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Research Article

Multiple Eye Disease Detection Using Deep Learning

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Abstract:

Human eyes are susceptible to various abnormalities due to aging, trauma, and diseases like diabetes. Glaucoma, cataracts, macular degeneration, and diabetic retinopathy are the leading causes of blindness worldwide. It is crucial to detect and diagnose these eye diseases early to provide timely treatment and prevent vision loss. Multiple eye disease detection through the analysis of medical images can aid in this process. The steps involved in the detection of multiple eye diseases using deep learning include image acquisition, region of interest extraction, feature extraction, and disease classification or detection. In this study, we proposed a model using deep learning algorithms, ResNet and VGG16, to detect eye diseases such as uveitis, glaucoma, crossed eyes, bulging eyes, and cataracts. We achieved a 92% accuracy rate using ResNet50 and 79% accuracy using the VGG16 model. By automating the detection process, we can save time for doctors and increase the accuracy and detection rate. The proposed model can be integrated into the healthcare system to assist in early diagnosis and effective treatment of eye diseases.

Keywords: Deep learning; Eye diseases prediction; Convolutional neural network

1. Introduction

Physical disorders of the eyes can have a significant impact on an individual's confidence, self-esteem, and productivity. These disorders not only affect a person's overall health by indicating the presence of serious underlying diseases, but they can also cause shame and bullying, particularly in children. Bulging eyes, cataracts, crossed eyes, glaucoma, and uveitis are major diseases that can affect both the appearance and health of an individual. Eyes that protrude or bulge from their normal position can be a sign of a serious medical condition. This condition is known as proptosis or exophthalmos in medical terms. If there is a visible white part of the eye between the upper eyelid and the iris, then there may be symptoms of abnormal bulging. Hyperthyroidism is a major cause of bulging eyes. The thyroid gland controls metabolism by releasing hormones, and in hyperthyroidism, the gland releases an excess of these hormones. Graves' disease, an autoimmune disorder, is a major cause of bulging eyes and hyperthyroidism. In hyperthyroidism, the tissues surrounding the eyes become swollen, which causes the bulging effect. There may be an underlying infection, thyroid issue, or some other medical problem associated with bulging eyes. Therefore, it is important to identify and diagnose eye disorders like bulging eyes, cataracts, crossed eyes, glaucoma, and uveitis in their early stages to prevent them from affecting an individual's appearance, health, and overall well-being.

In cataracts, there is a blurring of the clear lens of the eye. In cataracts, seeing via cloudy lenses are like a blurred window. Blurred vision due to cataracts causes difficulty in reading, driving, and analyzing the world. Cataract is a common cause of blindness in developing countries. Approximately 37 million people were blind in 1990 and of these 40% were due to cataracts (McCarty, Keeffe, & Taylor, 1999). Cataracts develop gradually and do not affect eyesight at first but with time, cataracts disturb the vision. In Strabismus, eyes are not synchronized and deviate from their original place i.e. one eye deviates in an opposite direction from the other. Strabismus occurs due to problems in the optic nerve, extraocular muscle, or brain (Rutstein et al., 2011). Normally, six muscles work together and control the movement of the eye due to which both eyes can point in the same direction. Patients having strabismus have problems controlling the movement of the eye and cannot maintain normal alignment. Crossed eyes are caused due to nerve damage or non-synchronization of eyes muscles. When different signals are sent to the brain, it ignores weaker eye signals. Patients having strabismus have problems controlling the movement of the eye and cannot maintain normal alignment. Crossed eyes are caused due to nerve damage or non-synchronization of eyes muscles. When different signals are sent to the brain, it ignores weaker eye signals. Glaucoma damages the optic nerve of the eyes. It becomes worse with time. It is linked to the creation of pressure inside the eye. Glaucoma can inherit in the offspring and diagnose in the later stage of life. The optic nerve which is responsible for sending images to the brain can be damaged by intraocular pressure. In worse conditions, vision can be permanently lost or complete blindness can occur within a few times. There are no early symptoms of glaucoma. Once vision is lost, it is impossible to recover it. But due to decreasing pressure of the eye further vision loss can be prevented.

Uveitis is a severe condition characterized by inflammation in the eyes. It affects the tissues of the uvea, which is the middle layer of the eye wall. The warning signs of uveitis can appear suddenly and can rapidly worsen over time. Symptoms include blurred vision, redness of the eye, and pain. This disease can harm one or both eyes, and people of all ages, including children, can be affected by it. The probable causes of uveitis include inflammatory disease, injury, or infection. However, in numerous cases, the root cause remains unidentified. It is crucial to diagnose and treat uveitis in its early stages to prevent permanent loss of vision.

1.2 Eye Disease Detection Using Deep Learning

Artificial Neural Networks are based on mathematical models that on a smaller scale copy mammalian neural structures. In neural networks, neurons are arranged in layers. ANN layers are fully connected having a non-linear 'activation function' that uses backpropagation for error reduction using gradient descent. The input layer recognizes patterns that are passed to the hidden layers for processing the pattern using weights adjustment. Hidden layers are linked to the output layer that apprehends patterns of retinal images. The weights of neurons are adjusted according to some learning rules and input patterns. But the conventional neural network doesn't analyze patterns in various places.

