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A Customized Model for Classification of Optical Coherence Tomography Images and Comparison with Preexisting Models

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Abstract: The retina is the sensory membrane that lines the inner surface of the back of an eyeball. There is a wide variety of problems, conditions, and diseases like Macular degeneration, Diabetic retinopathy, etc that affects the retina and thus affect the human vision. Chances of retinal damage increase as a person get aged or have retinopathic diabetes. Retinal damage can be cured if detected in the early state but if not cured on time it may lead to blurry vision and also can eventually lead to blindness. The probability of retinal damage is increasing as the number of diabetic patients is increasing therefore there is a need for an effective and efficient method with high accuracy to detect retinal damage. Chances of retinal Damage through classification of optical coherence tomography (OCT) images can be achieved with high accuracy using classical convolution neural networks (CNN), a commonly used deep learning network for computer-aided diagnosis. In this study, we attempt to improve classification accuracy by using CNN based custom model.

From an OCT dataset, we produced a training dataset of 83,484 images and a test and validation dataset of 1000 images. The dataset was further classified into images of choroidal neovascularization (CNV), diabetic macular edema (DME), drusen, and normal. We have built a custom model using Convolution Neural Network(CNN), Relu activation function, MaxPooling, and Dropout Layers. Classification of OCT images using our method achieved a high accuracy of 99.69% while using fewer numbers of parameters when compared with other models in the literature. We further compared the custom model with already existing models by training them in a similar manner.

Index Terms—Choroidal Neovascularization, Convolution Neural Network, Diabetic Macular Edema, Drusen, Optical coherence tomography.

BACKGROUND

Optical coherence tomography (OCT) is a noninvasive imaging technique that captures high-resolution images of biological tissues using coherent light. OCT is widely used by ophthalmologists to obtain high-resolution images of the retina of an eye. OCT images can be used to diagnose many retina related eye diseases as it offers non-invasive real-time, high-resolution imaging of highly scattering tissues. It is widely used by ophthalmologists to perform diagnostic imaging on the structure of the anterior eye and the retina.

Choroidal Neovascularization (CNV)

Age-related macular degeneration (AMD), a major cause of blindness worldwide, is a degenerative disease of the macula, often leading to progressive vision loss. According to the World Health Organization global eye disease survey report, 14 million people are blind or severely visually impaired due to AMD. AMD has an early and a late stage, with visual impairment occurring during the late stage of the disease. AMD is quite prevalent in the elderly population; in one large population-based study of subjects 75 years of age and older, 30% had signs of early AMD, and 7% had signs of late AMD. Currently, “late AMD” is defined by the presence of 1 of 2 key features: the growth of new choroidal vessels breaking through into the neuroretina, known as “choroidal neovascularization” (CNV). In choroidal neovascularization, there is a growth of new blood vessels, the blood vessels originate from the choroid layer through a break in the Bruch membrane into the subretinal pigment epithelium or subretinal space. CNV is a common cause of neovascular degenerative maculopathy (i.e. wet macular degeneration) commonly exacerbated by extreme myopia, myopic degeneration, or age-related developments.

Diabetic Macular Edema (DME)

DME is a complication of diabetes which is caused by fluid accumulation in the macula, and it can affect most detailed vision abilities, due to leaking blood vessels. The

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macula is at the central portion of the retina which is in the back of the eye and where vision is the sharpest. To develop DME, a person must first have diabetic retinopathy. Diabetic retinopathy is a disease that results in vision impairment as it damages the blood vessels in the retina. Diabetic Retinopathy and DME are common problems for a diabetic person. Vision loss from these can progress over a period of months and can make it impossible to focus clearly.

Drusen

Drusen are small yellow deposits of fatty proteins (lipids) that accumulate under the retina. A person with Drusen faces an increased risk of developing age-related macular degeneration (AMD), however, it is not the cause of AMD. Drusen are made up of calcium salts and protein and generally appear in both eyes.

Normal

Normal vision is the state when light is focused directly on the retina and not in front of the retina or behind it. A person with normal vision can see objects clearly, near and faraway.

