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Early Detection of EYE Cancer from Retinal Images

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***Abstract*— Globally, ocular fundus diseases—such as glaucoma, age-related macular degeneration (AMD), and diabetic retinopathy (DR)—are common causes of vision impairment. Retinal vein occlusion (RVO), retinal artery occlusion (RAO), retinal detachment (RD), and fundus tumours are uncommon but serious ailments that provide substantial obstacles, particularly in rural and disadvantaged locations. Early and accurate detection of such diseases is crucial for effective treatment and prevention of severe vision loss. This study aims to develop a deep learning model for the automated detection of eye cancer from retinal images, leveraging convolutional neural networks (CNNs) to enhance diagnostic accuracy and accessibility. This research highlights the potential of deep learning in early eye cancer detection, offering a step towards more accessible and reliable diagnostic tools in ophthalmology. The integration of such technologies can significantly improve patient outcomes, particularly in regions with limited access to specialized healthcare services.**

***Keywords*— Retinal vein occlusion, retinal artery occlusion, retinal detachment, and fundus tumors.**

I. INTRODUCTION

Eye cancer is an uncommon kind of cancer that mostly affects cells in and around the eyes. It can affect numerous regions of the eye, including the retina, iris, and choroid. Early identification of eye cancer is critical because it increases the likelihood of effective treatment and prevents visual loss. Traditionally, detecting eye cancer has been a manual procedure that relies greatly on the skill of medical professionals. However, this strategy is time-consuming and prone to human mistake.

The development of artificial intelligence and machine learning has created an opportunity to automate this procedure and increase detection accuracy. Deep learning, a subset of machine learning, has produced encouraging results in the field of medical image analysis. Convolutional Neural Networks (CNN), a type of deep learning model, have been used to detect different diseases by learning to recognize patterns in a huge collection of images. However, the use of these tools for detecting eye cancer is very unresolved, which is the subject of this investigation.

Millions of people worldwide are affected by ocular fundus illnesses, which include diabetic retinopathy (DR), age-related macular degeneration (AMD), retinal vein occlusion (RVO), retinal artery occlusion (RAO), glaucoma, retinal detachment (RD), and fundus tumours. In most populations, the most common causes of vision loss are glaucoma, AMD, and DR. These fundus illnesses can result in metamorphopsia, visual field abnormalities, persistent reduced vision, or even blindness if a proper diagnosis and timely treatment are not received.

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However, in rural and distant regions, particularly in developing nations, where ophthalmic services are insufficient and ophthalmologists are in short supply, early identification and quick referral for treatment may be difficult. Notably, fundus imaging, which offers basic identification of many disorders, is available and reasonably priced in most regions of the world. Non-professionals can manage a fundus image and submit it online for follow-up to prestigious optical institutes. Artificial intelligence (AI) can offer delivery capabilities.

The introduction of deep learning techniques in medical imaging has created new opportunities for illness identification and improved patient care. The present effort focuses on using deep neural networks to identify eye cancer by analyzing and recognizing retinal images. This endeavor is motivated by the rising frequency of eye-related disorders and the concomitant need for a more efficient and self-contained diagnostic system. The purpose of this research is to develop and use a deep learning model for detecting eye cancer using retinal pictures.

This study aims to leverage the potential of artificial intelligence and deep learning in medical imaging with the specific goal of increasing early detection of eye cancer, therefore improving prognosis and treatment results. The application of deep learning to medical image processing has been the subject of extensive research. Numerous subjects have been addressed in this research, including the diagnosis of retinal diseases such as glaucoma, maculopathy, and diabetic retinopathy. However, the use of deep learning algorithms to identify eye cancer has been relatively underexplored. This initiative intends to close the gap by creating a model for detecting eye cancer using retinal images.

The justification for pursuing this research is the potential benefits that an accurate eye cancer detection system might provide to the healthcare industry. Early detection of eye cancer allows for successful treatment, minimizing the risk of vision loss and enhancing patients' quality of life. However, current detection systems frequently rely largely on expert judgment, which is subjective and susceptible to human mistake. A deep learning model, if trained with enough and diverse data, may give consistent and objective analysis, possibly increasing detection accuracy.

