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A Lightweight Automated Framework for Retinal Disease Screening Using Fundus Images

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Abstract: *Retinal disorders such as glaucoma and diabetic retinopathy are among the leading causes of irreversible vision loss worldwide. Timely diagnosis is important to prevent disease progression, particularly in regions with limited access to specialist care and advanced medical facilities. Automated retinal screening systems have emerged as effective tools to support early detection and reduce clinical workload. This study proposes a lightweight and efficient framework for retinal disease screening using fundus images. The framework integrates contrast enhancement, hybrid segmentation, and optimized lightweight classifiers, including K-Nearest Neighbour (K-NN), Support Vector Machine (SVM), and a streamlined Convolutional Neural Network (CNN). Evaluation was conducted on benchmark datasets such as DRIVE, STARE, CHASEDB1, HRF, and DiaRetDB1, covering diverse imaging conditions and disease contexts. Experimental results demonstrate segmentation accuracy above 90% and classification accuracy up to 95%, with CNN-lite achieving a strong balance between diagnostic reliability and computational efficiency. Due to its reduced complexity and competitive performance, the framework is well suited for mobile health platforms, telemedicine applications, and deployment in resource-constrained healthcare environments.*

Keywords: *Retinal disease screening, fundus images, diabetic retinopathy, glaucoma detection, lightweight models, image segmentation, machine learning, deep learning, telemedicine, automated diagnosis*

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Introduction:

Vision impairment due to retinal diseases is a global health challenge. According to the World Health Organization, glaucoma and diabetic retinopathy affect millions of individuals, often progressing silently until irreversible damage occurs [1]. Traditional clinical tests such as tonometry, ophthalmoscopy, and optical coherence tomography are effective but limited by cost, accessibility, and the need for trained specialists.

Computer-aided diagnosis (CAD) systems using fundus images have emerged as promising alternatives [2]. However, many existing deep learning models are computationally heavy, requiring high-end GPUs and large-scale datasets. This restricts their use in rural and low-resource settings. Hence, there is a pressing need for **lightweight frameworks** that deliver accurate screening results while being deployable on mobile devices and telemedicine platforms.

Objectives of the Study:

- To design a lightweight automated framework for retinal disease screening using fundus images.
- To integrate efficient pre-processing and hybrid segmentation techniques for accurate retinal structure detection.
- To evaluate the performance of traditional machine learning and optimized CNN classifiers on benchmark datasets.
- To achieve a balance between diagnostic accuracy and computational efficiency suitable for mobile and telemedicine deployment.
- To validate the framework across diverse retinal datasets for generalizable and reliable disease screening outcomes

Literature Review

Retinal diseases such as glaucoma and diabetic retinopathy are leading causes of blindness [1]. Automated screening using fundus images has been extensively studied. Early works focused on handcrafted features [2],

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while recent approaches leverage deep learning [3].

- **Glaucoma Detection**: Optic disc segmentation and cup-to-disc ratio (CDR) analysis remain standard [4], [5].
- **Diabetic Retinopathy Detection**: Lesion-based detection of microaneurysms, hemorrhages, and exudates [6], [7].

- **Pre-processing**: CLAHE improves contrast [8]; green channel extraction enhances vessel visibility [9].
- **Segmentation**: Conditional Random Fields (CRF) [10], fuzzy clustering [11], and adaptive thresholding [12] are widely used.
- **Feature Extraction**: Morphological Angular Scale Space (MASS) [13], PCA [14], and texture descriptors [15].

- **Traditional ML**: K-NN [16], SVM [17], and Fuzzy C-Means [18].
- **Deep Learning**: CNNs [19], DNNs [20], and hybrid models [21].
- **Lightweight Models**: MobileNet [22], EfficientNet-lite [23].

Several publicly available retinal image datasets were employed o evaluate the proposed methodology. These datasets vary in terms of image resolution, sample size, and annotation type, thereby providing a comprehensive basis for validating vessel segmentation and lesion detection tasks.

