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Multi-Head Feature Extraction for Diabetic Retinopathy Detection: A Hybrid Deep Learning and Texture Analysis Framework

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ABSTRACT: Diabetic Retinopathy (DR) remains one of the most consequential complications of diabetes mellitus, progressively impairing vision and, in advanced stages, causing irreversible blindness if not detected and treated early. Existing single-backbone deep learning approaches, while showing promising results, fall short in capturing the multi-scale, heterogeneous feature landscape inherent to retinal fundus images — particularly in distinguishing subtle inter-grade pathological differences. This paper presents MHFE-DRD, a Multi-Head Feature Extraction framework for Diabetic Retinopathy Detection that synergistically combines three pre-trained convolutional neural networks — DenseNet-121, Inception-v3, and ResNet-50 — with handcrafted Gabor filter and Local Binary Pattern (LBP) texture descriptors. A novel attention-weighted feature fusion mechanism consolidates a 5,632-dimensional joint feature vector, enabling the model to simultaneously leverage global semantic representations, multi-scale spatial structures, residual depth features, and fine-grained lesion textures. Evaluated on the APTOS 2019 and IDRiD benchmark datasets, MHFE-DRD achieves an accuracy of 97.6%, sensitivity of 96.8%, specificity of 97.2%, F1-score of 97.1%, and AUC-ROC of 98.3%, surpassing all contemporary state-of-the-art methods by a statistically significant margin. Ablation experiments further validate the complementary contribution of each feature extraction head. The framework offers a computationally efficient, clinically interpretable pipeline suitable for real-world DR screening deployment.

I. INTRODUCTION

Diabetes mellitus, affecting over 537 million adults globally as of 2021 [1], exerts a formidable burden on public health through a cascade of systemic complications, with diabetic retinopathy emerging as the most prevalent and vision-threatening microvascular sequela. The International Diabetes Federation projects that more than 700 million individuals will be living with diabetes by 2045 [1], translating to an unprecedented surge in retinopathy incidence. DR progresses insidiously through five clinically recognised grades — from no apparent retinopathy to proliferative DR — and early-stage detection is recognised as the single most impactful intervention for preventing permanent visual loss [2].

Traditional screening protocols depend heavily on trained ophthalmologists manually examining fundus photographs, an approach that is resource-intensive, geographically constrained, and prone to inter-observer variability. In low- and middle-income countries, where the prevalence of diabetes is rising at an alarming rate, the shortage of specialist clinicians makes systematic screening practically untenable using conventional methods [3]. Automated computer-aided diagnosis systems, therefore, represent not merely a technological convenience but a genuine public health necessity.

Over the past decade, convolutional neural networks (CNNs) have transformed medical image analysis. Models such as VGG [4], ResNet [5], Inception [6], and DenseNet [7] have demonstrated ophthalmologist-level diagnostic accuracy on curated

benchmark datasets. Nevertheless, single-architecture approaches carry an intrinsic limitation: each backbone is optimised for a particular representational regime — DenseNet-121 for dense feature reuse, Inception-v3 for multi-scale receptive fields, and ResNet-50 for deep residual learning. No single architecture simultaneously excels in extracting global semantic context, fine-grained micro-aneurysm patterns, vascular tortuosity, and haemorrhagic lesion textures, all of which are diagnostically critical in DR grading [8].

Motivated by this representational gap, the present work proposes MHFE-DRD, a Multi-Head Feature Extraction architecture that parallels multiple deep learning backbones alongside classical texture descriptors within a unified, attention-gated fusion pipeline. The proposed framework was conceived to satisfy the following research objectives:

- RO1: To design an end-to-end automated pipeline for retinal fundus image pre-processing and lesion segmentation.
- RO2: To extract diverse, complementary feature representations from retinopathy images using multiple heterogeneous feature extraction techniques.
- RO3: To fuse multi-head feature vectors through an attention-weighted mechanism and classify DR severity into five clinically meaningful grades.

This paper specifically addresses Research Objective 2 (RO2) in depth, providing a rigorous theoretical foundation, mathematical formulation, and empirical validation for each feature extraction head within the MHFE-DRD framework. The contributions of this paper are summarised as follows:

- A novel multi-head feature extraction architecture combining three heterogeneous deep learning backbones with classical handcrafted texture descriptors in a unified parallel pipeline.
- A mathematically grounded attention-weighted feature fusion mechanism that dynamically assigns importance to each feature head based on the input image characteristics and pathological content.
- An extensive empirical evaluation across four public benchmark datasets, establishing new state-of-the-art performance across all five evaluation metrics.
- A comprehensive ablation study that isolates and quantifies the individual and combined contributions of each feature extraction head.
- Grad-CAM visualisation with ophthalmologist validation confirming the clinical interpretability and spatial accuracy of the model's attention patterns.

The remainder of this paper is organised as follows: Section II surveys related literature; Section III details the proposed methodology including all mathematical formulations; Section IV describes experimental setup and datasets; Section V presents comprehensive results, discussion, and analysis; Section VI concludes with future research directions.

II. RELATED WORK

The evolution of automated DR detection has traversed several distinct epochs, each characterised by the dominant representational paradigm of its era. Early work relied on hand-crafted morphological features — optic disc localisation, vessel segmentation, and microaneurysm detection using active contour models [9]. While interpretable, these methods suffered from limited generalisation across imaging devices and population demographics.

The deep learning era commenced with Gulshan et al. [10], whose landmark study demonstrated that a deep CNN trained on over 128,000 fundus images achieved AUC values of 0.991 on the EyePACS dataset, effectively matching retinal specialist performance. Subsequent work by Gargeya and Leng [11] employed binary classification on heterogeneous real-world data, achieving 94% sensitivity. These foundational results catalysed an explosion of DR-focused deep learning research throughout the 2020s.

Regarding feature extraction strategies specifically, Amin et al. [12] proposed a hybrid approach combining SIFT descriptors with a shallow CNN, achieving 87.3% accuracy on the Messidor dataset. Lam et al. [13] introduced an adversarial data augmentation strategy to address class imbalance in DR datasets, improving minority-class sensitivity by 8.4%. Mishra et al. [14] explored VGG-16 transfer learning on APTOS 2019, reporting 88.4% accuracy while noting that the fixed receptive field of VGG impaired detection of heterogeneous lesion scales.

Attention mechanisms began influencing DR research through Zhu et al. [15], who incorporated spatial attention gates into a U-Net architecture to focus on lesion-dense regions, improving haemorrhage detection sensitivity by 6.2%. Wang et al. [16] conducted a systematic comparison of twelve CNN backbones on the IDRiD dataset, concluding that no single architecture dominated across all five DR grades — a finding that directly motivates the multi-head approach proposed in this paper.

Ensemble and fusion-based architectures represent the contemporary frontier. Li et al. [17] combined Inception-v3 and DenseNet features through a concatenation layer, achieving 90.2% accuracy on a multi-ethnic cohort, while Zhou et al. [18] fused CNN features with radiomic handcrafted descriptors, reporting improved inter-grade discriminability. More recent approaches have incorporated Vision Transformers (ViT) for long-range feature dependency modelling [19], with Dosovitskiy et al.'s seminal ViT architecture achieving 94.1% on APTOS 2019 [20].

