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Bio-Geological and Ensemble Learning Based Diabetic Retinopathy Image Class Prediction

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Abstract- Diabetic Retinopathy (DR) is a progressive eye disease requiring early diagnosis for effective treatment. This study introduces a novel diagnostic framework named GARID (Genetic Algorithm-based Retinopathy Image Diagnosis), designed to enhance the accuracy of retinal image classification through intelligent feature optimization and robust classification. The proposed model operates in two primary phases: feature optimization using a modified Genetic Algorithm (GA) and classification via a Tree Bagger ensemble learning method. Initially, retinal images undergo preprocessing and denoising using Wiener filtering. Segmentation is performed using GA, where cluster centers are evolved through crossover and mutation strategies to identify regions of interest. Features are then extracted using histogram analysis and Discrete Wavelet Transform (DWT), capturing both spatial and frequency information. The final feature set is classified using a tree-based ensemble model, ensuring high generalization and detection precision. Experimental results confirm that GARID improves class-wise detection, recall, and F-measure, offering a reliable solution for automated diabetic retinopathy screening.

Keywords- Medical image diagnosis, Frequency Feature, Clustering, DIP.

I. INTRODUCTION

Diabetic retinopathy (DR) remains a principal cause of vision loss among the working-age population, affecting over one-third of the approximately 285 million individuals living with diabetes mellitus worldwide [1]. Since DR can progress silently without noticeable symptoms, even in its advanced stages, it is widely recommended that individuals diagnosed with diabetes undergo routine retinal screenings to reduce the risk of irreversible visual impairment [2]. Early pathological changes often involve retinal microvasculopathy, such as microaneurysms, capillary occlusion, and nonperfusion, followed by subsequent inner retinal degeneration [3][4].

Optical Coherence Tomography Angiography (OCTA) is a promising imaging modality that enables simultaneous assessment of both retinal vascular abnormalities and structural degeneration, using co-registered volumetric OCT data. Most current OCTA-based diagnostic studies rely on manually engineered features derived from established clinical knowledge, classifying healthy and diseased retinal conditions through traditional machine learning techniques. However, early and automated detection of DR is vital for timely intervention, prompting the development of numerous advanced algorithms in the literature [5].

The integration of artificial intelligence (AI) and machine learning (ML) into healthcare has significantly enhanced diagnostic capabilities, with particular success in image-based assessments. Fundus photography, a standard technique for capturing high-resolution retinal images, serves as the foundation for many DR detection models. In recent years, deep learning—particularly Convolutional

Neural Networks (CNNs)—has emerged as the dominant approach for analyzing these images, outperforming conventional methods by learning discriminative features directly from raw data [6]. Variations among current DR diagnostic systems arise from differences in image datasets, preprocessing methods, feature extraction techniques, and learning algorithms, with CNN-based solutions demonstrating exceptional accuracy in real-world clinical scenarios.

Research Gap: Most of work provide solution by simply applying the learning model, this need to be improved by feature optimization. Many of researchers just predict either patient is suffering from retinopathy or healthy. Images need to classify into multiple class as per stage of retinopathy, this help medical officers for suggesting medicines.

The structure of the paper is organized into several comprehensive sections to provide clarity and logical progression Section 2 presents an in depth review of related research highlighting the significant contributions made by various researchers in the domain of diabetic retinopathy detection and medical image analysis Section 3 introduces the proposed GARID model in detail supported by a systematic block diagram and the corresponding algorithm Section 4 is dedicated to the performance evaluation of the proposed model A comparative analysis is performed using multiple evaluation metrics to validate the effectiveness of the GARID model against existing techniques including the NSL MHA CNN model. Section 5 the conclusion summarizes the overall findings and discusses the implications of the results along with potential directions for future research

II. Related Work

Muthusamy D et al [7] introduced an innovative model named MAP Concordance Regressive Camargo's designed to detect diabetic retinopathy DR with high accuracy and reduced computational time The architecture incorporates an input layer multiple hidden layers and an output layer Fundus images from a standard dataset serve as the input followed by preprocessing through this model estimated local region filtering by layer one In layer two infected retinal regions are identified using Camargo's index based region of interest ROI extraction Texture features are extracted using Concordance Correlative Regression and color features are also derived The extracted features are then passed to the output layer where DR levels are classified using the swish activation function for enhanced precision.