The research began by collecting 1500 true color fundus photos in 24-bit RGB format from Kaggle. These photos represented 26 distinct types of retinal diseases and provided a solid dataset for training the deep learning model. The disorders included Background Diabetic Retinopathy, Cataract, Glaucoma, Drusen, Maculopathy, and others.

In this study, we used convolutional neural networks (CNNs) integrated into a customised two-step technique to construct a multi-disease automated detection platform that can classify 26 prevalent fundus diseases and conditions based on colour fundus photos. We developed a deep learning platform (DLP) that was trained, verified, and tested using 1500 fundus images from Kaggle. Finally, this effort is a step towards using the capabilities of deep learning for early eye cancer detection. It aims to contribute to the developing area of medical image analysis while also advancing the cause of artificial intelligence in healthcare.

II. Literature Survey

In their thorough analysis of machine learning methods in medical imaging, Deekshitha Varma et al. [1] concentrated on cancer detection with the use of Support Vector Machines (SVMs) and Decision Trees. They highlighted SVMs' high accuracy and robustness in handling complex, non-linear data, and Decision Trees' simplicity and interpretability, essential for clinical decision-making. Previous comparative studies indicate SVMs often outperform Decision Trees in accuracy but require more computational resources. Despite advancements, specific research on comparing these classifiers for eye cancer detection is limited. This study aims to fill this gap by implementing a novel SVM classifier for eye cancer detection and comparing its performance with a Decision Tree classifier, evaluating accuracy, computational efficiency, and interpretability.

Visual interpretability was the main emphasis of Da-Wen Lu et al.'s [2] investigation of glaucoma detection using deep learning models on colour fundus images. Their work adds to the continuing attempts to control and detect glaucoma early on, as it is a major cause of irreversible blindness globally, by using sophisticated computational tools.

By employing deep learning models, the authors aimed to enhance the accuracy and interpretability of glaucoma diagnosis, shedding light on the underlying features and patterns crucial for clinical decision-making. This study builds upon existing literature in medical image analysis, particularly in the context of ophthalmology, and underscores the significance of interpretability in ensuring trust and acceptance of deep learning-based diagnostic tools by healthcare professionals. The authors' investigation into visual interpretability offers valuable insights into the inner workings of deep learning models, facilitating their integration into clinical workflows and ultimately improving patient outcomes.

A.E. Narayanan et al. [3] present an extensive literature review on the critical issue of myopia detection and classification using advanced image processing and machine learning techniques. The authors delve into existing studies that explore various methodologies for identifying and classifying myopia, emphasizing the shift towards integrating machine learning approaches to enhance accuracy and efficiency. They review key works in the field, discussing advancements in image processing algorithms and their application to myopia detection. Furthermore, the authors examine the challenges and open issues in this domain, providing a critical analysis of current state-of-the-art techniques. This literature survey serves as a foundational component, contextualizing the authors' proposed approach within the broader landscape of myopia detection research, with an aim to prevent fatal road accidents caused by impaired vision.

Pankaj Kumar et al. [4] present an extensive literature review on the evolving field of eye disease detection using pre-trained deep learning models. They delve into existing studies that explore various methodologies for ophthalmic disease analysis, emphasizing the shift towards leveraging pre-trained neural networks. The authors review key works in image-based eye disease detection, discussing advancements in convolutional neural networks (CNNs) and their application to ophthalmic datasets. Furthermore, they examine the challenges and open issues in eye disease detection, providing a critical analysis of current state-of-the-art techniques. This literature survey serves as a foundational component, contextualizing the authors' proposed deep learning approach within the broader landscape of eye disease detection research.

Gauri Ramanathan et al. [5] present an extensive literature review on the emerging field of eye disease detection using machine learning at the 2nd Global Conference for Advancement in Technology (GCAT). They delve into existing studies that explore various methodologies for eye disease analysis, emphasizing the shift towards machine learning approaches. The authors review key works in image-based eye disease detection, discussing advancements in convolutional neural networks (CNNs) and their application to various medical imaging datasets. Furthermore, they examine the challenges and open issues in eye disease detection, providing a critical analysis of current state-of-the-art techniques. The authors' suggested machine learning approach is placed into the larger framework of eye disease detection research by this literature survey, which acts as a fundamental component.