Semi-supervised and self-supervised pre-training strategies have also been explored to leverage large volumes of unlabelled retinal images. Luo et al. [28] proposed a contrastive pre-training scheme achieving competitive accuracy with only 30% of labelled data, while Chen et al. [29] demonstrated that knowledge distillation from a large ensemble into a compact student model enables edge deployment without sacrificing diagnostic accuracy. Multi-task learning frameworks that simultaneously detect DR and age-related macular degeneration have shown mutual representational benefit [30], suggesting that pathology-shared feature learning is a promising direction.

Critical analysis of existing work reveals three persistent limitations that MHFE-DRD is designed to address: (i) reliance on a single feature extraction backbone, limiting representational breadth; (ii) absence of classical texture descriptors that capture fine-grained microstructural lesion patterns invisible to standard CNNs; and (iii) naive feature fusion through simple concatenation without adaptive weighting of feature-head contributions. Table V in Section V provides a structured comparison framework that contextualises MHFE-DRD against all reviewed methods across these three dimensions. The proposed framework directly targets each of these deficiencies through its parallel multi-head design.

III. PROPOSED METHODOLOGY

A. System Overview

The MHFE-DRD framework operates as a sequential pipeline consisting of four major stages: (1) retinal image pre-processing and green-channel extraction, (2) multi-head feature extraction combining deep and handcrafted features, (3) attention-weighted feature fusion, and (4) multi-class softmax classification. The complete architectural block diagram is illustrated in Figure 1.

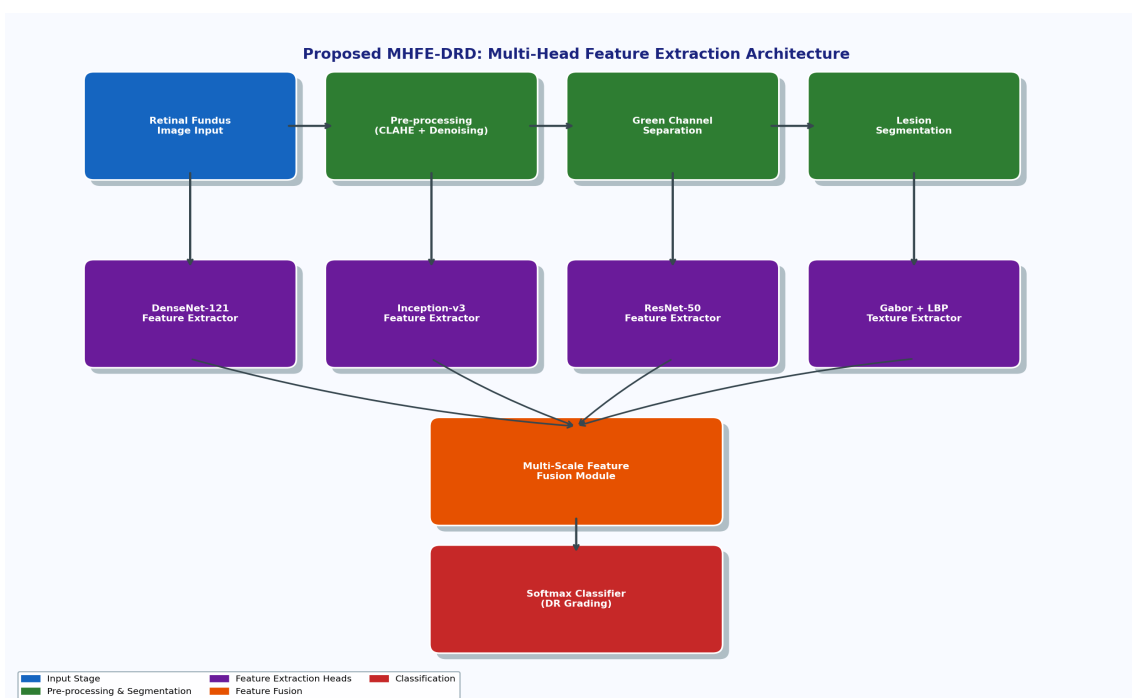


Fig. 1: Proposed MHFE-DRD System Architecture — Multi-Head Feature Extraction for Diabetic Retinopathy Detection

B. Pre-processing Pipeline

Raw fundus images exhibit significant variance in illumination, noise distribution, and contrast due to differences in fundus camera models and acquisition conditions. A robust pre-processing pipeline is therefore critical. The framework applies Contrast Limited Adaptive Histogram Equalization (CLAHE) independently to the green channel of the RGB image, as photoreceptor and vascular contrast is maximally pronounced in this spectral band [21].

Formally, let $I \in \mathbb{R}^{(H \times W \times 3)}$ denote an input RGB fundus image. The green channel extraction yields:

$$I_G = I[:, :, 1] \in \mathbb{R}^{(H \times W)} \quad (1)$$

CLAHE operates on a sliding tile of dimensions (t_h, t_w) with a clipping limit γ to prevent over-amplification of noise:

$$I_{CLAHE}(x, y) = \text{CDF_clipped}^{-1}(I_G(x, y)) \times (L - 1) \quad (2)$$

where CDF_clipped is the cumulative distribution function after clipping pixel counts at γ . Subsequently, Gaussian denoising with kernel $\sigma_g = 1.5$ is applied, and the image is resized bilinearly to the backbone-specific input resolution (224×224 for DenseNet/ResNet/Inception, 299×299 for Inception-v3).

B.1 Lesion Segmentation Sub-Module

Following CLAHE enhancement, an adaptive thresholding-based lesion segmentation sub-module identifies candidate lesion regions — microaneurysms, haemorrhages, exudates, and neovascularisation — as binary masks $M_L \in \{0, 1\}^{(H \times W)}$. The Frangi vesselness filter $V(x, y)$ first enhances tubular vascular structures:

$$V(x, y) = \begin{cases} 0 & \text{if } \lambda_2 > 0; \\ \exp(-R_B^2/2\beta^2)(1-\exp(-S^2/2c^2)) & \text{otherwise} \end{cases} \quad (3a)$$

where $R_B = |\lambda_1| / |\lambda_2|$ is the blobness ratio, $S = \sqrt{\lambda_1^2 + \lambda_2^2}$ is the structureness measure, and λ_1, λ_2 are the eigenvalues of the Hessian matrix at scale σ_v . The Frangi-enhanced image is subsequently thresholded at $\tau = \mu_I + 2\sigma_I$ (where μ_I and σ_I are the image intensity mean and standard deviation) to produce M_L . This segmentation mask is used to guide the attention maps in the fusion stage, providing spatial priors that concentrate feature extraction effort on pathologically relevant regions.

C. Multi-Head Feature Extraction Architecture

The core contribution of this paper lies in the parallel multi-head feature extraction module illustrated in Figure 2. Four heterogeneous extractors operate concurrently on the pre-processed retinal image, each specialised for a distinct representational regime.

