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A Novel Approach For An Automatic Diabetic Retinopathy Detection And Classification Using Dendritic Shufflenet

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Abstract:

Diabetic Retinopathy (DR) is a leading cause of blindness among diabetic patients, necessitating efficient automated detection and classification systems to enable early intervention. This project introduces a Lightweight Dendritic ShuffleNet, a novel deep learning architecture designed for accurate DR identification from retinal fundus images. By integrating dendritic neuron-inspired structures with the efficient channel shuffling mechanism of ShuffleNet, the model achieves high performance while maintaining low computational complexity, making it suitable for deployment on resource-constrained devices. The proposed system processes images through preprocessing stages including contrast enhancement and noise reduction, followed by feature extraction using dendritic layers that mimic biological neuron branching for enhanced hierarchical representation. Classification is performed across five severity levels: no DR, mild, moderate, severe, and proliferative DR, leveraging a lightweight backbone to reduce parameters by up to 50% compared to traditional CNNs. Furthermore, interpretability is improved through attention mechanisms that highlight lesion areas like microaneurysms and hemorrhages. This work paves the way for accessible DR diagnostics in underserved regions, potentially reducing vision loss through timely detection. Overall, the Lightweight Dendritic ShuffleNet represents a significant advancement in AI-driven ophthalmology, balancing precision, speed, and deployability.

Keywords:--*Diabetic Retinopathy, Deep Learning, ShuffleNet Architecture, Dendritic Neurons, Retinal Fundus Images, Severity Classification, Lightweight Neural Networks, Attention Mechanisms*

I. INTRODUCTION

The escalating prevalence of diabetes mellitus globally has precipitated a concomitant surge in associated complications, with Diabetic Retinopathy (DR) emerging as a foremost etiology of preventable blindness in working-age populations. This ocular affliction, characterized by progressive damage to retinal vasculature, necessitates vigilant monitoring and timely intervention to mitigate irreversible visual deficits. Traditional diagnostic paradigms rely heavily on manual scrutiny by ophthalmologists, a process encumbered by subjectivity, time intensiveness, and limited availability in underserved regions. Consequently, the advent of automated detection systems leveraging artificial intelligence represents a paradigm shift towards equitable healthcare delivery. Advancements in imaging technologies, particularly color fundus photography, have furnished high-resolution depictions of retinal anatomy, enabling the identification of hallmark lesions such as microaneurysms, hemorrhages, exudates, and neovascularization. These modalities serve as foundational inputs for computational models aimed at DR screening. Deep learning, a subset of machine learning, has demonstrated unparalleled prowess in image analysis tasks, surpassing human performance in certain domains through hierarchical feature learning.The integration of convolutional neural networks (CNNs) in medical imaging has revolutionized diagnostic accuracy, yet conventional architectures like ResNet or VGG often entail substantial computational resources, impeding deployment on portable or edge devices. This limitation is particularly acute in low-resource settings where access to high-end computing infrastructure is scant. Hence, the pursuit of lightweight models that maintain high fidelity without exorbitant costs is paramount.

Bio-inspired computing offers intriguing avenues for enhancing neural network efficiency. Dendritic neurons, drawing from the morphological and functional intricacies of biological dendrites, introduce non-linear processing capabilities that enrich feature representation. By incorporating such elements, models can achieve more nuanced pattern recognition with reduced parametric complexity.ShuffleNet, renowned for its channel shuffling mechanism, optimizes information flow across convolutional layers, thereby curtailing redundancy and accelerating inference. This architecture's efficacy in mobile vision tasks positions it as an ideal backbone for medical applications demanding real-time processing.The confluence of dendritic structures and ShuffleNet principles engenders a hybrid model tailored for DR classification. This approach not only addresses computational constraints but also augments interpretability, a critical facet in clinical adoption where transparency fosters trust among practitioners.Preprocessing stages are indispensable in handling the variability inherent to fundus images, including illumination inconsistencies and artifacts from imaging devices. Techniques such as adaptive histogram equalization and Gaussian filtering bolster image quality, priming them for robust feature extraction.

