DEEPRETINA: DEEP LEARNING APPROACH TO DETECT RETINAL ABNORMALITY IN COMPUTER VISION

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Approval

This Project titled "**DeepRetinal: Deep Learning Approach to Detect Retinal Abnormality in Computer Vision**", submitted by **Sonia Nasrin** to the Department of Computer Science and Engineering, Daffodil International University, has been accepted as satisfactory for the partial fulfillment of the requirements for the degree of M.Sc. in Computer Science and Engineering (MSc.) and approved as to its style and contents. The presentation has been held on **27th January 2024**.

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We hereby declare that, this thesis has been done by us under the supervision of Dr. S. M. Aminul Haque, Professor & Associate Head, **Department of CSE** Daffodil International University. We also declare that neither this thesis nor any part of this thesis has been submitted elsewhere for award of any degree or diploma.

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ABSTRACT

Currently, almost 1.2 million people in our country are blind, while around 3.51 lakh people have low vision. The pattern of eye abnormalities is changing along with an increasing rate of dry eye, cornea-related problems and eye problems related to diabetes. Early identification of eye diseases especially retinal abnormality plays a vital role to prevent the blurry vision in patients. In my research, a hybrid deep learning model is proposed to detect retinal abnormality by scanning a single retinal image of a patient. First, a new multi-label retinal disease dataset, Retinal Fundus Multi-Disease Image Dataset (RFMiD) version 02 is collected from a renewed journal website “Multidisciplinary Digital Publishing Institute” (mdpi), where 46 retinal diseases labels are available with high resolution. Next, dataset is going through analysis and preprocessing techniques to deals with data imbalance and large size (8gb) problem. Numerous analysis and experiments are performed to evaluate the models for better results. In the model, Convolutional neural models – EfficientNet, VGG16, NesNetMobile are used to analysis comparative result as well. EffectiveNet gives the highest accuracy among them and that is 85%. Voting Ensemble method is used to increase model accuracy (88%) for better prediction than could be gained from any of the constituent learning algorithms. This model is used to detect normal or abnormal retinal conditions for early treatment.

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CHAPTER 1

INTRODUCTION

1.1 Introduction

Retinal eye disease is one of the most leading causes of blindness and impairment worldwide, with age-related macular degeneration accounting for an estimated 8 million cases around the globe [1]. At least 1 billion people have a near or distance vision impairment that could have been prevented or has yet to be addressed. In the absence of timely detection, reduced or absent eyesight can have long-term personal and economic effects. Vision impairment affects people of all ages, with the majority being over the age of 50. Young children with early onset severe vision impairment can experience lower levels of educational achievement, and in adults it often affects quality of life through lower productivity, decreased workforce participation and high rates of depression [2].

The following figure 1.1.1 shows, according to a research report published by Spherical Insights & Consulting, the Global Ophthalmic Drugs Market Size to grow from USD 39.10 billion in 2021 to USD 66.22 billion by 2030, at a Compound Annual Growth Rate (CAGR) of 8.25% during the forecast period [3].

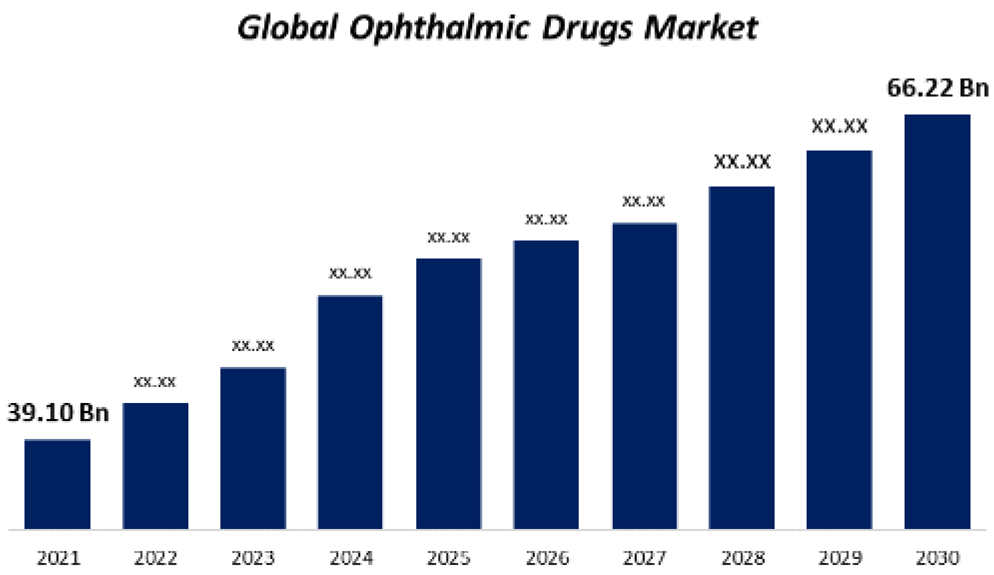

Figure 1.1.1: Global Ophthalmic Drugs Market worth $66.22 billion by 2030[3]

