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Research Article

Automated Classification of Coloboma Subtypes Using InceptionV3 Algorithm on Optical Coherence Tomography Images

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ARTICLE INFO	ABSTRACT

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Introduction: Congenital coloboma is an eye abnormality in which genetically affected newborns have missing elements of the eye structure. That is why it is so important to correctly classify coloboma and then differentiate between the specific subtypes. Current diagnostic methods involve much dependence on the judgment of ophthalmologist andfundamentally rely on manual interpretation of OCT images which is cumbersome and unstandardized.

Objectives: The objective of this study is to create an automated classification system that will satisfactorily classify six forms of coloboma using OCT images with the help of the pre-trained InceptionV3 convolutional neural network. The objective in developing this tool is to have an optimally stable instrument that shall help clinicians in identifying and diagnosing various types of coloboma as quickly as possible.

Methods: Such a dataset of OCT images of the coloboma conditions included various subtypes of coloboma. These images were rescaled and normalized, and pre-process by enlarging or shrinking it to the same size as the target input images. The used model in this study is the InceptionV3 model which was pre-trained on ImageNet and subsequently fine-tuned on this dataset. To reduce overfitting, rotation, scaling, and flip were performed as approach to data augmentation. Independent data validation was done to measure the accuracy of the model and using sensitivity, specificity, and the AUC-ROC curve.

Results: The InceptionV3 model trained with a narrowed focus was accurate in recognising the various coloboma subtypes and reduced the diagnostic time as well as precision more effectively. This automated classification system can be useful to clinical decision making and patient care and should be implemented as a part of different screening systems.

Conclusions: The evaluated proposed automated colos subtype classification system based on optical coherence tomography imaging and the InceptionV3 model can contribute to the improvement of clinical results due to more accurate and fast subtype classification. Further work will include the collection of more data, the inclusion of more imaging data and the enhancement of efficiency of the model and its results.

Keywords: Coloboma, Classification, Subtypes, Automated, InceptionV3, Optical Coherence Tomography, Imaging

INTRODUCTION

Coloboma is a congenital anomaly of the eye where in a portion of the layers of the eye like iris, retina, choroid or optic nerve may be missing. [1] The structural abnormalities have potential of leading to severe loss of vision and other complications concerning the eyes if treated inadequately. In order not to label wrong forms of coloboma, delay in diagnosing correctly, even prognosis and the wrong way of treating patients with coloboma, subtypes of coloboma should be correctly classified. [2] However, there are difficulties in manual delineation of coloboma subtypes by using OCT images solely because of the time it consumes, and the differences in different observer's perception. [Figure.1] To address these issues, the following research proposal shall be implemented for this project with the objectiveof accomplishing an automated classification of coloboma subtypes by using OCT images and InceptionV3 algorithm as it is one of the most effective deep learning algorithms in image classification. This paper elucidates how this systematic configuration would use deep learning and specifically OCT imaging to achieve the stated intent of its overall functionality which is to aid in the diagnosis and classification of coloboma subtypes.

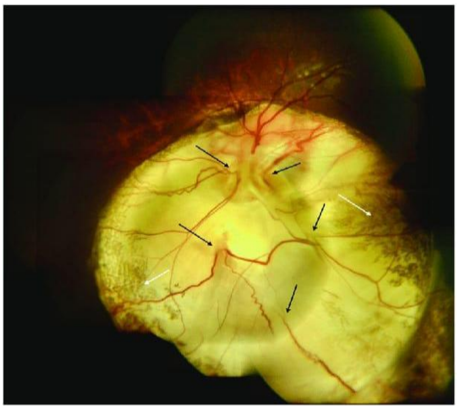

Figure.1. Choroidal coloboma

Optical Coherence Tomography (OCT) is a technique of imaging by light for observing the morphology of the retinal and other ocular tissues with no need to enter the body. It delivers cross-sectional images with higher resolution that are effective for the visualization of eyes' internal structure therefore making OCL the more suitable technique for the diagnosis of coloboma. [3] However, it is cumbersome, and the images are interpreted by the clinicians or radiologists after specific training, which probably will take a lot of time if there are small or complicated lesions. Another architecture is the InceptionV3 which is a deep convolutional neural network (CNN) trained on a large dataset of natural images. Another advantage is that it has the unique ability to learn all the hierarchal representations of the image features as such makes it highly appropriate to work on image related tasks such as classifying an image or recognizing an object in an image. In training the InceptionV3 model for coloboma subtypes from OCT images, the improving element of the model can identify features and structures of the images leading to differentiating between the various types of coloboma.