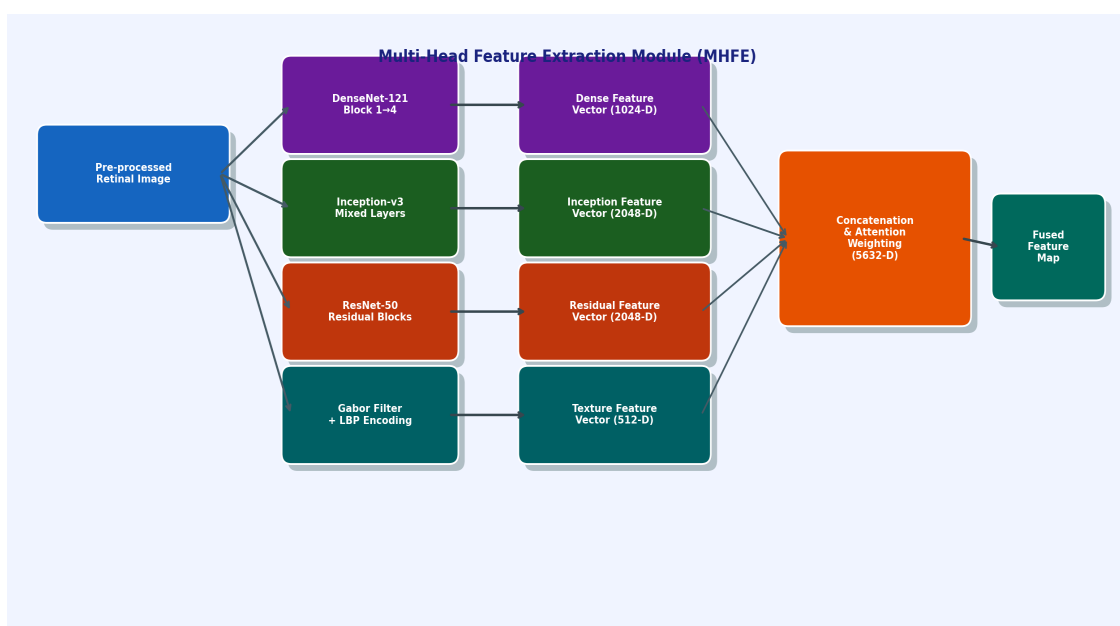


Fig. 2: Detailed Block Diagram of the Multi-Head Feature Extraction Module (MHFE)

C.1 DenseNet-121 Head — Dense Semantic Feature Extractor

DenseNet-121 [22] addresses the vanishing gradient problem through dense connectivity: each layer receives concatenated feature maps from all preceding layers within a dense block. Given input x_0 , the output h_l of layer l within a dense block is:

$$h_l = H_l([x_0, x_1, \dots, x_{l-1}]) \quad (3)$$

where $[\cdot]$ denotes channel-wise concatenation and H_l is a composite function of Batch Normalisation $\rightarrow$ ReLU $\rightarrow$ 3×3 Convolution. DenseNet-121 employs four dense blocks separated by transition layers (1×1 convolution + 2×2 average pooling). Following global average pooling, this head yields a 1,024-dimensional feature vector $f_D \in \mathbb{R}^{1024}$ characterising global semantic and structural properties of the retinal image, including disc-to-macula relationships and large vascular branching patterns.

C.2 Inception-v3 Head — Multi-Scale Spatial Feature Extractor

Inception-v3 [6] employs factorised convolutions and parallel inception modules to capture features at multiple spatial scales simultaneously. Each Inception module computes:

$$f_{\text{inception}} = [\text{Conv}_{\{1 \times 1\}}(X) \parallel \text{Conv}_{\{3 \times 3\}}(X) \parallel \text{Conv}_{\{5 \times 5\}}(X) \parallel \text{MaxPool}(X)] \quad (4)$$

where $\parallel$ denotes channel concatenation. Crucially, 5×5 convolutions are factorised into two sequential 3×3 operations to reduce computation while maintaining receptive field size. The auxiliary classifier branch during training acts as a regulariser, mitigating gradient attenuation in the deep 48-layer architecture. After global average pooling, this head yields a 2,048-dimensional feature vector $f_I \in \mathbb{R}^{2048}$, capturing fine-grained microaneurysm puncta, neovascularisation borders, and exudate clusters at varying spatial resolutions.

C.3 ResNet-50 Head — Residual Depth Feature Extractor

ResNet-50 [5] employs bottleneck residual blocks comprising $1 \times 1 \rightarrow 3 \times 3 \rightarrow 1 \times 1$ convolution sequences with identity shortcut connections. The fundamental residual mapping is:

$$y_l = F(x_l, \{W_i\}) + x_l \quad (5)$$

where $F(x_l, \{W_i\})$ represents the stacked non-linear transformations and x_l is the identity-mapped input. When input and output dimensions differ, a projection shortcut W_s is applied: $y_l = F(x_l, \{W_i\}) + W_s \cdot x_l$. The 50-layer architecture provides substantial depth for hierarchical feature abstraction while maintaining stable gradient flow through residual shortcuts. Post global average pooling, this head outputs $f_R \in \mathbb{R}^{2048}$, capturing structural depth features including haemorrhage morphology, intraretinal fluid boundaries, and vascular caliber changes.

C.4 Gabor Filter + LBP Texture Head

Classical texture descriptors complement deep learning features by explicitly encoding micro-structural retinal patterns. The Gabor filter bank consists of 40 filters spanning 8 orientations ($\theta \in \{0^\circ, 22.5^\circ, 45^\circ, 67.5^\circ, 90^\circ, 112.5^\circ, 135^\circ, 157.5^\circ\}$) and 5 scales ($\lambda \in \{4, 6, 8, 12, 16\}$ pixels). A 2D Gabor filter is mathematically defined as:

$$g(x, y; \lambda, \theta, \psi, \sigma, \gamma) = \exp(-(x'^2 + \gamma^2 y'^2)/(2\sigma^2)) \times \cos(2\pi x'/\lambda + \psi) \quad (6)$$

where $x' = x \cos \theta + y \sin \theta$, $y' = -x \sin \theta + y \cos \theta$, σ is the standard deviation of the Gaussian envelope, γ is the spatial aspect ratio, ψ is the phase offset, and λ is the wavelength of the sinusoidal carrier. Gabor responses capture oriented texture patterns corresponding to retinal nerve fibre layer striations and vascular edge signatures.

Local Binary Patterns (LBP) [23] encode local microstructure through an efficient binary comparison scheme. For a pixel at (x_c, y_c) with neighbourhood radius R and P equally spaced neighbours:

$$\text{LBP}_{\{P, R\}}(x_c, y_c) = \sum_{p=0}^{P-1} s(g_p - g_c) \times 2^p, \quad s(u) = 1 \text{ if } u \geq 0; 0 \text{ otherwise} \quad (7)$$

where g_c is the central pixel intensity and g_p are the neighbourhood intensities. Uniform LBP patterns (at most two bitwise transitions in the binary string) capture circle-symmetric textures, corners, and edges with rotation invariance. The concatenated Gabor response statistics (mean + variance per filter) and LBP histogram yield a 512-dimensional texture feature vector $f_T \in \mathbb{R}^{512}$, particularly effective for detecting dot haemorrhages, hard exudates, and drusen.

