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Coherent convolution neural network based retinal disease detection using optical coherence tomographic images

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A B S T R A C T

An optical coherence tomography images are used to visualize the retinal micro-architecture and perform an easy scan of its abnormalities. In this paper, a coherent convolutional neural network is proposed for four-class classification of retinal diseases and able to detect neovascularization (CNV), diabetic macular edema (DME), DRUSEN, and NORMAL class label in the OCT images. The new proposal overcomes three of the challenges by (1) more profoundly detect the irregular patterns of each class of retinal disease (2) manages consistency between input and output of the network (3) cohesively bound the layers of the network for easy flow of image features. The proposed convolution neural network model is having five layers. In order to adopt coherent behavior, the proposed model inculcating the batch normalization layer along with the every activity layer and obtained an accuracy of 97.19% for retinal disease detection. Moreover, the performance of this method is remarkably good as compared to other standard deep learning methods. This proposal is a promising step in revolutionizing the present scenario of ocular diagnostic system and has the potential to generate a significant clinical impact.

1. Introduction

Over the past few decades, the human race has witnessed enormous evolution at an accelerated rate in various diversified fields such as medical, transportation, global connectivity, intellectual quotient, and much more (Schick and Toth, 1994; Nei, 1982). Advancements in technology have acted as a catalyst in bringing the revolutionized outcomes, due to this, none of the area that remains unexplored. One such flare-up was the advent of artificial intelligence and deep learning models, the way these astounding technologies are being explored in the fields of speech recognition, image detection, navigation, stock prediction (Hee et al., 1995, Puliafito et al., 1995, Huang et al., 1991) making everything user friendly, making them more and more part of our daily life easier. This paper discusses one such application of deep learning in the field of medical science is automatic detection of retinal disorder using OCT images. The new approach for retinal disease detection has been proposed, and it significantly manage four class problem, able to differentiate the choroidal neovascularization (CNV), diabetic macular edema (DME), DRUSEN, NORMAL class of images.

Optical Coherence Tomography is a technique developed for non-invasive diagnosis of biological tissues (Huang et al., 1991), extensively used by Ophthalmologists to study the structure of the retina and related diseases. OCT is analogous to ultrasound where it uses low-coherence interferometry to produce a two-dimensional image of optical scattering (Puliafito et al., 1995). It has longitudinal and latitude spatial resolution which is capable of detecting very small reflected signals from retina which is approximately 10(-10) of the incident optical power (Horie-Inoue and Inoue, 2014).

The retina is the light-sensing thin layer of tissue present in our eyes, the main purpose of the retina is to convert the received light into neural signals and send these signals to the brain for recognition of the visual. It consists of a pigmented area in the center region to retina called as macula. During the lifetime of a human being, these critical tissues of retina often get damaged and lead to various types of disorders including vision weakening, eye shadow, blindness (Hee et al., 1995). Two prominent lesions are age-related macular degeneration (AMD) and diabetic macular edema (DME). AMD is irreversible macular damage that comes with age making the person's vision partially blurred or completely no

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vision (Merl-Pham et al., 2016). There are two types of AMD disorders dry and wet AMDs (Iejima et al., 2015). Although it stated that, it can be cured, if acknowledged primarily and provided with proper medication, it can surely helps in controlling the degeneration process (Evans and Lawrenson, 2017). Diabetic macular edema (DME) is another trivial macular damage, which leads to a complete blindness (Gregori et al., 2011; Engelgau et al., 2004). Patients who have been diagnosed with diabetes for more than 20 years are more likely to suffer from DME. Although it's early symptoms are almost undetectable and get unnoticed by the patients (Tapp et al., 2003; Kertes and Johnson, 2007). Hence, various CAD tools and techniques related to fundus photography are used to analyze the blood vessels, which are often narrowed or completely blocked and finally, when they get burst can lead a bleeding or blurring the vision. Unlike AMD, this can happen in related disease to anyone irrespective of the age. It is diffcult to cure but if diagnose at an early stage will help in tackling the battle against the vision loss. Drusen is accumulation of small yellow spots under the retina which are a complex composition of fatty proteins(lipids). These debris build up over time (Johnson et al., 2001; Johnson et al., 2000), drusen are basically of two types: soft drusen specify the large spots marked closely whereas hard drusen are small and more spread out. Drusen is not really the reason for causing AMD, but it definitely increases the chances of evolution (Sarks et al., 1994; Shen et al., 2007). It does not cause complete blindness but results in loss of central region which is essential for focusing on details straight ahead. Choroidal Neovascularization (CNV) as the etymology suggests is the development of new blood vessels which emerge from the Choroid (Grossniklaus and Green, 2004). Fig. 1, depict the different type of disorders, the arrows point towards the disorder occurred in the retina region of OCT images.

