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Comparative Study of CNN Architectures for Ophthalmic Disease Detection

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Abstract: Common eye conditions, including diabetic retinopathy, glaucoma, cataracts, and age-related macular degeneration, pose a significant challenge to global health due to the potential for irreversible vision loss when these diseases are not detected and treated early enough. Currently, with the decrease in the price of retinal imaging, the increased availability of retinal image databases, and the advancement of machine learning through deep learning techniques, especially through the use of Convolutional Neural Networks (CNNs), automated detection of these common eye diseases is now feasible on a large scale. The objective of this research is to compare results from several different CNN models in order to determine which type of architecture is most effective at diagnosing ophthalmic conditions from fundus and OCT images. Each architecture is evaluated based on a series of performance metrics, including overall accuracy, sensitivity, specificity, computational complexity, training time, and robustness in the presence of image variation. Results from this comparative study showed large performance differences between CNN architectures, emphasizing the importance of selecting an appropriate CNN architecture for optimal diagnostic accuracy. This research presents important evidence regarding the strengths and weaknesses of popular convolutional neural network architectures and serves as a useful resource for developing improved and more reliable automated systems for assisting in the diagnosis of ophthalmologic disease.

Keywords: Ophthalmic Diseases, Deep Learning, Fundus and OCT Images, Comparative Study, Computer-Aided Diagnosis.

1 INTRODUCTION

Diseases of the eye like diabetes related eye disease (Diabetic Retinopathy), glaucoma, cataracts, and macula degeneration related to age cause visual impairment and blindness worldwide. These diseases can take a long time to develop; so as a result a person who has these types of eye disease may not know they have them until they notice changes in their vision. Because of the gradual and asymptomatic development of these diseases, early detection can be the key to treating them effectively or preventing the person from losing their sight permanently. Early and accurate diagnosis can dramatically decrease how fast a person develops any disease state and subsequently improve patient care.

The traditional way professionals diagnose diseases of the eye is to examine images of the retina and oct (optical coherence tomography). Although methods of diagnosis may be correct, they take longer than they should and depend too much on trained specialists to interpret the data from images of the retina or scans. Because of the differences in interpretation of these tests ('inter-observer variability'), and because the number of available ophthalmologists, especially in many rural areas, and the number of people who see an eye doctor as often as they should are limited, there is an increasing need for new technologies that will help physicians diagnose diseases of the eye quickly and accurately.

The increased amount of medical imaging data and new developments in Artificial Intelligence has led to the use of deep learning methods in healthcare. One of the deep learning methods, Convolutional Neural Networks, have shown success in their capacity to automatically learn a hierarchy of features when using original raw image data for the purpose of analysing medical images. CNN-based models have also been used successfully for image classification, segmentation and disease identification within the field of ophthalmology.

There are multiple types of Convolutional Neural Networks (CNN) designed for deep learning challenges with many different benefits. Each type of CNN architecture has its own depth of the network (the number of layers), connection scheme (how layers are connected), method of extracting features from images (the process of finding important details) and process needed to compute information by training a model on data and making predictions with that model once it has been trained. Deeper models will tend to produce better prediction accuracy when evaluated against shallower models but shallower models can be used in time-sensitive environments and will typically work well in low resourced environments. Therefore, determination of which specific type of CNN architecture will provide optimal performance when detecting ocular diseases is extremely important.

This paper is divided into six sections. Section 2 provides an overview of previous literature in this area, including how the existing research has utilized convolutional neural networks (CNNs) for ocular disease diagnosis. In this part, the major contributions were also presented from these previous research studies and their limitations. Section 3 describes research method, including how data was collected, preprocessed, selected the CNN model to use, trained the model, and evaluated its effectiveness. Section 4 describes the results of experiments, including the performance metrics measured and provided graphical representations of the results obtained. Section 5 offers conclusions regarding the outcome of the study, as well as recommendations for future research. The bibliography is included as the last section of this paper.

2 Literature Survey

Gulshan et al. [1] made a new system using the deep learning method to use fundus images to detect diabetic retinopathy. Their CNN model achieved similar levels of sensitivity and specificity as board-certified ophthalmologists, showing that a large-scale AI-driven diabetic retinopathy screening system could be operated within a clinical environment. LeCun et al. [2] provided an introduction to core topics in deep learning starting with convolutional neural networks. In their research, they discuss how to learn through hierarchical features, how to backpropagate error signals, and what a convolutional operation is. Their explanation of these principles provides the theoretical framework for the development of current CNN architectures.

