A Comparison Between Deep Learning and Transfer Learning in the Detection of Diabetic Retinopathy

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***Abstract*— Diabetic retinopathy is a disease which affects the retinal tissues in the eyes of diabetic patients. If untreated, this disease may lead to complete loss of vision. The manual identification of this disease involves the presence of an ophthalmologist which makes the detection a time-consuming process but in an automated system artificial intelligence plays an important role in the early identification of the disease. Various deep learning and transfer learning techniques have been used in the detection of this disease. The main aim of this paper was to do a comparison between deep learning and transfer learning in the detection of diabetic retinopathy. In transfer learning experiments were conducted on VGG16 which was a pre-trained neural network architecture. In deep learning a customized Convolutional neural network was built and the experiment was conducted on the customized CNN. The results show that transfer learning performs well compared to deep learning. VGG16 achieved an accuracy of 93.75% in transfer learning. Transfer learning was able to achieve high accuracy with fewer epochs.**

Keywords*— Deep Learning, Transfer Learning, Diabetic Retinopathy (DR), Convolutional Neural Network (CNN)

I. INTRODUCTION

Diabetic Retinopathy is an eye disease caused by diabetics. It is a condition where the blood vessels in the retina of the eye are affected which is due to high sugar level. The condition can develop in anyone who has type 1 or type 2 diabetes. If we have diabetes for long time and if left untreated it can develop this eye complication. The early stage of diabetic retinopathy might cause no symptoms or only mild vision problems but this condition may cause vision loss if not treated. Some of the common symptoms of diabetic retinopathy is blurry vision, vision loss poor night vision etc. There are two types of diabetic retinopathy they are non-proliferative (early stage) and proliferative (advanced stage). There are five stages in diabetic retinopathy they are no DR, mild, moderate, severe, and proliferative. The diabetic retinopathy can cause serious eye problems like diabetic muscular edema (DME) and Retinal detachment. DME may occur when blood vessels in the retina leak fluid into the macula and Retinal detachment may occur when the scars pull your retina away from the back of your eye, it's called retinal detachment.

II. LITERATURE SURVEY

Qummar, Sehrish. et al [1] used the publicly available Kaggle dataset of retina images to train an ensemble of five deep Convolution Neural Network (CNN) models (Resnet50, Inceptionv3, Xception, Dense121, Dense169) to encode the rich features and improve the classification for different stages of DR. The experimental results showed that the proposed model detected all the stages of DR unlike the current methods and performed better compared to state-of-the-art methods on the same Kaggle dataset.

Darshit doshi. et al [3] used the publicly available EyePACs dataset of 351260 labeled high resolution colour fundus retinal images to train three Convolution Neural Network (CNN) models to classify into 5 stages of the disease. The best score of 0.3996 is obtained by the ensemble of these three models. The experimental results showed that the proposed model had obtained a greater accuracy by fine tuning the network parameters.

Wafaa M. Shalash. et al [5] described about the common fundus DR datasets which are publicly available and explained about the deep learning techniques. CNN is best for the classification and the detection of the DR images due to its efficiency. This paper also discussed the useful techniques that can be utilized to detect andto classify DR using DL and also discussed about the different challenging issues that require more investigation.

Shri Kant. et al [7] implemented transfer learning to classify DR into 2 classes with a much-reduced training data than other previous DR classification techniques employed. A smaller subset of size 2500 fundus images of the publicly available EyePacs dataset is uploaded on Kaggle DR Detection challenge was used for model training and testing. The pre-trained convolutional part of Inception-V3 is used to extract features of fundus images. The experimental results showed that the model has reached at a superior performance on account of the selected training algorithm, which is SGD with ascending learning rate and the cosine loss function. The model has reached higher accuracy of 90.9% than other techniques that have used transfer learning on the whole Kaggle DR challenge dataset for binary classification and showed better performance compared to other pre-trained deep convolutional networks in DR classification using small training data.

