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## Intelligent Diagnosis of Diabetic Retinal Disease Using Image Processing and Machine Learning Algorithms

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### Abstract

Untreated diabetic retinopathy, which develops as a result of prolonged elevated blood glucose levels, can ultimately cause permanent vision loss if it is not detected and managed at an early stage. Therefore, timely diagnosis and appropriate medical intervention are essential to prevent severe complications associated with this condition. However, manual diagnosis of diabetic retinopathy is often challenging and time-consuming, leading to delays in patients receiving consultation and treatment from ophthalmologists. To address this issue, automated diagnostic systems can assist in the early detection of diabetic retinopathy, enabling prompt treatment and reducing the risk of further ocular damage. The present study proposes a machine learning-based approach for extracting key retinal features, including exudates, hemorrhages, and micro aneurysms, and classifying them using a hybrid classifier that integrates Support Vector Machine (SVM), K-Nearest Neighbour (KNN), Random Forest, Logistic Regression, and Multilayer Perceptron (MLP) models.

**Keywords:** Skin disease, CNN, image processing, DNN, K-Nearest Neighbour (KNN), Random Forest, Logistic Regression, and Multilayer Perceptron (MLP)

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### I. Introduction

Diabetic retinopathy is an eye disorder that occurs as a direct consequence of persistently high blood glucose levels associated with diabetes mellitus. If the condition remains untreated, it may progress to severe vision impairment or complete blindness. Early symptoms of diabetic retinopathy include blurred vision, dark areas in the visual field, floaters, and difficulty in distinguishing colors. Early diagnosis and timely treatment are therefore crucial to prevent permanent vision loss[1][2]. Globally, diabetic retinopathy affects nearly one-third of the approximately 285 million individuals diagnosed with diabetes. The number of people suffering from this condition was estimated at about 126.6 million in 2010 and is projected to rise to 191 million by 2030. One of the earliest indicators of diabetic retinopathy is non-proliferative diabetic retinopathy (NPDR), which appears as small red spots in the retina. These spots may represent micro aneurysms, which are abnormal bulges in the retinal blood vessels, or small areas of bleeding. In addition, leakage from damaged blood vessels may release fluid and lipid deposits known as exudates. These abnormalities indicate progressive damage to the retinal structure.

Traditional methods for diagnosing diabetic retinopathy include clinical examinations such as pupil dilation tests, visual acuity assessment, and Optical Coherence Tomography (OCT). Although effective, these procedures are time-consuming and may be inconvenient for patients. To overcome these challenges, automated systems based on machine learning can be used to detect diabetic retinopathy in digital retinal images[3][4]. In

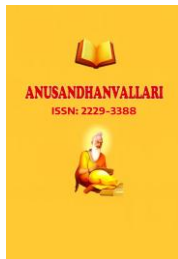


this study, a hybrid machine learning model is proposed to automatically identify diabetic retinopathy by extracting important retinal features such as hemorrhages, micro aneurysms, and exudates. The proposed method utilizes a classifier that integrates Support Vector Machine (SVM) and kernel-based neural network techniques for improved classification performance. Human eye health is influenced by multiple factors including type-2 diabetes and elevated blood glucose levels. These conditions may lead to several ocular diseases such as retinopathy, edema, cataracts, and others. Diabetic retinopathy, also referred to as diabetic eye disease, occurs when diabetes causes damage to the blood vessels of the retina. In many Western countries, diabetic retinopathy is considered one of the leading causes of blindness. Studies indicate that nearly 80% of individuals who have had diabetes for more than 20 years develop some form of diabetic retinopathy. However, early diagnosis, appropriate treatment, and regular monitoring can reduce new cases of severe vision loss by up to 90%. [5][6]

The likelihood of developing diabetic retinopathy increases with the duration of diabetes. In the United States, approximately 12% of new blindness cases each year are attributed to this disease. It is also one of the primary causes of vision loss among adults aged between 20 and 64 years. In many cases, diabetic retinopathy shows no early symptoms. Similarly, macular edema, a condition that can cause sudden vision loss, often develops without clear warning signs. Blurred vision is a common symptom of macular edema and may make daily activities such as reading or driving difficult. The initial stage of diabetic retinopathy, known as Non-Proliferative Diabetic Retinopathy (NPDR), often does not produce noticeable symptoms. Many patients maintain normal vision and remain unaware of the disease in its early stage. NPDR can usually be detected only through retinal imaging techniques such as fundus photography, which may reveal the presence of micro aneurysms. If a fluorescein angiography examination shows blocked or narrowed retinal blood vessels, it may indicate potential vision loss [7].

Macular edema may occur at any stage of NPDR when blood vessels leak fluid into the macula, leading to swelling of the retinal tissue. This condition may cause visual distortions or dimming of objects and colors. Approximately 10% of individuals with diabetes experience vision impairment due to macular edema. Optical Coherence Tomography (OCT) can detect retinal thickening caused by fluid accumulation in the macular region. The advanced stage of diabetic retinopathy is known as Proliferative Diabetic Retinopathy (PDR). In this stage, abnormal new blood vessels grow on the retinal surface, a process referred to as neovascularization. These fragile vessels may rupture and leak blood into the vitreous humor, which can significantly impair vision. Early bleeding episodes may not be painful and may only appear as floating spots or small blood patches in the visual field. However, over time, these symptoms may progress to blurred vision, floaters, flashes of light, and eventually severe vision loss. A healthy eye contains several important structures, including the retinal blood vessels, optic disc, and macula. Any structural changes in these components are often associated with ocular diseases. Diabetic retinopathy is generally classified into two stages: Non-Proliferative Diabetic Retinopathy (NPDR) and Proliferative Diabetic Retinopathy (PDR) [8].

