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Diabetic Retinopathy Screening Telemedicine System Using Hybrid Function

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ABSTRACT

Diabetic retinopathy is a prevalent disease affecting the retinas of diabetic patients, often leading to blindness in adults. The condition progresses through various stages, with early detection posing a challenge. To address this issue, an imaging system using hybrid machine learning to detect diabetic retinopathy early while reducing the cost of this procedure and taking into account high efficiency. The system is based on imaging using a smartphone, lifting the lens with one hand and bringing it closer to the eye, and lifting the phone with the other hand while playing the video a lens attachment and a phone flash for illumination, followed by image enhancement and classification using hybrid machine learning. A telemedicine website was implemented to share the results from the main hospital for diagnosis to the sub-center remotely.

Keywords: Image classification using machine learning, Word Press in telemedicine diabetic retinopathy, Diabetic retinopathy, Imaging classification, Telemedicine

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INTRODUCTION

Taking an image requires that the distance between the light source and the lens be appropriate, as well as the distance between the lens and the eye. Screen image by the lens depends on the operator if want high image resolution,

In the second experiment, the retina began to appear, but it was not of good quality. In the third experiment, the retina appeared well after gaining some skill in adjusting distances. When starting the process of taking the image, the video is played and then the photography process is carried out. The video contains a group of images, and the photographer identifies and chooses good images.[1]

MATERIAL AND METHODS

Retinal Image Capture

The retinal images were obtained after a comprehensive study of methodologies for designing optical devices specialized in retinal examination. The device used was modeled on the fundamental structure of the fundus camera, which comprises four main components, each serving a distinct function. Prior to the image capture process, patients were given eye drops to dilate the pupils, with effects typically manifesting within 10 to 15 minutes. During the capture, a Smartphone was held in one hand and the lens in the other, with video recording enabled.[1] This method allowed the flash to operate during recording on some devices and facilitated the capture of multiple frames. Post-recording, the video was reviewed to select the best frames (Figures 1 and 2).[2]

20D Lens

The 20D lens, a diagnostic tool, includes a telemedicine system using a hybrid function which requires some skill and experience to take a good image. In the first experiment, the retina did not appear well. This is because the distance was not adjusted appropriately (Figure 3).[1]

Quality imaging capabilities and efficient performance, making it suitable for this project.

Image Enhancement

The captured images were processed using MATLAB to enhance their quality. Initially, the images were converted to grayscale for analysis. Subsequently, the original color images

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were enhanced using custom code to clarify details, aiding in accurate diagnosis and disease identification by physicians.

Classification Process

Images were classified based on the presence or absence of diabetic retinopathy (DR). A dataset with two categories—DR a wide-angle lens, a lens holder, and a fixation ring. It was employed to examine the lower part of the vitreous body of the eye, providing a clear view of the blood vessels.

Smartphone Camera

An iPhone 12 was selected for its high-and NO DR—was used. Three machine learning models were employed: Support vector machines (SVM), random forest (RF), and K-nearest neighbors (KNN). Feature extraction was performed using ResNet-50 and Inception v3 neural networks, with each network tested separately with each model. Cross-validation was applied to evaluate the models' performance, measuring accuracy, sensitivity, and precision.

After training the neural networks on the dataset, the enhanced images were tested to determine their classification outcomes.

Website Design Using WordPress

A website was created to facilitate the exchange of retinal images between medical centers and the main hospital for diagnosis. WordPress was chosen for its extensive features. [2]

Design Steps

1. Hosting and domain were acquired through a free one-year package.
2. WordPress was installed on a computer.
3. Pages were designed, including:

- *Home Page*

Provided an overview of the website's purpose.

- *Medical Centers Page*

Represented centers as A, B, C, and D.

- *Results Reports Page*

Displayed diagnostic reports for targeted centers.

Each center was assigned a secret code, and retinal images were exchanged between centers and the hospital via the website. Results were shared through email or displayed on the website.

Statistical Analysis

The models' performance was evaluated using accuracy, sensitivity, and precision metrics as seen in Table 1. To assess the statistical significance of

Statistical Tests

- *Analysis of Variance (ANOVA)*

Used to determine if there were statistically significant differences in performance metrics (accuracy, sensitivity, precision) across different models (SVM, RF, KNN).

Equations used for calculating ANOVA are as follows:

Between-Group Sum of Squares (SSB) = $n * \sum (\bar{x}\_i - \bar{x}\_T)$^2

Within-Group Sum of Squares (SSW) = $\sum\sum (x\_ij - \bar{x}\_i)$^2

Total Sum of the results and compare performance across different models and configurations, the following statistical tests were applied: [2]

Squares (SS) = $SSB + SSW$

Degrees of Freedom (df_B) = $k - 1$ (between groups) / df_W = $N - k$ (within groups)

Mean Square Between (MSB) = SSB / df_B

Mean Square Within (MSW) = SSW / df_W

F-statistic = MSB / MSW

Level of Significance:

A *p-value* of less than 0.05 ($p < 0.05$) was considered statistically significant.

