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Cataract and Other Ocular Diseases Detection Using Machine Learning

M M Childvilas Chowdary[1], Akash D[2], Sandhyarani[3], Nethravathi B[4]

[1,2,4]Department of Information Science and Engineering, JSS Academy of Technical Education, Bangalore, India
[3]Department of Computer Science and Engineering, JSS Academy of Technical Education, Bangalore, India

Abstract
Doctors face great encounter in recognizing eye disorders exhausting fundus pictures. An automated ocular disease detection system will be helpful in diagnosing ocular illnesses than by hand using fundus pictures. The machine learning model can be developed that can assess the severity of ocular diseases, including cataracts, by analyzing fundus photographs of patients. Total 20 papers were studied that provides ophthalmologists with an automated and accurate method for evaluating the severity of ocular diseases. By utilizing this study, model can be proposed where, ophthalmologists will be able to assess the extent of cataract development and other eye conditions, enabling appropriate treatment and care for patients.

Keywords: Cataract, Ocular Disease, Fundus, Machine Learning.

1. Introduction

Early fundus screening in ophthalmology is a cheap and efficient technique to stop blindness brought on by ocular illnesses. Clinically, manual diagnosis is time-consuming and may delay the disease due to a lack of medical resources. Some studies on ocular disorders have produced promising outcomes since deep learning was developed, however most of them only focus on one disease [1-5]. Ophthalmologists frequently diagnose multiple diseases during fundus screening, so use a dataset with more number of diseases to better reflect the real medical environment. This work use some cutting- edge deep neural networks to conduct benchmark studies on it.

It is discovered that simply expanding the network's size would not produce positive results for multiple diseases. Even though there are already several deep learning models for ocular illness screening that perform remarkably well. It discovered some restrictions. A single illness. Most identification models exclusively focus on one type of ocular disease, and the majority of the datasets they utilize only contain annotations for that one type of ophthalmic disease [8-14]. However think that building a more thorough and effective fundus screening system that can identify many diseases is essential, considering the actual demands of individuals with fundus disease in everyday life. Just one eye. Although current datasets are based on a fundus scan, in actual clinical situations, ophthalmologists typically diagnose patients using data from both eyes. An affordable and efficient technique to stop blindness brought on by diabetes, glaucoma, cataract, age-related macular degeneration (AMD), and many other disorders is early ocular disease identification. According to the World Health Organization (WHO), at least 2.2 billion people worldwide today have vision-related issues, at least 1 billion of which might have been prevented. In order to relieve ophthalmologists' workload and prevent patients' vision from being impaired, rapid and automatic sickness diagnosis is crucial and urgent. After receiving high-quality photos of the medical eye fundus, computer vision and deep learning may automatically identify ocular illnesses which help for fast ocular disease assessment. Work use a publicly available dataset for numerous ophthalmic illnesses detection to address the issue. Our dataset, which has 5,000 pairs of binocular photos instead of the existing worldwide monocular dataset's single image, totals 10,000 images. Furthermore, annotate 8 diseases on binocular images, indicating that a patient may have more than one disease. Additionally, there are not many relevant research to draw from, and multi-disease screening is more difficult than the existing single disease screening. In order to classify several diseases, ran experiments on a number of well-known deep-learning-based classification networks. Numerous tests have shown that just expanding the network's size won't increase performance, but a method of feature fusion that integrates the traits of several diseases can.

