Multi Disease Eye Classification Using Deep Learning Model

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***Abstract*— Diabetic Retinopathy, Glaucoma, Cataract, and Age-related Macular Degeneration (AMD) are retinal disorders that cause blindness and irreversible cases of vision impairment in the world. The early detection of a disease is very important to avoid the final loss of the vision permanently, but the traditional methods of screening are time-consuming and require the skill of the specialist. A retinal fundus image analysis framework in the form of an automated multi-disease eye classification framework that employs deep learning is introduced. The system is developed in Python 3.10 and relies on the EfficientNetB0 Convolutional Neural Network architecture to find the optimal balance between the computational performance and the ability to represent the features. ODIR-5K correlates with eight ocular disease types which are used as model training. Image processing involves resizing of images, data normalization, and data augmentation, which involves rotation, zooming, and horizontal flipping of images to improve generalization. Class imbalance is dealt with the help of customized approach to class weighting. The Adam optimizer is used to train the model to ensure that 30 epochs are completed with a Binary Cross-Entropy loss. The performance evaluation shows a high level of accuracy, precision, recall and F1-score in various classes of diseases. Flask-based web app allows the real-time upload of images, prediction of the disease with the confidence probability, and the creation of PDF diagnosis reports that can be downloaded. Results of experiments confirm efficiency and high level of practical implementation in terms of large scale ophthalmic screening and computer aided clinical decision support systems.**

Keywords - Deep Learning, Convolutional Neural Network, EfficientNetB0, Retinal Fundus Imaging, Multi-Disease Classification, Diabetic Retinopathy, Glaucoma Detection.

I.INTRODUCTION

Retinal diseases like Diabetic Retinopathy, Glaucoma, Cataract, and Age-related Macular Degeneration (AMD) continue to be major causes of disability in the world, which is vision impairment. These conditions slowly destroy the retinal structures and with the absence of treatment, they can cause irreversible blindness. According to global health reports, millions of people are caused to lose their preventable sight because of late diagnosis. Traditional screening methods are based on manual scan of retinal fundus images of trained ophthalmologists. These methods are tedious, subjective and limited by overstretched availability of specialists, especially in the rural and underserved areas. The latest developments of the Artificial Intelligence, particularly, Deep Learning and Convolutional Neural Networks (CNNs), show great results in analyzing medical images. The automated systems will help clinicians by identifying the patterns of pathology with a high degree of accuracy and consistency. These technologies augment screening programs in large scale, diagnostic workload reduction and increase the rate of early detection. Nevertheless, the majority of current studies focus on the classification of individual diseases, especially Diabetic Retinopathy, and no attention is paid to multi-disease models that can detect several abnormalities in the retina at the same time.

The other shortcoming of previous research is the computer resource requirement that limits the possibility of clinical implementation in real time. The issue of class imbalance in medical datasets is also a burning aspect since rare diseases are often under-represented, which is likely to lead to biased predictions towards the prevalent classes. A lot of previous models are not enough sensitive to deal with the imbalance or to make more sense of underrepresented categories. In addition, some of these systems do not have user friendly deployment platforms that can be used in the clinical set ups. The increasing rate of preventable blindness and short supply of ophthalmologists in most areas signify the necessity of smart screening systems. Early diagnosis can greatly enhance the outcome of the treatment but many patients are not diagnosed until the advanced stages of the disease.