MODELS USED FOR COMPARISON

VGG16

Researchers from the Oxford Visual Geometry Group (VGG), developed the VGG network, a 16 layer architecture, which is characterized by its simplicity, using only 3 x 3 convolutional layers stacked on top of each other in increasing depth. Reducing the volume size is handled by max pooling. And in the end, two fully connected layers, each with 4,096 nodes, are then followed by a softmax layer. Pooling is carried out by max-pooling layers, which follow some of the convolution layers while not all the convolution layers are followed by max-pooling. Max pooling is performed over a 2 x 2-pixel window, with a stride of 2 and ReLU activation is used in each of the hidden layers. The number of filters increases with depth in most of the VGG variants.

MobileNetV2

The architecture of MobileNetV2 is based on an inverted residual structure where the input and output of the residual block are thin bottleneck layers, different from the traditional residual models that use expanded representations in the input. It uses lightweight depthwise convolutions to filter features in the intermediate expansion layer and it allows the decoupling of the input/output domains from the expressiveness of the transformation. This provides a convenient framework for further analysis.

The architecture of MobileNetV2 contains initially fully convolution layer with 32 filters, followed by 19 residual bottleneck layers. ReLU6 is used as the non-linearity because of its robustness when used with low-precision computation and kernel size 3 × 3 is used as it is standard for modern networks, and utilizes dropout and batch normalization during training. With the exception of the first layer, a constant expansion rate is used throughout the network.

The above models are used for comparison with the custom model.

DATASET

From an OCT dataset of 84,484 images, we produced a training dataset of 83,484 images and a test dataset of 968 and a validation set of 32 images. For training, the dataset comprises 37,205 images with CNV, 11,348 with DME, 8616 with Drusen, and 26,315 normal images. The test dataset has 242 images in each category, while the validation set has 8 images in each category.

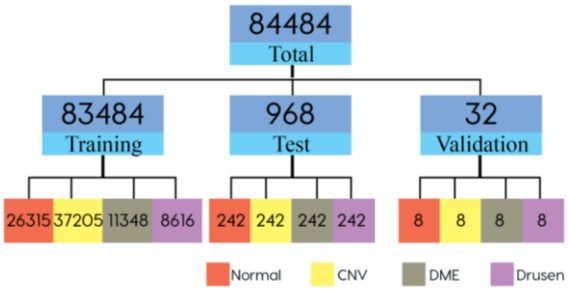

Figure 1: Distribution of Dataset

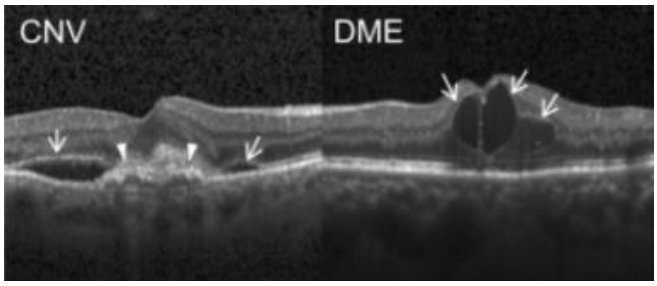

Figure 2(a): OCT of Image of CNV and DME

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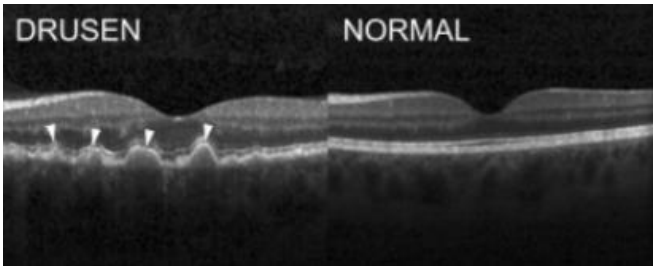

Figure 2(b): OCT of Image of DRUSEN and NORMAL

MODEL ARCHITECTURE

We have built Keras Sequential Model using Convolution Neural Network(CNN), Relu activation function, MaxPooling, and Dropout Layers. The detailed Structure of the model is shown in Table I.

