An Online Platform for Early Eye Disease Detection using Deep Convolutional Neural Networks

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***Abstract*— India has a blind population of about 12 million people, compared to 39 million people worldwide, and the sad fact is that 85 percent of these instances are curable. It has been found that the highest leading causes of eye blindness are due to Diabetic Retinopathy, Glaucoma and Cataract. Hence an automatic or self-diagnosing method using deep learning model is proposed in this paper to detect all the three diseases within a minute with high prediction rate. There have been various categorization systems developed throughout the years, all of which have improved significantly in the last decade or so. Logistic regression, SVM (Support Vector Machine), Decision tree, KNN (K- Nearest Neighbors), Random Forest, and Back propagation seem to be few of the numerous categorization models available. We propose a DCNN-based expert system in this study similarly to a human brain with input, neurons, hidden layers, and output for diagnosing three diseases through an online platform. Fundus images of both healthy and affected patients are acquired for this study under good lighting conditions so that any concealed characteristics may be recognised. The fundus images are then subjected to image processing techniques, including grayscale, resize, and power transform. Finally, a deep CNN with one hidden layer, 16 input neurons, and two output neurons that are either healthy or affected is generated. The detection accuracy was 91% for DR, 90 % for cataract and 86% for glaucoma affected images. A user-friendly, interpretable, online Graphical User Interface (GUI) was developed with the system.**

Keywords—deep learning, CNN, early eye disease detection, expert system, fundus images

I. INTRODUCTION

The human eye is a vital organ that is constantly responding to light. The human eye allows vision as a cognitive receptor; rod and cone cells in the retina allow cognizant light discernment and vision, including shade separation and depth perception. The doctor-to-ophthalmologist ratio is 1:10,000, which is considerably below the World Health Organization's recommended (WHO). In most cases, doctors are able to detect diseases only after it reaches the severe stage and takes more time to diagnose. Diabetic Retinopathy, often known as diabetic eye disease, is a condition in which the retina is damaged as a result of diabetes mellitus. It frequently has no early admonition signs. Glaucoma is a gathering of eye illness which brings about harm to the optic nerve and cause vision loss. It can be found just through ordinary eye check-ups. A Cataract is a blurring of the focal point of eye which prompts a lessening in vision. People with atomic sclerotic or brunescent cataracts regularly notice a decrease of vision. So that profound learning model is to be created to distinguish these infection by further developing expectation capacity and precision rate. And to foster an easy to understand connection point to interface with a model. Fig.1. depicts the normal vision, DR affected vision, Glaucoma affected vision and the cataract affected vision.

II. RELATED WORK

Now are a lot of AI-based illness diagnosis and classification systems out there that syndicate medical test conclusions with domain knowledge [1]. However, most of these systems lack the ability to link actual symptoms and clinical findings to the illnesses they are related with. This might be due to the fact that medical professionals use a range of observation recording methods.

The development of medical expert systems to automate diagnostic processes has sparked a lot of study [2-3]. Based on pre-defined rules, these expert systems may deliver proper responses; but, using static rules limits learning and, as a result, limits the ability to adapt to novel situations. The focus turned to machine learning through training data as machine learning algorithms improved. As a result, machine-based research efforts are rapidly expanding in practically all medical specialties, including ophthalmology.

Fig.1a. Normal Vision

Fig.1b. DR affected

Fig.1c. Glaucoma affected

Fig.1d. Cataract affected

For specific eye disorders, such as dry eye illnesses, refractive error, esotropic eyes, and development in glaucomatous visual field abnormalities, textual and numeric data was employed in References [4-5]. There were also probabilistic classifiers like naive Bayes and support vector machines used.

A research was undertaken in 2014 to assess clinical data in order to determine the link between dry eye disease symptoms and diagnosis [6]. Independent component analysis (ICA) and Pearson correlations were used to analyse the data, which came from 344 patients. The conjunctiva and corneal stains had the strongest relationships. Furthermore, the residual information in each component of the ICA mixing matrix was negligible. As a result, no consistent association between the most often utilised indications and symptoms was discovered.

