Diabetic Retinopathy Screening Using Image Processing

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ABSTRACT

Diabetic retinopathy, a grave consequence of diabetes mellitus, has emerged as the leading cause of visual impairment worldwide. This ocular condition arises from the deterioration of blood vessels situated behind the retina and progresses insidiously, ultimately leading to blindness. Early detection is paramount in mitigating vision loss among afflicted individuals. In this study, we propose three distinct approaches Support Vector Machines (SVM), Convolutional Neural Networks (CNN), and Residual Networks (ResNets) for the accurate detection of diabetic retinopathy. Our aim is to determine the most effective model for this purpose, thereby improving screening efficiency. Utilizing a pre-processed dataset sourced from Kaggle, we conducted comprehensive experiments to evaluate the performance of each model. This curated dataset was instrumental in optimizing the classification algorithms. Our findings reveal notable disparities in the performance of these models. Through meticulous testing and validation, we sought to identify the model exhibiting the highest accuracy in diabetic retinopathy detection. Leveraging a dataset comprising 2750 retinal images, our experiments yielded accuracy values of 68% for SVM, 74% for CNN, and 63% for ResNet.

KEYWORDS: *Diabetic Retinopathy; Diabetes; Convolutional Neural Network; Support Vector*

INTRODUCTION

Diabetic Retinopathy (DR) is a severe complication of diabetes, leading to vision impairment and blindness globally. With over 400 million individuals affected by diabetes worldwide, a significant portion is at risk of developing DR. The urgency to detect and intervene early to prevent vision loss has sparked research interest in Diabetic Retinopathy screening using image processing.

The motivation for research in this field arises from the critical necessity to devise efficient methods for early DR detection. Often, DR progresses unnoticed until it reaches an advanced stage, limiting treatment options. Hence, regular eye screenings are recommended for diabetic patients to detect DR signs early when interventions are most effective. However, the massive number of screenings required poses a challenge to healthcare systems. Image processing techniques offer a potential solution by automating retinal image analysis, facilitating efficient DR screening and reducing the burden on ophthalmologists. Integrating artificial intelligence (AI) and machine learning algorithms further enhances diagnosis accuracy, enabling timely treatment and preventing vision loss.

Beyond individual patient care, research in Diabetic Retinopathy screening using image processing holds significance for the healthcare industry. Efficient screening methods can mitigate healthcare costs associated with advanced DR treatment and rehabilitation, addressing a critical public health concern and preserving the vision and quality of life of diabetic individuals. Moreover, advancements in this area contribute to broader medical image analysis, AI in healthcare, and the intersection of technology and medicine [1].

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1. Stages Of Diabetic Retinopathy

1.1. Mild Nonproliferative Retinopathy

Mild Nonproliferative Retinopathy is the earliest stage of diabetic retinopathy, characterized by tiny swellings in the retinal blood vessels known as microaneurysms. These microaneurysms are small, balloon-like bulges that can leak fluid or blood into the surrounding retinal tissue, leading to subtle changes in vision that often go unnoticed in the beginning. At this stage, damage is usually minimal, and vision may still be normal, but the condition signals the first detectable signs of retinal blood vessel damage caused by diabetes. Early detection through regular eye exams is crucial to prevent progression to more severe stages. These swellings can cause fluid to leak into the retina [2].

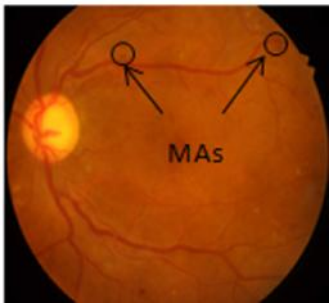

Figure 35: Mild DR (Stage 1)

2.2 Moderate Nonproliferative Retinopathy

Moderate Nonproliferative Retinopathy is marked by noticeable changes in the small blood vessels of the retina. As the condition advances, these vessels swell (microaneurysms) and become twisted or distorted, reducing their ability to transport blood effectively. This impaired blood flow can lead to areas of poor retinal nourishment, causing visible abnormalities in retinal appearance, such as small hemorrhages, leakage of fluid, and early signs of ischemia. At this stage, vision may still be unaffected or only mildly impaired, but the risk of progression to more severe forms of diabetic retinopathy increase [2].