Sanjana Rajeshwar et al [8] proposed a hybrid diagnostic model that combines advanced image processing and machine learning Their approach includes data augmentation and a multistep processing pipeline utilizing pretrained models like ResNet50 InceptionV3 and VGG 19 for feature extraction These features are classified using various machine learning techniques such as Decision Trees DT K Nearest Neighbors KNN Support Vector Machines SVM and a modified CNN integrated with spatial attention They further enhanced classification performance through a stacking ensemble approach using logistic regression as the meta classifier.

Shelke N et al [9] presented an ensemble based EfficientNet framework to improve the reliability of DR detection They utilized the Kaggle DR dataset applied thorough preprocessing and trained multiple EfficientNet variants with different hyperparameters An ensemble of these models was used to boost overall classification accuracy and stability.

Das Biswas and Bandyopadhyay [10] evaluated 26 deep learning architectures for DR detection using fundus images from the EyePACS dataset Their findings revealed that while models like DenseNet201 achieved the highest training accuracy EfficientNetB4 showed superior generalization achieving the best validation accuracy Other notable performers included InceptionV3 and InceptionResNetV2.

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O Daanouni et al [11] focused on the robustness of the MobileNet CNN model under adversarial conditions They integrated Neural Structure Learning NSL and Multi Head Attention MHA to mitigate vulnerability to Fast Gradient Sign Method FGSM adversarial attacks on OCT images The proposed NSL MHA CNN model demonstrated improved resilience against adversarial perturbations without incurring additional training costs reinforcing the importance of model stability in clinical environments

III. PROPOSED MODEL

A model for the analysis of diabetic retinopathy medical images, referred to as GARID (Genetic Algorithm-based Retinopathy Image Diagnosis), is proposed in this section. The entire approach is divided into two main modules: feature optimization and learning of optimized features. Various notations used for the explanation of whole work, all set of variables are shown in table 1. The flow of optimized feature processing is illustrated in Figure 1, with a detailed explanation of each block, including the corresponding inputs and outputs.

Image Pre-Processing

The experimental process begins with the retinopathy image dataset RID which often contains significant noise that can affect detection accuracy To address this the model applies a noise removal filter [9 10] as a preprocessing step aiming to restore pixel values to their true state Once the noise is filtered out the images undergo resizing and grayscale conversion to match the input requirements of the working environment and model architecture As a result the original input image RI is transformed into the preprocessed image Ip which serves as the clean and normalized input for the subsequent feature extraction and classification phases.

Ip<-Imagepreprcessing(RID)
Ipf<-Image_FilterWiener(Ip)

Image Ipf obtained after applying the wiener filter [12], on pre-processed image.

Image segmentation

The filtered image is subjected to a segmentation process, which divides pixel data into two regions: one designated for training and the other for non-training purposes. This segmentation is accomplished using a Genetic Algorithm approach. In the GA process, an initial population of candidate solutions undergoes selection, crossover, and mutation operations to evolve better solutions over generations.

This work introduces a modified GA, where partial solutions are selected for crossover, while the remaining candidates undergo mutation. This hybrid strategy aims to reduce the number of iterations required while improving the quality of the final solution.

Genetic Algorithm-Based Feature Optimization

In this section, a genetic algorithm-based approach is employed to optimize feature selection for diabetic retinopathy mage classification. The process involves several essential stages, including population initialization, fitness evaluation, selection, crossover, mutation, and feature filtering.