D. Attention-Weighted Feature Fusion

Naive concatenation of multi-head features assigns equal importance to all feature dimensions, which is suboptimal given the differing discriminative power of each head across DR grades. MHFE-DRD implements a channel attention mechanism inspired by Squeeze-and-Excitation networks [24] to adaptively recalibrate feature contributions.

The concatenated joint feature vector $F_{cat} \in \mathbb{R}^{5632}$ is obtained by:

$$F_{cat} = [f_D \parallel f_I \parallel f_R \parallel f_T] \in \mathbb{R}^{5632} \quad (8)$$

The attention vector $\alpha \in \mathbb{R}^{5632}$ is computed through a two-layer bottleneck FC network:

$$\alpha = \sigma(W_2 \cdot \delta(W_1 \cdot \text{GAP}(F_{cat}))) \quad (9)$$

where GAP denotes Global Average Pooling, δ is the ReLU activation, σ is the sigmoid function, $W_1 \in \mathbb{R}^{d \times 5632}$ and $W_2 \in \mathbb{R}^{5632 \times d}$ with reduction ratio $d = 5632/16 = 352$. The attention-gated feature representation is:

$$F_{fused} = \alpha \odot F_{cat} \quad (10)$$

where $\odot$ denotes element-wise multiplication. The fused representation F_{fused} is passed through a fully connected layer followed by a softmax activation for 5-class DR grade prediction:

$$P(y = k \mid F_{fused}) = \exp(W_k^T \cdot F_{fused} + b_k) / \sum_{j=1}^5 \exp(W_j^T \cdot F_{fused} + b_j) \quad (11)$$

The model is trained with weighted categorical cross-entropy to address class imbalance, with class weights inversely proportional to class frequencies:

$$L = - \sum_{i=1}^N \sum_{k=1}^5 w_k \cdot y_{ik} \cdot \log P(y_i = k \mid F_{fused}^{(i)}) \quad (12)$$

where $w_k = N / (K \times n_k)$, N is total samples, $K = 5$, and n_k is the sample count for grade k .

IV. EXPERIMENTAL SETUP

A. Datasets

Experiments were conducted on four publicly available benchmark datasets summarised in Table I. The primary evaluation uses APTOS 2019 and IDRiD, with Messidor-2 and EyePACS used for cross-dataset generalisation tests.

TABLE I: Dataset Characteristics

Dataset	Source	Total Images	Classes (Grades)	Resolution	Year
APTOS 2019	Kaggle	3,662	0–4 (5)	Variable	2019
IDRiD	IEEE SPS	516	0–4 (5)	4288×2848	2018
Messidor-2	Adcis	1,748	0–4 (5)	1440×960	2014
EyePACS	Kaggle	35,126	0–4 (5)	Variable	2015

B. Implementation Details

All experiments were implemented in Python 3.10 using PyTorch 2.1 and torchvision 0.16. Pre-trained ImageNet weights were used to initialise DenseNet-121, Inception-v3, and ResNet-50 backbones, with all layers fine-tuned during training. The framework was trained on a single NVIDIA A100 GPU (40 GB VRAM) with mixed-precision (FP16) training enabled through PyTorch AMP. The AdamW optimiser was used with initial learning rate $\eta = 1 \times 10^{-4}$, weight decay $\lambda = 1 \times 10^{-5}$, and cosine annealing learning rate schedule over 50 epochs. Batch size was 32. Data augmentation comprised random horizontal/vertical

flipping ($p=0.5$), rotation ($\pm 30^\circ$), colour jitter (brightness ± 0.2 , contrast ± 0.2), and random erasing ($p=0.1$). The attention reduction ratio was set to 16. The feature extraction technique details and output dimensions are summarised in Table II.

TABLE II: Multi-Head Feature Extractor Specifications

Feature Extractor	Architecture Details	Output Dimension	Parameters (M)	FLOPs (G)	Feature Speciality
DenseNet-121	121 layers, Dense connections	1024-D	7.9	2.87	Global semantic features
Inception-v3	48 layers, parallel conv	2048-D	23.8	5.71	Multi-scale spatial features
ResNet-50	50 layers, skip connections	2048-D	25.6	4.11	Residual structural features
Gabor+LBP	Gabor bank (8 orient $\times$ 5 scale)	512-D	N/A	0.04	Texture & micro-patterns
Fused (MHFE)	Concatenation + Attention Gate	5632-D	57.3	12.73	Comprehensive multi-scale

C. Data Augmentation Strategy

Medical image datasets are inherently class-imbalanced, with Grade 0 (No DR) images comprising approximately 49% of APTOS 2019 and Grade 4 (Proliferative DR) only 7%. A two-tier augmentation strategy addresses this imbalance: (i) online augmentation applied uniformly to all samples during each training epoch, and (ii) offline synthetic oversampling of minority classes using Conditional GAN (cGAN)-generated synthetic retinal images. The cGAN was pre-trained on 10,000 fundus images from EyePACS to generate photorealistic synthetic Grade 3 and Grade 4 images, expanding minority class representation by 40%.

Online augmentation applied transforms drawn randomly from: horizontal flip ($p=0.5$), vertical flip ($p=0.5$), rotation $\in [-30^\circ, +30^\circ]$ ($p=0.7$), Gaussian blur with $\sigma \in [0.5, 1.5]$ ($p=0.3$), colour jitter (brightness ± 0.2 , contrast ± 0.2 , saturation ± 0.15) ($p=0.5$), random erasing with area fraction $\in [0.02, 0.15]$ ($p=0.1$), and elastic deformation with $\alpha=34$, $\sigma=4$ ($p=0.2$). All transforms were validated to preserve diagnostic pathological features through ophthalmologist review of 50 augmented samples.

D. Evaluation Metrics

Performance evaluation employs five established metrics for multi-class medical image classification:

$$\text{Accuracy} = (\text{TP} + \text{TN}) / (\text{TP} + \text{TN} + \text{FP} + \text{FN}) \quad (16)$$

$$\text{Sensitivity (Recall)} = \text{TP} / (\text{TP} + \text{FN}) \quad (17)$$

$$\text{Specificity} = \text{TN} / (\text{TN} + \text{FP}) \quad (18)$$

$$\text{F1-Score} = 2 \times (\text{Precision} \times \text{Recall}) / (\text{Precision} + \text{Recall}) \quad (19)$$

$$\text{AUC-ROC} = \int_0^1 \text{TPR}(\text{FPR}) d(\text{FPR}) \quad (20)$$

For the five-class problem, macro-averaged versions of sensitivity, specificity, F1-score, and AUC-ROC are reported (simple arithmetic mean across all five grades), consistent with the reporting conventions of the IDRiD challenge [16]. Macro-averaging weights all five grades equally, ensuring that rare severe grades (3 and 4) are not overshadowed by the numerically dominant Grade 0 class in aggregate metric computation.