Simonyan and Zisserman [3] introduced the VGG architecture, which employs a series of stacked 3×3 convolutional layers to construct very deep networks and demonstrated that increasing depth improves feature representation and leads to a substantial gain in image recognition accuracy on a large scale. He et al. [4] introduced the ResNet architecture. It introduced residual connections. The vanishing gradients problem is addressed using residual connections. It was quite successful in training deep networks. Accuracy in image classification was improved.

Szegedy et al. [5] introduced the Inception architecture, which uses parallel convolutional filters of different sizes in the same layer, allowing for multi-scale feature extraction with a greatly reduced computational complexity. Huang et al. [6] introduced DenseNet, in which each layer is directly connected to all other layers in a feed-forward fashion. This helps in improving the reusability of features, enhancing the flow of gradients, and decreasing the number of parameters. Tan & Le [7] introduced EfficientNet, a scalable CNN architecture that equally scales the depth, width, and resolution of the network to attain better accuracy and efficiency than traditional CNNs while reducing computational complexity.

Litjens et al. [8] gave a very comprehensive overview of deep learning in medical imaging, emphasizing its success in classification, detection, and segmentation problems. The challenges, datasets, evaluation, and future work in medical applications were also discussed. Pratt et al. [9] reviewed the convolutional neural network-based methods for the detection of diabetic retinopathy and proved that deep learning models are capable of effectively learning the distinctive features of the retina and detecting the lesions. Ting et al. [10] investigated the practical application of artificial intelligence in ophthalmology, focusing on issues that arise from clinical validation, ethics, and legal issues, as well as data privacy and regulatory approval for the safe and effective application of artificial intelligence in healthcare.

Krizhevsky et al. [11] proposed AlexNet, a deep convolutional neural network that revolutionized image classification tasks by making effective use of large datasets and GPUs, thereby greatly improving the accuracy of image recognition and establishing deep learning as a leading paradigm in computer vision. Esteva et al. [12] showed that deep convolutional neural networks can provide dermatologist-level accuracy in the classification of skin cancer from clinical images, thus emphasizing the potential of deep learning systems in assisting accurate medical diagnostic decision-making.

Shorten and Khoshgoftaar [13] analyzed data augmentation methods for deep learning and described how methods like rotation, scaling, and transformation can be used to increase the diversity of the dataset and reduce overfitting. The literature review has shown many advances in computer vision systems using deep learning. Specifically, convolutional neural networks have performed very well with respect to accurate classification and medical imaging; however, because of the size of the data sets required for training, computational requirements, and complexity of architectures, there are limitations on their scalability and ability to be deployed on low-power or edge devices in real-time.

Traditional machine-learning techniques have computational requirements that are much simpler than deep learning methods, but these methods typically exhibit a lack of robustness against variations in real-world conditions such as lighting, noise, and occlusion, while simultaneously demonstrating inconsistencies from different forms of data. In addition, many current systems rely on operating offline and performing post-processing on the output of a system, which provides little opportunity for real-time visualization and interaction with the user, thus severely restricting the practical usability and integration of the system. As such, the overall conclusion from the literature is that a uni-method approach will not satisfy the needs of developers and users, and therefore there needs to be a movement toward integrated systems of lightweight deep learning methods, efficient optimization techniques, and modular architecture yielding real-time output to develop scalable, accessible and reliable intelligent systems for application to the real-world.

Most of the development of automated systems for the detection of eye diseases is based on already existing methodologies of deep learning that focus on the use of intelligent image processing techniques and precision in the process of image classification. Researchers have shown that Convolutional Neural Networks (CNNs) have proven effectiveness in the detection of discriminative features of retinal fundus images and OCT images. Gulshan et al. [1] underscored the significance of standardizing the image processing pipeline along with feature extraction in the overall context of detecting the presence of diabetic-related retinopathy. This has been done by showcasing the potential of CNN-based systems in providing comparable diagnostic accuracy to experts in the specific field of ophthalmology. Similar to structured radiomics-based systems, this methodology focuses on the accuracy of the overall images in the process of reliable disease classification

Moreover, according to Litjens et al. [8], researchers have emphasized the need for structured workflows (for example, the creation of a comprehensive set of protocols) that help to ensure repeatability in multi-stage diagnosis due to the inherent complexity present in most imaging systems. By providing a uniform way to perform the various stages required for processing images (data pre-processing, model development, and validation), existing systems will provide more consistent results because they all follow the same systematic method, which in turn improves the accuracy of the output. In addition, this structure is imperative for dealing with the many different types of ophthalmic imaging modalities, as, for example, fundus photography and optical coherence tomography (OCT).

