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Multiple Eye Disease Detection Using Image Processing & Deep Learning techniques

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ABSTRACT:
Human eyes can develop a variety of abnormalities as a result of age, injury, and illnesses including diabetes. The main causes of blindness in the globe are diabetic retinopathy, cataracts, macular degeneration, and glaucoma. Early detection and diagnosis of various eye conditions is essential for prompt treatment and stop eyesight loss. This approach can be aided by the diagnosis of many eye diseases through the analysis of medical photographs. Using deep learning, a number of eye disorders may be detected. These include acquiring images, extracting features, classifying or detecting diseases, and extracting regions of interest. In this paper, we suggested a model to identify eye illnesses as uveitis, glaucoma, crossed eyes, bulging eyes, and cataracts using deep learning methods, ResNet and VGG16. We used to get a 92% accuracy rate with ResNet50 and 79% accuracy with the VGG16 model . We can improve accuracy and detection rate while saving doctors' time by automating the detection procedure. The suggested methodology can help with early detection and efficient treatment of eye problems by being included into the healthcare system.

Keywords: CNN(Convolutional neural network),Eye disease prediction, Deep Learning

INTRODUCTION

The prevalence of eye diseases has been increasing globally, posing significant challenges to public health systems worldwide. Prompt and accurate diagnosis is crucial for effective management and treatment of these conditions. Traditional methods of eye disease diagnosis often rely on manual examination by ophthalmologists, which can be time-consuming, subjective, and prone to errors. With the advancements in deep learning techniques and the availability of large-scale medical imaging datasets, there is a growing interest in leveraging artificial intelligence (AI) for automated eye disease detection.

This research paper focuses on the application of deep learning techniques for the simultaneous detection of multiple eye diseases from medical images, such as retinal fundus photographs and optical coherence tomography (OCT) scans. Deep learning, a subset of machine learning, has demonstrated remarkable success in various medical image analysis tasks, including but not limited to, cancer detection, organ segmentation, and disease classification. By harnessing the power of convolutional neural networks (CNNs) and other deep learning architectures, this study aims to develop a robust and accurate system for the detection of multiple eye diseases.

The significance of this research lies in its potential to revolutionize the field of ophthalmology by providing automated, fast, and reliable diagnostic tools. Early detection of eye diseases can lead to timely interventions, thus preventing irreversible vision loss and improving patient outcomes. Furthermore, an automated system can assist healthcare professionals by providing them with additional diagnostic support, reducing their workload, and enabling better allocation of resources.

In this paper, we will review the existing literature on deep learning-based approaches for eye disease detection, highlighting the strengths and limitations of current methods. We will then present our proposed

methodology, detailing the deep learning architectures, pre-processing techniques, and dataset used for training and evaluation. Subsequently, we will discuss the experimental results, including performance metrics such as accuracy, sensitivity, and specificity. Additionally, we will compare our approach with existing methods and discuss potential areas for future research and improvements.
Overall, this research aims to contribute to the growing body of knowledge in the field of medical image analysis and deep learning, with a specific focus on the early detection and simultaneous diagnosis of multiple eye diseases. By developing an accurate and reliable automated system, we hope to make significant strides towards improving the quality of eye care and reducing the burden on healthcare systems globally.

LITERATURE REVIEW

Krishna et al. (2019) proposed a method for the simultaneous detection of Diabetic Retinopathy (DR) and Glaucoma using deep neural networks trained on datasets obtained from Kaggle. Their system achieved an accuracy of 80%, showcasing promising results in automated disease detection. Building upon this work, subsequent studies have further advanced the field by exploring different deep learning architectures and methodologies for the detection and classification of eye diseases.