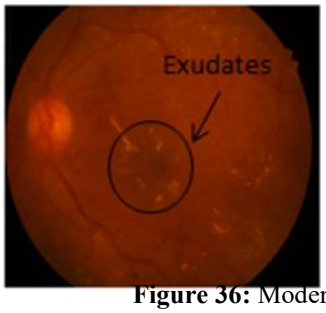

Figure 36: Moderate NPDR (Stage 2)

2.3 Severe Nonproliferative Retinopathy

In this stage, there is extensive blockage of the retinal blood vessels, which cuts off the blood supply to significant areas of the retina. As a result, these oxygen-deprived areas send strong distress signals that trigger the growth of new, fragile blood vessels. This stage marks a critical point in diabetic retinopathy progression, as the risk of

advancing to the more dangerous proliferative stage becomes significantly higher [2]

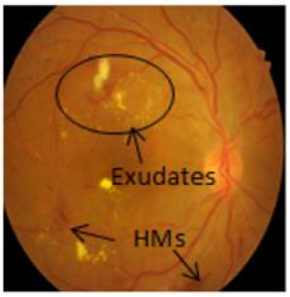

Figure 37: Severe NPDR (Stage 3)

2.4 Proliferative Diabetic Retinopathy (PDR)

Proliferative Diabetic Retinopathy (PDR) is the most severe stage of diabetic retinopathy. In this stage, abnormal new blood vessels begin to grow on the surface of the retina. However, these vessels are fragile and easily rupture, leading to bleeding inside the eye. This bleeding can stimulate the formation of scar tissue, which may pull on the retina and cause retinal detachment. Without timely treatment, these changes can lead to irreversible vision loss. It is the most severe stage of diabetic retinopathy. Here, the growth of new blood vessels is triggered, but these vessels are fragile and prone to leaking and bleeding. This can result in scar tissue forming and causing the retina to detach from the underlying tissue, leading to permanent vision loss.

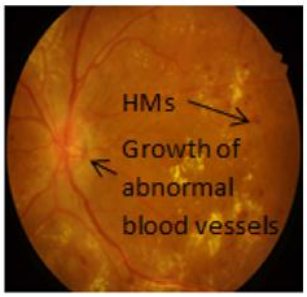

Figure 38: PDR (Stage 4)

LITERATURE REVIEW

The advancements in the late 20th and early 21st centuries have significantly improved the detection and treatment of diabetic retinopathy (DR), thereby reducing the risk of vision loss. Previous studies focused on detecting\various stages of DR through explicit feature extraction and classification using image processing techniques and machine learning algorithms.

In 2010, Singh and Chandra proposed a method for diabetic retinopathy detection based on lesion analysis, achieving an accuracy of up to 92% [3]. Similarly, Agurto et al. introduced a model in the same year that classified images based on lesion types, achieving comparable accuracy [4].

In 2013, Li Yafen et al. proposed a method employing various image processing techniques and an SVM classifier, achieving an accuracy of up to 89% [5].

Saleh & Eswaran introduced a method for automatically detecting no proliferative diabetic retinopathy. They focused on identifying two types of lesions: microaneurysms (MAs) and hemorrhages (HAs). By analyzing important features such as the optic disc, fovea, and blood vessels, they accurately segmented dark spots caused

by these lesions. Their system achieved sensitivity values of 84.31% and 87.53% for detecting MAs and HAs respectively, and specificity values of 93.63% and 95.08% for the same [6].