The automation of existing systems has been very important to reduce the workload of clinicians and improve efficiency in screening. There is now a body of research on the use of ophthalmic artificial intelligence (AI) tools to automate the analysis of images using convolutional neural networks (CNNs) and provide fast identification of images that suggest a potential diagnosis, allowing specialists to concentrate on more difficult cases. To create an efficient and effective solution, lightweight networks and transfer learning are typically used to achieve the appropriate level of accuracy without sacrificing computational efficiency for use in real-world applications.

Recent studies indicate that implementing intelligent algorithms can improve clinical decision making and workflow management in the field of ophthalmology. Current systems that utilize deep learning algorithms to help make predictions about disease development can provide physicians with tools for early diagnosis, personalized treatment planning and implementation of large-scale screening programs. The majority of the current algorithms utilize only one architecture, the convolutional neural network (CNN) model, which indicates a need for comparative evaluation to identify which model will provide the best results for detecting ophthalmic diseases.

By exploiting information obtained from previously published research materials within the domains of deep learning paradigms, image processing in medical environments, and intelligent automation in ophthalmic diagnosis and detection, effective CNN-based eye disease detection systems can be developed by following a well-structured approach and workflow. In addition, all research contributions within the domains of retinal image processing and intelligent automation have emphasized the significance of correctly developed workflows and approaches within CNN-based system architectures for the determination and detection of diseases within the eye and human body by making a significant contribution to the development and growth of intelligent medical diagnostic and detection systems.

3 METHODOLOGY

Fig. 1 shows the overall methodology adopted for ophthalmic disease detection using Convolutional Neural Networks (CNNs). The process begins with data collection, where retinal fundus and OCT images, along with their corresponding disease labels, are gathered from publicly available ophthalmic datasets. These datasets contain images representing multiple eye conditions, such as diabetic retinopathy, glaucoma, cataract, and normal cases. Proper labeling of images is essential, as the system follows a supervised learning approach in which the CNN models learn to associate image features with specific disease classes. In this next step of preprocessing data, set out to enhance both the accuracy and the consistency of models. The retinal images in the dataset will contain different resolutions, levels of light, and contrast due to the way in which they were taken. In order to ensure that all of the images are as consistent (or "normalized") as possible, will resize all of the images in the dataset to one size and scale the pixel intensity in the same way across all images.

Normalizing the images in this way will allow us to build a better-trained (more accurate) CNN (convolutional neural network) model than would otherwise be possible, because the patterns that will be used to train the models will be representative of true underlying patterns rather than noise or random variations. After preprocessing the data, it will be necessary to split the data into training, validation, and testing sets. The goal of the training set is to train model parameters; the purpose of the validation set is to keep track of the performance of the trained models; and the test set will be used to evaluate how well the models perform (with the test data) that the model has not been trained on. Therefore, the use of data for training, validation, and testing purposes will help prevent the model from being over-fit, thus allowing the model to generalize when provided with previously unseen retinal images.

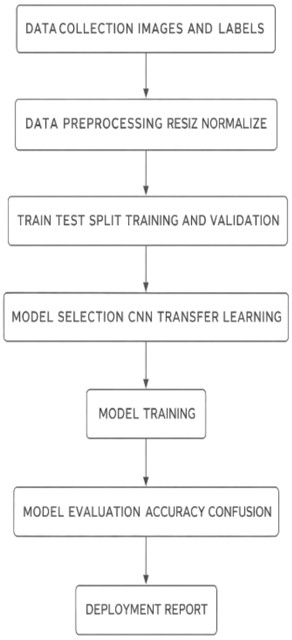

Fig. 1. Workflow of the Proposed Eye Disease Classification Model

With this methodology, a stepwise process is used by proceeding to the model selection stage. Various types of CNNs developed through a process called "transfer learning" will be explored. The pre-trained convolutional neural networks (CNNs) used during this phase have been found useful to develop general feature representations based on data collected from large sets of images and adapted to identifying the different types of ophthalmic diseases. Using transfer learning allows for faster training during the classification of these diseases due to having identified transfer learning as being appropriate for environments with small datasets, such as the use of medical images.

