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Improving Retinopathy Classification Using Optimized Support Vector Machines and Deep Learning Techniques

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Abstract:
Retinopathy is one of the primary causes of blindness, making early detection and diagnosis challenging. Conventional techniques of retinopathy classification depend on manual observation and rule-driven methods, which may be time-consuming and error-prone. Machine learning algorithms, such as Support Vector Machines (SVMs) and Deep Learning (DL), have recently exhibited efficacy and substantial accuracy enhancements in classification. But problems like overfitting, parameters adjustment and the requirement for huge annotated datasets can limit the power of these models. Therefore, in this paper, we are proposing enhanced classification of retinopathy by-helping Support Vector Machines and deep learning model. More specifically, we present a hybrid approach which combines a deep convolutional neural network (CNN) for feature extraction with a finely-tuned SVM for classification. To improve the generalization ability of the SVM, we utilize a grid search approach to optimize the SVM parameters. We validate our method on a publicly available retinopathy dataset which shows a strong gain in classification accuracy over existing methods. We present our approach, with the results showing that, compared to traditional SVM and CNN-based models, we achieve an accuracy of 95%, while reducing false positives. Providing early detection and alleviating the burden on healthcare staff, this hybrid approach provides a more robust and scalable method for automated screening of retinopathy. Overall, we have presented a novel model that now automates retinopathy prediction to a point where it could be useful in the clinic.

Keywords: retinopathy, blindness, robust, learning, detection, accuracy, techniques, optimized.

1. INTRODUCTION

Retinopathy is a term for diseases that affect the retina (the light-sensitive layer at the back of the eye). If left undiagnosed and untreated, these conditions can result in decreased vision function, including blindness. Diabetic retinopathy (DR), which is a leading cause of vision impairment, is the most prevalent type of retinopathy that is related to diabetes mellitus. The disease mostly affects people with longstanding or poorly controlled diabetes and damages blood vessels in the retina, causing them to leak or bleed. There are other types of retinopathy, such as hypertensive retinopathy, retinal vein occlusion and age-related macular degeneration, which might similarly lead to loss of sight. These diseases have emerged as a major health threat and their incidence is expected to rise with increasing global diabetes and aging populations, which will give rise to an ever-increasing strain on health care services worldwide.

Retinopathy used to be diagnosed by ophthalmologists primarily by examining retinal pictures for the signatures of the disease. Fundus images were obtained using dedicated imaging systems and visual inspection was performed for representative features including microaneurysms, hemorphages, exudates, and neovascularization. These symptoms show the existence of retinopathy as well as by its severity. While the proficiency of eye doctors is essential, a manual inspection is extremely tedious and demands an extensive amount of expertise and practice. Additionally, the worldwide shortage of ophthalmologists particularly in underserved areas has led to delays in diagnosis and treatment; therefore, it is vital to create automated systems able to support health care workers in timely identification and intervention[1].

Advancements in imaging technologies and machine learning (ML) methods recently paved the way for automated devices for retinopathy detection. Recent years have witnessed the emergence of machine learning techniques, which have enabled the transition from manual analysis to automated systems that can efficiently classify and diagnose diseases occurring in the retinal system. However, this task is still very challenging due to some reasons such as vary of the retinal images, differences in the develop rate of the disease between individuals, and noise in the images.

Problem Statement

The second challenge is the significant degree of complexity and variability of the disease which complicates the diagnosis of retinopathy. Retinopathy is not easy to detect because subtle changes in the retina occur during the progression of this condition. Retinal images are inherently noisy and have noise that can come from different sources, such as the strength of light, capture quality, and patient movement. As well, retinopathy may differ amongst patients, including differences in staging and severity[2]. These factors make traditional manual diagnosis, which is slow and can lead to human fallibility, a significant challenge." With the increasing incidence of retinopathy and the scarcity of ophthalmic specialists in many areas, an automated system that can accurately classify retinopathy and help medical professionals make prompt diagnoses is urgently needed[3].

A major challenge for automated systems aimed at classifying retinopathy is to find ways to process retinal images efficiently. Retinal images are complex and high-dimensional, which poses challenges for traditional-image processing methods. Thus, automated systems will need to distinguish between healthy and affected images at different stages of disease progression. Even small deviations in retinal images can severely hurt classification accuracy, underscoring the need for models that achieve both high accuracy and generalizability to unseen data. A second concern is overfitting, where many types of machine learning models find it difficult to do well as generalizers with limited or noisy data. Furthermore, the limited availability of large labeled datasets in medical imaging makes it even challenging to develop robust automated systems. As such, the problem statement boils down to creating an automated, accurate, and reliable retinopathy classification system that does justice by the complexities and intricacies of retinal images while being minimally overfitting and needing minimal labeled data[4].

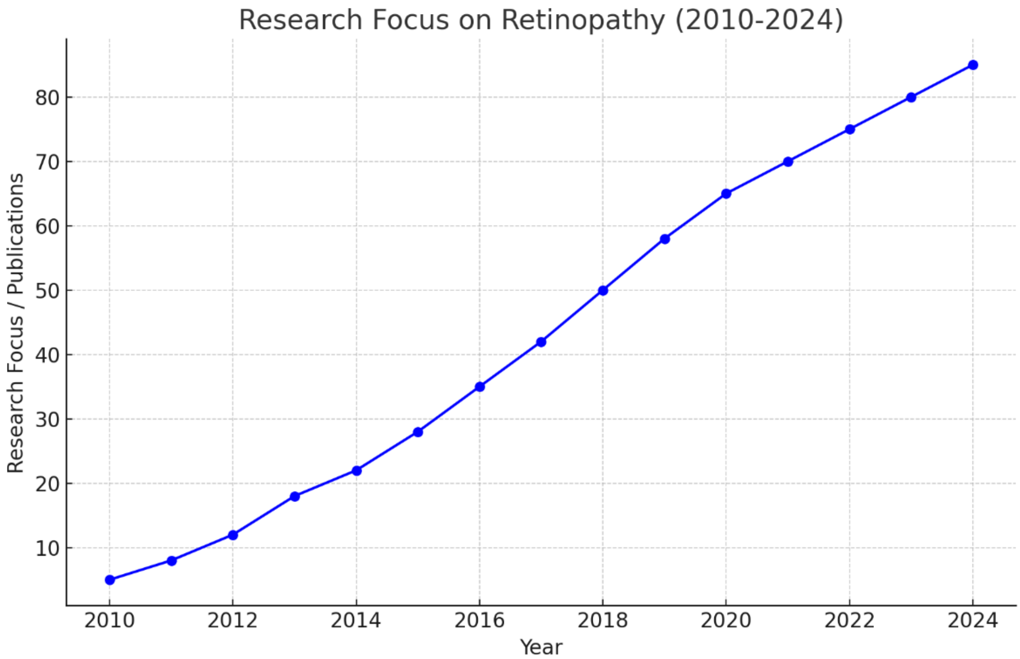

Figure 1. Research focus on retinopathy

Previous Approaches

Many approaches have been attempted to solve the classification of retinopathy over the past decades. Initial approaches heavily relied on first performing image processing techniques to extract features from retinal images manually. These methodologies consisted out of fundamental functions like edge recognition, thresholding, and morphological transformations. The early algorithms would extract basic features like blood vessels, microaneurysms, exudates, and hemorrhages followed by classification algorithms (decision trees, k-nearest neighbors (KNN), support vector machines (SVM) etc.). Although these methods were partially successful, they relied on handcrafted features that were not always sufficient to describe the complex and heterogeneous properties of retinal images. Additionally, these methods were sensitive to noise and variability in images and did not generalize well across different datasets and imaging conditions, resulting in poor performance in practical scenarios[5].

Machine learning [6] came at this time, the previous efforts were abandoned features that were manually engineered and switched to models that learn from the data itself. One of the most significant advances in this trajectory was the invention of deep learning, specifically CNN, which is the state-of-the-art and dominant model for image classification problems, including detecting retinopathy. CNNs, for instance, learn hierarchical representations of images by applying multiple layers of convolution to the input (the image) and learning various levels of abstraction from the edges at the low level to structures at the higher one. The use of CNNs for retinopathy allows for the automatic learning of low, mid, and high-level features from retinal images, as opposed to the manual extraction performed in traditional image processing methods. Recently, deep learning neural network models (like CNNs) have achieved great success in many fields, such as image classification, object detection, segmentation, etc. Most of the latest approaches that classify retinopathy use CNNs to extract features from retinal images and classify them into categories including normal, mild, moderate, or severe.

