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Enhancement of Diabetic Retinopathy Prediction Based Capsule Network and DenseNet-121 Utilizing Wavelet Decomposition

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Abstract— **Diabetic retinopathy is a medical condition connected with the leakage of blood vessels in the retina, which can potentially lead to vision loss. This medical condition impacts a broad population of people, particularly those suffering from diabetes. The worst challenge about this medical condition is that it appears without any symptoms during its initial stage, which makes its detection at an early stage a very challenging task, especially since its treatment is based on the early detection task. In this paper, we shall propose a new automatic approach for early and severity-stage diabetic retinopathy detection based on DenseNet-121 and capsule network architectures, in addition to the discrete wavelet transform in the preprocessing step. However, the proposed approach generated an advanced image using the discrete wavelet transformation technique to feed it to the model. The model starts with the DenseNet-121 architecture and transfers the pieces of information to the capsule network to make decisions. In order to validate this approach, we used the APTOS dataset, and as a result, we achieved a good accuracy score of 86.72%.**

Keywords— Capsule Network; Deep Learning; Diabetic Retinopathy; Image Classification; Diabetic Retinopathy

I. INTRODUCTION (HEADING 1)

Diabetic retinopathy (DR) is considered one of the most common diseases that can cause blindness. According to the statistics of the 10th edition of the International Diabetes Federation (IDF) Atlas [1], about 537 million patients are suffering from diabetes, and patients with type 2 diabetes are more at risk of developing DR. Thus, in the majority of cases, ophthalmologists still based on the manual method to detect diabetic retinopathy, which is a very challenging task, especially since the detection of diabetic retinopathy requires experienced, trained clinicians [2]. This manual method has many troubles, such as being time-consuming and the hardest to detect in its early stages, especially with the increase in the number of patients that suffer from DR.

Diabetic retinopathy (DR) is considered an eye condition that involves the damage or growth of abnormal blood vessels on the retina. The blood vessels may be blocked or bleed on the surface of the retina. Thus, this disease can even cause blindness to a patient [3]. In fact, diabetic retinopathy rat almost the most awful disease that causes blindness in the world's working-age population, especially for patients with diabetes. According to [4], patients suffering from diabetes are at risk of increasing the chance of having diabetic retinopathy for more than half as long as they have diabetes over time.

Diabetic retinopathy can be divided into two main stages: the early stage, which is called non-proliferative diabetic retinopathy (NPDR), and the advanced stage, which is called proliferative diabetic retinopathy (PDR). The NPDR stage usually begins with no symptoms; this stage can also be divided into three main subsection stages, which are the Mild, Moderate, and Severe stages, presented respectively based on their advancement [5]. As this disease develops, the patient's condition progresses to the PDR stage. At this stage, a serious issue emerges where new blood vessels grow and may lose sight [5].

In the same regard of detection of the severity stage of diabetic retinopathy based on a new deep learning

technique. Proposing a new and fast automatic approach for diabetic retinopathy severity stage detection method became a necessity. In this paper, we propose a new approach that is based on the discrete wavelet transform (DWT) in the pre-processing step and the denseNet-121 with capsule network architecture in the training step. Where in the pre-processing step, we applied the DWT to the retinal fundus image in order to feed it to the training step. The first part of the training step is the denseNet-121 architecture, which is pre-trained on the ImageNet Dataset. The second part of the training step is the capsule network, which receives features from the first part to apply the dynamic routing between the PrimaryCaps and the DigitCaps in order to predict the exact stage of diabetic retinopathy.

II. Related Work

Ophthalmologists and clinical specialists still defy a challenge in the task of detecting the severity of diabetic retinopathy. Indeed, several approaches have been proposed in the field of diabetic retinopathy detection that are based on deep learning and machine learning methods. Whereas, deep learning has shown excellent results in detecting disease [2,6] and segmenting tumors [7,8] in medical images. In the task of detecting DR based on retinal fundus images, many approaches have been proposed. These approaches have focused either on identifying DR which is done by classifying the retina fundus image into normal (without DR) or abnormal (with DR), or severity grade detection, which is done by classifying the retina fundus image into the severity level of DR.

