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A Review on the Detection and Classification of Glaucoma Disease Based on Transfer Learning

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ABSTRACT- An eye infection is a condition affecting the eyes that can be caused by a bacterium, virus, or fungus. Numerous eye infections exist, such as glaucoma, cellulitis, keratitis, and conjunctivitis. A few of the symptoms may be itching, discharge, altered eye sight and others. Antibiotics are not effective in treating viral infections. Antibiotics treat infections caused by bacteria exclusively. A class of eye infection known as glaucoma can result in blindness and visual loss by harming the optic nerve, a nerve located at the back of the eye. You might not notice the symptoms at first because they can appear so slowly. A thorough dilated eye exam is the only way to determine if you have glaucoma. Efforts have been done to automate the procedures for the recognition and classification of glaucoma. In this paper, we have proposed a transfer learning model by reviewing pre-trained models and the model is able to provide a better accuracy. Our model is classifying the datasets into positive and negative cases during testing and validation. We utilize different prêt rained models, that are ResNet50 (90%), EffiecintNet (78%) and CNN(79%) evaluate how well they perform when trained using various optimizers. Our results show differences in accuracy and provide important information about the possibility of these models for the detection of glaucoma. An important first step towards improving the precision and dependability of glaucoma detection models in clinical settings is represented by this work.

KEYWORDS- Glaucoma, Transfer learning, ResNet50, EffientNet, CNN.

I. INTRDUCTION

There are various infectious disease that may affect different organs of the human, out of which eye infection is most dangerous and my lead to vision loss. A dangerous condition that affects the eyes called glaucoma can result in permanent blindness or visual loss. Effective therapy depends on early discovery and prevention. The primary cause of glaucoma is the loss of optic nerve fibres as a result of elevated intraocular pressure and/or decreased blood supply to the optic nerve. Nevertheless, an intraocular pressure reading alone does not provide sufficient evidence of glaucoma [1].The structure and size of the optic cup disc , which is visible in retinal imaging is one of the most important parameter that should be considered while diagnosing glaucoma[2] , hereby efforts have been done to help ophthalmogist by utilizing the information of the images of the typical state of the eye and glaucoma impacted eye picture has been considered for the recognition and classification of the disease, because glaucoma steals the sight silently. Early glaucoma detection is nearly impossible, and there is currently no treatment for advanced glaucoma.[3]Efforts have been made for the early identification of the disease may help in diagnosing the disease in very effective way.Preprocessing of the data , feature extraction, it can be feature selection approaches and by using different machine learning (ML) algorithm helps in this process. The deep learning models and transfer learning techniques [4] also contribute in doing this work in more efficient manner this learning models are also utilized for the classification and detection of cancers, pneumonia, skin infection, tumour detection etc. Different electronic records such as images have been considered as datasets that can be utilized for testing and training purpose to accomplish several automated detection systems.The paper is sectioned in such a way that, In Section II some of the summarized related research work that used deep learning architectures for glaucoma detection is shown. Section III gives the details of pre-processing as well as classification methods used, Specifics of the deep learning models and the datasets are detailed. The performance evaluation results are specified, analyzed and discussed in Sections IV and V respectively. Finally the conclusion is given in section VI.

II. RELATED WORK

There are various techniques previously utilized for the classification and identification for the glaucoma detection. The use of CNN for Transfer Learning for Early and Advanced Glaucoma Detection is one such paper where author called Sertan et al have been employed Transfer learning and used to train and optimize the deep convolutional neural network algorithms ResNet-50 and GoogLeNet for classification. Research indicates that the GoogleNet model is providing better performs than ResNet-50 in detecting both early and advanced cases of glaucoma[5].M Shanmugan et al, have Used a local real-time dataset of diabetics, the suggested method employs a Bayesian support vector machine, yielding an accuracy of 96 percent [6].An further relevant work was done by Siamak et al. Many machine learning classifiers, comprising various families, were used in this study, including Bayesian, Lazy, Meta, and Tree classifiers. The relative efficiency of each aspect was as certainly by ranking combinations of structural and functional features [7] .The article by Vigneswaran et al, addresses a few methods for diagnosing glaucoma. This research presents a supervised learning method for glaucoma detection and compares it with other current methods. It is possible to classify the image by using support vectors and on linear transformation [8]. Anuradha et al's paper, which offered three distinct strategies for the identification of glaucoma disease utilizing image processing techniques, machine learning techniques, and a Convolutional neural network model of deep learning on the Bin Rushed database, is another excellent example. Following the extraction of features like CDR and RDR from the images, a support vector machines, decision trees, neural network, and the K-nearest model are employed for classification[9][18].According to Shu et al.'s research, the eye are early signs of eye strain. A 52-patient with biomechanics data set comprises 20 glaucoma patients (20 eyes) and 32 healthy people (64 eyes). The following four classifiers called linear logistical regression, the support vector machine, the random forest classifier, and gradient boosting classifier are assessed for discriminating using this data set. The results indicate that among the investigated approaches, linear logistic regression (LLR) has greatest correlation accuracy, with 98.3 percentage accuracy [10].