In addition, a lot of research focused on interpreting picture data in order to convert it directly into diagnostic data. Blood vessel segmentation [7] was studied in 2018 utilising image-processing algorithms based on machine-learning methods.

A lot of exploration has been led on creating clinical master frameworks to robotize demonstrative cycles [8-10]. These master frameworks can create precise reactions in view of pre-characterized rules; be that as it may, the utilization of static standards brings about confined learning and subsequently disappointment to react to new circumstances. With the progression in AI calculations, the concentration moved toward AI through preparing information. Henceforth, practically all clinical fields, specifically ophthalmology, are currently encountering quick development in machine-based exploration exercises.

Existing model suggested the design and implementation of image processing techniques in diagnosing retinal disease. Methodology used to diagnose the images [11-12]. Glaucoma-super pixel segmentation, morphological operation. Diabetic retinopathy-median filter, morphological operation. Cataract-Adaptive histogram equalization.

Deep learning has been extensively praised for its potential to automate the screening and diagnosis of common vision-threatening diseases such as diabetic retinopathy (DR), glaucoma, age-related macular degeneration (AMD), and retinopathy of prematurity[13-15].

Further DL integration into ocular clinical practise is expected to enhance and innovate the present illness and management process, resulting in prior identification and, ultimately, enhanced disease outcomes.

The Deep Neural Network model [16] employs advanced mathematical activity to interpret pixel values in images, and training is done by integrating the network with a variety of instances, rather than the classic techniques' solid rule-based programming[17]. In the DED sector of Deep Learning, the Convolutional Neural Network (CNN) has been widely investigated [18-19], outperforming prior approaches such as image recognition. The goal of neural networks is to learn deep characteristics in order to detect the sophisticated dimension of mild DED[20]. Regardless, deep learning-based DED detection continues to focus on high performance in extreme scenarios, whereas moderate DED detection remains a challenge.

The above methodologies have the following limitations.

- For Low resolution fundus images, prediction accuracy is <85%.
- Different methodologies used to diagnose different disease.
- Time consuming process.

III. Proposed system

For picture segmentation, the suggested system employs a Convolutional Neural Network (CNN). Convolution layer, pooling layer, and fully linked layer are the three layer mechanisms employed here. The neural network is utilised since it is a trial and error process that requires a large quantity of data to train on. It's no accident that neural networks gained popularity only after most businesses adopted big data analytics and amassed massive data sets. Same mechanism is used to diagnose all the three disease. In this proposed system, the images were pre-processed and were subjected to a deep CNN model. An online GUI platform was developed for the users to detect the defect in the eye. The proposed system model is depicted in Fig.2. Early detection of eye disease and their timely management can prevent significant vision loss. The proposed model showed an increase in the aaccuracy level up to >90%.

IV. Methodology

There are standards for storing and organising picture datasets on disc in order to make them load quickly and efficiently, as well as for training and testing deep learning models. Tools like the Image Data Generator class in the Keras deep learning package were used to automatically import photos into train, test, and validation datasets after they were formatted. Furthermore, the generator will load the photos in the dataset in stages, allowing it to function with both small and huge datasets comprising hundreds of millions of images that may not fit in system memory. The data from the source is divided into three processes.

- Training data
- Validation
- Testing data

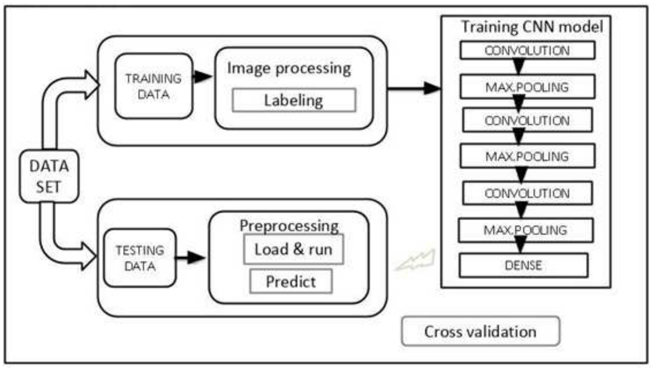

Fig 2. System Model

A. Training data set

The experience that the algorithm learns is based on the observations in the training set. Each observation in supervised learning issues has an observed output variable and one or more observed input variables.