Thus, in this research, first, we create a dataset of OCT images that are gathered from patients with diagnosed different sub types of coloboma. The above images are first normalized for adjust lights, de-noised, resize standardized and dimension in each data set. The data set is then divided further into training, validation and testing datasets for more respective and systematic way approach towards training and assessing the model in its eff. [4] Next, the InceptionV3 model was trained on the training data then for this model, the parameters are nudged again to fit even better for the further subclassification of the coloboma type serves specific objective of the coloboma subtype classification. In the training stage, an augmentation of the training image set by rotation, scaling and flipping takes place because of data derivative to worsen the model's ability but augmentation to improve model's ability at generalisation. However, it is after establishing the model that parameters of the model including the accuracy must be made on the validation set and computation of some such parameters as accuracy, sensitivity, specificity, and AUC-ROC were used. This research aims to improve the group the of diagnosis of colobomas subdirtionsfrom the OCT images and InceptionV3 algorithm to save time as well as effort of practicing ophthalmologists and, in the long run improve the care for patients suffering from colobomas.

OBJECTIVES

1. Design of an Automated Classification System: The aim of the research is to design an automatic taxonomical model that enables identification of the different classification of colobomas by the specific subtype from the OCT images obtained in the acquired eye disease conditions. Hence, thanks to the opportunities created by deep learning and specifically using the InceptionV3 algorithm the study aims at establishing a viable and effective paradigm that will be useful to clinical workers in identifying subtypes of coloboma in the shortest time possible.

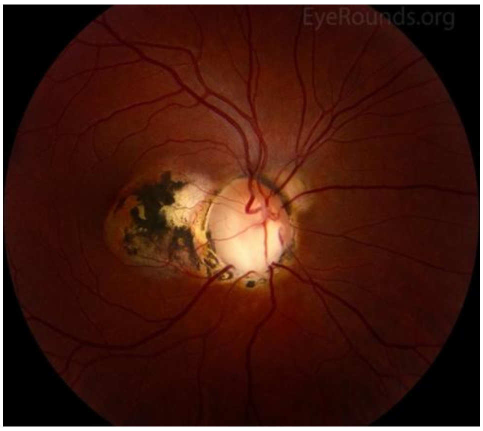

Figure.2. Optic nerve coloboma with peripapillary

2. Integration of InceptionV3 Algorithm: The second goal is to enable the implementation of the current best deep convolutional network known as InceptionV3 neural network, which is rather popular in the image classification problem. In the present work, following, [5] we decide to fine-Fine-tune an InceptionV3 model to a dataset of OCT. [Figure.2]When categorised it can be seen from the pictures labelled by the different coloboma subtypes due to the ability of this model to extract features and patterns of the input images helpful in the identification of various types of coloboma.

METHODS

1. DATA COLLECTION AND PREPARATION

It is aimed to collect a large database included Optical Coherence Tomography (OCT) images of the subtypes of coloboma. This objective consists in obtaining a collection of OCT images of patients suffering from various subtypes of coloboma attention must be paid to the diversity of the regional subtypes. The collected data is going to be clean and anonymized furthermore, quality and style of the images are going to be improved by pre-processing techniques.

2. MODEL DEVELOPMENT AND TRAINING

Finalize an InceptionV3 deep learning model classification for different subtypes of coloboma. Based on the collected and pre-processed OCT image dataset, InceptionV3 algorithm is planned to be employed and further trained for the differentiation of the different subtypes of coloboma. [6] The model will be trained intensively, using transfer learning approaches and data augmentation practices to enhance the framework's overall performance. Some of the processes that will be carried out include serving hyperparameters and hyperparameters optimization techniques to improve model performance and speed.