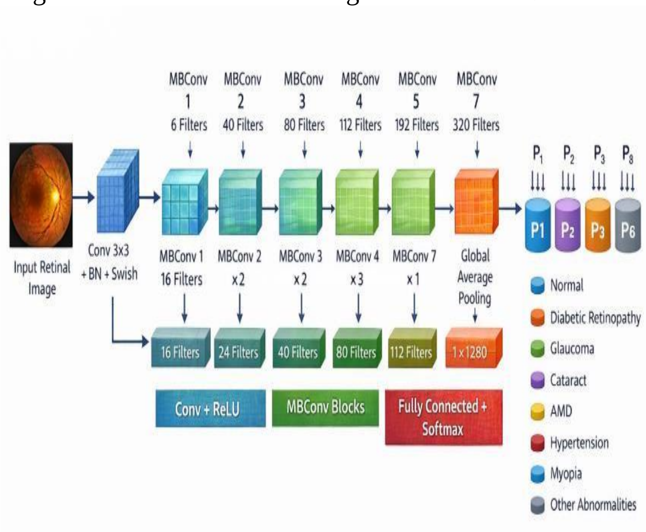

Figure 1. EfficientNetB0 CNN Architecture

Automated diagnostic support systems are used to make clinical decisions faster and more accessible to healthcare. State of the art CNNs like EfficientNetB0 make it possible to achieve high accuracy and stay computationally efficient. Combination of prediction results, confidence marking, and report-generating improves the use in practice and the dissimilarity between research models and executable clinical systems. The design of a multi-disease eye system brings many technical problems. Imbalanced data between classes influences predictive sensitivity of rare conditions. The differences in the illumination, resolution, noise, and quality of the images affect the extraction of features in retinal fundus images. Strong preprocessing and augmentation methods are needed to augment the model. Reduced labeled medical data enhances overfitting risk and when designing a system, the choice of an architecture that balances the accuracy and efficiency increases the complexity of the system design. The deployment must have a smooth integration between the back-end prediction modules and the front-end web frameworks to assure of good real time performance. Project scope: The project involves design, development, and implementation of a multi-disease classification system using retinal fundus images which is based on deep learning. Detection has eight diagnostic categories which include normal and pathological conditions. The web-based interface to real-time picture upload, prediction, and downloadable medical report are also implemented. System is not a substitute of professional medical assessment but instead a computer-aided professional diagnostic support. Future developments can include incorporation of bigger data, mobile implementation, cloud-based information and explainable AI methods to improve interpretability and scalability of automated ophthalmic screening frameworks.

II. LITERATURE SURVEY

Deep learning methods have evolved quickly and there has been a growing interest in automated retinal disease diagnosis because vision threatening diseases are becoming more common. Initial studies focused on the detection of single diseases but the latest studies focus on the classification of multi diseases in order to handle the clinical needs of the real world. A diagnostic system based on artificial intelligence introduced in [1] showed the use of deep learning in the analysis of ocular images to identify the disease. The focus was on the use of strong preprocessing and feature extraction methods to improve the accuracy of the classification. Equally, [2] presented a CNN-based method of diabetic retinopathy detection that received high accuracy and sensitivity thus confirming the usefulness of convolutional architectures in medical image processing. Despite being condition-specific, early contributions were in favour of going to multi-disease models [3]. The development of transfer learning and attention-based architectures were very instrumental in the process of ocular disease recognition. A study in [4] suggested a self- attention-based and dense-layered transfer learning-based architecture to recognize various ocular diseases. Higher feature representation and greater generalization in different categories were realized. In [5], multi-label deep learning classification of fundus images was also developed where simultaneous detection was highlighted on a single system. Sensitivity and specificity were high, and the results were reported in standardized imaging conditions, which supports the assumptions of autonomous AI-based screening systems [6].

Ensemble learning methods showed good capabilities with regard to retinal classification. A heterogeneous deep learning combination was used in Study [7] to improve robustness and reduce misclassification errors. On the same note, [8] proposed a Multi-Disease Classification Framework (MDCF) that uses ensemble CNN structures and reported better reliability and performance. The issues of data imbalance and scalability were recognized. Curated data sets are important in the study of multiple diseases [9]. RFMiD data used in [10] offered an annotation of multi- diseases that were structured, thus making it possible to benchmark effectively. The SUSTECH-SYSU data in [11] also added extra material to exudate detection and grading tasks, which hastened the routine standardized evaluation activities. Methodological advancements were also improved with disease-specific studies. In [12], a hybrid deep learning system that was used to grade progression in glaucoma incorporated retinal ganglion cell awareness in classification models. The effectiveness of multi-scale feature extraction was presented in [13], which proposed a multiscale and multipath CNN architecture of detecting AMD by using the OCT images. In [14], transfer learning- based multi-class multi-label detection of networks ensured enhanced efficiency using pretrain networks. Computational efficiency at scale was facilitated by lightweight architectures like MobileNetV2 in [15] which could be deployed at scale.