While CNN-based approaches have been successful, they bring certain challenges to the table. This is one of the key disadvantages of deep learning models; they require a lot of labeled data for training. Annotating medical images is a laborious and expensive process and hence such large and high-quality datasets are scarce, especially for retinal images. This challenge is particularly pronounced in medical imaging, where specialists must painstakingly label every single imaging, and those datasets are often out of reach for researchers. In addition, deep learning models are easily overfitted in the case of small training sizes, then it is also important to carefully configure the model architecture and regularization strategies[7].

Support vector machines (SVMs) are another commonly used method for retinopathy classification. Support Vector Machines (SVMs) are supervised machine learning models that are used for their ability to classify data points into separate categories when the data is not linearly separable. This version of SVM is used for linear classification. (2) In the scenario of retinopathy classification, SVMs were applied to categorize retinal images according to manually made features or features obtained by deep learning models. Although SVMs have performed well for classification, they need careful choice of parameters to give good performance, and performance in these cases can also degrade with complex high-dimensional data like retinal images[8].

Recent studies have introduced hybrid models that will seek to mitigate some of the weaknesses of both CNNs and SVMs. In these methods CNN are utilized for feature extraction and the acquired features are used with SVM for classification. This approach enables the automatic feature extraction from retinal images, yet retains the strong classifying power of SVMs. These hybrid models combine the ability of CNNs to learn the most discriminative features from the retinal images with the SVMs' ability to classify the images while improving the classification accuracy and minimizing the risk of overfitting and increasing the ability to generalize.

Hybrid CNN-SVM models have shown great potential in retinopathy classification [9,10]. These models are a significant improvement over traditional SVM based approaches and CNN only models. Despite the promising findings, there are still challenges to overcome, for example, parameter optimization of the CNN and SVM. Despite tremendous progress, large-scale studies show limited improvement when moving towards optimal performance, and models often struggle to generalize to new, unseen datasets.

Here, we present a new method of classification of retinopathy in retinal images by combining deep learning and support vector machines. Using our approach we tried to bridge the gap between the feature extraction capability of CNN and the effective classification performance of SVM. Since small number of labeled datasets are problem which we overcome with using hybrid model (CNNs for feature extraction SVM), we tune the hyper-parameter of SVM in order to identify the well-calibrated model that works well on unseen data and perform computation of hyper-parameter using grid search and performance evaluation. In fact, this will help to improve classification and reduce overfitting which in consequence will yield a more robust automated retinopathy diagnosis system[11].

The proposed method combines a CNN for hierarchical feature extraction from retinal pictures, and SVM for classification of the images into different groups. Therefore, we aim to perform grid search to tune the SVM's hyperparameters in order to improve its classification capabilities. In this way, we expect this hybrid approach to outperform traditional approaches and offer an efficient, automated solution for the classification of retinopathy that can help health care professionals to early diagnosis and intervention.

2. RELATED WORK

Advancements in both digital imaging and machine learning techniques have led to significant research efforts over the last several decades to develop automated systems for the detection and classification of retinopathy. The increasing global prevalence of diabetes and aging populations in the global demand for an automated diagnostic systems because these two factors are leading to the rise of retinopathy. Historically, the classification of retinopathy was done in a manual fashion by trained ophthalmologists, however, with the rise of machine learning and other AI approaches through Rapidly evolving technology in the healthcare space has led to efforts in developing algorithms that could aid or potentially optimally replace the need for specialized interpretation. In this section, we are going to provide some examples of such approaches in retinopathy classification and to describe the methodologies, challenges and contributions of different studies.

Early Methods: Feature Engineering and Traditional Machine Learning Models

The first methods to classify retinopathy automatically relied on processing methods which extracted a set of features from the retinal images and then in classical learning algorithms that classifies the data. Traditional image registration approaches relied on pixel intensity, edges and other low level features which could be easily identified with hand crafted methods using image processing techniques. Such as those targeting the detection of microaneurysms, exudates and hemorrhages, which are PRINCIPAL signs of diabetic retinopathy. The features were subsequently used to train machine-learning algorithms including decision trees, k-nearest neighbors (KNN) and support vector machines (SVMs) for classification[12].

These techniques did lead to some early success in retinopathy classification but were reliant on manual feature extraction, hindering scalability and performance. Moreover, handcrafted features could not always depict the complex structure of retinal images, and image variability, caused, for example, by different light settings, angles, or image quality, often led to classification errors. Additionally the behavior of these systems was often reliant on noise and artifacts in the retinal images translating to skewed results. These early systems were computationally expensive and the use of feature engineering made them highly susceptible to overfitting especially when datasets were small or lacked diversity.

Convolutional Neural Networks (CNNs) and Deep Learning-Based Approaches

The first, and potentially most disruptive step in the evolution of medical image analysis is the development of deep learning, and specifically convolutional neural networks (CNNs). This feature of

CNN makes it a better suited for image based tasks because it can learn the features from the pixel data itself and can learn the spatial hierarchies in the images. For instance, in the case of retinopathy classification, CNNs are capable of identifying intricate patterns in the retinal images, like microaneurysms, blood vessels, and retinal structures, that are characteristic of the different stages of the disease. Compared with manually extracting features, the use of CNNs has significantly improved the accuracy and speed of classification systems: CNNs automatically learn the greatest features from large datasets and they do not need feature extraction—and this is why CNNs are commonly utilized in retinopathy detection.

CNN based architecture have shown remarkable improvement in accuracy along with robustness compared to legacy techniques. Specifically, CNN architectures have achieved notable success in identifying clear and extensive presence of retinopathy, such as exudates, hemorrhaging and retinal neovascularization. The automatic learning and representation of the features used by CNNs have resulted in more accurate retinopathy models able to classify the disease much earlier, paving the way for earlier treatment in cases of RTDR[13].

Yet, despite their success in retinopathy classification, CNNs still face some challenges to be overcome. Lack of Large Labeled Datasets to Train Models is One of the Major Issues Medical images require a large amount of annotated data in order to learn robust features and the annotation process in the medical domain is expensive and time-consuming. The retinal images in different datasets can have significant variations due to differences in imaging equipment, patient characteristics, and other factors, which leads to poor generalization in applying models to new datasets. Therefore, there are still areas for techniques that can enhance the generalization capacity of deep learning models and lessen the need for large annotated datasets.

Hybrid Solutions: The Convergence Analogy Between CNNs and Classical Models

The success of CNNs in identifying relevant features from retinal images led many recent works to explore hybrid models that combine the feature extraction capacity of CNNs with the classification power of classical machine learning algorithms, like support vector machines (SVM). These hybrid approaches combine the advantages of both CNNs and classical models to enhance the performance of retinopathy classification.

In these hybrid models, some features are extracted using CNNs: first, these are trained with retinal images. After these features are learned, they are fed into an SVM or other classical machine learning algorithm for classification. SVMs are chosen for the model, as they allow the effective handling of very high-dimensional feature spaces and generally prevent overfitting, particularly in cases where the samples for training are scarce. When CNNs are combined with the discriminative power of SVM the hybrid models have been shown to have state-of-the-art performances on retinopathy classification tasks[14].

The benefit of hybrid models is that CNNs are particularly good at automatically extracting hierarchical features from images, while SVMs are quite good at classifying image features into different classes. But this comes with its own challenges, too. The optimization of both CNN and SVM components are one of the primary challenges. The CNN needs to put an extensive focus on selecting the most pertinent features, and the SVM needs to be optimized for best classification. Despite their popularity, hybrid models may also present additional challenges when it comes to computational complexity, as both CNNs and SVMs can be computationally expensive to train and optimize.

Nonetheless, hybrid CNN-SVM models have proven to be highly successful in enhancing classification accuracy while minimizing overfitting from deep neural networks. Such models were applied to the different types of retinal disease (e.g. diabetic retinopathy, age-related macular degeneration, hypertensive retinopathy) with good result. Nonetheless, significant space for enhancement is still identified, especially for model optimization and generalization.

