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Diabetic Retinopathy Detection Using a Hybrid Model

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Abstract

Among people with diabetes, diabetic retinopathy is considered the main cause of vision loss. Early detection is crucial to prevent vision loss. To identify diabetic retinopathy, A regular scheduled checkup is critical before the occurrence of vision loss. Because it progresses through multiple stages and the early stages usually do not contain noticeable symptoms,

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routine eye examinations are required. Relying on manual checkups can be prone to human error, and it is time-consuming. This can postpone the initiation of necessary interventions. Automated Artificial Intelligence (AI) based detection is therefore essential. This study aimed to explore further the Convolutional Neural Network (CNN) and the Singular Value Decomposition (SVD), Support Vector Machine(SVM) model, combining CNN for feature extraction, SVD for reducing the number of features, and SVM for classification. The model was applied to the Messidor dataset, which consists of images of the retina. The model achieved 69% accuracy.

Keywords: CNN, Diabetic Retinopathy, MESSIDOR, RESNET50, SVM.

1. INTRODUCTION

There is a globally increasing number of patients who have diabetes. Some studies indicated that by the year 2030, the estimated number of adults aged 20 to 79 will have diabetes. The number of patients is estimated to be around 439 million individuals, which represents 7.7% of the global population [1]. Patients with diabetes are at a higher risk of getting DR, which is short for diabetic retinopathy. Diabetic retinopathy is one of the primary causes of unaddressed vision loss in diabetic patients [2]. The cause of diabetic retinopathy is the complication of the microvascular system, which affects the retina. The damage is gradually occurring due to high blood pressure, which can affect the tiny blood vessels inside the retina. This can lead to visual impairment and vision loss in severe cases.

There are stages of Diabetic Retinopathy, which are mild non proliferative diabetic retinopathy (NPDR), and are considered to be at an early stage when there is an increase in vascular permeability, that is, when the small vessels in the retina start leaking. At this stage, there were usually no symptoms. The next stages of diabetic retinopathy (DR) are Moderate and Severe when some blood vessels are blocked, which deprives the retina of oxygen and causes significant damage. The advanced stage, called Proliferative Diabetic Retinopathy (PDR), occurs when the retina suffers from low oxygen levels and starts to create new weak and abnormal blood vessels, known as neovascularization. In addition, Macular Edema, which can occur at any stage, is swelling of the macula. This occurs when small blood vessels become leaky [3].

Early and regular checkups are crucial because, as mentioned earlier, the early stage usually does not show symptoms. Around 21% of type 2 diabetes patients will develop some level of diabetic retinopathy because they are typically diagnosed long after developing it. In the next 20 years, most type 1 diabetic patients will develop retinopathy to some extent [3].

Over the past few years, many machine and deep learning models have been developed by researchers to automatically detect and classify DR from a given image, since manual checkups can have some level of limitation. Several methods have been developed to detect diabetic retinopathy. Some methods have been developed for lesion detection, such as microaneurysms, and classification using deep learning Convolutional Neural Network (CNN) models, as presented by Lam et al. (2018) [4], who tested several models such as AlexNet, VGG16, GoogLeNet, ResNet, and Inception-v3. In addition, some studies used machine learning models to detect diabetic retinopathy, as shown by Odeh et al. (2021) [5], who used an ensemble learning framework to combine machine learning algorithms for classifying diabetic retinopathy. They used a combination of Neural Networks (NN), Random Forest (RF), and Support Vector Machine (SVM). On the other hand, there are studies that use machines and deep learning together.

A hybrid model is used in this study that combines both deep learning and machine learning. We used CNN ResNet50 for feature extraction, and Singular Value Decomposition (SVD) to compress high-dimensional CNN features into 1024 features. For classification, we used a Support Vector Machine (SVM). A Messidor dataset was used in this study.

2. RELATED WORK

Researchers have introduced many approaches in order to either extract features from fundus images to improve the detection or to address DR grading, which have all helped in increasing the accuracy of the detection. The approaches vary between the use of machines and deep learning. Some of these studies incorporated a hybrid approach using machine learning and deep learning. Some researchers have used deep learning for extraction and machine learning for classification.

Two components were used to specify and detect diabetic retinopathy grading. These components are deep and machine learning. As in the study of Rahman et al. (2024) [6], they used hybrid techniques where they used ResNet50 for feature extraction while using K-Nearest Neighbors (KNN), Support Vector Machine (SVM) and Histogram Gradient Boosting (HGB) for classification. Each machine learning model was used individually. They used a hybrid model on the APTOS 2019 dataset (Asia Pacific Tele-Ophthalmology Society), which contained 3662 fundus images originally labeled in five categories (0 to 4). The model results showed accuracies of 96.9% for SVM, 95.6% for KNN, and 95.6% for HGB.