Silvia et al. state that because the clinical signals in the retinal images are so delicate, the human eye typically misses them. It has been evaluated with the convolutional neural networks and it functioned well at automatically identifying the minute details in the image. In this study, investigation have been done with the potential of residual networks for glaucoma early detection and have presented a dataset of early-stage colour photos of glaucoma fundus that is proprietary. The ResNet50 system is employed for trained using the dataset provided by ImageNet. On the validation set , the correctness level was 96.95 percentage. The findings suggest that an assessment tool for prompt and affordable identification of glaucoma may be developed utilizing deep learning algorithms [11].Convolutional neural networks (CNNs) included with Deep learning networks, can infer an ordered arrangement of pictures to discriminate between glaucoma and non-glaucoma patterns for diagnostic choices, according to the Chen et al. Work, Six learn layers make up the suggested DL architecture: two fully- connected layers and four convolutional layers. The improvement in performance metric is done using data augmentation for the glaucoma diagnosis even more effective. A great deal of research is done using either SCES / ORIGA datasets. The findings demonstrate that the receiver operating characteristic curve's area under the curve (also known as the AUC) for glaucoma detection at 0.831 and 0.887 in the two databases, which is significantly superior than state-of-the-art techniques [12]. According to Javier et al.'s work, some studies employ segmentation and feature extraction strategies to identify glaucoma, while others concentrate on training a convolutional neural network (CNN) by brute force [13]. This work develops, trains, and tests a diagnostic assistance tool to identify glaucoma from eye fundus photos. It is composed of two subsystems that are taught and tested separately, then their combined findings are used to enhance the identification of glaucoma. The first subsystem detects the optic disc and cup separately, combines them, and extracts their positional and physical properties using machine learning and segmentation techniques. In the second, a whole eye fundus image is analyzed using transfer learning techniques to identify glaucoma in a CNN that has already been trained. The two systems' combined outputs are used to distinguish between positive and negative in the images [16][19].In this study, which was proposed by Touhidul et al propose a transfer learning approach that achieves 94.71 Percentage of accuracy in classifying glaucoma after comparing it with many pre-trained models. In addition, The Local Interpretable Model-Agnostic Explanations (LIME) have been employed to incorporate explain ability into our system. That advancement makes it possible for medical practitioners to get crucial and thorough information to support their decision-making. Additionally, it reduces the customary deep learning frameworks [14].

III. METODOLOGY

A. Pre-processing

To determine which pixels in the optic disc region were most likely employed a simple Convolutional neural network. They use a threshold to categories those potential pixels. There is a clinical justification for cropping photos within the optic disc because glaucoma primarily affects this structure and its environs. Additionally, Orlando et al, demonstrated that cropping images around the optic disc proved to be a better [15].The dataset was obtained from public platform called Kaggle and subjected to the conventional machine learning method in Python. It has been performed to enhance glaucoma treatments. In this step, the unnecessary details have been omitted. The method is explained using block diagram in figure 1.