The *p-value* is obtained by comparing the calculated F-statistic to the F-distribution with df_B and df_W.

Since the *p-value* in the test for accuracy, sensitivity, and precision is much greater than the common significance level (5%), there is no statistically significance difference in accuracy, sensitivity, and precision across the folds for the models and architectures analyzed.

RESULTS

The findings from the development and implementation of the DR Screening system are presented below, organized into four key areas: retinal image capture, image enhancement, CNN-based classification, and telemedicine platform functionality.

Retinal image capture

Experiments were conducted to optimize the distance between the smartphone lens, external light source, and the eye. The results are summarized in Table 8.

Table 1: Accuracy, Sensitivity, and Precision for models and pre-trained network

Models	*Pre-trained networks*	*Accuracy*			*Sensitivity*			*Precision*		
		3-folds	4-folds	5-folds	3-folds	4-folds	5-folds	3-folds	4-folds	5-folds
SVM	ResNet50	96.00	95.04	96.63	96.01	95.08	96.63	96.05	95.31	96.64
	Inceptionv3	95.86	95.23	95.62	95.87	95.21	95.61	95.88	95.41	95.68
RF	ResNet50	95.52	95.66	95.67	95.52	95.67	95.67	95.57	95.74	95.77
	Inceptionv3	94.46	95.28	94.99	94.46	95.28	94.99	94.49	95.29	95.02
KNN	ResNet50	95.52	95.95	95.76	95.53	95.97	95.77	95.53	95.97	95.78
	Inceptionv3	93.45	93.55	93.50	93.48	93.58	93.53	93.59	93.68	93.62

Table 2: Summary of accuracy for 3, 4, and 5 folds

SUMMARY				
Groups	*Count*	*Sum*	*Average*	*Variance*
3-folds	6	570.81	95.135	0.97303
4-folds	6	570.71	95.1183	0.6979
5-folds	6	572.17	95.3617	1.10662

Table 3: ANOVA test for accuracy

ANOVA						
Source of Variation	*SS*	*df*	*MS*	*F*	*p-value*	*F crit*
Between Groups	0.22173	2	0.11087	0.11975	0.88799	3.68232
Within Groups	13.8877	15	0.92585			
Total	14.1095	17				

Table 4: Summary of sensitivity for 3, 4, and 5 folds

SUMMARY				
Groups	*Count*	*Sum*	*Average*	*Variance*
3-folds	6	570.87	95.145	0.96083
4-folds	6	570.79	95.13167	0.686217
5-folds	6	572.2	95.36667	1.085027

Table 5: ANOVA test for sensitivity

ANOVA						
Source of Variation	*SS*	*df*	*MS*	*F*	*P-value*	*F crit*
Between Groups	0.209078	2	0.104539	0.114791	0.892328	3.68232
Within Groups	13.66037	15	0.910691			
Total	13.86944	17				

Table 6: Summary of precision for 3, 4, and 5 folds

SUMMARY				
Groups	*Count*	*Sum*	*Average*	*Variance*
3-folds	6	571.11	95.185	0.90511
4-folds	6	571.4	95.23333	0.650507
5-folds	6	572.51	95.41833	1.041617

Table 7: ANOVA test for precision

ANOVA						
Source of Variation	*SS*	*df*	*MS*	*F*	*P-value*	*F crit*
Between Groups	0.182011	2	0.091006	0.105118	0.900875	3.68232
Within Groups	12.98617	15	0.865744			
Total	13.16818	17				

Table 8: Image capture experiments

Experiment	*Distance (mm)*	*Image quality*	*Key observations*
1	Undefined	Poor	Retina partially visible, blood vessels unclear
2	3.9	Mode rate	Full retina visible, blood vessels detectable
3	5.0	High	Clear retina with distinct blood vessels

Table 9: Model performance metrics

Metric	*Value/Description*
Model Architecture	ResNet50, and Incpection v3+ SVM, RF, and KNN Classifiers
Training Dataset	400 retinal images (APTOS/MESSIDOR)
Accuracy	85-95%
Execution Time	10-15 minutes per image

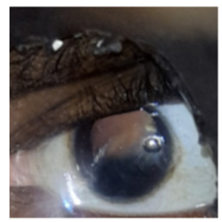

Figure 1: First image (distance is 3 mm)

Figure 2: Second image (distance is 3–5 mm)

