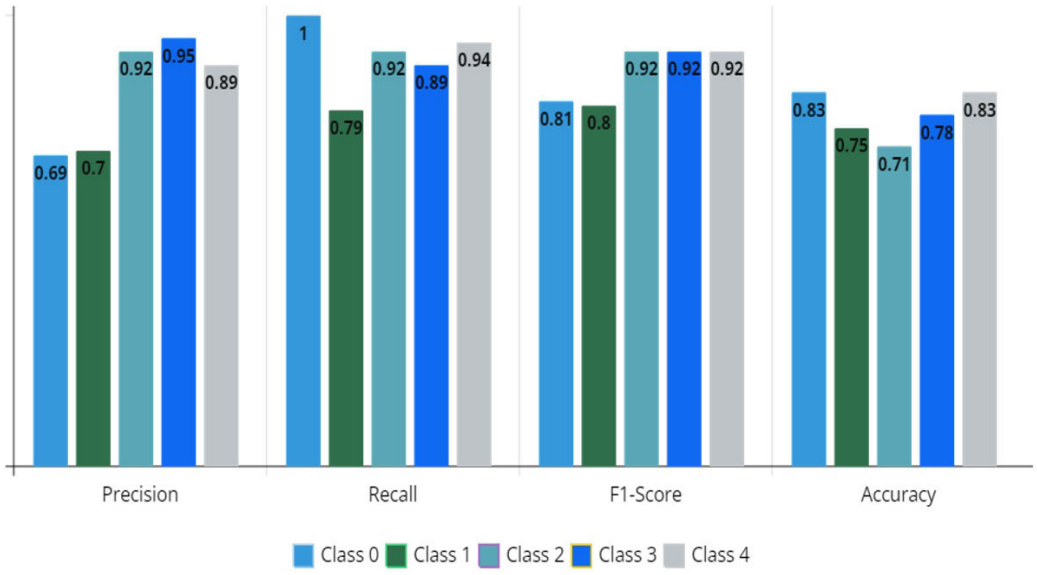

FIGURE 18. The evaluation of the accuracy of radial-based SVM.

TABLE 7. Comparative analysis with previous studies.

Ref.	Method	Model	Lesions	Precision	Recall	F1-Score	Accuracy
[24]	CNN	LeNet	Microaneurysms. Haemorrhages	**99.8%**	**99.6%**	**96%**	93.4%
[25]	CNN	AlexNet	Hard Exudate, Soft Exudates	**100%**	93%	88%	96.5%
[26]	CNN	AlexNet, GoogLeNet	Blood vessels, Microaneurysms	86.03%	97.11%	91%	89%
[27]	CNN	U-Net	Exudate, Microaneurysms, Haemmorhages	87%	89%	96%	88%
[28]	CNN	Inception-v3	Exudates, Haemmorhages, Blood vessels, Red Lesions	90.1%	98.2%	89%	95%
[29]	CNN	VGGNet	Red Lesions	80.3%	85.5%	82%	98%
[30]	CNN	AlexNet	Haemorrhages	96.8%	87.0%	87%	86%
[31]	CNN	VGGNet	Hard Exudate, Microaneurysms, Haemmorhages	77.79%,	97.80%	79%	89%
[32]	CNN	SVMGA	Micro-aneurysm, retinal hemorrhage, and exudates	N/A	N/A	N/A	98.4
[33]	Transfer Learning	SVM, Naive Bayes	Micro-aneurysms Hemorrhages and Hard Exudates, and Cotton Wool Spots	N/A	N/A	N/A	**99.0%**
[34]	Transfer Learning	AlexNet, VGG16, ResNet, Inception-v3, NASNet, DenseNet, and GoogLeNet	Exudates, Hard Exudate	N/A	N/A	N/A	98.4%
[35]	CNN	Hybrid model structures Hybrid-a, Hybrid-f, and Hybrid-c	Microaneurysms, Haemorrhages	91.37%	N/A	93.9%	86.34%
Proposed Method		GoogleNet + ResNet	Cotton wool spots, venous beading, as well as severe intraretinal microvascular abnormalities (IRMA), the diffuse-intraretinal, hemorrhages, capillary degeneration, an activated-microglia, a retinal pigment epithelium (RPE) damage, exudates, aneurysms, hemorrhages and the blood vessels	**97%**	89%	**96%**	94%

E. PERFORMANCE COMPARISON WITH EXISTING STUDIES

The proposed system leverages feature vectors from pre-trained models like GoogleNet and ResNet-16, ensuring efficient classification without compromising processing time. Combining features from two CNN-based pre-trained models proved to show superior performance for multiclass classification of diabetic retinopathy. A comparative analysis of the current study with existing state-of-the-art studies is presented in Table 7.