B. Validation data set

A validation dataset is a subset of your training data kept hidden from machine learning algorithms. After you've chosen and changed your machine learning algorithms on your training dataset, you may test the learned models on the validation dataset to get a final objective view of how the models will perform on unknown data. Cross validation is the golden standard in applied machine learning for determining model accuracy on unknown data.

C. Testing data set

A test dataset differs from the training dataset in that it has the same probability distribution. There has been little overfitting if a model that fits the training dataset well also fits the test dataset. The training dataset is often more fitted than the test dataset, indicating overfitting.

V. IMAGE PRE PROCESSING

For better performance, pre-processing the image for feature extraction is essential. It was also discovered that publicly available fundus photos are made up of low-fidelity data and fundus photographs acquired with different fundus cameras, resulting in quality variations.

A lack of data is another issue that must be addressed. A huge quantity of data is required to train a deep learning system. If the size of the data set for training is too little, the accuracy performance may suffer. Cropping, rotating to various degrees, and mirroring photographs are examples of data augmentation techniques that may be used to tackle this problem.

A. Image Enhancement

Green Channel Extraction is a technique for extracting the green band from an image's RGB. The green channel of a picture gives additional insight information. To boost the contrast of the photos, CLAHE (Contrast Limited Adaptive Histogram Equalization) contrast enhancement is applied. After the contrast has been improved, the lighting has been corrected to raise the image's brightness and luminance. Finally, smooth out an image by removing noise with Gaussian filtering.

B. Resizing

Each image has a distinct aspect ratio, such as 2000x1800 or 1500x1200 pixels. We must resize the image to a consistent size in order to train a network. 1000x1000 is the size we utilise. RGB images have three colour channels. It is possible to extend the training period from days to weeks. As a result, we can only utilise grayscale pictures with one channel, which reduces training time and accuracy.

C. Grayscale

The grayscale image has been represented with an 8-bit brightness value. A grayscale picture's pixel value ranges from 0 to 255 in brightness. When converting a colour image to a grayscale image, the RGB values (24 bit) are turned into grayscale values (8 bit) as depicted in fig. 3.

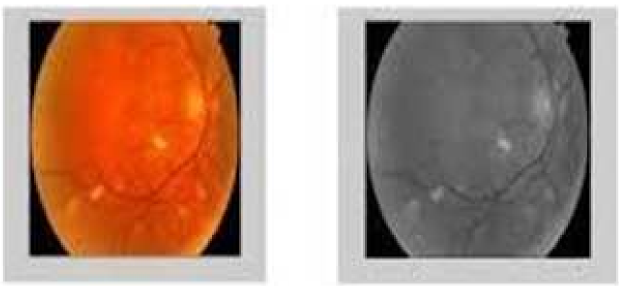

Fig.3.Color Space Conversion

VI. CONVOLUTIONAL NEURAL NETWORK ARCHITECTURE

Due to its high level of performance across a wide range of data sources, deep learning is becoming a particularly popular subset of machine learning. Using convolutional neural networks (CNNs) to recognize pictures is an excellent approach to leverage deep learning. The Keras module in Python makes creating a CNN very simple. Pixels are used by computers to display pictures. This is how convolutions help in picture identification. In a picture, for example, a certain set of pixels might represent a pattern or an edge. Convolutions make advantage of this to aid picture identification.

A. Convolution layer

A convolution is a mathematical procedure that transforms one function into another. To obtain more information, the original function is transformed into a form. Convolutions have been used to blur and sharpen pictures, as well as conduct other operations like embossing and enhancing edges.

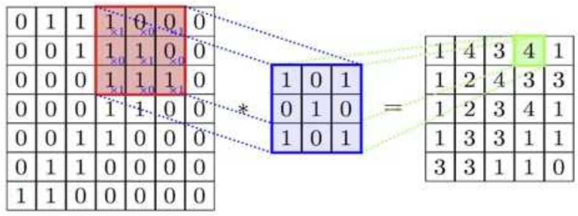

Fig.4.Convolution Layer

B. Pooling layer

Pooling layers lessen the dimensionality of data by combining the outputs of neuron clusters at one layer into a single neuron at the next layer. In max pooling, the greatest value from each cluster of neurons from the preceding layer is utilised. Average pooling uses the average value from each cluster of neurons from the preceding layer.