Badah et al. [6] proposed a Deep Learning (DL) model such as Convolutional Neural Network (CNN) based on Resnet152 model to detect human eye infections of Glaucoma disease. The evaluation of the proposed approach is performed on the Ocular Disease Intelligent Recognition dataset. The obtained results showed that the deep learning model (CNN model: Resnet152) provides an accuracy of 84%.

A deep learning-based algorithm using the Retinal Fundus Multi-disease Image Dataset (RFMiD) was proposed by Gany et al. [7] for the automatic detection of eye abnormalities brought on by both uncommon pathologies and the most frequent ocular diseases. The 1920 fundus retina images in the RFMiD collection were taken with three distinct fundus cameras, and 46 conditions were labelled based on the adjudicated consensus of two senior retinal experts. The model is built on the top of some prominent pretrained convolutional neural network (CNN) models. From the experiment, the model could achieve the accuracy level and recall 0.87, whereas precision and F1 score are 0.86, and area under receiver operating characteristic (AUROC) is 0.90.

III. PROPOSED WORK

This proposed work showcases a systematic and thorough approach to the development and evaluation of a deep learning model for eye cancer detection. The utilization of diverse and representative data, coupled with rigorous preprocessing and model development, sets the stage for a promising application of deep learning in medical imaging.

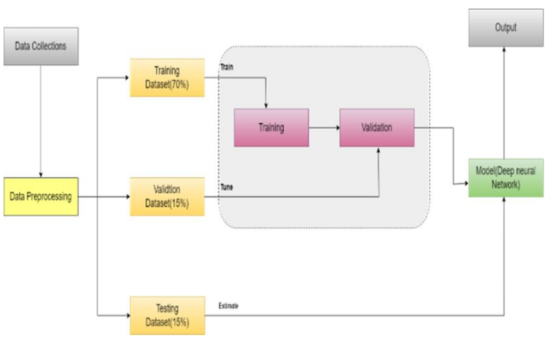

Figure 1. Workflow of Proposed Model

The workflow of this study as shown in figure 1, which focuses on the detection of eye cancer from retinal images using a convolutional neural network (CNN), consists of several key steps: data collection, preprocessing, data augmentation, model development, training, evaluation, and prediction. Each step is critical for ensuring the model's accuracy and robustness. Below, we outline each component in detail.

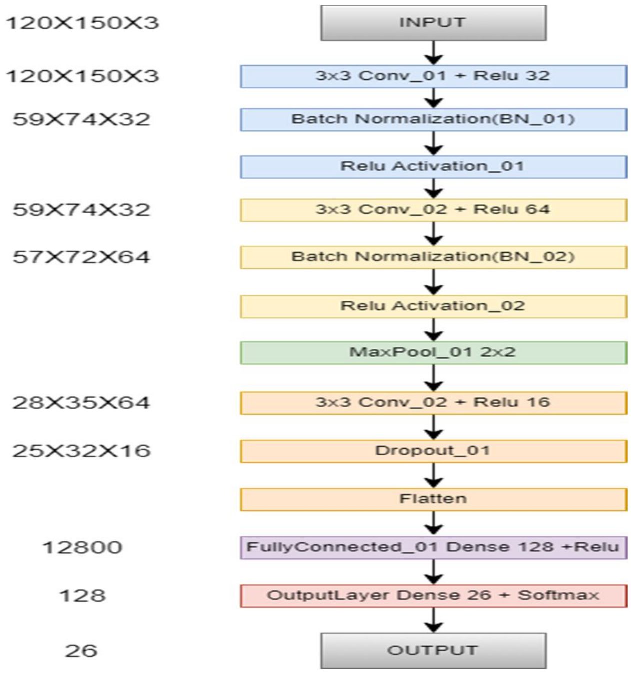

Figure 2. Architecture of proposed model

A. Data Collection

The initial step in this study involved collecting a comprehensive dataset of retinal images. We sourced 1500 true-color fundus images in 24-bit RGB format from eight open-access databases. These images represent 26 distinct types of retinal diseases, including both normal and pathological cases such as Background Diabetic Retinopathy, Cataract, Glaucoma, Drusen, and Maculopathy. The diversity and representation in this dataset are crucial for training a robust deep learning model capable of accurately detecting eye cancer.The dataset was meticulously curated to ensure it covers a wide range of retinal conditions, thereby enhancing the model's ability to generalize across different disease presentations.