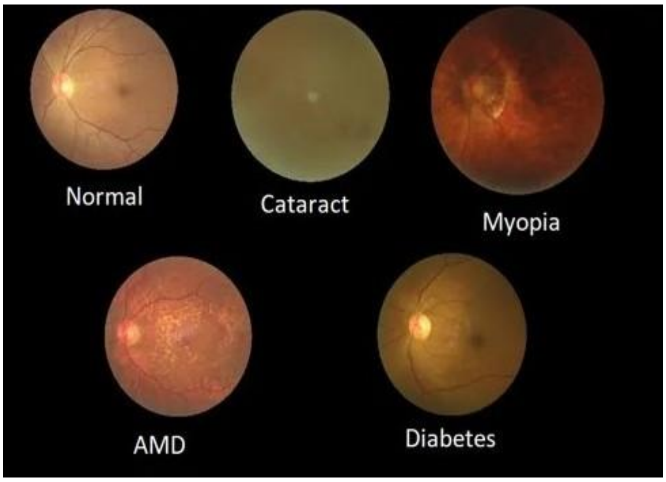

Figure 1. Illustration of different eye diseases.

Figure 5. Illustration of different eye diseases. Clearly Diabetes seems to be the most challenging in detecting and cataract is the easiest as varies the most from the normal fundus

2. Literature Survey

In [1] Md Shakib Khan et al. proposed that, the dataset was balanced by using an equal amount of data for each class, and the VGG-19 architecture was used to train the classes. The dataset and associated images were first loaded into the model using an equal number of photos for both classes. In this study, the VGG-19 model was used, and the transfer learning approach was used. When the dataset was properly balanced, the accuracy of each class increased. After training, the work sought to determine the correct class. It demonstrates how each left and right eye image was trained separately using the pre trained VGG- 19 model. After training, they were put into one of two categories: Class 1 (illness) or Class 2. (normal). Following that, VGG-19 was used to train the binary classifications. The VGG-19 model has an accuracy of 98.13% for the normal (N) versus pathological (M) myopia class, 94.03% for the normal (N) against cataract (C) class, and 90.94% for the normal (N) versus glaucoma (G) class (G). When the data are balanced, the accuracy of every other model increases as well.

In [2] Jing et al. proposed an ensemble model using convolutional neural networks (CNNs) to find one or more illnesses in the fundus pictures. The process initially splits up each image's multi label classification issue into two separate problems for each label. Second, the problem of a small dataset is addressed using transfer learning and ensemble learning approaches. The model is composed of two elements, the first of which is an EfficientNet model used for feature extraction. Neural networks are used in the second section to solve the multi-label classification problem. Finally, the results are combined using the output probabilities from both models. The suggested model can perform well even when trained with minimal data, according to the results of the model's testing on the ODIR dataset. The findings demonstrate that EffecientNetB3 works better than other models, with a 90% accuracy rate and a 67% Area Under Curve (AUC). A CNN-based multi-label ocular illness categorization model was put up by Junjun et al. to address the issue of left and right eye correlation. The suggested framework is capable of handling severe eye disorders. Three modules make up the dense correlation network (DCNet) the authors created. Various backbone CNNs are used for feature extraction, including ResNet-18, 34, 50, and 101. For feature correlation, the Spatial Correlation Module (SCM) is employed. The classifier is then employed for scoring and classification. The model was developed and evaluated using the color fundus photography (CFP) images from the ODIR dataset. The findings demonstrate that the model using SCM and ResNet-101 for feature extraction performs at the highest level, with an AUC of 92.7%. In order to enhance the performance of the categorization of various eye disorders, this work proposes the study of contemporary deep learning architectures along with various data augmentation strategies.

In [3] Rachana Devanaboina et al. proposed a Convolutional Neural Network (CNN) a Deep Learning algorithm that can take in a picture of information, assign significance to various angles and objects inside the picture, and then have the option to distinguish between them. When compared to other grouping calculations, the amount of pre-handling required by a ConvNet is significantly less. While in crude tactics channels are hand-designed, ConvNets can become accustomed to these channels/qualities with adequate preparation. Through the utilization of crucial channels, a ConvNet can efficiently detect the Spatial and Temporal conditions better fitting to the image collection is produced by the planning since fewer boundaries are included and loads can be reused. Convolution is a method for removing important level highlights, such as edges, from an information image. There is no reason why ConvNets must just have one convolution layer. Typically, the primary CovLayer is responsible for capturing low-level details like edges, shading, slope- direction, and so forth. With additional later layers, the developer adjusts to high-level details as well, giving us a group that has a healthy understanding of the images in the dataset. The I-th layer of a convolutional neural network is made up of the convolutional layer and the pooling layer.

