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Detection of Pathological Myopia Using Convolutional Neural Network

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Abstract--- *A study reveals that 3% of the world population suffers from pathological myopia. Pathological myopia is an extreme case of nearsightedness which affects individuals during their most productive years, leads to vision loss which is progressive and irresistible. High myopia is defined as refractive error of at least -6.00 D or an axial length of 26.5mm or more. Of all the Pathological Myopia cases, thirty percent occur at birth. Most of the patients are diagnosed with the condition between the ages 6 and 13, and it continues to progress throughout life. It is crucial to examine children at risk, as failure to detect high myopia at an early age may lead to further vision loss from amblyopia. Conventional methods involve manual detection of Pathological Myopia which have led to inaccurate diagnosis and has resulted in complete vision loss. Deep Learning architecture have achieved state-of-the-art performance; performed better than their human counterparts in problems of Computer Vision since 2016, so the chances of inaccurate diagnosis are minute. As mentioned above, Deep Learning network architectures have achieved high accuracy in Computer Vision problems. We approach this problem as an Image Classification task using deep convolutional neural networks such as Residual Networks (ResNet) and Dense Convolutional Network (DenseNet). We were able to achieve an accuracy of 95.34% using ResNet-50 and 98.08% using DenseNet121.*

Keywords--- *Deep Learning, Convolutional Neural Network, Retina, Detection, Myopia.*

I. INTRODUCTION

Pathological Myopia is an extreme case of nearsightedness which causes a major change in the shape or globe of the eye. According to the recent (2019) report submitted by the World Health Organisation (WHO), almost 1.89 billion people worldwide are affected by myopia and it is expected to increase up to 2.56 billion people by the year 2020. Pathological myopia leads to elongation of the eye, which in turn stretches and thins the retina and sclera of the eye. Thirty percent of all cases of pathological myopia occur at birth. Sixty percent of patients are diagnosed with the condition between the ages of 6 and 13, and it continues to progress throughout life. Early diagnosis of pathological myopia is therefore very important. With the advancement of imaging technologies, deep learning methods and computer vision, diagnosis of colour retinal fundus images can be performed, which will aid in the detection of pathological myopia. Convolutional neural networks, developed by LeCun et al. [1], were observed to be effective in Computer Vision tasks such as image classification and segmentation. In 2015, He et al. [2] developed residual neural networks using the concept of skip connections to solve the problem of vanishing gradients. As a result, they were able to develop very deep neural networks, increasing the accuracy of predictions.

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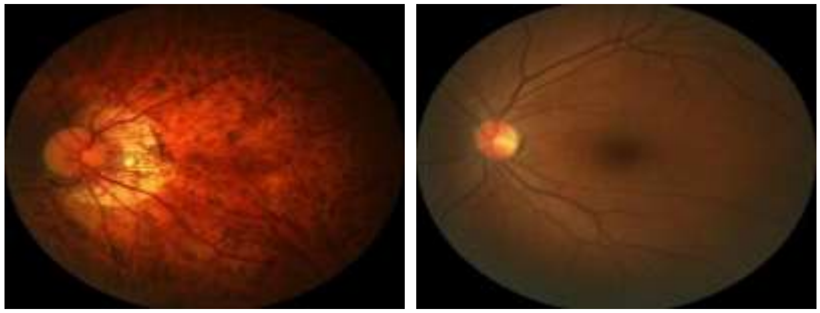

Fig. 1: Left: Pathological Myopia present in the eye. Right: A normal eye

Our contributions to this paper can be summarized as: 1) Applying the DenseNet architecture to achieve state-of-the-art accuracy. 2) Conducting a survey of the algorithms used so far.

II. Literature Survey

Traditional methods deal with the manual diagnosis of the fundus image, which takes up to 4-5 hours. With the advent of Deep Learning, this time has been significantly reduced to the order of seconds. Based on a critical and systematic review of recent research papers published over the last three years, different approaches of dealing with the detection of pathological myopia have been analyzed in this paper. This survey investigates the role of several deep learning architectures in the detection of pathological myopia, focusing on the characteristics of the different techniques and approaches to detect pathological myopia.