Comparative analyses in [16] pointed out benefits of deep learning against the conventional machine learning. Naive Bayes and Random Forest applications in [17] showed the weaknesses of the handcrafted features. In [18], hybrid CNN-based models showed the use of both spatial and sequential features. Transformer-based multi-label retinal classification in had better contextual learning, whereas transformer applications in [19] demonstrated scalability of attention mechanisms. Further research in accentuated on optimization, real-time application, and flexibility of models in imaging fields, thus adding to the strength and scalability in medical imaging [20].

III. PROBLEM STATEMENT

Retinal diseases, which pose risks to the vision of individuals like Diabetic Retinopathy, Glaucoma, Cataract, and Age-related Macular degeneration (AMD) are contributing factors to blindness in the world. Even with the development of medical imaging technologies, early diagnosis is still a major challenge because it is relying on manual retinal examination conducted by trained ophthalmologists. Current screening processes are time consuming, expensive and often unavailable in rural and resource strained areas. The growing number of patients and the shortage of specialists results in the majority of patients receiving late diagnoses and treatment. The majority of the existing automated diagnostic systems are focused on the detection of a single disease and do not include a multi-disease classification model. The medical image datasets are usually characterised by the class imbalance that diminishes the detection accuracy of less prevalent conditions. The difference in the quality of the image, light, contrast, and resolution also makes it even more difficult to extract reliable features and identify the disease. A deep learning- based system that is efficient, precise, and scalable is thus needed in the automatic classification of various eye diseases using retinal fundus images. An early identification, increased screening efficiency, and informed clinical decision-making can be supported using such a system.

IV. EXISTING SYSTEM

The retinal disease diagnosis system in place relies mostly on manual analysis of fundus examination on skilled ophthalmologists. In a clinical practice, retinal photographs are examined with the help of ophthalmoscopes or fundus cameras in order to identify the presence of abnormalities, namely, microaneurysms, optic nerve damage, lens opacification, and macular degeneration. Despite the fact that expert assessment is a reliable way to diagnose a patient, it is lengthy, subjective, and depends on the availability of specialists significantly. In rural and underdeveloped areas, ophthalmic care is not easily accessible, thus hindering its timely diagnosis and treatment, thus leading to the high probability of loss of vision permanently. A number of automated diagnostic systems, which are research oriented, have been presented though most of them focus on individual disease detection, especially Diabetic Retinopathy. Most of those methods use conventional image processing techniques or superficial machine learning models that rely on manual feature identification. Also, many of the models do not sufficiently consider class imbalance or real-time deployment limitations, limiting their use to more realistic application in multi-disease clinical screening settings.

V. METHODOLOGY

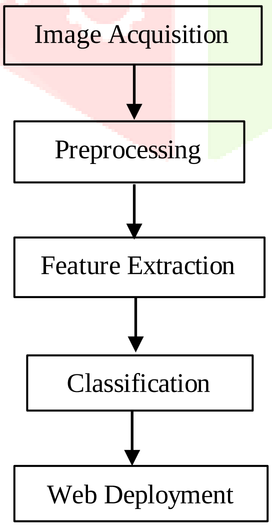

Figure 2. Proposed Methodology

A. *Image Acquisition*

The Image Acquisition Module will aim at capturing high quality retinal fundus images that will be used in the training and testing of the deep learning model. The used dataset is the ODIR-5K dataset, where there are labeled images depicting various types of eye diseases. Photographs are taken in the conventional fundus cameras in regulated clinical settings. Retinal images could be uploaded via a web-based interface during the deployment to be diagnostic. It supports such common image formats as JPG and PNG. The data are well organized and labeled to enable supervised learning to be accurate. The module provides a stable base to extract features as well as classification of the disease.