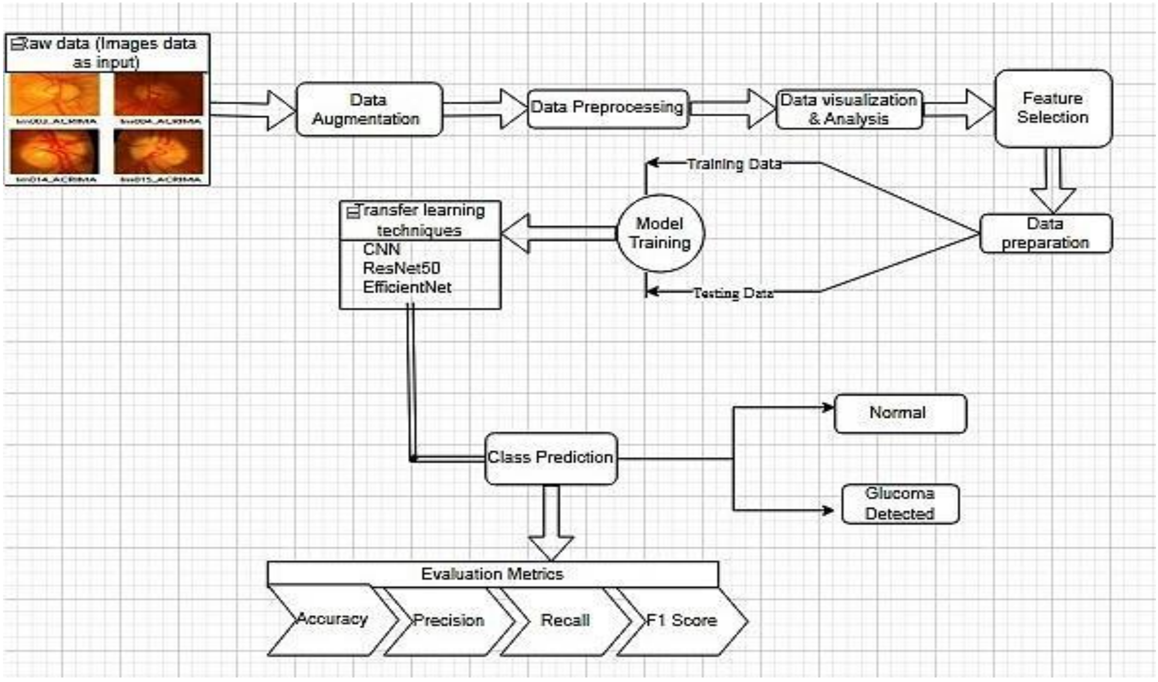

Figure 1: Block Diagram of the proposed work

B. Classification

In this model we have suggested a transfer learning approach for the classification of the glucoma condition, In which by examining previously trained models, and the model can now deliver greater accuracy. During testing and validation, our model divides the datasets in to positive and negative cases. We use three distinct pre-trained models ResNet50, and VGG16—and assess the way they work after being trained with different optimization techniques.

C. Dataset used

Data is the fuel when you work on prediction systems. It plays a crucial role in the identification and classification. So selection of data is the first and the critical step which should be performed properly, we have collected data from the public open source platform. These data sets were available for all. There are other tons of websites who provide such data. The various factors and constraints we were going to take into consideration for our prediction system influenced the data set we chose.We have suggested a transfer learning approach for the classification of condition glucoma by examining previously trained models, and the model can now deliver greater accuracy. During testing and validation, our model divides the datasets into positive and negative cases. We use four distinct pre-trained models ResNet50,and Xceptionand assess the way they work after being trained with different optimization techniques. There are 168 positive samples , and 482 negative samples incorporated in this process. Some samples are shown in figure 2.