Lin et al. [3] uses the Random Forest Algorithm for the detection of pathological Myopia. Ten-fold cross-validation and Out-Of-) bag (OOB methods) were used for internal validation and Root Mean Square for evaluation. They were able to achieve an accuracy of 85%.

Xie et al. [4] in their paper, used the ImageNet pretrained ResNet50 with the cross-entropy loss function for pathological myopia and non-pathological myopia classification. They modified the ImageNet pretrained VGG19 model by mixing the features in the 4^{th} and 5^{th} blocks to detect the position of the fovea in a fundus image. They achieved an accuracy of 60%. Jiang et al. [5], introduces conditional generative adversarial network (cGANs) for the task of linear lesion segmentation, they proposed a new partial densely connected network as the generator of cGANs that tries to encourage the reuse of the features. Dice loss and weighted binary cross-entropy loss is used as the loss function to deal with the data imbalance problem. The problem is formulated as three-class segmentation tasks so that the network can be trained to learn the differences between linear lesions and retinal vessels. Hence, they used GANs to generate the segmentation masks of the fundus image and passes them through a classifier and achieves an accuracy of 96%.

Zhang et al, [6], presents a computer-aided diagnosis framework for Pathological Myopia diagnosis through Biomedical and Image Informatics (PM-BMII). PM-BMII intelligently fuses heterogeneous biomedical using the multiple kernel learning (MKL) methods to improve the accuracy of disease diagnosis. Retinal fundus imaging data and genotyping data were collected, are used to evaluate the proposed framework. The experimental results show that PM-BMII achieves an AUC of 0.888.

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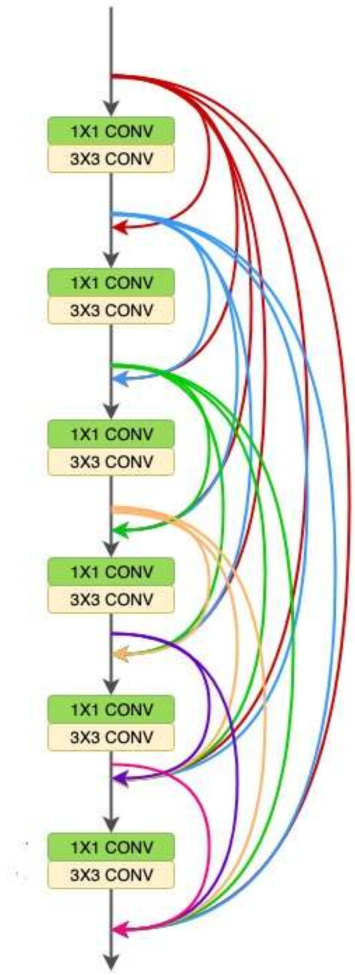

Fig. 2: Dense block with a growth factor of 6

Liu et al. [7], proposes a system for the automatic detection of pathological myopia. In particular, the focus of their work is on the texture-based component of PAMELA (Pathological Myopia Detection Through Peripapillary Atrophy). Peripapillary atrophy (PPA) is a pathological cue highly associated with pathological myopia. The component automatically takes in a retinal fundus image, and performs region of interest (ROI) extraction and detection of the optic nerve head. Subsequently, texture-based metrics are generated, categorized and grouped into zones for the context-based generation of features. These features are then used in a support vector machine to determine the presence of PPA, and correspondingly, pathologic myopia. They were able to achieve an accuracy of 87.5%.

Zhang et al. [8], proposes a framework for Minimum Redundancy–Maximum Relevancy (mRMR) based classification optimization, mRMR is used as a filter approach to generate a ranked feature pool. Their method aims at selecting a maximally relevant and minimally redundant set of features for the discriminating job. They use the Support Vector Machine (SVM) [9] for the task of classification to discriminate pathological myopia subjects from normal ones. They were able to achieve an accuracy of 89.3%.