The table provides an in-depth analysis of the many approaches and models used in the context of diabetic retinopathy to identify and categorize lesions in retinal fundus pictures. Different research or methodology is represented by each row in the table, and key performance indicators including precision, recall, accuracy, and F1-score are shown

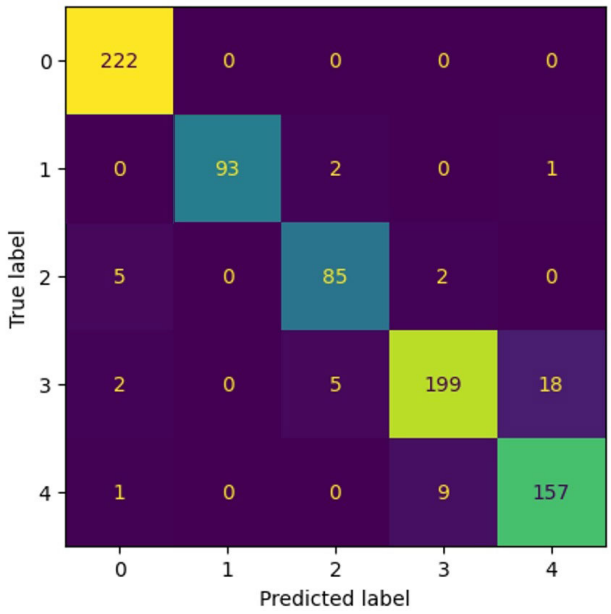

FIGURE 19. Confusion matrix based on the radial-based SVM classification.

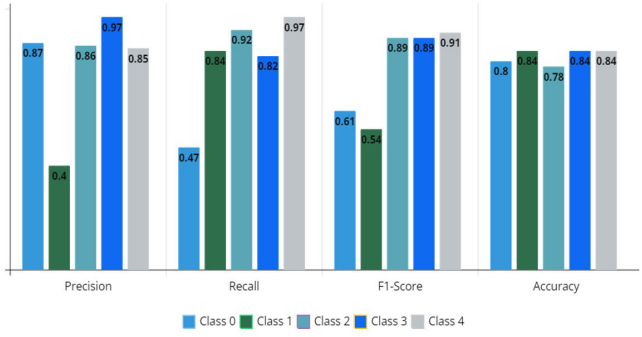

FIGURE 20. Classification results for NB classifier.

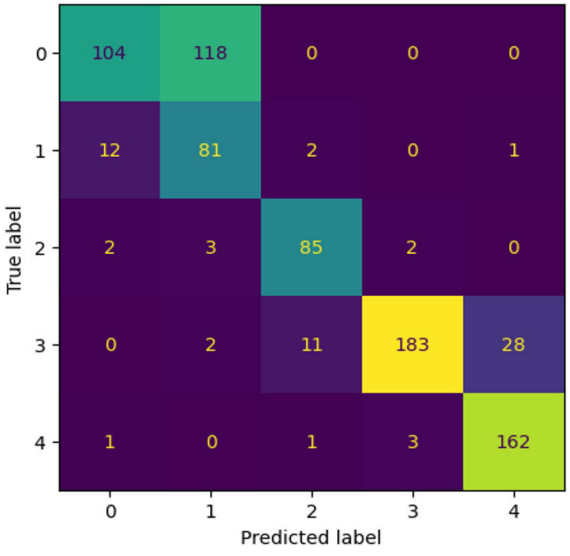

FIGURE 21. Confusion matrix for NB classifier.

in the columns. LeNet is a convolutional neural network (CNN) architecture used in one of the featured research [24] to detect hemorrhages and microaneurysms. Although the F1 score is significantly lower at 93.4%, this method achieves excellent recall (99.6%) and precision (99.8%), yielding a total accuracy of 96%. Using the AlexNet CNN architecture, another noteworthy technique referred to as [25] focuses on identifying Hard Exudates and Soft Exudates. The recall rate is 93%, and the accuracy is 100%, meaning there are no false positives. With an F1-Score of 88%, the model attains a 96.5% accuracy rate. Results of this study are in accordance with existing studies [36].