Another study incorporated a mix of deep and machine learning models. It used a deep learning model to extract features and machine learning to classify them. Like the research of Jabbar et al. (2024) [7], where they used a mix of GoogleNet + ResNet for feature extraction and Random Forest (RF), Linear SVM, Naive Bayes (NB), Radial SVM, and Decision Tree (DT). They used the EyePACS dataset to test each machine learning model. Furthermore, Qomariah et al. (2019) [8], used a hybrid method with two components: pre-trained CNN and SVM machine learning, and tested them on the Messidor (Base12 & 13) dataset.

The other approaches used three-component models to detect diabetic retinopathy. These include Singular Value Decomposition (SVD) was used to reduce the number of features before the decision was made using machine learning. Nahiduzzaman et al. (2021) [9], used a hybrid approach in which they used a CNN for feature extraction, SVD for feature limitation, and ELM for classification. The model was tested using APTOS 2019 and Messidor-2. Several studies were also conducted by Bilal et al. (2023) [10], Bilal et al. (2024) [11, 12]. Although published under different titles (EdgeSVDNet, DeepSVDNet, and ISVM-CNN), they proposed a hybrid model using three components: CNN, SVD and ISVM. This study also compared other machine learning models for classification however, the compensation of CNN + SVD + ISVM yielded the best results. Each study used slightly different variations and tested the model using the IDRiD dataset. The model achieved an accuracy of 99.89%.

However, this research uses this methodology on a different dataset, the Messidor dataset, to evaluate its generalizability. However instead of using ISVM, this research uses only SVM.

3. METHODOLOGY

The methodology of this study is explained in this section. A brief description of the dataset and pre-processing was used. Feature extraction was performed using ResNet50, dimensionality reduction using SVD, and classification using an SVM. Simple illustration of the pipeline is: Images → (224x224x3) → ResNet50 (imagenet, fine-tuned) → GAP features: 2048 dims → SVD: 1024 dims → StandardScaler → SVM (RBF, class weights)

Table 1: Class distribution by split after filtering to grades {0,1,2,3}. Percentages are within-set.

Set	#Images	Class 0	Class 1	Class 2	Class 3
Train	2247	1248 (55.5%)	317 (14.1%)	437 (19.4%)	245 (10.9%)
Test	562	313 (55.7%)	79 (14.1%)	109 (19.4%)	61 (10.9%)
Overall	2809	1561 (55.6%)	396 (14.1%)	546 (19.4%)	306 (10.9%)

3.1 Dataset and Pre-Processing

In this paper we used Messidor and Messidor-2 [13, 14], public retinal funds dataset

For the Messidor (ADCIS) dataset which consists of 1,200 images of the retina. Without pupil dilation, a total of 400 images were captured and 800 images were captured with pupil dilation. The data set came with an Excel file that contained graded images for the diagnosis of diabetic retinopathy, which ranged from 0 (no DR) to 3 (severe). The images were captured using a nonmydriatic retinal camera. In our work, we used an Excel sheet to obtain labels. Base 33 was not used in our experiments.

For the Messidor-2 (ADCIS) dataset [15], it came with CSV listing for right and let eyes there were no DR grade included. To obtain the DR labels we used a third-party file from the Google Brain Kaggle release "Messidor2 DR Grades" [16]. The file contain 5 grades from 0 to 4. But since our study is focusing in only 4 classes we had to exclude the images that contained grade 4 from our study.

After merging the two dataset. We dropped grade 4 rows before any splitting or traning and we only retained images from grade 0 to grade 3. From the code log: Total loaded images: 2,809 Overall label distribution: 0: 1,561; 1: 396; 2: 546; 3: 306

For image processing, we attempted to resize the images to fit the ResNet50 model, which uses images of size 224 × 224 pixels. In addition, we converted the OpenCV color model from BGR to RGB for use with TensorFlow and for better detection. We performed a stratified 80/20 split on the merged dataset with random state=42. The resulting per-class counts for train/test are shown in TABLE 1. The enhancement and balancing were only applied to the training data.

Since the classes were imbalanced, we oversampled minority classes by generating SVD-based variants (small singular-value perturbations channel-wise). Also, we added an extra augmentation for class 0. For the test set, no synthetic samples were created.