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III. DATASET

The dataset was downloaded from the PathologicAL Myopia (PALM) challenge as a part of the IEEE International Symposium of Biomedical Imaging 2019 conference [10]. The goal of the challenge is to compare the performance of various algorithms and deep learning architectures on the PALM dataset for the diagnosis of Pathological Myopia (PM). The task is to classify the images as “PM” or “non-PM”. The dataset consists of 400 images of variable dimensions of which 213 images were labelled as “PM” and the rest were labelled as “non-PM”. Since the data was slightly biased towards PM, we assigned a greater weight for the non-PM images to penalize PM predictions. During training, 320 images were used as the training set and the remaining 80 images were used for validation. In addition, the testing set consists of 400 images. The images were resized to dimensions of 256x256 to maintain uniformity in the images’ dimensions. The dataset was normalized by dividing the pixel values of the images by 255 to bring the values to lie in a range of {0,1}. A standard data augmentation scheme of flipping, shifting was used on the dataset.

IV. PROPOSED METHOD

A. Architecture

In our paper, we have used the Densely Convoluted Neural Network (DenseNet) developed by Huang et al. [11] DenseNet architecture is a logical extension of ResNet. While skip connections are used to add the input of the previous layer to a layer in the ResNet architecture; previous layers are

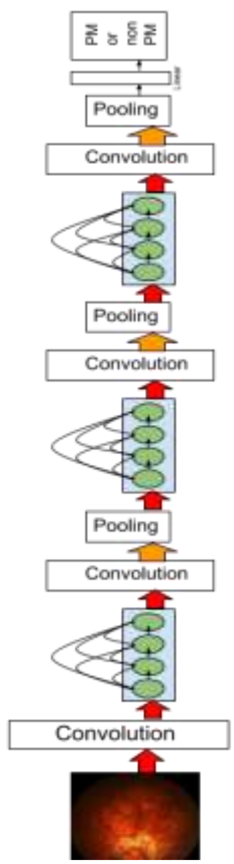

Fig. 3: An example of a simple DenseNet architecture containing dense blocks.

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connected to a layer using concatenation. Traditional convolutional networks with a depth of L have L connections, one between each layer and its subsequent layer. A DenseNet of depth L has L(L+1)/2 direct connections. For each layer, the feature-maps of all preceding layers are used as inputs, and its own feature-maps are used as inputs into all subsequent layers. Feature maps received from other layers $x_0,x_1,...,x_{l-1}$ are fused through concatenation. These dense connections allow a better information flow. Since DenseNet uses the concatenation operation on feature representations of previous layers, fewer parameters are involved compared to the addition operation used in ResNet and hence it is computationally efficient as well.

$$x_l = H([x_0,x_1,...,x_{l-1}]) \qquad (1)$$

where H is a composition of three consecutive operations: batch normalization followed by RELU, followed by a 3x3 convolution. An essential part of convolutional networks is down-sampling layers that change the size of feature-maps. To facilitate down-sampling, the DenseNet architecture divides the network into multiple densely connected dense blocks. A dense block comprises n dense layers. The dimensions of the features (width, height) stay the same in a dense block. The layers between the dense blocks are called the transition layers, which perform convolution and pooling operations.

B. Loss function

In our paper we have used the cross-entropy function, developed by Mannor et al [12], as the network's loss function. Cross-entropy is a loss function used to measure the performance of a classification model whose output's value lies between 0 and 1. Cross-entropy loss decreases as the predicted probability becomes similar to the actual label. Mannor et al [12] defines cross entropy loss as:

$$H_p(q) = \frac{1}{N}\sum_{i=1}^{N} y_i \cdot (1-\hat{y_i}) + \hat{y_i} \cdot (1-y_i) \qquad (2)$$

where y is the label and $\hat{y}_i$ is the predicted probability.