The architecture contains fully convolution layers with 60 and 30 filters respectively followed by Maxpooling and Dropout layers. We used Relu as activation function as it takes less time to compute because there are no complicated calculations. We have used different Kernel sizes of 5x5, 4x4, and 3x3 and utilized dropout during training.

Table I: Architecture of Custom Model

Input	Layer	Output
128x128x1	Conv2d 5x5, Relu	124x124x60
124x124x60	Conv2d 5x5, Relu	120x120x60
120x120x60	Conv2d 4x4, Relu	117x117x30
117x117x30	Conv2d 4x4, Relu	114x114x30
114x114x30	MaxPooling(2x2)	57x57x30
57x57x30	Dropout(20%)	57x57x30
57x57x30	Conv2d 5x5, Relu	53x53x60
53x53x60	Conv2d 4x4, Relu	50x50x30
50x50x30	Conv2d 4x4, Relu	47x47x30
47x47x30	MaxPooling(2x2)	23x23x30
23x23x30	Dropout(20%)	23x23x30
23x23x30	Conv2d 4x4, Relu	20x20x60
20x20x60	Dropout(20%)	10x10x60
10x10x60	Conv2d 3x3, Relu	8x8x30
8x8x30	Conv2d 3x3, Relu	6x6x30
6x6x30	MaxPooling(2x2)	3x3x30

IMPLEMENTATION

Image Pre-processing:

The dataset we have used consists of OCT images of DME, CNV, DRUSEN, and NORMAL in three sections of training, test, and validation. The images are OCT images of the retina which are 3 channeled black and white images so if we convert it into 1 channeled images the feature loss or data loss will be minimal. We used this converted 1 channeled images for training all the models.

Training Setup:

We trained our model using TensorFlow and used the standard Adam Optimizer with the learning rate set to 0.0001 and the learning rate decay rate of 0.9 per epoch. We have used a batch size of 64 and all the models were trained for 10 epochs, 25 epochs, and 50 epochs.

We have compared our network against VGG16 and MobileNetV2. All the models are trained using the same dataset under the same environment. The training accuracy of all the models, when trained for 10, 25 and 50 epochs are shown in Figure 3(a), Figure 3(b) and Figure 3(c).