To detect blood vessels and microaneurysms, several CNN architectures including AlexNet and GoogLeNet are used in the research shown as [27]. With 86.03% precision and 97.11% recall, respectively, the high accuracy of 89% is achieved. But for this specific procedure, the F1 score is not given. In [25], the U-Net design is used with the goal of detecting exudate, microaneurysms, and hemorrhages. With an F1-Score of 96%, this approach yields accuracy, recall, and precision of 88%, 97%, and 89%, respectively. The Inception v3 CNN architecture is used in the [27] research to identify exudates, hemorrhages, blood vessels, and red lesions. The model reaches a 95% accuracy with an F1-Score of 89%, recall of 98.2%, and precision of 90.1%. The research [29] focuses on Red Lesions and uses VGGNet to achieve 80.3% precision, 85.5% recall, 98% accuracy, and an 82% F1-Score.

The [30] research focuses on hard exudate, microaneurysms, and hemorrhages and also makes use of VGGNet. With an F1-Score of 79% and stated precision and recall of 77.79% and 97.80%, respectively, the accuracy is 89%. With an accuracy of 94%, recall of 89%, precision of 97%, and F1-Score of 96%, the suggested approach which blends GoogleNet and ResNet shows promise in diagnosing a range of lesions.

Results indicate that the proposed approach can obtain competitive results while covering more lesion types that are not covered by existing studies. For example, it can cover cotton wool spots, venous beading, hemorrhages, as well as severe intraretinal microvascular abnormalities and provide 97% precision which is competitive to existing models that cover only a few lesion types, as shown in Table 7. Figure 21 shows the evaluation of the proposed model by comparing it with previous research.

The first analysis aimed to follow the development of testing and training accuracy across several epochs. The model's continual learning is indicated by the rising trend of both training and testing accuracy in Figure 23, where each data point represents an epoch. Training accuracy measures how well the model fits training data, whereas testing accuracy assesses how well the model performs on data that hasn't been seen before. A steady increase in testing accuracy is a sign of good generalization, which is essential to the model's dependability in practical applications.

The model's learning curve and error-minimization capabilities were revealed with the addition of classification error as a performance metric. The model's improved accuracy and refinement are highlighted by Graph 6, which shows

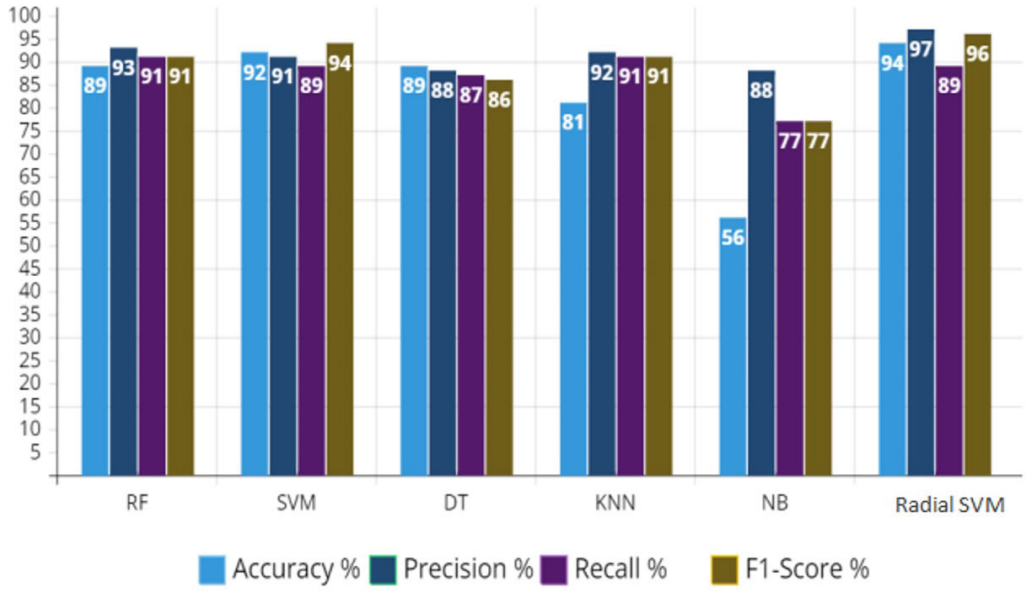

FIGURE 22. Performance comparison of all classifiers.