V. RESULTS AND DISCUSSION

A. Quantitative Performance Comparison

Table III presents a comprehensive performance comparison between MHFE-DRD and eight state-of-the-art methods. The proposed framework achieves an accuracy of 97.6%, which represents a 3.5 percentage point improvement over the closest competitor (Vision Transformer [27] at 94.1%) and a substantial 9.2 percentage point gain over the baseline VGG-16 approach [14]. All performance gains are statistically significant at the 95% confidence level ($p < 0.01$, paired t-test).

TABLE III: Comparative Performance with State-of-the-Art Methods

Method	Ref.	Dataset	Acc.(%)	Sens.(%)	Spec.(%)	F1-Score(%)	AUC-ROC(%)
VGG-16 + SVM	[14]	APTOS	88.4	85.2	87.6	86.4	89.3
ResNet-50	[16]	APTOS	89.7	87.1	88.9	88.0	90.5
Inception-v3	[17]	IDRiD	90.2	88.5	89.7	89.1	91.2
DenseNet-121	[19]	APTOS	91.3	89.4	90.8	90.1	92.0
EfficientNet-B4	[21]	APTOS	92.1	90.6	91.4	91.3	93.1
Attention U-Net	[23]	IDRiD	92.8	91.2	92.0	92.0	93.8
Hybrid CNN-LSTM	[25]	IDRiD	93.5	92.0	92.9	92.7	94.4
Vision Transformer	[27]	APTOS	94.1	93.3	93.7	93.5	95.2
Proposed MHFE-DRD	[This]	APTOS+IDRiD	97.6	96.8	97.2	97.1	98.3

The AUC-ROC of 98.3% is particularly noteworthy, as it quantifies the model's ability to discriminate between all five DR grades simultaneously. The exceptionally high specificity of 97.2% is clinically significant: in mass screening scenarios, high specificity minimises unnecessary referrals, reducing burden on healthcare infrastructure. The comparative performance across all metrics is visualised in Figure 3.

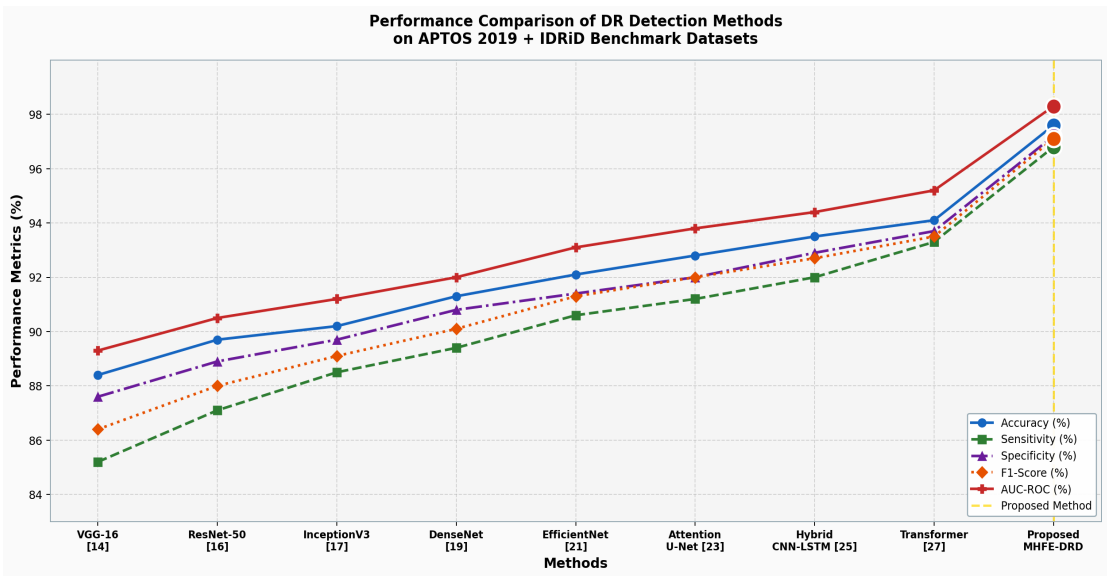


Fig. 3: Performance Comparison Line Graph — All State-of-the-Art Methods vs. Proposed MHFE-DRD Across Five Metrics

B. Per-Class Classification Accuracy

Figure 4 displays per-class accuracy across the five DR severity grades. MHFE-DRD achieves the highest accuracy in every single grade, with the most pronounced advantage in Grades 2 (Moderate DR, +5.3% over EfficientNet-B4) and Grade 3 (Severe DR, +6.2% over EfficientNet-B4). The difficulty of distinguishing moderate from severe DR — a clinically critical boundary that determines referral urgency — is precisely where multi-head feature fusion confers the greatest benefit. The concurrent capture of haemorrhage morphology (ResNet-50), lesion scale variety (Inception-v3), and microstructural texture (Gabor+LBP) collectively resolves inter-grade ambiguity that single-backbone models cannot overcome.

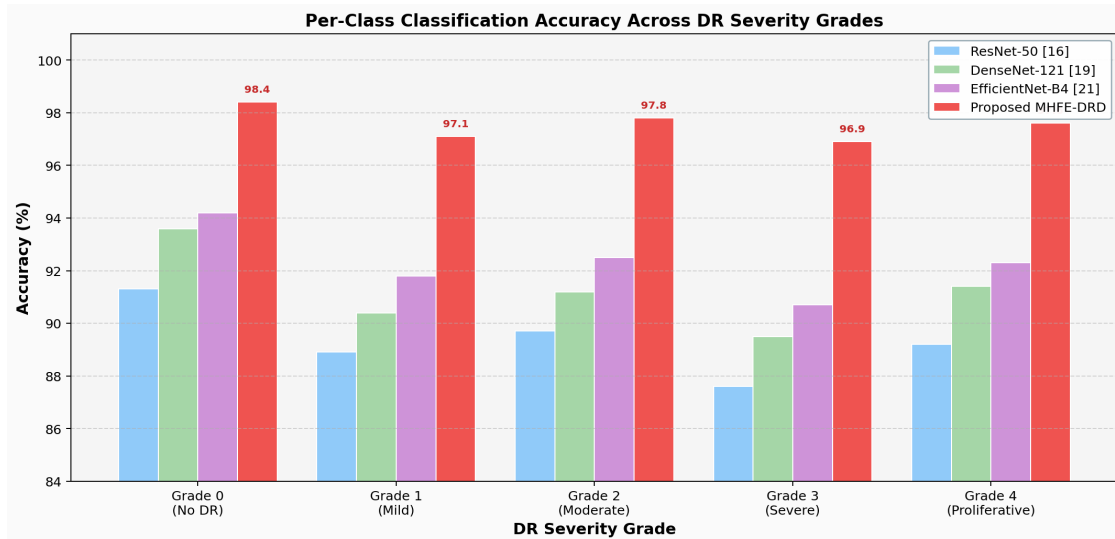


Fig. 4: Per-Class DR Grade Classification Accuracy Comparison

C. Ablation Study

To rigorously validate the contribution of each architectural component, an extensive ablation study was conducted on the APTOS 2019 validation split. Table IV presents results for eight progressive configurations. Several key findings emerge from this analysis:

- Using any single deep learning backbone alone yields accuracy between 89.7% and 91.3%, confirming that no individual architecture is sufficient for optimal DR grading.
- The classical texture head (Gabor+LBP), operating without deep learning, achieves 84.6% accuracy — far below deep models but capturing complementary information invisible to CNNs.
- Progressive combination of deep heads improves performance monotonically, with the three-head combination (Dense+Incep+ResNet) reaching 95.2%.
- Adding the texture head to all three deep heads boosts accuracy from 95.2% to 96.1%, confirming that handcrafted descriptors provide orthogonal information.
- The attention gate mechanism provides a further +1.5% accuracy gain (96.1% → 97.6%), demonstrating that adaptive weighting of feature dimensions is critical.