This paper, entirely based on four class classification problem of ocular disorders and able to detect choroidal neovascularization (CNV), diabetic macular edema (DME), DRUSEN, and NORMAL in optical coherence tomography (OCT) images using proposed network.The new proposal as coherent convolutional neural network, includes two of the vital properties as coherency and convolution in the desired network for the OCT image dataset (Rajagopalan et al., 2021; Hod et al., 2021). The convolution governs an invariant property towards the attributes of input image such as scale, orientation and translation. Due to this reason, CNN considered to be the foundation of proposed network which are used to detect the retinal disorders more robustly. In addition to that, the new proposal includes coherency in existing CNN network and it helps to propagate the image features between the blocks of layer more logically to improve the computational time.

The proposed network mimics the concept of binding, it generally occurs in the cortical region of human brain network. The concept of binding signifies that the different features concise to a single percept in the brain visual cortex, this concept incorporate in the proposed network for various image feature, which helps to predict single disease class, out of many available classes, based on their limit weights of neurons at any time instance. This section describes the overview of retinal disease and its characteristics, the remaining article is organized as Section II describes the non-invasive approaches, use to developed by various scientists and researchers for performing screening and detection of retinal diseases. A majority of the work has been completed in this field and produced some astonishing results based on similar modality of image. In addition to this, Section III discusses about the development of proposed approach as coherent convolutional neural network. Moreover, Section IV focuses on the results obtained from proposed approach and its comparison is drawn with other standard deep learning methods and its performance can be measured with certain measures such as confusion matrices, loss and accuracy curves, and other statistical measures. The results achieved from the new proposal have proven to be more helpful for retinal disease detection. In continuation of this, Section V confined the article with achievements as well discuss the potential benefits of retinal OCT images for this problem.In addition to this, it also states about the network inferences used in the new proposal and it also talks about future possibilities and improvements.

2. Related works

Over the few decades, there has been enormous research in the field of medical imaging and the advent of several machine learning and deep learning models has been developed by the researchers to obtain a more refined result. The usability of AI prove to be beneficial in the medical industry. The detailed description of machine learning models and AI approaches by various scientist and medical experts on OCT images are discussed in this section.

In terms of abnormality, an image object has to be depicted in the OCT images by analysis and processing methods and divided it into two sequential cluster, one after the other. The primary work is based on feature descriptor with machine learning approaches whereas other were based on deep learning methods. The Lematre et, al.(Lemaitre et al., 2016) develop the technique for small dataset which describes the retinal layers flattening using NLM filtering with LBP-TOP feature extraction and classification using BoWs-RBF-SVM classifier. In addition to this, the Farsiu et al. (2014) develop a quantative binary classification technique for retinal disorder by manually extracting the feature and applying regression technique with the accuracy of 99% and leave one out-of-CV. In extension to this, the Liu et al. (2010) consider the 4 classes classification of retinal abnormalities and address the solution noninvasively using OCT images. The suggested technique describes the retinal layer alignment by extracting the multi-scale LBP feature and further classified with radial basis SVM classifier. The obtained accuracy is 93% with 10-fold CV. For the further improvement, another group of researchers, Srinivasan et al. (2014), reveal an approach based on Histogram of gradient(HOG) feature descriptor and supervised SVM classifier. The obtained results are quite promising, but the ML computation performed on a small dataset. In addition to this, Wang et al. (2016) consider 3 classes of retinal disease with large dataset of 3000 SD-OCT images and drawn the comparision of various machine learning techniques such as SMO, BPNN, polynomial based SVM, ensemble based random forest and it depicts that out of these technique, the SMO generates best results with the overall accuracy of 99.3%. Although, Due to different dataset, the direct comparision based on performance metrices for these techniques are not possible, but that can be reported profoundly to fullfill all the objectives related to retinal diseases diagnosis as well as prognosis.