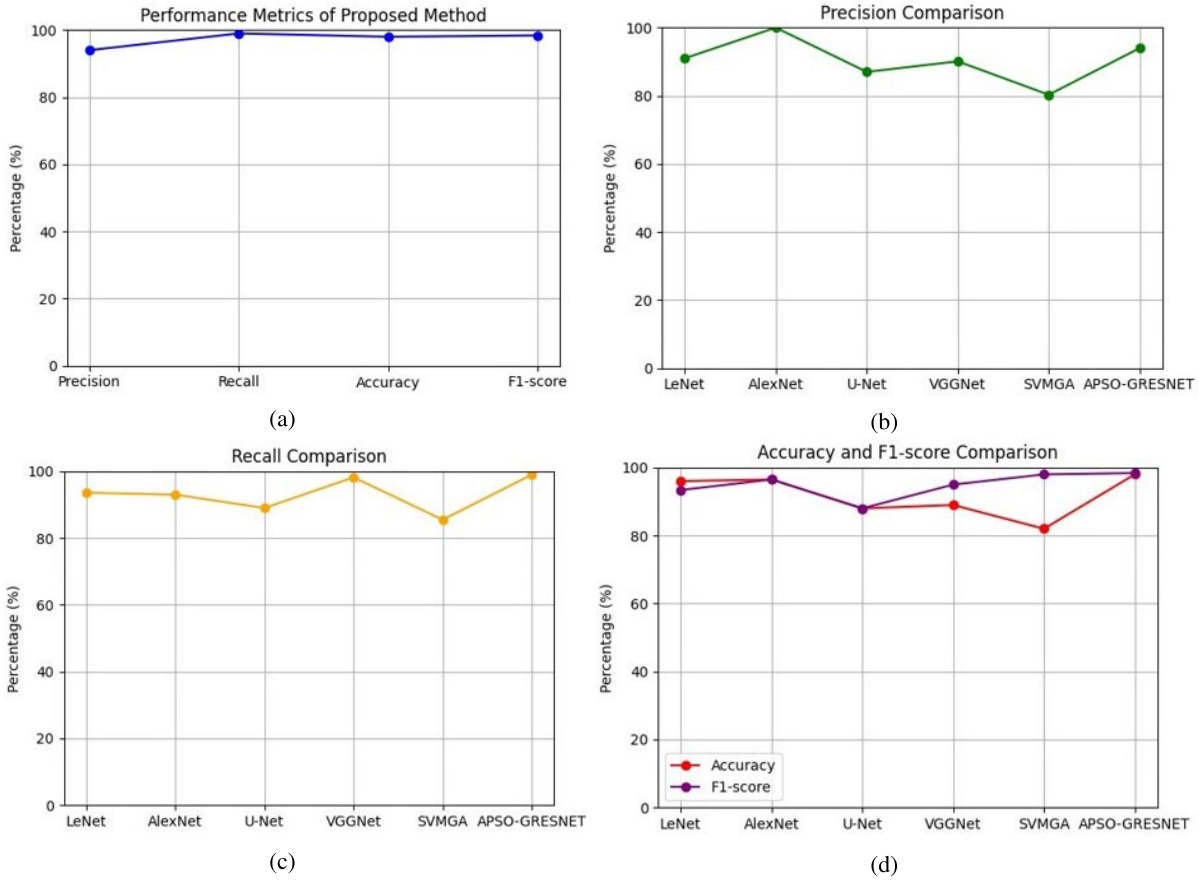

FIGURE 23. The evaluation of the proposed model by comparing it with previous research.

a steady drop in classification error throughout epochs. A useful guide for choosing the best model checkpoint to deploy is the annotation that indicates the epoch of minimal error.

The proposed system leverages feature vectors from pre-trained models like GoogleNet and ResNet-16, ensuring efficient classification without compromising processing time. Future research could explore the development of a

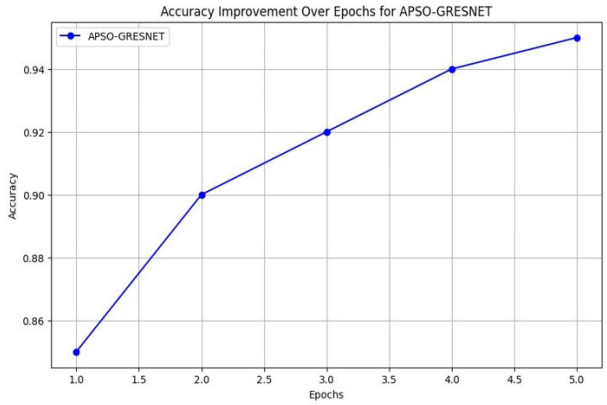

FIGURE 24. The accuracy improvement over epochs for APSO-GRESNET.