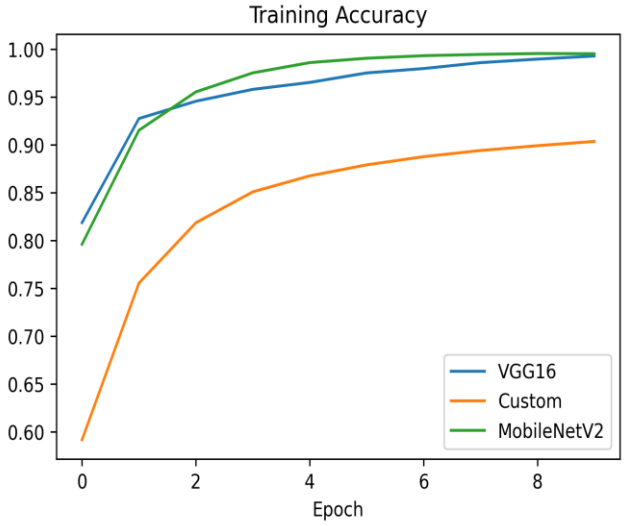

Figure 3(a): Training Accuracy Graph for 10 epochs

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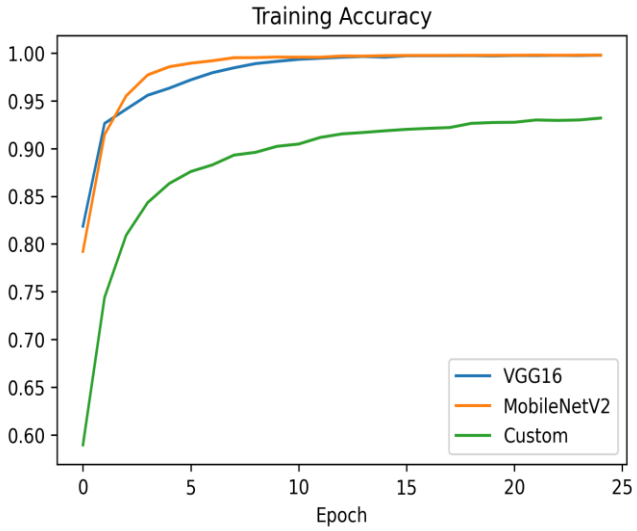

Figure 3(b): Training Accuracy Graph for 25 epochs

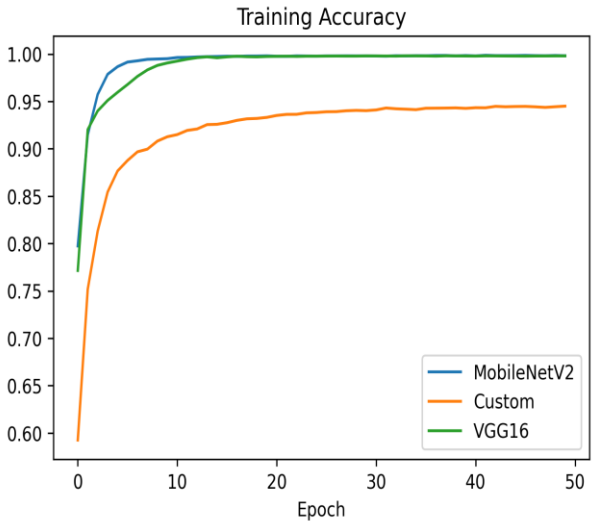

Figure 3(c): Training Accuracy Graph for 50 epochs

Table II: Parameters and Testing Accuracy of Models

Models	Parameters	Testing Accuracy (After Training)		
		10 Epochs	25 Epochs	50 Epochs
Custom	1.6M	99.48	99.58	99.69
MobileNetV2	2.3M	98.97	98.45	98.55
VGG16	14.7M	98.96	99.48	99.48

The training accuracy of our model reaches 99.48% for 10 epochs, 99.58% for 25 epochs, and 99.69% for 50 epochs (Table II). The training accuracy of the custom model is less compared to other models as we have used dropout layers due to which the training accuracy of our model suffers, but as a result of that, the testing accuracy of the model gets higher than VGG19 and MobileNetV2.

We also trained the custom model for 100 epochs and applied a custom check model callback function to know the maximum accuracy that our model can reach. We observed that the maximum accuracy that the custom model can reach is 99.69% with minimum loss and it reaches that at the 40th epoch. We also found out the custom model with a lesser number of parameters can reach a higher accuracy when compared to the VGG16 model which has a much higher number of parameters than our custom model. When compared with the MobileNetV2 which also has a comparably higher number of parameters than the custom model it was observed that the accuracy that our model reached is much higher than the accuracy of the MobileNetV2 model.

RESULT

We have evaluated the custom model based on the test dataset. The accuracy of each category were: 1 (100%) for DME, 0.99 (99%) for CNV, 1(100%) for DRUSEN and 1 (100%) for NORMAL. The Accuracy of the custom model got up to 99.69%.