In [4] Sushma K Sattigeri Analyzing a variety of symptoms is necessary in order to correctly diagnose eye illnesses. Present a novel approach to provide an automated eye illness identification model utilizing visually discernible symptoms, combining deep learning techniques like convolution neural network and digital image processing techniques like segmentation and morphology. Using the suggested procedure, four eye diseases—crossed eyes, bulging eyes, cataracts, uveitis, and conjunctivitis—are examined and grouped. The deep neural network model that has been proposed helps with the early diagnosis of eye problems. The model advises individuals to visit an ophthalmologist for screening if necessary.

In [5] Nadim MahmudDipu et al. proposed that, Deep learning algorithms' increased picture categorization capabilities have made such a system possible. This article presents four deep learning-based algorithms for localising ocular tumours. In this work, model is trained leading image classification algorithms such Resnet-34, EfficientNet, MobileNetV2, and VGG-16 using the ODIR dataset, which comprises of 5000 fundus pictures separated into 8 groups. Each of these categories represents a different eye condition. The Resnet-34 model's accuracy was 90.85%, the MobileNetV2 model's accuracy was

94.32%, and the EfficientNet classification model's accuracy was 93.82%. The VGG-16 model's accuracy was 97.23%. All of these models will be quite helpful in developing a real-time system..

In [6] L Monisha et al. proposed that, Artificial intelligence is significantly influencing several fields of medicine, and ophthalmology is no exception. Deep literacy techniques have been successfully used, in instance, to identify clinical indicators and classify ocular diseases. This offers a wonderful opportunity to enhance the number of people who receive accurate diagnoses. Deep literacy techniques in ophthalmology have mostly been used with optic consonance tomography and images of the eye fundus. On the one hand, these designs have demonstrated exceptional performance in the identification of visual disorders comparable to diabetic retinopathy, glaucoma, diabetic macular degeneration, and age-related macular degeneration. On the other hand, numerous international difficulties have included large eye imaging datasets with the segmentation of individual eyes, clinical indicators, and expert optical assessments.

In [7] M Seetha et al. proposed that, four deep learning models are employed to detect glaucoma, age-related macular degeneration, and diabetic retinopathy (DR), all of which are quite adept at processing images (ARMD). The main causes of vision loss and blindness in India are DR, glaucoma, and ARMD because the symptoms of these diseases frequently manifest extremely late and occasionally result in permanent vision damage. Applying data augmentation in the offline mode allows for the incredibly sparse data that Kaggle provided to be magnified. On the dataset acquired using different train- test split ratios, deep learning models like VGG16, DenseNet201, and Resnet50 are employed. For a 70–30% split of the dataset, VGG16 delivers an accuracy of 29.5%, DenseNet201 produces an accuracy of 44.5%, and ResNet50 delivers 93.9% accuracy. Using the same dataset, an ensemble model is trained using VGG16, DenseNet201, and ResNet50. The ensemble model provides an accuracy of 72.8% for both the 60–40% and 70–30% train–test splits. It has been found that the ensemble model is more accurate when compared to deep learning models with various inputs.