B. Splitting and Balancing

To ensure robust evaluation, the dataset was split into training, validation, and test sets in a 70:15:15 ratio. This stratified split helps in maintaining the distribution of classes across the sets, which is crucial for a fair evaluation of the model's performance. However, the initial analysis revealed a class imbalance, with certain diseases being underrepresented. To address this, resampling techniques were employed to balance the training set. By randomly oversampling the minority classes and under sampling the majority classes, the dataset was made more balanced, reducing the bias towards more frequent classes and improving the overall model performance. This balancing act is crucial to prevent the model from becoming biased and to ensure it performs well across all classes.

C. Data Augmentation

By generating altered versions of pre-existing photographs, data augmentation is an essential way to artificially increase the size of the training dataset. The model's capacity to generalise to fresh, untested data is enhanced by this procedure. Numerous augmentation techniques, such as rotations, shearing transformations, and shifts both vertically and horizontally, were used in this work. By adding diversity to the training set, these modifications lessen the likelihood of overfitting and increase the model's resilience. The ImageDataGenerator class from Keras was utilized to apply these augmentations in real- time during the training process. By augmenting the dataset, we ensured that the model encountered a wide range of variations, thereby improving its ability to handle diverse real- world scenarios.

D. Model Implementation

Using the Keras Sequential API, a convolutional neural network (CNN) model was created. The architecture of the proposed model is shown in figure 2. Many convolutional layers, batch normalisation layers, activation layers, max pooling layers, dropout layers, and fully connected layers made up the architecture. Convolutional layers were used to extract features from the input images, with batch normalization applied to stabilize and accelerate the training process. ReLU activation functions were employed to introduce non-linearity, enabling the model to learn complex patterns. Max pooling layers were added to reduce the dimensionality of the feature maps, making the model computationally efficient. Dropout layers were incorporated to prevent overfitting by randomly omitting neurons during training. The fully connected layers integrated the extracted features and performed the final classification, with the output layer using a softmax activation function to generate probabilities for each class.