B. *Preprocessing*

The Preprocessing Module improves the quality of an image and preconditions the efficient training of a deep learning. Each fundus image is downsampled to a constant resolution of 500 ks which matches the EfficientNetB0 architecture. Normalization of pixels is used to scale the values of the intensity of 0-1 to enhance convergence. The method of data augmentation, such as rotation, horizontal flipping, and zooming, is used to increase generalization and decrease overfitting. These transformations are a simulated way of varying retinal imaging in the real world. Reduction of noise and amplification of contrast is also used to make important retinal structures salient. The uniformity, robustness, and better classification performance are guaranteed with the help of the module.

C. *Feature Extraction*

The Feature Extraction Module uses EfficientNetB0 convolutional neural network architecture to perform the extraction of discriminative features automatically when retinal images are given to the module. The patterns that are detected by deep convolutional layers include microaneurysms, optic nerve damage and lens opacities without manually engineered features. Transfer learning takes the pretrained weights as the initialisation of the model to speed up the convergence and enhance the accuracy. Extracted feature maps: Both local and global retinal property is captured by the extracted feature maps. The learned representations are passed through the fully connected layers where they are classified. The module has greater detection accuracy and is not computationally expensive.

D. *Classification*

Classification Module- This is a multi-class prediction module based on extracted deep features. Images are classified into eight diagnostic classes with a fully connected dense layer with an appropriate activation function. During the training, a class weighting method is used to deal with the imbalance in the dataset used and improve sensitivity in the underrepresented categories. Adam optimizer and Binary Cross-Entropy loss function are used to train through several epochs to ensure that convergence is stable. Accuracy, precision, recall, and F1- score are the performance measures that are calculated to determine reliability. Clinical interpretation is provided by generating probability scores and end diagnostic predictions.

E. Web Deployment

The Web Deployment Module adopts the skilled deep learning model into a flask-based user-friendly application. The retinal fundus images, as well as patient information, can be uploaded and transmitted via a secure interface by medical practitioners. The backend system takes the submitted images and then runs them through a processing system to come up with real time predictions and confidence percentages. An auto-generated PDF medical report is downloaded automatically to be used to document it. The workflow is also efficiently ensured by the seamless communication between the frontend and backend components. The implementation platform improves the accessibility and promotes real-time clinical screening software.

VI. PROPOSED SYSTEM

Retina Scan PRO is a computer-aided diagnostic (CAD) framework based on deep learning that is designed to perform automated multi-disease diagnosis of retinal fundus image. The framework will identify and identify eight classes, such as, Normal, Diabetic Retinopathy, Glaucoma, Cataract, Age-related Macular Degeneration (AMD), Hypertension, Myopia, and other retinal abnormalities. Python is used to run development on 3.10 and it is implemented with the EfficientNetB0 Convolutional Neural Network (CNN) model to run with high accuracy, optimized computational power.

