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CNN-Based Framework for Early Diagnosis of Ocular Disease

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Abstract
In the world, there is a minimum of 1 billion persons who near or distance vision is impaired but this is preventable or still pending addressed. Loss of eyesight or impaired eyesight may produce long-term individual and financial consequences without early diagnosis. Vision impairment it is a disease that involves individuals of all ages with most of them being above 50 years of age. The young children who have acquired early onset severe vision impairment are capable of experiencing poor levels of education attainment, in the middle-aged some years earlier it may translate into poor quality of life terms of low productivity, reduced participation of the workforce. As well as high levels of depression. Eye diseases are the situations of any component of your eye and the conditions affecting the structures just around the eyes. These conditions may be acute (i.e. occur at a fast pace) or chronic (i.e. they appear slowly and persist over a long period of time). Visual illnesses are serious problems to health worldwide and it will be of great concern to deal with them through early detection and prediction to limit their effects. Ocular disease refers to any condition that affects the health and function of your eyes, ranging from mild issues like dry eye to serious conditions such as glaucoma and macular degeneration. This helps in early diagnosis, personalized risk prediction, and better resource allocation in clinical practice. To reduce vision loss that could be avoided by developing a practical and dependable system for detecting and understanding eye diseases through images.
Keywords: *Ocular diseases, Glaucoma, Deep learning, Convolutional Neural Networks (CNNs).*

1. Introduction
Eye health is a very vital aspect. They are indispensible in almost all in the daily life yet they are usually not appreciated. It is important to have the reminder of healthy eyes. It assists in the prevention of severe conditions. These are macular degeneration, glaucoma, as well as cataracts. Loss of vision can be caused by such diseases. Eye tests, healthy lifestyle and use of sun glasses to prevent the atmospheric UV rays are essential. It assists in maintenance of your sight and health. [1] Eye disorders are broad terms that cover a lot of the problems that occur in the eye and result in cases of impaired vision or worse still, causes blindness in case of negligence. The diseases mentioned above may be classified into the ones that affect the front and the back parts of the eye such as the cataracts and glaucoma respectively and age related macular degeneration and diabetic retinopathy respectively. The vision impairment and blindness, according to the World Health Organization (WHO), concern millions of people around the globe and heavily decrease social and economic conditions as well as a quality of life of their owners. Availability of eye care services is scarce in much of the world and specifically in low- and middle-income countries, worsening the burden of ocular diseases. This highlights on the necessity of prevention, early detection and treatment measures to curb the effects of these conditions globally. Eye problems at birth, newer conditions, infections or environmental causes, may cause loss of sight [2]. An estimate has it that India has a population of about 15 million blind people and the most sadding fact is that 75 per cent of the blind population suffered a curable condition at one point in time. In India, the doctor to

patient ratio is 10,000:1. Many eye complications such as trachoma, corneal ulcers and cataracts among others are able to affect the sight [3]. Early detection of ocular diseases is crucial for several reasons. First and foremost, many ocular diseases, such as glaucoma and diabetic retinopathy, often progress asymptomatically in their early stages. By the time symptoms manifest, irreversible damage to vision may have already occurred. Early detection allows for timely intervention, potentially preserving vision and improving treatment outcomes. Not only do these type of data-driven methods improve the accuracy of the diagnosis, but also help enable personalized medicine by customizing the data. 30 treatment interventions to the profiles of separate patients. Moreover, the improvement in deep learning, one of the branches of ML, has provided the opportunity to the learning of the following: 6 building the next-generation neural networks model, which is able to process high scale data and seek high-level features of medical of recording images with more precision than ever before. Convolutional neural network is a kind of feed-forward neural network and is usually employed in examining visual images by processing information with grid-based topology. It is also referred to as ConvNet. To recognize items in image convolutional neural network is applied [4]. Moreover, early prediction of ocular diseases can enable targeted screening efforts and personalized treatment plans. Predictive models can identify individuals at higher risk of developing certain ocular conditions based on demographic factors, genetic predisposition, lifestyle habits, and other clinical markers. This proactive approach not only reduces the burden on healthcare systems but also enhances patient outcomes through preventive measures and early therapeutic interventions. Vision has always been critical to our independence and high quality life as we grow older. It enables us to do our day to day activities safely and comfortably such as driving, reading, understanding the environment around us and identification of loved ones. Not only was the visual loss able to reduce our living independence considerably but also it even may lead us to social isolation and depression [5].