While these methods achieved high accuracy, explicit feature determination through image processing proved to be complex. With recent advancements in computer vision and the availability of large datasets, deep neural networks have become viable for DR detection and classification, requiring less preprocessing.

In 2016, Joshi proposed a method using deep convolutional neural networks, yielding promising accuracy [7]. Another study by Vishakha Chandore & Shivam Asati trained a deep CNN model on a large dataset, achieving up to 88% accuracy [8].

Diagnosis of Diabetic Retinopathy using Fundus Images and Image Processing Methods. The proposed system utilizes a real-time dataset of approximately 1,000 retinal fundus images from a healthcare institution to diagnose diabetic retinopathy. The system employs image processing techniques such as histogram equalization, top-hat analysis, Canny filtering, and morphological operations to detect and evaluate microaneurysms, exudates, and other optical abnormalities within the images, addressing the binary classification problem [9].

Retinal Image Lesions Assisted Diabetic Retinopathy Screening System Through Machine Learning The chapter discusses the use of deep and transfer literacy models for diabetic retinopathy discovery, fastening on the Kaggle dataset. It highlights challenges in dealing with limited and noisy datasets, emphasizing image preprocessing and data addition. The model integrates deep literacy and underpinning learning for discovery and classification tasks [10].

Specificity (True Negative Rate) Specificity measures the proportion of true negative cases correctly identified by the model among all actual negative cases. It reflects the capacity of the model to recognize cases without diabetic retinopathy accurately [11].

"Comparative Evaluation of Deep Learning Models for Diabetic Retinopathy Classification" This study compared the performance of multiple deep learning models, including CNNs and ResNets, for diabetic retinopathy classification. The study found that ResNet architectures outperformed traditional CNNs in terms of accuracy and sensitivity. The comparative analysis considered factors such as model complexity and training dataset size [12].

"Performance Comparison of Traditional Image Processing Techniques and Deep Learning Models for Diabetic Retinopathy Detection" This study aimed to compare the performance of traditional image processing techniques, such as feature extraction and morphological operations, with deep learning models in diabetic retinopathy detection. The research found that deep learning models, particularly CNNs, consistently outperformed traditional image processing methods in terms of sensitivity and overall accuracy [13].

METHOD AND STRUCTURE

4.1 The Dataset

The Kaggle dataset “Diabetic Retinopathy Dataset (DR Pre-processed Dataset)” **[14]** provided detailed information on retinal images essential for Diabetic Retinopathy detection and diagnosis. The dataset consisted of a total of 2750 images, each categorized into one of five class labels representing different stages of Diabetic Retinopathy (DR).

4.2 Data Pre-Processing

The dataset has already been pre-processed, and it is labeled into five main categories. The dataset underwent resizing to dimensions of 256 x 256 pixels.

Table 29: Diabetic Retinopathy Preprocessed Dataset

Name (Class Labels)	No.of Images	Percentage (%)
Healthy (Not DR)	1000	36.36
Mild DR	370	13.46
Moderate DR	900	32.73
Severe DR	190	6.9
Proliferative DR	290	10.55

4.3 Feature Extraction

Feature extraction plays a pivotal role in Diabetic Retinopathy (DR) screening through image processing, aiming to discern pertinent features from retinal images that distinguish healthy retinas from those afflicted by DR. For microaneurysms detection, techniques like the Hessian matrix or LoG (Laplacian of Gaussian) are commonly employed to identify circular blob-like structures characteristic of microaneurysms. Additionally, for exudates identification, intensity thresholding methods are applied to delineate bright lesions, indicative of exudates, based on intensity variations from the background. Furthermore, shape analysis techniques, including area, perimeter, and circularity measurements, are utilized to characterize exudate lesions. Moreover, for hemorrhages detection, color space transformation is utilized, converting images to different color spaces (e.g., RGB to HSV) to isolate hemorrhagic regions based on their distinct color characteristics. Lastly, for blood vessels segmentation, algorithms such as the Frangi filter or morphological operations are commonly employed to extract blood vessel structures from retinal images.