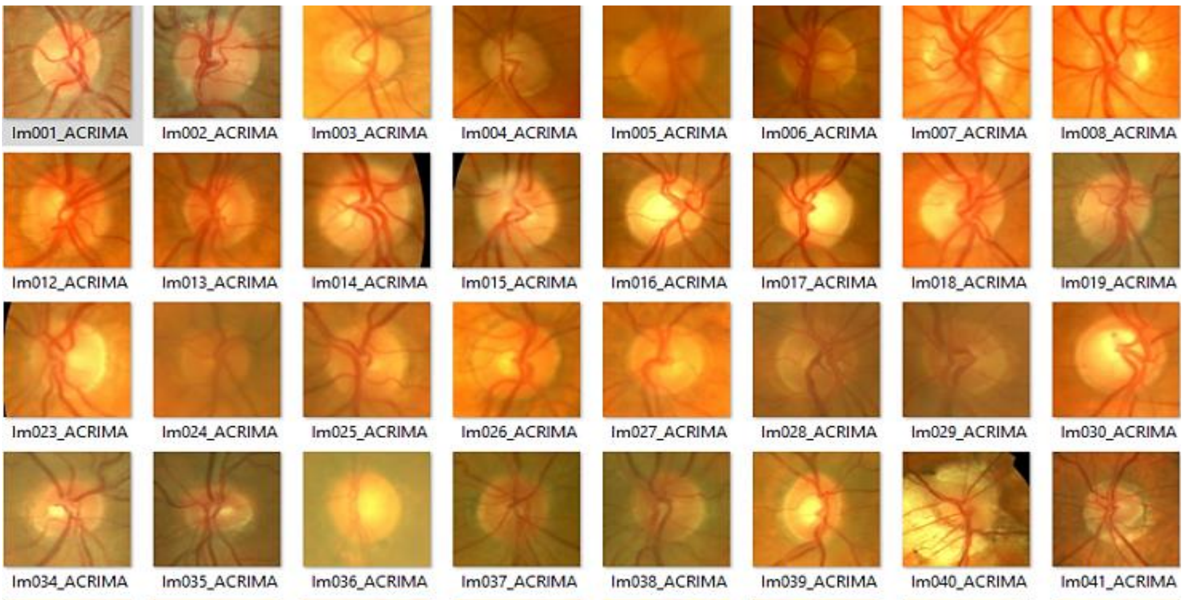

Figure 2: Dataset images used in the experiment.

D. Dataset Cleaning and Transformation

Data is the fuel when you work on prediction systems. It plays a crucial role in the identification and classification.

The next step after selecting a data set is to clean and transform it into the desired format. This is essential because the chosen data set may have varying formats or come from different sources with different file formats. To use these data sets, they need to be converted into a format compatible with the prediction system or the desired type. This step is crucial to eliminate unnecessary constraints that may complicate the system and increase processing time. Data cleaning is also necessary to address issues such as null values and garbage values in the data set.

E. Data pre-processing

After cleaning and transforming the data, it is ready for further processing. Once the necessary constraints are identified, the data set is divided into two parts, typically in ratios of 70-30 or 80-20. The larger portion is allocated for processing. Subsequently, various data mining techniques are applied to the data set. Data preprocessing is highlighted as a crucial technique employed to convert raw data into a clean and analyzable format. This step becomes essential when data is collected from different sources in a raw format that is not suitable for analysis.

Training:

Training in machine learning involves using an initial set of data, known as training data, to enable a program to grasp the application of technologies like neural networks. This process is fundamental in teaching the program how to learn and generate advanced results effectively.

Testing:

A test dataset is independent of the training dataset but shares the same probability distribution. If a model, trained on the training dataset, performs well on the test dataset, it indicates minimal overfitting. Essentially, the test dataset serves as a measure of how well the model generalizes beyond the specific data it was trained on.

IV. PERFORMANCE EVALUATION

In order to evaluate the algorithm's efficiency, sensitivity/specificity comparisons and Receiver Operation Characteristic (ROC) analysis were carried out. The number of photos with glaucoma that were correctly identified, or true positives, divided half the total number of false negatives (images that were mistakenly categorized as normal) is how we calculated sensitivity, also known as true positives rate. Thus, the sensitivity displays the proportion of glaucoma cases that the algorithm accurately identified. The quantity of genuine negatives that is, the amount of normal photos that were correctly identified in our instance is how we defined specificity. A ratio called specificity indicates the proportion of typical cases that are accurately identified. This is the mean of both specificity and sensitivity. To visualize the networks performance, we employed the ROC graph. The ROC graph is a two-dimensional representation where the X axes reflects specificity and the Y axis represents sensitivity. We used the area under the receiver operating curve(AUC), which is produced by the receiver operating curve, to compare the algorithms performances.

A. Evaluation on ResNet50

It has been demonstrated that convolution neural networks function well at automatically identifying minute details in photos. In this study, we investigate the potential of residual networks for glaucoma early detection .We present a dataset of color photos of early-stage glaucoma fundus that is pro-prietary.On the testing set, the correctness level was 96.95percentage.The findings suggest that a screening tool for early and affordable glaucoma detection could be developed utilizing deep learning methods[10] and the metrics representation is shown in figure 5.

B. Evaluation on EfficientNet

Employing an additive coefficient, EfficientNet is a kind of CNN design and scaling technique that evenly scales in terms of depth, breadth, and accuracy. EfficientNet scales up models in a straightforward but efficient way through the application of a method referred to as compound coefficient. Compound scaling regularly applies a given set of scaling coefficients to each dimension, as opposed to randomly increasing width, length, or precision the models metric evaluation is shown in Tab.1

C. Evaluation on ConvNet

Deep learning, or learning networks that adapt from real data use convolution neural networks, often known as ConvNets or CNNs.The CNN net, which comprises six layers with weights—four of which are parabolic and the other two which are fully connected—is the foundation for the framework for deep learning developed in this study. For the purpose of glaucoma estimation, the product of the final fully-connected layer is entered into a soft-max learner.

