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Deep learning approach for retinopathy identification in combined clinical datasets

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Research Article

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***Abstract*—** A technique for automatically identifying different stages of diabetic retinopathy (DR) based on patient fundus photographs is presented in this paper. The "Dataset of fundus images for the study of diabetic retinopathy" version v3 CastilloBenitez21, a relatively young and underutilized image collection, served as the foundation for the system's construction. Clinical fundus photos obtained from Wroclaw Medical University's Department of Nephrology were used to augment the main dataset. Convolutional neural networks (CNNs) that were pre-trained on ImageNet data served as the foundation for the development of the diagnostic system. With a global accuracy of 83.15%, the CNN classifier—which is based on VGG16 with transfer learning—proved to be successful. An accuracy of 89.7%, a sensitivity of 94.9%, a specificity of 88.3%, and a Matthews Correlation Coefficient of 0.7665 were obtained from the assessment of discriminating between the non-DR and DR states.

***Keywords*—**CNN-VGG16, sequential transfer learning, deep learning, and diabetic retinopathy detection

I. INTRODUCTION

One particular consequence of diabetes is diabetic retinopathy (DR) [4], [34], which often remains asymptomatic in its early stages. It may result in blindness or visual impairment. Studies [11], [10] indicate that retinopathy is associated with a higher risk of nephropathy and cardiovascular diseases in diabetics. Therefore, early diagnosis and treatment of DR may improve the overall clinical outcome in the treatment of diabetes.

Using a combination of digital signal processing and artificial intelligence algorithms, the computational analysis of fundus photography makes it possible to execute large-scale screening and early diagnosis. The large corpus of computer science research devoted to the categorization of retinal pictures, which addresses both illness detection and severity grading, reflects the need for such automated methods. Given that DR affects about one-third of the diabetic population, according to clinical data [11], automated screening provides a technique to enhance diagnostic throughput, lower costs, and less need on human expert assessment.

Digital image databases provide pixel-by-pixel visualizations of normal retinal structures and common alterations in diabetic retinopathy. For the creation and testing of automated screening algorithms for DR symptoms at various levels, representative sets of retinal pictures of diverse retinas are crucial. The International Clinical Diabetic Retinopathy (ICDR) Severity Scale is employed in the field of computerized DR classification algorithms [34]. Based on the severity of the DR, standard fundus pictures are categorized into five groups.

TABLE I
GRADING SCALE OF DIABETIC RETINOPATHY SEVERITY USED IN THE STUDY

Class Label	Clinical Description
Class 0	Normal (no signs of DR)
Class 1	Mild Non-Proliferative DR (NPDR)
Class 2	Moderate NPDR
Class 3	Severe NPDR
Class 4	Proliferative Diabetic Retinopathy (PDR)

In [4], Class 5 (Clinically significant macular oedema) is added. These symptoms are observed as large red disks. In the case of the EPDRS (Early Treatment of Diabetic Retinopathy Study) classification [34], the division of DR

symptoms is even more detailed. Occasionally, other detailed classification systems occur. For example, the taxonomy adopted in [18] distinguishes six classification levels, defining Class 4 as very severe NPDR and assigning PDR samples to Class 5. The fundus image data set for the study of diabetic retinopathy (DFISDR) [3] consists of 757 color images (DFISDRv2). In addition, an extended database (DFISDRv3) containing 1,437 images is available. The classification of fundus images has been done in 7 categories: No DR signs, Non-Proliferative diabetes Retinopathy (NPDR mild, moderate, severe, very se- vere), Proliferative diabetes Retinopathy (PDR) and Advanced PDR.

Unlike more serious lesions in the retinal vessels, class 1 is the most difficult to identify. The development of microa- neurysms (MA) in the retina is the first sign of DR. MA usually manifests itself as punctate dark red lesions, with a diameter marginally larger than that of the finest retinal capillaries [29], [9].

This paper continues the problem presented in [36]. The purpose of this paper is to investigate the usefulness of creating an image database consisting of fundus images obtained from patients in a nephrology clinic at Wrocław Medical University (WMU). Unfortunately, that data set was relatively small, consisting of only 71 images. Therefore, the study utilized the DFISDRv2 dataset, a recently introduced and less common collection, distinguished by its rigorous expert an- notation. Subsequently, a straightforward convolutional neural network architecture was constructed to evaluate classification performance within a controlled environment. The average classification accuracy obtained was 84.7%. The classifier built on data from a source other than WMU did not correctly classify WMU images. After combining both sets, the new classifier was trained on 80% of the images and tested on the remaining 20%; the classification accuracy was similar to the previous results. It should be emphasized that the images from the WMU and the DFISDRv2 database were divided in the same proportions, and all 13 test images from Wrocław were correctly classified. In the binary classification task (Healthy vs. DR), the average accuracy reached 96%. This result suggests that the algorithm proposed in [36] is effective, but not fully robust. We believe that the primary limitation is the relatively small training data set, which reduces confidence, even for this basic identification task.

