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The Survey on Eye Diseases Detection using Transfer Learning-based CNN

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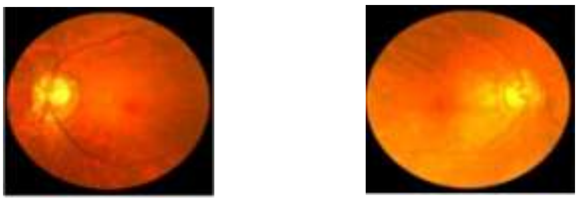
Abstract: *The objective of this paper is to detect wide range of ophthalmological disorders. Early detection of eye disorders aids in prevention of blindness in both infants and adults. Fundus images of eyes are used both o identify and classify ophthalmological diseases. Observation of fundus images and anomalies in it can detect a wide range of ocular diseases. A person can posses more thanone eye disease. Publicly available ODIR dataset containing eight classification of eye disorders is being used. Different Convolutional Neural Networks (CNN) architectures are proposed and compared along with ADAM and SGD optimizers to attain maximum accuracy. Among them, VGG16 with SGD is found to perform better with ODIR dataset.*
Keywords – *Ophthalmology, CNN, Fundus, Detection*

I. Introduction

Ophthalmology is a part of medication that arrangements with the determination and treatment of eye problems. Identification of eyes problems in beginning phases can help in visual deficiency counteraction. Tele-clinical identification of ophthalmological problems and classification have acquired significance from the pandemic. The target of this discussed work is to advance a computerized fundus picture classification model equipped for distinguishing a more extensive scope of eye diseases. It intends to utilize fundus pictures for multiple-name multiple-class classification of eye diseases. The discussed method incorporates the high performance and generalization capabilities of profound learning procedures for classification. Two exchange learning based previously designed CNN are discussed to classify fundus pictures into 8 classifications of eye diseases.

The study of retinal tissue is essential for a person's overall health. Fundus imaging, as discussed is an OCT imaging technology which is also cost-effective and congenital method of screening and detecting eye diseases. Ophthalmologists use fundus images as a main technique for detecting diseases such as glaucoma, hypertension, age-related macular degeneration (AMD), diabetic retinopathy, cataract, and myopia. Fig 1(a) shows the fundus image of a patient's right eye and Fig 1(b) shows the fundus image of a patient's left eye.



(a) (b)

Fig 1 (a) Right eye fundus image and (b) Left eye fundus image

II. Literature Survey

Radifa H Paradisa[1] proposed a model on Utilizing deep CNN technique for detection of diabetic retinopathy (2021). Deep CNN algorithm with InceptionV3 architecture and various optimizers like SGDM, RMSprop, Adam is used to detect diabetic retinopathy using fundus imaging. The InceptionV3 model with the Adam optimizer gave best results with 96% accuracy.

Astri Handayani[2] proposed an approach on A hybrid model for detection of diabetic retinopathy (2020). SVM algorithm with MobileNetV2 hybrid model is used to classify diabetic retinopathy on colour retinal images of dataset APTOS 2019. This small-scale architecture produced an accuracy of 85%.

Juan J Gomez[3] proposed an approach on Classification of glaucoma using transfer learning (2019). Various CNN architecture's performance has been studied in classification of ocular disease on OCD database and on other databases too. Segmented input outperformed the original input images.

X Wang[4] proposed an approach on Detection of ocular disease using preprocessing techniques of CNN (2022). Various CNN architecture's performance has been studied in classification of ocular disease on OCD database and on other databases too. Segmented input outperformed the original input images.

Mo Tiwari[5] proposed a work on Differentiation of Infections in cornea using Deep Learning (2022). VGG16 architecture of CNN is trained to classify and identify ulcers and scars on the cornea from SCUT, MUTT and Byers Eye Institute of Stanford University. CNN model was trained using cross-entropy and Adam optimizer. Accuracy of 97% on Indian dataset and 94% on California dataset was achieved.

Abhilasha Singh[6] proposed an approach on A trustworthiness control framework in light of watermarking for retinal image (2021). Detection of non-medical images using watermark technique is proposed here. It is important for the any tele medical approach to preserve the integrity of the classification.

Veena Mayya[7] proposed an approach on Accurate Corneal Segmentation Using a Multi-Scale CNN in the Early Detection of Fungal Keratitis (2021). Multi Scale CNN with ResNet architecture is used to classify fungal keratitis and non- fungal keratitis. Loo et al's dataset is used for proposed approach.