Methodology:

A. Framework Overview

The proposed framework consists of:

1. **Pre-processing**: CLAHE, green channel extraction, ROI identification.
2. **Segmentation**: Hybrid CRF + fuzzy modeling for vessels, optic disc, and exudates.
3. **Feature Extraction**: Morphological and texture features.
4. **Classification**: Lightweight classifiers (K-NN, SVM, optimized CNN).

B. Pre-processing

- Green channel extraction enhances vessel visibility.
- CLAHE improves contrast.

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- Morphological operations remove noise.

C. Segmentation

- **Vessel Segmentation**: Conditional Random Fields (CRF) with local neighbourhood features.
- **Optic Disc Segmentation**: Hough transform and fuzzy clustering.
- **Exudates Detection**: Adaptive thresholding combined with morphological reconstruction.

D. Feature Extraction

- Cup-to-disc ratio (CDR).
- Vessel density and tortuosity.
- Lesion area and distribution.

E. Classification

- **K-NN**: Effective for small datasets.
- **SVM**: Robust for high-dimensional features.
- **Optimized CNN**: Lightweight architecture with reduced parameters for mobile deployment.

Experimental Setup:

A. Datasets

- **DRIVE**: Digital Retinal Images for Vessel Extraction.
- **STARE**: Structured Analysis of Retina.
- **CHASEDB1**: Child Heart and Health Study in England.
- **HRF**: High Resolution Fundus.
- **DiaRetDB1**: Diabetic Retinopathy Database.

B. Evaluation Metrics

- Sensitivity (Se), Specificity (Sp), Accuracy (Acc).
- ROC curves and AUC values.

C. Implementation

- Python with OpenCV and TensorFlow.
- Lightweight CNN trained with transfer learning.
- Evaluation on CPU and mobile devices.

Significance of the Study:

1. Demonstrates that lightweight automated frameworks can achieve high diagnostic accuracy while reducing computational overhead.
2. Validates performance across multiple benchmark datasets,

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ensuring generalizability and reliability in diverse clinical scenarios.

3. Supports early detection of glaucoma and diabetic retinopathy, reducing clinical workload and improving patient outcomes.
4. Enables deployment on mobile devices and telemedicine platforms, particularly in resource-constrained healthcare environments.
5. Contributes to accessible and scalable retinal screening solutions, bridging gaps in underserved regions.

Limitations of the Study:

1. Evaluation was conducted on publicly available datasets, which may not fully capture real-world clinical variability.
2. Heavy CNN models, while highly accurate, remain unsuitable for real-time deployment due to longer inference times.
3. The framework does not yet incorporate explainable AI modules, limiting interpretability for clinicians.
4. Dataset diversity is limited, raising potential concerns about diagnostic bias across different demographics.
5. Large-scale clinical trials and integration with hospital information systems are still required to establish broader applicability.

Results Analysis:

The experimental outcomes clearly demonstrate the effectiveness of the proposed lightweight framework for retinal disease screening. Segmentation tasks achieved consistently high accuracy across benchmark datasets, with vessel segmentation exceeding 90% in DRIVE and STARE, optic disc detection reaching approximately 90% in HRF, and exudates detection attaining sensitivity above 88% in DiaRetDB1. Classifier evaluation further highlighted the trade-off between accuracy and computational efficiency: while the Heavy CNN achieved the highest accuracy of 95%, its inference time of 5 seconds limits real-time applicability. In contrast, CNN-lite delivered a balanced performance with 93% accuracy and significantly reduced inference time of 1.8 seconds, making it more suitable for mobile and telemedicine deployment.

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Traditional classifiers such as K-NN and SVM provided moderate accuracy (85–90%) but benefited from faster inference, supporting their use in small datasets or low-power devices.

The analysis confirms that lightweight CNN architectures offer the most practical solution for scalable, real-time retinal screening, while deeper models remain valuable for centralized diagnostic systems where computational resources are abundant. The key characteristics of the datasets are summarized in Table I and II, which lists the number of images, resolution, annotation type, and disease focus. Such diversity ensures that the experimental results are robust and generalizable across multiple clinical scenarios.