CNN is a special neural network type that has good performance in image classification. Convolution neural networks can recognize various objects after training on a large dataset. It uses correlations between the images. It can detect diseases within seconds that are difficult to recognize manually. Yet the selection of hyperparameters like the selection of layers, and the size of the CNN filter is important in this regard. Here we have used CNN for the detection of a particular disease in which we have used five convolution layers for the extraction of features and three dense layers for classification. Features are extracted using convolution layers but a large number of parameter requirements is problematic for training deep neural networks. Max-pooling summarizes the outputs of a particular layer and rescales them. Flatten layer performs the transition from convolution to dense layers. The dense layer learns nonlinear combinations from convolution layer outputs. Softmax has been used in the output layer as an activation function for classifying outputs.

A Convolutional Neural Network (CNN) recognizes the structural features of an image. CNN can capture the input pattern across the image by sliding the filter on the entire image to perform pattern matching.

Stride decides the movement of the window for matching the image pattern. CNNs are comprised of processing elements having self-learning biases and weights. Input is received by a neuron that performs the dot product of these inputs with weights, adding the result with bias and passing it to the activation function. The entire neural network uses a single score function from the input image pixels to class scores. The CNN takes images as input for encoding characteristics into architecture making forward function implementation efficient and reduction of network parameters. Unlike ANN, neurons in CNN layers are arranged in three dimensions (width, height, and depth). CNN is comprised of a minimum of 5 layers. Input 3D data is transformed into 3D output using a differentiable function. There are three components in CNN. The convolutional layer is the first one that is used for identifying patterns in the entire image. Secondly, the max-pooling layer is used for performing down sampling and thirdly the fully connected dense layer is used to output results.

Deep CNN and neural networks are different in the sense that in the neural network, all the image pixels are fed to a single layer and then it is connected with the next layer, this can cause overfitting if there are abnormal patterns at various positions of the retina. The edges and core can be detected by different neurons. These are moved to the whole image using the locality principle with a particular stride(steps) and it is ensured that different localization pattern data (abnormal patterns) is passed to different neurons. In this way, patterns are well learned than searching out the location as opposed to the ordinary neural network. A CNN model will be trained on a dataset for the classification of diseases. After training model will be able to classify multiple diseases. So the system will be able to detect the diseases when the image of a specific disease will be placed before the system. After analyzing the image, the system will predict the name of the disease. So multiclass classification will be performed. A disease detection architecture of CNN is shown in Figure 1.

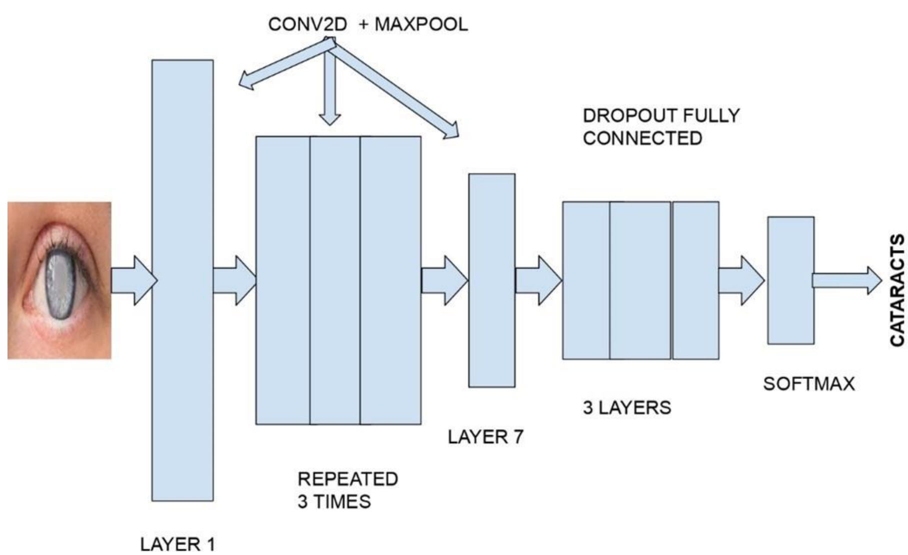

Figure 1: Disease detection CNN architecture

The rest of the paper is organized as follows. Section 2 discusses the related work. Material and methods are presented in Section 3. Results and related discussions are presented in Section 4. Lastly, Section 5 concludes the work.