Sonal Yadav[8] proposed a work on Deep neural network performance analysis using transfer learning in ocular dispersion prognosis using fundus images (2022). Transfer learning's role is being discussed on classification of retinal detachment and non- retinal detachment based on fundus images. Performance of different architectures like AlexNet, InceptionV3, GoogleNet, VGG19, DenseNet, and ResNet50 are analysed. Publicly available datasets on RD is used.

Chaymaa Lahmar[9] proposed an approach on Deep Learning Approach for Diabetic Retinopathy Classification (2022). Light weight dual CNN architecture is used. As other approaches are complex and difficult to deploy. 84,645 parameters are involved in training and deployment. ATPOS dataset is used.

Turimerla Pratap[10] proposed a model on Deep learning method for computer-based eye diseases diagnosis. (2019). Feature extraction is done using AlexNet architecture of CNN model. Fundus images are obtained from various publicly available datasets and image quality selection is applied to obtain good quality images, which plays an important role. Pre-trained CNN is then sent to SVM classifier for cataract diagnosis classification.

Arun Das[11] proposed a model on IoT teleophthalmology cloud distributed machine learning for predicting AMD disease progression (2019). A wearable head mounted band is worn by the patient to send fundus imageof retina, which s sent to the private cloud for diagnosis. CNN model with ResNet architecture of 152 layersused to detect AMD severity. Accuracy of 90% is achieved.

Rahul Kapoor[12] proposed an approach on Artificial Intelligence and Other Ophthalmology and Beyond Applications (2021). VGG16 architecture of CNN is trained to classify and identify ulcers and scars on the cornea from SCUT, MUTT and Byers Eye Institute of Stanford University. CNN model was trained using cross- entropy and Adam optimizer. Accuracy of 97% on Indian dataset and 94% on California dataset was achieved.

Sivakumar Ramachandran[13] proposed an approach on A deep learning approach for detecting Plus illness in preterm newborns' retinal fundus pictures (2021). Infant retinal images from KIDROP Bangalore, India are obtained to classify for plus disease. A CNN model of 33 layers, each containing a leaky ReLU is used. Results are compared with U-COSFIRE filter. Accuracy of 99% is obtained for the dataset.

Adir C Sommer[14] proposed an approach on the light of the growing COVID-19 outbreak, Telemedicine in ophthalmology (2020). Pandemic situations led to difficulty in ophthalmological disease detection in the clinical setup. Tele-medicine and tele-ophthalmology are found to be the best solution to it. Development of many remote and handy devices led to data collection of 'PubMed' database.

III. Proposed Methodolgy

Model 1: Two input CNN using transfer learning

The left and right eye fundus images are applied individually to the input from the CNN. Two feature maps areobtained from parallel CNN architectures. They are stacked together into GAP layer. Fig 2 represents the first model architecture discussed in the paper.

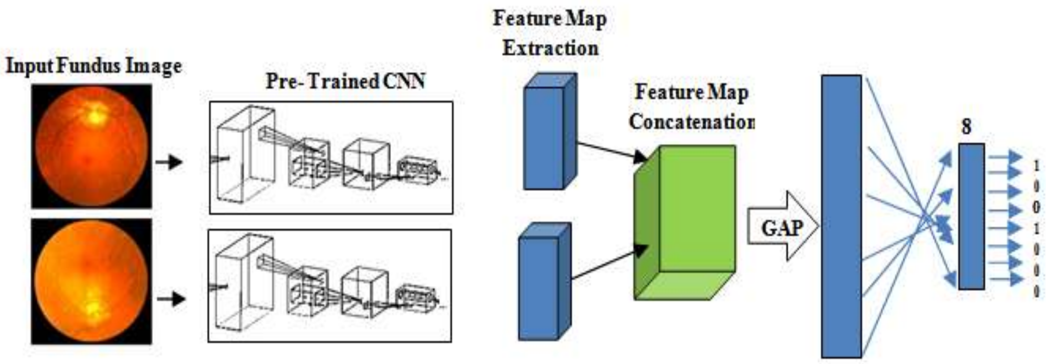


Fig 2 Model 1 Architecture

Model 2: Concatenated input CNN using transfer learning
Left and right eye fundus images are concatenated and applied to the input of CNN. Feature maps obtained from CNN architectures is passed to GAP layer. Fig 3 represents the second model architecture discussed in the paper.