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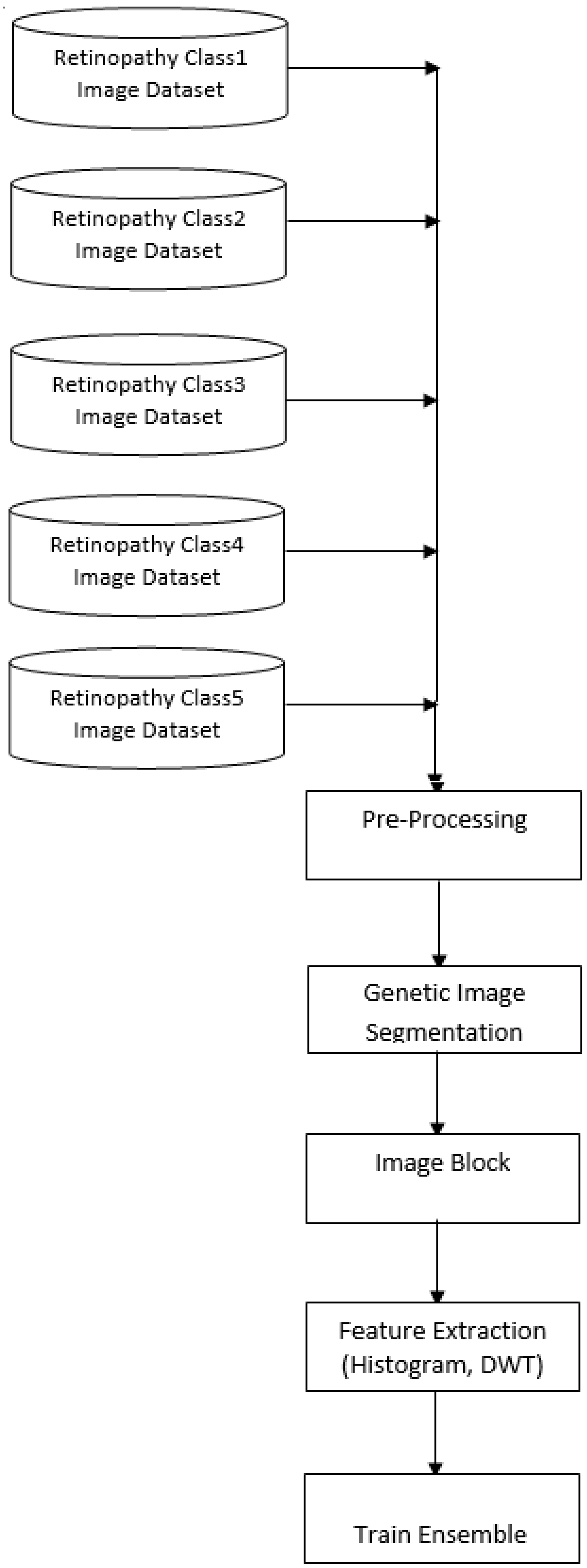

Fig. 1 Proposed GARID block diagram.

Table 1 GARID model notation table.

Notation	Meaning
RID	Retinopathy Image Dataset
Ip	Processed RID
B	Image Feature Bins
I_H	Image Histogram Feature
I_w	Image Wavelet Features
GP	Genetic Population
GPF	Fitness
m	Chromosome count
Is	Segmented Retinopathy Image
Isn	Segmented Image Block
GB	Best Chromosome
IF	Image Final Feature Set
REM	Retinopathy Ensemble Model

Population Initialization Initially, a random binary matrix is generated, where each row (chromosome) symbolizes a potential solution—specifically, a collection of cluster center pixel values extracted from the retinal image dataset [14]. These cluster centers guide the segmentation process. The population comprises m such chromosomes, each containing c cluster centers.

GP ← Initialize_Population(m, c)

Fitness Evaluation Each chromosome is evaluated using a fitness function based on Euclidean distance [15]. This function quantifies how effectively the selected cluster centers represent distinct pixel classes in the preprocessed image. The goal is to minimize intra-cluster similarity and maximize inter-cluster separation. A lower fitness value indicates a better solution.

$GPF(i) = \sum_1$^c $\sum_1$^p Min(Distance(GP(i,c), Ip(p)))

Selection and Crossover The chromosome with the lowest fitness score is identified as the current best solution. A subset of top-performing chromosomes is selected for reproduction. These selected chromosomes undergo crossover operations with the best solution to produce new offspring, promoting the exchange of useful features.

GB ← Select_Best(GP, GPF)
GP ← Apply_Crossover(GP, GPF, GB)

Mutation To maintain genetic diversity and avoid premature convergence, chromosomes with below-average fitness scores undergo mutation. Mutation is implemented by randomly altering some cluster centers within a chromosome, encouraging exploration of new potential solutions. This strategy reduces computation while enabling the algorithm to discover promising alternatives.