NPDR is characterized by several types of retinal lesions such as micro aneurysms, hemorrhages, hard exudates, and soft exudates. The severity of NPDR depends on the number and location of these lesions. Micro aneurysms are considered the earliest clinical sign of diabetic retinopathy and appear as tiny red dots on the retina. Hemorrhages occur as the disease progresses and may appear either as small bright red dots (dot hemorrhages) or larger blot-like lesions. These abnormalities may contribute to vision impairment. Exudates represent another stage of retinal damage in diabetic retinopathy. They consist of lipid and protein deposits that leak from damaged blood vessels. Exudates are categorized as either hard or soft based on their appearance and structural characteristics. Hard exudates appear as bright yellow deposits, whereas soft exudates, also known as cotton-wool spots, appear as grayish-white patches and represent more severe retinal damage. Since diabetic retinopathy is a serious vision-threatening disease, early detection is essential. Manual analysis of retinal fundus



images by specialists can be time-consuming and may sometimes lead to diagnostic errors. Therefore, automated detection systems using image processing and machine learning techniques provide a more efficient and reliable approach for early diagnosis and screening of diabetic retinopathy[9].

## II. Literature Review

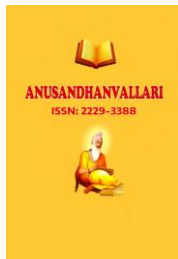
**P. Saranya et. al.** [1] A convolutional neural network-based automated approach for the detection of non-proliferative diabetic retinopathy is presented. Specifically, we employ two datasets, The MESSIDOR and the IDRiD. To begin, we up and down-sample equally to ensure that all data is representative. Removal of the optic disc is also performed to prevent false positives. The picture is preprocessed to improve the final output. Canny edge detection, resizing, interpolation, and normalizing are the four stages of preprocessing. Different stages of diabetic retinopathy may be categorized with the help of a convolutional neural network (CNN). In comparison to IDRiD's 90.29 percent accuracy, MESSIDOR's is 96.3 percent. With Inception V3, diabetic retinopathies may better train the model VGG16.

**K.Shankar et al.** [2] study to identify and categorise diabetic retinopathy, we present a model called Hyperparameter Tuning Inception-v4 (HPTI-v4). Here, the contrast limited adaptive histogram equalisation (CLAHE) model is used to boost the image's contrast in the preprocessing step. Segmentation of processed pictures is performed using histogram-based segmentation. Here, Bayesian optimization is used to fine-tune the hyperparameters. An epoch, a learning rate, and a momentum are the hyperparameters used. For this categorization, we use the multilayer perceptron (MLP). The results from this approach are more precise. The resulting 99.49% accuracy, 98.83% sensitivity, and 99.68% specificity are all quite impressive. The categorization model is a useful addition to this procedure.

**Nataly Ilyasova et al** [3] The efficiency of employing decision trees for feature selection was investigated in this paper. , we were able to zero down on the selection traits technology's most relevant textural properties. In order to address the issue of identifying areas of interest, the method allowed for intelligent analysis of characteristics utilizing colour subspaces. In this research, we build decision trees using texture characteristics for a previously suggested technique. More accurate decisions were made because to the use of decision trees, which identified additional indicators of interest. When the size of the window is more than 15, the optimal number of features is 3. Accuracy exceeding 98 percent was achieved using decision trees with more than six texture characteristics for 12-by-12-inch windows.

**D. K. Prasad et al** [4] In order to identify blood vessels, exudates, and micro aneurysms, you should offer a thresholding technique and segmented procedure. Histogram equalisation is used to improve contrast in pre-processing, and canny edge detection is used to improve performance. Blood vessels, exudates, and micro aneurysms are extracted using a threshold-based segmentation technique based on morphological operation. Both the Haar wavelet transform and principal component analysis (PCA) are used for feature selection. Diabetic retinopathy is classified using a One-Rule and Back propagation neural network (BPNN) classifier. A 97.75% accuracy rate is achieved by the One Rule classifier, while a 93.8% success rate is achieved by the BPNN classifier. This approach has the potential for future integration of multistage classification for hazard identification.

**K. Shankar et al.** [5] created a cooperative deep learning model for automatically detecting and categorising photos of diabetic retinopathy in the fundus. Here, preprocessing is employed to get rid of the fuzziness around the edges. Histogram equalisation is then used to do the segmentation once the first processing is complete. The technique aids in identifying and removing those parts of the picture that will be of value later on. For this categorization, we use the Synergic deep learning (SDL) model. Accuracy in the model was found to be 99.28,



sensitivity was 98.54, and specificity was 99.38. Filters before processing, AlexNet, and the inception method for hyperparameter tweaking are all ways to enhance the model.