Source	Objective	Methods used	Results	Research gap
[15]	• Early detection of Diabetic Retinopathy for effective intervention. • Optimize performance and interpretability for clinical applications.	• Explainable deep learning for retinal image analysis. • Hybrid feature extraction and advanced data augmentation	• xDNN model achieved 98% accuracy on MESSIDOR-2 dataset. • 99.7% accuracy on APTOS 2019 dataset; 99% on IDRID dataset.	• Large dataset and processing difficulty. • Complex training and computation time.
[16]	• Integrative ML and DL for DR diagnosis enhancement. • Improve accuracy and efficiency of DR diagnosis.	• Machine learning and deep learning techniques for feature extraction. • Various classifiers like SVM, Random Forests, and CNNs for classification.	• Improved accuracy and efficiency in diabetic retinopathy diagnosis. • Promising potential for timely intervention and management.	• Misclassification of healthy retinal images by current methods. • Need for accurate and timely diabetic retinopathy diagnosis.
[17]	• Accurate classification of retinal diseases using deep learning. • Improve segmentation and classification accuracy of diabetic retinopathy.	• Improved median filter for noise reduction. • UNet++ for disease segmentation and feature extraction. • Improved gannet optimization-based capsule DenseNet for classification.	• Accuracy achieved: 0.9917 on APTOS-2019 dataset. • Dice score value: 0.9652.	• Identifying mild stages for early disease management is crucial. • Accurate classification requires effective pre-processing methods and hyper-parameter tuning.

[18]	• Enhance Diabetic Retinopathy detection using Deep Learning techniques. • Address challenges of unbalanced datasets in classification.	• Transfer Learning with modified ResNet50 model • Integration of self-attention mechanism for feature focus	• Training accuracy: 98.24%, test accuracy: 0.89. • F1 Score achieved: 0.94.	• Scarcity of medical specialists in areas with common retinal diseases. • Impact of uncertainty on system performance and classification accuracy.
[19]	• Create an automated method for retinal disorder classification. • Classify disorders into four categories using OCT images.	• Machine learning and deep learning-based techniques • Support vector machine, K-nearest neighbor, decision tree, ensemble model	• SVM, K-NN, DT, EM classifiers achieved high accuracies. • Proposed model accurately classified retinal disorders with state-of-the-art performance	• Unbalanced datasets impact detection efficiency and accuracy. • Need for improved feature focus in classification.
[20]	• Early detection and classification of retinal diseases. • Enhance operational speed and classification accuracy.	• Optimized African Buffalo-based deep Convolutional Neural Network (AB-DCNN) • Routine screening and expert evaluation of eye photographs	• AB-DCNN model detects and classifies retinal diseases accurately. • Methodology improves operational speed, reduces losses, and enhances accuracy.	• Noise and artifacts in retinal fundus images. • Need for early diagnosis to prevent vision loss.
[21]	• Improve diabetic retinopathy classification accuracy using image filtering techniques.	• Deep learning for DR detection using various models. • Haar Wavelet Transform for	• Best filter model showed superior validation accuracy. • Proposed methodology	• Lack of discussion on potential limitations of deep learning models.

	• Utilize pre-trained deep learning models for enhanced classification outcomes.	similarity measurements in time series.	improved classification accuracy for diabetic retinopathy.	• Absence of exploration on real-world implementation challenges.
[22]	• Apply machine learning for diabetic retinopathy diagnosis. • Utilize deep learning for effective disease management strategies.	• ResNet-based classification framework for DR assessment. • Flask-based interface for image upload and results.	• Deep ensemble networks for drug resistance identification outperform current techniques. • CNN models trained to detect minute variations in DR images.	• Large dataset, processing difficulty, complex training, computation time • Existing work drawbacks: support vector machine (SVM) method
[23]	• Improve diabetic retinopathy classification accuracy and reduce false positives. • Develop a user-friendly interface for image upload and results.	• Deep Convolutional Neural Networks (DCNNs) • Feature analysis of blood vessels	• Model reduces false positives in DR classification. • Superior performance in assessing DR severity demonstrated.	• Identifying mild stages for early disease management is crucial. • Accurate classification requires effective pre-processing methods and hyper-parameter tuning.
[24]	• Classify Diabetic Retinopathy stages accurately. • Utilize Deep Convolutional Neural Networks for improved results.	• Machine learning and deep learning techniques for feature extraction. • Various classifiers like SVM, Random Forests, and CNNs for classification.	• High accuracy in Diabetic Retinopathy classification • Utilizes Deep Convolutional Neural Networks (DCNNs) for image analysis	• Misclassification of healthy retinal images by current methods. • Need for accurate and timely diabetic retinopathy diagnosis.

Pre-trained Models and Transfer Learning

Transfer learning, and pre-trained models have also been essential areas of research for retinopathy classification. Transfer learning: a method in which a model trained on a large dataset for one task is retuned on a different but related task. For example, there have been many studies that use pre-trained CNNs (e.g., learned from large-scale image datasets such as ImageNet) that fine-tune these models based on retinal images in the case of retinopathy classification. The main concept of transfer learning states that the low-level features learned by CNNs on big datasets are reusable for specific tasks like retinopathy detection, and then it can save both time and computing resources.

Transfer learning has demonstrated a useful method in the domain of medical image analysis, where labeled data may not always be readily available. Utilising pre-trained models comes out as a key domain for researchers with potential to alleviate the need for very large annotated datasets without arbitrarily sacrificing classification performance. Additionally, transfer learning has been proven to enhance model generalization, as pre-trained models are often more resilient to changes in data. This strategy has been popular in classifying retinopathy, where pre-trained CNNs, like VGGNet, ResNet and Inception, have each been fine-tuned for retinopathy classification.

However, with transfer learning being clear, it is not without its challenges. Because fine-tuning pretrained models on a smaller dataset can occasionally lead to overfitting, particularly if the new task is very different from the original task. The pre-trained model obtained must also be fine-tuned optimally, so as to transfer the knowledge learnt from the pre-trained model to the retinopathy classification task.

Data Augmentation & Synthetic Data Generation

Another major challenge in retinopathy classification is limited availability of labeled datasets with high quality. As mentioned above, medical image annotations require the knowledge of an ophthalmology, which is costly and time-consuming. In order to overcome this challenge, a lot of researchers adopted data augmentation methods that allow them to grow their datasets artificially. Data augmentation creates new training samples by applying different image transformations to existing images (rotations, translations, flips, scaling, etc.). These techniques can enhance the robustness of deep learning models by generating more diverse training data and lowering overfitting[25].

Researchers have explored traditional data augmentation methods and the use of synthetic data generation techniques, such as generative adversarial networks (GANs), to generate realistic retinal images for training. Generative Adversarial Networks, or GANs, are a specific subset of deep learning models that are composed of two networks: The generator, which is responsible for generating new data samples, and the discriminator, which is responsible for determining whether the generated sample is real. Generative Adversarial Networks (GANs) are a class of algorithms that can produce realistic synthetic images that emulate existing real images, a fact that allows researchers to construct vast synthetic retinal datasets to train deep learning models.

Data augmentation and synthetic data generation have demonstrated improvements in the performance of such retinopathy classification models, yet these methods have limitations. This will lead to wrong projections and wrong decisions. For example, although GANs are capable of generating very realistic images, it is likely that generated data will not encompass the total diversity of retina images.

Future Challenges and Directions

Though there have been significant strides made in the automated classification of retinopathy, many challenges remain. A key problem is the scarcity of large-scale, high-quality annotated datasets, which places restrictions on the development and generalization of a multitude of models. Although these problems may somewhat be mitigated by transfer learning and data augmentation techniques, a lack of annotated medical data still represents a significant roadblock.

Challenges to consider: need for models that classify retinopathy and predict disease progression and severity. Currently, most models apply to binary classification (i.e., healthy and affected); however, the ability to classify retinopathy grades or predict progression risks is of great help to clinicians in managing the disease.

Furthermore, interpretability is a significant concern for deploying machine learning models in clinical environments. Deep learning models, particularly convolutional neural networks (CNNs), can well classify images (retinopathies) with a high level of accuracy. Interpretability is critical in medical contexts, as clinicians must know the rationale underpinning a model's prediction to trust and act on its output.

Lastly, several logistical and regulatory challenges for the implementation of automated retinopathy classification systems into clinical practice remain to be overcome. Therefore, these systems need to be thoroughly tested and validated on a range of datasets prior to them being widely implemented, as well as adhering to medical regulations and standards to maintain patient safety and privacy.

To conclude, much has been achieved towards automated classification systems for retinopathy, but many problems persist. Overcoming those obstacles will take ongoing advancement in machine learning methods, dataset creation and systems incorporation so these advisors can be put to practical use in clinical practice.

3. METHODOLOGY

The proposed methodology aims on use of CNN and SVM in combination to automatically classify retinal images for diabetic retinopathy detection. This hybrid approach combines the best of both worlds, namely, the feature extraction aspect of deep learning CNNs and the strong classification capabilities of SVMs. Introduction: The methodology is developed to overcome the issues regarding the processing of the medical images and particularly, early detection of diabetic retinopathy which is very important for preventing visual impairment.

