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A Hybrid Retinal Fundus Image Processing and Neural Network Framework for Diabetic Retinopathy Screening

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Abstract

Diabetic retinopathy (DR) is a retinal disorder that can be screened from fundus photographs using computer-aided image analysis. This paper presents a texture-based framework that combines image preprocessing, Gray-Level Co-occurrence Matrix (GLCM) feature extraction, Principal Component Analysis (PCA), and neural-network classification for automated retinal image screening. The APTOS 2019 Blindness Detection dataset is used as the experimental data source. The preprocessing stage improves retinal structure visibility through normalization and morphological operations. GLCM is employed to represent spatial texture information, while PCA is used to reduce redundancy in the extracted feature space. The reduced representation is supplied to a feedforward neural-network classification stage for automatic discrimination of retinal disease classes. The framework combines interpretable handcrafted texture descriptors with learned nonlinear classification rather than relying on a single representation. Three experimental executions produced accuracies of 90.00%, 90.63%, and 96.00%, with corresponding specificities of 93.44%, 93.44%, and 95.00% and sensitivities of 91.90%, 95.12%, and 95.50%. The highest observed accuracy was 96.00%. These values are reported as experimental observations, and the best result should be interpreted in the context of the dataset partition and evaluation protocol used.

Keywords: *Diabetic Retinopathy, Fundus Images, APTOS 2019, GLCM, Texture Features, Principal Component Analysis, Neural Network, Retinal Image Analysis, Image Preprocessing, Automated Screening.*

1. Introduction

Diabetic retinopathy is one of the major complications associated with diabetes and can progress without obvious symptoms during its early stages. Retinal fundus photography provides a non-invasive source of visual information for identifying changes in retinal structures. Manual examination of large numbers of fundus images can be time-consuming and depends on expert availability. Consequently, computer-aided screening systems have received significant attention for assisting retinal image analysis. Fundus images present several computational challenges, including uneven illumination, noise, contrast variation, background artifacts, and differences in image acquisition conditions. Preprocessing is therefore important before extracting discriminative information. Texture descriptors such as GLCM can capture spatial relationships among neighboring gray levels and provide interpretable statistical features. However, handcrafted features alone may not represent all complex visual patterns present in retinal images.

Fundus images present several computational challenges, including uneven illumination, noise, contrast variation, background artifacts, and differences in image acquisition conditions. Preprocessing is therefore important before extracting discriminative information. Texture descriptors such as GLCM can capture spatial relationships among neighboring gray levels and provide interpretable statistical features. However, handcrafted features alone may not represent all complex visual patterns present in retinal images. Neural-network learning can model nonlinear relationships in the extracted feature space. The motivation of the present work is to combine the interpretability of GLCM texture information with dimensionality reduction and neural-network learning. The framework is designed as an extension

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of the earlier retinal image-processing workflow, with emphasis on explicit texture analysis and a neural-network classification stage.

2. Related Work

Previous retinal screening studies have explored both conventional image-processing methods and deep-learning architectures. Gulshan et al. demonstrated the potential of machine-learning for detecting diabetic retinopathy from retinal fundus photographs. Pratt et al. investigated CNN-based diabetic retinopathy classification. Residual, densely connected, and depthwise-separable convolutional architectures have subsequently provided effective feature learning strategies for image recognition.

GLCM, originally introduced for texture classification, remains useful when spatial gray-level relationships are informative. In retinal images, texture statistics can complement learned representations by providing compact descriptors related to local structural patterns. PCA is commonly used to transform correlated features into orthogonal components and can reduce the dimensionality of feature representations. Alavee et al. [1] investigated early diabetic retinopathy detection using transfer-learning models including DenseNet121, Xception, ResNet50, VGG16, VGG19, and InceptionV3, together with SVM, RNN, and a proposed CNN model, and also considered explainable AI. The gap addressed here is the limited explicit integration of interpretable GLCM texture representation and PCA-based feature reduction within this retinal deep-learning direction. The present work therefore focuses on a structured GLCM–PCA–neural-network pipeline rather than claiming a new CNN architecture.