In this article, we investigate the properties of a classifier based on the combination of two datasets from different sources, with the external set chosen as DFISDRv3 [3], which is twice as large as DFISDRv2 used in [36] and [3].

The paper is structured as follows. The next section presents a review of the current literature on automatic systems for identifying and classifying DR based on fundus images and publicly available retinal datasets. Information about the data sets used in our experiments, the DR detection method, performance metrics, and experiment results is explained in Section 3. Finally, we discuss our approach and results and conclude the article.

II. Problem statement

The purpose of this paper was to investigate the extent to which it is possible to create our own system for the automatic classification of patients with nephrology at risk for the potential or observed development of DR. At the same time, due to further research concepts, it is essential that the image database used by the system in the future come from a population selected for kidney diseases.

Currently, due to the available data from WMU, the main significant problem is discrimination between asymptomatic images (no DR) and those indicating the presence of changes associated with the existence of DR. From this point of view, the DFISDRv3 database is balanced, as it contains 711 sample images in class 0, which is about half of all data in this database containing a total of 1437 images.

The choice of the DFISDRv3 [3] database was driven not only by its relatively small size, but also by the fact that it was unlikely to be used as data for an automatic classification system. This allows both sets of data to be considered new and unencumbered by any additional prior knowledge beyond their source.

Limiting the size of the database, which we intend to treat as a supporting dataset, should allow the construction of a practical classification algorithm with a relatively small number of parameters. This algorithm was the CNN VGG16 network mentioned earlier [36] and was presented at the DepCoS-RELCOMEX 2025 conference.

III. Related works

Computational experiments in the field of automatic DR de- tection are based on many publicly available image databases, such as Kaggle base DRD [8], APTOS19 [35], MESSIDOR [7], EyePACS [6], IDRiD [26], Dataset for Diabetic Retinopa- thy (DDR) [14], among many others. A specific database is the DeepDRiD database [16], which helps to evaluate and improve the quality of fundus images intended for the construction of DR classification systems.

Automated systems for detecting and grading Diabetic Retinopathy typically utilizes the following computational strategies:

- image processing algorithms related to improving the quality of photographs, variation in color attenuation, in- tensity conversion, denoising, and contrast enhancement
- advanced algorithms for detecting objects, image segmen- tation, or background analysis,
- classification methods based on machine learning algo- rithms that analyze the selected features of images subject

to classification,

- deep learning methods such as various variants of con- volutional networks (CNN),
- hybrid methods, visual transformers.

A. Advances methods of image processing and analysis

Reference [20] describes Computer-Aided Diagnosis (CAD) frameworks designed specifically for the binary classification of DR pathology. Computational experiments were conducted on the Kaggle 2015 dataset. The main component of the algo- rithm was a combination of image processing with EGMM- based Retinal Blood Vessel Detection and Segmentation, Blob analysis and Connected Components Analysis, Retinal Blood Vessel ROI Identification, Alaxnet-based feature extraction, Feature Selection, dimensionality reduction, and finally SVM- based DR classification.

The crucial problem in quickly starting appropriate therapy is the detection of the early stages of DR symptoms, such as microaneurysm (MA) lesions (mild NPDR) [9]. Some articles deal with the detection of MA [18], [22]. The paper [29] applies traditional image processing methods related to the occurrence of visual symptoms on a multi-scale in the context of MA.

B. Machine learning methods

Beyond a general literature survey, reference [12] investi- gates specific image enhancement protocols and feature ex- traction techniques used in DR staging. The study evaluates

a broad spectrum of computational models, ranging from classical classifiers (SVM, Random Forest, Naive Bayes, k-NN, k-Means) to neural network architectures, including Auto- encoders.

C. Deep learning methods

Reference [1] benchmarked 26 distinct pre-trained CNN architectures using transfer learning. The study utilized the DRGF dataset, comprising 3,662 Gaussian-filtered images derived from the APTOS19 archive and resized to 224 × 224 pixels. Despite the variety of models tested, the classification accuracy for DR detection remained below the 80% threshold. The paper [25] presents a multiclass classification of fundus images to detect eye diseases (including DR identification) based on a transfer learning approach and various CNN net- work architectures. The authors showed that eliminating bad quality images using an integrated quality evaluation system
improves classification performance.