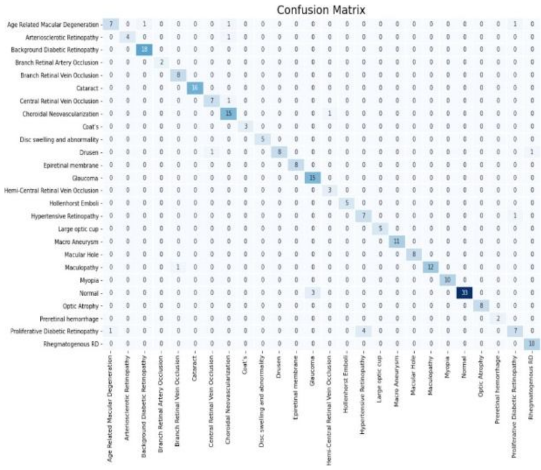

Figure 3. Confusion Matrix

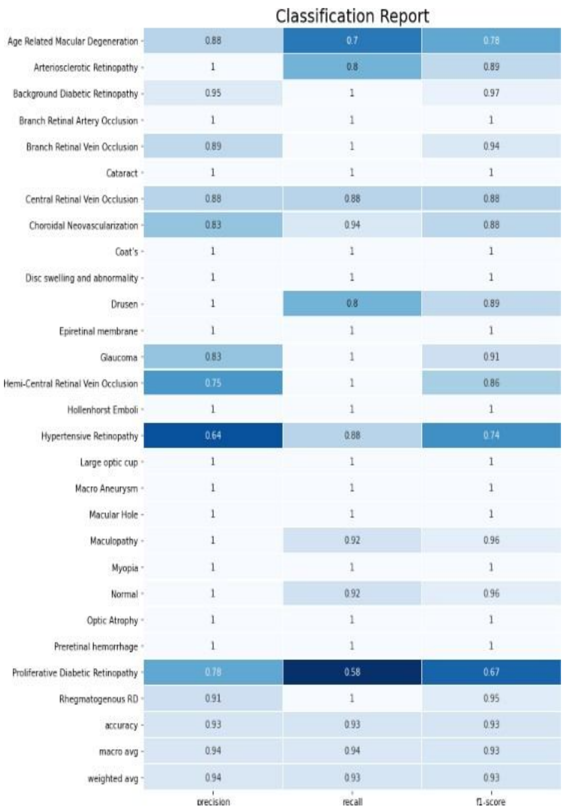

Figure 4. Classification Report

E. Training the Model

The Adam optimiser, renowned for its adjustable learning rate and efficiency, was used to train the model. For multi-class classification issues, categorical cross-entropy was the employed loss function. The training process was monitored using callbacks, including a learning rate scheduler to adjust the learning rate dynamically and model checkpointing to save the best-performing model. The training was conducted over 30 epochs, with the training and validation sets being fed into the model in batches. The data augmentation generator was used to supply the augmented images during training, ensuring that the model was exposed to a wide range of variations. The training process aimed to minimize the loss and maximize the accuracy, with the validation set used to monitor the model's performance and detect any overfitting.

F. Evaluation

A variety of metrics, including accuracy, precision, recall, F1-score, and loss, were used to assess the model's performance on the training, validation, and test sets. The confusion matrix showed the examples that were successfully identified and the ones that were misclassified, giving precise insights into the model's performance across several classes. The classification report provided a thorough assessment of the model's capacity to differentiate between various retinal illnesses by going into additional depth regarding the precision, recall, and F1-score for each class. The model obtained training accuracy of 98.66%, validation accuracy of 98.43%, and test accuracy of 92.94%, according to the assessment results. These metrics demonstrate the model's high efficacy in detecting eye cancer from retinal images, with the detailed analysis helping to identify areas for further improvement and refinement.

IV. EXPERIMENTAL RESULTS

A. Dataset

The dataset comprises of 1500 true color fundus images in 24-bit RGB format is gathered from Kaggle. These images represent 26 distinct types of retinal diseases, including Background Diabetic Retinopathy, Cataract, Glaucoma, Drusen, Maculopathy, and others, providing a rich and representative dataset for training the deep learning model.

B. Model Performance

The convolutional neural network (CNN) developed for this study demonstrated significant efficacy in detecting eye cancer from retinal images. The model was trained on a dataset of 1500 fundus images, categorized into 26 different types of retinal diseases. The training, validation, and test sets were split in a 70:15:15 ratio, respectively, to ensure robust evaluation. With 98.43% validation accuracy and 98.66% training accuracy, the model performed well. The model achieved an accuracy of 92.94% on the test dataset. With a training loss of 0.2468 and a validation loss of 0.2510, the loss values were likewise successfully minimised, suggesting a well-generalized model with little overfitting. These results illustrate that the CNN model has learned to identify complex patterns in the retinal images with high precision.

As depicted in figure 3, the confusion matrix provides detailed insights into the model’s performance across different classes. The high values along the diagonal indicate that the model correctly classifies a majority of the images. However, some misclassifications were noted, particularly in classes with fewer training examples, suggesting the need for a more balanced dataset or further augmentation strategies. The confusion matrix also reveals which classes are frequently confused with one another. For instance, diseases with similar visual features, such as different stages of diabetic retinopathy, might be more challenging to distinguish. This insight can guide future improvements in the model, such as incorporating more sophisticated feature extraction techniques or increasing the training data for those specific classes.

The classification report, which highlights precision, recall, and F1-score for each class, offers a thorough examination of the model's performance across several classes, as shown in figure 4. This thorough analysis highlights the model's advantages and shortcomings.