2. Related Work

Krishna et al. (Prasad, Sajith, Neema, Madhu, & Priya, 2019) proposed multiple eye disease detection using deep learning. Diabetic Retinopathy (DR) and Glaucoma are the diseases that have been detected using the proposed method. Deep neural network models have been trained on datasets. This dataset has been obtained from Kaggle. The accuracy of the system is 80%. Aun et al. (Nazir et al., 2020) proposed a technique for diabetes-based eye diseases. Fast Region-based Convolutional Neural Network (FRCNN) algorithm is used for disease localization that is used for object detection. Fuzzy k-means (FKM) clustering is used for the segmentation of disease after detection. DIARETDB1, ORIGA, MESSIDOR, DR-HAGIS, and HRF datasets are used for performance evaluation.

Grassmann et al. (Grassmann et al., 2018) proposed a deep learning-based approach for age-related macular degeneration from color fundus photography. Classification of age-related diseases has been performed for analysis of fundus images. Thirteen classes have been trained over an independent dataset using a deep neural network. Overall classification of 94.3% healthy fundus images was performed successfully. Chen et al. (Chen, Xu, Wong, Wong, & Liu, 2015) proposed Glaucoma detection based on a deep convolutional neural network. Classification between glaucoma and non-glaucoma patterns has been performed. Strategies of data augmentation and dropout have been used for performance enhancement. A deep neural network is used for the segmentation and classification of diseases. Response-normalization layers and overlapping-pooling layers are used for the reduction of over fitting.

Chen et al. (Chen, Xu, Yan, et al., 2015) presented an approach for feature learning specifically for Glaucoma detection. In their work, CNN is used for feature learning. The micro neural network has been used to obtain the input. A deep learning structure is used for obtaining a hierarchical representation of fundus images. The authors used SCES and ORIGA datasets for the training of DNN. Sarkari et al. (Sarki, Ahmed, Wang, & Zhang, 2020) conducted a survey related to diabetic eye disease detection which covers several aspects like deep learning models, image processing techniques, available datasets, and performance evaluation metrics. A comprehensive synopsis of all the approaches has been presented.

Chelaramani et al. (Chelaramani, Gupta, Agarwal, Gupta, & Habash, 2020) used fundus images for three tasks relating to eye diseases. Firstly, the category of the disease has been detected then the subcategory of the disease has been detected, and at last textual diagnoses have been generated. ResNet models have been used for the detection of disease using multi-task learning. Experiments on the dataset with 40658 images of 3502 patients have been performed. Accuracy of 86% for category detection and 67% for subcategory have been achieved.

Nguyen et al. (Nguyen et al., 2020) explored a method for automating the screening process for diabetic retinopathy (DR) that can enhance the efficiency of detection and decision-making. They presented a classification system that uses deep learning models like VGG16 and VGG19 to analyze and categorize fundus images. The disease was classified into four categories based on its severity, and the system achieved an accuracy of 82%, with 80% sensitivity and 82% specificity. Mishra et al. (Nguyen et al., 2020) conducted a study using deep learning to analyze different stages of diabetic retinopathy (DR). They used the DenseNet model to classify 3662 fundus images obtained from the Kaggle (Aptos) dataset into five DR stages. The DenseNet model extracted features from the fundus images for classification, resulting in an accuracy of 96%. The study also compared the performance of VGG16 and DenseNet. Qummar et al. (Qummar et al., 2019) proposed an automatic approach for detecting DR disease. Manual detection of DR can be laborious and prone to errors; thus, computer vision-based techniques are used for the automatic detection of the disease from retinal images. They trained a classifier on the Kaggle dataset using CNN models such as ResNet50, Inception v3, etc. The system successfully detected all DR stages.

Ramanathan et al. proposed a model that detects cataract, glaucoma, and retinal diseases in patients. To achieve this, the system uses Logistic Regression, Random Forest, Gradient Boosting, and Support Vector Machine algorithms. By enabling early detection of these diseases, the proposed system can help people receive proper treatment and reduce the incidence of blindness. The system also evaluates the safety and effectiveness of cataract surgery in eyes with age-related degeneration, while detecting glaucoma and retinal diseases (Ramanathan, Chakrabarti, Patil, Rishipathak, & Kharche, 2021).

The early detection of diseases can increase the likelihood of a cure and prevent blindness. Medical professionals can diagnose retinal issues, such as diabetic retinopathy and retinitis pigments by examining retinal fundus images. Recently, machine learning research has focused on using feature extraction and image classification to diagnose diseases like diabetic retinopathy. Jain et al. classified retinal fundus images automatically, without explicit segmentation or feature extraction. This is achieved using a simple and fast deep-learning model that can classify any image as healthy or diseased. The model has been tested on two datasets, including real patient retinal fundus images from a local hospital, and has shown an accuracy range of 97% (Jain, Murthy, Patel, & Bansal, 2018).