Zubair khan. et al [6] used imbalanced versions of the Kaggle dataset to validate the performance measures of the proposed VGG-NiN model and can process a DR image at any scale due to the SPP layer's virtue. Moreover, the stacking of NiN adds extra nonlinearity to the model and tends to better classification. The experimental results show that the proposed model performs better in terms of accuracy, computational resource utilization compared to state-of-the-art methods and also low in computation.

Abu Sayeed. et al [8] developed a deep learning model with transfer learning from VGG16 model followed by a novel color version preprocessing technique. The model reduces the training time and provided an average accuracy of 0.9132683 implemented to new Kaggle dataset "APTOS 2019 Blindness Detection" and to avoid the over-fitting problem for long run we used Stratified K-fold cross validation. The only limitation is that the dataset was an imbalanced dataset.

G.U. Parthasharthi [10] used the publicly available Kaggle dataset of 1000 retina images. A convolutional neural network model has been successfully created using the VGG19 framework that detects diabetic retinopathy and provides information on the severity of the disease. The accuracy of the model achieved is 92%. This model helps doctors diagnose the disease more quickly.

III. PROPOSED SYSTEM

A) *Dataset Description*

For our comparison between deep learning and transfer learning, we have used 1427 retinal fundus images which were downloaded from the TensorFlow platform. The collected images were of high resolution and were taken under a variety of imaging conditions. The collected data is then put into a CSV file. It has two columns where the first column corresponds to the image label and the second column specifies the different levels of diabetic retinopathy.

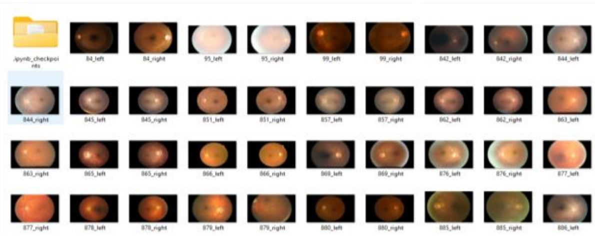

Fig.1 Retinal fundus images

B) *Pre-Processing*

Preprocessing is the initial step of the image processing techniques. It is used to enhance the image quality which gives clear visualization. A single image from the dataset is taken for data visualization which highlights the blood vessel regions and we perform channel splitting on that RGB formatted image and the green channel image is taken for further processing. Then, Contrast Limited Adaptive Histogram Equalization (CLAHE) operation is performed to increase the brightness and contrast of the images. We then performed the four morphological operations namely open, close, erosion and dilation to shapes and structures inside of images in order to increase or decrease the size of objects inside an image which helps to increase the quality of the image to identify the features distinctly. We then found that the dataset was unbalanced which may cause the problem of overfitting. Hence, we augmented the images to balance the dataset. Finally, the balanced dataset is split into 80% for training set and 20% for testing set. There are 4065 validated images for training and 286 validated images for testing.

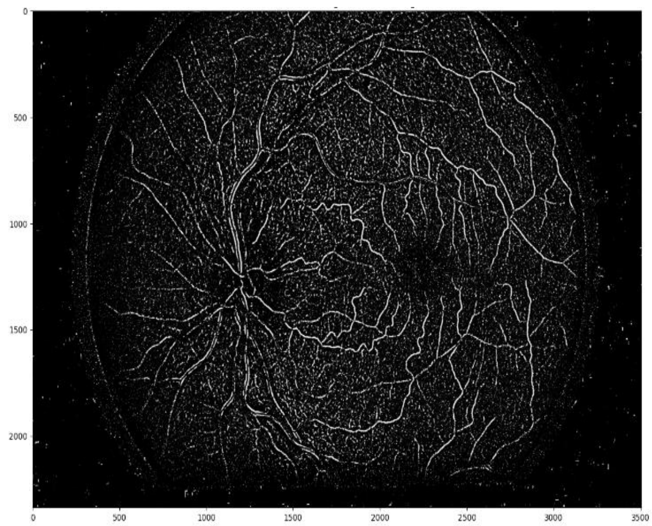

Fig.2 Image after pre-processing

C) *Architecture Design of Transfer Learning Model*

Transfer learning involved using an already trained model for training our model. In transfer learning model, we used the VGG16 model as the pre-trained model to extract the features efficiently. VGG16 has a total of 13 convolutional layers that use 3x3 kernels with a stride of 1 and use same padding. We have added five more convolutional layers with a kernel size of 1x1 and use same padding. The Relu activation function is used to solve vanishing gradient problem. The average pooling layer is used for down sampling the input. The dense layer is added to collect the neurons from the previous layer and to pass it on to the next layer. The dropout layer is added to avoid the problem of overfitting and underfitting during the training of the model. The Adam optimizer was used to speed up the process of training and to avoid local optimum and thus to provide a good learning result.