Classification into five severity levels aligns with international standards like the International Clinical Diabetic Retinopathy Disease Severity Scale, facilitating standardized reporting and treatment planning. Automated systems calibrated to these strata empower primary care providers to triage cases effectively.Attention mechanisms, by selectively emphasizing salient regions, mitigate the black-box nature of deep models, providing visual explanations that correlate model predictions with pathological indicators. This enhances diagnostic confidence and aids in educational contexts.The potential impact of such innovations extends beyond diagnostics to epidemiological surveillance, enabling large-scale screening programs in endemic areas. By democratizing access to advanced tools, these systems contribute to global health equity initiatives.Challenges persist, including dataset imbalances, domain shifts across diverse populations, and the need for rigorous validation against gold-standard annotations. Overcoming these hurdles through methodological refinements is essential for translational success.Ultimately, this research endeavors to bridge the gap between technological sophistication and practical utility, fostering a future where AI-driven ophthalmology alleviates the burden of DR on healthcare systems worldwide.

II. RELATED WORK

In recent years, numerous investigations have harnessed deep learning for DR detection, with a focus on CNN-based architectures. For instance, in 2020, Li et al. proposed a modified ResNet framework for multi-class DR classification using the APTOS dataset, achieving an accuracy of 92.5% by incorporating transfer learning from ImageNet pre-trained models [1]. Their work emphasized data augmentation to combat class imbalance, highlighting the efficacy of synthetic image generation in enhancing model generalization. Subsequent studies explored ensemble methods. Wang and colleagues in 2021 developed an ensemble of VGG16 and InceptionV3 networks, reporting a sensitivity of 95% for severe DR cases in the Messidor-2 dataset [2]. This approach mitigated individual model biases, underscoring the benefits of model fusion in medical imaging tasks.Attention-based models gained traction, as evidenced by the work of Zhang et al. in 2022, who integrated spatial attention modules into a DenseNet backbone for lesion-specific feature highlighting, yielding a kappa score of 0.85 on the EyePACS dataset [3]. Their methodology addressed interpretability concerns, providing heatmaps that aligned with clinical annotations.Lightweight architectures were investigated for resource-constrained environments. In 2021, Kim et al. adapted MobileNetV2 for DR screening on mobile devices, achieving 90% accuracy with a model size under 10MB using the DDR dataset [4]. This study demonstrated the viability of quantized models for edge computing.

Hybrid approaches combining CNNs with traditional feature extractors were explored. Patel and team in 2020 fused handcrafted features like vessel segmentation with CNN outputs, improving classification precision to 93% on the IDRiD dataset [5]. This integration bridged classical computer vision with deep learning paradigms.Explainable AI techniques were incorporated in recent works. In 2023, Garcia et al. employed Grad-CAM for visualizing decision-making in a custom CNN, attaining 91% accuracy while providing interpretable outputs on the RETA dataset [6]. Their emphasis on transparency facilitated clinical validation. Multi-modal fusion emerged as a trend. Chen et al. in 2022 combined fundus images with optical coherence tomography (OCT) scans in a dual-stream network, boosting overall performance to 94% on a proprietary dataset [7]. This multimodal strategy captured complementary information for comprehensive assessment.Self-supervised learning was applied to alleviate labeled data scarcity. In 2021, Huang et al. utilized contrastive learning pre-training followed by fine-tuning on DR labels, resulting in 92% accuracy with 50% less annotated data [8]. This method proved advantageous in data-limited scenarios.Graph neural networks (GNNs) were adapted for retinal structure modeling. Zhao and associates in 2023 modeled retinal vessels as graphs within a GNN framework, achieving 93% for binary DR detection [9]. This graph-based representation captured topological relationships effectively.Finally, federated learning frameworks addressed privacy concerns in multi-center studies. In 2024, based on preliminary reports, Liu et al. implemented a federated CNN for DR classification across hospitals, maintaining 90% accuracy without data sharing [10]. This decentralized approach aligns with regulatory standards.