2. Introduction

The objective of paper aims to improve the performance of eye disease detection.

- Improve eye disease detection by classifying disease types from images.
- To help identify different eye diseases early and more accurately so patients can receive timely treatment and avoid vision loss.

3. Literature Review

As is presented in this paper author, Ocular disease prediction with the use of energy bases has been a matter of much interest because the disease of the eyes can be predicted with its use. make quick diagnosis of medical imaging such as retinal fundus photography and optical coherence tomography make high quality fast and automated diagnosis of imaging like retina fundus photography and optical coherence tomography OCT tomography scans. A part of the studies has been devoted to application of convolutional neural networks (CNNs) to classification and detection of eye disorders, particularly diabetic retinopathy (DR), glaucoma and age-related macular degeneration (AMD). As an example, Gulshan et al. (2016) created the deep learning algorithm based on CNNs to recognize diabetic retinopathy in the retina. [9] performance that is equal to ophthalmologist use of fundus photographs. They trained their model using a retinal dataset of 128,175. 2 images and they obtained an AUC of 0.991 on the detection of a moderate or worse DR [6]. Likewise, Li et al. (2019) proposed a system, which is called DeepDR as a combination of image enhancement, and transfer learning, a concept of automated diabetic retinopathy screening tactics of enhancing diagnostic precision [7]. In this paper author said about glaucoma detection, Chakravarty and Sivaswamy (2016) proposed a deep learning framework based on CNNs trained on optic disc-centered fundus images. Their approach used segmentation of the optic cup and disc followed by classification based on the cup-to-disc ratio (CDR), achieving promising results in early glaucoma detection [8]. Another notable study by Raghu et al. (2019) used a transfer learning approach on pre-trained CNN architectures (like VGG16 and ResNet)

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to classify OCT images for AMD and DME (Diabetic Macular Edema), obtaining high sensitivity and specificity [9]. These studies highlight the growing use of deep learning, especially CNN-based architectures, in the field of ocular disease screening. Most approaches follow a similar pipeline—image preprocessing (segmentation and morphology), model training on labeled datasets, and performance evaluation using accuracy, sensitivity, and specificity metrics. A deep combination of integration. clinical learning holds the potential of improved early detection and treatment planning, particularly in distant or resources scarce areas. In the present article author wrote that Two sources of retinal fundus photographs were used in order to compact a total amount of eight sample sets. In the given study, the author resorts to existing information, pretreatment methods of images. algorithms of deep learning and evaluation standards. The article [10] published in paper there was a model made on how to have automated diagnosis of diabetic eye disease. Works that have used Tl are incorporated by him in this paper. developed DL network structure, and incorporated a mixed DL and ML framework in the aspect of classifiers. From medical illustrations, we can arrive at the conclusion that CNN has already become the most trendy deep neural network, particularly, in the identification of diabetic eye. disease and the identification of other abnormality signs. The efficiency of various existing models such as neuron networks and deep learning algorithms, in diagnosing eye disease has been studied in the research work [11].

4. Methodology

This dataset taken from Kaggle.com [12]. The dataset comprises 6,392 patients, each with two fundus images (left and right eye), totaling 12,784 images. Among these patients, 3,424 are male and 2,968 are female. The patients' ages range from as young as 1 year to as old as 91 years, with an average age of approximately 58 years. This diverse dataset provides a balanced view across genders and a broad age range, supporting comprehensive ocular disease analysis. One of the deep learning algorithms is the CNN that can be applied to input an image and thus assign significance to the different objects in the image and subsequently distinguish and differentiate the image with the others. It is applied to enhance the performance of the facial electromyography (FEMG) and speech signals as far as classification is concerned. Video and image recognition, natural language processing, and image classifications and analysis are the main areas where CNN is applied. It is possible to classify the pictures based on objects presented in them. They go to an extent of recognizing human feelings in an image by classifying the impact of what the particular person feels (seems to be)[13]. Neural architectures are constructed by hand by humans who are experts in the fields of ML and deep learning, and this can be time consumption and possibly allow mistakes [14]. A CNN is a deep learning network primarily intended to classify images and find objects. It is analogous to the perception of the human perceptual system with starting with the basic such as edges, textures, and slowly picking up more elaborate forms and patterns Shown in Figure 1.