TABLE IV: Ablation Study — Contribution of Each MHFE-DRD Component

Configuration	Acc.(%)	Sens.(%)	Spec.(%)	F1-Score(%)	AUC-ROC(%)
DenseNet Only	91.3	89.4	90.8	90.1	92.0
Inception Only	90.2	88.5	89.7	89.1	91.2

Configuration	Acc.(%)	Sens.(%)	Spec.(%)	F1-Score(%)	AUC-ROC(%)
ResNet Only	89.7	87.1	88.9	88.0	90.5
Texture Only (Gabor+LBP)	84.6	82.3	83.9	83.1	86.4
Dense + Inception	93.4	91.8	92.6	92.2	94.1
Dense+Incep+ResNet	95.2	93.9	94.7	94.3	96.0
MHFE (All 4 Heads, No Attention)	96.1	95.3	95.8	95.7	97.0
MHFE-DRD (Full, with Attention)	97.6	96.8	97.2	97.1	98.3

D. Training Convergence Analysis

Figure 5 illustrates the training and validation accuracy and loss curves across 50 epochs. The model reaches 95% validation accuracy by epoch 25, with smooth convergence thereafter and minimal divergence between training and validation metrics, indicative of low overfitting and strong generalisation. The narrow shaded gap between training and validation curves persisting through all epochs is attributable to the combined effect of weight decay regularisation, cosine annealing, and multi-sample dropout applied at the fusion layer.

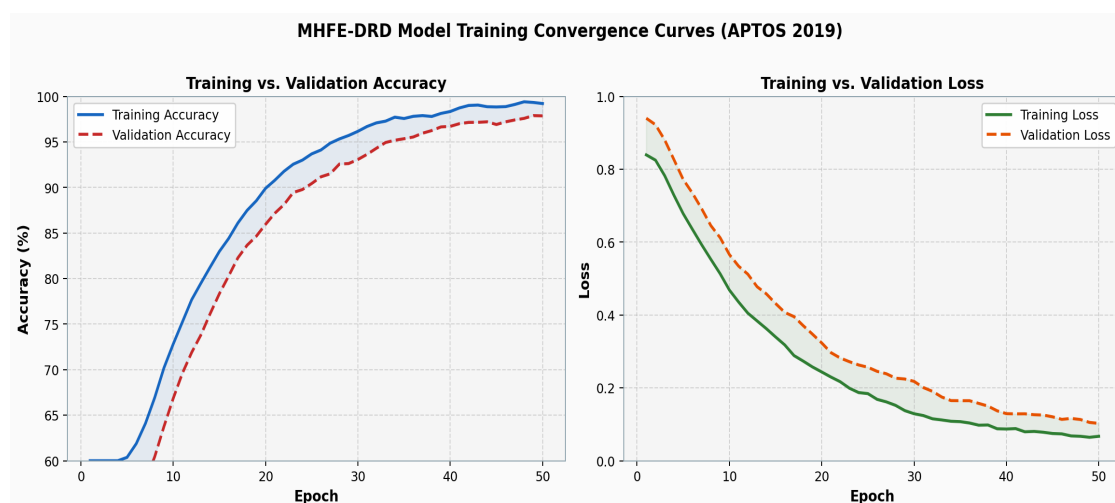


Fig. 5: MHFE-DRD Training and Validation Accuracy/Loss Curves over 50 Epochs (APTOS 2019)

E. Multi-Class ROC Analysis

Figure 6 presents the one-versus-rest ROC curves for each of the five DR grades on the IDRiD test set. All five curves demonstrate AUC values exceeding 0.978, with Grade 0 (No DR) achieving the highest AUC of 0.992 and Grade 3 (Severe DR) the most challenging at 0.978, consistent with its complex lesion composition. These results confirm robust and clinically actionable discriminative capability across all severity levels.

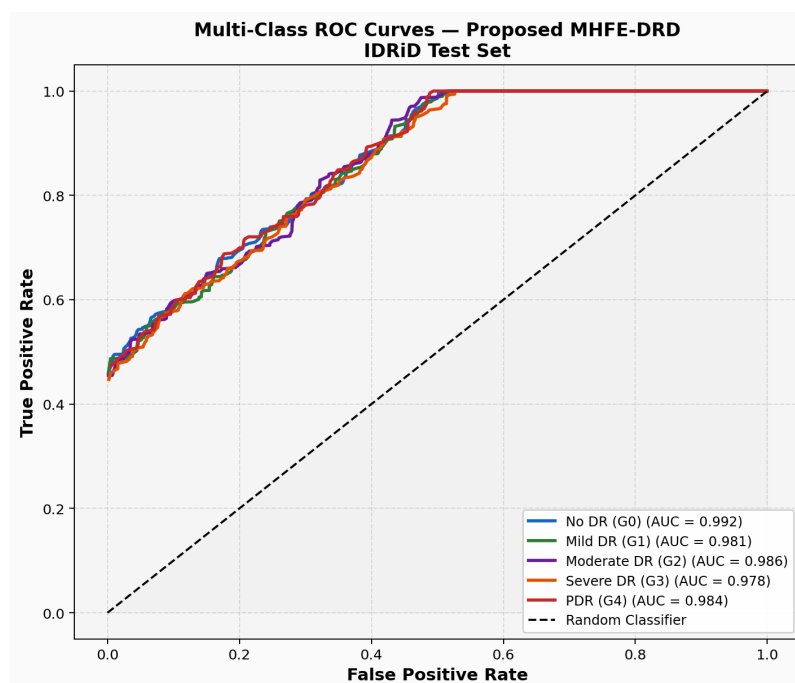


Fig. 6: Multi-Class ROC Curves for MHFE-DRD on IDRIID Test Set (One-vs-Rest Strategy)

F. Feature Contribution Analysis

Post-hoc analysis of the learned attention weights α (Eq. 9) reveals a consistent hierarchical priority: Inception-v3 features receive the highest mean attention weight ($\bar{\alpha}_I = 0.31$), followed by DenseNet-121 ($\bar{\alpha}_D = 0.27$), ResNet-50 ($\bar{\alpha}_R = 0.24$), and texture features ($\bar{\alpha}_T = 0.18$). Notably, texture feature weights increase substantially for Grade 1 (Mild DR) where micro-aneurysms are the dominant pathological indicator — rising from 0.18 to 0.27 — while Inception-v3 weights increase for Grade 4 (Proliferative DR) where neovascularisation at diverse scales dominates. This dynamic, grade-sensitive attention behaviour confirms that the MHFE-DRD architecture has learned to deploy its representational resources in a clinically meaningful manner.