3.2 Feature Extraction Using ResNet50

Before we begin the experiment, we hold-out test split first: stratified 80/20 with random state=42. In addition, inside the training data, we also hold another split, which was a train/val split of 80/20 of the balanced train data.

This study used a Convolutional Neural Network (CNN) for feature extraction. A ResNet50 pre-trained model was used to extract the deep features. The original head layer was removed. For the input images, the images were resized to 224×224 pixels and then normalized using the preprocessing input function, which made the images match the ResNet50 expected input distribution. We also apply a global average pooling layer to produce a compact feature vector and to reduce the spatial dimensions.

This global average pooling is followed by two dense layers using ReLU activation functions. After each dense layer, dropout layers with rates of 0.4 and 0.3 were added. The final classification was not handled by the CNN; however, a softmax layer was used to enable the supervised learning. To fine-tune the model, all layers were unfrozen to allow for better learning based on the dataset.The Adam optimizer was used in the model with low learning rate (1e-5). A focal loss was also added to make the model focus more on the hard-to-classify samples. To learn good features, we let the CNN train on softmax for training data only. For the final evaluation we extract the GAP features from testing data After training, the final classification layer is removed. Subsequently, the features extracted from the layer are reduced using Singular Value Decomposition (SVD). Finally, the output is used as the input for the Support Vector Machine (SVM) classifier.

3.3 Dimensionality Reduction Using SVD

Following CNN feature extraction, we applied truncated singular value decomposition (SVD) for dimensionality reduction. The extracted CNN features have high dimensionality and may have been redundant. Applying SVD with a set number of components (1024) reduced the feature dimensions, excluded redundant data, and removed noise, making the features ready to be classified using the SVM.

3.4 Classification Using SVM

After reducing the feature dimensions extracted from the CNN using SVD, these data were used as inputs for the Support Vector Machine (SVM) classifier to make the final classifications. To ensure that all input features had zero mean and unit variance, these features were standardized using `StandardScaler`. This step improves the performance of the SVM. We used an RBF-kernel SVM with default regularization (C=1.0) and `gamma='scale'`. Class weighting was applied to address class imbalance **for the minority classes (1–3)** with weights {0:1, 1:2, 2:2, 3:2} **.** The data were divided into 20% for testing and 80% for training this split was performed before any augmentation happened.

4. EXPERIMENTAL RESULTS AND DISCUSSION

4.1 Evaluation Metrics

We evaluated DR classification performance using accuracy, precision, recall, F1 score, and a confusion matrix.

Accuracy: Percentage of correct predictions of the model. This provides an overview of the accuracy of the model in predicting a given dataset. In medical images, this metric alone is not sufficient because sometimes for imbalanced data, the model can be biased towards the class with the majority number, which is considered an issue in medical imaging because there could be mistakes in diagnosis. Formula:

$$Accuracy = \frac{(CorrectPredictions)}{TotalPredictions} = \frac{(TP(TruePositive) + TN(TrueNegative))}{(TP + TN + FP(FalsePositive) + FN(FalseNegative))}$$

Precision (Positive Predictive Value): This provides an overview of the accuracy of the model for a specific class. The number of predictions is true for all predictions of a specific class. Formula:

$$Precision = \frac{TP}{TP + FP}$$

Recall (Sensitivity or True Positive Rate): is the share of actual positive cases the model correctly identifies.

$$Recall = \frac{TP}{TP + FN}$$

F1-Score: providing a single measure that balances false positives and false negatives, which combines precision and recall via their harmonic mean. Formula:

$$F1 - score = \frac{2 * (Precision * Recall)}{Precision + Recall}$$

Specificity (True Negative Rate): This indicates how well the model recognizes the negative cases. This helps to avoid false positive cases. A class with high specificity indicates that an image does not belong to a certain class. Formula:

$$Specificity = \frac{(TN(TrueNegatives))}{(TN(TrueNegatives) + FP(FalsePositive))}$$

Confusion Matrix: A visual diagram of the overall model performance showing how it classified each class. This helps to identify the class in which the model struggles with the most.

Test Accuracy: This is the final test accuracy for the model in predicting all the classes.