A. Binary Classification Of The Retina Images

Several approaches have been proposed in the field of identifying the DR, which is done by binary classification of the retina fundus images with or without DR. Such as Rao et al.[9] presented a comprehensive experimental study for diabetic retinopathy identification and severity level detection utilizing five CNN architectures. For the binary classification, they found that the Resnet50-based architecture achieves the best accuracy of 96.59%. While, for the five multi-task classifications, they found that the InceptionResNetV2-based architecture achieved the best accuracy of 85.02%. Their approach has some limitations related to memory due to the huge number of trainable parameters of the ResNet50. In the same regard, Jain et al.[10] also used three CNN architectures to automatically identify DR and multi-level DR classification. They focused on the data augmentation besides the three CNNs (VGG16, VGG19, and Inception-V3) to attain the best accuracy for the binary classification of 80.4% using the VGG19 model and 76.9% for the five-grad task. While Al-Antary and Arafa [6] proved an approach based on the extraction of features using an attention system to train their model. They achieved an accuracy of 84,6% for the binary classification and 98.1% for multi-task classification on the APTOS dataset.

B. Multi-Task Classification Of The Retina Images

To provide a deeper diagnosis for the patient various approaches have been proposed in the field of multi-task classification (0— non-DR, 1—mild, 2—moderate, 3—severe, and 4—PDR). Recently, Oulhadj et al.[11] developed a new approach for diabetic retinopathy severity detection based on a modified capsule Network and wavelet transformation. The wavelet transformation consists of decomposing the fundus image into three levels of decomposition utilizing discrete wavelet transformation. They achieved an accuracy of 86.54% on the APTOS dataset. Their approach still suffers from a crucial drawback, which is centered on the difficulty of applying the DWT on the noisy images. Besides, Mondal et al. [12] presented an approach for the detection and classification of diabetic retinopathy based on ensemble deep learning named EDLDR. They enhanced the retinal fundus images by using the CLAHE method and GAN as augmentation techniques in the pre-processing step. An ensemble deep learning system includes DenseNet101, and ResNext receives those images to classify them to the severity DR levels. They achieved a good accuracy score of 86.08%. They introduced the problem of imbalanced limited data for the five classes as the major limitation of their approach. In addition, Sugeno et al.[13] proposed a method based on transfer learning using the EfficientNet architecture for the task of DR severity level detection. They achieved an accuracy of 84.2% on the APTOS dataset. Furthermore, Islam et al.[14] proposed an approach for the automatic detection of diabetic retinopathy using contrast-limited adaptive histogram equalization (CLAHE) in the pre-processing step, and they used a pre-trained Xception model as the encoder. They attain an accuracy of 84.35%. Another model has been presented by Kumar et al.[15], where they suggested another approach named DRISTI for the severity of diabetic retinopathy detection. DRISTI is a new Hybrid model that is based on Capsule Network in addition to VGG16. They attain an accuracy of 82.06% for the task of multi-class classification. Additionally, Bodapati et al.[16] presented a new automatic approach for diabetic retinopathy severity levels detection and validated their approach on APROS and IDRID datasets. The proposed approach is based on a stacked convolutional auto-encoder and spatial attention. They had a good accuracy score of 84.17% on the APTOS dataset and an accuracy score of 63.24% on the IDRID dataset. Besides, Vijayan et al.[17] proposed a new technique for diabetic retinopathy detection based on the Efficientnet-B0. Their technique is based on a preprocessing step before feeding the retinal fundus image to their model. They validated their approach on two datasets, which are the APTOS and DDR datasets, and achieved an accuracy of 86.2%, and 84.8% respectively. Their approach has some limitations related to the interrelationships between different severity levels in the model. Finally, Oulhadj et al.[18] presented an automatic method for diabetic retinopathy detection based on ensemble voting of five transferred learning models (Resnet50, Xception, DenseNet121, InceptionV3, VGG16) and a comparison result of the five models with the proposed approach. They validated their approach on the APTOS dataset and achieved an accuracy of 83.63%.

III. Materials and Methods

A. *Discrete Wavelet Transform*

Discrete Wavelet Transform (DWT) is widely used in medical imaging. Particularly in the field of image denoising, extracting features from images, and also providing a multi-resolution representation of the images and multi-levels of decomposition.

The decomposition of an image using the DWT can decompose the image into four bands, including the low-low (LL), the Low-high (LH), the High-Low (HL), and the High-High (HH). The LL band performs the approximated version of the original image, the HL represents the horizontal edges, the LH represents the vertical edges, and the HH the diagonal edges.