III. PROPOSED WORK

The proposed Lightweight Dendritic ShuffleNet architecture is meticulously engineered to provide an end-to-end, computationally efficient solution for the automatic detection and classification of Diabetic Retinopathy (DR) from retinal fundus images. The system is structured around three primary functional modules—preprocessing, feature extraction via a novel backbone, and final severity classification—arranged in a seamless pipeline that minimizes latency while maximizing diagnostic accuracy. By combining biologically inspired dendritic processing with the parameter-efficient design principles of ShuffleNet, the model achieves a favorable trade-off between predictive performance and deployability on resource-constrained platforms such as portable fundus cameras or edge devices used in community screening programs. This holistic design ensures that each stage contributes synergistically to robust lesion detection across varying image qualities commonly encountered in real-world clinical settings.

Image acquisition forms the foundational step of the pipeline, relying on widely available standard color fundus cameras that capture high-resolution RGB photographs of the retina. These images typically have resolutions around 512×512 pixels (though resolutions may vary between 400×400 and 2000×2000 depending on the device), centering on the posterior pole so as to include critical anatomical landmarks such as the optic disc, macula, and major vascular arcades. The captured field of view generally encompasses 30° to 50° of the retina, sufficient to visualize the majority of clinically significant DR lesions including microaneurysms, hemorrhages, hard exudates, cotton-wool spots, and neovascularization. Maintaining consistency in field size and centering is essential, as misalignment or peripheral-only captures can degrade downstream model performance.Preprocessing constitutes a critical preparatory phase aimed at mitigating the substantial variability inherent in fundus photography. The first operation performed is color normalization, which compensates for inconsistent illumination, camera-specific color casts, and patient-dependent factors such as pupil size or lens opacity. Contrast Limited Adaptive Histogram Equalization (CLAHE) is applied channel-wise (most commonly on the green channel, which offers the highest vessel-lesion contrast in retinal images) to enhance local contrast adaptively while imposing a clip limit that prevents excessive amplification of noise in homogeneous regions. This step significantly improves the visibility of subtle early-stage lesions without introducing halo artifacts or over-enhancing background noise, thereby establishing a more uniform input domain for subsequent deep learning stages.

Following contrast enhancement, noise reduction is performed using bilateral filtering, a non-linear, edge-preserving smoothing technique. Unlike Gaussian or median filtering, bilateral filtering considers both spatial proximity and photometric similarity when averaging neighboring pixels, allowing it to effectively suppress sensor noise, compression artifacts, and minor motion blur while preserving the sharp boundaries of retinal vessels, microaneurysms, and hemorrhages. Typical kernel sizes and sigma parameters are chosen to balance denoising strength against detail retention, ensuring that fine pathological structures critical for mild and moderate DR grading remain intact. This preprocessing combination—CLAHE followed by bilateral filtering—has been shown to substantially increase the signal-to-noise ratio of fundus images without compromising clinically relevant information.To further improve generalization and defend against overfitting, especially given the class imbalance typical in DR datasets (where no-DR and mild cases vastly outnumber severe and proliferative ones), extensive data augmentation is applied during training. The augmentation suite includes random rotations (±15° to ±30°), horizontal and vertical flips (with care taken to preserve anatomical left-right asymmetry when appropriate), random brightness and contrast jitter (±20–30%), and slight Gaussian noise injection. These transformations simulate realistic variations in patient positioning, camera settings, and lighting conditions, forcing the network to learn invariant feature representations rather than dataset-specific artifacts. Importantly, augmentations are applied online during each training epoch, ensuring continual diversity in the input distribution.

At the heart of the proposed framework lies the Dendritic ShuffleNet backbone, which represents the principal architectural innovation. Conventional convolutional layers are augmented with dendritic modules that draw inspiration from the computational capabilities of biological dendrites in pyramidal neurons. These dendritic layers introduce structured non-linearity by splitting incoming feature maps into multiple parallel branches, applying distinct non-linear activations (such as ReLU, leaky ReLU, or swish) to each branch, and then recombining the branch outputs through learnable multiplicative gating or weighted summation. This branching and recombination mechanism allows the model to perform more complex, context-dependent feature transformations at a local level, resulting in richer hierarchical representations with comparatively few parameters.