3. Proposed Methodology

The proposed system consists of five major stages: dataset preparation, image preprocessing, GLCM-based texture extraction, PCA-based feature reduction, and neural-network classification. The workflow is designed to transform raw fundus images into a compact feature representation suitable for automated classification.

3.1.Dataset Preparation

The experiments use the APTOS 2019 Blindness Detection dataset, a publicly available retinal fundus image dataset hosted on Kaggle. The images are organized according to the disease severity classes provided by the dataset. Before model training, the images are assigned to training and testing subsets so that the same samples are not unintentionally reused across evaluation stages. The dataset split and preprocessing settings are retained for the experimental evaluation. This dataset-driven organization is important because classification performance can vary with class imbalance and the choice of train/test partition. Therefore, the dataset split and preprocessing settings should remain fixed when comparing the reported experimental configurations.

3.2.Image Preprocessing

Each retinal fundus image is normalized and resized to a fixed input dimension of 224 × 224 pixels. Preprocessing is applied to reduce acquisition-related variation and improve the visibility of retinal structures. Morphological filtering is used to suppress unwanted regions and emphasize relevant structural information. Curve or vessel-related enhancement can be applied where required by the selected preprocessing pipeline. The preprocessed image is subsequently converted into an appropriate intensity representation for texture computation. The objective of this stage is not to alter the diagnostic information but to provide a more consistent input for feature extraction and classification. The representative input and filtered images are shown in Figure 1 Representative retinal fundus images: (a) input image and (b) filtered image after preprocessing.

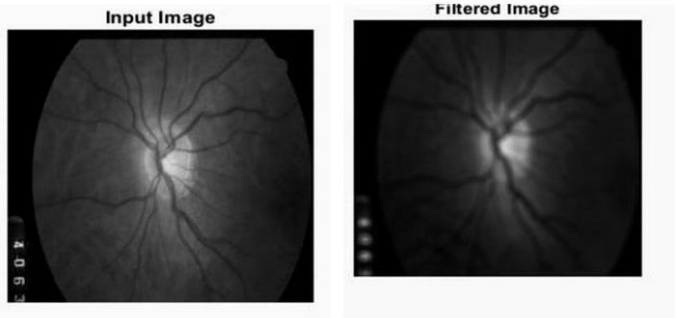

Figure 1 Representative retinal fundus images: (a) input image and (b) filtered image after preprocessing

3.3.GLCM Feature Extraction

The Gray-Level Co-occurrence Matrix describes the

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frequency with which pairs of gray levels occur at a specified spatial relationship. From the GLCM, texture measures such as contrast, energy, entropy, homogeneity, and maximum probability can be derived. These descriptors provide a compact representation of spatial texture patterns in the retinal region.As shown in Table 1 Interpretation of Selected Glcm Texture Measures[2].

Table 1 Interpretation of Selected Glcm Texture Measures

GLCM Measure	Interpretation
Contrast	Measures local intensity variation.
Energy	Indicates textural uniformity.
Entropy	Represents texture randomness.
Homogeneity	Measures similarity of neighboring gray levels.
Maximum probability	Largest normalized GLCM entry.

The GLCM feature representation used in the associated MATLAB workflow produced the values shown in Table III. These values are treated as experimental feature outputs rather than as universal values for all retinal images. The extracted feature distribution is visualized in Fig. 4(a).