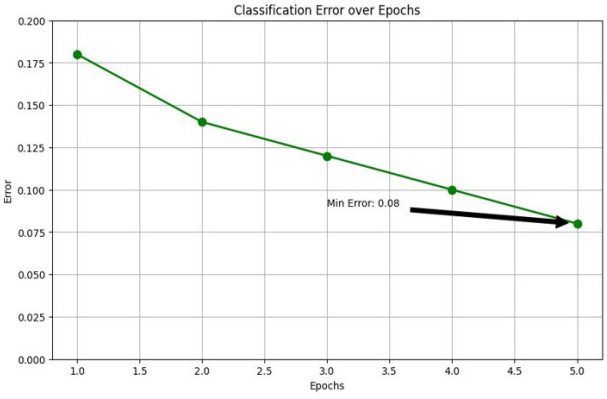

FIGURE 25. The representation of classification error over epochs.

tailored CNN, specifically crafted to accurately capture inter-class similarities across all diabetic retinopathy classes while maintaining high-performance metrics. Moreover, automated detection of additional diseases with the potential to induce irreversible retinal lesions through fundus images and optical coherence tomography-based images is anticipated to be a prominent field of inquiry in the future research environment.

Despite showing encouraging outcomes, both the suggested methodology and the research include drawbacks that should be carefully considered. To provide a fair assessment and direct further studies in the area, a thorough examination of these constraints is necessary. The dataset utilized for assessment and training has one noteworthy restriction. Because the research is dependent on the EyePACs dataset, it may be problematic to extrapolate the suggested model to other datasets or actual clinical contexts. The model's performance may be affected when it is applied to a larger population depending on how representative the dataset is in terms of both demographic variety and image quality variability. Furthermore, the choice of classifiers and transfer learning models (ResNet-16 and GoogleNet) may have an impact on how well the suggested hybrid model performs. Although their performance in image-related tasks drove these decisions, investigating other models and classifiers may shed light on the resilience and applicability of the suggested strategy.

While the primary emphasis of the work is the automated identification of lesions associated with Diabetic Retinopathy, more research on the interpretability of the model may be beneficial. Gaining confidence and acceptance in clinical applications requires understanding how the model makes certain predictions and recognizing the important characteristics that influence its choices. Furthermore, the computing resources needed to train and implement the suggested model are not specifically covered in the paper. Evaluating the scalability and resource efficiency of the model is essential for practical implementation, particularly in real-world clinical settings with heterogeneous technology. Additionally, the suggested model assumes that everything is static and ignores how retinal pictures evolve over time as a result of several screenings. Including a temporal component in the model may improve its capacity to track the course of the illness or the response to therapy across time.

V. CONCLUSION AND FUTURE WORK

This study presents a hybrid approach to early diabetic retinopathy detection by extracting features from fundus images by transfer learning from ResNet-16 and the GoogleNet model based on adaptive particle swarm optimization. Then, using the EyePACs dataset, these features are input into a variety of classifiers for multiclass diabetic retinopathy classification. The combination of features from both models significantly boosts performance metrics for diabetic retinopathy classes, enhancing overall system effectiveness. The proposed technique holds promise in aiding ophthalmologists with early diabetic retinopathy detection. The results underscore the efficacy of combining CNN feature extraction with machine learning classifiers, yielding rapid and incredibly precise results. Notably, the hybrid model with SVM outperforms current binary and multiclass diabetic retinopathy detection techniques with an astounding average accuracy of 94%. The results demonstrate the efficiency of merging machine learning classifiers with CNN feature extraction, yielding quick and very accurate results. Remarkably, the hybrid model using SVM outperforms existing binary and multiclass diabetic retinopathy detection methods with an average accuracy of 94%.

Looking forward, it is clear that the ongoing development and investigation of machine learning-based algorithms for diagnosis and detection will be the primary focus of future research in this field. In order to successfully remove noise and artifacts, ongoing work should focus on improving strategies like data augmentation and other preprocessing approaches. This field of study continues to be important, with ongoing efforts to enhance and progress the precision and effectiveness of DR detection systems. The potential for transforming the early detection and treatment of diabetic retinopathy is enormous when medical experts and artificial intelligence work together, especially as technology advances. Future studies should address these possible biases in the dataset to improve the robustness of the proposed model and its generalizability to a variety of patient groups. By using

techniques like stratified sampling, data augmentation, and meticulous evaluation of demographic parameters, biases may be reduced and more equitable and clinically useful Diabetic Retinopathy detection models can be developed. Furthermore, openness in disclosing dataset attributes and biases is essential for a more comprehensive comprehension and analysis of the research outcomes.

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