The advent of deep learning has revolutionized medical diagnostics, particularly in the field of ophthalmology, where the early detection and precise classification of retinal diseases are paramount for effective treatment and management. Retinal diseases, encompassing a broad spectrum of pathologies affecting the delicate tissue lining the back of the eye, pose a significant global health challenge. According to the World Health Organization (WHO) [2], an estimated 285 million people worldwide are visually impaired, of which approximately 80% of cases are considered preventable or treatable, with retinal diseases constituting a significant proportion of these conditions.

Retinal diseases encompass a diverse array of disorders, ranging from age-related macular degeneration (AMD) and diabetic retinopathy (DR) to glaucoma and retinopathy of prematurity (ROP), among others. These conditions not only impair vision but also significantly impact the quality of life, productivity, and economic well-being of affected individuals and communities worldwide.

Traditional methods of diagnosing retinal diseases often rely on subjective interpretation by trained ophthalmologists, which can be time-consuming, labor-intensive, and prone to interobserver variability. However, recent advancements in deep learning-based image analysis offer a promising avenue for automating and enhancing the accuracy and efficiency of retinal disease diagnosis.

This thesis explores the application of deep learning techniques for retinal disease classification, aiming to develop a robust and scalable framework capable of accurately identifying and categorizing various retinal pathologies from optical coherence tomography (OCT) and fundus photography images. By leveraging large-scale datasets and state-of-the-art deep learning architectures, this research seeks to address existing challenges in retinal disease diagnosis, including early detection, classification accuracy, and scalability.

Through the integration of advanced deep learning models, such as different types of image Net Convolutional neural models – EfficientNet, VGG16, NesNetMobile, with innovative data augmentation strategies and transfer learning techniques, this thesis endeavors to contribute to the ongoing efforts in leveraging artificial intelligence for improving the diagnosis and management of retinal diseases on a global scale.

As it is delved deeper into the complexities of retinal disease classification using deep learning, this research aims to not only advance the state-of-the-art in medical image analysis but also pave the way for more accessible, efficient, and equitable healthcare solutions for individuals affected by retinal pathologies worldwide.

1.2 Motivation

Eye disease is most common health threats of Bangladesh. The rate of the diseases is increasing day by day in an alarming rate. Most of the people diagnosis the disease in severer blurry vision conditions. This disease plays important role in:

- **Clinical Significance:** Retinal diseases, including age-related macular degeneration, diabetic retinopathy, and glaucoma, are major causes of visual impairment and blindness worldwide.
- **Global Health Impact:** With millions of individuals affected by retinal diseases globally. The Global Ophthalmic Drugs Market Size to grow from USD 39.10 billion in 2021 to USD 66.22 billion by 2030
- **Challenges in Diagnosis:** Traditional methods of diagnosing retinal diseases often rely on subjective interpretation by trained ophthalmologists, leading to variability in diagnoses and potentially delaying treatment initiation
- **Potential for Clinical Translation:** The ultimate goal of this research is to develop a practical and clinically relevant framework for retinal disease classification that can be integrated into existing healthcare systems.

Early detecting can prevent from massive damages of the problem. Deep learning-based approaches offer the promise of automating and standardizing the diagnostic process, thereby improving efficiency, accuracy, and consistency in disease classification. By addressing key challenges such as data scarcity, model interpretability, and real-world deployment, this work seeks to bridge the gap between cutting-edge research and tangible clinical impact

1.3 Research Objective

The intention of developing the model is to identify retinal abnormality early enough to preventative measures of blurry vision in health care. The primary objective of this research is to develop and evaluate deep learning models for the classification of retinal diseases, aiming to enhance the accuracy, efficiency, and scalability of diagnostic processes in ophthalmology. A large size of retinal fundus image dataset [4] is used in the model from a reputed journal website “Multidisciplinary Digital Publishing Institute” for building an effective model. After analysis the data. The objectives of the particular research are:

- Create positive impact on health care institute for analysis retinal Image
- Align with computer science in health care industry for better evaluation
- Statistical analysis to figure out dataset’s attribute, complexity and informatics
- Build a hybrid model with neural network.
- Performance Evaluation and suggest suitable transfer learning model for this type of medical problem.