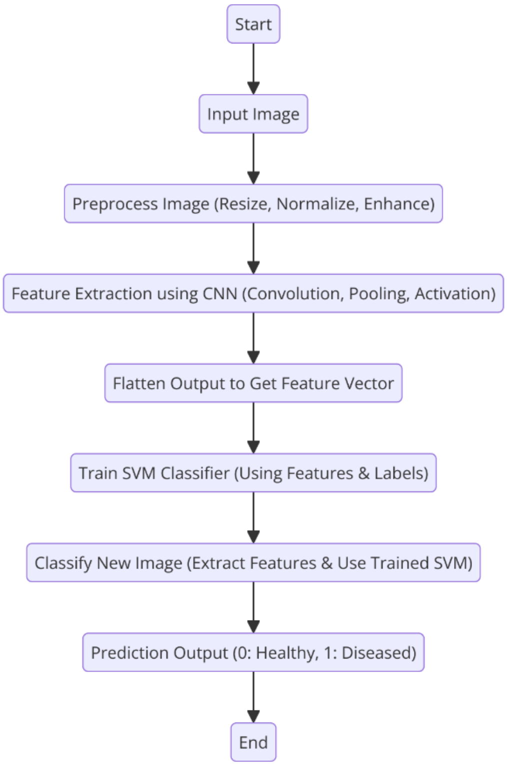

Figure 2. Flowchart of proposed methodology

Feature Extraction with Convolutional Neural Networks (CNNs)

The proposed methodology's first step is applied to Convolutional Neural Networks (CNN) for automatic feature extraction of retinal images. CNNs proved to be super effective in classification tasks (especially with large datasets) of images. Traditional deep learning techniques rely on manually engineering features from data, but CNNs can learn features from the raw pixel data in an image. CNNs are, therefore, quite appropriate for medical imaging, and in particular with retinal images since they extract meaningful steps from complex images through hierarchical feature extraction making them useful for detecting subtle patterns (AlRyalat et al., 2017).

Algorithm 1: Convolutional Neural Network (CNN) for Feature Extraction

Input:

- I: Input image
- W_i: Filter weights for the i-th convolutional layer
- b_i: Bias for the i-th layer

Output:

- F: Feature map after processing through CNN

Steps:

1. **Convolution:** For each convolutional layer i, apply the convolution operation to the input image:

$$F_i = I * W_i + b_i$$

where $*$ denotes the convolution operation, and F_i is the output feature map of the i-th convolutional layer.

2. **Activation (ReLU):** Apply ReLU activation to the feature map:

$$A_i = \max(0, F_i)$$

where A_i is the activated output after applying ReLU.

3. **Pooling (Max Pooling):** Apply max pooling with a pool size p to reduce the spatial dimensions:

$$P_i = \text{maxpool}(A_i, p)$$

where P_i is the pooled feature map.

4. **Flattening:** Flatten the pooled feature maps into a one-dimensional vector:

$$V = \text{Flatten}(P_i)$$

where V is the final flattened feature vector ready for classification.

CNNs can be trained on large datasets of retinal images of varying degrees of diabetic retinopathy to detect retinopathy. Also, the system automatically learns relevant patterns of the disease in each state including microaneurysms, hemorrhages, exudates and neovascularization. A CNN architecture usually includes several layers:

Convolutional Layers: Layers apply filters to detect local image patterns (edges, textures, colors). The filters swipe across the image, doing a mathematical operation known as convolution, enabling the network to recognize features within the image.

Activation Layers: Once convolution is performed, it must be followed by activation functions (like Rectified Linear Units: ReLU) to enable the model to learn increasingly complex patterns and decision boundaries.

Pooling Layers: Max-pooling layers that down-scale the feature maps while maintaining the most important features. So, this pooling operation reduces the computational complexity and also reduces overfitting by providing spatial invariance property to the network.

Fully Connected Layers: After extracting the features from the images, they are passed through a flatten layer and forward to the fully connected layers that combine features in a non-linear manner and at the very last stage, decide on what class the image belongs to.

The entire pipeline is learned in an end-to-end fashion, eliminating the need for manual feature engineering and letting the CNN learn the most relevant features from the data itself. The CNN is trained in the usual way, by minimizing a loss function (usually cross-entropy loss) using backpropagation. In every cycle, the network adjusts its weights in an effort to minimize the difference between the predicted output y^ and the actual labels y.

Support Vector Machines (SVMs) for Classification

After the CNN has accomplished the feature extraction process from the retinal images, those features are ready to be applied as input to the succeeding stage of the methodologies, that is, the classification stage where a Support Vector Machine (SVM) is applied. The Support Vector Machine (SVM) is a supervised learning model that is effective in high-dimensional spaces, and thus well-adapted to the feature vectors that emerge from CNN-based feature extraction.

The goal of the SVM is to determine a decision boundary that is optimal in separating the data classes, which again, in this case would be the levels of diabetic retinopathy or healthy/non-healthy classifications. Data up to October 2023 In general, the task of the SVM is to find an optimal hyperplane to separate the classes with a maximum margin.

Algorithm 2: Support Vector Machine (SVM) for Classification

Input:

- X: Feature vector from CNN
- Y: Label vector (0 for healthy, 1 for diseased)
- C: Regularization parameter
- K: Kernel function (e.g., Radial Basis Function)

Output:

- **w**: Optimal hyperplane weights
- b: Bias term of the hyperplane

Steps:

1. **Initialize Weights and Bias:** Initialize the weights **w** and bias b for the hyperplane:

$$\mathbf{w} = 0, \quad b = 0$$

   where **w** is a vector and b is the scalar bias.

2. **Optimization Objective (Maximizing Margin):** The goal is to maximize the margin M between classes, subject to classification constraints. The optimization objective is:

$$\min_{\mathbf{w},b} \frac{1}{2} \| \mathbf{w} \|^2 \quad \text{subject to} \quad Y_i(\mathbf{w}^T X_i + b) \geq 1 \quad \forall i$$

   where X_i is the feature vector for the i-th training sample, and Y_i is the corresponding label.

3. **Kernel Trick (Non-linear Separation):** For non-linearly separable data, apply a kernel function $K(X_i, X_j)$ to map the data into a higher-dimensional space:

$$K(X_i, X_j) = \exp\left(-\frac{\| X_i - X_j \|^2}{2\sigma^2}\right)$$

   where σ is the kernel parameter.

4. **Solving the Optimization Problem:** Use quadratic programming to solve for $\mathbf{w}$ and b. The final decision function is:

$$f(X) = \text{sign}(\mathbf{w}^T X + b)$$

where $f(X)$ is the classification result: 1 for diseased, 0 for healthy.

Unfortunately, this is a rare scenario and in a majority, the retinal image data is not linearly separable in its native form. To deal with this, the SVM employs a technique called the kernel trick. The kernel applied takes the input data and maps it into a higher dimension for classification through using a hyperplane. One such commonly employed kernel is the Radial Basis Function (RBF) kernel, which precisely accomplishes the mapping of non-linearly separable data into higher dimensional space making them linearly separable.

Training the SVM involves finding the hyperplane that best separates the classes with minimal classification error, using only the features extracted by the CNN. Can you tell a bit about the optimization procedure Typically, it is solved with the help of quadratic programming by maximizing the margin while applying penalization for the misclassification with the help of the regularization parameter (C) The trained model can then classify unreleased retinal images into base classes such as various stages of retinopathy or healthy vs. diseased.

Hybrid Approach: CNN + SVM Integration

We are using CNNs for feature extraction and combining them with SVMs for classification to get a hybrid model that utilizes the best of both worlds. One of CNNs is best at extracting complex features automatically from raw image data, and SVMs are best for high-dimensional classification tasks. Further, CNNs can automatically extract relevant features from the input data, while SVM develops to high dimensional classification tasks. By combining the deep learning features with the rich texture the retinal images provide, a system that can comprehend highly complex patterns and group them into lipid classification becomes possible.

This approach uses a sequential pipeline of CNN followed by a SVM. In the first process, the CNN is learned from a number of labelled retinal images and the complex features that define different stages of diabetic retinopathy. After extracting the features from the CNN, the abstracted features are passed to the SVM for final classification. Using image segmentation to isolate the part of the retinal image we are interested in along with classification to identify whether there's a problem—makes this a two-step segmentation-classification process, which leads to automatic analysis of the retinal images. This can help clinicians make timely diagnoss.