**Abhishek Samanta et al. [6]** propose Use of convolutional neural networks for automated diabetic retinopathy identification on a limited dataset. In this case, contrast adaptive adaptive histogram equality (CLAHE) is employed in the preprocessing step to improve the picture. As a classifier, DenseNet121 was put to good use. The data are skewed, therefore precision is not useful. Here, Cohen's Kappa is the appropriate statistic to employ (k). It measures how accurately one class compares to another in close proximity. For validation data, the kappa is 0.8836, while for training data, it is 0.9809. With this model, the F1 score for mild DR is 0.64, whereas the score for moderate DR is 0.74. Semantic segmentation may be utilised to improve the performance of this model.

**C. Harshitha et al. [7]** use deep learning to create a system that can identify the onset of diabetic retinopathy and its progression through its many phases. Images in a new dimension are included in the dataset. It becomes a 256-by-256 representation. The prediction is made using a CNN model. The accuracy is 73% over the 15 epochs and 79% over the 50 epochs. When just a small set of neurons is employed, accuracy improves to 86%.

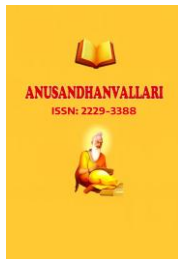
**Juan wang et al. [8]** could use deep learning to provide a simultaneous diagnosis of diabetic retinopathy severity and characteristics. Here, a hierarchical multi-task deep learning architecture is used for identifying the degree of DR and DR-related features in the fundus picture. There is just one spine and a pair of heads. The SE network is the backbone of the system. To get features out of a picture, this tool is put to use. Two separate forward neural networks (one for feature identification and another for severity assessment) serve as the heads. Cohen's kappa and the receiver operating characteristic curve are used to evaluate this model. This model is restricted by the fact that it is only equipped to handle a modest NPDR training image (2%). As time goes on, the dataset may be enhanced by include additional photos with moderate NPDR.

**Lam C et al. [9]** Using deep learning it is proposed that diabetic retinopathy may be detected automatically. CLAHE is used to improve contrast during the preprocessing phase. Overfitting is mitigated by the data augmentation procedure. An image categorization system (pre-trained convolutional neural networks) from the deep learning GPU training system (DIGITS). Methods based on transfer learning were used, with the ImageNet-trained AlexNet and GoogLeNet architectures serving as the data source. Including the identification of mild illness in the model will help it perform better in the future.

**García Gabriel et al. [10]** diabetes eye disease detection via convolutional neural networks is proposed. Image resizing to 256x256 occurs during the preparation phase. Application of CNN architecture to the diagnosis of exudates, micro aneurysms, and haemorrhages. When it comes to speed and precision, VGG16noFC2 is superior. Future iterations of the model will benefit from a fully linked layer that facilitates the merger of two networks.

## Classification

There are two basic types of diabetic retinopathy: proliferative and nonproliferative. "proliferative" refers to the presence or absence of neovascularization. Retinal angiogenesis abnormality (abnormal growth of blood vessels). Nonproliferative diabetic retinopathy describes an asymptomatic, early stage of the disease (NPDR). Proliferative retinopathy (PDR) is the next stage of the illness and is characterised by the development of neovascularization, which may have devastating visual effects.



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## NPDR

Retinal capillaries are damaged by hyperglycemia. This causes micro aneurysms, or weakening of the capillary walls that lead to pouching of the vessel lumens. Hemorrhages caused by the rupture of micro aneurysms are contained by the inner limiting membrane deep into the retina (ILM)[8]. These hemorrhages are referred to as "dot-and-blot" hemorrhages because of their pinpoint appearance. The fluid seeps into the retina because the weaker arteries have become leaky. Macular edema, the accumulation of fluid directly beneath the macula, is thought to be a frequent cause of visual loss in people with DR.

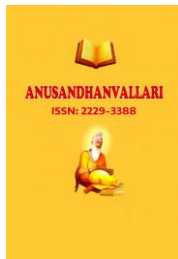
Fluid lakes that dry out may leave silt behind, much like a river that drains after a flood. The lipid waste products that make up this silt are easily recognizable by its waxy, yellow coatings. The damaged vessels gradually get blocked as NPDR advances. Infarction of the nerve fiber layer may result in the characteristic cotton-like white patches known as "cotton spots" if blood flow to the area is impeded (CWS).

### Micro aneurysm Detection

Automated detection of micro aneurysms plays a significant role in the early diagnosis of diabetic retinopathy and is essential for preventing vision loss. The integration of automated screening systems can reduce the overall cost of diabetic retinopathy detection and lessen the dependency on ophthalmologists. In general, micro aneurysm detection methods involve two major stages: identifying potential micro aneurysm candidates and classifying them. The first step involves preprocessing the retinal image to eliminate noise and enhance image contrast. Since micro aneurysms are more clearly visible in the green channel of RGB fundus images, this channel is typically selected for further processing. After preprocessing, candidate regions that may represent micro aneurysms are identified. However, blood vessels in the retinal image may sometimes be incorrectly detected as potential candidates. To address this issue, blood vessel segmentation techniques are applied to separate blood vessels from the candidate regions and thereby reduce the number of false positives. Once the candidate regions are identified, feature analysis is performed, which includes feature extraction and feature selection processes.