For the large dataset, the deep learning techniques has been adopted for the diagnosis of various retinal diseases. The Lee et al. (2017) perform the computation on gold standard OCT images and resultant approach has a modification of classical VGG-16 model. The results obtained as Accuracy: 87.63%, Sensitivity: 84.63% and Specificity: 91.54%. Furthermore, Yanagihara et al. (2020) adopt generative adversial network(GAN) for the detection of retinal disease. The obtained accuracy is improved by involving

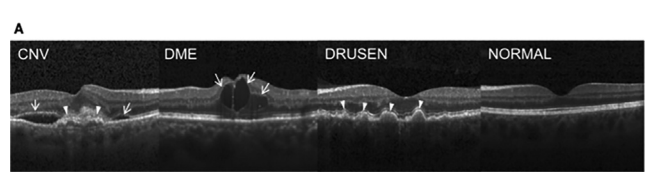

Fig. 1. OCT different types of retinal Disease Vs Normal Retina.

graphical processing unit(GPU) for computation. Although, OCT images and deep learning models completely transformed ophthalmology. It also helps to optimize the non-invasive detection and progressively accelerate the intergral efforts of combined technology in this field. The Li et al. (2019),perform the similar task on 21357 images having four classes and the adopted method for computation is another variant of deep learning model i.e ResNet 50. The obtained results are quite promising 10-fold: Accuracy 97.3%, Sensitivity: 96.3%, Specificity: 98.5%. But, Lu et al. (2018) increases the number of image samples with similar classes and consider a model of ResNet 101, but the accuracy is slightly reduced and the achieved results, marked as Accuracy: 95.9%, Sensitivity: 94.2%, Specificity: 96.4%. The above discussion depict that the data handling and big data computation are quintessential major in machine learning or deep learning methods. In addition to this, another essential phenomenon is the decision of stop clause features which are solely responsible for class differentiation. The limitation of above discussed models were the model complexity. In the complex model, if the number of layers are more, it surely requires more computation time.

In this paper, automated detection of retinal diseases was performed by new approach of deep learning for OCT images that generate reliable solutions with high sensitivity and specificity. OCT, which can visualize retinal microstructures, is currently a powerful essential source to diagnose retinal diseases and direct to suitable treatment. To address the aforesaid issues, we present a novel approach that makes use of another variant of VGG model having 5-layers called as Coherent Convolutional Neural Network. The proposed model is structurally efficient and also provide results that are more competent than already existing models (Rajagopalan et al., 2021) by making use of the correct set of hyperparameters (Landau and Sompolinsky, 2018). The proposed model simplifies the neural network by reducing the number of layers in the standard VGG deep network by identifying the efficient features in coherent blocks.

3. Proposed Work: Coherent Convolution Neural Network (CCNN)

The CCNN is a biological conceivable network structure in which processing is purely based on incoming information from the preceding areas. The coherent behavior helps to analyze the information change between the network layer as similar to the activity change in the different brain region during different perceptual states and generate the processing output more promptly. The proposed model signifies the efficient communication between layered block, developed with synchrony in the network and perceptually handle the flow of feature vectors as shown below in the Fig. 2 of lower networks transformed from upper standard VGG-16.

Fig. 2, depicts the transformation of functional block diagram from VGGNet to the proposed model. In the upper image the number(x2, x3) represents the number of times the convolution performed in the block1 & 2 on the network whereas these operations minimize in the proposed approach to single unit in lower image.

In addition to this, these are the following reasons for considering CNN for retinal disease detection:

• CNN mimics the behavior of mammals visual system, which signifies as how they perceive the world around them using a layered architecture of neurons in the brain. This concept of CNN inspired to develop a model which is not only robust but perceptually fast.

• Convolutional neural network governs the time invariance property of convolution, which signifies that when we translate, rotate, shear and scale the OCT input image, can merely affect the performance of the retinal disease detection.

• For grid like topological data, CNN considered to be the best selection. With this approach, Image data which can be thought of as a 3D grid of pixels and it is going to process at different levels with the simple structured way. Say as an example, for subsampling of the image there is pooling layer to highlight the essential neurons and they propagated the next layer of the network and the rest of them are dropped out.

• CNN has sparse interactions and it signifies for local information rather than taking the complete global information.

Due to these attribute, CNN's considered to be the best performer in image-related tasks because in images neighboring pixels are more burly correlated than distant ones. This concept is all coherency, and it helps to inculcate this concept in convolution neural network. To evaluate the behavior of neurons which belongs to region of interest as retinal disease in proposed model is being discussed in the next section.