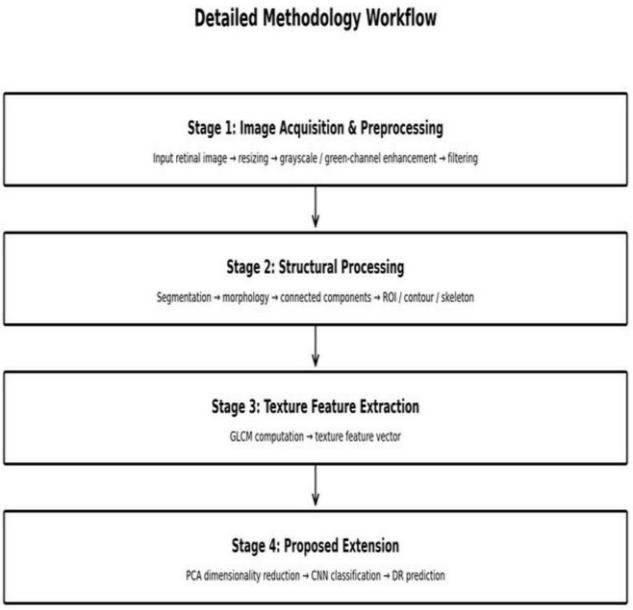

Figure 2 Detailed workflow of the extended retinal image-processing and classification framework

3.4.Principal Component Analysis

The extracted GLCM features can contain correlated or redundant information. PCA transforms the original feature matrix into a new orthogonal coordinate system[3] ordered by explained variance. The dominant components can then be retained as a compact representation. The number of retained components should be fixed before final testing and reported explicitly, because the selected variance-retention criterion affects both dimensionality and classification performance. As shown in Figure 3 Structural analysis outputs: (a) ROI supplied to contour detection and (b) skeleton representation.

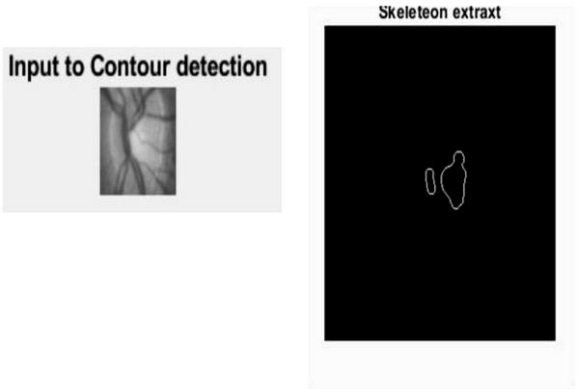

Figure 3 Structural analysis outputs: (a) ROI

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supplied to contour detection and (b) skeleton representation

3.5.Neural Network Classification

A feedforward neural-network classifier is used as the learning stage of the proposed framework. The supplied MATLAB implementation shows a compact feedforward network and reports the observed classification metrics. The reduced GLCM feature vector is supplied to this classifier; therefore, the classifier is described as a neural network rather than as a CNN architecture. The hybrid design combines handcrafted texture information with machine learning. GLCM[4] provides interpretable spatial descriptors, PCA controls feature redundancy, and the neural network provides nonlinear classification capability. This combination is intended to improve the robustness of the overall pipeline while maintaining an interpretable feature-extraction stage.

4. Experimental Results

Three experimental executions produced separate performance sets. The results are reproduced below to document the observed experimental variation. The reported values are not statistically pooled; the highest result is treated as an observed execution rather than as a statistically validated improvement over the baseline. As shown in Table 1 Observed MATLAB[5].

Table 2 Observed MATLAB

Observed MATLAB execution results
Run 1 — Accuracy 90.00% | Specificity 93.44% | Sensitivity 91.90%
Run 2 — Accuracy 90.63% | Specificity 93.44% | Sensitivity 95.12%
Run 3 — Accuracy 96.00% | Specificity 95.00% | Sensitivity 95.50%

The highest observed accuracy was 96.00% in Run 3. Run 3 also produced the highest observed specificity of 95.00% and sensitivity of 95.50% among the three executions. These results indicate measurable variation across executions and reinforce the importance of fixed partitions and repeated evaluation[6].