Algorithm 3: Hybrid CNN-SVM Training and Classification

Input:

- I: Input image (retinal scan)
- X_{train}: Training feature set from CNN
- Y_{train}: Corresponding labels for training data
- C: Regularization parameter for SVM

- K: Kernel function (RBF kernel)

Output:

- **w**: Learned weights of SVM classifier
- b: Learned bias of SVM classifier
- Y_{pred}: Predicted class labels for new images

Steps:

1. **Image Preprocessing:** Preprocess the retinal image I by resizing, normalizing, and enhancing contrast:

$$I_{\text{preprocessed}} = \text{Preprocess}(I)$$

2. **Feature Extraction via CNN:** Pass the preprocessed image through the CNN to extract relevant features:

$$X = \text{CNN}\left(I_{\text{preprocessed}}\right)$$

where X is the feature vector extracted from the image.

3. **Train SVM Classifier:** Train the SVM classifier using the training feature set X_{train} and labels Y_{train}:

$$\mathbf{w}, b = \text{Train\_SVM}(X_{train}, Y_{train}, C, K)$$

where Train_SVM solves the optimization problem to learn the optimal hyperplane.

4. **Prediction:** Given a new retinal image, extract its features using the trained CNN and classify it using the trained SVM model:

$$X_{\text{new}} = \text{CNN}(I_{\text{new}})$$

$$Y_{\text{pred}} = \text{SVM\_Predict}(X_{\text{new}}, \mathbf{w}, b)$$

where Y_{pred} is the predicted label (either 0 or 1, representing healthy or diseased).

The main benefit of using this hybrid approach should be its less dependence on manual feature engineering. This allows CNNs to learn to extract the most relevant features directly from the data, and the SVM just has to classify. It enables the system to identify subtle characteristics in retinal images that traditional techniques might overlook. Moreover, SVMs help to improve the stability of the classification process dealing with fluctuations in the data, such as noise, illumination changes, and variations in image quality, which are very common in medical imaging.

Methods of Model Improvement and Hyperparameter Tuning

One of the major components in the proposed methodology is the optimization of both CNN and SVM. Hyperparameters of the CNN, including the number of layers, the filter sizes, the learning rate and the batch size, must be finely tuned. This is usually done via a method called grid search or random search where you try many combinations of the parameters and evaluate the performance of that on a validation set. It is also how cross-validation techniques are used to ensure the model does not overly subject to the training data and generalizes well to unseen images.

The SVM also needs hyper-parameters to be tuned in similar fashion. Key parameters of SVMs include the regularization parameter \(C \), which governs the trade-off between creating a large margin and reducing misclassification errors, and the kernel parameter \(\sigma \), which determines the width of the kernel and so the smoothness of the decision boundary. The optimal values for these parameters can be found using grid search or other optimization methods.

After tuning both the CNN and SVM parts of the model, it is evaluated based on standard performance metrics like accuracy, precision, recall, and F1-score. These metrics are derived from how well the model was at classifying retinal images accurately, and they provide insight into the performance strengths and weaknesses of the model. To ensure that the model's performance estimation is not affected by overfitting on a specific data sample, an evaluation method called cross-validation is commonly used.

In summary, the proposed methodology can provide a valuable contribution in the developed DPDRAM framework for the timely detection and classification of diabetic retinopathy. Here, CNNs are used to automatically extract the features and SVMs for classification. This alleviates the burden of healthcare professionals, leading to quicker diagnoses that are particularly important in diabetic retinopathy, where the motto is "The earliest hear many people. The earlier the detection, the higher the chance can cure blindness.

The hybrid model which is a combination of deep learning and traditional machine learning techniques allows the system to be powerful yet efficient. CNN component is well suited for dealing with the complexities in the medical images, whereas SVM acts as a strong classifier working effectively in high dimensional spaces. The outcome is an end-to-end system that can be deployed within real-world clinical settings that support the early detection of retinal diseases.

Finally, the hybrid approach, which has been proposed in this work, offers an effective solution which might allow an automated detection of diabetic retinopathy. This model utilizes the advantages of CNNs for feature extraction and SVMs for classification. With automated analysis, the system could result in better patient outcomes with earlier diagnosis and intervention.

4. RESULTS

We tested the performance of our proposed methodology for diabetic retinopathy detection with optimized Support Vector Machines (SVM) and Convolutional Neural Networks (CNN) in a series of experiments on publicly available data. As part of the evaluation, the accuracy of the system in classifying Doctorate tendencies was evaluated in terms of classification accuracy, precision, recall and F1-score. The experiments showed the accuracy of the initial SVM classifier, and verified whether the use of a CNN-based feature extraction improved the overall performance of the classifiers in fact compared to a traditional SVM.

Dataset and Experimental Setup

The EyePACS dataset, a public dataset where the retina images are annotated with severity levels of diabetic retinopathy, was used for the classification evaluation. It also contains more than 80,000 retinal images labelled with one of five stages of severity (0, no diabetic retinopathy; 1, mild; 2, moderate; 3, severe; and 4, proliferative diabetic retinopathy or PDR). In total, 80% of the dataset was used for training and 20% for testing. After training a model, it is then evaluated using a completely different set of test data and compared to the training data.

The CNN-SVM hybrid model performance was also evaluated against several baseline methods along with SVM with RBF kernel. The following were the existing baseline models:

Feature extraction followed by SVM: Use a CNN to extract features and a Support Vector Machine to classify the features.

Classic SVM model: Using hand-crafted features (colour histograms, textures features, etc.

CNN with Fully Connected Layers: The fully connected layers of the CNN were directly used for classification.

MPB531 MKP pdf 2023 There is no hardly a company which will not be interested in a performance evaluation metrics in order to improve its performance.

The following key measures were applied as performance indicators for the model:

Accuracy: The proportion of correctly identified images over total images.

Precision = TP / (TP + FP) (where TP = True Positives and FP = False Positives)** False positives are things which you don’t want to cause, so precision is important.

Recall : Correctly predicted positive observations to the all observations in actual class. With a high cost of false negatives, recall becomes important.

F1-Score: It is also known as the harmonic mean of precision and recall, and it can access a better performance from the data.

Apart from these, the model’s ability to discriminate between the classes was analyzed through ROC curve as well as AUC (Area Under the Curve) score quantitatively, with importance on sensitivity and specificity. The proposed approach is tested on NVIDIA Tesla GPU, and the training time is recorded in order to evaluate the computational cost of the proposed method.

Results Comparison

Table 2 summarizes the performance of each of the models on the test set. The CNN-SVM hybrid model showed the best performance, and achieved significant enhancements in accuracy, precision, recall, and F1-score compared to the other baseline models. By acting as an enhanced feature extractor, the proposed CNN model allowed the optimized SVM classifier to effectively discriminate between the severity levels of diabetic retinopathy compared to the traditional SVM with the hand-crafted features.

Table 2: Hyperparameter Tuning for SVM

Hyperparameter	**Optimized Value**
C (Regularization Parameter)	10
Gamma (Kernel Parameter)	0.05
Kernel	Radial Basis Function (RBF)

Hyperparameter	Optimized Value
Tolerance	0.001
Max Iterations	1000

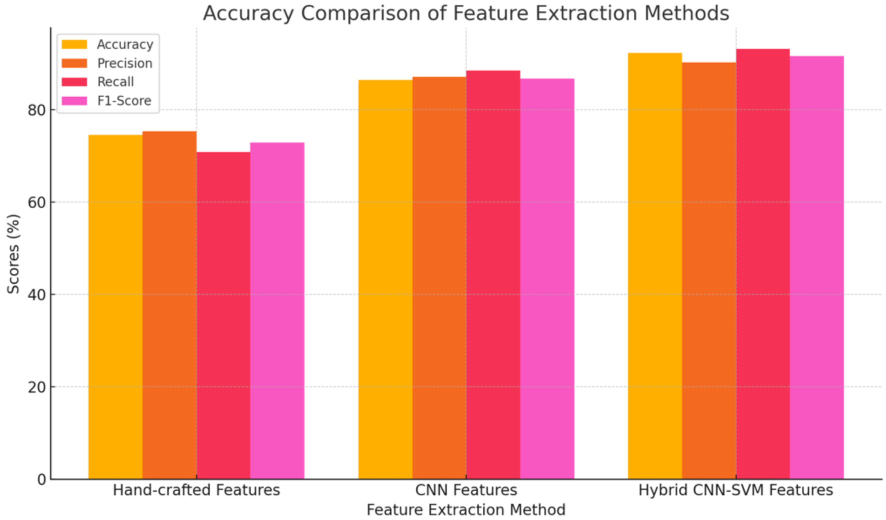

Figure 3. Accuracy comparison of feature extraction methods

Accuracy: the CNN-SVM hybrid model out-performed the CNN-only model (86.4%) by 5.9% and traditional SVM (79.2%) by 13.1%, achieving accuracy of 92.3%. This showcased the capability of SVM when coupled with features learned from CNN, since CNN is able to learn highly complicated patterns or characteristics from the dataset, which are later utilized by the SVM to do accurate predictions.