GP ← Apply_Mutation(GP, GPF)

Feature Selection and Image Segmentation After a predefined number of generations, the chromosome with the best fitness value is chosen as the final feature set. The cluster centers represented by this chromosome are then used to segment the image into foreground (regions of interest) and background. Pixels belonging to the selected clusters are retained for further analysis, while others are discarded.

GB ← Select_Best(Population, Fitness)
Isn ← Segment_Image(Ip, GB)

Image Blocking and Feature Extraction

The segmented image is divided into uniform n × n pixel blocks to extract spatially consistent features. Two primary types of features are computed: histogram features and wavelet-based features.
Isn ← BlockImage(Is, n)

Histogram Features

Histogram features are computed using B bins, capturing the distribution of pixel intensities. Each bin represents a specific range of pixel values (e.g., 0–15, 16–31, etc.), allowing for a compact representation of the image's visual content [13]. This simplifies feature comparison during classification.

Hf ← Compute_Histogram(Isn, B)

Discrete Wavelet Transform (DWT)

The Discrete Wavelet Transform is applied to extract texture-related features from multiple frequency sub-bands: LL (approximation), LH (horizontal details), HL (vertical details), and HH (diagonal details) [16]. From each sub-band, statistical measures such as mean, entropy, energy, and contrast are computed, capturing both coarse and fine texture patterns critical for diagnosing retinopathy.

Wf ← Apply_DWT(Isn)
Iff ← [Hf, Wf]

Classification Using Ensemble Model

The Tree Bagger model, based on the multiple decision tree ensemble method [17], is used to classify retinal images by utilizing features obtained from earlier processing steps. This approach constructs multiple decision trees, each trained on a different bootstrap sample and a randomly selected subset of features, enhancing model robustness through diversity. Tree construction is carried out using the CART algorithm, which recursively splits data based on the Gini index to maximize node purity. To avoid overfitting, pruning is applied to remove branches that offer minimal predictive benefit. The final prediction is made through majority voting across all trees, with the ensemble achieving high accuracy and generalization by selecting the optimal tree set using cross-validation or a separate validation dataset.

Algorithm: GARID – Retinopathy Image Class Prediction Model
Input: Retinopathy Image Dataset RID
Output: Retinopathy Ensemble Model REM

1. Ip ← ImagePreprocessing(RID) // Resize and convert image to grayscale
2. Ipf ← Image_FilterWiener(Ip)
3. GP ← Initialize_Population(m, c)
4. For each chromosome a in GP
5. GPF·Fitness(GP)
6. GB ← Select_Best(Population, Fitness)
7. GP ← Apply_Crossover(GP, GPF, GB)
8. GP ← Apply_Mutation(GP, GPF)
9. Endloop

10. GPF▪Fitness(GP)
11. Is ← Segment(Ip, GB)
12. Isn ← BlockImage(Is, n)
13. Hf ← Compute_Histogram(Isn, B)
14. Wf ← Apply_DWT(Isn)
15. Iff ← [Hf, Wf]
16. REM ← Ensemble_Train(Iff)

This hybrid approach integrates the exploratory power of GARID feature selection with the robustness of ensemble classification, tailored for accurate and early-stage retinopathy diagnosis based on retinal fundus images.

IV. EXPERIMENT AND RESULTS

The proposed model was implemented using MATLAB software version 2016a. All experiments were conducted on a system equipped with 4 GB of RAM and a 6th generation Intel i3 processor. To evaluate the performance of the proposed approach, results were compared against the NSL-MHA-CNN method as described in reference [11].

Dataset: The experimental analysis utilized a real-world dataset. Detailed descriptions and feature information related to the dataset are provided in Table 2 [18].

Table 2 Diabetic Retinopathy dataset.