Macro avg: treats all the classes as if they were equal Formula:

$$\text{Macro-}m \;=\; \frac{1}{K}\sum_{k=1}^{K} m_k$$

$$\text{Weighted-}m \;=\; \sum_{k=1}^{K} w_k\, m_k, \qquad w_k \;=\; \frac{n_k}{\sum_{j=1}^{K} n_j}, \;\; n_k = \text{support of class } k$$

ROC Curves AUC Formula:

$$\text{TPR}_k(t) = \frac{TP_k(t)}{TP_k(t) + FN_k(t)}, \qquad \text{FPR}_k(t) = \frac{FP_k(t)}{FP_k(t) + TN_k(t)}$$

$$\text{ROC}_k : \; \big(\text{FPR}_k(t),\, \text{TPR}_k(t)\big) \text{ as the threshold } t \text{ varies}$$

$$\text{AUC}_k \;=\; \int_0^1 \text{TPR}_k\big(\text{FPR}_k^{-1}(u)\big)\, du$$

$$\text{Macro-ROC-AUC} = \frac{1}{K}\sum_{k=1}^{K} \text{AUC}_k, \qquad \text{Weighted-ROC-AUC} = \sum_{k=1}^{K} w_k\, \text{AUC}_k$$

4.2 Results

The CNN (ResNet50) + SVD + SVM model achieved a 69% accuracy. Precision, recall, and F1 for Class 0 (no DR) were 73%, 97%, and 84%, respectively. Per-class metrics are summarized in TABLE 2. Class 1 has achieved a recall of 32%, precision of 60% and F1-score of 41%. Class 2: precision 56%, recall 36%, F1 44%. Finally, for Class 3 (severe case), the precision was 56%, recall 31%, and the F1-score was 40%. The class that performed best was class 0 (No DR).

Table 2: Classification report (with threshold).

Class	Precision	Recall	F1-score	Support
0	0.733173	0.974441	0.836763	313
1	0.595238	0.316456	0.413223	79
2	0.557143	0.357798	0.435754	109
3	0.558824	0.311475	0.400000	61
Accuracy	0.690391	0.690391	0.690391	0.690391
Macro avg	0.611094	0.490043	0.521435	562
Weighted avg	0.660718	0.690391	0.652044	562

In FIGURE 1, shows the confusion matrix.

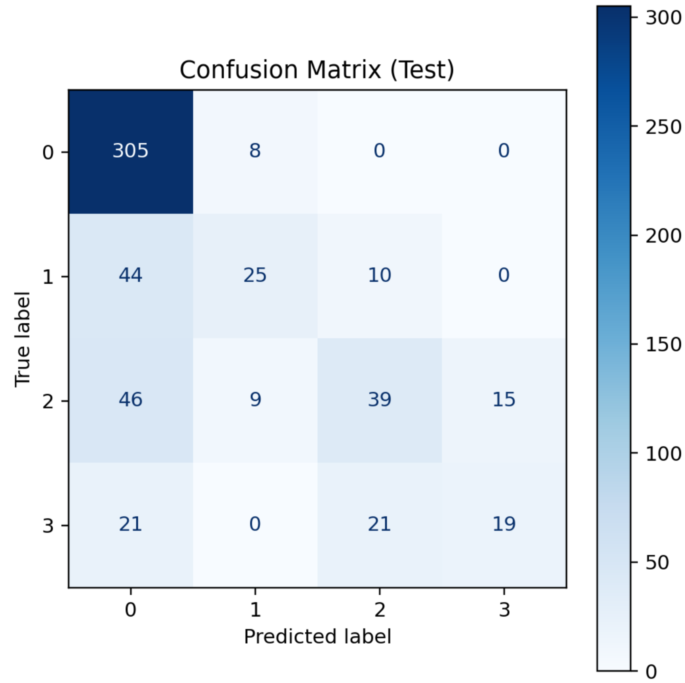

Figure 1: Confusion Matrix

In FIGURE 2, One-vs-Rest ROC (TEST) plot.