Nazir et al. proposed an automated approach for disease localization and segmentation using the FRCNN algorithm combined with FKM clustering. The FRCNN algorithm is an object detection approach that requires bounding-box annotations to work, but these annotations are often not available in datasets. Therefore, ground-truth annotations were generated and used to train the FRCNN for localization, which was then segmented out using FKM clustering. The segmented regions were compared against the ground-truth annotations using intersection-over-union operations. The performance of the approach was evaluated on several datasets (Nazir et al., 2020). Adding too many layers to a deep neural network can lead to several potential issues, including:

Overfitting: Overfitting occurs when a machine learning model is trained too well on the training data, resulting in poor performance on unseen data. It happens when the model captures noise and idiosyncrasies in the training data, rather than learning the general patterns. Adding too many layers to a neural network can cause it to become too complex, leading to the overfitting of the training data. Overfitting occurs when the model learns the noise in the training data rather than the underlying patterns.

Vanishing gradients: Vanishing gradients are a problem that can occur when training neural networks. It happens when the gradients used to update the weights in the network during backpropagation become very small, making it difficult to optimize the network. As the number of layers in a neural network increase, the gradients used to update the weights during backpropagation can become very small. This can make it difficult for the model to learn the underlying patterns in the data.

Slow training: Slow training refers to the problem of long training times for machine learning models. This can be caused by a variety of factors, such as large amounts of data or complex models that require many iterations to converge. A deep neural network with many layers can take longer to train than a simpler network. This is because the backpropagation algorithm must propagate errors through many layers, which can be computationally expensive.

Gradient explosion: Gradient explosion is the opposite of vanishing gradients, where the gradients become too large during training, resulting in instability and difficulty in finding a good set of weights. In some cases, the gradients used to update the weights during backpropagation can become very large, leading to numerical instability and divergence during training.

Difficulty with hyperparameter tuning: Hyperparameters are parameters of a machine learning model that are not learned during training, but rather set manually. Tuning these hyperparameters is important for achieving good performance, but it can be a challenging and time-consuming task. Adding more layers to a neural network increases the number of hyperparameters that must be tuned, making it more difficult to find the optimal combination of hyperparameters.

Decreased interpretability: As machine learning models become more complex, they can become harder to interpret. This can be a problem, as understanding how a model makes decisions is important for trust and accountability. Interpretability techniques can be used to help understand these models. As the number of layers in a neural network increases, it can become more difficult to interpret how the model is making predictions. This can make it challenging to diagnose and fix problems with the model.

3. Materials and Methods

Various eye diseases can cause vision impairment or blindness, including bulging eyes, cataracts, crossed eyes, glaucoma, and uveitis. Detecting these diseases in their early stages is crucial for effective treatment and prevention of further damage to the eyes. However, the current process of detection often involves subjective assessments by doctors, which can lead to errors and delays in diagnosis. Therefore, there is a need to develop an automated detection system for these diseases. Automating the detection process of eye diseases will provide several benefits. It will help doctors to make faster and more accurate diagnoses, and decrease the chances of human errors. By using computer algorithms, the detection process can be standardized, and objective measurements can be obtained, leading to more reliable and consistent results. Moreover, an automated detection system can handle a large number of patients simultaneously, which can reduce the waiting time for diagnosis and treatment. To develop an automated detection system for eye diseases, a multi-stage approach will be taken. Initially, the eyes will be detected in the images using the Haar Cascade classifier, which is a widely used computer vision technique. Then, the detected eyes will be fed to a deep neural network for the classification of diseases. The deep learning model will be trained on a large dataset that contains images of eyes with various diseases. After training, the model will classify the images of a particular disease, enabling the automated detection of eye diseases. Overall, the development of an automated detection system for eye diseases has the potential to revolutionize the way in which these diseases are diagnosed and treated, leading to improved health outcomes for patients.

3.1 Dataset

3.1.1 Class Label

The dataset consists of five classes labeled with disease names. These class labels will be used in training and testing the model. Class labels will be given to the classifier as the names of folders. Each folder will represent a separate disease and will contain images of that disease. These class labels will be represented as follow:

- Crossed eyes, also known as strabismus, is a condition where the eyes do not align properly. This can result in one eye looking straight ahead while the other eye turns inward, outward, upward, or downward.
- Cataracts are a common eye disease that affects the clarity of the eye's lens. It causes blurry vision and can make it difficult to see clearly. The condition develops slowly over time and is often associated with aging, but can also be caused by genetics, trauma, or certain medications.

- Uveitis is a condition that causes inflammation in the uvea, the middle layer of the eye. It can be a serious condition that can lead to vision loss if left untreated. Symptoms of uveitis include eye redness, pain, blurred vision, and sensitivity to light. It can affect people of all ages, but it is more common in those between the ages of 20 and 50.
- Glaucoma is a serious eye disease that can cause irreversible damage to the optic nerve, which is responsible for transmitting visual information from the eye to the brain. It is often associated with increased pressure inside the eye, which can lead to gradual loss of vision if left untreated.
- Bulging eyes, also known as proposes or exophthalmos, is a medical condition that causes one or both eyes to protrude from the eye socket. This can be due to various underlying medical conditions such as thyroid eye disease, orbital cellulitis, or a tumor behind the eye.

3.1.2 Images

Each class label contains approximately 100 train and 20 test images for training and testing the deep learning model respectively. These images will be given to the classifier for identification of the person and the folder containing these images will be named the same as the name of the student. A snapshot of the dataset is shown in Figure 2.