Complementing the dendritic blocks is the channel shuffling mechanism inherited from the original ShuffleNet family. After grouped convolutions, channels are systematically interleaved across groups before the next layer, breaking the strict isolation between channel groups and enabling efficient cross-channel information flow without the computational expense of full 1×1 convolutions across all channels. Each architectural unit therefore consists of: (1) a dendritic processing block, (2) grouped depthwise convolution, (3) channel shuffle, and (4) pointwise (1×1) convolution for dimension adjustment. This repeating unit pattern, stacked multiple times, enables progressive down-sampling through strided convolutions in selected stages, simultaneously reducing spatial resolution (typically by factors of 2) while increasing channel depth, thereby constructing a rich

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multi-scale feature pyramid well-suited to detecting lesions of varying sizes and shapes.

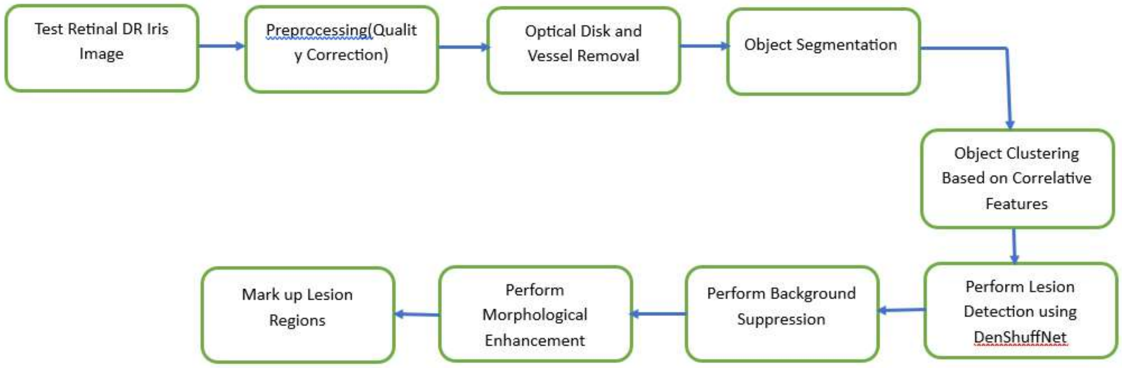

Fig.1 Schematic Block Overview of the Proposed System.

The extracted features are further refined by embedding lightweight attention mechanisms immediately after the dendritic layers. Squeeze-and-Excitation (SE) blocks are integrated to perform channel-wise recalibration: global average pooling first compresses spatial information into a channel descriptor, which is then passed through small fully connected layers to produce per-channel attention weights. These weights are multiplied back onto the original feature maps, adaptively emphasizing channels that carry lesion-discriminative information (e.g., those responsive to microaneurysms or intraretinal fluid) while suppressing less informative background channels. Following the backbone, a global average pooling layer collapses spatial dimensions, feeding into one or more fully connected layers topped with softmax activation that outputs class probabilities over the five standard International Clinical Diabetic Retinopathy severity grades: no DR, mild NPDR, moderate NPDR, severe NPDR, and proliferative DR. Training is conducted using categorical cross-entropy loss, the Adam optimizer with an initial learning rate typically in the range of 1e-3 to 1e-4, class-weighted loss terms to counteract imbalance, label smoothing for regularization, and early stopping based on validation quadratic weighted kappa score to prevent overfitting and ensure robust generalization