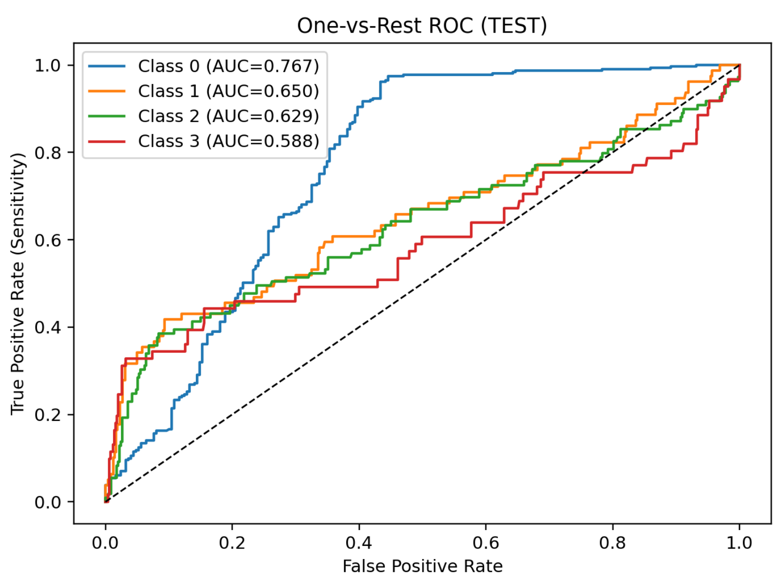

Figure 2: One-vs-Rest ROC (TEST) plot.

In FIGURE 3, One-vs-Rest Precision–Recall (TEST).

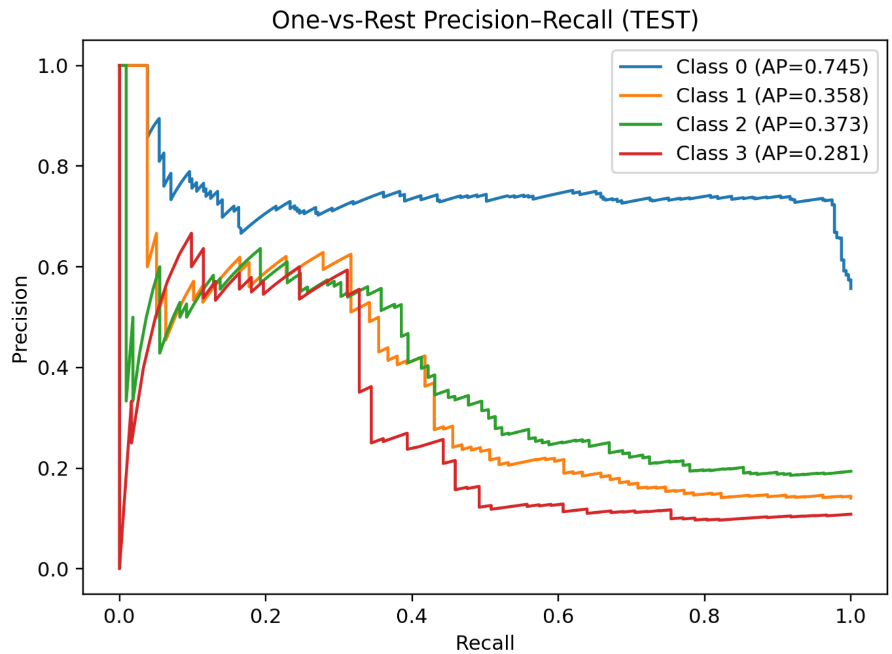

Figure 3: One-vs-Rest Precision–Recall (TEST).

4.3 Discussion

Overall, the proposed model achieves an accuracy of 69%. Class 0 exceeded the other classes and attained precision 0.73. From the result we see that the model favors specificity for the healthy class over the sensitivity for the disease. There are many factors that have contributed to this result. The test sample was imbalanced and contained most images from class 0 which we see in the result the model seems to recall it the most. There was limited support for the class 1 - 3. Second factor was the labels file for the Messidor-2 was not provided from a third-party file which can create some noise or inconsistency with the Messidor file that was obtained from the original data. Finally the GAP feature extraction and SVD discard fine-grained lesion cues.

This study encounters some limitations such as The analysis is image-level rather than patient-level which limits the generalizability.

5. CONCLUSION AND FUTURE WORK

The use of a CNN (ResNet50) is considered a good feature extraction method, especially for medical images, and its combination with machine learning models has achieved good performance and high accuracy. The CNN-SVD-SVM model achieved an accuracy of 69% accuracy for the Messidor dataset. The best-performing class was Class 0. One of the issues that remain with deep learning is that it is a black box, and there is no clear explanation of how it performs the classification. This is especially important in medical images and diagnoses, where there is a need to explain why a condition is classified into a certain grade. Therefore, fairness is a major concern in this regard. If the dataset mostly contains one type of image or patient group, the model may perform worse for the others. This could lead to unfair or unequal diagnosis. In future studies, there is a need to explore models with larger and more diverse datasets for better generalization. In addition, different machine learning models can be added and compared for classification purposes. Also, improving the accuracy in the current model.

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