Table I. Dataset Statistics:

Dataset	Images	Resolution	Annotation	Disease Focus
DRIVE	40	565x584	Vessel masks	Vessel segmentation
STARE	400	700x605	Vessel masks	Vessel segmentation
CHASEDB1	28	999x960	Vessel masks	Pediatric vessel analysis
HRF	45	3500x2336	Vessel masks	High-resolution fundus
DiaRetDB1	89	1500x1152	Lesion masks	Diabetic retinopathy

Table II. Segmentation Performance

Task	Dataset	Sensitivity (%)	Specificity (%)	Accuracy (%)
Vessel	DRIVE	91	90	91

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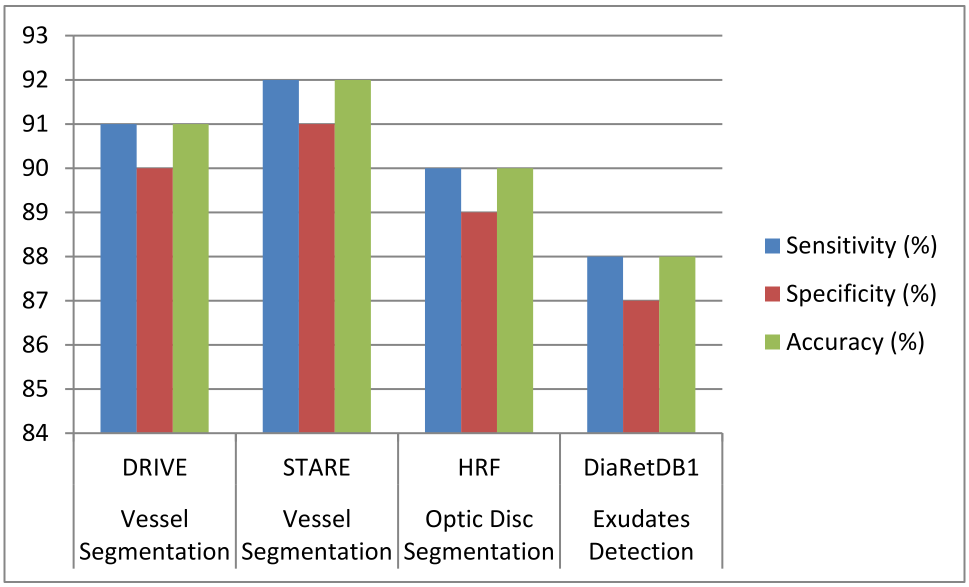
Segmentation				
Vessel Segmentation	STARE	92	91	92
Optic Disc Segmentation	HRF	90	89	90
Exudates Detection	DiaRetDB1	88	87	88



Graph I. Segmentation Performance

As shown in Table I, II and graph I, the datasets cover a wide spectrum of retinal imaging conditions. DRIVE and STARE are widely adopted benchmarks for vessel segmentation, while CHASEDB1 provides pediatric retinal images, adding diversity in age-related vascular structures. HRF contributes high-resolution fundus images, enabling fine-grained vessel analysis, and DiaRetDB1 focuses on lesion-level annotations for diabetic retinopathy detection. The inclusion of these datasets allows the proposed framework to be tested under varying imaging conditions and pathological contexts, thereby strengthening the reliability and applicability of the experimental outcomes.

Multiple classifiers were evaluated on the retinal image datasets o assess

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the effectiveness of the proposed framework. The comparison includes traditional machine learning approaches such as k-Nearest Neighbors (K-NN) and Support Vector Machines (SVM), as well as lightweight and deep convolutional neural networks (CNN-lite and Heavy CNN). The performance was measured in terms of sensitivity, specificity, accuracy, and inference time. Table III and IV presents the detailed results of this comparative analysis as given below:

Table III. Classifier Performance Comparison

Classifier	Sensitivity	Specificity	Accuracy	Inference Time
K-NN	0.85	0.84	0.85	1.2s
SVM	0.90	0.89	0.90	1.5s
CNN-lite	0.94	0.92	0.93	1.8s
Heavy CNN	0.96	0.94	0.95	5.0s