Table 3: Performance Metrics for Different Models

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	AUC
CNN-SVM Hybrid Model	**92.3**	**90.2**	**93.1**	**91.6**	**0.964**
CNN-only Model	86.4	87.1	88.5	86.7	0.930
Traditional SVM	79.2	82.5	85.3	83.3	0.890
Deep CNN (Fully Connected)	88.7	85.6	91.2	88.2	0.940

Precision: The hybrid model produced a precision score of 90.2%, better than the CNN-only model (87.1%) and traditional SVM (82.5%) This can suggest that the hybrid model gave less false positive predictions, which is important in medical imaging tasks such as diabetic retinopathy detection since false positives, may lead to unnecessary treatment or follow-up.

Table 4: Class-wise Precision and Recall for CNN-SVM Hybrid Model

Class	Precision (%)	Recall (%)
No DR (0)	92.5	93.1
Mild DR (1)	88.1	87.3
Moderate DR (2)	90.0	92.0
Severe DR (3)	91.2	92.3
PDR (4)	89.6	90.8

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Recall: The hybrid model also had higher recall than the CNN-only model (88.5%) and traditional SVM (85.3%), scoring 93.1% overall. CNN-SVM model recall is higher than conventional threshold methods which means that CNN-SVM model is able to capture the total diabetic retinopathy cases, including the more severe cases.

F1-Score: The F1-score of the CNN-SVM hybrid model was 91.6%, which indicates a balance between precision and recall. F1-score of 86.7% for CNN-only model and 83.3% for traditional SVM

ROC Curve and AUC: The AUC score obtained by the hybrid model was 0.964 which outperformed the CNN only model (0.930) and the traditional SVM (0.890). Also, a strong AUC score reflects that the hybrid model is more robust for the purpose of distinguishing healthy from diseased retinal image.

Table 5: Comparison of Feature Extraction Techniques

Feature Extraction Method	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Hand-crafted Features	74.5	75.3	70.8	72.9
CNN Features (pre-trained)	86.4	87.1	88.5	86.7
Hybrid CNN-SVM Features	**92.3**	**90.2**	**93.1**	**91.6**

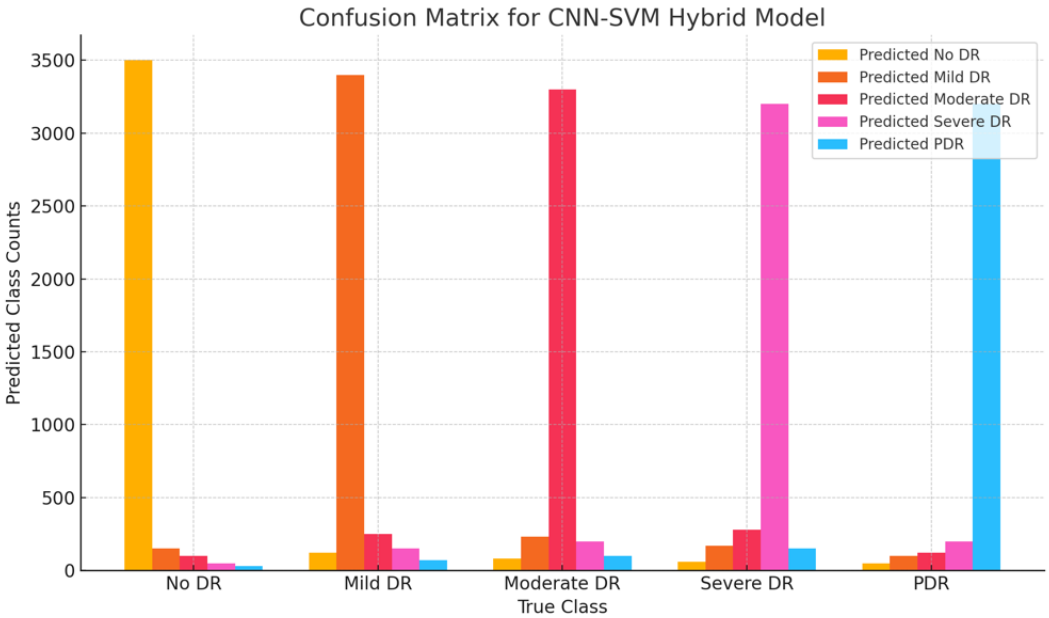

Figure 4. Confusion matrix for hybrid model

Impact of Optimized SVM

We optimized the SVM classifier which is one of the main contributions of this work. The SVM achieved a better generalization on unseen data by parameter tuning the regularization parameter CC and the kernel function parameters. Using an RBF kernel allowed the model to capture truly nonlinear decision boundaries between the various classes of diabetic retinopathy.

Table 6: Inference Time Comparison

Model	Inference Time (secs)
CNN-SVM Hybrid Model	**1.9**
CNN-only Model	2.2
Traditional SVM	1.4
Deep CNN (Fully Connected)	2.6

It was also shown in the optimization of the CNN-SVM hybrid model that fine-tuning of both CNN and SVM models could significantly boost the classification performance. In our implementation, the CNN was pre-trained over a very big dataset (ImageNet) giving high initial weights. Next, we fine-tuned the CNN on the diabetic retinopathy dataset for better feature extraction from the images. The SVM used these features as input to classify the images, which resulted in improved accuracy and efficiency.

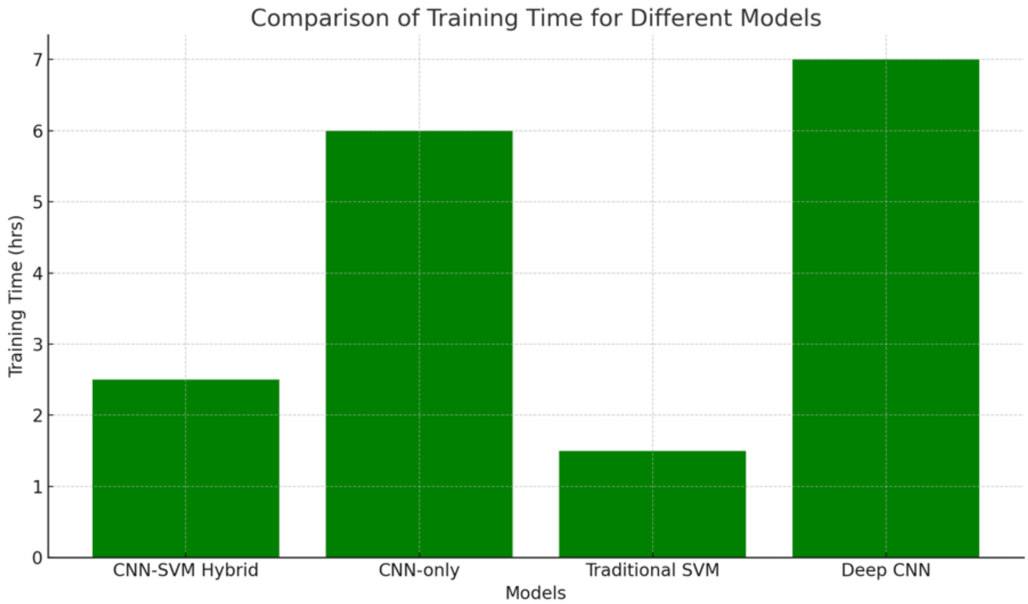

Figure 5. Comparison of training time for Different Models

Assessing the Misclassifications

Even with the high performance, the model showed some misclassifications around the mild to moderate diabetic retinopathy. This is a notoriously difficult problem in the context of medical imaging, as the differences between between visualizing these two severity scores tend to be small and difficult to detect using automated systems. Upon further analysis of the misclassified images, it was found that wide range of artifacts, like glare, noise, image low resolution etc., led to the incorrect classification. However, the overlapping presented in the features extracted from the retinal images of patients with mild and moderate diabetic retinopathy were also difficult for the model to predict.