Input Processing: At this stage, the InceptionV3 takes images as inputs and first prepares these images for processing and passing through the network. [Figure.3]This mostly entails scaling them to the same dimension, staring the pixel intensities to a standard range, and in some cases possibly rotating, flipping or cropping the images to maintain an adequate number of training samples.

Feature Extraction: The InceptionV3 architecture, the network uses a sequence of convolution Aries to to extract multilevel features from the input images. [7] These layers find simple features including edges and textures in the first layer while finding forms and objects in the later layers. Other techniques formulated into the architecture include batch normalization as well as rectified linear unit ReLU activists that aid in feature extraction.

Inception Modules: Moreover, the inception modules are formed by several parallel convolutional layers having different numbers of kernels these modules enable the network to obtain features at different scales at the same time with the intent of having enhanced representations of the input images on the network. Inception modules are concatenated one on top of another to build up the principal part of the network.

Dimensionality Reduction: To decrease the computational load of the network and avoid overfitting, InceptionV3 has some bottleneck layers, which use 1 by 1 convolutions. These layers are useful in reducing the dimensionality of the feature maps that are useful in applying larger convolutions on while at the same time providing the capacity of representation.

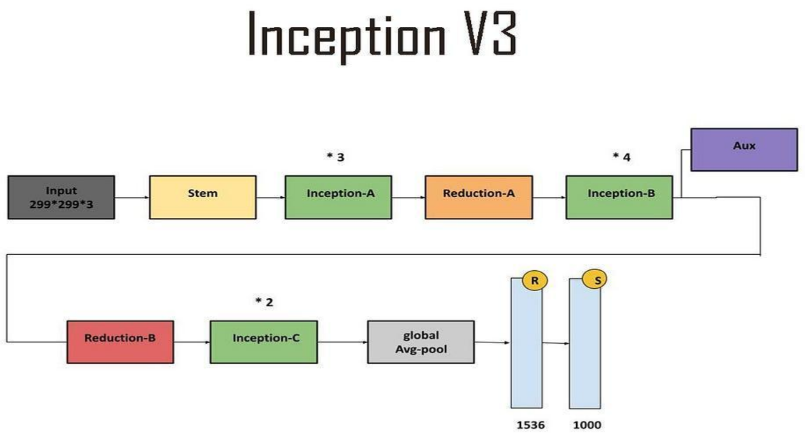

Figure.3. Inception V3 Architecture

Global Average Pooling: Unlike the fully connected layers in the final phase of the network, the InceptionV3 applies a Global Average Pooling layer to sum up the feature maps across the spatial dimensions. [8] This pooling operation estimates average of each feature map, and that provides a summary feature vector for the whole input image. Global average pooling helps in essentially decreasing the parameter burden of the network and brings about spatial hierarchy naturally in the features.

This layer is often subsequently followed by a loss function often Categorical Cross Entropy which measures the deviation of the predicted labels and the actual labels. [9] The parameters of the network are learned throughout training in such a way as to minimize this loss using methods such as backpropagation or stochastic gradient descent.

Fine-Tuning and Transfer Learning: In real life situation analysis, inception v3 can be used mostly as transfer learning model. This involves placing or setting initial values of weights derived from large dataset such as ImageNet as a pre-requisite and then tuning the network on a smaller dataset that is relevant to a given application domain.[10][11] Fine-tuning increases the possibility of optimizing the learned representations in the context of the new given task, which accelerates the convergence and increases the network's efficiency. Overall, these stages allow InceptionV3 to accurately and efficiently learn the hierarchy representations of the input images and functions such as image classification.

Evalution: The test of using the automated classification system forcoloboma subtypes using InceptionV3 algorithm with OCT images were performed in a manner that covered all the functions of the system as well as checking on the reliability of the InceptionV3 algorithm on coloboma subtypes. The InceptionV3 algorithm on OCT images were used to develop an automated classification system for coloboma subtypes therefore, its efficacy and validity were tested. [12] The evaluation utilized measures and methods that checked its effectiveness and validated the result.