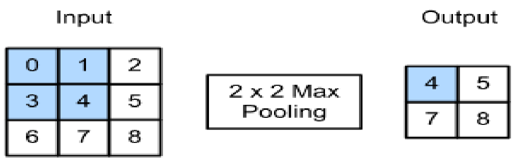

Fig. 5. Pooling Layer

C. Fully Connected Layer

In completely linked layers, every neuron in one layer is connected to every neuron in the next layer. In principle, it functions in the same way as a traditional multilayer perceptron neural network (MLP). The flattened matrix is sent through a fully connected layer to categorise the photographs.

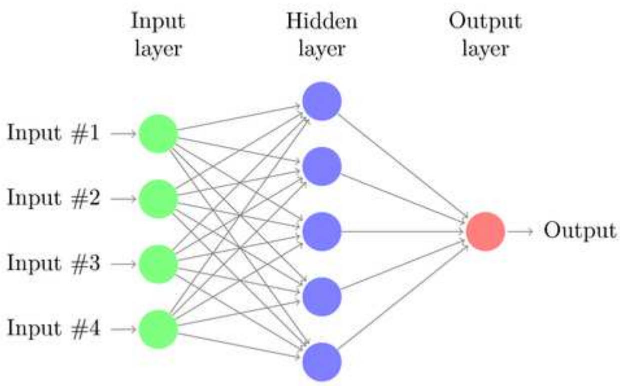

Fig.6.Fully connected layer

VII. User Interface

One or more text files created in the Hypertext Markup Language form the foundation of a web page (HTML). JavaScript code for dynamic behaviour and Cascading Style Sheets code for exhibition semantics are similarly used in web pages. Web sites frequently include images, movies, and other multimedia items. Our website is Jarvis Eye Care. The HyperText Transfer Protocol is used by web browsers to connect with web servers (HTTP). The browser sends an HTTP Request to the server when you click a link on a web page, fill out a form, or conduct a search.

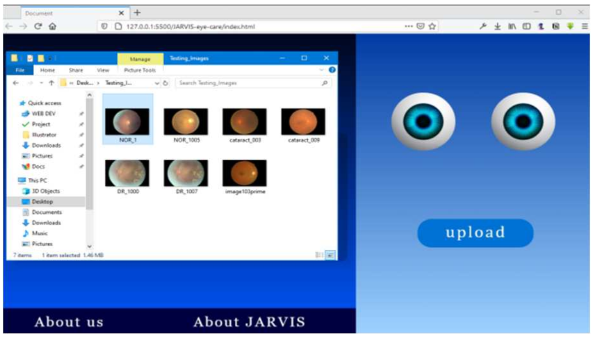

Fig.7.Web Interface

VIII. Results

A comparison was made between the suggested approach and decision tree and random forest algorithms for accuracy for DR, glaucoma and cataract affected images. The accuracy achieved was up to 91% for DR, 90 % for cataract and 86% for glaucoma affected images as depicted in Table 1. The tensor board output and accuracy checking output are depicted in Fig 8. and Fig.9. respectively.

One or supplementary text files formed in the Hypertext Markup Language (HTML) form the foundation of a web page. JavaScript code for dynamic behavior and Cascading Style Sheets (CSS) code for presentation semantics were used in web pages too. Web sites frequently include images, movies, and other multimedia items. Jarvis Eye Care, a website was developed to see the diagnosis results as shown in Fig. 10, Fig.11, Fig.12. and Fig 13. for different eye diseases. The Hypertext Transfer Protocol is used by web browsers to connect with web servers (HTTP). The browser sends an HTTP Request to the server when you click a link on a web page, fill out a form, or conduct a search.