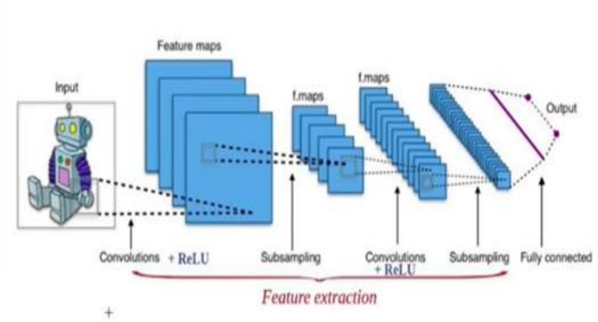

Figure 1 Convolutional Neural Network

In the model, the Convolutional Neural Network (CNN) is an architecture that will automatically learn object features by performing feature representation and feature extraction to help classify cataracts. The model starts with convolutional layers applied with filters to extract such patterns as edges and cloudiness, then ReLU activates to add non-linearity. Then the layers of max pooling are used which perform downsizing of feature maps with respect to the most significant features and weight as less computations are made. Once through several convolution and pooling layers, feature maps are

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converted into 1D vector by flatten layer and then through dense (fully connected) layers. The last layer applies sigmoid activation producing the probability of a single category (e.g., normal, mild, or severe cataract) so that the image data could be correctly classified to different types of eye diseases. ReLU is not differentiable at zero and bounded. Data at a negative input region will not be changed when back propagated because the gradients are zero. This may end up in dead neurons which never fire. ReLU does not focus on the zero, and this disrupts the work of a neural network. The weights gradient will either be a positive or negative value in the course of backpropagation. This would tend to create unwanted effects in the form of zig-zag pattern in the updates of the weights[15]. The prediction of ocular disease commonly uses numerous clinical indicators as well as classical methods to determine the prospect of the risk or existence of the different eye diseases. Visual acuity is the measure of the clearness or sharpness, in conventional terms. It can be checked through a Snellen chart, and a subject reads letters at a certain distance.VA plays a significant role in investigating such conditions as refractive errors (myopia, hyperopia) and determining the intensity of such diseases of the eye as cataract or macular degeneration. The pressure of the fluid in the eye is known as intraocular pressure. Increased IOP has been discovered to cause high risks of having glaucoma, which is described as a condition that may result in an optic nerve and vision impairment. Standard practices of measuring IOP are the tonometry whereby device records the opposition of the cornea to the test of indentation or applanation tonometry where the pressure necessary to indent a given region of the cornea is measured. Fundus The back of the eye (the retina, the optic disc and the blood vessels) are examined under good light with specialized equipment (an ophthalmoscope or fundus camera). The test can be useful in diagnosing what is not normal like diabetic retinopathy, hypertensive retinopathy and macular degeneration. The method provides in-depth analysis of anterior segment of the the eye (cornea, iris, lens), as well as the posterior segment (vitreous, retina); it is provided by the use of a slit lamp. It helps to identify such conditions as cataracts, problems with corneas and uveitis. OCT is a non-contact imaging modality that gives a high-resolution in-plane picture of the retina and the optic nerve. It is applied to the diagnosis and monitoring of conditions like macular edema, macular holes and glaucoma. Neural networks, specifically deep learning models, have become famous in the case of predicting ocular diseases. Convolutional Neural Networks (CNNs) work well when applied to understanding medical images (e.g. retinal scans) to identify abnormalities that indicate a disease such as diabetic retinopathy or age-related macular degeneration. Deep learning (DL) is a transformative technology in various sectors, with ocular disease prediction being one of them because DL allows models to acquire complex. patterns and representations direct out of data. CNNs have been developing quickly to deal with medical images due to their powerful performance. retinal images acquired by any method of imaging such as optical coherence tomography (OCT) or fundus photography. They can do so. problems or anomalies in an image that represent a healthy and healthy image in terms of an upper level after extracting the features of the image. 20 vision conditions such as diabetic eye diseases, glaucoma or macular degeneration that occur with aging. The CNNs are a complex of layers that contain convolutional, pooling and fully connected one. Convolutional layers use filters over the input image to extract features, and have pooling layers down sample the featuremaps to decrease computation. complexity. There are fully connected layers that will do the classification of the features extracted. Chart (b) illustrates the deployment framework of the ocular disease prediction system, focusing on the real-time diagnosis process. The pipeline starts with the user uploading an eye image, which is then handled by the backend system. Within the backend, the image undergoes segmentation to highlight critical anatomical regions followed by image processing to refine quality and enhance disease markers. This processed image is passed to a pre-trained CNN model that analyzes and classifies the image based on learned disease patterns. Finally, the system delivers the diagnostic result to the user, offering a fast and automated assessment that can support clinical decision-making and early detection of ocular conditions Shown in Figure 2.