In [8] P. Glaret subi et al. proposed that, According to the Globe Health Organization (WHO), there are around 2.2 billion visually impaired persons in the world, who are primarily affected by age-related eye illnesses like age-related macular degeneration (AMD), cataract, diabetic retinopathy (DR), and glaucoma. If these illnesses are not identified early on, blindness results. This study uses retinal fundus photos from an online dataset that have been pre-processed using the maximum entropy transformation to identify age-related eye disorders at an early stage. A convolution neural network (CNN), which was tuned using a flower pollination optimization algorithm (FPOA) for feature extraction, was fed the pre- processed photos. For training the CNN, hyperparameters were tuned using FPOA. This improved the network's accuracy and speed around 2.2 billion people worldwide are visually impaired, with age-related eye diseases like age-related macular degeneration (AMD), cataract, diabetic retinopathy (DR), and glaucoma being their main causes, according to the World Health Organization (WHO). If these conditions are not identified in the earliest stages, blindness results. This work evaluates retinal fundus photos from an online dataset that have been pre-processed using the maximum entropy transformation in order to identify age-related eye issues at an early stage. A convolution neural network (CNN), which was modified using a flower pollination optimisation algorithm (FPOA) for feature extraction, was fed the pre-processed photos. To train the CNN, hyperparameters were adjusted using FPOA. This improved the accuracy and effectiveness of the network..

In [9] Vedant Chutke et al. proposed a platform that, via a base system, connects patients, medical devices, ophthalmologists, and intelligent eye disease analysis tools. By efficiently integrating discriminative data from a different domain and combining pre-learned SVM (Support Vector Machine) classifier at the same time, our system is able to train the quick prediction model. Experiment conducted with three of the most common ocular diseases: glaucoma, pathological myopia, and age-related macular degeneration using MKLclm (Multiple Kernel Learning). Using data from specific domains and the traditional MKL approach, the new result shows that MKLclm is generally superior to the regular SVMs. The technology supports an integrated ecosystem that makes ocular illness screening and monitoring efficient and affordable.

In [10] Kai Wang et al. proposed that, early fundus screening in ophthalmology is a cheap and efficient technique to stop blindness brought on by ocular illnesses. Clinically, manual diagnosis takes time and could prolong the problem due to a lack of medical resources. Some studies on ocular disorders have produced promising outcomes since deep learning was developed, however most of them only focus on one disease. Ophthalmologists frequently diagnose multiple diseases during fundus screening, so released a dataset with eight diseases to better reflect the real medical environment. This dataset contains 10,000 fundus images from both eyes of 5,000 patients and contains information on eight different diseases. Model used some cutting-edge deep neural networks to conduct benchmark studies on it. Discovered that just expanding the network's size is insufficient to effectively classify several diseases; instead, a well-organized feature fusion strategy that incorporates the traits of multiple diseases is required. Model anticipate that this effort will promote relevant field research.

In [11] Karen Simonyan et al. proposed that, examine how the convolutional network's depth affects its accuracy in the context of large-scale picture recognition. Our key contribution is a thorough analysis of networks with increasing depth utilizing an architecture with very small (3 3) convolution filters, which demonstrates that raising the depth to 16–19 weight layers can significantly outperform existing setups. These results served as the foundation for our entry to the 2014 ImageNet Challenge, which helped our team win first and second place in the localization and classification tracks, respectively. Also demonstrate how well our representations generalize to other datasets, producing cutting-edge outcomes. Our two top-performing ConvNet models have been made available to the general public.

In [12] Raffaele Nuzzi et al. proposed that, First off, DL algorithms are difficult to describe in terms of ophthalmology. This so-called "black box" phenomena might eventually cause clinicians to accept this technology less. A "black box" denotes a lack of comprehension of the algorithm's decision-making process that results in a particular outcome. This phenomenon is constrained by a few techniques, including the "occlusion test, in which a blank area is systemically moved across the entire image and the largest drop in predictive probability represents the specific area of highest importance for the algorithm", or "saliency maps (heat maps) generation techniques, such as activation mapping, which, again, highlights areas of importance for classification decisions within an image". Despite the advancements, the visualization technique indicated non-traditional diagnostic interest areas in some instances, and it is unclear how to take into account the saliency analysis of those regions' attributes. The legal ramifications of applying DL algorithms in clinical practice should also be noted. In reality, who is responsible to suffer the legal repercussions of an adverse outcome owing to an erroneous forecast given by an artificial intelligence algorithm? If a machine thinks similarly to a human ophthalmologist who can make errors? These extremely complicated medical legal problems are still pending.