TABLE I. PERFORMANCE COMPARISION

Disease type	Accuracy in %		
	Decision tree	*Random forest*	*Proposed (DCNN)*
Diabetic Retinopathy	88	90.27	91
Glaucoma	85.81	86.63	86
Cataract	84	91	90

```
Model: "sequential_4"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
conv2d_20 (Conv2D)           (None, 998, 998, 16)      160
_________________________________________________________________
max_pooling2d_20 (MaxPooling (None, 499, 499, 16)      0
_________________________________________________________________
conv2d_21 (Conv2D)           (None, 497, 497, 32)      4640
_________________________________________________________________
max_pooling2d_21 (MaxPooling (None, 248, 248, 32)      0
_________________________________________________________________
conv2d_22 (Conv2D)           (None, 246, 246, 64)      18496
_________________________________________________________________
max_pooling2d_22 (MaxPooling (None, 123, 123, 64)      0
_________________________________________________________________
conv2d_23 (Conv2D)           (None, 121, 121, 64)      36928
_________________________________________________________________
max_pooling2d_23 (MaxPooling (None, 60, 60, 64)        0
_________________________________________________________________
conv2d_24 (Conv2D)           (None, 58, 58, 64)        36928
_________________________________________________________________
max_pooling2d_24 (MaxPooling (None, 29, 29, 64)        0
_________________________________________________________________
flatten_4 (Flatten)          (None, 53824)             0
_________________________________________________________________
dense_8 (Dense)              (None, 1024)              55116800
_________________________________________________________________
dense_9 (Dense)              (None, 512)               524800
_________________________________________________________________
dense_10 (Dense)             (None, 4)                 2052
=================================================================
Total params: 55,740,804
Trainable params: 55,740,804
Non-trainable params: 0
```

Fig.8.Tensorboard output

```
Epoch 1/10
 2/74 [..............................] - ETA: 29s - loss: 269.0057 - accuracy: 0.3750WARNING:tensorflow:Callbacks method `on_train_bat
74/74 [==============================] - 34s 457ms/step - loss: 11.5184 - accuracy: 0.6162 - val_loss: 0.5571 - val_accuracy: 0.7423
Epoch 2/10
74/74 [==============================] - 35s 468ms/step - loss: 0.5341 - accuracy: 0.7128 - val_loss: 0.4927 - val_accuracy: 0.7269
Epoch 3/10
74/74 [==============================] - 35s 468ms/step - loss: 0.4654 - accuracy: 0.7504 - val_loss: 0.4116 - val_accuracy: 0.7846
Epoch 4/10
74/74 [==============================] - 34s 464ms/step - loss: 0.4034 - accuracy: 0.7953 - val_loss: 0.3993 - val_accuracy: 0.8577
Epoch 5/10
74/74 [==============================] - 35s 468ms/step - loss: 0.3348 - accuracy: 0.8504 - val_loss: 0.2981 - val_accuracy: 0.8462
Epoch 6/10
74/74 [==============================] - 35s 466ms/step - loss: 0.2009 - accuracy: 0.9103 - val_loss: 0.2418 - val_accuracy: 0.9077
Epoch 7/10
74/74 [==============================] - 34s 464ms/step - loss: 0.2092 - accuracy: 0.9175 - val_loss: 0.1789 - val_accuracy: 0.9154
Epoch 8/10
74/74 [==============================] - 34s 466ms/step - loss: 0.1505 - accuracy: 0.9410 - val_loss: 0.2089 - val_accuracy: 0.9192
Epoch 9/10
74/74 [==============================] - 35s 467ms/step - loss: 0.1285 - accuracy: 0.9436 - val_loss: 0.1432 - val_accuracy: 0.9308
Epoch 10/10
74/74 [==============================] - 35s 466ms/step - loss: 0.1073 - accuracy: 0.9543 - val_loss: 0.1516 - val_accuracy: 0.9423
<tensorflow.python.keras.callbacks.History at 0x7f725a8936d8>
```