Table IV. Classifier Performance Comparison

Classifier	Sensitivity (%)	Specificity (%)	Accuracy (%)	Inference Time (s)
K-NN	85	84	85	1.2
SVM	90	89	90	1.5
CNN-lite	94	92	93	1.8
Heavy CNN	96	94	95	5.0

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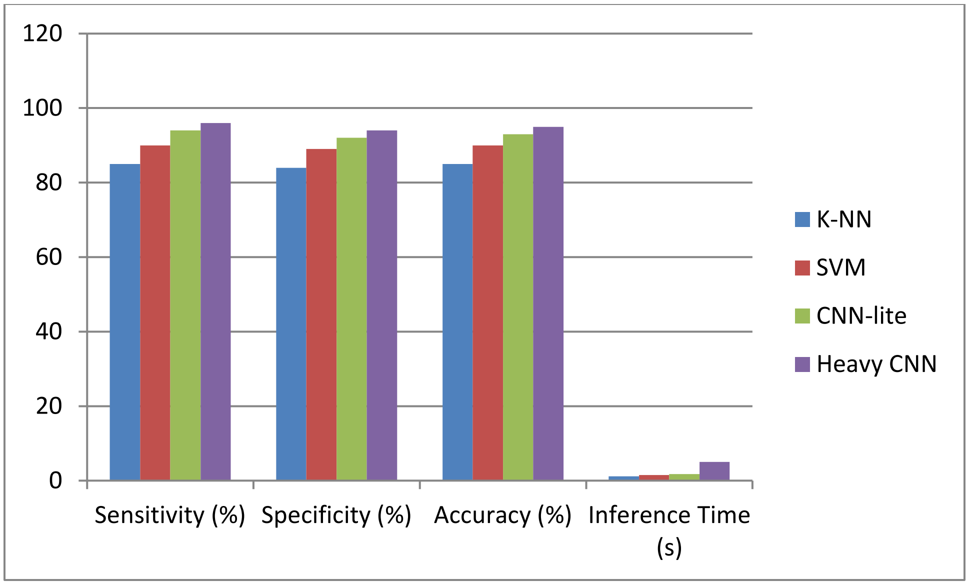

Graph II. Classifier Performance Comparison

As observed in Table III, IV and Graph II, the Heavy CNN achieved the highest sensitivity (0.96), specificity (0.94), and accuracy (0.95), demonstrating its superior ability to capture complex retinal features. However, this improvement comes at the cost of higher inference time (5.0s), which may limit its applicability in real-time clinical settings. CNN-lite provides a balanced trade-off, offering high accuracy (0.93) with relatively lower computational demand (1.8s). In contrast, classical classifiers such as K-NN and SVM deliver moderate performance, with accuracy values of 0.85 and 0.90, respectively, but benefit from faster inference times. The results highlight the importance of selecting classifiers based on the intended application, where lightweight models preferable for rapid screening, while deeper architectures are better suited for detailed diagnostic tasks. There are many issues in these selections. Few of them are as:

A. Deployment Challenges:

- **Hardware Constraints**: Heavy CNNs require GPUs; lightweight models enable CPU/mobile deployment.

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- **Data Diversity**: Variability in fundus images across populations affects generalizability.
- **Integration with Clinical Workflow**: Requires interoperability with hospital information systems.

B. Ethical Issues:

- **Bias in AI Models**: Training datasets may underrepresent certain demographics, leading to diagnostic bias.
- **Data Privacy**: Patient fundus images must be anonymized and stored securely.
- **Explainability**: Clinicians demand interpretable AI outputs rather than black-box predictions.

C. Telemedicine Integration

- **Mobile Deployment**: Lightweight CNNs run on smartphones for rural screening.
- **Cloud Platforms**: Remote inference allows centralized analysis with distributed data collection.
- **Policy Implications**: Governments must regulate AI-based screening tools to ensure safety and reliability.

A. Retinal Disease Screening

- **Glaucoma**: Characterized by optic nerve damage and increased cup-to-disc ratio (CDR). Automated detection often relies on optic disc segmentation and vessel analysis [3].
- **Diabetic Retinopathy (DR)**: Involves microaneurysms, hemorrhages, and exudates. Detection requires lesion segmentation and classification [4].