The study in [33] evaluates both binary detection and multi- class DR classification. The authors proposed an ensemble framework integrating established architectures (InceptionV3, Inception-ResNetV2, Xception) across various input resolu- tions with data augmentation. Although the reported accuracy was exceptional, it relied on a massive, non-public dataset.

In contrast, reference [32] focuses on hyperparameter op- timization. The authors demonstrated that the adjustment of global parameters could elevate the classification accuracy from a baseline of 0.48–0.83 to a peak of 0.96. These experiments utilized the 5-class Kaggle 2015 dataset [8] and standard backbones (AlexNet, VGGNet, GoogLeNet, ResNet) facilitated by transfer learning.

In [19] a multitask deep learning framework is introduced for DR staging. The architecture comprises two distinct com- ponents: a primary classification network and a stand-alone regression model. Their outputs are fused and subsequently processed by a Multilayer Perceptron (MLP) to generate the final prediction.

D. Hybrid methods

Hybrid methods combine deep learning methods (DL) with classical methods of digital image processing and analysis. On the other hand, hybrid models can use CNNs in combination with simpler machine learning algorithms such as multilayer perceptron (MLP), support vector machine (SVM), random forest (RF), transformers and vision transformers (ViT), or boosting methods. Adaboost, Gradient boost, and Extreme gradient boost (XGBOOST) are based on combining built se- quentially simple predictors [1]. Naturally, almost all methods, even those that we do not call hybrid, use some kind of pre- processing of input images.

Reference [23] leverages Vision Transformers (ViT) to capture long-range spatial dependencies within image data. The methodology was validated on the FGADR dataset, a recently introduced large-scale repository featuring fine-grained annotations, which served as the benchmark for both DR identification and grading tasks. This data set has 1,842 images with pixel-level DR-related lesion annotations, and 1,000 images with image-level labels graded by board-certified ophthalmologists. Because the FGADR base is an unbalanced data set, the authors of the paper combined several tech- niques to deal with this issue. It achieved satisfactory results compared to the baseline ViT models, namely F_1

= 0.825 and accuracy = 0.825. The paper [30] uses for a similar purpose a dynamic recurrent CNN (R-CNN) solution. In both works, small image patches are recursively used to determine long-range dependencies in images. In this work, the authors achieved very high classification accuracy using the Kaggle DRD base. The Kaggle DR dataset (DRD) consists of 88,702 color fundus images, including 35,126 samples for training. After initial preprocessing, all images are processed using the Gray Level Co-occurrence Matrix (GLCM), the method proposed by Haralick et.al. in 1973.

The method proposed in [24] is based on the independent extraction of local information from multiple rectangular im- age regions. The machine learning system to detect diabetic retinopathy from fundus images uses a multiple learning paradigm with an integrated attention mechanism. Reference
[23] leverages Vision Transformers (ViT) to capture long- range spatial dependencies. The method was validated on the FGADR dataset—a recently introduced large-scale repository with fine-grained annotations. Crucially, the architecture em- ploys an attention mechanism that explicitly localizes patho- logical regions and DR-induced lesions to facilitate classifica- tion.

Only selected examples of the methods have been presented in more detail. The topic of DR diagnostics is very popular, as evidenced by the large number of review articles published over the last few years. See, for example, [1], [2], [12], [14],
[18], [21], [19], [22], [27], [28], among many others.

IV. Data characterization

The primary training material consists of 1437 color retinal images from the database DFISDRv3 [3]. These clinical samples were acquired at the Department of Ophthalmology, Hospital of Cl´ınicas (FCM-UNA), Paraguay. We selected this recently published repository to assess the feasibility of automatic DR classification as a training set, we chose ”Dataset from fundus images for the study of DR” (DFIS- DRv3) described in [3], which is a relatively new set, and we even found a preliminary examination of its usefulness in the detection and classification of DR interesting and useful. The data set containing 1437 color fundus images was acquired in the Department of Ophthalmology of the Hospital of Cl´ınicas, Facultad de Ciencias Me´dicas (FCM), Universidad Nacional de Asuncio´n (UNA), Paraguay. The fundus images are initially divided by the authors of the database into seven classes: Normal (no signs of DR)- 711 images, mild (early) NPDR
- 6 images, moderate NPDR - 110 images, severe NPDR - 210 images, very severe NPDR - 139 images, PDR - 116 images, and advanced PDR -145 images. For the purpose of this study, the original 7-class grading system was assigned to 5 classes to balance the data set. Specifically, ’Advanced PDR’ was excluded due to the limited number of samples, and ’PDR’ was merged with ’Very Severe NPDR’. The ground truth in DFISDRv3 base was established by annotation by two independent ophthalmology specialists. The repository con- tains JPEG files at a resolution of 2124 × 2056 pixels. During data set construction, samples that exhibited blur, artifacts, or insufficient quality were rigorously excluded. The primary objective of this collection is to facilitate research into the detection of both Non-Proliferative (NPDR) and Proliferative (PDR) stages.