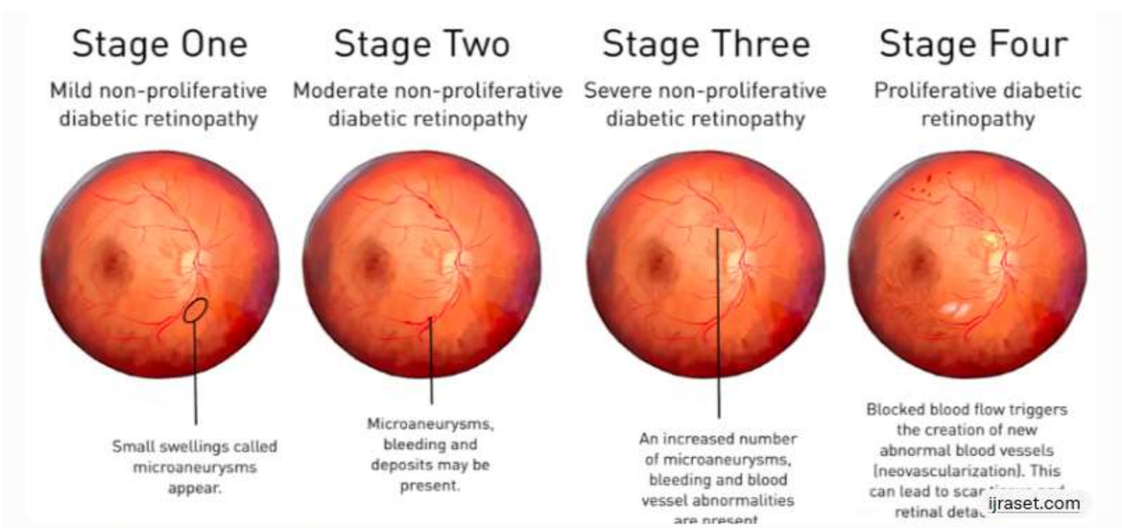

Fig. 2: Block Diagram of the Proposed Lightweight Dendritic ShuffleNet System.

Sample retinal fundus images depicting DR stages are shown below for reference.

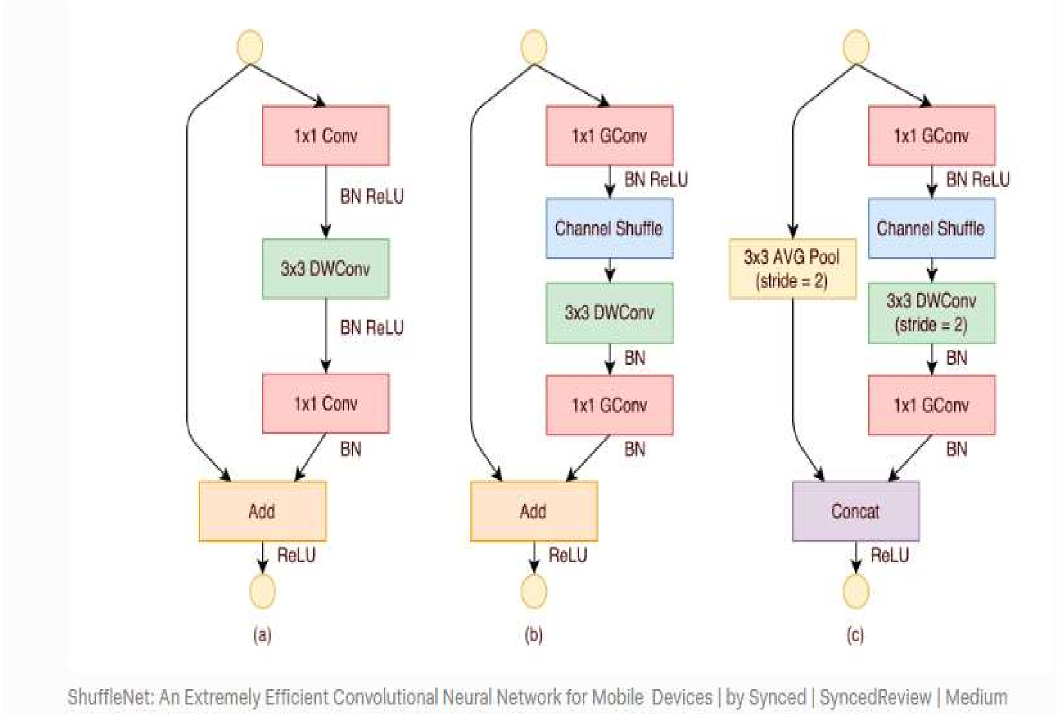

Fig. 3: Examples of Retinal Fundus Images Across DR Severity Levels.