3.1. Need of CCNN

In the proposed work, a transformation of pre-trained model has been performed to generate a more cohesive approach of deep

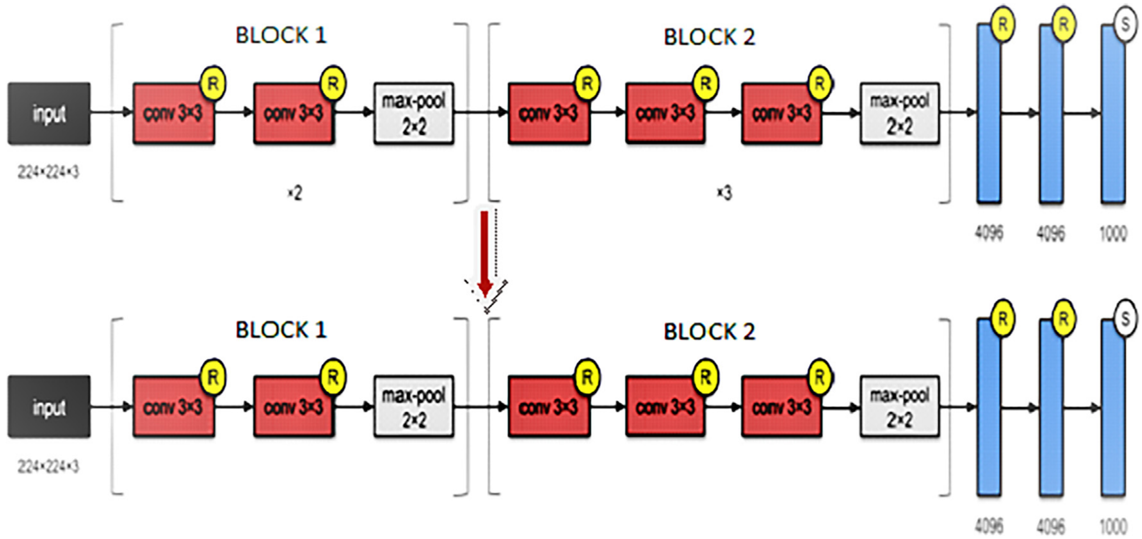

Fig. 2. Proposed Coherent Convolution Neural Network obtained from standard benchmarks network.

neural network. The following attributes encourages for new proposal:

• Coherence has been found enormous applications in the surrounding world, including change of mental states in perceiving an object through eye (Hod et al., 2021). Identical concept has been incorporated in the proposed network to improve the accuracy of abnormalities detection and disease classification. Due to incoherency in perceptual effect, it causes high error rate as well as increases the computation time for retinal disease prediction.

• In a signal processing it depicts the behavior of input image with respect to filters in 2D Convolution.The selection of the 2D convolution type is also a criteria for tightly coupled features and performs robust computation in the funnel (hierarchical model at the last fully connected layer generate output) like architecture of CNN.

The proposed network model for retinal disease prediction in OCT images is described below in the next section.

3.2. Proposed model description

In the proposed model, Coherent behavior of convolutional neural network is indented to explore the disease abnormalities based on synchronous structure of tissues found in various ocular diseases.

This model consist of 5 layers as shown in the Fig. 2 and Fig. 3, the new model obtained high accuracy when the image size was 64x64, but it certainly reduces with decreasing in image size. Moreover, to understand how the layers are connected to each other and how they helps to transform from the pre-trained architecture of VGG-16. The coherent block concept restructures the network and attains more stability for retinal disease detection.

As evident from the name VGG-16, the pre-trained model consists of 16 layers. The proposed model reduces the block repetition as marked in VGG-16 as B1 block (two times) and B2 block (three times). The activity undergoes in these two blocks are depicted above:

• In the sequential model, **Block-1** consist of two convolution layers with a filter size of 3X3 followed by maxpooling layers.

• In subsequent of **Block-1**, there is **Block-2** consist of three convolution layers with a filter size of 3X3 followed by maxpooling layers.

In the standard neural network, there is only one block having three convolution layers incorporated with maxpooling at each layer, very similar to Block-2. The standard model give the right direction to proceed, it was basically for finding out the distribution of dataset. The obtained accuracy in standard neural network is 95.2%. These results overwhelm us and develop a deep interest in creating a more intelligent model having substantially improved accuracy. The functionality of new network are describe in the following steps:

• In continuation of this, and adding another block(B1) in the appropiate direction to generate more cohesive network, that is coherent convolution neural network.

• The proposed models, having 5 layers marked as two blocks, but it essentially had to use both the block in the defined order as describe in the Fig. 2.

• The above Fig. 2, clearly depict the significance of the order, if the block order reciprocate as B2 followed by B1 with incorporated maxpooling layers, gave us an accuracy of 96%.

• After correcting the block order, a consistent problem of learning persist in the proposed network i.e. overfitting.