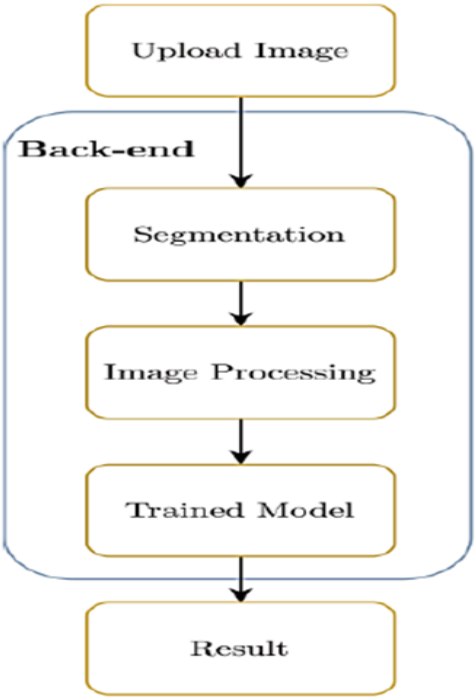

Figure 2 Proposed Model

Rectified Linear Unit (ReLU) constitutes a common activation functions applied in a neural network, particularly deep learning models. It has now defaulted as the choice in most of the architectures because of its simplicity and efficiency.

Def ReLU(x):
If x>0:
Return x
Else:
Return 0

The ReLU function is defined as:

$$f(x) = \max(0, x)$$

This means:

- **If the input x is positive, output is x.**
- **If the input x is negative or zero, output is 0.**

In Mathematical way:

F(x) = x if x>0

0 if x<=0

Sigmoid is the most commonly used activation function in neural networks. The need for sigmoid function stems from the fact that many learning algorithms require the activation function to be differentiable and hence continuous Shown in Figure 3.

def sigmoid(x):
return 1 / (1 + np.exp(-x))

The Sigmoid function is defined as:

$$f(x) = \max(0, x)$$

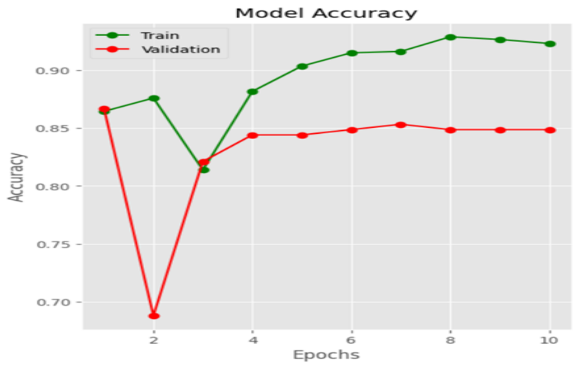

Figure 3 Model Accuracy

The model accuracy diagram depicts training and validation accuracy over the same epochs. The training accuracy (green) consistently improves from about 0.86 to over 0.92, showing the model effectively fits the training data. However, validation accuracy (red) exhibits a significant dip at epoch 2 (around 0.69), likely linked to the earlier loss spike, before recovering and stabilizing near 0.85 across subsequent epochs. This divergence between steadily rising training accuracy and flatter validation accuracy indicates possible overfitting, where the model continues to learn the training patterns well but shows only limited improvement on unseen data Shown in Figure 4. The model loss diagram shows how both training and validation loss change over 10 epochs. The training loss (green) steadily decreases from around 0.32 to about 0.21, indicating good convergence. In contrast, the validation loss (red) spikes sharply at epoch 2, reaching over 0.6, before dropping and stabilizing between 0.33 and 0.35

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toward the later epochs. This pattern suggests the model struggled with generalization initially but recovered afterward, though the slight plateau in validation loss after epoch 6 hints at a potential mild overfitting issue as training loss continues to decrease Shown in Table 1.

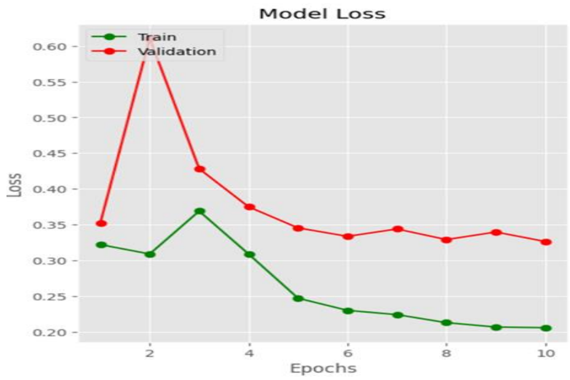

Figure 4 Model Loss

Table 1 Training and Testing data

Data	Patients	Images
Training	5,113	10,226
Testing	1279	2558

Chart (d) shows the main pipeline on how to generate an ocular disease prediction model based on convolutional neural networks (CNN). The first is image acquisition where image retinal or optical coherence tomography (OCT) is captured based on the databases. The images are then taken through a series of preprocessing procedures entailing segmentation to select relevant structures in the eyes followed by the morphological operations to improve the features of individual images. The transformed data is then entered into a CNN where the model is trained with annotated data that has healthy and diseased eye images. The validated model is then tested on testing data and finally is used to confirm its capability in the precise prediction and classification of the eye diseases like glaucoma, diabetic retinopathy, and macular degeneration Shown in Figure 5.

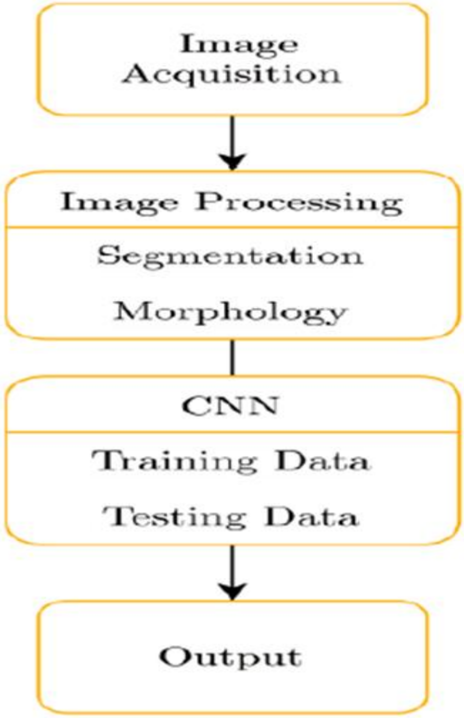

Figure 5 Training Model

5. Result

In this paper, the validity of the proposed deep learning model of ocular disease-based classification to the data-set consisting of 6,392 cases and 12,784 pictures of fungal fundus; was evaluated. They split the data set to 20 per cent test data and 80 per cent training data. This model was being trained in 10 epochs, and its outcome upon respective parameters of measuring evaluation including accuracy, precision, recall and F1-score was established. The results of training behaviour of the model, performance on the test and accuracy of classifications of each of the different ocular conditions have been summarized in the subsequent subsections as key findings.