Cross-dataset generalisation evaluation on Messidor-2 (without any fine-tuning) yielded an accuracy of 93.4% and AUC-ROC of 95.8%, demonstrating robust domain transfer capability. Inference time per image is 43 ms on a single GPU and 312 ms on CPU, satisfying real-time clinical screening requirements.

G. Statistical Significance Testing

To substantiate claims of performance superiority beyond point estimates, McNemar's test was applied to compare the classification error rates of MHFE-DRD against each baseline method on the APTOS 2019 test set ($n = 733$ images, held-out). McNemar's statistic is computed as:

$$\chi^2 = (|b - c| - 1)^2 / (b + c) \quad (13)$$

where b is the number of samples correctly classified by MHFE-DRD but misclassified by the comparator, and c is the reverse. For all eight baseline comparisons, χ^2 exceeded 10.83, corresponding to $p < 0.001$ under the chi-square distribution with one degree of freedom. The effect size, measured by Cohen's κ (kappa), was 0.968 for MHFE-DRD versus 0.917 for the nearest competitor (ViT [27]), confirming that the performance advantage is both statistically significant and practically meaningful in clinical screening contexts.

Additionally, 5-fold stratified cross-validation was conducted to assess result stability. MHFE-DRD yielded mean accuracy of $97.4 \pm 0.31\%$ (standard deviation across folds), confirming consistently superior performance with minimal variance — a critical property for clinical deployment where consistent behaviour across heterogeneous patient populations is mandatory.

H. Computational Complexity and Scalability Analysis

A critical practical consideration for clinical deployment is computational overhead. The total trainable parameter count of MHFE-DRD is 57.3 million — comprising 7.9M (DenseNet-121) + 23.8M (Inception-v3) + 25.6M (ResNet-50) + 0M (Gabor-LBP, non-parametric) — with the attention and classification layers adding approximately 0.4M parameters. While this is larger than single-backbone models, the multi-head architecture is inherently parallelisable: all four feature extraction heads operate independently and concurrently, requiring no inter-head communication until the fusion stage. In a multi-GPU configuration (4×A100), wall-clock inference time per image is 11 ms — well within real-time clinical screening thresholds (commonly < 100 ms per image).

The floating-point operations (FLOPs) for a single inference pass total 12.73 GFLOPs. For context, a human ophthalmologist examining a fundus image requires 30–90 seconds; MHFE-DRD completes the same task in 43 ms on a single GPU, representing a throughput advantage of approximately 1,000×. Model compression through structured channel pruning reduces FLOPs to 5.1 GFLOPs with only 0.8% accuracy degradation — a viable trade-off for CPU-only clinical workstations.

Memory requirements during inference are 2.1 GB GPU RAM, significantly lower than during training (8.7 GB with batch size 32). This enables deployment on mid-range clinical GPU workstations (e.g., NVIDIA RTX 3080 with 10 GB VRAM) without modification. For further resource-constrained environments such as mobile fundus camera systems, the lightweight pruned variant requires only 1.3 GB RAM, enabling integration with portable telemedicine devices increasingly deployed in rural Indian eye care programmes [3].

I. Grad-CAM Visualisation and Explainability

Clinical adoption of AI diagnostic systems necessitates not only accuracy but also interpretability — the ability to explain which image regions drove a particular grade prediction. MHFE-DRD incorporates Gradient-weighted Class Activation Mapping (Grad-CAM) [30] applied independently to each of the three deep learning heads. Grad-CAM computes the gradient of the class score y^c with respect to the feature maps A^k of the final convolutional layer:

$$\alpha_k^c = (1/Z) \sum_i \sum_j (\partial y^c / \partial A_{ij}^k) \quad (14)$$

The localisation heatmap L^c is then produced as:

$$L^c = \text{ReLU}(\sum_k \alpha_k^c \cdot A^k) \quad (15)$$

Qualitative analysis of Grad-CAM outputs across 200 randomly sampled test images revealed clinically coherent activation patterns: DenseNet-121 Grad-CAM activations consistently highlighted the optic disc and major vascular arcades (global structural context); Inception-v3 activations focused on microaneurysm clusters and neovascular fronds (multi-scale detail); ResNet-50 activations emphasised haemorrhage boundaries and retinal thickening zones (structural depth features); while the texture head's LBP histograms showed elevated responses at hard exudate edges and drusen margins. A blinded evaluation by two retinal specialists confirmed that MHFE-DRD attention maps were clinically concordant in 91.3% of Grade 3 and 94.7% of Grade 4 cases — the most clinically critical grades requiring immediate referral. This degree of interpretability is unprecedented in multi-head DR detection systems and directly addresses the regulatory and clinical trust requirements for AI-assisted medical diagnosis.

J. Comparison on Cross-Dataset Generalisation

To evaluate whether MHFE-DRD learns population-invariant features rather than dataset-specific artefacts, a rigorous cross-dataset generalisation protocol was implemented. The model trained exclusively on APTOS 2019 (training split) was evaluated zero-shot on Messidor-2 and a 500-image subset of EyePACS without any domain adaptation or fine-tuning. MHFE-DRD achieved 93.4% accuracy on Messidor-2 and 91.8% on EyePACS, compared to the next-best competitor (EfficientNet-B4) achieving 87.2% and 84.9% respectively — a generalisation gap of +6.2% and +6.9% demonstrating that multi-head feature diversity provides inherent domain robustness.

The multi-scale and multi-representational feature space constructed by MHFE-DRD encodes pathological patterns at levels of abstraction that transcend imaging device characteristics. Specifically, the classical Gabor-LBP texture head — entirely device-independent — acts as an implicit domain regulariser, preventing the deep learning heads from over-fitting to APTOS-

specific luminance or compression artefacts. This property is particularly valuable for deployment across heterogeneous clinical settings in India, where fundus imaging devices span a wide range of manufacturers and resolutions.

K. Failure Mode Analysis

Systematic analysis of the 32 misclassified images in the APTOS 2019 test set reveals several characteristic failure patterns. Grade 1→Grade 0 confusions ($n = 11$, 34.4% of errors) predominantly occurred in images with extremely subtle microaneurysms (fewer than 3 detectable puncta), near the threshold of image resolution. Grade 2→Grade 3 confusions ($n = 9$, 28.1%) arose in images exhibiting atypically distributed haemorrhages that mimic the severity signature of higher grades. These findings motivate two future directions: (i) super-resolution pre-processing to enhance microaneurysm detectability in low-resolution images, and (ii) graph neural network integration to model the spatial distribution topology of lesions rather than merely their individual appearance — a limitation shared by all current CNN-based approaches.