B. *Dense Convolutional Network*

In this paper, we used the DenseNet (Dense Convolutional Network) [19] architecture which is a type of convolution neural network. More specifically, we used DenseNet-121, this type of CNN model is made to be more profound. This is done by making the output layer receive information directly from each layer. This type of connection between layers makes this architecture more effective and solves problems such as redundant layers.

C. *Capsule network*

The capsule network (CapsNet) is a new deep-learning architecture that is based on routing between capsules. The capsule network is presented in the original paper named "Dynamic Routing between Capsules" by Sabour et al.[20]. As Hinton claims, CapsNet is proposed to deal with many issues that came with CNN's architecture. Problems such as the loss of useful information during the pooling operation, in addition to the huge amount of data needed to train a CNN model, and the most important is the unaffected of CNN by the minor change in the input image.

Unlike traditional CNN, CapsNet can deal with these issues by using a system of capsules and dynamic routing between them. Besides, the CapsNet output is represented by vectors, unlike the traditional CNNs which are represented by a scalar. The original Capsule Network architecture comes with two parts: the encoder and the decoder. The encoder part is responsible for the classification task, and the decoder part is responsible for the reconstruction of the input image.

1) *Encoder*

The main architecture of CapsNet starts with the encoder part, which consists of three main layers. The main objective of the encoder part is to classify the input image.

The first layer is the convolution layer. In this layer, we apply the convolution operation on the input image. the convolution kernel consists of 256 filters with a kernel size of 9x9 and a stride of 1.

The second layer is the PrimaryCaps layer which is the subsequent layer of the first layer. It also consists of a convolution operation, with kernel filters of 256, a kernel size of 9x9, and a stride of 2. This is followed by a Reshape function, which reshapes the tensor generated from the last convolutional layers to a set of 32 capsule activation maps of eight dimensions of each one. Then a squash function is applied in order to squash the content of each capsule between 0 and 1. The main task of the squash function is to shrink the small vectors to zero and the large ones to 1. The squashing function is computed using the expression in equation (1).

$$v_j = \frac{\|S_j\|^2}{1+\|S_j\|^2} \frac{S_j}{\|S_j\|} \quad (1)$$

Where v_j is the output of the capsule j. and S_j is calculated using the equation (2), which represents the weighted sum of the capsule j.

$$S_j = \sum_i c_{ij}\, \hat{u}_{i/j} \quad (2)$$

The c_{ij} represents the coupling coefficient and $\hat{u}_{i/j}$ represents the prediction vector and is calculated using the equation (3).

$$\hat{u}_{i/j} = W_{ij} u_i \quad (3)$$

The third layer is the DigitCaps, which is based on the dynamic routing algorithm to generate its output. This layer generates an output represented by a vector dimension of 16-D for each class in the dataset. In our case, we generate map vectors of a dimension of (5, 16-D), where 5 represents the 5 levels of diabetic retinopathy in the APTOS dataset and 16-D represents the dimension of each vector. These capsule outputs are generated using the dynamic routing algorithm as presented in the original paper.

After that, they generate the DigitCaps output which is represented by vector maps of 5 capsules of dimension 16-D named v_i, where j represents the capsule j of the class j. To diagnose the class that the image input belongs to they calculated the length of each capsule, which represents the probability that the image input belongs to that class j.

2) *Loss function*

This capsule network architecture came with its own loss function. The loss function is presented in equation (4) As proposed by Sabour et al.[20].

$$L_c = L_c \max(0, m^+ - \|v_c\|)^2 + \lambda (1 - T_c) \max(0, \|v_c\| - m^-)^2 \quad (4)$$

3) *Decoder*

The decoder part is responsible for reconstructing the input image by receiving the output of the DigitCaps layer as its input and reshaping it into an image. After that, the encoder part classifies the input image, and the decoder part takes only the correct DigitCaps vector (16-D) responsible on its class and ignores the other vectors.

The decoder part reconstructs the 28 by 28 pixels image using three successive fully connected layers. The first fully connected layer came with 512 units and the ReLu activation function. The second with 1024 units and a ReLu activation function. The third one is with 784 units representing a 28 by 28 pixels image and a sigmoid activation function. And based also on the Euclidean distance as a loss function between the input image and the reconstructed image.

IV. METHODOLOGY

In this paper, we present an automatic method for diabetic severity level detection based on discrete wavelet transformation in the preprocessing step and a suitable combination between a DensNet-121 model and a Capsule Network decoder model. Our approach pipeline is illustrated in Figure 1.