Figure 2: Dataset images of diseases

3.1.3 Training and Testing Module

There are separate modules for training and testing. Each module contains a separate dataset of images for training and testing the model. The training module will contain separate 100 images for training and the test module will contain separate 20 images for testing the model.

- Test
- Train

3.2. ResNet

Deep neural network (DNN) pre-trained models are widely used in machine learning due to their ability to solve complex problems. However, adding too many layers to a DNN can cause vanishing gradient problems, where the gradients become too small to update the weights in the initial layers using backpropagation. To solve this issue, Residual Networks (ResNets) were developed, which introduced identity connections to the architecture. Identity connections, also known as skip connections, allow gradients to move backward from later to initial filters in the network. This allows for the preservation of the gradient of error while backpropagating through the layers. The addition of these identity connections improved the performance of convolutional neural networks (CNNs) by reducing the effects of vanishing gradients and facilitating the training of deeper networks. The ResNet architecture consists of a backend that starts with a 7x7 convolution and a 3x3 max pool layer with strides of 2, which downsamples the input tensor (Conv1). This is followed by four residual blocks, with the stride of 1 used in all layers except the initial layer, where the stride of 2 is used for further downsampling of the input. To obtain a feature map of a single value, a global average pooling layer (GAP) is used, which is then passed to a fully connected layer with a sigmoid activation function for classification.

We have developed a DNN based on the ResNet architecture that takes input images of size 224x224x1. The model starts with a 7x7 convolution, followed by a 2x2 max pooling layer. A ResNet block is then used, which contains one convolution and three identity blocks. In the identity blocks, there are three layers and an identity connection. These consist of 1x1, 3x3, and 1x1 convolutions. The convolution block consists of three layers of 1x1 and 3x3 convolutions stacked on top of each other, with a kernel size of 1x1. The stride of 2 is used in a 3x3 convolution layer, which reduces the input size and prevents size mismatch. Finally, an average pooling layer, a flattened layer, and two fully connected layers are used respectively. This DNN model has been trained on a large dataset and has achieved high accuracy in image classification tasks. The use of the ResNet architecture with identity connections has enabled the model to learn complex features from the input images and improved its performance. Additionally, the use of a sigmoid activation function in the fully connected layers has helped to improve the model's ability to accurately classify the image. Overall, the ResNet architecture with identity connections has been a significant improvement in CNN architecture, particularly for solving complex problems. The addition of skip connections has allowed for the training of deeper networks, which was previously difficult due to vanishing gradients. The model we have developed based on the ResNet architecture has demonstrated the effectiveness of this approach in achieving high accuracy in image classification tasks. Future research may explore the use of ResNet in other areas of machine learning, such as natural language processing and time-series analysis. ResNet architecture is shown in Figure 3.

3.3 VGG16

At Oxford University, VGG16 has been proposed by K. Simonyan and A. Zisserman (Simonyan & Zisserman, 2014). As a convolutional neural network model, VGG16 achieved a remarkable test accuracy of 92.7% when tested on ImageNet, a large dataset that contains over 14 million images belonging to 1000 different classes. The model was submitted to the ILSVRC-2014 competition and has since become a popular choice for image recognition tasks. The VGG16 model improved upon the AlexNet architecture by using multiple 3×3 filters of kernel size in place of large kernel-size filters. The model was trained over several weeks using NVIDIA GPUs for processing. With its impressive accuracy and robustness, VGG16 has proven to be a valuable tool in the field of image recognition, particularly for large-scale datasets such