1.4 Research Questions

Every technique has a complicated work that makes ourselves wonder to think about how it operates by overcoming its limitations. In medical science, computer vision plays a tremendous role to diagnosis disease with more accurate than human. Again it can be used in suggestion or confirmation purpose of double check the medical conditions so that proper treatment can be started without any misconception. The questions that are followed from the beginning –

- How can make a contribution on world health problem?
- How can we built a model for retinal abnormality detection?

1.5 Report Layout

Total six (6) chapters are included in this report for describing the research work on “DeepRetinal: Deep Learning Approach to Detect Retinal Abnormality in Computer Vision” which will be followed given by instructions:

Chapter 1 is focused on the introductory analysis of this research work. The importance of retinal disease diagnosis and prediction is discussed on the part. Research Objective, motivation, Research question have also discussed in this introductory part.

Chapter 2 is designed to review existing related work on retinal disease prediction by highlights authors work, analysis, suggestion, approaches, limitations, results, methods and so on. The scope of the problem and Research scope and challenges are also discussed.

In Chapter 3, research work methodology is discussed with proper diagram and description. This chapter highlights the data collection & its procedure, data description, instruments details, statistical analysis, model workflow, sampling and implementation requirement,

In Chapter 4, experimental results of this research is shown by using tabular format for better understanding. This chapter provides the analysis of different performance accuracy as well.

In Chapter 5, discuss how the work can impact in our society and world. Why it is essential and how it will sustain in this arena.

In Chapter 6, there is a discussion and conclusion of the retinal abnormality detection research work with a valuable summary. It is also focused on future work and scope of the area along with the limitations.

CHAPTER 2

BACKGROUND

2.1 Introduction

Retinal diseases are responsible for partial or complete vision impairment. Numerous equally significant causes of vision impairment must be addressed, including age-related macular degeneration and Glaucoma [24]. Bangladesh is one of the 7 countries of the IDF SEA region. 537 million people have diabetes in the world and 90 million people in the SEA Region; by 2045 this will rise to 151.5 million [4]. World faces difficulties in terms of eye care, including treatment, quality of prevention, vision rehabilitation services, and scarcity of trained eye care experts. But specially Bangladesh is suffering the problem due to diabetics' retinopathy syndrome.

Early detection and diagnosis of ocular pathologies would enable forestall of visual impairment. To enable development of deep learning model for automatic retinal disease classification along with the rare pathologies. Figure 2.1.1 and Figure 2.1.2 indicated the normal retinal condition and effected retinal condition accordingly.

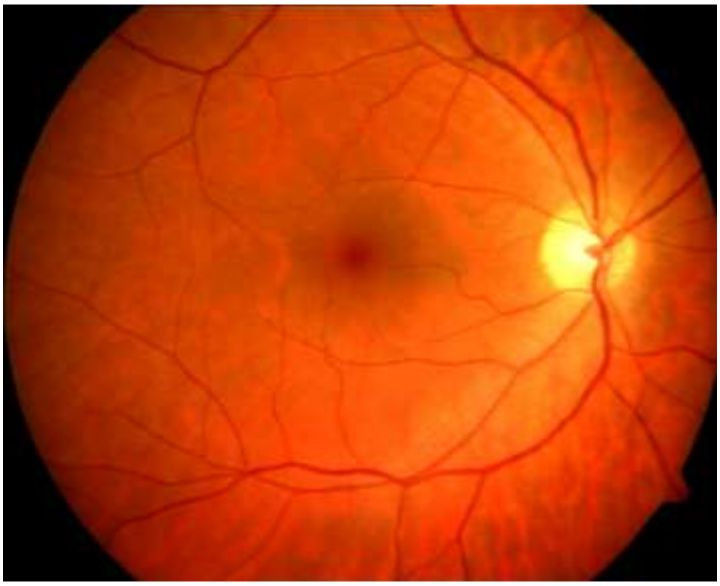

Figure: 2.1.1: Normal condition of human retina

The abnormality of retinal disease due to several problem for presence of several retinal problems like: diabetic retinopathy, media haze, myopia, branch retinal vein occlusion and tessellation etc.

Figure 2.1.2: Abnormality of retinal image due to the presence of age-related macular degeneration

This dataset has high resulation image of retinal condition with 46 medical conditions. Deep learning models are used to build effective model for eye problem identification for preventing blurry problem in early stage.