Aun et al. (Nazir et al., 2020) introduced a technique specifically targeting diabetes-based eye diseases. They employed the Fast Region-based Convolutional Neural Network (FRCNN) algorithm for disease localization and utilized Fuzzy k-means (FKM) clustering for disease segmentation post-detection. Performance evaluation was conducted on various datasets including DIARETDB1, ORIGA, MESSIDOR, DR-HAGIS, and HRF, demonstrating the effectiveness of their approach.
Grassmann et al. (2018) proposed a deep learning-based approach for the classification of age-related macular degeneration (AMD) from color fundus photography. Their method involved training deep neural networks on an independent dataset with thirteen classes, achieving an overall classification accuracy of 94.3% for healthy fundus images. This highlights the potential of deep learning models in accurately identifying age-related eye diseases.
Chen et al. (2015) focused on Glaucoma detection utilizing deep convolutional neural networks (CNNs). They employed strategies such as data augmentation and dropout to enhance performance and mitigate overfitting. Additionally, they utilized response-normalization layers and overlapping-pooling layers for further improvement in disease segmentation and classification.
Chen et al. (2015) presented an approach specifically tailored for feature learning in Glaucoma detection. Their method utilized CNNs for feature extraction, enabling the hierarchical representation of fundus images. They trained their model on SCES and ORIGA datasets, showcasing the effectiveness of deep learning in capturing discriminative features for disease detection.
Sarkari et al. (2020) conducted a comprehensive survey on diabetic eye disease detection, covering various aspects including deep learning models, image processing techniques, datasets, and performance evaluation metrics. This work provides a valuable overview of the current state-of-the-art approaches in the field, facilitating further research and development in diabetic eye disease detection.
Chelaramani et al. (2020) addressed multiple tasks related to eye diseases using fundus images, including disease category detection, subcategory detection, and textual diagnosis generation. Leveraging ResNet models and multi-task learning, they achieved promising accuracies of 86% for category detection and 67% for subcategory detection on a large dataset comprising 40,658 images from 3,502 patients.

METHODOLOGY:

CNN is a unique kind of neural network that performs well in the categorization of images. Once trained on a sizable dataset, convolution neural networks are capable of recognizing a wide range of objects. Correlations between the photos are used. It may quickly identify illnesses that are hard to identify by hand. However, the choice of hyperparameters, such as the CNN filter's size and layer selection, is crucial in this context. In this case, CNN was utilized to diagnose a specific ailment. Three dense layers were employed for classification and five convolution layers were used to extract information. Convolution layers extract features, however training deep neural networks is hindered by their high parameter needs. Max-pooling compiles the results of a specific resizes and layers them. The transition from convolution to dense layers is handled by the flatten layer. The outputs of the convolution layer are used by the dense layer to learn nonlinear combinations. In order to categorize outputs, Softmax has been employed as an activation function in the output layer. An image's structural characteristics are recognized using a Convolutional Neural Network (CNN). By swiping the filter across the full image, CNN may do pattern matching and collect the input pattern throughout the image. Stride controls how the window moves to fit the pattern of the image. CNNs are made up of processing components with weights and biases that learn on their own. A neuron receives input and uses weights to produce the dot product of the inputs. It then adds bias to the output and sends it to the activation work. From the pixels in the input image to the class scores, the whole neural network makes use of a single score function.

The CNN uses images as input to encode features into the architecture, resulting in more efficient forward function implementation and a decrease in network parameters. In contrast to ANN, CNN layers have three-dimensional (width, height, and depth) neuron arrangements. CNN consists of at least five levels. Using a differentiable function, 3D input data is converted to 3D output. CNN consists of three different parts. The first layer to be utilized to find patterns throughout the entire image is the convolutional layer. Second, down sampling is carried out by the max-pooling layer, and finally, findings are generated by the completely connected dense layer. A dataset will be used to train a CNN model for disease categorization. The model will be able to categorize various ailments after training. Thus, when a certain image of a sickness appears, the system will be able to identify it. Illness will come before the framework. The system will identify the disease's name after evaluating the picture. Thus, multiclass categorization is going to be done.A disease detection architecture of CNN is shown in Fig 1:-

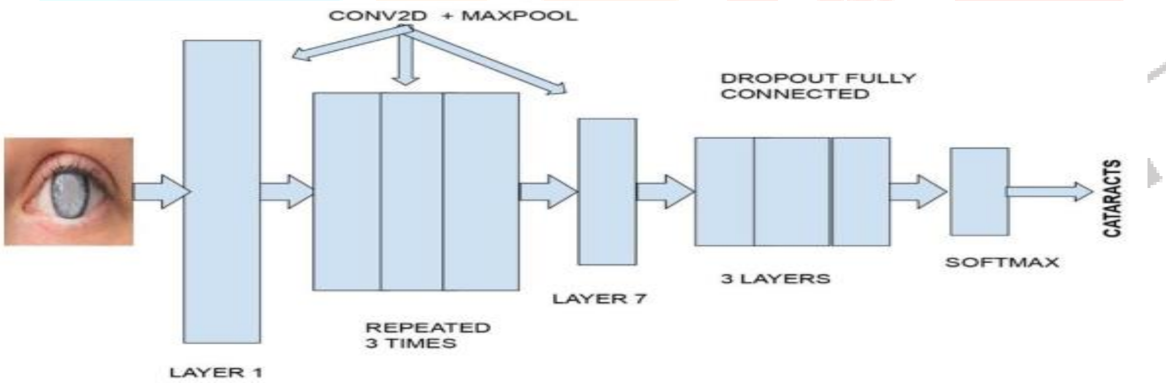

Figure 1 : Disease detection CNN architecture

Dataset

There are five classifications in the dataset, each labeled with a disease name. The model will be trained and tested using these class labels. The classifier will receive class labels in place of folder names. Pictures of each sickness will be included in each folder, which will symbolize a different illness. These class labels will be represented as follow:

▪ Strabismus, or crossed eyes, is a condition in which the eyes do not align correctly. As a result, one eye may focus directly ahead, while the other may turn upward, downward, inward, or outward.
▪ A common condition affecting the clarity of the lens of the eye is cataracts. It might produce hazy vision and make it challenging to see properly. The disorder appears gradually over time and is frequently linked to aging, however it can also be brought on by trauma, genetics, or specific drugs.
▪The illness known as uveitis results in inflammation of the uvea, the central layer of the eye. If treatment is not received, this can be a dangerous condition that results in visual loss. Uveitis can cause redness in the eyes, pain, blurry vision, and light sensitivity. All ages can be affected, although individuals between the ages of 20 and 50 are most likely to experience it.

▪ Glaucoma is a dangerous eye condition that can permanently harm the optic nerve, which is in charge of sending visual data from the eye to the brain. It is frequently linked to elevated intraocular pressure, which, if addressed, can cause progressive visual loss.
▪ Prominent eyes, medically referred to as proposals or exophthalmos, are conditions where one or both eyes protrude from the eye socket. This may be the result of a number of underlying medical disorders, including orbital cellulitis, thyroid eye disease, or an ocular malignancy.

ResNet

Because deep neural network (DNN) pre-trained models can answer complicated problems, they are commonly utilized in machine learning. Nevertheless, vanishing gradient issues, in which the gradients get too small to update the weights in the first layers using backpropagation, can result from overbuilding a DNN. The ResNet architecture consists of a 3x3 max pool layer with strides of 2, which downsamples the input tensor (Conv1), and a backend that begins with a 7x7 convolution. Four residual blocks are then employed, with the first layer using a stride of 1 and the other levels using a stride of 2 for additional input downsampling. A global average pooling layer (GAP) is used to create a feature map of a single value. The feature map is then transferred to a fully connected layer that uses a sigmoid activation function for classification.

VGG16

VGG16, a convolutional neural network model, evaluated on ImageNet, a sizable dataset with over 14 million photos divided into 1000 distinct classes, and obtained an astounding test accuracy of 92.7%. Since it was entered into the ILSVRC-2014 competition, the model has gained popularity as a solution for image identification problems. The VGG16 model replaced the big kernel-size filters in the AlexNet architecture with several 3×3 filters of the same kernel size. The model was trained over a few weeks with processing power provided by NVIDIA GPUs. The VGG16 algorithm has demonstrated remarkable accuracy and resilience, making it a useful instrument in the image recognition domain. The creation of more deep convolutional neural networks has been fastened by its success with greater accuracy.

EXPERIMENTATION

Each class label contains approximately 80 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.

Figure 2 : Dataset images of diseases

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 80 images for training and the test module will contain separate 20 images for testing the model.

- Test
- Train

RESULT

The photographs that are taken live and the test images that correspond to various eye illnesses are entered into the system to test it. The output in the form of accuracy has been displayed. The test picture results indicate that there is an impact on the eye's image.

The result 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 below:

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

The prevalence of eye diseases is expected to increase due to the aging population worldwide. Conventional diagnosis methods relying on human judgment pose a risk of misdiagnosis. To tackle this, automated detection using deep learning can enhance accuracy and save time for doctors. While previous studies focused on single disease detection, our research aims to detect multiple eye diseases like crossed eyes, uveitis, and glaucoma using deep learning techniques. By training our model on a large dataset, we achieved promising results in accurately identifying these conditions. This approach could revolutionize ophthalmology by enabling early, automated detection of various diseases, reducing the burden on doctors, improving diagnosis accuracy, and ultimately enhancing patient outcomes. Further research in deep learning-based ophthalmology could significantly impact the prevention and treatment of eye diseases (Yehezkel, Belkin, & Wygnanski-Jaffe, 2020).