4.1.GLCM Feature Representation

Table 3 Extracted Glcm Feature Values

Feature	Extracted Value
Contrast	0.27
Correlation	0.26
Energy	1.67
Homogeneity	1.73
Entropy	0.13
Mean	0.15
Variance	0.41
Standard Deviation	0.40
RMS	0.95
Smoothness	0.93

The extracted feature vector demonstrates that GLCM produces a compact numerical description of the processed retinal region. The feature values can be transformed using PCA before classification. The feature representation and performance outputs are illustrated as shown in Figure 4 Experimental outputs: (a) extracted GLCM texture features and (b) accuracy, sensitivity, and specificity across executions.

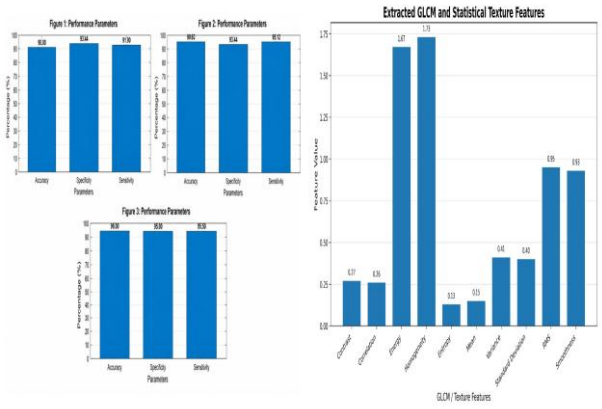

Figure 4 Experimental outputs: (a) extracted GLCM texture features and (b) accuracy, sensitivity, and specificity across executions

4.2.Performance Evaluation

For binary classification, accuracy, sensitivity, and specificity are computed from the confusion-matrix terms true positive[7] (TP), true negative (TN), false positive (FP), and false negative (FN). Accuracy measures overall correct classification, sensitivity measures the ability to identify positive cases, and specificity measures the ability to identify negative cases.

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- Accuracy = (TP + TN) / (TP + TN + FP + FN)
- Sensitivity = TP / (TP + FN)
- Specificity = TN / (TN + FP)

For a multi-class dataset, macro-averaged precision, recall, F1-score, and class-wise confusion matrices should also be reported. This is particularly important when the Kaggle dataset contains unequal numbers of samples across disease categories.

5. Discussion

The experimental results demonstrate that the retinal image-processing pipeline can produce satisfactory classification performance, while also showing variation between executions[8]. The highest observed accuracy of 96.00% is encouraging, but it should be interpreted as an observed run rather than a statistically established improvement. Differences in image partitions, class distributions, preprocessing settings, and model initialization can influence the final score. The proposed GLCM–PCA–neural-network framework provides a systematic feature-learning pipeline. GLCM contributes interpretable texture information, PCA reduces redundant dimensions, and the neural network contributes nonlinear learning. The combination is particularly useful when retinal patterns contain both local texture characteristics and higher-level visual structures. For conference-quality validation, the final experiment should use a fixed[9] APTOS 2019 dataset split, identical preprocessing across all models, and the same evaluation protocol for GLCM-only, neural-network-only, and GLCM–PCA–neural-network configurations. Such an ablation-based comparison would make it possible to determine the contribution of each component.

6. Comparative Analysis

The earlier conference implementation reported 94.54% accuracy, 94.56% specificity, and 94.55% sensitivity. The present work treats that result as a baseline reference and does not combine it mathematically with the additional experimental executions. A direct statistical comparison is avoided because the available records do not establish that identical image sets and train/test partitions were used. As shown in Table 4 Extended Framework.

Table 4 Extended Framework

Extended framework components
Preprocessing: normalization and morphological processing
Texture: GLCM feature representation
Reduction: PCA-based feature reduction
Classifier: feedforward neural network
Evaluation: accuracy, sensitivity, specificity and extended metrics

The comparison highlights the methodological extension and the newly observed experimental results rather than claiming that one reported accuracy is directly superior to another. The proposed framework is therefore positioned as an experimentally testable extension that can be validated under the same dataset and partition.