Figure 1 presents sample photographs from the DFISDRv3 base. The image in the upper left corner is an asymptomatic example, while the other three illustrate different types of DR symptoms. *Data preprocessing*

Recognizing the critical role of input fidelity, the study implemented an automated preprocessing pipeline to ensure accurate data processing. This stage involved histogram equal- ization to enhance local contrast, followed by a resizing oper- ation to standardize the spatial dimensions of the DFISDRv3 dataset against the WMU samples. Due to the different profiles of the photos from both databases, a special mask was used to eliminate these differences. A specific preprocessing technique was applied in which the green channel of the fundus image was extracted, histogram-equalized to enhance contrast, and then replicated to form a 3-channel input tensor compatible with the VGG16 backbone.

A. Algorithms

The classification system is built on the VGG16 convolu- tional neural network architecture, using a transfer learning approach with weights pre-trained on the ImageNet dataset.

The VGG16 architecture was selected for its structural simplicity and proven robustness in medical imaging tasks. In contrast to more complex models, VGG16 relies on a uniform arrangement of small convolutional filters (3 × 3), which facilitates stable feature extraction and reduces the risk of overfitting in limited datasets. To adapt the model to detect diabetic retinopathy, the original fully connected layers were replaced with a custom classifier block. This block consists of two dense layers with 4,096 neurons, each followed by a ReLU activation function and a Dropout layer (rate = 0.5) to mitigate overfitting. The final output layer contains
5 neurons, equivalent to the severity classes labeled (0–4) defined in the study. The model accepts input images resized

to a resolution of 176 × 176 pixels. The network is optimized using the CrossEntropyLoss function with label smoothing (0.1) to improve generalization.

The training process employs a two-stage fine-tuning strat- egy. Initially, the convolutional base is frozen and only custom classifier layers are trained to map high-level features to the 5 severity classes of DR. This initial phase prevents the large gradients typical of randomly initialized layers from distorting the pre-trained feature extractors (catastrophic for- getting). Upon reaching the $20th$ epoch (set specifically for this experimental setup), the entire network is unfrozen. At this critical stage, the learning rate is reduced by a factor of ten. Simultaneously, the AdamW optimizer and scheduler are re-initialized to update the weights of the full model. This approach ensures stable adaptation of feature extraction layers. As evidenced in Table IV (specifically experiment exp 1), this configuration yielded the highest validation accuracy compared to other experimental setups, confirming the benefits of the controlled fine-tuning procedure.

B. Optimizers

As an optimization method, we used the AdamW method, which works faster than its classic version, Adam [15]

AdamW [17] is a fast variant of the Adam optimizer. The AdamW optimizer distinguishes itself by decoupling weight decay from gradient adaptation. Unlike the standard L_2 reg- ularization, which modifies the objective function, AdamW applies the decay term directly to the parameters during the update step. Separating the regularization from the optimiza- tion step in AdamW improves its generalization performance.

C. Hyper-parameter selection

The computations were performed on an Nvidia RTX 3000 Ada Generation Laptop GPU using mixed precision (FP16) to optimize performance. In every training cycle, the model utilized pixel normalization for input data, along with Dropout and L2 Regularization (Weight decay) to prevent overfitting. In addition, we have employed an adaptive learning rate to ensure stable convergence.

TABLE II
HYPER-PARAMETER SELECTION

	Exp 1	***Exp 2***	***Exp 3***	***Exp 4***	***Seq 5***
Epoch no.	50	100	100	50	50
Batch size	16	64	64	16	16
LR value	3.1e-07	1.95e-08	1.95e-08	7.81e-08	1.56e-07
Train ACC	99.36%	99.36%	99.63%	99.45%	99.54%
Test ACC	83.15%	82.78%	81.68%	80.59%	76.92%
Time	00:11:43	00:11:52	00:11:46	00:11:33	00:11:43



Fig. 3. Confusion matrix for training data

Based on the comparative analysis of the experimental results presented in Table I, the configuration labeled 'Seq 1' demonstrated the highest classification performance in the test set (83.15% accuracy). Consequently, the final model was established using a batch size of 16 and trained for 50 epochs. The optimization process was driven by the AdamW algorithm with an initial learning rate of 10^{-7}, which was dynamically adjusted by the adaptive scheduler to ensure optimal convergence. A dropout rate of 0.5 was maintained to effectively regularize the network.