Table I

Architecture	Error rate
Random forest	14.4
PAMELA + SVM	14.4
VGG-16	9.17
ResNet-50	4.66
cGAN + classifier	4.41
DenseNet-121	1.92

V. IMPLEMENTATION

```
def dense_block(x, stage, nb_layers, nb_filter, growth_rate, dropout_rate=None, weight_decay=1e-4, grow_nb_filters=True):
        concat_feat = x
```

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```
eps=1.1e-5

for i in range(nb_layers):
branch = i+1
x = conv_block(concat_feat, stage, branch, growth_rate, dropout_rate, weight_decay)
concat_feat = merge([concat_feat, x], mode='concat', concat_axis=concat_axis,
name='concat_'+str(stage)+'_'+str(branch))


if grow_nb_filters:
nb_filter += growth_rate


return concat_feat, nb_filter
def DenseNet(nb_dense_block=4, growth_rate=32, nb_filter=64, reduction=0.0, dropout_rate=0.0,
weight_decay=1e-4, classes=1000, weights_path=None):


    compression = 1.0 - reduction
    eps=1.1e-5

    global concat_axis
    if K.image_dim_ordering() == 'tf':
    concat_axis = 3
    img_input = Input(shape=(224, 224, 3), name='data')
    else:
    concat_axis = 1
    img_input = Input(shape=(3, 224, 224), name='data')
    nb_filter = 64
    nb_layers = [6,12,24,16] # For DenseNet-121
    x = ZeroPadding2D((3, 3), name='conv1_zeropadding')(img_input)
    x = Convolution2D(nb_filter, 7, 7, subsample=(2, 2), name='conv1', bias=False)(x)
    x = BatchNormalization(epsilon=eps, axis=concat_axis, name='conv1_bn')(x)
    x = Scale(axis=concat_axis, name='conv1_scale')(x)
    x = Activation('relu', name='relu1')(x)
    x = ZeroPadding2D((1, 1), name='pool1_zeropadding')(x)
    x = MaxPooling2D((3, 3), strides=(2, 2), name='pool1')(x)
```

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```
for block_idx in range(nb_dense_block - 1):
stage = block_idx+2
x, nb_filter = dense_block(x, stage, nb_layers[block_idx], nb_filter, growth_rate,
dropout_rate=dropout_rate, weight_decay=weight_decay)
x = transition_block(x, stage, nb_filter, compression=compression, dropout_rate=dropout_rate,
weight_decay=weight_decay)
nb_filter = int(nb_filter * compression)


final_stage = stage + 1
x, nb_filter = dense_block(x, final_stage, nb_layers[-1], nb_filter, growth_rate,
dropout_rate=dropout_rate, weight_decay=weight_decay)
x = BatchNormalization(epsilon=eps, axis=concat_axis,
name='conv'+str(final_stage)+'_blk_bn')(x)
x = Scale(axis=concat_axis, name='conv'+str(final_stage)+'_blk_scale')(x)
x = Activation('relu', name='relu'+str(final_stage)+'_blk')(x)
x = GlobalAveragePooling2D(name='pool'+str(final_stage))(x)
x = Dense(classes, name='fc6')(x)
x = Activation('softmax', name='prob')(x)
model = Model(img_input, x, name='densenet')


if weights_path is not None:
model.load_weights(weights_path)


return model
```

VI. RESULTS

We trained the deep learning models for 100 epochs on a NVIDIA GeForce 1050Ti. The learning rate was set to a value of 0.1 initially and divided by 10 at the 50th and the 75th epoch. For training, the loss function used was the cross-entropy function. A batch size of 4 was adopted due to memory restrictions. The optimizer used was Adam with a beta-1 value of 0.9 and a beta-2 value of 0.999. We evaluated the results using the error rate metric for the task of Image Classification. We were able to achieve an accuracy of 90.83 % and 95.34% using the VGG-16 and ResNet-50 architectures respectively. We used a growth factor of 32 for the dense blocks and achieved an accuracy of 98.08% using the DenseNet-121 architecture on the test set.

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VII. CONCLUSION

We proposed to apply the DenseNet architecture on the PALM dataset. We also conducted a survey on the performance of previous architectures. Our proposed model was then compared with the performance of other state-of-the-art architectures. We used data augmentation techniques to expand the dataset. For training we used 320 images and validated the model on 80 images. These images were then trained on the DenseNet architecture using the cross-entropy loss function for 100 epochs. The best model was tested on 400 unseen fundus images and achieved an accuracy of 98.08%. In future, the classification can be further improved by using a higher batch size for a better generalization.

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