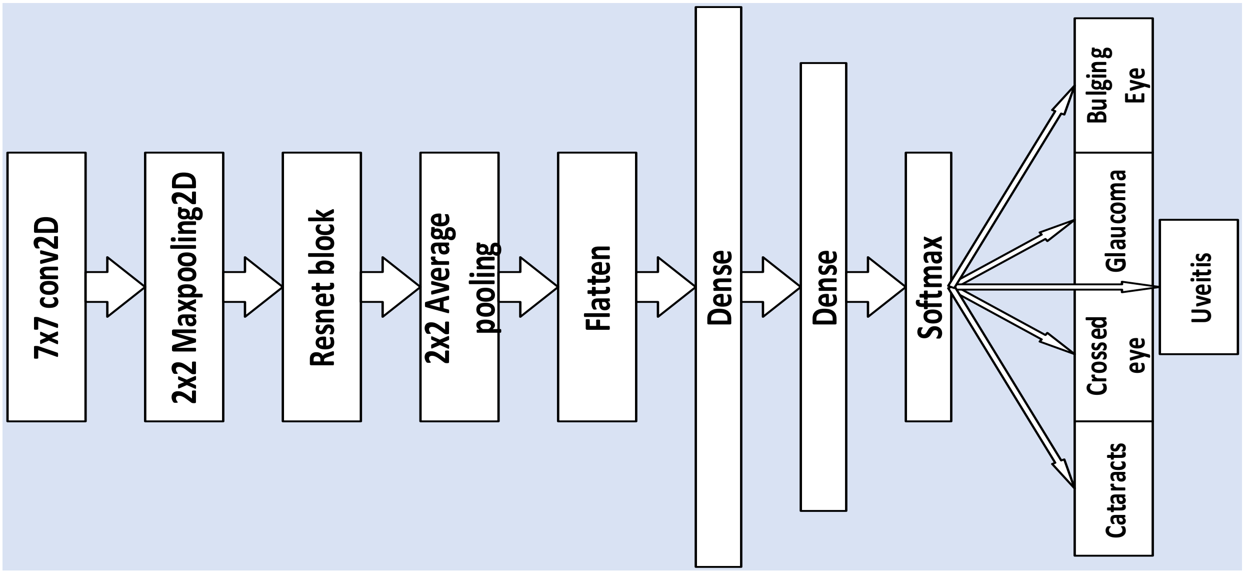

Figure 3: ResNet architecture

as ImageNet. Its success has also inspired the development of other deep convolutional neural network models that have achieved even greater accuracy in image recognition tasks. The architecture of VGG16 is shown in Figure 4.

3.3.1 ImageNet Dataset

The ImageNet dataset is a collection of over one million high-resolution images that have been labeled with over 22,000 categories. The labeling was done by human labelers and the images were gathered from the internet. In 2010, the ILSVRC (ImageNet Large Scale Visual Recognition Challenge) was held, where the ImageNet dataset was used with approximately 1000 categories, resulting in a total of around 1.2 million training images. To make the dataset compatible with the competition, the images were resized to 256×256 and the central 256×256 portion of the images were cropped and rescaled.

The VGG16 model was proposed at Oxford University by K. Simonyan and A. Zisserman in their paper "Very Deep Convolutional Networks for Large-Scale Image Recognition". The model is a convolutional neural network that achieved a test accuracy of 92.7% on the ImageNet dataset. The ImageNet dataset is a collection of over 14 million images that belong to 1000 classes and was submitted to the ILSVRC-2014 competition, making the VGG16 model one of the most popular models used in deep learning. The model improved on the AlexNet architecture by replacing large kernel-size filters with multiple 3×3 filters of kernel size. The VGG16 model was trained for several weeks using NVIDIA GPUs for processing.

The Conv1 layer of the VGG16 model takes input in a 224 x 224 size, and after passing through the convolutional layers, a receptive field filter of 3×3 is used. One of the configurations of the model utilizes 1×1 convolution filters as a linear transformation of the input channels. The convolution stride of 1 pixel is used to preserve spatial resolution after convolution, and spatial pooling is carried out by five max-pooling layers on a 2×2-pixel window with a stride of 2. The VGG16 model also utilizes three fully-connected convolutional layers, with 4096 channels used in the first two layers and 1000 channels used in the third layer for classification. The final layer of the model is the Soft-max layer, and the same configuration is used in all fully connected layers of the network. The hidden layers of the VGG16 model use Rectification

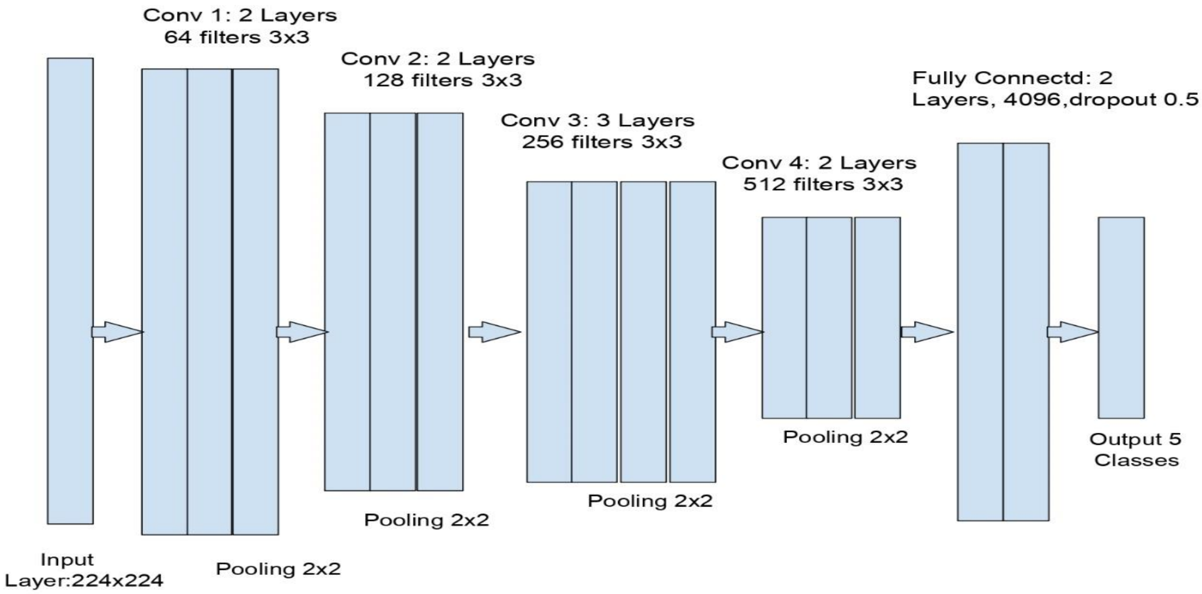

Figure 4: VGG16-Architecture

(ReLU) non-linearity, but Local Response Normalization (LRN) is not included, as the ILSVRC dataset showed that normalization did not improve performance and only increased computation time and memory consumption.