• To overcome this problem, a dropout layer has been incorporated in the network. The added layer, randomly drops neurons during the training phase from the adjacent layers of the network in each of the iteration.

• Due to this reason, the proposed model certainly perform a phase shift of high variance to high bias.

• So we incorporated dropout layers after every convolutional layer and then evaluate the task by performing training on the updated network. After the training process, the model will

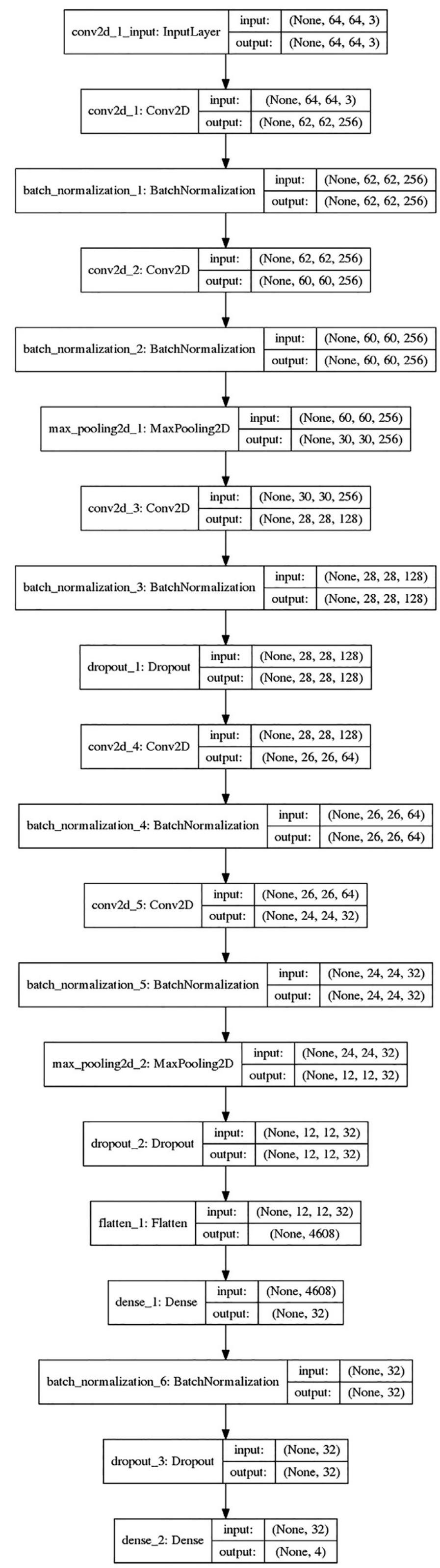

Fig. 3. Layer Architecture of Proposed CCNN.

definitely not overfit as evident from the fact that validation accuracy was not that much higher than the training accuracy, making our model improved. We realised the problem was dropout and we abused its power, as describe in Fig. 3.

• Finally, removed regularizer after every layer and put it after convolution layers only. This caused our model to properly fit and achieved a fairly good accuracy of 97.19%.

Now it was time to also experiment with a proposed model (that is B1 followed by B2). Lightweight CCNN keeps the bare minimum layers by only adding in the dropout parameter in the junction of two blocks B1 and B2. Moreover, each layer was followed by batch normalisation which is a technique to normalise the output before being sent to next layer. When this model was trained, the accuracy score achieved was 98.6% which is by far the highest we've got with our image size of 64 $\times$ 64. Even pretrained deep models like MobileNet and ResNet were not able to perform up to this level of accuracy.

High accuracy and minimum loss has been obtained by new proposal of CCNN, which is remarkably better than the existing layered model by giving a boost from 95.8% to 97.9%. Moreover, it seemed that model accuracy improve by increasing pruing effect in the neural network. To increase the model accuracy of more than 5 layer model, but it slightly deteriorates when increase in the number of layers to seven. At seven layer architecture, it is ascertain that our network performance desceases. Fig. 2 describes the functioning of five layer proposed model architecture whereas Fig. 3. illustrate the detail mechanism as a network architecture for identification of disease detection. The robustness of the proposed model is being discussed in next section as an experimental result.

4. Results and discussions

This intelligent system was evaluated for four classes of retinal diseases such as CNV, DME, DRUSEN and normal samples in OCT images.The fully automated algorithm was coded in Keras API on tensorflow framework of deep neural network and tested on a 2-core system architecture with a Windows-8.1 having 64-bit operating system, Core i5-5558 CPU at 3.4 GHz (Intel, Santa Clara, CA), and 8 GB of RAM and 2 GB GPU.