As depicted in figure 5, the training and validation loss and accuracy curves show a steady decrease in loss and an increase in accuracy over the epochs. The close alignment of the training and validation curves indicates that the model does not suffer from significant overfitting. This balance can be attributed to the use of regularization techniques such as dropout and batch normalization, as well as the extensive data augmentation applied during training.

Despite the promising results, several challenges were encountered. The primary challenge was the class imbalance, which, although mitigated through resampling, still posed a risk of biased predictions. Additionally, the reliance on handcrafted preprocessing techniques might limit the model's adaptability to different datasets without modifications.

Another limitation is the model’s reliance on a relatively small dataset. While the current dataset was sufficient for initial model training and validation, a larger and more diverse dataset would likely improve the model’s performance and generalizability. Furthermore, the model's reliance on expert-labeled data highlights the need for collaboration with healthcare professionals to obtain high-quality annotated images for training.

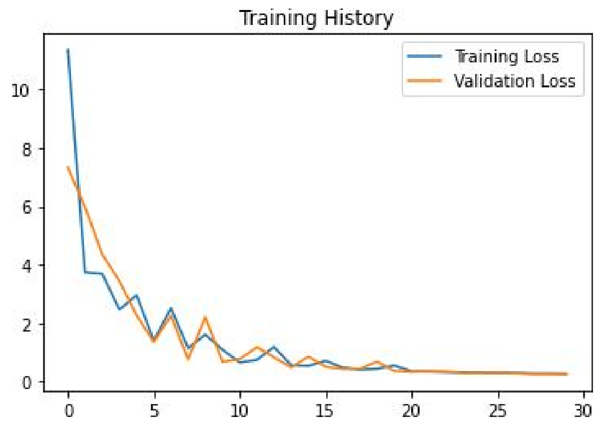

Figure 5. Training and Validation loss

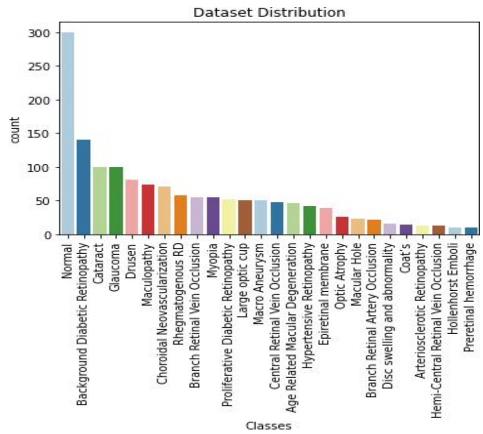

Figure 6. Dataset Distribution

Figure 7. After balancing the dataset

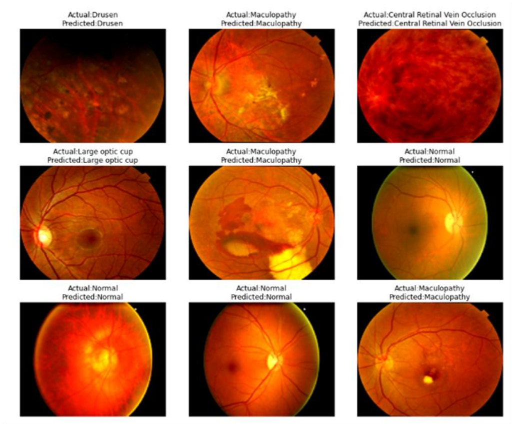

Figure 8. Evaluating with Real Life Fundus Images

V. Conclusion

In this study, we explored the potential of leveraging convolutional neural networks (CNNs) to develop an automated system for detecting eye cancer from retinal images. This effort is rooted in the critical need for early detection of ocular fundus diseases such as diabetic retinopathy (DR), age-related macular degeneration (AMD), glaucoma, and specifically eye cancer, which, if left untreated, can lead to severe visual impairment or blindness. The study's overarching goal was to harness the power of deep learning to create a reliable and efficient diagnostic tool that can assist healthcare professionals, particularly in regions with limited access to ophthalmic services.

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