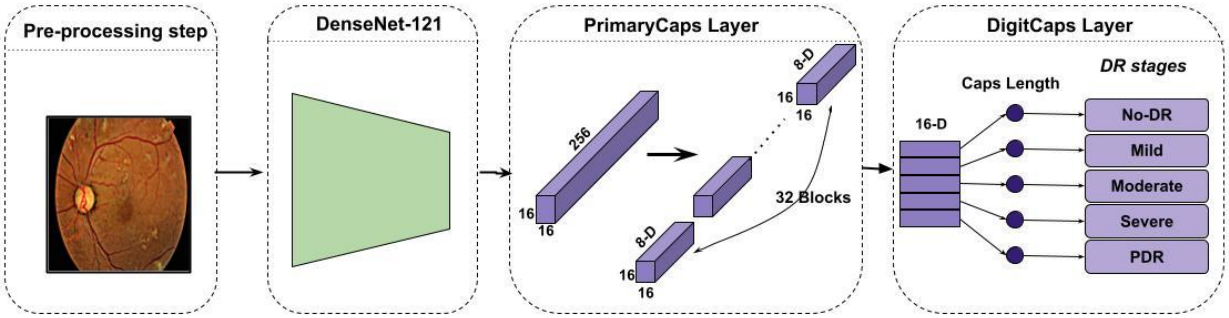

Figure 1. **The overall of the proposed approach**

In the pre-processing step, we apply the DWT to the retina image to enhance its quality. Since the DWT applies only to one channel of the image as grayscale, we split the RGB image into three channels, which represent the red, green, and blue channels. After that, we resize all the retina fundus images to the same size (500, 500, 3) and apply the DWT. Further, this decomposition yields four subband images (LL, LH, HL, and HH) with a size of half of the original image. Then, we merge the selected LL subband generated for each channel into one RGB image to feed as the input of our model.

Furthermore, we feed the image generated in the pre-processing step to the DenseNet-121 model. We used a pre-trained DenseNet-121 model that was trained on the ImageNet dataset to avoid training the model from scratch. Then, fine-tuned the DenseNet-121 model by removing the output layer to connect directly to the PrimaryCaps layer. The DenseNet-121 model we used is made up of one convolution layer of size (7, 7), fifty-eight convolutions of size (3, 3), and sixty-one convolutions of size (1, 1). In addition to four AvgPooling layers, The feature maps generated in this part are of size (16, 16, 2048), which is fed directly to the PrimaryCaps layer in the Capsule Network architecture. As we already presented in the Materials and Methods section, the PrimaryCaps consist of three steps. The first one is the convolution step, where we apply a convolution operation with a kernel of 256 filters, a size of 9x9, and a stride of 2. The second is the reshaped operation, which consists of reshaping the output of the convolution layer into a set of 32 capsule activation maps with dimensions of eight for each one. The third one is applying the squash function, which is represented in equation (1), to shrink the small vectors to zero and the large ones to 1.

Then we feed these generated features to the DigitCaps layer, which is based on the dynamic routing algorithm and capsule length to provide a diagnosis for the image output. The output of the dynamic routing algorithm is represented by capsules of dimensions (5, 16-D). the five in that output represent the five classes of DR in the APTOS dataset, while the 16-D is a vector indicating the probability of which class this image belongs to. All these layers' mechanisms are further and more explained in detail in the Materials and Methods section.

V. EXPERIMENTAL RESULTS AND DATASET

A. *Train and Test set*

To validate and evaluate our proposed approach, we used the retina fundus image from the APTOS dataset [21]. The retina fundus images in this dataset have different sizes, so we have resized all the fundus images into the same size of (500, 500).

To train, validate, and test our approach, we split the dataset into 85% for the training and validation steps and 15% for the testing step.

B. *Experimental results*

TABLE I. THE DISTRIBUTION OF THE DATASET

	Precision	***recall***	***F1-score***	***Support***
0	0.99	0.99	0.99	293
1	0.66	0.74	0.69	57
2	0.76	0.80	0.78	127
3	0.57	0.50	0.53	32
4	0.87	0.66	0.75	41
Accuracy	-	-	0.87	550
Macro	0.77	0.75	0.75	-
weighted	0.87	0.87	0.87	-

To prove the performance of our proposed approach, we used several measure metrics, such as accuracy, the mean square error (MSE), and the Kappa score. As we can observe in Table I, we achieved a high test accuracy score of 86.72%, an MSE score of 0.2309, and a high Kappa score of 79.28%. Furthermore, we can notice in Table I, that for the No-DR stage (label 0) approximately 99% of examples are correctly predicted.