4.1. Data collection

Optical coherence tomography (OCT) for retinal disorder is an imaging technique used to capture high-resolution cross sections of the retinas of live subjects. Approximately, 30 million OCT scans are performed each year, and the analysis and interpretation of these images takes up a significant amount of time (Swanson and Fujimoto, 2017). To assess the performance of our coherent convolutional neural network on this data and its ability to generalize the dataset obtained from the internet resources available on the kaggle Kermany, 2018.

4.2. Training of a CNNModel

To train a CCNN model, 83,484 of 84,495 OCT images [Table 1] were chosen randomly. The input OCT images belongs to the benchmark dataset. The input OCT images belong to the benchmark dataset. The complete dataset include data augmented images and perform preprocessing with the following steps:

1. Scale the input images
2. In order to allow the proposed model rotational invariant, rotate the images through any degree between 0 and 360 by providing the integer value
3. Perform horizontal flip on the input images
4. To make them location invariant, perform height and width shift

Preprocessing helped in perfect fitting of the model, but also reduced the training time.

The training dataset are from the homogenous source i.e. same hardware source. Keras API based TensorFlow, an opensource deep learning framework, was used. A proposed CCNN is based on standard VGG-16 model with two blocks in which block 1 having two convolution followed by block-2 having three convolution layers accompanied by a "max pooling" layer. The regularizer as "dropout" layer is added for managing the coherency among the blocks of proposed model. Original 8,300 images were augmented with horizontal flipping, rotation, and translation as shown above in the Fig. 3. Finally, the accuracy of the trained CNN model reached 97.19% after parameter tunings.

Table 1
OCT image Dataset.

Classes	Retinal Disorder Classes	No.-Training	No.-Validate	No.-Test
3	CNV	37205	8	242
0	Normal	26315	8	242
2	DNE	11348	8	242
1	DRUSEN	8616	8	242

4.3. Performance analysis of the proposed model

To evaluate the performance of the proposed network, there are certain statistical measures which are computed from the confusion matrix as shown in the Fig. 6. We implemented overall accuracy, sensitivity, specificity measures to evaluate the performance of our model, and compared these parameters of proposed model with the results obtained by other standard deep network depicted in Fig. 6. Accuracy was calculated by dividing the number of correctly labeled images by the total number of test images. Sensitivity and specificity were derived by dividing the total number of correctly labeled abnormal class with the total number of correctly labeled normal class respectively by the total number of test images. Confusion matrix were used to assess the ability of our model on retinal OCT images for discriminating the various abnormalities of eye. It provided the tradeoff between the sensitivity and specificity. Confusion matrix was used to summarize the diagnostic accuracy for multilabel classification of occular disease categories. Performace evaluation metrics helps to analyse the deep understanding of each class label and give more generalized training and test results.

4.4. Comparison with related networks

The performance of proposed network was further assessed by comparing the obtained results with other standard deep learning network on the same data as shown in the Fig. 4, Fig. 5 and Fig. 6.

The tuning parameter for the proposed network strictly follows the size of image. If size of input image is 224x224 has been adopted for the proposed network, it performs certainly better than pretrained models of MobileNet, ResNet and VGG-16, as described in the Fig. 6. In addition to this, the proposed model has been compared with densenet, inception-resnetv2 or inceptionv3 on the same dataset of OCT images and it highlights the following issues:

Large network architecture affects the computational cost: The other network architecture like densenet, inception-resnetv2 or inceptionv3 is complex network of 50–100 layers. In this system, a mid level (input: image to output: features) image

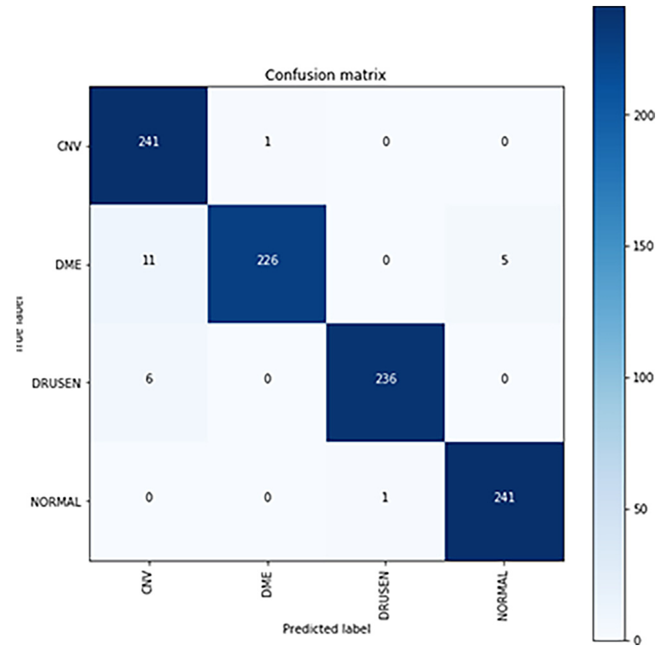

Fig. 4. Confusion matrix of Proposed Network.

processing has been performed and obtained images features are updated at several levels or layers of the network.