2.2 Related Works

Many researches contributes in the domain of the retinal diseases but most of them is curtailed to the major few diseases of the problem of eye. RFMiD is important data source at the present time with large scale of class label that provides 45 different diseases. There is a limited literature available using the multi-labeled fundus disease RFMiD dataset [5], specially diabetes retinopathy vs healthy condition of eye image. Initially the dataset was available on a Grand Challenge as a Retinal Image Analysis for multi-Disease Detection (RIADD). First 27 classes are the main classes with more images while the rest 18 minor classes are labeled as "OTHER". The challenge and individual paper do not test the OTHER 18 classes as it contains very few images per disease making it difficult to include in the model (RIADD (ISBI-2021) - Grand Challenge, n.d.). Also there is a huge data imbalance where normal or health image and diabetes Retinopathy have the same amount pf samples approximately. Work of Muller et al. ¨ (2021) [6], has implemented extensive strategies for the development models for disease classification. He used ResNet152, InceptionV3, DenseNet201 and EfficientNetB4 with cross validation and ensemble. After the high model complexity they were able to achieve an AUC from 0.93- 0.97. Another similar work by (Dabholkar et al.)[7], used multiple deep learning architectures such as ResNet152, InceptionV3, DenseNet201, and EfficientNetB4 with AUC from 0.92-0.97 (Dabholkar, 2021). E. Sudheer Kumar used three networks, Densenet201, EfficientNetB4 and ResNet150 for 28 classes. Their model was able to achieve AUC scores to 0.97. They tested the model on the ODIR dataset Kumar and Bindu (2021)[8]. Oh and Park [9] participated in the RIADD challenge, worked on the 1920 training and 620 test cases. They got a multi disease average score of 0.78 with efficientNet-b0, b1 and b2. Work by Wang et al. [10] used multiple disease learning to diagnose 36 diseases. They did this by collecting and relabeling a total of 200,817 images. From the total 17,385 images had more than one label, making it a multi-label problem. They used Inception-ResNet-v2 as the backbone network for the classification task of retinal diseases. Work of A. Nawaz (2017) use CNN using 32 class labels of retinal image with 95% accuracy [11]. All works in literature are unique and have used different techniques towards getting better results in diagnosis of retinal diseases but all other works are very complex in terms of computation which is difficult to use in real-life scenarios [12]. The thesis research work is focused on simplicity with more accurate, more efficient and less complex model methods with the addition of real-life application. Also, diabetics retinopathy can be found out with classification techniques specially for our country.

J. Anitha et al. introduces an automated classification system for eye diseases using a Back Propagation Neural Network (BPN), trained on a dataset of 205 digital fundus images from Aravind Eye Hospital, encompassing conditions like Non-Proliferative Diabetic Retinopathy, Central Retinal Vein Occlusion, Choroidal Neo-Vascularisation Membrane, and Central Serous Retinopathy. The approach entails preprocessing images for contrast enhancement, extracting relevant features, and utilizing these features for disease classification through the neural network. The BPN model demonstrated high effectiveness, achieving a classification accuracy of 92%, sensitivity of 84%, and specificity of 97.33%, surpassing the performance of a minimum distance classifier. Despite its success, the study recognizes potential limitations related to the dependency on feature selection and parameter settings, hinting at opportunities for further improvement through the exploration of additional features and fine-tuning of network parameters, thereby underlining the significant promise of neural computing in advancing the early and accurate diagnosis of retinal diseases [13].

R. Saha et. al. proposes a computer-aided diagnosis system for identifying lesions associated with non-proliferative diabetic retinopathy (NPDR) and dry age-related macular degeneration (AMD) from fundus images. The system employs image processing techniques, including Gaussian filtering and multilevel thresholding, to segment candidate lesions which are then classified using machine learning models such as single-layer perceptron, support vector machine (SVM), and Naïve Bayes classifiers. The dataset comprises images from the DIARETDB0 and DIARETDB1 databases, along with 25 dry AMD images from a city eye hospital, forming a composite database for experimentation. The methodology focuses on preprocessing, lesion extraction, and classification. The classification accuracy of the SVM for dark lesions reached 97.13%, while the single-layer perceptron achieved 95.13% accuracy for bright lesions with an optimal feature set. Despite the high accuracy rates, the study acknowledges limitations, such as the potential for over-segmentation and challenges in dealing with images with uneven illumination or significant variability in lesion appearances, indicating areas for future improvement [14].