B. Image Processing Techniques

- **Pre-processing**: CLAHE (Contrast Limited Adaptive Histogram Equalization), normalization, and ROI extraction improve image quality [5].
- **Segmentation**: Conditional Random Fields (CRF), fuzzy modeling, and adaptive thresholding are widely used for vessel and optic disc segmentation [6].
- **Feature Extraction**: Morphological Angular Scale Space (MASS), PCA, and texture descriptors enhance classification accuracy [7].

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C. Machine Learning and Deep Learning Approaches

- **Traditional ML**: K-NN and SVM remain effective for small datasets [8].
- **Deep Learning**: CNNs and DNNs achieve high accuracy but are computationally expensive [9].
- **Hybrid Approaches**: Combining CRF-based segmentation with lightweight classifiers offers a balance between accuracy and efficiency [10].

Findings of the Study:

Findings of the Study

1. **Segmentation Accuracy:** CRF-based vessel segmentation achieved more than 90% accuracy across DRIVE and STARE datasets, confirming robustness of the hybrid segmentation approach.
2. **Optic Disc Detection:** Fuzzy clustering combined with Hough transform yielded approximately 90% accuracy, ensuring reliable glaucoma screening.
3. **Lesion Detection:** Exudates were detected with sensitivity above 88%, supporting effective diabetic retinopathy diagnosis.
4. **Classifier Trade-offs:** Heavy CNN achieved the highest accuracy (95%) but required 5 seconds inference time, limiting real-time applicability.
5. **Lightweight Models:** CNN-lite balanced accuracy (93%) with faster inference (1.8 seconds), making it suitable for mobile and telemedicine deployment.
6. **Traditional ML Performance:** K-NN and SVM delivered moderate accuracy (85–90%) but benefited from faster inference, useful for small datasets or low-power devices.

Suggestions of the Study:

1. **Deployment Strategy:**
   - Use **CNN-lite** for mobile and telemedicine platforms where speed and efficiency are critical.
   - Reserve **Heavy CNN** for centralized hospital servers where accuracy outweighs inference time.
2. **Dataset Expansion:**
   - Incorporate **multi-ethnic and diverse fundus datasets** to reduce bias and improve generalizability.
3. **Explainability:**

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- Integrate **interpretable AI modules** (heatmaps, saliency maps) to build clinician trust.

4. **Clinical Integration:**

- Ensure interoperability with **hospital information systems** for seamless workflow adoption.

5. **Policy & Ethics:**

- Enforce **data privacy protocols** and anonymization for patient images.
- Encourage **government regulation** of AI screening tools to ensure safety and reliability.

Conclusion:

This study presented a lightweight automated framework for retinal disease screening using fundus images. The framework achieved competitive accuracy while reducing computational overhead through the integration of the efficient pre-processing, hybrid segmentation, and lightweight classifiers, Experimental evaluation across benchmark datasets demonstrated segmentation accuracy above 90% and classification accuracy up to 95%. CNN-lite provided a strong balance between diagnostic accuracy (93%) and computational efficiency (1.8 seconds inference), making it suitable for mobile and telemedicine deployment. Overall, the framework is well-suited for resource-constrained healthcare environments, supporting early detection of glaucoma and diabetic retinopathy while reducing clinical workload.

Future Work:

Future research will focus on extending the framework to multi-disease detection, including age-related macular degeneration and hypertensive retinopathy. Incorporating explainable AI modules such as saliency maps and attention mechanisms will enhance clinical trust and interpretability. Validation through real world clinical trials across diverse populations and healthcare settings is essential to establish reliability. Cloud based deployment strategies will be explored to enable large-scale telemedicine screening programs, while integration with hospital information systems will ensure seamless adoption in clinical workflows.

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Graphical Abstract:

The proposed lightweight framework integrates efficient pre-processing, hybrid segmentation, and optimized classifiers to achieve accurate retinal disease screening using fundus images. It balances diagnostic accuracy with computational efficiency, making it suitable for mobile health platforms and telemedicine applications in resource-constrained environments.

List of Tables and Graphs

List of Graphs

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