In the subsequent stage, classification algorithms are applied to the extracted features to determine whether the detected candidates correspond to true micro aneurysms (abnormal) or non-micro aneurysm regions (normal). For this purpose, classifiers utilize a set of micro aneurysm-specific features computed for each candidate region. The ability to accurately detect micro aneurysms in retinal fundus images is a crucial component in diabetic retinopathy screening systems because micro aneurysms are typically the earliest visible signs of the disease. Therefore, reliable detection of micro aneurysms is vital for computer-aided diabetic retinopathy diagnosis using medical image processing techniques. One effective approach for improving detection accuracy is the Ensemble-based Micro aneurysm Detection (E-MD) method, which integrates multiple preprocessing techniques with candidate extraction methods. The E-MD architecture enhances the performance of micro aneurysm detection and supports the accurate diagnosis of diabetic retinopathy. This framework mainly consists of two stages: preprocessing operations and candidate extraction methods, which work together to detect micro aneurysms in digital fundus images.

Selecting appropriate preprocessing methods and candidate extraction components for the E-MD system can be challenging. Preprocessing techniques are applied before candidate extraction to improve the quality of the retinal images by reducing noise and enhancing important features. This process makes the images more suitable for disease detection and analysis. During the candidate extraction stage, image regions that exhibit characteristics similar to micro aneurysms are identified and marked for further evaluation. Many micro aneurysm detection approaches employ individual detectors to eliminate false candidates and improve detection reliability.



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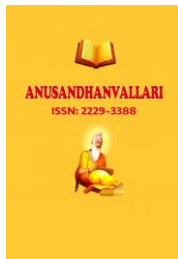
### Exudate-Based Diabetic Macular Edema Detection In Fundus Images

Diabetic macular edema (DME) is one of the most serious complications associated with diabetic retinopathy and is a significant cause of vision impairment. Large-scale screening programs for DME rely heavily on the accurate detection of exudates in retinal fundus images. To support the diagnosis of DME, the Feature-Based Macular Edema Detection (FMED) method has been developed. This approach utilizes a set of features derived from color information, wavelet decomposition, and automated lesion segmentation. In the FMED framework, a single feature vector is generated from each retinal image and used for classification to determine the presence of DME. The feature vector is analyzed using three main techniques: exudate probability mapping, color analysis, and wavelet analysis.

During the preprocessing stage, background subtraction is applied to estimate the probability of exudate regions in the retinal image. Exudate detection is performed by assigning a probability score to each candidate region in the exudate candidate map. Connected component analysis with eight-neighbor connectivity is then used to identify significant exudate regions. The FMED method further examines the boundary values of the detected exudates to determine possible lesion borders. Edge detection is performed using kernel estimation in eight different directions around each candidate exudate region. The outputs from these kernels are combined by selecting the maximum value for each pixel, which helps identify the most prominent boundaries associated with potential exudates. Color analysis is incorporated in the FMED framework to reduce variations in color intensity among images obtained from different patients. Wavelet analysis, which allows signal examination at multiple resolutions, is also employed for tasks such as noise reduction and feature extraction. The mother wavelet plays a crucial role in this process by enabling the decomposition of images into multiple components using scaling and wavelet functions, thereby facilitating more effective image analysis. Selecting an appropriate feature vector for DME detection is a complex task. In the FMED approach, training images are annotated to mark exudates and other lesion or pigmentation variations at the pixel level. The method characterizes lesion regions using probability maps, color features, and wavelet-based attributes. The exudate probability map is analyzed on a per-pixel basis, and statistical measures such as mean, median, standard deviation, maximum, and minimum are computed for each group of extracted pixels. The FMED technique integrates these statistical values with the results obtained from color and wavelet analysis to generate a comprehensive feature representation. This process also helps retain difficult images that may contain higher rates of false positives or additional irrelevant detections. By combining both weighted and un-weighted statistical measures, the FMED framework produces a large set of features for each image. However, using a very high number of features during classification may lead to the curse of dimensionality, which can negatively affect model performance. Therefore, an automated feature selection process is necessary. In the FMED approach, feature selection is performed using the Information Gain method, which is based on conditional entropy and helps evaluate the relevance of each feature. The HEI-MED dataset is divided into three subsets, and feature selection is performed separately on each subset. The final importance score for each feature is obtained by averaging the results from the three subsets, and the most relevant feature subsets are then selected to form the final DME feature vector used in classification.

### Methodology

To facilitate the selection of optic cup features from digital fundus images for diabetic retinopathy (DR) detection, the Diabetic Fundus Image Retrieval (DFIR) method has been introduced. This approach segments digital fundus images to extract relevant structural information. A sliding window technique is applied to determine an optimal window size for analyzing the image. Within each sliding window block, the DFIR framework computes two histogram-based performance measures. These histograms are then combined into a



unified representation using a Group Sparsity approach. The histogram intensity range function without overlap is utilized to represent the optic cup characteristics in fundus images.