- **Precision:** Precision is the ratio between the True Positives and all the Positives. It shows how many of the "yes" predictions made by the model were actually correct. It helps us reduce wrong "yes" guesses which are called false positives (FP). Precision is calculated as:

$$\text{Precision} = \frac{\text{True Positives (TP)}}{\text{True Positives (TP)} + \text{False Positives (FP)}}$$

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Recall: Recall tells us how well a model finds all the correct "yes" cases in the data. It checks how many real positive cases the model was able to correctly identify. The formula to calculate recall is:

$$\text{Recall} = \frac{\text{True Positives (TP)}}{\text{True Positives (TP)} + \text{False Negatives (FN)}}$$

F1 – score: F1 score is some measure that is a combination of precision and one-shot adding of the second value to result in the recall enable simultaneous optimization between the two. Precision is a measure of the number of the positives that are predicted. are actually correct and how many actual. The positives the model accurately identified. [16] The F1 score is obtained by means of the formula:

$$\text{F1-score} = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

Error is computed by using the loss function. The paper introduces various loss functions, e.g. mean squared error (MSE), mean absolute error (MAE), hinge loss, and cross entropy (binary entropy and categorical cross entropy). By deep learning, the use of a loss function is thought of as a challenge [17] Shown in Table 2.

Table 2 Epoch Accuracy

Epoch	Accuracy	Loss
1.	0.86	0.31
2.	0.89	0.27
3.	0.77	0.43
4.	0.89	0.30
5.	0.90	0.24
6.	0.92	0.22
7.	0.92	0.23
8.	0.92	0.22
9.	0.93	0.20
10.	0.92	0.20

The model began at an accuracy of 0.86 and the loss of 0.31 in epoch 1, showing a solid initial performance. Over the next few epochs, accuracy generally improved, reaching 0.92 by epoch 6 and stabilizing around 0.92–0.93 for the remaining epochs. Loss followed a consistent downward trend overall, decreasing from 0.31 to as low as 0.20 by the tenth epoch, though there was a spike in loss at epoch 3 (0.43) that suggests temporary overfitting or a difficult batch. After that, the model recovered well, demonstrating good generalization and steady convergence, with minimal fluctuations in the final few epochs, indicating the model has likely reached a stable training state Shown in Table 3.

Table 3 Model Accuracy

	Precision	Recall	F1-score
0	0.83	0.84	0.83
1	0.87	0.86	0.86
Accuracy			0.85

Convolutional Neural Networks (CNNs) can automatically extract levels of features in retinal or ocular images and this greatly improves the accuracy of prediction in detecting ocular diseases like the classification of cataracts. CNNs could obtain high precision in identifying whether ocular conditions are healthy or diseased by utilizing convolutional layers, pooling mechanisms and dense layers. Their complex abilities to learn features and train effectively on labeled ocular datasets make the models a very strong means through which early detection of reliable diagnoses of ocular diseases may be done, which ultimately enables the ophthalmologists to better attend to their patients. These results validate that the CNN can robustly classify multiple eye disease types, particularly cataract, and support early and accurate identification of patients at risk, addressing the study's objective of improving timely treatment and reducing preventable vision loss. These model gives us identification of eyes in some categories like Normal, Diabetic Retinopathy, Glaucoma, Cataract to help identify different eye diseases.