Fig.9.Accuracy checking output

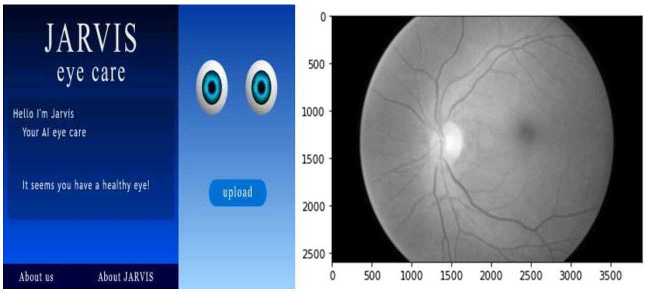

Fig.10. A DL model diagnosed a fundus image with no issues

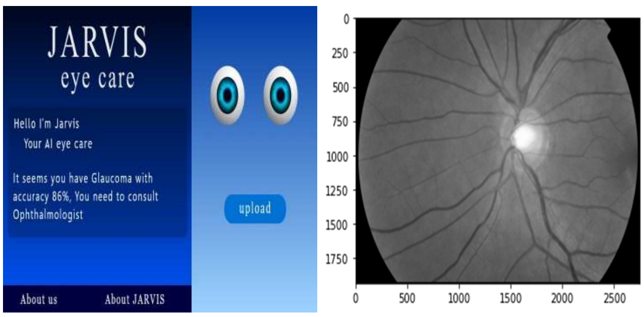

Fig.11. A DL model diagnosed a fundus image with glaucoma at accuracy 86%.

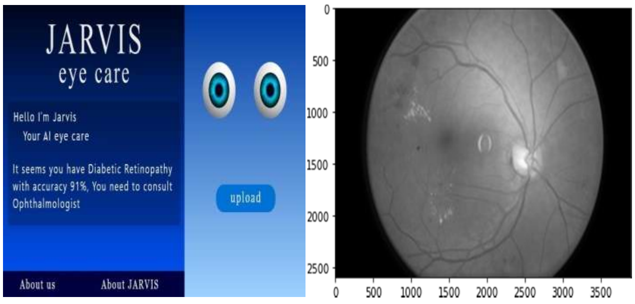

Fig.12. A DL model diagnosed a fundus image with DR at accuracy 91%.

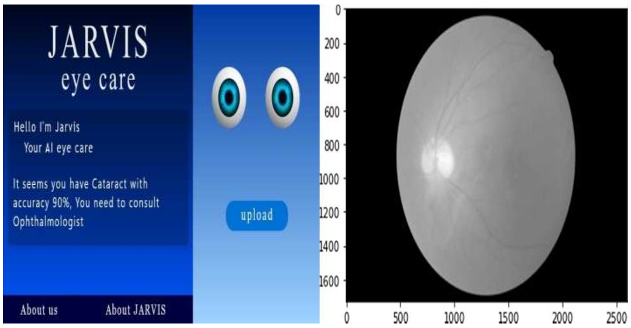

Fig.13. A DL model diagnosed a fundus image with cataract at accuracy 90%.

IX. Conclusion

In this groundbreaking study, a deep convolutional neural network was used to create an intelligent expert system for detecting the most serious eye conditions (Glaucoma, DR, Cataract) early on. The detection and accuracy of deep learning algorithms were both good. This method primarily serves as a referral trigger, telling the patient that if a positive result is found, a retinal expert should be visited. The less complicated pre-trained model was evaluated using a test set and real-time photographs. The accuracy achieved was up to 91% for DR, 90 % for cataract and 86% for glaucoma affected images. The system also had a user-friendly and interpretable graphical user interface (GUI) where the patients can view their results.

References

[1] An, G.; Omodaka, K.; Tsuda, S.; Shiga, Y.; Takada, N.; Kikawa, T.; Nakazawa, T.; Yokota, H.; Akiba, M. Comparison of machine-learning classification models for glaucoma management. J. Healthc. Eng. 2018, 2018.

[2] Saito, K.; Nakano, R. Medical diagnostic expert system based on PDP model. In Proceedings of the IEEE International Conference on Neural Networks, San Diego, CA, USA, 24–27 July 1988; pp. 255–262.

[3] Naser, S.S.A.; Ola, A.Z.A. An Expert System for Diagnosing Eye Diseases using CLIPS. J. Theor. Appl. Inf. Technol. 2008, 4, 923–927.