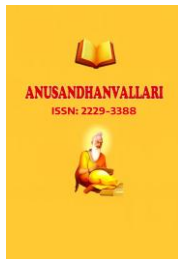
Histograms play a crucial role in describing optic cup features in retinal images. The Group Sparsity Non-Overlapping Function in the DFIR method eliminates overlapping pixel values, allowing for efficient identification of optic cup characteristics. This strategy significantly reduces the computational complexity associated with feature selection in DR diagnosis. Furthermore, the severity level of diabetic retinopathy can be ranked using a Support Vector Machine (SVM), which evaluates the extracted optic cup features and improves diagnostic accuracy.

Another approach proposed for extracting optic cup features from digital fundus images is the Top-hat Mathematical Transform Fuzzy-based Feature Clustering (TMTF-FC) technique. One of the major advantages of this method is its ability to reduce noise in retinal images. By applying gray-scale mathematical morphology, the TMTF-FC technique enhances the visualization of retinal blood vessels in diabetic fundus images. A fuzzy-based feature clustering algorithm is then used to efficiently retrieve optic cup features from the images in a shorter time period. As a result, the feature extraction process becomes faster and more effective for DR diagnosis.

The TMTF-FC method extracts pixel-level color features such as mean intensity and standard deviation from the original image using the Top-hat mathematical transform. These features facilitate improved clustering performance during disease detection. Consequently, the method enhances the identification of significant retinal structures associated with diabetic retinopathy. In addition, a Spectral Classifier with Predictive Rules (SC-PR) framework has been developed to improve the early detection performance of diabetic retinopathy. The SC-PR framework uses a sliding window mechanism to efficiently identify relevant optic cup features from digital fundus images. Feature clustering is then applied to accelerate the extraction of optic cup characteristics, thereby reducing the time required for disease diagnosis. For classification, the SC-PR framework utilizes a spectral classifier that effectively categorizes the extracted features and supports accurate disease identification. In general, diabetic retinopathy detection involves several stages, including preprocessing, segmentation, and feature ranking. Preprocessing ensures that the dataset is consistent and contains only relevant image features. This step helps reduce the computational burden on subsequent processing stages. After preprocessing, image segmentation is performed to separate normal retinal structures from abnormal pathological regions. Among the three color channels of an RGB image (red, green, and blue), the green channel is typically preferred for retinal analysis because it provides better contrast between blood vessels, exudates, and hemorrhages without being excessively bright or poorly illuminated compared to the other channels.[10]

### Dataset Description

For the experimental evaluation, the Kaggle dataset was utilized, which was originally collected and annotated by EyePACS. This dataset is considered one of the largest publicly available collections of retinal fundus images for diabetic retinopathy analysis. The EyePACS dataset contains approximately 94,702 retinal images, of which 55,126 images are labelled while the remaining images are unlabeled. Since the task of detecting and classifying the stages of diabetic retinopathy is a supervised learning problem, only the labelled images from the dataset were used for training and testing purposes. In future work, a semi-supervised learning approach could be explored to take advantage of both labelled and unlabeled data within the dataset. The dataset is categorized into five classes, each corresponding to a different stage of diabetic retinopathy severity[11-13].



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### Image Pre-Processing and Augmentation

In deep learning applications, the dataset plays a crucial role as it forms the foundation for model training and evaluation. The fundus images used in this study were captured using different imaging devices under varying environmental conditions. As a result, the dataset exhibits significant variability in factors such as brightness, contrast, and resolution. To address these inconsistencies, several preprocessing steps were applied to normalize the images, remove redundant information, and reduce environmental artifacts.

First, the images were resized while maintaining their original aspect ratio so that the height of each image became 299 pixels. The images were then cropped along their longer dimension to retain the central region, resulting in standardized images of size  $299 \times 299$  pixels. This standardization also facilitates comparison with the monocular approach proposed in previous studies.

Second, an image enhancement technique was applied by subtracting the average intensity of neighboring pixels from each pixel value and then adding 50% grayscale to the result. This operation functions similarly to a high-pass filter used in image editing software, improving the visibility of retinal structures such as blood vessels and lesions. After this enhancement, a circular mask was applied to crop the fundus region to approximately 95% of its original size, thereby removing boundary artifacts introduced during the previous processing stage. This step follows the algorithm proposed by Graham[14].

Third, before inputting the images into the neural network, pixel values were normalized from the range  $[0, 255]$  to  $[-1, 1]$ . This normalization helps reduce the influence of poorly scaled values and improves the stability and convergence of the neural network during training.

Since the available dataset is relatively small for effectively training deep learning models for medical image classification, various data augmentation techniques were applied to improve the generalization capability of the proposed model. However, it is important to preserve important physiological information contained in the original fundus images. For example, even when images appear inverted due to different imaging conditions, the relative position of anatomical structures such as the macula and optic nerve can still indicate whether the image corresponds to the left or right eye. Typically, the connecting line between the macula and optic nerve shows a negative slope for the left eye and a positive slope for the right eye. Therefore, the binocular model must preserve these physiological relationships during augmentation [15].

The augmentation process was performed between the first and second preprocessing stages, ensuring that both left and right eye images of the same patient underwent identical transformations. The augmentation procedures include the following steps:

**Horizontal flipping and swapping:** The left and right eye images were randomly flipped and interchanged horizontally before being fed into the network, taking advantage of the natural symmetry of human eyes.