Conclusion

Ocular disease prediction models here Ocular disease prediction models use wide range of data such as Ocular disease prediction models imaging fundus photography, OCT, and data (genetic data, and clinical records). These are the types of data that give a lot of information that is necessary. an accurate diagnosis of diseases, risk levels and tracking. Technical algorithms The algorithms machine learning, like CNNs and RNNs have not only greatly increased the accuracy and dependability of forecasting models in ophthalmology but also reduced the time required to discover new medications and these models are used today to develop new medications. These techniques automate feature extraction, enable multimodal data integration, and make possible real-time monitoring, and begin a revolution in their use. clinical decision-making. In glaucoma, age-related macular degeneration (AMD), and diabetes retinopathy prove to be clinically useful by providing early detection, individual risk assessment and optimization of treatments. They empower valuable information that clinicians can use in order to enhance patient outcomes and the quality of care. Such challenges include data heterogeneity, model. 6 The issues of interpretability, ethical issues, and regulatory compliance remain. Nevertheless, current advances in computing, however, have continued to give rise to investments in computing. use of methods, the multimodal composition of information and embracing telemedicine may promise to work around these obstacles and increase use of predictive models in varied clinical areas. Privacy of patients, informed consent, reduction of The key elements of ethical application of predictive models use in healthcare are biases, and the transparency of their development. There should be regulatory frameworks, and that should breed trust between the patient and the medical practitioners.

Reference

[1]. lonestarneurology.net www.cnib.ca Sushma K Sattigeri, Harshith N, Dhanush Gowda N, K A Ullas, Aditya M S." EYE DISEASE IDENTIFICATION USING DEEP LEARNING". www.simplilearn.com. www.remagin.com

[2]. Gulshan, V., et al. (2016). Development and Validation of a Deep Learning Algorithm for Detection of Diabetic Retinopathy in Retinal Fundus Photographs. JAMA, 316(22), 2402–2410, J. Clerk Maxwell, A Treatise on Electricity and Magnetism, 3rd ed., vol. 2. Oxford: Clarendon, 1892, pp.68–73.

[3]. Li, Z., et al. (2019). DeepDR: A Deep Learning Framework for Detecting Diabetic Retinopathy. BMC Ophthalmology, 19(1), 80.K. Elissa, "Title of paper if known," unpublished.

[4]. Chakravarty, A., & Sivaswamy, J. (2016). Glaucoma Classification with a Combination of Segmentation and Image-Based Features. 2016 IEEE 13th International Symposium on Biomedical Imaging (ISBI).

[5]. Raghu, M., et al. (2019). Diabetic Retinopathy Detection using Deep Learning on Eye Fundus Images. Medical Imaging 2019: Imaging Informatics for Healthcare, Research, and Applications, Vol. 10954.M. Young, The Technical Writer's Handbook. Mill Valley, CA: University Science, 1989.

[6]. Sarki, R., Ahmed, K., Wang, H., & Zhang, Y. (2020). "Automatic detection of diabetic eye disease through deep learning using fundus images: A survey". IEEE Access, 8, 151133-151149.

[7]. Rajyaguru, V., Vithalani, C., & Thanki, R. (2020). "A literature review: various learning techniques and its applications for eye disease identification using retinal images". International Journal of Information Technology, 1-12. www.kaggle.com

[8]. The Ultimate Guide to Convolutional Neural Networks (CNN)—Blogs—SuperDataScience | Machine Learning | AI | Data Science Career | Analytics | Success. Available online: https://www.superdatascience.com/blogs/the-ultimate-guide-to-convolutional-neural-networks-cnn

[9]. Elsken, T.; Metzen, J.H.; Hutter, F. Neural Architecture Search: A Survey. arXiv 2019,

International Research Journal on Advanced Engineering Hub (IRJAEH)
e ISSN: 2584-2137
Vol. 03 Issue: 10 October 2025
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https://irjaeh.com
https://doi.org/10.47392/IRJAEH.2025.0557

arXiv:180805377. Available online: http://arxiv.org/abs/1808.05377

[10]. A Comprehensive Guide to Convolutional Neural Networks—The ELI5 Way|by Sumit Saha|Towards Data Science. Available online: https://towardsdatascience.com/a-comprehensive-guide-to-convolutional-neural-networks-the-eli5-way-3bd2b1164a53 www.scikit-learn.org

[11]. Sharma, O. Deep Challenges Associated with Deep Learning. In Proceedings of the 2019 International Conference on Machine Learning, Big Data, Cloud and Parallel Computing (COMITCon), Faridabad, India, 14–16 February 2019; pp. 72–75.