[4] Sample, P.A.; Boden, C.; Zhang, Z.; Pascual, J.; Lee, T.W.; Zangwill, L.M.; Weinreb, R.N.; Crowston, J.G.; Hoffmann, E.M.; Medeiros, F.A.; et al. Unsupervised machine learning with independent component analysis to identify areas of progression in glaucomatous visual fields. Investig. Ophthalmol. Vis. Sci. 2005, 46, 3684–3692.

[5] Arbelaez, M.C.; Versaci, F.; Vestri, G.; Barboni, P.; Savini, G. Use of a support vector machine for keratoconus and subclinical keratoconus detection by topographic and tomographic data. Ophthalmology 2012, 119, 2231–2238.

[6] Sullivan, B.D.; Crews, L.A.; Messmer, E.M.; Foulks, G.N.; Nichols, K.K.; Baenninger, P.; Geerling, G.; Figueiredo, F.; Lemp, M.A. Correlations between commonly used objective signs and symptoms for the diagnosis of dry eye disease: Clinical implications. Acta Ophthalmol. 2014, 92, 161–166.

[7] Moccia, S.; De Momi, E.; El Hadji, S.; Mattos, L.S. Blood vessel segmentation algorithms—Review of methods, datasets and evaluation metrics. Comput. Methods Programs Biomed. 2018, 158, 71–91

[8] Automated glaucoma diagnosis using deep learning approach." 2017 14th International Multi-Conference on Systems, Signals & Devices (SSD). IEEE, 2017.

[9] D. Shamia, D. Abraham Chandy, "Intelligent system for cross-spectral and cross-distance face matching", Computers & Electrical Engineering, Volume 71, 2018.

[10] Gargeya, R. & Leng, T. Automated identification of diabetic retinopathy using deep learning. Ophthalmology **124**, 962–969, 2017.

[11] Al-Bander, Baidaa, "Automated glaucoma diagnosis using deep learning approach." 2017 14th International Multi-Conference on Systems, Signals & Devices (SSD). IEEE, 2017.

[12] Huang, M.L.; Chen, H.Y. Development and comparison of automated classifiers for glaucoma diagnosis using Stratus optical coherence tomography. Investig. Ophthalmol. Vis. Sci. 2005, 46, 4121–4129.

[13] Rahimy E. Deep learning applications in ophthalmology. Curr Opin Ophthalmol. 29:254–260, 2018.

[14] Gulshan V, Peng L, Coram M, Stumpe MC, Wu D, Narayanaswamy A, et al. . Development and validation of a deep learning algorithm for detection of diabetic retinopathy in retinal fundus photographs. *JAMA,* 316:2402–10, 2016.

[15] Dong Y, Zhang Q, Qiao Z, Yang J. Classification of cataract fundus image based on deep learning. In: *2017 IEEE International Conference on Imaging Systems and Techniques (IST)*. Beijing,. pp. 1–5, 2017.

[16] Poplin, R., Varadarajan, A.V., Blumer, K., Liu, Y., McConnell, M.V., Corrado, G.S., Peng, L. *et al.*, Prediction of cardiovascular risk factors from retinal fundus photographs via deep learning. *Nature Biomedical Engineering* 2(3): 158, 2018.

[17] Gardner, G., Keating, D., Williamson, T.H. and Elliott, A.T. "Automatic detection of diabetic retinopathy using an artificial neural network: a screening tool". British journal of Ophthalmology 80(11): 940–944, 1996.

[18] Ahn, J.M., Kim, S., Ahn, K.S., Cho, S.H., Lee, K.B. and Kim, U.S. Correction: A deep learning model for the detection of both advanced and early glaucoma using fundus photography. PloS one 14(1): e0211579, 2019.

[19] Sahlsten, J., Jaskari, J., Kivinen, J., Turunen, L., Jaanio, E., Hietala, K. and Kaski, K., "Deep learning fundus image analysis for diabetic retinopathy and macular edema grading". Scientific reports 9(1): 1–11, 2019.

[20] Pratt, H., Coenen, F., Broadbent, D.M., Harding, S.P. and Zheng, Y. "Convolutional neural networks for diabetic retinopathy". Procedia Computer Science 90: 200–205, 2016.