V. DISCUSSION

The ResNet 50 model has a preferable precision over the other three models that we used in this paper. The examination of the three models' precision is shown in the Table 1.

Table 1: Evaluation metric with different machine learning models

Comparison Table				
Model	Precision	Recall	F1-Score	Accurac y
ResNet0	0.81	0.73	0.79	90%
EffiecintNet	0.88	0.82	0.79	78%
ConvNet	0.74	1.00	0.85	79%

VI. CONCLUSION

One of the main issues facing the human vision is glaucoma. The human eye exhibits signs of glaucoma, which can result in loss of vision. The Glaucoma is a serious condition that can lead to blindness if early detection is skipped. Different methods for dividing retinal pictures into normal and glaucoma types have been reported, taking into account the importance of early glaucoma identification for ophthalmologists. the methods discussed here can be improved and further expanded to get a more accurate and faster classification by increasing the datasets with real-time data and increasingly effective deep learning models are used to complete the task thereafter. Using a variety of pictures of the retina, image classifications are carried out and the performance metrics for different methods can be evaluated.

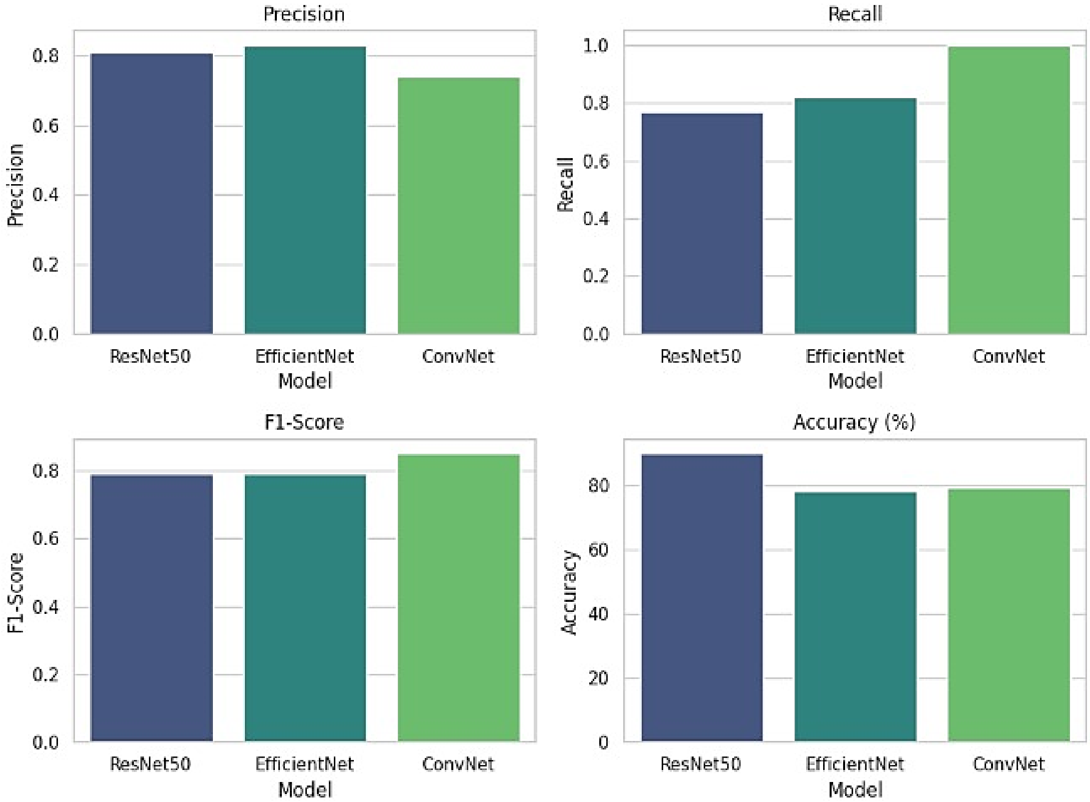

Figure 3: Graphical representation of the specified models' categorization metrics

CONFLICTS OF INTEREST

The authors declare that they have no conflicts of interest.

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