Layer (type)	Output Shape	Param #	Connected to
input_1 (InputLayer)	[(None, 256, 256, 3)]	0	[]
inception_v3 (Functional)	(None, 6, 6, 2048)	21802784	['input_1[0][0]']
batch_normalization_94 (BatchNormalization)	(None, 6, 6, 2048)	8192	['inception_v3[0][0]']
dropout (Dropout)	(None, 6, 6, 2048)	0	['batch_normalization_94[0][0]']
conv2d_94 (Conv2D)	(None, 6, 6, 64)	131136	['dropout[0][0]']
conv2d_95 (Conv2D)	(None, 6, 6, 16)	1040	['conv2d_94[0][0]']
conv2d_96 (Conv2D)	(None, 6, 6, 8)	136	['conv2d_95[0][0]']
conv2d_97 (Conv2D)	(None, 6, 6, 1)	9	['conv2d_96[0][0]']
conv2d_98 (Conv2D)	(None, 6, 6, 2048)	2048	['conv2d_97[0][0]']
multiply (Multiply)	(None, 6, 6, 2048)	0	['conv2d_98[0][0]', 'batch_normalization_94[0][0]']
global_average_pooling2d (GlobalAveragePooling2D)	(None, 2048)	0	['multiply[0][0]']
global_average_pooling2d_1 (GlobalAveragePooling2D)	(None, 2048)	0	['conv2d_98[0][0]']
RescaleGAP (Lambda)	(None, 2048)	0	['global_average_pooling2d[0][0]', 'global_average_pooling2d_1[0][0]']
dropout_1 (Dropout)	(None, 2048)	0	['RescaleGAP[0][0]']
dense (Dense)	(None, 128)	262272	['dropout_1[0][0]']
dropout_2 (Dropout)	(None, 128)	0	['dense[0][0]']
dense_1 (Dense)	(None, 5)	645	['dropout_2[0][0]']

Total params: 22,208,262
Trainable params: 399,334
Non-trainable params: 21,808,928

Fig.3 VGG16 Architecture

D) Architecture Design of Deep Learning Model

In deep learning model, a customized Convolutional Neural Network (CNN) was built from scratch. We have used the Keras Conv2D class and convolutional layers. The first parameter for the Conv2D is the number of filters that the convolutional layer learns. The number of filters is first set to 512 and then it is reduced to 256,128,64 and finally to 32 filters. The kernel size which specifies the width and height of the convolutional window is set to (11,11) for the filter sizes 512 and 256. The kernel size is set to (3,3) as the number of filters reduce. The stride parameter specifies the step of convolution along the x and y axis of the input volume. It is set as (4,4) for the filter size of 512 and is set as (1,1) for all the other filters. The padding parameter is set as valid in order to reduce the spatial dimensions of the input volume. The activation layer is set as Relu to all the convolutional layers. The MaxPooling layer is used to reduce the spatial dimensions of the output volume. Then the dense layer is added where every output is formed by the function based on every input. The dropout layer is used to ignore randomly selected neurons during training and thus reduces overfitting problem. The Adam optimizer is used which updates the learning rate for each network weight individually.