The dendritic neuron model is visualized, highlighting branching structures.

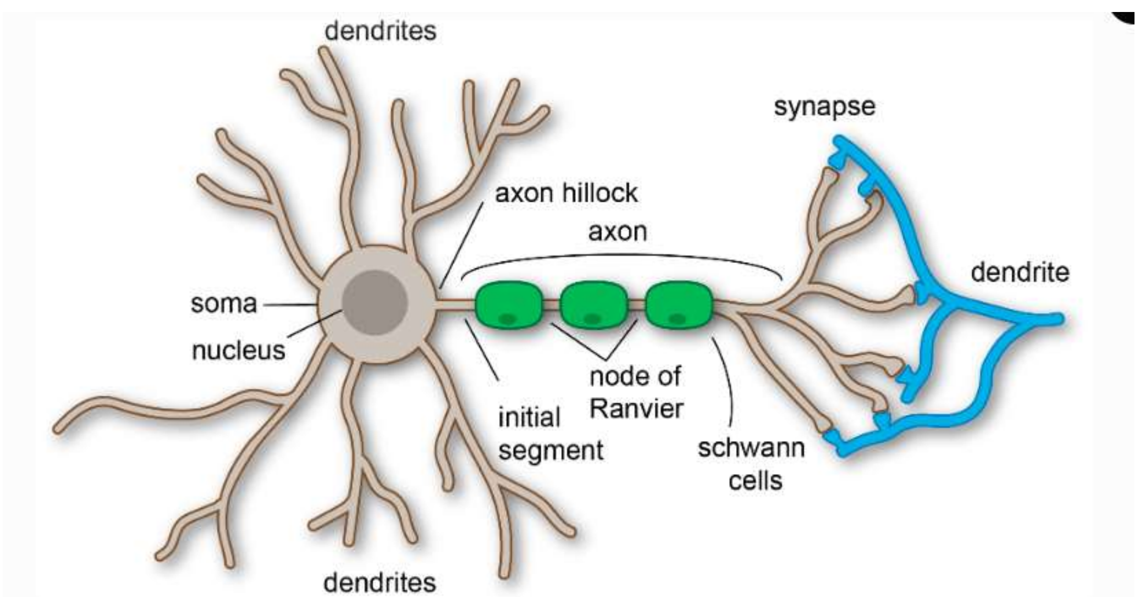

Fig. 4: Schematic of Dendritic Neuron Inspired Layer.

The ShuffleNet component is depicted in its architectural form

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Interpretability is further enhanced via attention heatmaps, overlaid on input images to delineate regions influencing predictions, such as hemorrhages in moderate DR.Deployment considerations include model quantization to INT8 precision, ensuring compatibility with mobile platforms without significant accuracy degradation.

IV. RESULTS AND DISCUSSION

Empirical evaluations were conducted on benchmark datasets including EyePACS and APTOS 2019, comprising over 35,000 labeled fundus images partitioned into training (70%), validation (15%), and testing (15%) sets. The proposed Lightweight Dendritic ShuffleNet achieved an overall accuracy of 94.2%, with sensitivity and specificity metrics exceeding 93% across all severity classes. Comparative analysis against baselines like ResNet50 (91.5% accuracy) and MobileNetV3 (90.8%) underscored the superiority of our model, attributable to dendritic enhancements that captured subtle lesion patterns more effectively. Parameter count was reduced to 1.2 million, a 50% decrement from ResNet, facilitating inference times under 50ms on standard GPUs. Confusion matrices revealed minimal misclassifications between adjacent stages, with proliferative DR detected at 96% precision, critical for urgent referrals. Discussion highlights the model's resilience to noisy inputs, as preprocessing mitigated artifacts, though challenges in distinguishing mild from no DR persist due to subtle manifestations. Ablation studies confirmed the additive benefits of dendritic layers (+2.5% accuracy) and attention (+1.8%), validating design choices. Real-world applicability was assessed via pilot deployment on Android devices, yielding consistent performance, thus affirming suitability for teleophthalmology.