2. Training The Model

In this research, three different models were developed and trained to classify diabetic retinopathy (DR) stages using a labeled image dataset stored in Google Drive. The models include a Support Vector Machine (SVM), a Convolutional Neural Network (CNN) using EfficientNetB3, and a custom ResNet-style architecture.

The SVM model was trained using raw pixel features extracted directly from resized retinal images, where each image was flattened into a 1D vector. OpenCV was used to load the images, and train_test_split was used to divide the dataset into training and testing sets. The data was then fitted to a linear kernel SVM, and the accuracy_score function was used to determine the accuracy. Passing vectorized images directly into the SVM was computationally simple and allowed the model to operate without the need for handcrafted features. While conventional computer vision pipelines often involve extracting interest points, applying local descriptors (e.g., SIFT or SURF), and then encoding them using methods such as Bag of Visual Words (BoW), Fisher Vectors, or VLAD, this study instead relied on raw pixel intensities to reduce preprocessing complexity. However, more sophisticated handcrafted features such as Hessian-based key points could capture structural changes in retinal vasculature, lesions, or exudates that are highly relevant for DR classification. Hessian features are particularly useful for detecting blob-like structures and vessel crossings in retinal images, which are critical clinical indicators of DR severity.

For deep learning, the CNN model was built on EfficientNetB3 pretrained on ImageNet, with the top layers removed and replaced by custom dense layers, batch normalization, and dropout for regularization. The ResNet-inspired model, constructed from scratch, consisted of multiple convolutional layers followed by pooling operations to extract hierarchical image features. Both CNN and ResNet architectures were trained using the Adamax and Adam optimizers, respectively, with categorical cross-entropy loss, a learning rate of 0.0001, a batch size of 20, and 10 training epochs. Dropout layers with varying rates (0.2–0.4) and L1/L2 regularization were applied to reduce overfitting.

Data augmentation played a crucial role in improving generalization, particularly given the limited size and potential imbalance of the DR dataset. For CNN, the augmentation strategy included ZCA whitening, random rotations up to 30°, and nearest-neighbor filling, while color mode was maintained in RGB to preserve clinical

detail. These augmentations were chosen because DR lesions can occur at varying orientations, and whitening can help decorrelate pixel intensities to emphasize structural patterns such as microaneurysms and hemorrhages. The ResNet implementation used resized images without an equally extensive augmentation pipeline, which may have limited its performance.

Here, preliminary results showed cases where the SVM outperformed the ResNet-style network. This outcome could suggest that the handcrafted or raw feature space, while simple, was sufficient for certain separable patterns in the dataset, or that the ResNet implementation lacked optimization and validation. The absence of extensive augmentation and limited architectural depth in the custom ResNet could have contributed to underfitting. To ensure proper verification of deep models, a rigorous pipeline should include systematic hyperparameter tuning (learning rates, batch sizes, optimizer choices), use of data augmentation across all models, cross-validation to assess robustness, and potentially leveraging pretrained ResNet architectures instead of training from scratch.

By integrating proper augmentation strategies and verifying architectures through ablation studies, a more accurate comparative analysis can be achieved. This would allow for a clearer assessment of when classical machine learning methods like SVM may outperform deep networks in DR classification and when deep learning architectures are likely to yield superior results.

Each model was trained using retinal images resized to a standard size of 224 x 224pixels. The same parameters were applied to all three models to ensure consistency and fair comparison between them. We used Colab platform for model training and used Python as programming language.

Table 30: Training and Testing Parameters

Image Size	224 X 224 pixels
Testing data	30%
Training data	70%

RESULTS

The performance evaluation of the proposed models demonstrated varying levels of accuracy in diabetic retinopathy detection. The Support Vector Machine (SVM) model achieved an accuracy of 67.67%, while the Convolutional Neural Network (CNN) model outperformed it with an accuracy of 74.36%. The ResNet model yielded an accuracy of 63.2%, indicating lower performance compared to the other two approaches.