Dynamic filter size at leach layer: The other network architecture like inception-resnetv2 or inceptionv3 having different size of filters at each layer of the network.

Moreover, the proposed network controls the indifferent behaviour of VGG for retinal disease prediction is that, it behave poorly when the classes was unbalanced but with balanced class performance of the diagnostic system suddenly improves. In order to balance the imbalance class, it simply optimizes the loss function and forms a weighted loss function to obtain the high level of accuracy. For example, in a binary classification, the number of samples in the image dataset is 10, out of them 8 considered to be normal and 2 abnormal. The predicted probability is 0.5 i.e. log (1–0.5) = 0.3, for each image sample. The loss for each image sample is 0.3 i.e (wn = 2/10,wp = 8/10), is calculated from the modified loss function formula as given below:

$$L(x,y) = \begin{cases} wp * -log(P(Y = 1/x) & if \quad y = 1 \\ wn * -log(P(Y = 0/x) & if \quad y = 0 \end{cases}$$

Where, wp = number of positive samples/total number and wn = number of negative samples/total number.

In this way, the shortcoming of dataset (class imbalance problem) for occular disease prediction has been managed. Despite that the obtained results are robust and more accurate in overall performances of the system. Various methodological changes has been added and enomorous difficulties in translating the standard VGG-16 to CCNN proposed model are found to improvize the clinical practice. These identified difficulties are (1) manage large-image datasets obtained from OCT devices, (2) data imbalance problem related to classification due to oversampling (3) limited graphics processing unit (GPU) capabilities, and (4) inconsistency of layers in standard deep models for retinal disease detection. The results discuss in this section, clearly justify the above-mentioned difficulties with potential solutions. In addition to this, three of the performance metrics are used to evaluate the robustness of deep learning model: Accuracy, Specificity and Sensitivity. The training and validation accuracy of proposed model in comparison of standard benchmark models is described in the Figure [5].

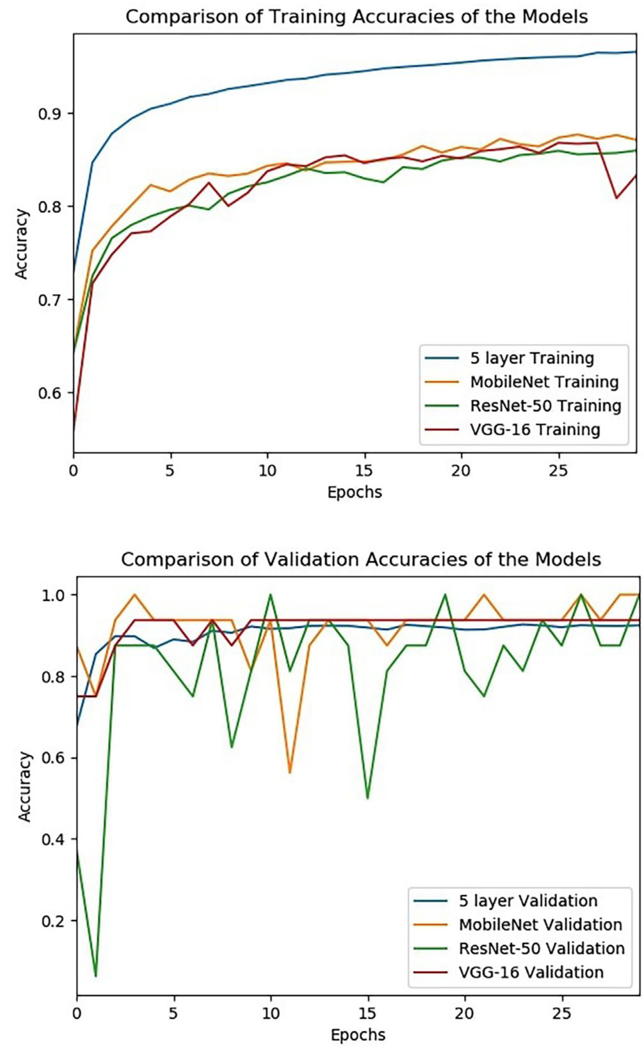

Fig. 5. Performance Measure.