Each of the models selected is used with the training dataset for the purpose of training the models, and each of the CNNs will learn the hierarchical feature sets contained within the retinal images through the convolutional and activation functions and pooling layers associated with these images. Through back propagation algorithms and gradient descent techniques, each model is optimized against the likelihood of a misclassification and has its probability of providing an accurate prediction greater than that of the supporting training data. While a model is trained for several epochs, its training process is completed once sufficient performance stability is established when evaluating the validation dataset.

Lastly, the evaluation of human models takes place, whereby the efficiency of the trained CNN models is evaluated. Accuracy and confusion matrix evaluation are used as efficiency indicators to measure how well a certain disease is classified by the CNN model. These performance measures will showcase the ability of the CNN model to perform classifications for various ophthalmic-related diseases. This concludes the methodology, as it is followed by the deployment report, which consists of the experiment, performance evaluation, and conclusion of the proposed methodology, indicating that it is ready for real-world applications in detecting ophthalmic diseases.

4 Results and Discussion

Fig. 2 depicts the login interface for the proposed ophthalmic disease detection system developed in this comparative study of CNN architectures. The interface ensures secure access to authorized users via the login module provided by the service provider and thus restricts the interaction with the system. In order to proceed, users must enter valid credentials to maintain data integrity and system security. The background visual indicates ophthalmic application, emphasizing that this is applied to eye diseases. This mechanism allows logging into systems based on roles, for the given different levels of users to perform tasks like model execution, prediction analysis, and result visualization within the system.

Fig. 3 illustrates how the proposed CNN-based ophthalmic disease detection system's eye disease prediction interface operates. The eye disease prediction interface provides input fields for patient attributes and diagnostics (e.g., age, gender, diagnostic keyword, glucose level, body mass index (BMI), and other parameters needed to predict disease) to the user. Once the user has provided input information, it will be processed through the trained deep learning model, and the predicted status of the patient's eye disease will be output.

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Fig. 2. Login Interface of the Ophthalmic Disease Detection System

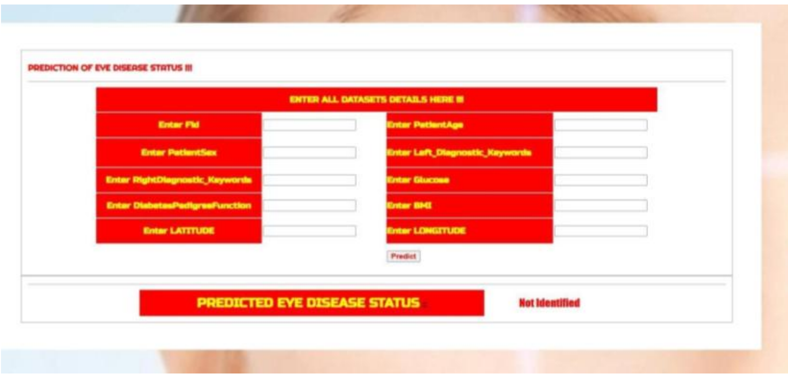

Fig. 3. Eye Disease Prediction Interface

The output of the system's prediction for the eye disease demonstrates that the proposed system is capable of performing real-time inference and delivering classification results efficiently. The eye disease prediction interface demonstrates that the proposed system will have a useful application for assisting automated diagnosis of ophthalmic diseases. The proposed ophthalmic disease detection system displays the identified eye disease status page, as shown in Fig. 4. The interface has classified results displayed using a tabular representation of patient data (age, gender, etc.), and predicted ophthalmic disease based on how well the patient fits the criteria of each type of identified disorder (diabetes, glucose, etc). This tabular format provides for quick and simple interpretation/verification of prediction results for potential follow-up analysis or comparison; thus demonstrating that the system has an efficient ability to retain, evaluate, and present classification outputs (predictions) and facilitate an increase in transparency and usability of the automated ophthalmic disease diagnostic procedure.