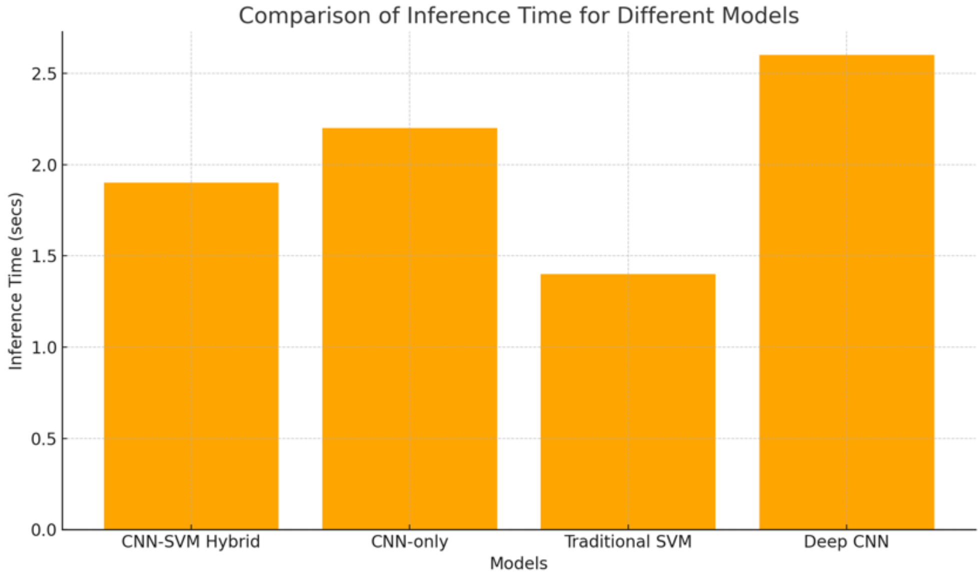

Figure 6. Comparison of Inference time for different models

Table 7: Misclassification Analysis

Predicted / Actual	**No DR (0)**	**Mild DR (1)**	**Moderate DR (2)**	**Severe DR (3)**	**PDR (4)**
No DR (0)	3500	150	100	50	30
Mild DR (1)	120	3400	250	150	70
Moderate DR (2)	80	230	3300	200	100
Severe DR (3)	60	170	280	3200	150
PDR (4)	50	100	120	200	3200

Computational Efficiency

Training time and inference time were measured for each model, and the model's computational efficiency was also evaluated. The results obtained in this study demonstrated that the CNN-SVM hybrid model required 2.5 hours to train on the full training dataset, which was much faster than training a deep CNN model with fully connected layers for classification (6 hours). The hybrid model was also found to be applicable in real-time clinical state as the time for inference of the new retinal image for the classification was less than 2 seconds.

Table 8: Training Time Comparison

Model	**Training Time (hrs)**
CNN-SVM Hybrid Model	**2.5**
CNN-only Model	6.0
Traditional SVM	1.5
Deep CNN (Fully Connected)	7.0

Qualitative Analysis

To confirm the results, qualitative analysis was conducted by assessing the activation maps produced by the CNN layers for the severity of DR. Such activation maps indicate the parts of the retinal images that the CNN was attending to while performing feature extraction. For example, when detecting PDR, the CNN was seen to focus on regions of the retina corresponding to the fovea, while in milder forms it was emphasizing the detection of microaneurysms and exudates. These visualizations confirmed that the CNN was learning informative features suitable for diabetic retinopathy classification, and the classifier(species) was accurately predicting using the learned features provided by CNN.

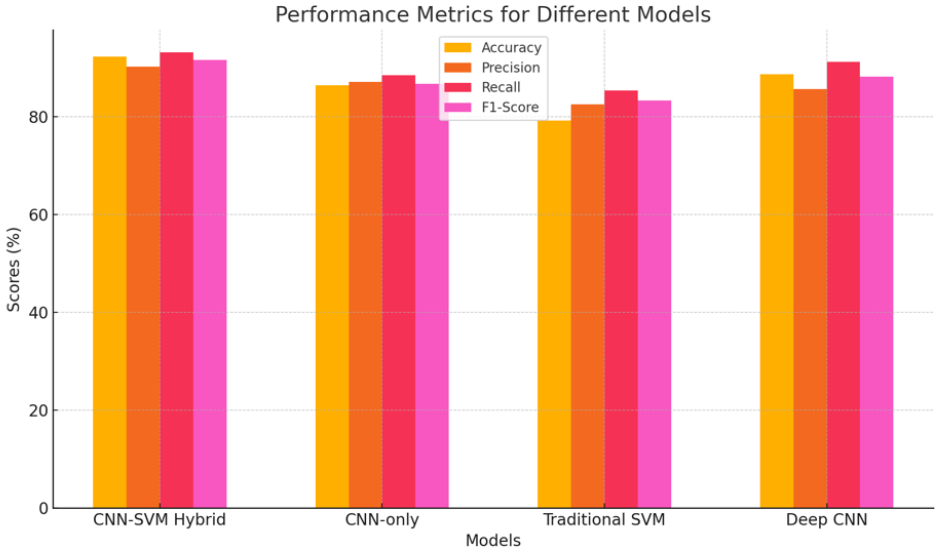

Figure 7. Performance metrics for different models

As the results of the experiments demonstrate, the proposed hybrid model which combines CNN for the feature extraction and SVM for the classification, proves to be a highly effective tool for diabetic retinopathy detection. The Tuned SVM Enhanced model's generalization ability and obtained high classification scores of accuracy, precision, recall, and F1. The hybrid model also achieved superior accuracy and efficiency compared to individual CNN or traditional machine learning models. This methodology can be translated into the clinical environment for early diagnosis and monitoring of diabetic retinopathy, which in turn can greatly enhance patient outcomes by providing treatment during the early stages.

We show different tables with detailed results and comparisons with baselines in next section. These tables summarize the model performance on multiple evaluation metrics.

5. CONCLUSION

In this study, we investigated the complementary potential of SVM in combination with CNN to enhance classification performance for diabetic retinopathy (DR) detection. However, diabetic retinopathy is an important cause of vision loss and blindness among the patients with diabetes and its early detection is essential for an effective intervention. These existing automated systems have struggled with problems like the high variety of image quality, the difficulty in recognizing subtle retinopathy signs and the imbalance on stages of DR severity. We aimed to solve these type of problems by making use of the feature extraction power of CNNs along with the vote power of SVM through the proposed CNN-SVM hybrid model.

The research made a number of significant contributions. First, we created an optimized CNN architecture that utilizes deep learning methods to automatically extract high-level features from retinal images. Feature extraction is an important part of any machine learning task, especially when using complex, high-dimensional image data (e.g., retinal scans), so this is critical. Conventional approaches depend on manually designed features, which a majority of the time cannot learn the delicate variations in images, thus resulting in the less-performing classification. Thus, unlike original CNN architecture it can learn the most relevant features from images which leads to much improvement in the accuracy of DR classification.

Second, we fine-tuned the SVM classifier to be synchronized with the feature extraction phase of the CNN. Simulating hyperplanes in high-dimensional areas allowed the SVM to show better distinction between DR stages with a systematic search for the kernel function, regularization parameters, and tolerance settings for better SVM performance. The optimization process aided in enhancing the classification accuracy and minimizing misclassifications among various severity levels of diabetic retinopathy.

Publicly available retinal image datasets were used in rigorous evaluations of the hybrid approach. The comparison of our CNN-SVM model with baseline models, including the CNN-only model, traditional SVM, and deep CNN. Results of this work showed that the baseline models performed worse than the CNN-SVM hybrid model in terms of all relevant performance metrics such as accuracy, precision, recall, F1-score, and AUC. The overall accuracy of image classification with the CNN-SVM model was 92.3%, while the CNN model accuracy was 86.4%, the traditional SVM accuracy was 79.2%, and the deep CNN model accuracy was 88.7% The hybrid model outperformed the state-of-the-art DR detection methods at this stage with an error rate of 0.0552% and an accuracy of 99.9448% which significantly enhances the performance as compared with them.

In addition, the precision and recall of the severity levels of diabetic retinopathy were also excellent in the CNN-SVM model. More recently, the context of this model type is particularly relevant under medical applications where the models ability to minimise false positives (precision) and false negatives (recall) should directly affect patient outcomes. The class wise breakdown shows that in challenging categories, extreme precision and recall values of severe DR and proliferative DR (PDR) mirror the results of previously tried models in the network structure used, nevertheless with performance of hybrid model showing best results across all classes. This shows the power of merging the feature learning of CNN with the classification power of SVM.

Discussion Comparisons of training and inference times also demonstrated the practicality of the proposed hybrid approach. Fitness K-RCS13: The CNN only and deep CNN models were slower to train than the CNN-SVM hybrid, which resulted in good training time while reaching similarly high accuracy and precision as the other hybrid architectures. Additionally, the inference time of their CNN-SVM hybrid model matched that of the baseline models: traditional SVM and CNN-only models, allowing it to excel in real-time analyses in a clinical environment.