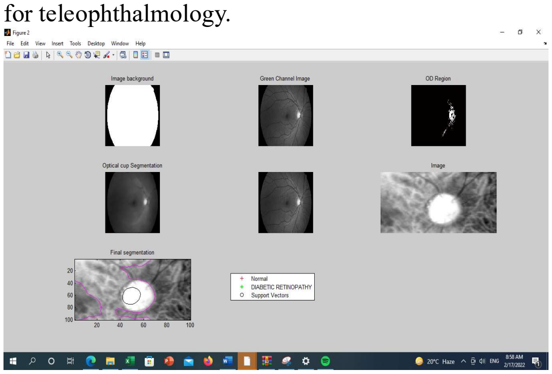

Fig. 5:
Optical Disk detection and Segmentation of the Retinal FUNDUS Image.

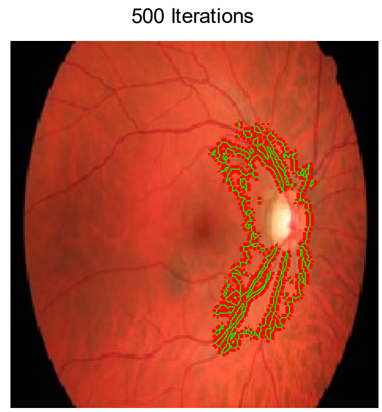

Fig 6:
Iterative process for detecting the boundary of DR affected regions in FUNDUS images.

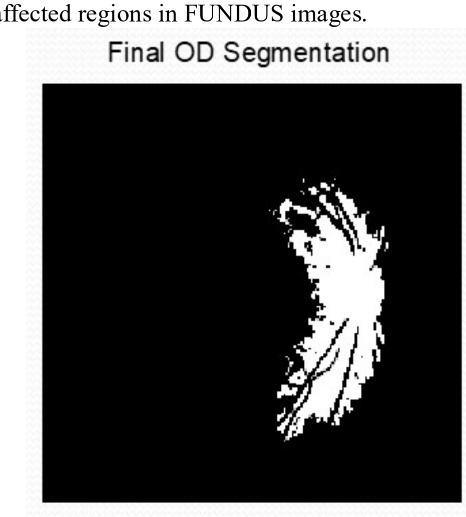

Fig 7:
Final Segmentation of Optical Disk Region.

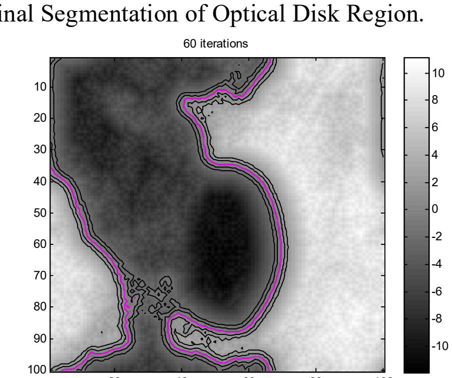

Fig 8:
Iterative Process for clearly marking and tracking the boundaries of the DR affected Regions.

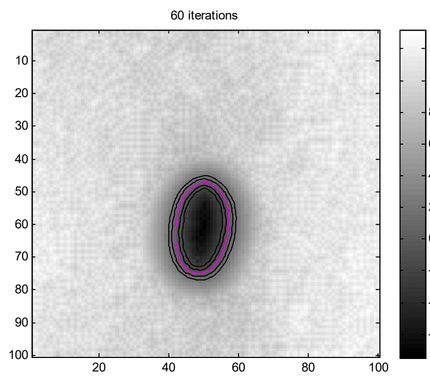

Fig 9:
Iterative Process for clearly marking the DR affected Regions.