**Random geometric transformations:** Various geometric operations were applied randomly, including image inversion, random cropping of 0–5% of image height or width, scaling between 90% and 110% of the original size, translation within a range of  $-5$  to  $+5$  pixels, rotation between  $-30^\circ$  and  $+10^\circ$ , and shearing between  $-10^\circ$  and  $+10^\circ$ .

**Random brightness and contrast adjustment:** Image intensity was randomly modified by multiplying or dividing pixel values, adjusting brightness between 85% and 115%, and altering contrast within the range of  $-100$  to  $+100$ .

During the training process, each augmentation step and its associated operations were applied with a probability of 50%. This strategy helps increase dataset diversity and improves the robustness and generalization performance of the deep learning model.

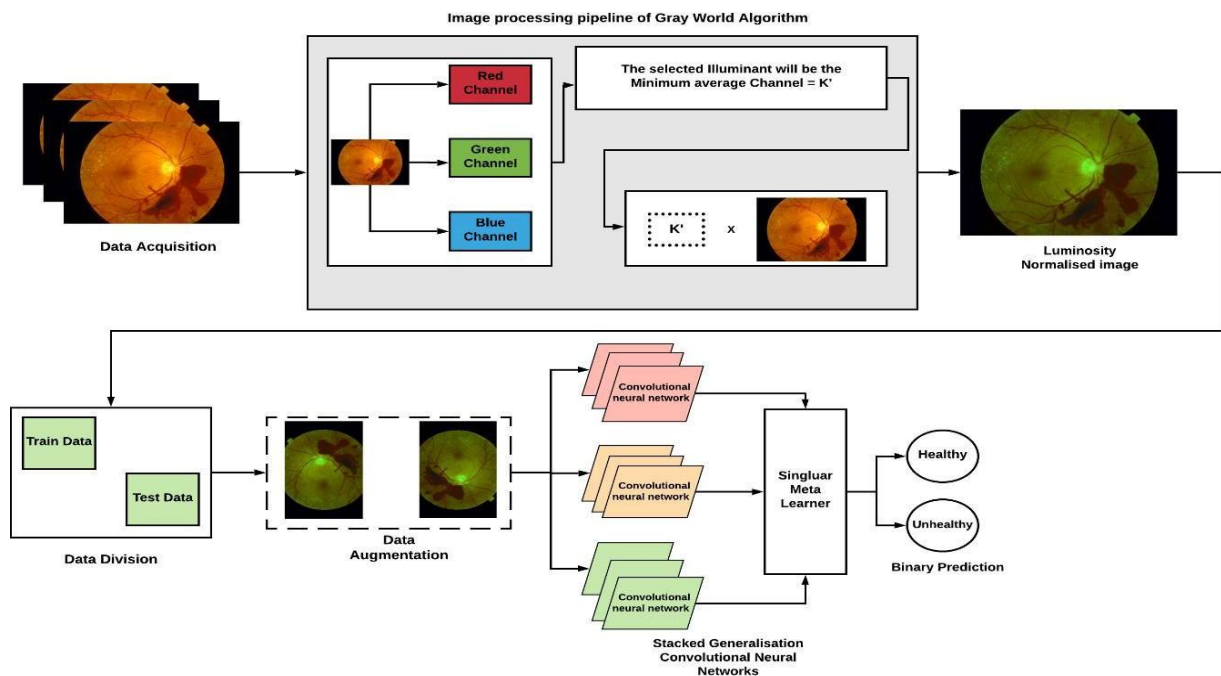


FIGURE 1. A diagrammatic flow of the proposed methodology and the training process