4. Results and Discussion

The testing of the system is done by inputting both the test images and the images that are taken live corresponding to multiple eye diseases. The output has been shown in form of accuracy. The results that are obtained for test images show that the image of the eye is affected. Experiments performed on images for crossed-eye detection is shown in Figure 5.

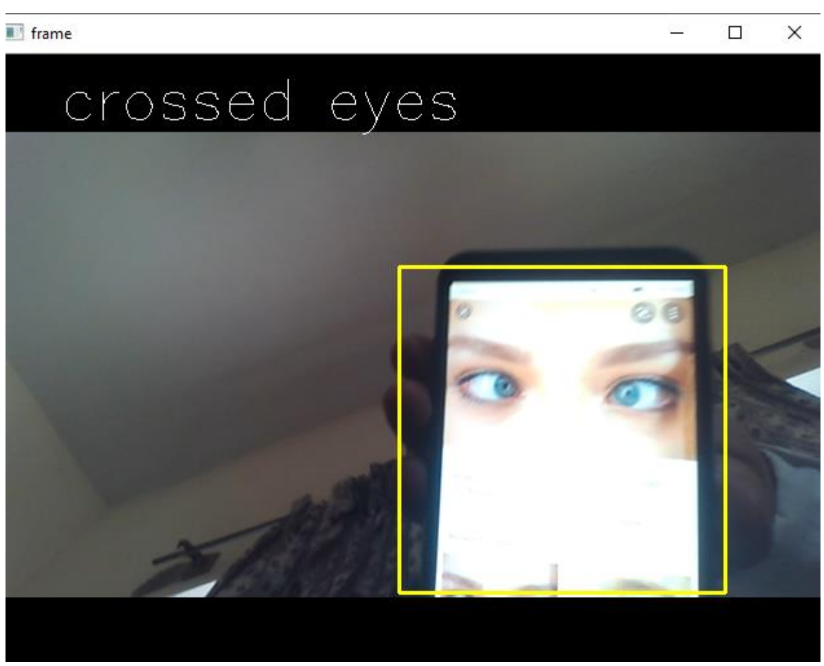

Figure 5: Detection of crossed eyes

The results show that the proposed system has successfully recognized particular diseases. However, the model has achieved 92% training accuracy and 89% validation accuracy. Training loss is 67% while validation loss is 69% as described in Table 1.

Table 1: Model evaluation results

Models	**Train Accuracy**	**Train Loss**	**Validation Accuracy**	**Validation Loss**
ResNet50	0.920	0.670	0.890	0.690
VGG16	0.798	0.495	0.821	0.840

4.1 Need for Multiple Eye Disease Detection

With the increase in the aging population worldwide, the incidence of eye diseases is also predicted to rise gradually. Early detection and appropriate treatment are crucial for preventing vision loss and promoting a better quality of life. However, conventional diagnosis approaches involving human judgment have a higher risk of misdiagnosis. To address this issue, automated detection of eye diseases using deep learning can greatly improve the accuracy and detection rate while saving doctors' time. Previous research has focused on the detection of single diseases such as strabismus in children using deep learning. However, in this study, we aim to detect multiple diseases such as crossed eyes, uveitis, glaucoma, and others using deep learning techniques. By training our deep learning model on a large dataset of labeled images, we have achieved promising results in accurately detecting these various eye diseases. This approach has the potential to revolutionize the field of ophthalmology by enabling the early detection of multiple diseases through an automated process. This will not only reduce the burden on doctors but also improve the accuracy of diagnoses, ultimately leading to better patient outcomes. With further research and development, deep learning-based approaches to ophthalmology could have a significant impact on the prevention and treatment of various eye diseases.(Yehezkel, Belkin, & Wygnanski-Jaffe, 2020). In this paper, we have performed the detection of multiple diseases like crossed eyes, uveitis, glaucoma, etc.