Dataset Feature	Values
Class	5
Total Images	2750
Size	256x256
Format	Gray

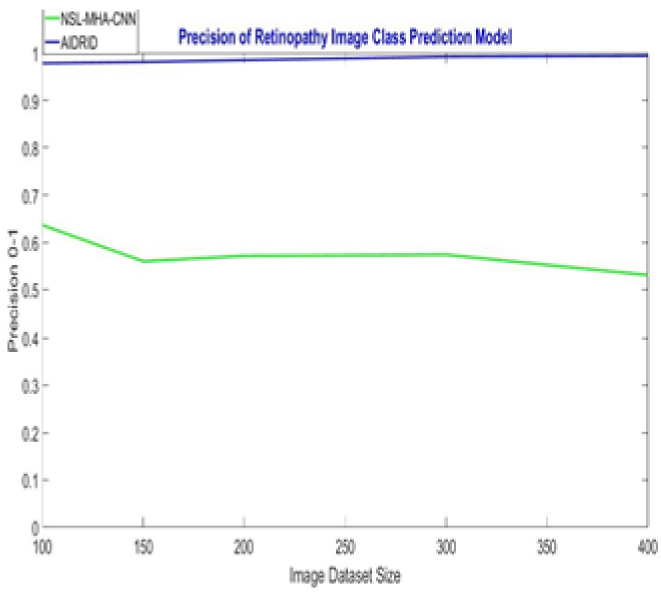

Fig. 2 Precision value of retinopathy image class detection models.

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As illustrated in Fig. 2, the precision rates for various retinopathy image classification models are presented. The proposed model significantly outperforms the existing DRDLOFLM model, demonstrating a improvement in correctly identifying image classes. This improvement is primarily due to the integration of the artificial immune-based classification mechanism, which effectively minimizes noise in the training data and boosts learning accuracy.

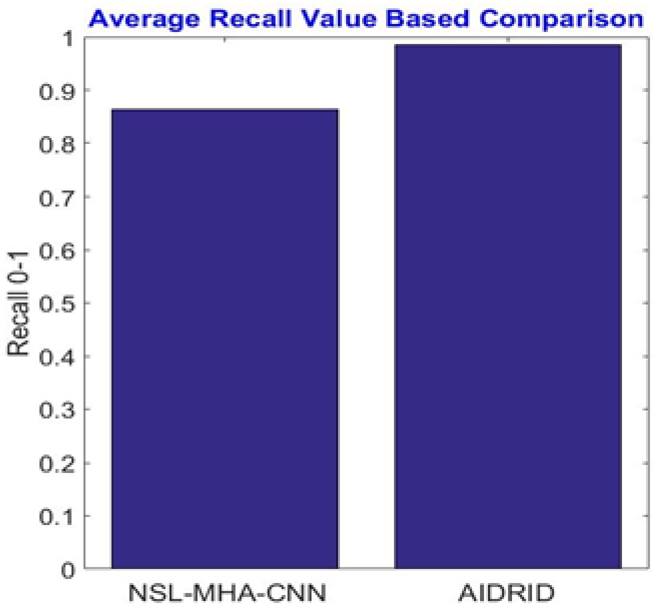

Fig. 3 Average recall value of retinopathy image class detection models.

Fig. 3 presents the average recall metrics for the detection of retinopathy image classes. The results indicate that the tree bagger ensemble approach enhances the learning capacity by leveraging diverse outputs from multiple decision trees, each focusing on different class patterns. Additionally, the study highlights that incorporating histogram and frequency-based features in models like DRDLOFLM and GARID contributes to better class identification accuracy.

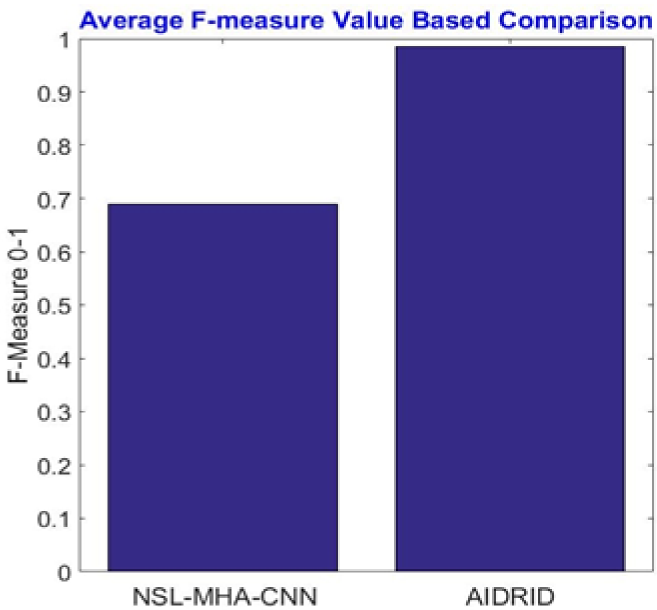

Fig. 4 Average F-measure value of retinopathy image class detection models.