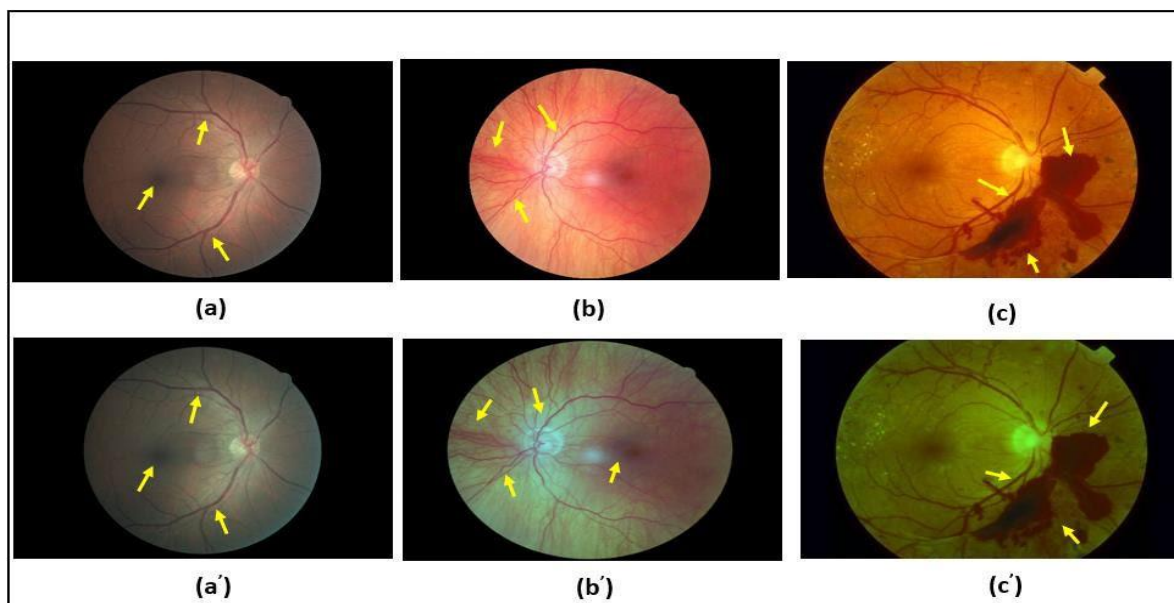


FIGURE 2. Color constancy algorithm image normalization outcomes. Three photos, one in its original form and two with their colours adjusted using the grey world technique, are shown in the top row. Blood vessels, the macula, and hemorrhages are still discernible after luminosity normalization, as shown by the yellow arrow.