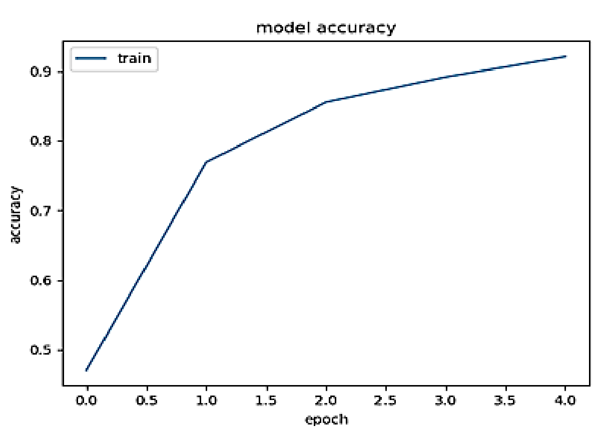

Figure 6: ResNet accuracy

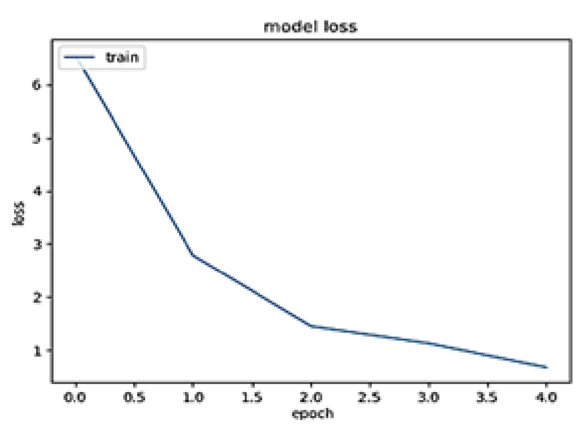

Figure 7: ResNet loss

We utilized the ResNet model on our dataset and achieved a training accuracy of 92%. However, we also obtained a loss of 0.67 during the training process, as shown in Figures 6 and 7 respectively. Our ResNet model was successful in making accurate predictions.

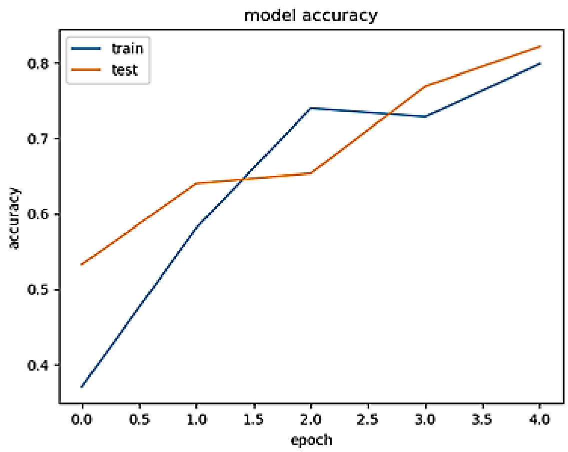

Figure 8: VGG16 accuracy

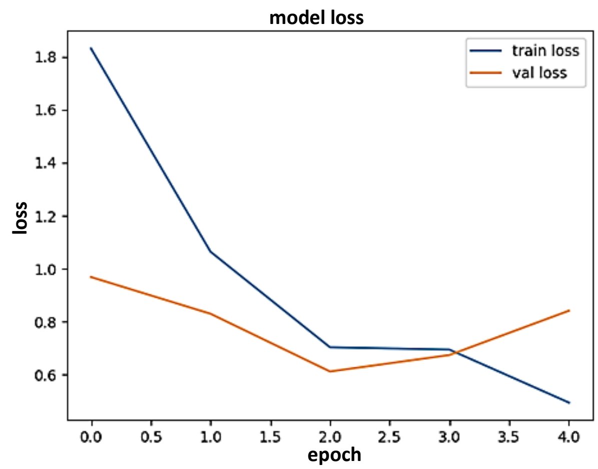

Figure 9: VGG16 loss

Using VGG16, we have achieved 79% train accuracy, and the accuracy we have obtained while testing is 82% as shown in Figure 8. The training and testing loss using the VGG16 model is 0.49 and 0.82 respectively as shown in Figure 9. So ResNet has performed better than VGG16 not only while making predictions but also during testing and training.

5. Conclusion

The eyes are one of the most important organs in the human body, and eye disorders can have a significant impact on a person's life. The early detection and treatment of eye diseases such as glaucoma, uveitis, cataracts, crossed eyes, and bulging eyes are crucial for maintaining good eye health and overall well-being. This paper has proposed an automated detection system that can aid in the diagnosis of these diseases using deep learning algorithms. Specifically, we have utilized ResNet50 and VGG16 models for the detection process. During the training process, ResNet50 demonstrated higher accuracy compared to VGG16. The automated detection system has the potential to revolutionize the way eye diseases are diagnosed and treated, as it can save time and increase the accuracy of detection. This system can also be utilized to aid medical professionals in their decision-making process, leading to better patient outcomes. Future research can be done to improve the accuracy of the detection system and to expand its capabilities to detect other eye disorders. Additionally, the integration of this technology into clinical settings can be explored to enhance the efficiency of eye disease diagnosis and treatment. Overall, the proposed system shows promise in improving the detection and treatment of eye diseases, ultimately contributing to better eye health and quality of life for individuals. In the future, we will extend this work for Optic neuritis disease.

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