7. Contributions

- Integration of GLCM-based texture representation with a neural-network-oriented retinal classification framework.
- Use of PCA to reduce redundant information in the extracted texture feature space.
- Use of the APTOS 2019 Blindness Detection retinal fundus image dataset as the experimental data source.
- Explicit reporting of accuracy, sensitivity, and specificity across three experimental executions[10].
- Separation of baseline results from additional experimental observations to avoid unsupported performance claims.
- Definition of a reproducible evaluation protocol for future GLCM-only, neural-network-only, and hybrid comparisons.

8. Limitations

- Further validation on independent data and repeated controlled experiments is required to establish the generalization capability of the framework.
- The reported results are based on the experimental runs conducted in the present implementation and should be interpreted within the stated evaluation protocol.
- The GLCM configuration and PCA settings can influence the extracted representation and final classification performance.
- The present evaluation is based on a texture-oriented feature representation; performance

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may vary with image quality, illumination, and acquisition conditions.

9. Future Work

Future experiments will use the same fixed APTOS 2019 Blindness Detection dataset partition for all compared models and will evaluate GLCM-only, neural-network-only, and GLCM–PCA–neural-network configurations under identical conditions. Cross-validation or repeated runs can be used to quantify variability. Confusion matrices, precision, recall, F1-score, ROC/AUC where applicable, and class-wise performance should be included. The complete neural-network architecture, optimizer, learning rate, batch size, number of epochs, PCA retention criterion, and preprocessing parameters should also be documented. Robustness testing across image quality, illumination, and acquisition conditions can further establish the generalization capability of the proposed system. Such controlled evaluation would strengthen the technical contribution and improve the reproducibility of the study.

10. Implementation and Reproducibility

For a reliable conference evaluation, the final implementation should preserve a fixed version of the APTOS 2019 Blindness Detection dataset and record the dataset version information, total number of images, class labels, and class-wise sample counts. All images should pass through the same preprocessing sequence before feature extraction. No test image should be used during training, PCA fitting, threshold selection, or model tuning. The GLCM configuration should be kept constant for all experiments, including the gray-level quantization, spatial offsets, and the statistics extracted from the matrix. PCA should be fitted using the training feature matrix only. The number of retained principal components or the variance-retention threshold should be selected before evaluation and then applied unchanged to the held-out test features. For a fair ablation study, three configurations can be evaluated: a GLCM-based classifier, a neural-network-only classifier, and the proposed GLCM–PCA–neural-network framework. The same training and test images, preprocessing rules, evaluation metrics, and randomization policy should be used for all configurations. Reporting the confusion matrix and class-wise precision, recall, and F1-score will provide more information than accuracy alone, especially when the dataset is imbalanced. The final MATLAB or Python implementation should also record the neural-network architecture, optimizer, learning rate, batch size, number of epochs, augmentation settings, initialization policy, stopping criteria, and hardware/software environment. Repeated runs or cross-validation can then be used to report mean performance and standard deviation. This protocol will allow the reported results to be independently reproduced and will provide stronger evidence for the effectiveness of the proposed hybrid approach.

Conclusion

This paper presented a retinal fundus image screening framework based on GLCM texture analysis, PCA-based feature reduction, and neural-network classification. The framework combines interpretable handcrafted texture descriptors with nonlinear neural-network classification. The APTOS 2019 Blindness Detection dataset was used as the experimental data source, and the associated MATLAB executions demonstrated observed classification accuracies ranging from 90.00% to 96.00%. The highest observed accuracy was 96.00%, with 95.00% specificity and 95.50% sensitivity in Run 3. However, the available execution records do not support treating this value as a statistically validated improvement over the earlier conference result. The principal contribution of the present work is the structured GLCM–PCA–neural-network framework and its experimentally reproducible evaluation protocol. Future controlled experiments using fixed dataset partitions and complete model specifications can establish the quantitative contribution of each component.

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