In [13] Neetu Sharma et al. proposed that, the importance of image processing for disease diagnosis on medical imaging cannot be overstated. These methods for identifying and categorizing diseases are particular to the type of human organ and image. One of these disease classes includes the detection of retinal conditions like glaucoma or diabetes. The study on illness recognition techniques, including SVM, DCT, HMM, and PCA methodologies, has been defined in the publication. The image processing techniques used to separate disease areas and filter medical images were also defined in the paper.

In [14] Vedank Mishra et al. proposed that, to avoid total blindness, it's critical to discover ocular diseases (OD) as soon as possible. Ophthalmologists can identify the condition with the use of a wealth of information that is readily available online, but the growing variety in fundus photos also presents a number of difficulties. In nations like India, where there are almost 16 million blind people, manual diagnosis of this condition us- ing hand-crafted approaches would take too long. This research, proposed a method for automatically diagnosing OD, where detection is carried out in two steps. The Mobile Net architecture is utilized for feature extraction since users of smartphones and iPhones without home computers can use it. Other architectures like VGG and RESNET are slower than the one being used. When validated, the network's accuracy, which was trained using data from more than 3500 patients and evaluated on more than 1500 patients, is 95.68

In [15] Sudheer Kumar et al. proposed that, the goal of fundus imaging is to look at anomalies associated with eye disorders. The monitoring and identification of various ophthalmological illnesses depends heavily on a fundus image. The majority of prior studies focused their methods on deciphering specific diseases from fundus images. But simultaneously detecting multiple diseases from a fundus picture is still quite difficult. While diagnosing one or both eyes, there is a potential that the patient will have more than one condition. There- fore, it is intended to address this issue by developing a framework that can more accurately identify several diseases from fundus images. Using ensemble neural architectures, this paper suggests a unique Multi- Dis- ease Classification Framework (MDCF). The first task in the suggested approach is to preprocess the dataset using techniques like contrast enhancement, oversampling, scaling, and normalization. The MDCF will be granted in two phases: the first phase will determine whether the fundus image is at risk for disease, and the second phase will classify any multiple diseases present on the image. For illness risk assessment, the convolutional neural networks Densenet201 and EfficientNetB4 were employed, while ResNet105 was incorporated for multi-disease classification. The suggested study uses Retinal Fundus Multi-disease Image Dataset (RFMiD) for training and validation.

In [16] Coll Corbilla et al. proposed that, the most common cause of childhood blindness worldwide is retinal diseases. It is vital and crucial to diagnose diseases quickly and automatically in order to lighten the strain of ophthalmologists. Ophthalmologists use direct or indirect visualization of the eye and its surrounding structures to diagnose disorders using pattern recognition. The use of deep learning algorithms in the field of ophthalmology is excellently suited due to its reliance on the fundus of the eye and its examination. By confirming the presence of distinct lesions, it is possible to determine the severity of each disease. Each lesion is distinguished by specific morphological features, however numerous lesions from various pathologies have some of the same traits. The detection of eye disorders has a multi-label classification with a complex resolution approach since patients may be affected by multiple pathologies at once. For the automatic identification of various eye disorders, two deep learning techniques are being investigated. GoogleNet and VGGNet were the two solutions picked because examine the various traits of lesions and outline the Then, determine the hardware .