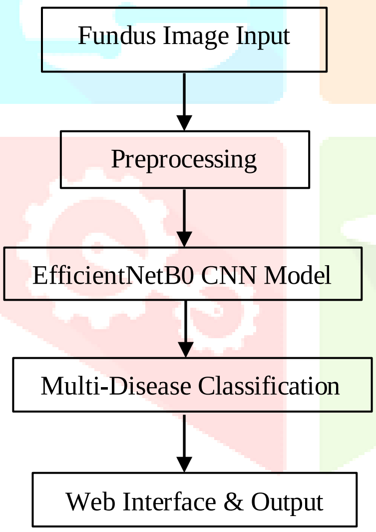

Figure 3. Proposed System Architecture

The fundus images are adjusted by adjusting to a constant resolution and normalization to enhance the uniformity of pixels. It uses data augmentation methods such as rotation, zooming and horizontal flipping to improve generalization and minimize overfitting. The integrated learning with a tailored training approach is a class weighting approach used to handle the imbalance in datastones and enhance sensitivity against uncommon disease types. The training of the model is done with Adam optimizer and loss function: Binary Cross-Entropy in various epochs, which are made to stabilize the convergence and successful extraction of features. Accuracy, precision, recall and F1-score are used to test the performance of the trained model against reliability and to deploy the trained model, the trained model is incorporated into a web-based app that is designed on the Flask framework. Healthcare providers are able to post retinal fundus aids, patient information and get real time diagnostic forecasts along with confidence ratings. Clinical documentation is assisted by automated creation of downloadable PDF medical reports. The framework comprises of five key modules namely Image Acquisition Module, Preprocessing Module, Feature Extraction Module, Classification Module and Web Deployment Module. The retinal images will be captured, resized, and augmented, then processed on the deep feature extraction with EfficientNetB0, categorized into various disease groups, and provided at a probability score, and presented in the form of a Flask-based interface with the ability to predict and generate a report in real-time.

VII. RESULT AND DISCUSSION

The multi-disease eye classification system was proposed and implemented in Python 3.10, with the deep learning model development libraries of TensorFlow and Keras. EfficientNetB0 architecture was chosen based on the fact that it has been optimally tuned in terms of accuracy and computation efficiency. ODIR-5K dataset was used to train and validate, and the methods of preprocessing, including resizing, normalization, and data augmentation, were used to increase robustness. The class weighting strategy became customized in order to control class imbalance during training.

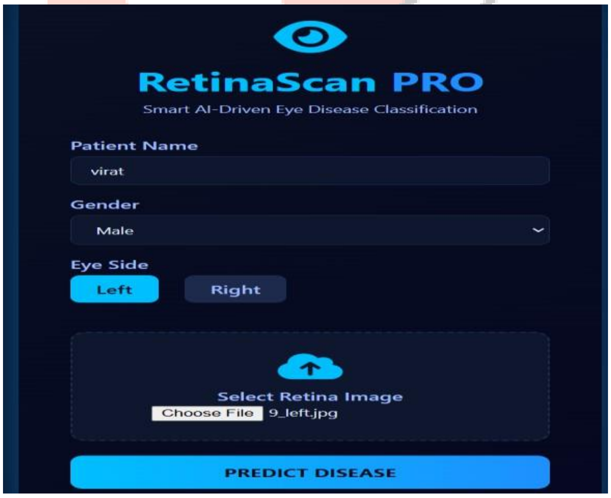

Figure 4. Input Image Uploading

The 30 epochs of training were performed by use of Adam optimizer and the Binary Cross-Entropy loss function to be converted to achieve stability. The evaluation of performance metrics, such as accuracy, precision, recall, and F1-score was calculated. The trained model was incorporated into a web application written in Flask and allows uploading images and prediction in real-time. A PDF report creation functionality was also added to deliver downloadable diagnostic summaries of clinical documentation and record-keeping.

It is shown through experimental results that the EfficientNetB0-based model has high accuracy in classifying eight eye diseases. The quality of high accuracy and balanced values of precision-recall suggest the reliability of detecting common and rare conditions. The use of class weighting enhanced sensitivity of underrepresented categories as well as reduced prediction bias.

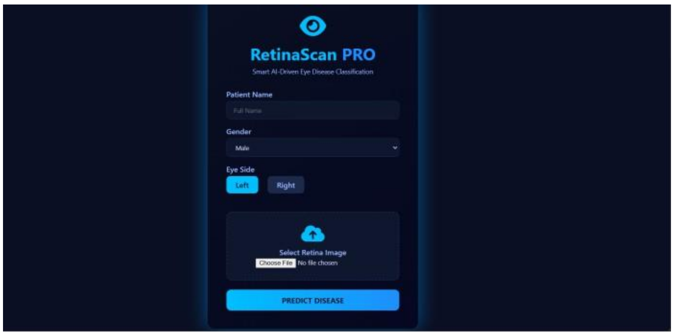

Figure 5. Input Data entry

Data augmentation improved the generalization and reduced overfitting, leading to the stable validation performance. Predictions with confidence scores are provided, and can be deployed in real-time, by a web based implementation, to assist in practical clinical screening applications.