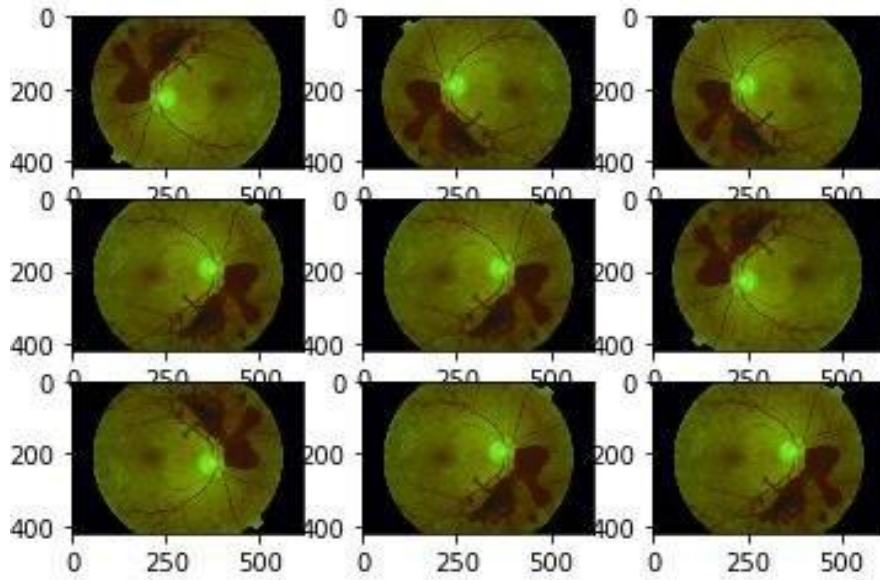


FIGURE 3. An Illustration of data augmentation in retinal images

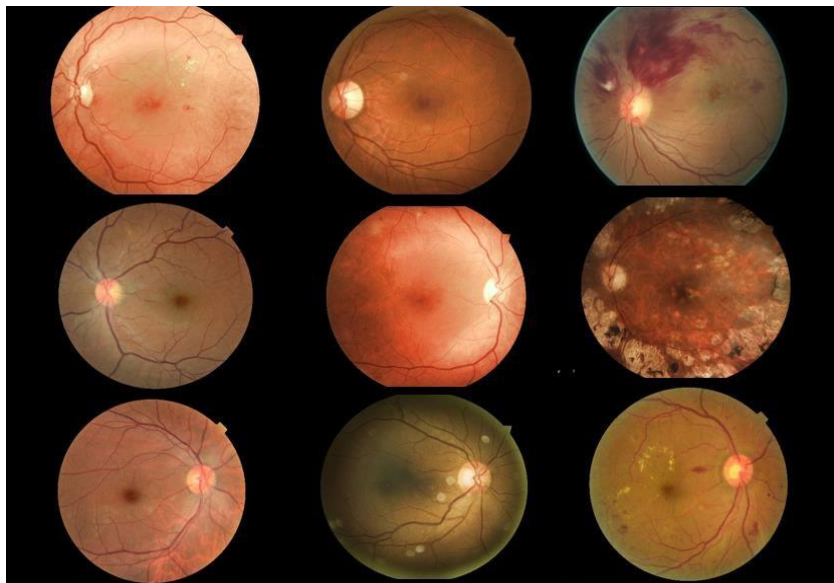
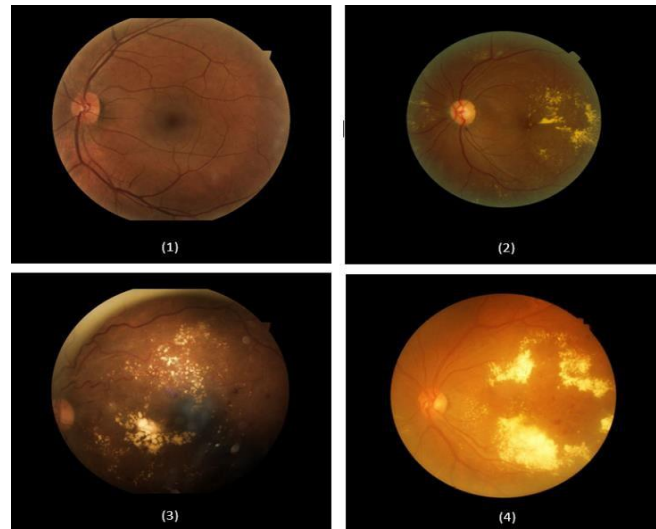
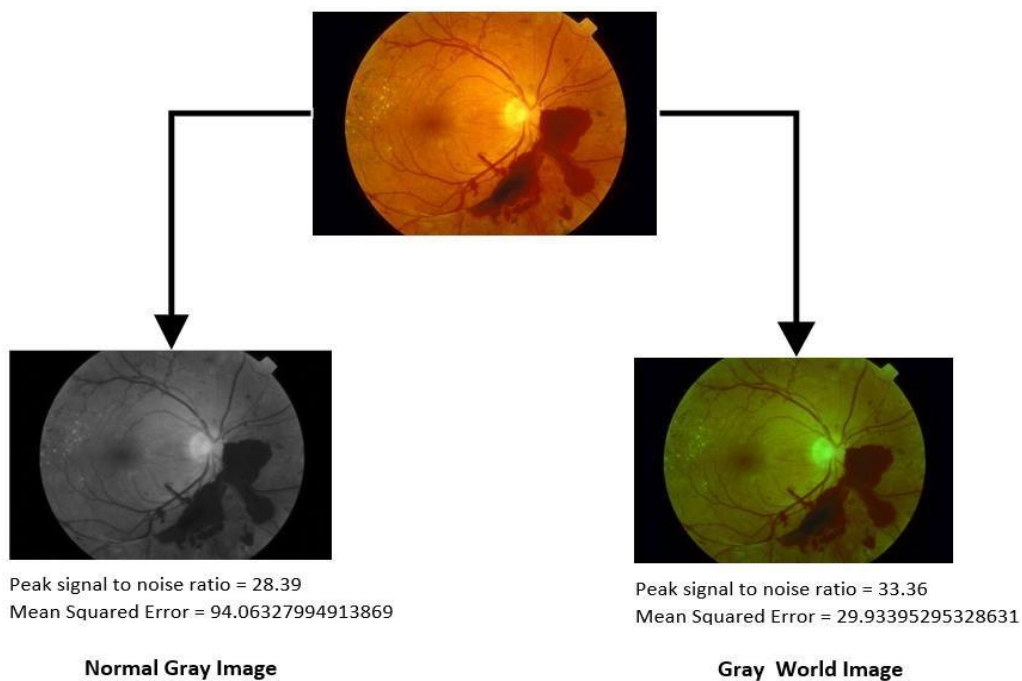


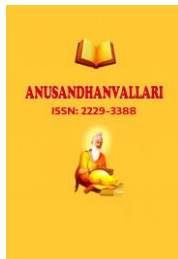
FIGURE 4. Sample fundus images from the Kaggle dataset



**FIGURE 5.** Diagnosis using DR images of the fundus. In Figure 5 (1), we see a normal retina without any lesions or bleeding.. Due to the presence of a few lesions, the unhealthy retinal picture in Figure 5 (2) is classified as having mild stage DR. In the picture of an unhealthy retina, as shown in Figure 5 (3), yellowish uneven margins may be seen. These are the hard exudates.. Cotton-wool patches, indicative of axoplasmic material accumulations in the retina, characterize the unhealthy retinal picture with advanced DR seen in Figure 5(4).



**FIGURE 6.** Statistical comparative analysis between normal gray image and gray world normalized image based on PSNR and MSE values



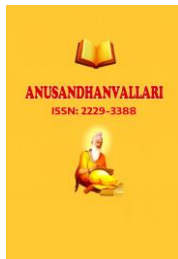
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## Conclusion

In this study, the Gray World algorithm is employed to correct illumination inconsistencies in retinal fundus images and to support the development of a fully automated diabetic retinopathy (DR) prediction system. To improve classification performance, an ensemble framework composed of three Convolutional Neural Networks (CNNs) is developed, enabling better generalization across diverse datasets. The effectiveness of the image normalization process is evaluated using statistical performance measures such as Peak Signal-to-Noise Ratio (PSNR) and Mean Squared Error (MSE) between the original and enhanced images. The proposed stacked ensemble model represents an advanced technique that integrates the strengths of multiple neural networks into a single predictive framework. This fusion-based approach combines the outputs of individual networks to enhance the overall classification capability. Machine learning algorithms are then applied to classify retinal fundus images and identify the presence of diabetic retinopathy. However, the performance of these models can be significantly influenced by variations in image acquisition conditions. Fundus images are often captured using different cameras and under varying lighting environments, which can introduce inconsistencies in color and brightness. To address these challenges, effective preprocessing and feature extraction methods are incorporated into the system. In particular, a color constancy technique is applied to minimize color variations and ensure more consistent image representation. Extensive experiments are conducted to evaluate the effectiveness of the proposed model in both binary classification and multi-class classification tasks for diabetic retinopathy detection. The experimental results are analyzed using several evaluation metrics, demonstrating that the proposed approach achieves superior performance compared to existing state-of-the-art models in both classification scenarios.

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