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The F-measure values, depicted in Fig. 4, compare the effectiveness of various classification models using different retinopathy image datasets. The results show that the GARID model, which integrates Discrete Wavelet Transform (DWT) frequency features with histogram-based color features, achieves a higher F-measure than the DRDLOFLM model, indicating a more balanced precision and recall performance.

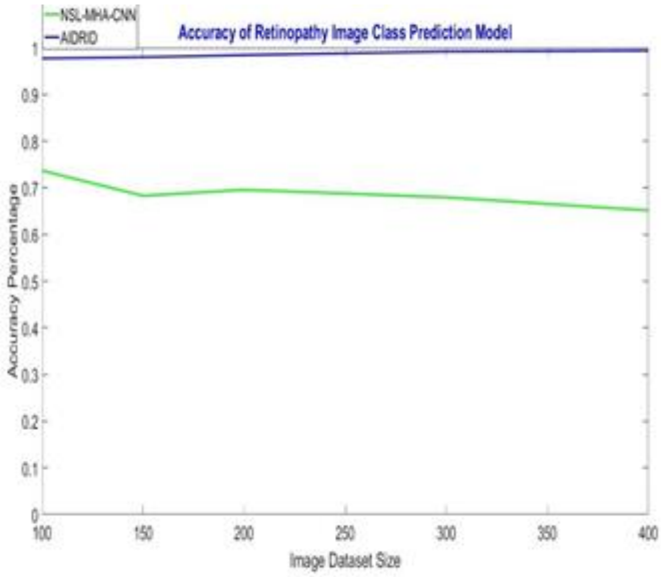

Fig. 5 shows correct class detection accuracy of retinopathy prediction model.

In Fig. 5, the accuracy results of different retinopathy detection models are shown. The findings reveal that the combination of optimized image data, selected via the artificial immune algorithm, with the tree bagger model leads to improved classification accuracy. Specifically, the proposed model achieves a higher detection accuracy compared to the NSL-MHA-CNN model.

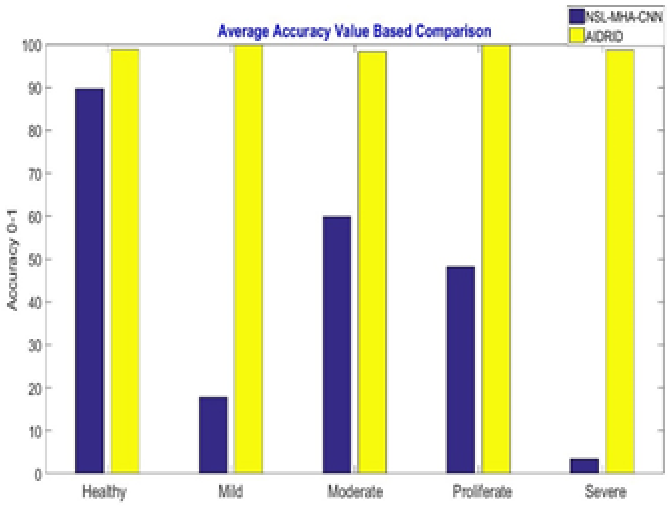

Fig. 6 shows correct class detection accuracy of various classes of retinopathy prediction models.

Fig. 6 displays the class-wise accuracy rates for the retinopathy detection models. The implementation of the artificial immune optimization significantly enhances the model's learning capability. Furthermore, the use of the tree bagger ensemble strategy proves effective in accurately distinguishing between various retinopathy image classes.

V. CONCLUSION

The proposed GARID model offers a comprehensive solution for diabetic retinopathy image classification by combining genetic algorithm-based feature optimization with ensemble learning. The model effectively processes retinal images through preprocessing, segmentation, feature extraction, and classification stages. The use of a modified genetic algorithm enables efficient selection of informative clusters for segmentation, while histogram and DWT-based features ensure detailed representation of image patterns. The Tree Bagger ensemble classifier enhances classification accuracy by leveraging multiple decision trees trained on diverse feature subsets. The experimental results demonstrate substantial improvements in precision, recall, F-measure, and overall classification accuracy, validating the model's effectiveness in diagnosing diabetic retinopathy. The GARID framework, with its optimized learning pipeline, contributes significantly to medical image analysis and presents a scalable approach for automated disease diagnosis.