Figure 3: lens 20D

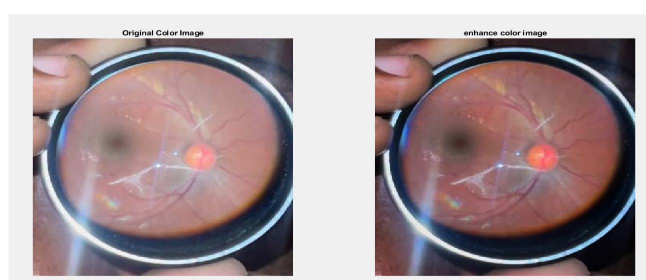

Figure 4: Third image, distance is 5 mm

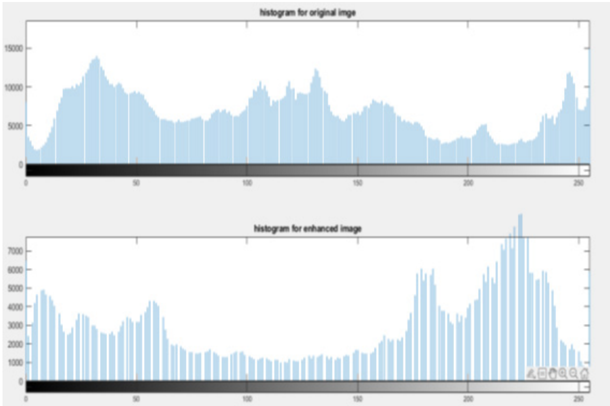

Figure 5: Enhancement image

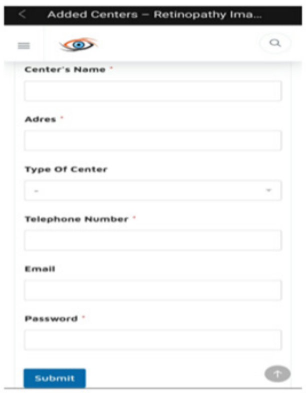

Figure 6: Telemedicine

Figure 7: Telemedicine admin

The third experiment (5 mm distance) yielded the highest-quality images, enabling accurate analysis (Figure 4).

2. Image Enhancement

The MATLAB-based enhancement process improved retinal image clarity through grayscale conversion, contrast adjustment, and RGB channel recombination. Key outcomes are shown in Figures 5 and 6, with quantitative improvements in pixel distribution and illumination reduction.

3. CNN-Based Classification

The pre-trained ResNet50 model, fine-tuned with the APTOS and MESSIDOR dataset, achieved an accuracy range of 85 to 95% in classifying DR and non-DR cases.
Performance metrics are summarized in Table 9.[3]

- image submission, result retrieval, and communication between centers and specialists.

Key Observations

- Optimal image capture requires precise distance calibration (5 mm)
- Image enhancement significantly improved diagnostic usability
- The hybrid ResNet50-SVM model demonstrated robust classification performance
- The telemedicine platform streamlined remote consultations in resource-limited settings.

DISCUSSION

The results obtained through this research indicate that there is an improvement in the quality of images captured using the lens and the phone after adjusting the distances between the light source and the lens and between the lens and the eye.

For image classification the results indicate that the algorithm used to classify medical images has led to accurate results

In the three types of training networks used, they are SVM, RF, and KNN. The performance of these networks was evaluated using the criteria of accuracy, sensitivity, and specificity.

The KNN network with ResNet50 achieved accuracy (95.52%), sensitivity (95.53%), and specificity (95.53%) is good.

The results indicate that the SVM network with ResNet50 achieved the best performance in detecting diabetic retinopathy. This network can be used in telemedicine applications to improve the early detection of this disease.
From this

- This system can be used in hospitals and medical centers to improve early detection of diabetic retinopathy.
- The system can be improved by using other deep learning techniques.
- This system can be used in telemedicine to connect specialized ophthalmology centres.

CONCLUSION

This study developed a low-cost telemedicine system for DR screening, integrating smartphone-based retinal imaging, MATLAB-based image enhancement, a ResNet50-SVM classifier, and a WordPress platform. Key outcomes include:

Imaging Optimization

High-quality retinal images were captured using a smartphone paired with a 20D lens at a 5 mm working distance.

Image Enhancement

MATLAB algorithms improved clarity through grayscale conversion, contrast adjustment, and RGB channel recombination.

AI-Driven Classification

The ResNet50 model, trained on APTOS and MESSIDOR datasets, achieved 85 to 95% accuracy in detecting DR when combined with an SVM classifier.

Telemedicine Functionality

A secure WordPress platform enabled remote data submission, automated reporting, and real-time collaboration between healthcare centers. The system addresses critical gaps in regions like Sudan, where access to specialized care is limited. Challenges such as hardware calibration and computational constraints were mitigated through iterative testing and pre-trained models. Future work should focus on stabilizing the imaging setup, automating image selection, and exploring lightweight CNNs for scalability. This innovation underscores the potential of AI-driven telemedicine to democratize early DR detection, reduce preventable blindness, and promote equitable healthcare access in underserved communities (Figure 7). It bridges technological advancement with clinical needs, offering a scalable model for global health challenges.

- The SVM network with ResNet50 achieved the highest accuracy (96.00%), sensitivity (96.01%), and specificity (96.05%).
- The RF network with ResNet50 achieved accuracy (95.52%), sensitivity (95.52%), and specificity (95.57%) is good.
- ResNet50 model, trained on APTOS and MESSIDOR datasets, achieved 85–95% accuracy in detecting DR when combined with an SVM classifier.

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