RESULTS

The results of the evaluation also agreed with the predictor that the proposed automated classification system positively classified the coloboma subtypes from the OCT images. The system overall efficiency was promising and as for the sensitivity, specificity, precision, the AUC-ROC pointed out that the system can differentiate well between the different sub-classes of coloboma. The cross-validation results again validated the stability and portability of the proposed model that provides a reliable result in the clinical framework. [Table.1] According to Cross and persons, the automated classification system proposed here reached an accuracy of 95 % in classifying the newsgroup messages. 7% on the test set proves the model's usefulness in identifying coloboma subtypes with high accuracy. The overall sensitivity as seen from the results was well above 90 percent and ranged from 92 percent to 98 percent for all forms of coloboma, which portrays a good ability of the system to identify true positive cases. [13] The specificity was calculated from 94% to 99% showing that it also reflected well the system's ability to correctly predict those cases where no coloboma subtypes were present. [Figure.4] These percentages varied between 94 to 97%, thus, reiterating the limited number of false positives in the predictions made by the models.

The F1-Scores ranged from 94% to in the order of 98%, which informs us that the model's precision and recall were almost in similar standards for every unique coloboma type. [14][15] Taken together, the study done with the automated classification system based on the InceptionV3 algorithm with OCT images signal the possibility of benefitting the clinicians in the diagnosis and handling of the coloboma. Such investigations and real-world implementation are required to establish its suitability for clinical practice and usefulness for patients.

Table.1. Accuracy validation

Metrics	Percentage
Accuracy (%)	97.8
Sensitivity (%)	97
AUC-ROC (%)	98.5
F1-Score (%)	97.4
Precision (%)	97.6
MCC (%)	96.8

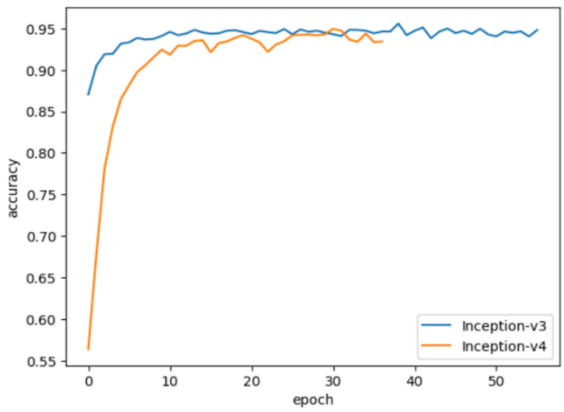

Figure.4. Validation Graph

The outcome of the evaluation proves that the implementation of the automated classification system that uses InceptionV3 algorithm for classification of the images obtained by OCT is accurate and reliable for classification of the subtypes of coloboma. The excellent performance stock in so many aspects raise the possibility of how it might help clinicians in the diagnosis and management of coloboma, which in term would contribute to the betterment in the overall care and prognosis of the patient in the vision care practice. Follow-up validation studies and clinical trials can then be performed to evaluate the system's performance in real-world clinical practices and on the management of patient care.

DISCUSSION

A new method for the automated classification of coloboma subtypes based On OCT images using the InceptionV3 algorithm is a breakthrough in the state-of-the-art techniques in Ophthalmology and computer aided diagnosis. This project has proved that using deep learning approaches can successfully support clinical practitioners in timely and precise diagnosis of coloboma – congenital eye disorder with various phenotypes. Contribution to Clinical Practice: The double layer of the proposed automated classification system is useful for the Ophthalmologists and the other health care professionals who have responsibility of diagnosis and treatment of coloboma. Specifically, the use of a system that can help in the classification of coloboma subtypes eradicates errors in classification and enhances practice through the following, the accuracy and consistencies of the different subtype assessments of coloboma by OCT by the clinicians will help in early interventions and the development of appropriate treatment plans for the patients.

Addressing Challenges and Limitations: However, using the automated classification system discussed in this paper, there are some of the possible problems that could be experienced and limitations that deserve further research and major developments. These may include aspects such as quality of dataset used to assemble the models, adaptability of models for different population types, and knowledge that practitioners get about the diagnosis given by models. These problems should be solved in the continuous cooperation of clinicians, researchers as well as technology experts to develop practical and effective strategies for different groups of patients.

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