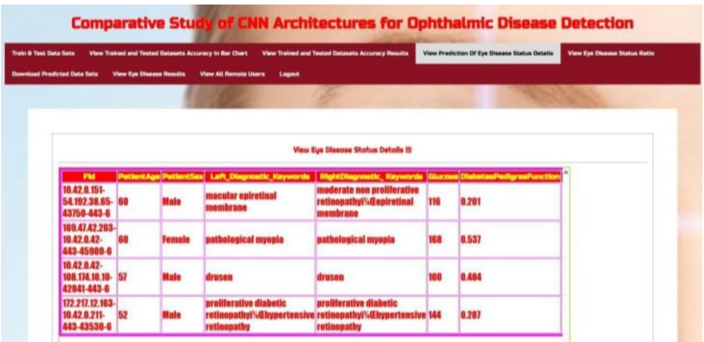

Fig. 4. View of Identified Eye Disease Status Details

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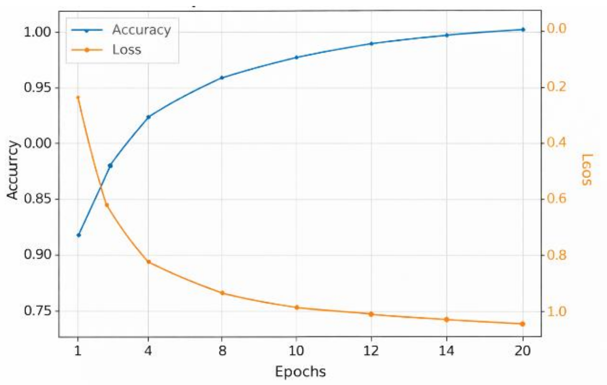

Fig. 5. Accuracy and Loss Curve of the CNN Model During Training

In Fig. 5, the relationship between the training accuracy and the training loss over multiple epochs is demonstrated for the training process of the CNN model. It is observed that as the number of epochs increases, the trend of the accuracy curve rises steadily. This is an indicative representation that the CNN model is efficiently training more meaningful features from the supplied data set regarding the ophthalmic attribute. At the same time, the trend of the loss curve decreases consistently, reflecting the effectiveness of the training model in minimizing the classification error. Thus, the above graph represents the effectiveness of the training process of the CNN model for the proposed approach, indicating high accuracy and low error rate for the detection of the ophthalmic disease.

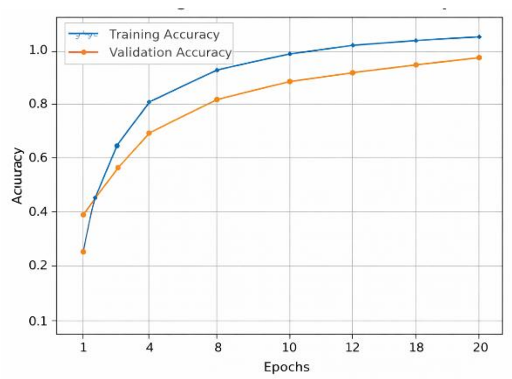

Fig. 6. Training and Validation Accuracy Curve

The Fig. 6 describes the diagram for the training and validation accuracy of the CNN model for different epochs. As represented in the above graph, the value of the training accuracy increases consistently as the number of epochs increases. This clearly shows the ability of the model to learn feature representations from the set of ophthalmic images. It can also be interpreted that the model does not tend to forget, as the values for validation accuracy increase consistently, closely resembling the corresponding values for the training accuracy. The above statement clearly confirms the convergence of the given CNN model, and the graph clearly represents the success rendered by the CNN model.

5 CONCLUSIONS

The research classifying eye diseases using deep learning in images of the retina illustrates successful application of automated detection of some of the most common eye diseases using images of the retina; the deep learning algorithm has been trained using more than 4,000 labeled images of retina of patients with the four diseases of interest (normal, cataract, diabetic retinopathy, and glaucoma) and demonstrated classification accuracies of approximately 92%, as well as the ability to effectively differentiate between multiple medical conditions. Several strategies have been used to improve the performance of the model: augmentation of the data set, fine-tuning the model parameters, etc., in order to improve the ability of the model to generalize and avoid overfitting due to the limited size and diversity of the medical image data. The results of this study illustrate the potential of CNN's in the area of medical imaging classification and also highlight how a CNN can be used as an automated system to support clinicians in the early detection of diseases that threaten vision. Although this implementation performed well, increasing accuracy and making it more applicable to real-world clinical practices will be enabled by future improvements, such as including larger and more diverse datasets, advanced transfer learning techniques, and cross-validation. This work meets its intended goals and also provides insight into the development of new and improved diagnostic systems using deep learning in clinical ophthalmology.

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ETHICS STATEMENT

This study did not involve human or animal subjects and, therefore, did not require ethical approval.

STATEMENT OF CONFLICT OF INTERESTS

The authors declare that they have no conflicts of interest related to this study.

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