In addition, Figure 2 represents the confusion matrix, which proposes an overview of our model performance during the test set. As we can observe, our model correctly predicted 290 images, while 3 images were misclassified in stage No-DR. For the mild stage, our model accurately identified 42 images. Also, the model correctly identified 102 images out of 127 for the moderate stage. For the stage severe, our model predicted 16 out of 32 images. For the stage PDR, our model correctly predicted 27 images.

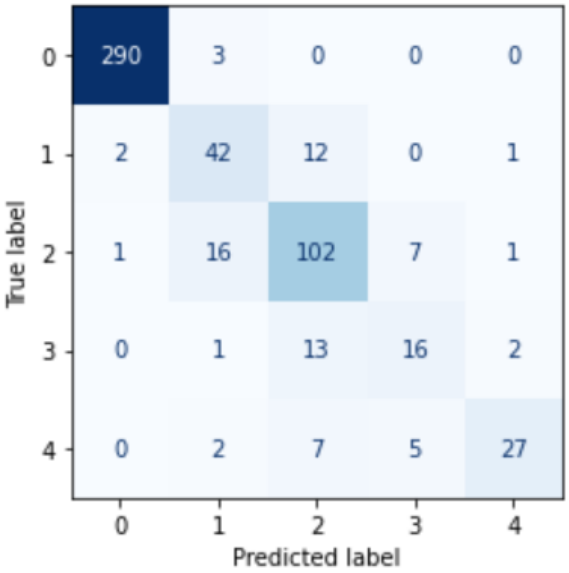

Figure 2. The Confusion Matrix.

We compared the results obtained from our approach in the test set with those of state-of-the-art approaches. These approaches are worked on the same dataset and for the same task of detecting the severity levels of DR. As Kumar et al.[15], which validated his approach on the APTOS dataset and achieved an accuracy of 82.06 for the task of 5-class classification, Besides, Sugeno et al.[13] also validated their approach on the same dataset for the same task and achieved an accuracy of 84.2%. In addition, Islam et al.[14], also proposed an approach for DR prediction validated on the APTOS dataset; they achieved an accuracy, precision, and recall score of 84.35%, 74%, and 71%, respectively. Furthermore, Mondal et al.[12] validated their proposed approach on the APTOS dataset and achieved recall, precision, and accuracy scores of 82%, 76%, and 86.08%, respectively. A new approach proposed by Oulhadj et al.[11] achieved accuracy, precision, and recall scores of 86.55%, 76%, and 70% for the same task and on the same dataset. All these approaches in Table II are carefully explained in the Related Works section. Notably, our results are better than many art-of-stat results.

TABLE II. THE COMPARISON OF OUR PROPOSED APPROACH WITH RELEVANT EARLIER RESEARCH.

Architecture	Years	Accuracy	Precision	Recall
Kumar et al.[15]	2021	82.06	-	-
Sugeno et al.[13]	2021	84.2	-	-
Islam et al.[14]	2022	84.35	74	71
Oulhadj et al.[11]	2023	86.54	76	70
Mondal et al.[12]	2022	86.08	76	82
Proposed approach	2024	86.72	77	75

VI. CONCLUSION

Diabetic retinopathy remains one of the dangerous problems that affect the patient in working age and its detection at an early stage remains a challenging task that requires experts in this field. Therefore, proposing an automatic approach for the detection of DR in order to help clinicians make decisions and detect it at an early stage became an urgent need. In this paper, we propose a new approach for diabetic retinopathy detection based on DenseNet-121 architecture and capsule net-work architecture in addition to DWT in the preprocessing step. In the preprocessing step, we apply the DWT in the retinal fundus image before feeding it as input to the proposed model. Besides, the first part of the proposed model is composed of pre-trained DenseNet-121, and the second part is the capsule network which receives information directly from the first part. To evaluate our proposed approach we used the APTOS dataset, where we achieved a good accuracy score of 86.72%. In future work, we aim to propose a new architecture of capsule network that can serve the multi-modalities of the retinal images and propose a new pre-processing step that is suitable for this type of problem.

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