In [17] Dr. D. Kerana Hanirex et al. proposed that, About 15 million people are blind in India, and the awful truth is that 75% of these instances may be cured. The doctor-patient ratio in India is 1:10,000. Glaucoma and diabetic retinopathy (DR) are the main causes of blindness in India, according to studies. In both industrialized and developing nations, diabetic retinopathy, which is the primary cause of blindness among individuals of working age, is mostly brought on by a person's diabetes. Blindness is a result of optic nerve damage from glaucoma. Both illnesses are difficult to diagnose in their early stages due to their lack of symptoms, and if neglected, they can result in irreversible eyesight damage. Machine learning techniques have advanced to the point that early detection of diabetic eye disease by an automated system offers significant advantages over manual detection. Recent publications on cutting-edge studies on the early identification of diabetic eye ill- ness. In this article, automated methods for detecting diabetic eye disease are systematically reviewed from a number of angles, including I datasets that are currently accessible, ii) picture pre-processing methods, iii) deep learning models, and iv) performance evaluation metrics. The survey aims to offer insightful information to research communities, medical professionals, and diabetes patients by providing a thorough review of diabetic eye disease detection tools, including cutting-edge field approaches.

In [18] Dr. Christian Horn et al. proposed that, to avoid irreparable vision loss, it is important to diagnose eye illnesses early. Ophthalmologists often manually review fundus images—images of the back of the eye—that have been taken. An increase in patients and a shortage of skilled ophthalmologists are detrimental to patient treatment. In this study, the classification of fundus pictures into cataract, glaucoma, and retinal disorders is the main objective. In a number of issues including illness categorization, the Convolution Neural Network-Recurrent Neural Networks (CNNRNN) model has shown to be successful. The suggested hybrid CNN- RNN models combine the benefits of Long Short-Term Memory (LSTM) with Transfer Learning. In- ceptionV3, InceptionResNetV2, and DenseNet169 are three Transfer Learning models that extract a variety of distinct properties from fundus pictures. Utilizing LSTM, the extracted features are categorized. The Kaggle dataset, which includes an unbalanced quantity of photographs in each category, serves as the foundation for the research. As a result, techniques for augmentation are applied to balance the dataset. When trained and evaluated on more and more balanced data, the models' performance rose. With a 69.50% accuracy (87.40% specificity and 69.50% sensitivity), the hybrid DenseNet169-LSTM model was the most accurate.

In [19] Manunee Dave et al. proposed that, India is one of the nations that has recently made strides in the field of telemedicine still far from achieving our targeted objective. Additionally, the number of people with eye disorders is also rising quickly. The major objective is to give them better care at a reduced cost. People in metropolitan locations can still manage an eye exam, but it gets more challenging for those in rural areas. Telemedicine has become viable because to the widespread use of mobile phones across the nation. In order to make this happen, need to find a solution. It is used in machine learning and image processing. For the purpose of identifying diseases, image processing is important. With the technology revolution, data is quickly expanding in all fields. Thus, using this data to tell two photos apart becomes our main objective. The preprocessing method improves the boundaries and feature extraction process, along with picture type conversion, and then able to create the algorithm by merging the image processing component with the machine learning part employing the idea of template matching for this. A template is simply a tiny sub image. The objective is to compare the template and input image for similarities. This concept will make the procedure easier and faster.

In [20] Aruna Ramanan et al. proposed that, In order to quickly diagnose eye diseases, medical health systems have been focusing on artificial intelligence tools. To make machine learning more accurate and dependable by taking into account different aspects, health data must still be recorded in a consistent format. The objective of this work is to create a comprehensive framework for storing diagnostic data in an international standard format to facilitate the prediction of eye illness diagnosis based on symptoms utilizing decision tree algorithms, such as cataract, glaucoma, and retinal. A user-friendly interface was created in an effort to assure error-free data entering. The diagnosis was established using the ICD-10 coding published by the American Academy of Ophthalmology, and the data was organized in accordance with hierarchical hierarchies created by medical specialists. Furthermore, new categories for symptoms as well as diagnoses will be added as part of the system's self-learning evolution. The classification results using tree-based approaches showed that, given enough data, the suggested framework works adequately. In contrast to more sophisticated techniques like neural networks and the naive Bayes algorithm, the decision tree algorithm's prediction rate is greater than 90% because of the organized data organization.