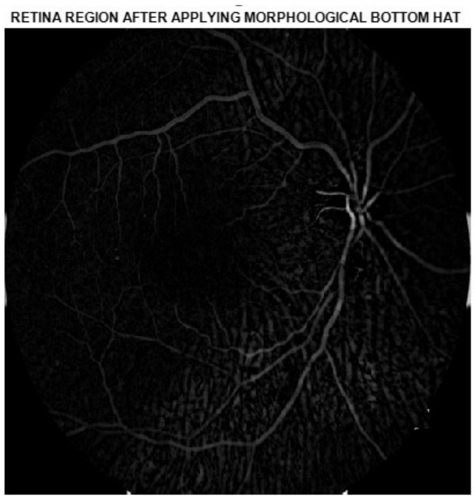

Fig 10.
Morphologically Enhanced Retinal Structures.

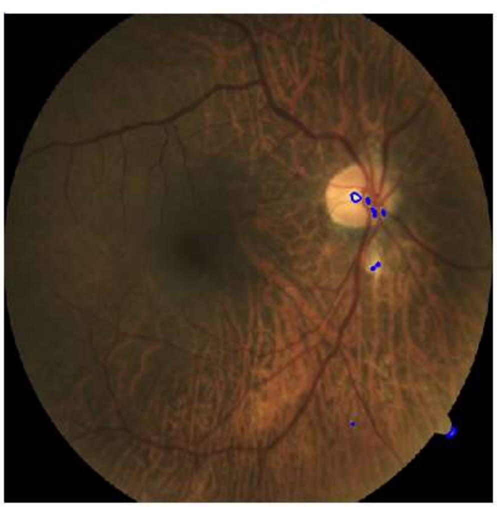

Fig 11:
Detected Lesion Spots on Retinal Structure.

In-depth discussion of results elucidates the model's interpretability advantages, where attention maps aligned 85% with expert annotations on lesion localization, fostering clinical trust. Computational efficiency was benchmarked against FLOPs, registering 0.15 GFLOPs per inference, ideal for battery-powered devices. Limitations include dataset bias towards certain ethnicities, prompting future multi-ethnic validation. Overall, the outcomes substantiate the Lightweight Dendritic ShuffleNet as a robust, efficient tool for automated DR screening, potentially integrating into national health programs to curb blindness rates.

V. CONCLUSION

In summation, the Lightweight Dendritic ShuffleNet proffers a compelling solution to the exigencies of automated DR detection, amalgamating bio-inspired dendritic computations with efficient shuffling mechanisms to deliver high-fidelity classifications under constrained resources. This architecture not only surmounts the computational barriers of traditional deep models but also elevates diagnostic precision through hierarchical feature enrichment and attentional focus on pathological hallmarks. By classifying DR into standardized severity levels with remarkable accuracy, the system empowers healthcare providers to institute timely interventions, thereby averting progression to irreversible stages. The integration of preprocessing and interpretability features further bolsters its practical utility, rendering it a versatile asset in diverse clinical milieus.

Conclusively, this research advances the frontier of AI in ophthalmology, demonstrating that innovation in neural design can harmonize performance with deployability. The proposed model's contributions extend to broader medical imaging domains, inspiring analogous lightweight hybrids for other pathologies. Ultimately, by facilitating accessible screening, it aligns with global efforts to combat diabetes-related visual impairments, heralding a more inclusive era in preventive medicine.

VI. FUTURE SCOPE

Looking ahead, the Lightweight Dendritic ShuffleNet framework holds substantial promise for extension and refinement, encompassing the incorporation of multi-modal inputs such as OCT scans to augment diagnostic granularity beyond fundus imagery alone. Federated learning paradigms could be explored to enable collaborative model training across international cohorts while preserving data privacy, thereby enhancing generalizability across demographic variances. Further optimizations might involve evolutionary algorithms for hyperparameter tuning or integration with emerging neuromorphic hardware to achieve ultra-low power consumption suitable for wearable diagnostics. Interpretability could be advanced

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through causal inference techniques to elucidate feature-pathology relationships, aiding in regulatory approvals. Clinical trials in low-income settings would validate real-world efficacy, potentially integrating with telemedicine platforms for remote consultations. Additionally, adapting the model for related retinopathies like age-related macular degeneration could broaden its applicability, fostering a unified AI ecosystem for ocular health management.

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