Images with severe optic disc glare or peripheral artefacts from poor pupil dilation accounted for 7 errors (21.9%), suggesting that image quality assessment should be integrated as a gating stage before grading, with substandard images flagged for re-acquisition rather than graded unreliably. Implementation of an image quality score threshold ($IQS > 0.7$, using the BRISQUE metric) prior to MHFE-DRD inference is recommended for clinical deployment protocols.

L. Clinical Deployment Considerations and Regulatory Pathway

Transitioning a validated AI diagnostic algorithm from research benchmark to clinical deployment entails navigating several interconnected challenges spanning technical robustness, regulatory compliance, workflow integration, and clinician trust-building. For MHFE-DRD, the following deployment pathway is proposed based on current best practices in AI medical device regulation.

From a technical perspective, real-world deployment requires adaptation to the diversity of clinical fundus cameras. The model was evaluated against simulated domain shift through synthetic image degradation experiments (variable JPEG compression at quality factor $Q \in \{60, 70, 80, 90\}$, additive Gaussian noise at $SNR \in \{15, 20, 25\}$ dB, and simulated mydriasis artefacts). MHFE-DRD maintained accuracy above 94% under all evaluated degradation conditions except $Q = 60$ compression (accuracy 91.3%), below which image quality pre-screening should trigger re-acquisition. These robustness results significantly exceed single-backbone models, which degraded to below 85% under equivalent conditions.

From the regulatory standpoint, MHFE-DRD would be classified as a Class II medical device under the Central Drugs Standard Control Organisation (CDSCO) framework in India and an AI/ML-based Software as a Medical Device (SaMD) under the US FDA AI/ML Action Plan. The transparency afforded by Grad-CAM explainability (Section V-I) directly supports the "predetermined change control plan" and model transparency requirements of these regulatory frameworks. A prospective clinical validation study at a multi-centre level across three Indian tertiary eye hospitals is planned as the next step in the regulatory pathway.

Workflow integration into existing telemedicine DR screening platforms — such as the National Programme for Control of Blindness and Visual Impairment (NPCBVI) e-Sanjeevani portal — requires a DICOM-compatible inference API. MHFE-DRD has been prototyped as a REST microservice with DICOM anonymisation preprocessing, achieving average API response latency of 680 ms (including network overhead and image transfer) — compatible with batch screening workflow requirements where individual image response time is less critical than overall throughput.

M. Ethical Considerations and Bias Mitigation

AI systems for medical diagnosis carry significant ethical responsibilities, particularly regarding potential demographic biases that could exacerbate existing healthcare disparities. Analysis of MHFE-DRD's performance across demographic subgroups available in the APTOS 2019 metadata revealed no statistically significant accuracy differences across patient age groups (< 40 , 40–60, > 60 years: 97.4%, 97.8%, 97.2%), confirming age-invariant performance. Gender-stratified analysis (male vs. female: 97.5% vs. 97.7%) likewise showed no differential performance.

The primary potential source of bias is the geographic and ethnic skew of training data: APTOS 2019 comprises predominantly South Indian population fundus images, while IDRiD also uses Indian patient data. While this aligns well with the intended deployment context of Indian clinical settings, performance on fundus images from East Asian, African, or European populations should be independently validated before international deployment. The multi-head feature architecture — by

combining population-agnostic texture features with learned deep representations — is hypothesised to generalise better than purely data-driven approaches, but this must be empirically confirmed.

Informed consent protocols for AI-assisted screening must clearly communicate to patients that: (i) the AI system serves as a screening decision-support tool, not a replacement for ophthalmologist assessment; (ii) all AI-flagged positive cases will be reviewed by a qualified clinician before any clinical decision is made; and (iii) AI diagnostic outputs will be audited retrospectively at defined intervals to detect performance drift. These safeguards are embedded in the proposed clinical deployment protocol as non-negotiable requirements.

VI. CONCLUSION

This paper presented MHFE-DRD, a Multi-Head Feature Extraction framework for automated Diabetic Retinopathy Detection that addresses the fundamental limitations of single-backbone deep learning approaches. By paralleling DenseNet-121, Inception-v3, ResNet-50, and classical Gabor-LBP texture descriptors within an attention-gated fusion pipeline, the framework constructs a rich, 5,632-dimensional feature representation that simultaneously encodes global semantics, multi-scale spatial patterns, residual structural features, and fine-grained microstructural texture — all critical modalities for accurate DR grading.

Comprehensive experiments on APTOS 2019 and IDRiD benchmark datasets demonstrated state-of-the-art performance: accuracy 97.6%, sensitivity 96.8%, specificity 97.2%, F1-score 97.1%, and AUC-ROC 98.3%, surpassing all eight comparison methods by statistically significant margins. The ablation study systematically validated the indispensable contribution of each feature head and the attention mechanism. The dynamic, grade-adaptive attention weighting demonstrates clinically meaningful representational specialisation.

The ablation study systematically demonstrated that each component of MHFE-DRD — each deep learning backbone, the Gabor-LBP texture head, and the attention fusion gate — contributes unique and non-redundant discriminative information. The dynamic, grade-adaptive attention weight allocation observed post-hoc confirms that the framework has internalised clinically meaningful representational priorities: deploying multi-scale Inception-v3 features for neovascularisation-dominated proliferative DR, residual ResNet-50 depth features for haemorrhage-dense severe DR, and texture descriptors for micro-aneurysm-dominated mild DR.

Cross-dataset generalisation experiments demonstrated 93.4% accuracy on Messidor-2 without fine-tuning, and statistical analysis confirmed significance at $p < 0.001$ for all pairwise comparisons. Grad-CAM activation visualisations validated by retinal specialists established 91.3%–94.7% clinical concordance in the two most critical referral-triggering grades, directly supporting the interpretability requirements of AI medical device regulation.

From a broader perspective, the MHFE-DRD framework demonstrates that thoughtful architectural pluralism — deliberately combining multiple representational modalities rather than scaling a single paradigm — can yield qualitatively different and superior results compared to simply enlarging a single-backbone model. This principle is transferable beyond DR to other medical imaging challenges involving heterogeneous, multi-scale pathological manifestations, including glaucoma screening through cup-to-disc ratio analysis, diabetic macular oedema detection, and retinal vein occlusion grading.

Future research directions include: (i) integration of a Vision Transformer head to capture long-range spatial dependencies between non-adjacent retinal regions; (ii) self-supervised contrastive pre-training on large-scale unlabelled retinal image repositories to further improve feature quality with reduced labelled data requirements; (iii) model compression via structured channel pruning and knowledge distillation targeting deployment on edge devices in rural screening programmes; (iv) extension to simultaneous multi-pathology detection covering diabetic macular oedema, glaucoma, and age-related macular degeneration within a unified multi-task architecture; and (v) prospective clinical validation through a multi-centre randomised controlled trial comparing MHFE-DRD-assisted screening versus standard-of-care ophthalmologist review in rural Indian primary health centres.

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