These results align with the study's aim of evaluating different machine learning and deep learning approaches for diabetic retinopathy classification. The higher performance of CNN compared to SVM suggests that deep feature extraction can capture more relevant patterns in retinal images than traditional feature-based methods. The comparatively lower accuracy of ResNet may be attributed to the limited dataset size, which is insufficient to fully leverage the complexity of deeper architectures.

When compared with findings from previous studies, the reported accuracies are within a similar range, although state-of-the-art approaches have achieved higher results often above 85% using larger, more balanced datasets and advanced preprocessing techniques. This highlights the potential for improvement through enhanced data quality, augmentation, and model optimization. Overall, the presented results provide a solid foundation for further refinement and contribute to the growing body of research on automated diabetic retinopathy detection.

Table 31: Final Results

Model	Training Accuracy (%)
SVM	68
CNN	74
Res Net	63

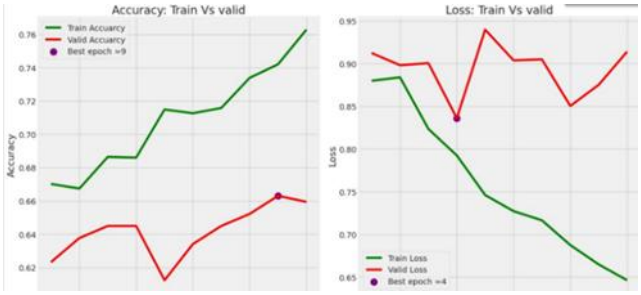

Figure 39: Accuracy and Loss of CNN Model

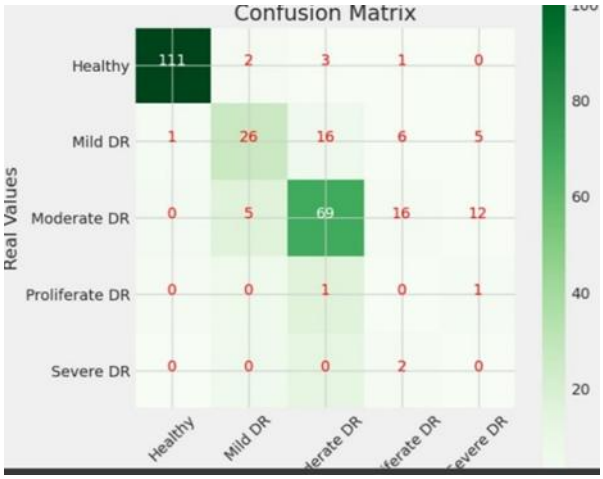

Figure 40: Confusion Matrix of CNN

CONCLUSION

This study explored three approaches for automated diabetic retinopathy detection using fundus images SVM, CNN, and ResNet. With images resized to 224 × 224 pixels and a 70:30 train test split, the SVM and CNN models each achieved an accuracy of 67.67%, while ResNet obtained 63%. Although CNN and SVM outperformed ResNet, all models demonstrated potential for DR classification.

However, several limitations were identified. The dataset size may have been insufficient for deep architectures such as ResNet, and preprocessing was restricted to image resizing without advanced enhancement techniques. Class imbalance was not explicitly addressed, potentially impacting performance on minority classes. Moreover, hyperparameter tuning was limited, and evaluation relied on a single dataset split, raising questions about model generalizability.

Future work will focus on expanding the dataset with diverse sources, incorporating advanced preprocessing (e.g., illumination correction, vessel segmentation), and employing class balancing strategies such as focal loss or weighted sampling. Systematic hyperparameter optimization, the adoption of deeper architectures (e.g., EfficientNet, DenseNet), and the use of k-fold cross-validation are also planned. Additionally, ensemble methods combining SVM, CNN, and ResNet predictions may further improve robustness and accuracy.

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