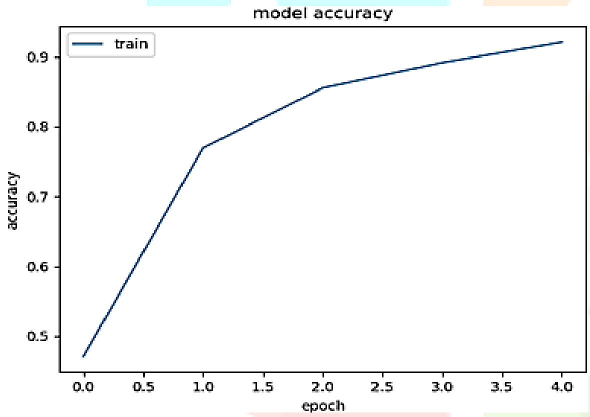

Figure 3: ResNet accuracy

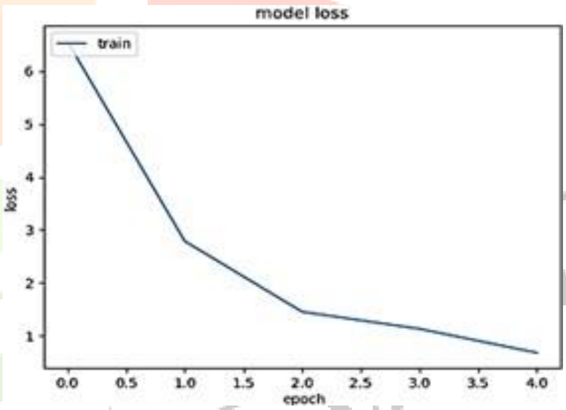

Figure 4: ResNet loss

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 fig 6 and 7 respectively. Our ResNet model Was successful in making accurate predictions.

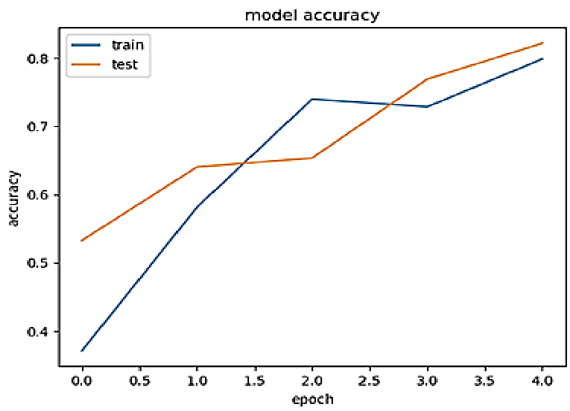

Figure 5: VGG16 accuracy

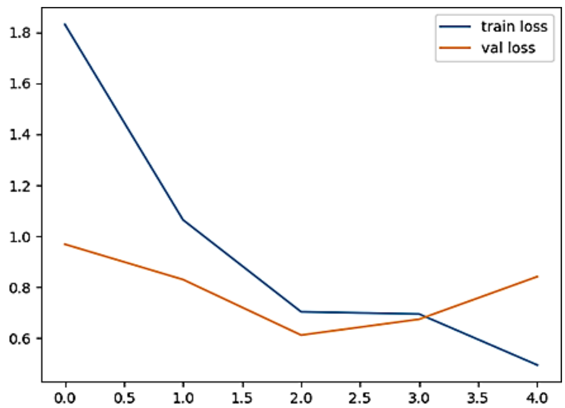

Figure 6: VGG16 loss

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.

CONCLUSION

One of the most vital organs in the human body is the eye, and eye conditions can significantly affect a person's quality of life. Maintaining good eye health and general well-being depends on the early detection and treatment of eye illnesses such as glaucoma, uveitis, cataracts, crossed eyes, and protruding eyes. Using deep learning techniques, this paper has suggested an automated detection system that can help diagnose various disorders. To be more precise, we used the ResNet50 and VGG16 models for detection. In comparison to VGG16, ResNet50 showed better accuracy during the training phase. Due to its ability to save time and improve detection accuracy, the automated detection system has great promise for transforming the diagnosis and treatment of eye illnesses. Better patient outcomes can result from using this approach to support medical practitioners in making decisions. Subsequent investigations could enhance the precision of the identification mechanism and broaden its scope to identify more ocular conditions. Furthermore, investigating the incorporation of this technology in clinical environments can improve the effectiveness of diagnosing and treating eye diseases. All things considered, the suggested method appears to have potential for enhancing the identification and management of ocular disorders, which will eventually benefit people's quality of life and eye health. We plan to expand our study to include optic neuritis in the future.

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