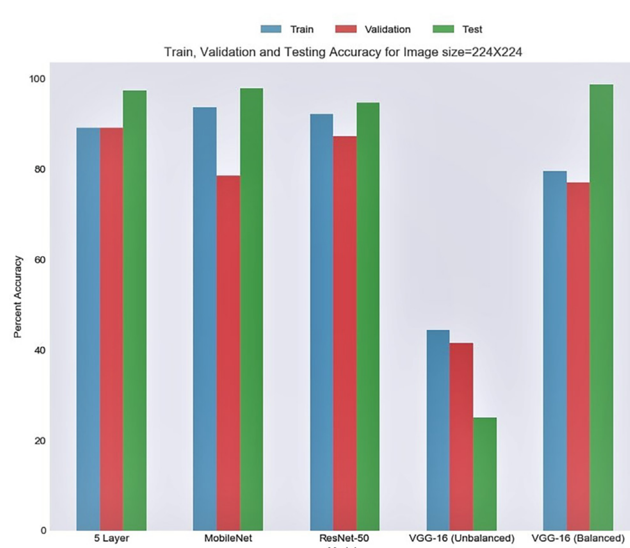

Fig. 6. Comparision of proposed network with other standard network.

Fig. 6 depicts the comparison of the proposed model (CCNN) with the more recent convolutional neural networks. There are the cases where model fail to detect the retinal disease accurately. This image shown below is actually a normal retinal image, but predicted as retinal disease.The model accuracy majorly depends on, how fine the hyper-parameters tuning has been performed. The hyper-parameters considered for the proposed model are size of image, learning rate, no of epochs, regularizer as dropout applied to each layer of the proposed model after performing the batch normalization. The cohesiveness of the network is all selection of essential neurons by inculcation of significant level of dropout at each layer of the proposed network. In order to attain the model explainability more profoundly for retinal disease detection, the understandability and Interpretability has been considered. These two aspects help to reduce the efforts of Medical experts by the following ways:

Understandability: The appropriate image understanding is required for the new proposal. Although, retinal disease detection is a well understood problem for fundus images, with the benchmark dataset of STAR and DRIVE, transient to optical coherence tomography images as an input considered to be more advantageous and it eases the process of retinal disease detection at tissue level for four classes(DME,CNV,DRUSEN,NORMAL) with the following reasons:

- The naive approach can easily handle clinical and technical issues of OCT images such as numerous variability, field of view, image magnification, image quality.
- A Disease like DME, CNV are the sever class of diabetic retinopathy where as DRUSEN is the only deposition of fatty protein under the retina region, as depicted in Fig. 1. Retina is a thin layer of tissue that support optic nerve and optic nerve connect the eye to the brain. These are all tissue level disorder. In order to analyze tissue level artifacts requires OCT images and its analysis is to be performed by the coherent convolution neural network (CCNN).
- The CCNN is able to detect connected set of pixels in an entitled image which belongs to any of the available class patterns of ocular disease based on their attributes, and these attributes extracted from image pixels by adopting the property of coherence.

Interpretability: Identify the factor which increases the social acceptance of a new proposal by the following reasons:

- Evaluate the model not only with accuracy, but with more robust performance measures, such as specificity and sensitivity and ability to increase the global acceptance of the new proposal.
- Evaluate the bias in the existing models for the retinal disease detection and compare them with the proposed network
- The new proposal adopts the binding concept of visual cortex for retinal disease prediction and able to perform processing in less computation time.

5. Conclusion and future works

This paper, proposed a novel deep learning method that can resolve the problem of automated retinal diseases classification in OCT images with robust results. More oftenly, Deep Neural networks considered to be mysterious path for data handling. The proposed network(CCNN) has been developed by pruning the pretrained model of VGG-16 and generate more refine connection of neuons and develop more optimized layers to perform salient activities for occular disease detection. To obtain the accuracy of 97.16%, there is need to identify the most essential neurons of network and it can be possible by using efficient regularizer such as dropout layer. The dropout layer helps to prune the network as described in the proposed model. The identified neurons are cohesive and it helps to tightly bound the network. It also flows the features quite efficiently between blocks architecture of proposed model. Due to this attribute, it will be easily inferences on various heterogeneous device accelerators like the GPU, TPU and FPGA and able to create cost-effective and robust computer vision applications in the domain of ophthalmic.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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