Layer (type)	Output Shape	Param #
conv2d_99 (Conv2D)	(None, 64, 64, 512)	186368
max_pooling2d_4 (MaxPooling2D)	(None, 32, 32, 512)	0
conv2d_100 (Conv2D)	(None, 22, 22, 256)	15859968
max_pooling2d_5 (MaxPooling2D)	(None, 11, 11, 256)	0
conv2d_101 (Conv2D)	(None, 9, 9, 128)	295040
conv2d_102 (Conv2D)	(None, 7, 7, 64)	73792
conv2d_103 (Conv2D)	(None, 5, 5, 32)	18464
max_pooling2d_6 (MaxPooling2D)	(None, 2, 2, 32)	0
flatten (Flatten)	(None, 128)	0
dense_2 (Dense)	(None, 4096)	528384
dropout_3 (Dropout)	(None, 4096)	0
dense_3 (Dense)	(None, 4096)	16781312
dropout_4 (Dropout)	(None, 4096)	0
dense_4 (Dense)	(None, 144)	589968
dropout_5 (Dropout)	(None, 144)	0
dense_5 (Dense)	(None, 64)	9280
dense_6 (Dense)	(None, 5)	325

Total params: 34,342,901
Trainable params: 34,342,901
Non-trainable params: 0

Fig.4 CNN Architecture

IV. RESULTS AND DISCUSSION

The total number of epochs for the VGG16 model is set to 15 with 31 steps for each epoch. Epoch is defined as the total number of iterations for training the model with all the training in one cycle. And the total number of epochs for the customized CNN model is set to 7 with 31 steps for each epoch. The results showed that the VGG16 model in transfer learning outperforms the deep learning model with a training accuracy of 93.75%. Fig 5 and Fig 6 shows the transfer learning model's training and validation accuracy and deep learning model's training and validation accuracy respectively.

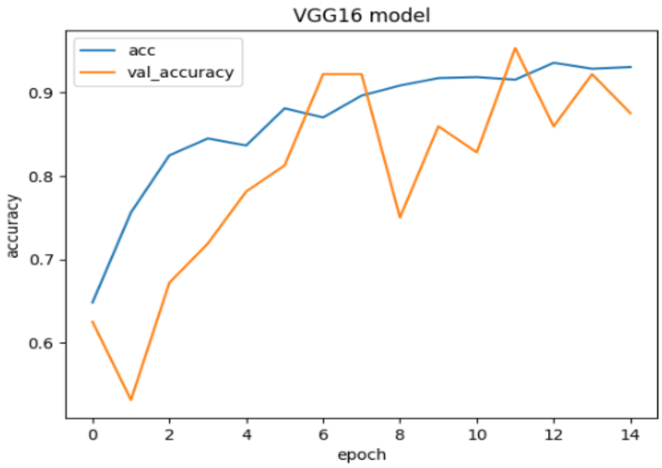

Fig 5 Transfer learning model

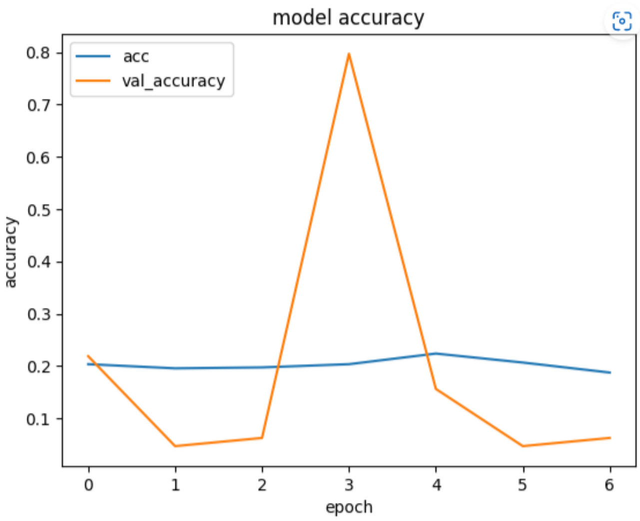

Fig 6 Deep learning model

V. CONCLUSION

Deep learning and transfer learning are the most widely used techniques in image processing and classification. In this project, we have used the VGG16 model in transfer learning as a pre-trained model and we have built a CNN model from scratch in deep learning. The results show that the VGG16 model outperforms the deep learning model with an accuracy of 93.75 %. Hence, VGG16 model is the best suited model for the classification and detection of diabetic retinopathy.

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