Figure 6. Report analysis

The framework provides a multi-disease classification model in a single architecture as compared to traditional manual diagnosis models and single-disease models. The general results affirm success, scalability, and feasibility of use in the facilitation of early detection and massive ophthalmic screening programs.

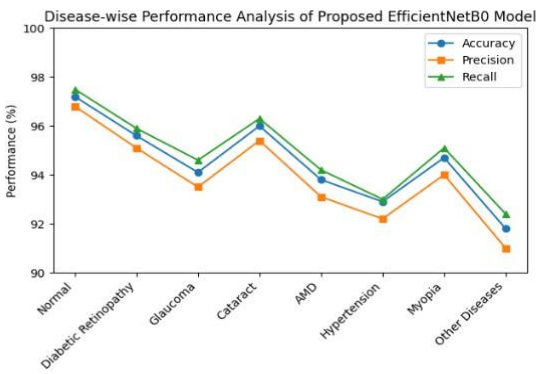

Figure 7. Performance Metrices Graph

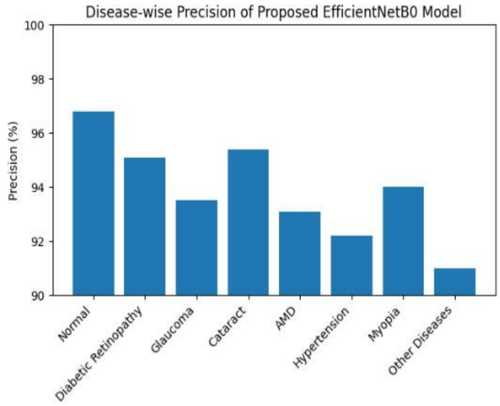

Figure 8. Comparision of model Precision

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
CNN (Basic Model)	89.4	88.7	87.9	88.3
VGG16	91.8	91.2	90.5	90.8
ResNet50	93.6	93.1	92.4	92.7
MobileNetV2	92.3	91.9	91.1	91.5
EfficientNetB0 (Proposed)	**95.8**	**95.2**	**94.6**	**94.9**

Table 1. Comparison Metrics

VIII. CONCLUSION

It describes a multi-disease eye classification system that is based on deep learning and which is aimed at helping clinicians detect large retinal disorders in their early stages. With the help of the EfficientNetB0 Convolutional Neural Network architecture, the system is able to identify discriminative features of retinal fundus images and successfully classify retinal fundus images to eight categories of eye diseases. High-quality preprocesses and a tailored class weighting scheme contribute much to enhancing model resistance and sensitivities, especially on the underrepresented diseases. The practical use of the trained model incorporation into a Flask-based web application allows adding to the functionality of the trained model in real-time image analysis, confidence score, and automated PDF report generation. The experimental findings indicate that the proposed framework has a high accuracy, precision, and recall thus reliable when used to assist in clinical screening.

IX. FUTURE SCOPE

More improvements are possible to achieve better accuracy, scalability and clinical applicability. The next step of development could be the training on bigger and more varied datasets that are gathered in various hospitals to enhance the generalization of various populations and imaging machines. By incorporating Explainable AI (XAI) methods, including Grad-CAM visualization, it is possible to create heatmaps to indicate the areas of the retina that were affected, which will contribute to transparency and trust in the clinician. The framework extension to identify other ocular diseases and aid in multi-label classification would support the cases of multiple coexisting diseases. As a mobile or a cloud based application, deployment can increase access to rural and remote areas. Live integration with hospital information systems and electronic health records can facilitate the clinical processes. Federated learning can also be used to continuously update the model and enhance performance without compromising patient data privacy.

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