Table 1: Detailed Analysis

Ref.	Defined problems in papers	Conclusion and future work
[1]	Balancing of Dataset	In this study, the dataset was balanced by utilising an equal amount of data for each class, and the VGG-19 architecture was used to train the classes. When the dataset was appropriately balanced, the accuracy of each class increased. After training, the work sought to determine the proper class. It demonstrates that each of those left and right eye pictures was trained separately using the pre-trained VGG-19 model.
[2]	Detection of one or more disease	Using an ensemble model based on convolutional neural networks (CNN), one or more illnesses may be found in fundus pictures. The process initially splits up each image's multilabel classification issue into two separate problems for each label. Second, the problem of a small dataset is addressed using transfer learning and ensemble learning approaches.
[3]	Pre-Handling in Conv Net compared to other grouping techniques.	The pre-handling needed in a ConvNet is a lot of lower when contrasted with other grouping calculations. While in crude strategies channels are hand designed, with enough preparing. The goal of the convolution operation is to remove the significant level highlights like edges, from the information picture. ConvNets need not be restricted to just a single convolution layer.
[4]	To accurately diagnose eye diseases	It is necessary to examine a variety of symptoms. A novel approach to provide an automated eye illness detection model utilising visually discernible symptoms, combining deep learning techniques like convolution neural network with digital image processing techniques like segmentation and morphology.
[5]	Early screening and diagnosis of ocular diseases	Such a system can now be accomplished because deep learning algorithms' improved picture categorization skills. Four deep learning-based models for pinpointing ocular tumours are presented in this work. Used the ODIR dataset, which contains 5000 fundus pictures, to train cutting-edge image classification algorithms including Resnet-34, EfficientNet, MobileNetV2, and VGG-16 for this work.

[6]	Role of AI	Artificial intelligence is significantly influencing several fields of medicine, and ophthalmology is no exception. Deep literacy techniques have been effectively used, in instance, to identify clinical indicators and classify ocular diseases. In this study, the most recent deep literacy techniques employed in ophthalmic pictures, databases, and implicit difficulties for optical opinion are discussed.
[7]	Usage of deep learning models	Four deep learning models are employed to identify glaucoma, age-related macular degeneration, and diabetic retinopathy (DR), all of which are quite adept at processing images (ARMD). The main causes of visual impairment and blindness in India are DR, glaucoma, and ARMD. It is suggested to develop an automated method using deep learning models to detect these eye disorders early on.
[8]	Early detection and diagnosis of ocular disease	Four deep learning models that are excellent at processing images are used to identify glaucoma, age- related macular degeneration, and diabetic retinopathy (DR) (ARMD). In India, the main causes of vision loss and blindness are DR, glaucoma, and ARMD. For the purpose of identifying these eye disorders in their early stages, an automated system built using deep learning models is suggested.
[9]	Enabling a platform for the doctors and patients	This work, provide a platform that, via a base system, connects patients, medical devices, ophthalmologists, and intelligent eye disease analysis tools. By efficiently integrating discriminative data from a different domain and combining pre-learned SVM (Support Vector Machine) classifier at the same time, our system is able to train the quick prediction model. The platform supports an integrated ecosystem that makes it possible to screen for and monitor eye diseases in an effective and affordable manner.
[10]	Ophthalmologists usually give diagnoses of multi- disease on binocular fundus image.	Ophthalmologists frequently diagnose multiple diseases during fundus screening, so released a dataset with eight diseases to better reflect the real medical environment. This dataset contains 10,000 fundus images from both eyes of 5,000 patients and contains information on eight different diseases. It used several cutting-edge deep neural networks to conduct benchmark studies on it. discovered that just expanding the network's size would not produce satisfactory results for classifying several diseases.
[11]	Effect of the convolutional network depth on its accuracy in the large- scale image recognition setting.	This study examine how the convolutional network's depth affects its accuracy in the context of large-scale picture recognition. Our key contribution is a detailed analysis of networks with increasing depth utilising an architecture with extremely tiny (3 3) convolution filters, which demonstrates that raising the depth to