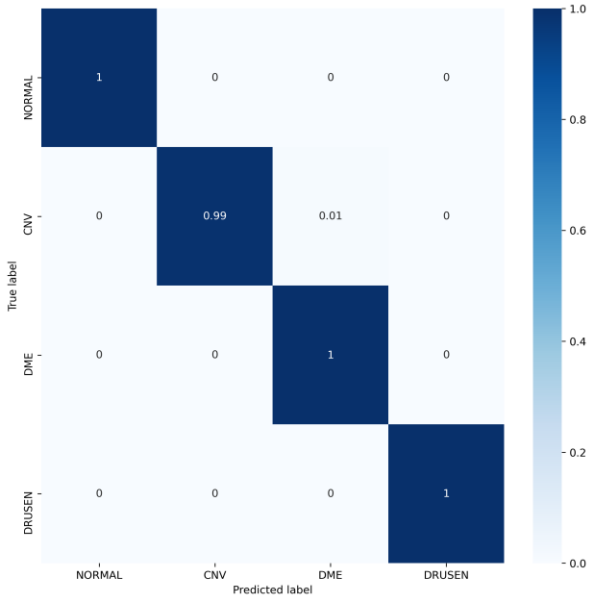

Figure 4(a): Confusion Matrix of Custom Model

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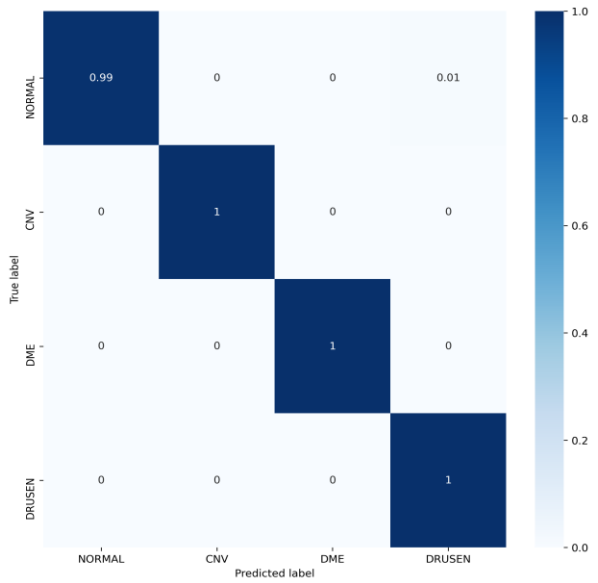

Figure 4(b): Confusion Matrix of VGG16

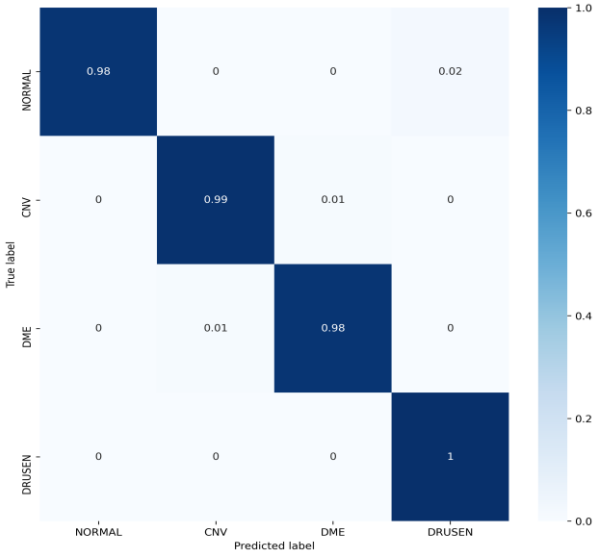

Figure 4(c): Confusion Matrix of MobileNetV2

Similarly, we have evaluated VGG16 and MobileNetV2 models. From the confusion matrix of each model we can observe that for VGG16, accuracy for each category is 1(100%) for DME, 1 (100%) for CNV, 1(100%) for DRUSEN and 0.99 (99%) for NORMAL and for MobileNetV2, accuracy for each category is 0.99(99%) for DME, 0.98 (98%) for CNV, 1 (100%) for DRUSEN and 0.98 (98%) for NORMAL.

CONCLUSION

The proposed custom CNN model with 16 layers achieved a high accuracy of 99.69%, which is higher than VGG16 and MobileNetV2. The custom model while working with significantly lesser numbers of parameters when compared to VGG16 and MobileNetV2 archives higher accuracy.

Results obtained from our research for the classification of Choroidal Neovascularization (CNV), Diabetic Macular Edema (DME), Drusen, and Normal compare favorably with those reported from earlier research. This system can also help in reducing the burden of ophthalmologists and can reduce treatment time for the patients.

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