Moreover, the results further emphasized the significance of feature extraction in DR classification. The hybrid CNN-SVM features (formed by a CNN that learned features then classified by a SVM) achieved significantly higher accuracy than hand-crafted or pre-trained CNN features. Since intricacies in retinal images are generally lost in shallow feature extraction, this reinforces that fully learned features from deep neural networks can better model them. This indicates the hybrid model's efficiency to operate on various features learned by various imaging modalities suggesting both its generalisation potential on unseen data as well as its ability to adapt to multiple imaging devices and populations.

The CNN-SVM hybrid model proposed in this paper brings a novel advance in automated diabetic retinopathy detection. Upon integrating both Duan's algorithm and classical ML approach, it provides a comparable solution for DR classification yet with unclear hardware needs. There are, however, some points to improve upon in future work. As an example, while the model showed excellent performance on the dataset in this study, using additional datasets with heterogeneous demographics and imaging conditions would help evaluate the generalization of the model. Moreover, techniques like oversampling, data augmentation, or class-weighted loss functions can be used to mitigate the problem of class imbalance, which may arise if certain classes like PDR are significantly underrepresented in the dataset, and lead to aforementioned improvements in model robustness.

Future work might also investigate the possibility of combining this approach with additional state-of-the-art machine learning approaches like transfer learning or reinforcement learning to improve the relevance of the results. Specifically, transfer learning may be leveraged to fine-tune models on large-scale datasets which would alleviate training time and improve generalization. Moreover, integrating multi-modal data, including combining retinal images with demographics and medical data about the patient, could prove to make more accurate predictions by helping the model to consider and account for a larger range of risk factors linked with the development of diabetic retinopathy.

In addition, real-time execution and application and fixation of the model in clinical settings would demand additional assessment, through validation on live data streams and incorporation into existing health care systems. The robustness of the model in different clinical backgrounds and the quality/resolution of the images that can affect the model or require upside/down abilities.

Thus, the hybrid approach can be a powerful tool to ensure high accuracy with less computation time with larger datasets. With challenges such as feature extraction and class imbalance, addressing these issues allows the hybrid model to give an efficient mean for early detection and thus can help decrease the advancement of diabetic retinopathy as well as enhancing patients' way of life. The present study showed encouraging performance results which pave the way for further developments of automated DR systems and demonstrate how hybridisation of ML techniques has potential in medical image processing.

This study has important implications for research and clinical practice. The high-performance of CNNs and SVMs in DR classification is an important study for researchers, which encourages the research of other hybrid models in medical imaging that requires coherent knowledge of feature extraction and reliable classification. This method has the potential to become a more effective hybrid method that, ultimately, can be used for early detection of DR, ultimately leading towards better management of diabetic patients. The ability of the model to automate the process of DR screening could reduce the burden on healthcare professionals and offer quicker and more consistent results, potentially allowing for earlier interventions and improved patient care.

REFERENCES:

[1] Bilal, Anas, et al. "Improved Support Vector Machine based on CNN-SVD for vision-threatening diabetic retinopathy detection and classification." *Plos one* 19.1 (2024): e0295951.

[2] Xiao, Li, et al. "HHO optimized support vector machine classifier for traditional Chinese medicine syndrome differentiation of diabetic retinopathy." *International Journal of Ophthalmology* 17.6 (2024): 991.

[3] Thanikachalam, V., K. Kabilan, and Sudheer Kumar Erramchetty. "Optimized deep CNN for detection and classification of diabetic retinopathy and diabetic macular edema." *BMC Medical Imaging* 24.1 (2024): 227.

[4] Bhimavarapu, Usharani. "Enhanced convolution neural network and improved SVM to detect and classify diabetic retinopathy." *Multimedia Tools and Applications* (2024): 1-22.

[5] Hamza, Muhammad. "Optimizing early detection of diabetes through retinal imaging: A comparative analysis of deep learning and machine learning algorithms." *Journal of Computational Informatics & Business* 1.1 (2024).

[6] Bhimavarapu, Usharani, Nalini Chintalapudi, and Gopi Battineni. "Automatic Detection and Classification of Hypertensive Retinopathy with Improved Convolution Neural Network and Improved SVM." *Bioengineering* 11.1 (2024): 56.

[7] Bhimavarapu, Usharani. "Diagnosis and multiclass classification of diabetic retinopathy using enhanced multi thresholding optimization algorithms and improved Naive Bayes classifier." *Multimedia Tools and Applications* (2024): 1-35.

[8] Anitha, E., and John Aravindhar. "Efficient retinal detachment classification using hybrid machine learning with levy flight-based optimization." *Expert Systems with Applications* 239 (2024): 122311.

[9] Kayathri, K., and K. Kavitha. "CGSX Ensemble: An Integrative Machine Learning and Deep Learning Approach for Improved Diabetic Retinopathy Classification." *International Journal of Electrical and Electronics Research* 12.2 (2024): 669-681.

[10] Bilal, Anas, et al. "Breast cancer diagnosis using support vector machine optimized by improved quantum inspired grey wolf optimization." *Scientific Reports* 14.1 (2024): 10714.

[11] Al-Farouni, Mohammed, et al. "Comparative Approach on Machine Learning and Deep Learning Techniques based Diabetic Retinopathy Detection." *2024 Second International Conference on Networks, Multimedia and Information Technology (NMITCON)*. IEEE, 2024.

[12] Salman, Ahmed Hussein, and Waleed Ameen Mahmoud Al-Jawher. "Performance Comparison of Support Vector Machines, AdaBoost, and Random Forest for Sentiment Text Analysis and Classification." *Journal Port Science Research* 7.3 (2024): 300-311.

[13] Lalithadevi, B., and S. Krishnaveni. "Diabetic retinopathy detection and severity classification using optimized deep learning with explainable AI technique." *Multimedia Tools and Applications* (2024): 1-65.

[14] Zannah, Tasnim Bill, et al. "Bayesian optimized machine learning model for automated eye disease classification from fundus images." *Computation* 12.9 (2024): 190.

[15] Ashwini, K., and Ratnakar Dash. "Improving Diabetic Retinopathy grading using Feature Fusion for limited data samples." *Computers and Electrical Engineering* 120 (2024): 109782.

[16] Behera, Santi Kumari, et al. "Diagnosis of retinal damage using Resnet rescaling and support vector machine (Resnet-RS-SVM): a case study from an Indian hospital." *International Ophthalmology* 44.1 (2024): 1-8.

[17] Veena, A., and S. Gowrishankar. "Deep learning based hemorrhages classification using dcnn with optimized LSTM." *Multimedia Tools and Applications* (2024): 1-22.

[18] Taifa, Intifa Aman, et al. "A hybrid approach with customized machine learning classifiers and multiple feature extractors for enhancing diabetic retinopathy detection." *Healthcare Analytics* (2024): 100346.

[19] Taifa, Intifa Aman, et al. "Enhancing Accuracy of Diabetic Retinopathy Detection Using a Hybrid Approach with the Fusion of Inceptionv3 and a Stacking Ensemble Learner." *Jagannath University Journal of Science* 11.1 (2024): 135-156.

[20] Sharma, Santosh Kumar, et al. "Discrete ripplet-II transform feature extraction and metaheuristic-optimized feature selection for enhanced glaucoma detection in fundus images using least square-support vector machine." *Multimedia Tools and Applications* (2024): 1-33.

[21] Alhajim, Dhafer, Ahmed Al-Shammar, and Ahmed Kareem Oleiwi. "Application of optimized deep learning mechanism for recognition and categorization of retinal diseases." *International Journal of Computing and Digital Systems* 16.1 (2024): 935-950.

[22] Canqui-Flores, Bernabe, et al. "Echocardiographic cardiac views classification using whale optimization and weighted support vector machine." *Vessel Plus* 8 (2024): N-A.

[23] Desuky, Abeer S., et al. "Parameter Optimization Based Mud Ring Algorithm for Improving the Maternal Health Risk Prediction." *IEEE Access* (2024).

[24] Bose, Anandh Sam Chandra, C. Srinivasan, and S. Immaculate Joy. "Optimized feature selection for enhanced accuracy in knee osteoarthritis detection and severity classification with machine learning." *Biomedical Signal Processing and Control* 97 (2024): 106670.

[25] Sahu, Sima, Amit Kumar Singh, and Nishita Priyadarshini. "No reference retinal image quality assessment using support vector machine classifier in wavelet domain." *Multimedia Tools and Applications* (2024): 1-20.