V. Experiments

Both sets, DFISDRv3 and WMU, were combined with all WMU images included in class 0 (no DR). The DFISDRv3 database contains 711 sample images in class 0 and the WMU consists of 71 images, all of class 0. Thus, a total of 782 im- ages with no signs of DR are present in the combined database. Figs. 3 and 4 show the results of training the classifier and the results of testing in the form of confusion matrices for training and testing, respectively. Table III presents the results of discriminating between the class without DR (healthy eyes) and images representing different classes of DR. These results, especially the MCC measure, show that the classifier used has good discriminatory properties. In the examined database, the number of images without DR (class 0) and images with

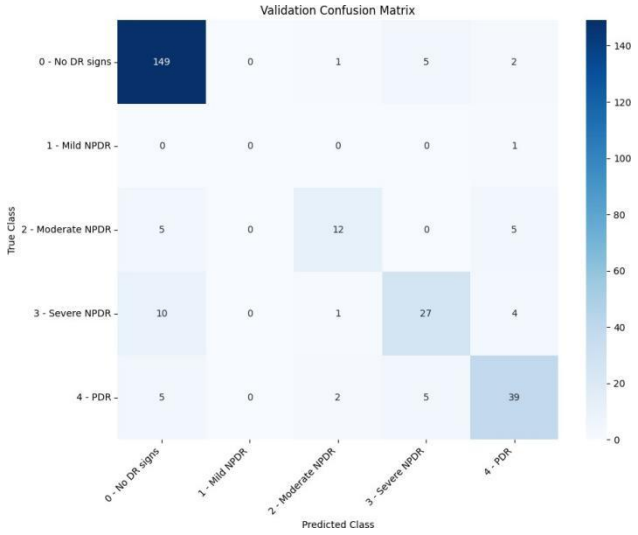


Fig. 4. Confusion matrix for testing data

TABLE III
Results of test classification - no DR class identification

ACC	Recall	Prec	Spec	F1	bACC	MCC
0.897	0.949	0.882	0.883	0.911	0.916	0.7665

DR symptoms were almost equal. In order to evaluate the DR detection level and the degree of identification of the remaining picture classes that were recovered from the database, we used a multi-class classifier. Because there were fewer representatives, it was more challenging to classify the remaining classes. The DR detection level was evaluated using a multi-class classifier, which also allowed us to analyze the degree of identification of the other picture classes that were taken from the database. We chose not to include the mild NPDR class in the assessment of the classification results due to its very small number of photos. Table IV presents the identification findings for the other classes in a manner similar to those of class 0.

TABLE IV
Discrimination results of symptomatic classes

class	ACC	Recall	Prec	Spec	F1	bACC	MCC
m NPDR	0.949	0.545	0.462	0.984	0.632	0.765	0.614
s NPDR	0.908	0.643	0.730	0.957	0.684	0.800	0.632
PDR	0.912	0.765	0.765	0.946	0.765	0.855	0.711

VI. Conclusions

The following are our article's primary contributions:

•A special collection of 71 photos from Wrocław Medical University (WMU) was added to the 1,437 images in the DFISDRv3 dataset. Experiments confirmed that a feasible method for training automated screening systems is to combine local clinical data with public databases.• For this particular set of data, the CNN classifier, which is based on VGG16 with transfer learning, worked well. The best setup (Sequence 1) produced an 83.15% test ACC. This implies that for this classification problem, a conventional design with few parameters is enough.

•The validation of a particular two-stage fine-tuning technique (including controlled unfreezing and optimizer re-initialization) is a significant addition. This methodological modification proved crucial for adjusting the pre-trained backbone to the constrained medical dataset as it successfully reduced catastrophic forgetting and guaranteed sustained convergence.

•A thorough investigation revealed a significant difference between Class 4 (PDR/Advanced) and Class 0 (No DR). This implies that the system is especially good at differentiating between severe disease and healthy eyes, which is a crucial component of medical triage.

•A test accuracy of 89.7%, a sensitivity of 94.9%, and a specificity of 88.3% were obtained from the examination of the binary classification task (Healthy vs. DR). The classifier gives a very excellent, if not perfect, prediction if the Matthews Correlation Coefficient value is much higher than 0.7.

• Accurately classifying early-stage illness, particularly Mild NPDR (Class 1), is still a difficulty. To provide a thorough first representation, we will try to include other examples from this class. By obtaining appropriate photos from WMU, future study will concentrate on improving the identification of these small traits and extending the model's performance throughout the whole seven-level grading range.

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