REFERENCES

1. Cheung N, Mitchell P, Wong TY. Diabetic retinopathy. Lancet. 2010; 376(9735): 124–136.
2. Yau JWY, Rogers SL, Kawasaki R, et al. Global prevalence and major risk factors of diabetic retinopathy. Diabetes Care. 2012; 35(3): 556–564.
3. Antonetti DA, Klein R, Gardner TW. Diabetic retinopathy. N Engl J Med. 2012; 366: 1227–1239.
4. Friedenwald J, Day R. The vascular lesions of diabetic retinopathy. Bull Johns Hopkins Hosp. 1950; 86(4): 253–254.
5. Mondal SS, Mandal N, Singh KK, Singh A, Izonin I. EDLDR: An Ensemble Deep Learning Technique for Detection and Classification of Diabetic Retinopathy. Diagnostics (Basel). 2022 Dec 30;13(1):124.
6. Sikder, N.; Masud, M.; Bairagi, A.K.; Arif, A.S.M.; Nahid, A.-A.; Alhumyani, H.A. Severity Classification of Diabetic Retinopathy Using an Ensemble Learning Algorithm through Analyzing Retinal Images. Symmetry 2021, 13, 670.
7. Muthusamy, D., Palani, P. Deep learning model using classification for diabetic retinopathy detection: an overview. Artif Intell Rev 57, 185 (2024).
8. Sanjana Rajeshwar, Shreya Thaplyal, Anbarasi M., Siva Shanmugam G.. "Diabetic Retinopathy Detection Using DL-Based Feature Extraction and a Hybrid Attention-Based Stacking Ensemble". Advances in Public health, 13 March 2025.
9. Shelke, N., Somkunwar, R., Pimpalkar, A., Maurya, S., & Chhabria, S. (2025). Ensemble EfficientNet: a novel technique for identification, classification and prediction of diabetic retinopathy. Automatika, 66(3), 543–558.
10. Das D., Biswas S. K., and Bandyopadhyay S., Detection of Diabetic Retinopathy Using Convolutional Neural Networks for Feature Extraction and Classification (DRFEC), Multimedia Tools and Applications. (2023) 82, no. 19, 29943–30001.
11. O. Daanouni, B. Cherradi and A. Tmiri, "NSL-MHA-CNN: A Novel CNN Architecture for Robust Diabetic Retinopathy Prediction Against Adversarial Attacks," in IEEE Access, vol. 10, pp. 103987-103999, 2022.
12. Chan Rok Park, Seong-Hyeon Kang, Youngjin Lee,Median modified wiener filter for improving the image quality of gamma camera images,Nuclear Engineering and Technology,Volume 52, Issue 10,2020,Pages 2328-2333.
13. Blachnik, Marcin & Laaksonen, Jorma. (2008). Image Classification by Histogram Features Created with Learning Vector Quantization. 5163. 827-836.
14. Siddhartha Tiwari, Prof. Dr. Dwarka Prasad. "A Genetic Algorithm Approach for the Solution of Economic Load Dispatch Problem". International Journal of Scientific Research & Engineering Trends Volume 7, Issue 1, Jan-Feb-2021, ISSN (Online): 2395-566X.
15. Mussabayev, R. Optimizing Euclidean Distance Computation. Mathematics 2024, 12, 3787.

ISSN: 2348-4098, P-ISSN: 2395-4752

16. Varun Srivastava, Ravindra Kumar Purwar. "A Five-Level Wavelet Decomposition and Dimensional Reduction Approach for Feature Extraction and Classification of MR and CT Scan Images". Applied Computational Intelligence and Soft Computing 24 December 2017.
17. Heisler M, Karst S, Lo J, et al. Ensemble deep learning for diabetic retinopathy detection using optical coherence tomography angiography. Trans Vis Sci Tech. 2020;9(2):1–11. doi:10.1167/tvst.9.2.20
18. https://www.kaggle.com/datasets/sachinkumar413/diabetic-retinopathy-dataset.