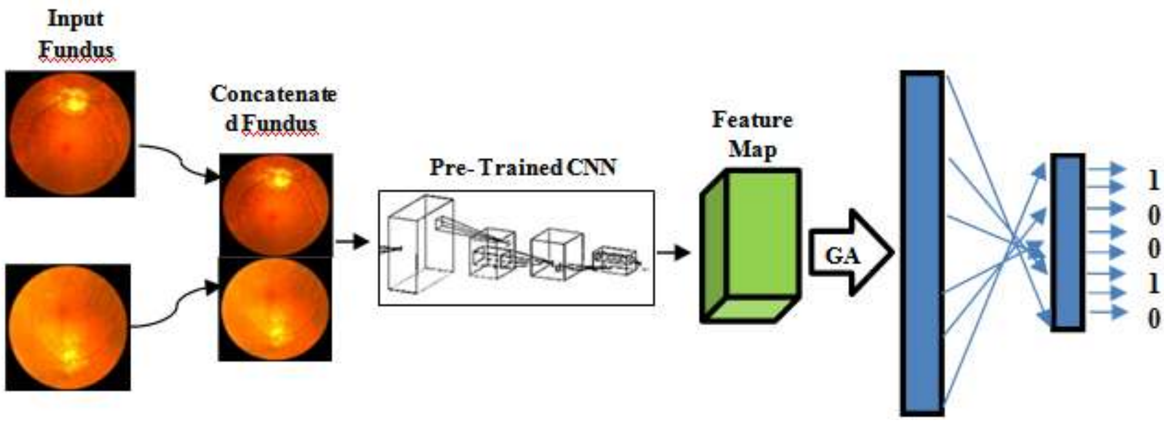


Fig 3 Model 2 Architecture

After the GAP layer, a thick layer with 8 activation units for each eye disease class is placed. For multilabel classification of fundus pictures, the final feature vector is optimized using a mix of sigmoidactivation function and binary cross entropy loss function. Every feature's predicted value is limited between [0, 1] by the sigmoid activation function.

$$f(s) = \frac{1}{1+e^{-s}} \quad \text{……….} \ (1)$$

Because multi-label multi-class labels should be addressed independently, the sigmoid function is utilized instead of the softmax function. The binary cross-entropy function is used to optimize the activatedunits. For N training samples, binary cross-entropy loss is a function of ground truth labels (y) and predicted labels (y). For each of the eight classes, the loss function calculates the difference between the predicted andtrue values.

$$L(y, \hat{y}) = -\frac{1}{N} \sum_{i=0}^{N} (y * \log(\hat{y}) + (1 - y) * \log(1 - \hat{y})) \quad \text{……….} \ (2)$$

Fine tuning is done, and a batch size of 16 is chosen, with Adam and SGD being used to optimize each model. The predicted labels are compared to the ground truth labels and the area under curve (AUC) and F1 score are calculated using confusion matrix-based parameters.

IV. Conclusion

Model 1: VGG16 CNN architecture with SGD optimizer gave the best results with training accuracy of 96.49, validation accuracy of 87.16, AUC of 84.93 and F1 score of 85.57. Hence, SGD optimizer will be used for best results. To confirm and compare this, model 2 is proposed to train and test for all the architectures with SGD optimizer using concatenated fundus image input.

Model 2: VGG16 CNN architecture with SGD optimizer gave the best results with training accuracy of 99.78, validation accuracy of 89.06, AUC of 68.88 and F1 score of 85.57

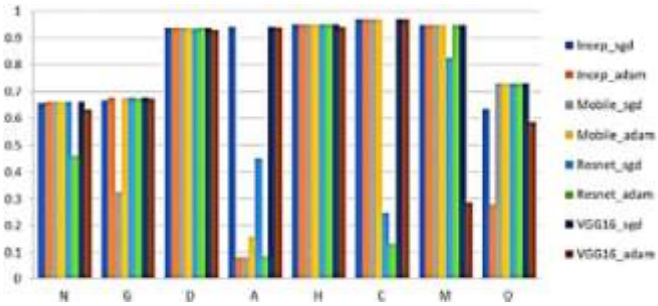


Fig. 4 Eye disease classification performance accuracy

This paper discusses an automated transfer learning-based CNN for eye disease detection. Two different methods are used for classification of images into eight eye diseases. In one model input images are individual from left and right eye whereas in the other model input image in concatenated form. Combinations of different CNN architectures with optimizers were tested and two input VGG16 model with SGD optimizer performed better for all disease classes. This discussed CAD system can be used for real small clinical setup. For hospital and large setups, wide range of classification can be used.

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