		16–19 weight layers may significantly outperform existing set-ups.
[12]	Black box phenomenon	First off, DL algorithms are difficult to describe in terms of ophthalmology. This is the "black box phenomenon," which may eventually cause physicians to embrace this technology less readily. In reality, "who is liable to suffer the legal repercussions of an adverse event owing to an erroneous forecast given by an artificial intelligence algorithm? If a machine thinks similarly to a human ophthalmologist who may make errors? These extremely complicated medical legal problems are still pending.
[13]	Image Processing	The importance of image processing for disease diagnosis on medical imaging cannot be overstated. These methods for identifying and categorising diseases are particular to the kind of human organ and picture. The image processing techniques used to separate disease areas and filter medical images were also outlined in the paper.
[14]	The early identification of ocular disease	This research, suggested a method for automatically diagnosing OD, where detection is carried out in two phases. The Mobile Net architecture is utilised for feature extraction since users of smartphones and iPhones without home computers may use it. Other architectures like VGG and RESNET are slower than the one being utilised.
[15]	To examine the anomalies related to diseases that affect the eye.	The monitoring and identification of different ophthalmological illnesses depends heavily on a fundus picture. Using ensemble neural architectures, this article suggests a unique Multi-Disease Classification Framework (MDCF). The first job in the suggested approach is to preprocess the dataset using techniques like contrast enhancement, oversampling, scaling, and normalisation.
[16]	Retinal pathologies are the most common cause of childhood blindness	It is vital and crucial to diagnose illnesses quickly and automatically in order to lighten the strain of ophthalmologists. Ophthalmologists use direct or indirect vision of the eye and its surrounding tissues to diagnose disorders using pattern recognition. The use of deep learning algorithms in the field of ophthalmology is ideal due to its reliance on the fundus of the eye and its examination. First examine the various characteristics of lesions and outline the basic procedures of data processing. Then, determine the hardware and software required to implement deep learning solutions. Finally, look at the experimental concepts used to assess the different approaches.,

[17]	Doctor-patient ratio	The doctor-patient ratio in India is 1:10,000. Glaucoma and diabetic retinopathy (DR) are the main causes of blindness in India, according to research. In both industrialised and developing nations, diabetic retinopathy, which is the primary cause of blindness among individuals of working age, is mostly brought on by a person's diabetes. In this article, automated methods for detecting diabetic eye illness are systematically reviewed from a number of angles, including I datasets that are currently accessible, ii) picture pre-processing methods, iii) deep learning models, and iv) performance assessment metrics.
[18]	Early diagnosis of eye diseases is essential to prevent irreversible vision loss.	In this study, the classification of fundus pictures into cataract, glaucoma, and retinal disorders is the main objective. In a number of issues including illness categorization, the Convolution Neural Network-Recurrent Neural Networks (CNNRNN) model has shown to be successful.
[19]	Recent Tele Medicine Emergence	The major objective is to give them better care at a reduced cost. People in metropolitan locations can still manage an eye exam, but it gets more challenging for those in rural areas. Due to the widespread use of mobile phones throughout the nation, telemedicine is now possible.
[20]	Speedy diagnosis of eye disease	The objective of this work is to create a comprehensive framework for storing diagnostic data in an international standard format to facilitate the prediction of eye illness diagnosis based on symptoms utilising decision tree algorithms, such as cataract, glaucoma, and retinal.

3. Conclusion

The goal of this work is assessment of ocular disease. Six different eye disorders, including normal, glaucoma, cataract, age-related macular degeneration, hypertension, and pathological, were taken in to consideration when developing the models for this survey. This work conclude that it is possible to detect various eye diseases using convolutional neural networks. Examining all the diseases at one time might have significantly lower results. With the ODIR dataset providing all-important variations of a specific disease to the training model is not always possible, which affects the final metrics. Although, sure that having a bigger dataset, would increase the accuracy of predictions and finally automate the process of detecting ocular diseases.

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