S. Giraddi et. al. proposes a computationally efficient method for the classification of retinal images into diseased or healthy categories, focusing on diabetic retinopathy detection. Utilizing the Diaretdb0 and Diaretdb1 databases, which consist of high-quality medical images, the authors employ Haar wavelet transformation for feature extraction from RGB components of retinal images, followed by the application of first-order statistical features from the detailed coefficients obtained. The study compares the performance of Decision Tree and K-Nearest Neighbors (KNN) classifiers, achieving encouraging results with a classification accuracy of 85% using the KNN classifier and 75% with the Decision Tree classifier. This method offers a quick and less resource-intensive alternative to conventional segmentation and classification techniques, presenting a significant contribution to the development of automated systems for diabetic retinopathy detection. However, the study acknowledges the potential for improvement in classification accuracy, suggesting further research to enhance the robustness and reliability of the proposed system [15].

A. Nawaz et. al. introduces a deep convolutional neural network (CNN) tailored for the efficient classification of 32 distinct retinal diseases, utilizing the comprehensive EyeNet dataset for evaluation. This research stands out for its focus on optimizing memory usage within the CNN model, making it particularly relevant for medical image analysis where diverse conditions must be identified with high accuracy. The methodology encompasses image preprocessing, feature extraction, and classification, enhanced by data augmentation and the Adam optimizer to achieve a notable classification accuracy of 95%. This performance not only surpasses many existing models in accuracy but also in computational efficiency, addressing a critical challenge in the clinical application of deep learning technologies. Despite its success, the paper acknowledges the necessity for ongoing research to further harness deep learning's capabilities in medical diagnostics, hinting at future work aimed at refining model performance and broadening its applicability across different medical imaging modalities [16].

M. A. Rodríguez, et. al. proposes a novel approach for the simultaneous detection of multiple retinal diseases using fundus images. The research introduces the MuReD dataset, a new multi-label retinal disease dataset assembled from various publicly available sources, processed with a series of post-processing steps to enhance image quality and disease representation. This study is pioneering in applying a transformer-based model for fundus image analysis in multi-label disease classification, demonstrating significant improvements over existing methods with a 7.9% and 8.1% increase in AUC score for disease detection and classification, respectively. The transformer model, optimized through comprehensive experimentation, showcases the potential of transformer architectures in medical imaging, particularly for tasks requiring analysis across multiple conditions. Despite its achievements, the study acknowledges challenges like class imbalance and the need for extensive data to train such sophisticated models, pointing towards future research directions for further enhancing model performance and adaptability in medical imaging tasks [17].

H. S. Alghamdi et. al. introduces a novel end-to-end supervised deep learning model for detecting optic disc (OD) abnormalities in retinal images, a crucial indicator for diseases such as glaucoma, diabetic retinopathy, and retinal vein occlusion. The proposed model leverages convolutional neural networks (CNNs) to learn discriminative features directly from retinal images without relying on pre-defined rules or assumptions, addressing the limitations of traditional rule-based and intensity-based methods. The model comprises two successive deep learning architectures: one for efficient OD localization using cascade classifiers integrated with CNNs, and another for learning abnormality feature representations. The model was evaluated on a variety of datasets, including DRIVE, STARE, DIARETDB1, MESSIDOR, and others, showing promising results in terms of fast OD localization and high sensitivity in detecting abnormalities. The approach's ability to generalize well to previously unseen data highlights the potential of deep learning models in automated fundus image analysis, offering a fast, accurate, and scalable solution for large-scale screening programs and epidemiological studies [18].

V. Raman et. al. focuses on developing a computer-aided detection (CAD) system for diagnosing diabetic retinopathy by leveraging machine learning techniques. The paper outlines the challenge of accurately extracting exudates and micro-aneurysms, which are crucial for detecting and classifying diabetic retinopathy, due to their similarity in color and size to the optic disc and proximity to blood vessels. The authors aim to enhance image quality, filter noise, detect blood vessels, identify the optic disc, and extract relevant features to classify diabetic retinopathy into various stages including mild, moderate, severe non-proliferative diabetic retinopathy (NPDR), and proliferative diabetic retinopathy (PDR) using proposed machine learning methods. The expected outcome of this research is a preliminary design and a pilot prototype that improves the accuracy of detection and classification across different datasets, addressing the limitations of existing approaches [19].

R. Murugan, et. al. presents a deep convolutional neural network (CNN) based method for detecting retinal abnormalities, particularly diabetic retinopathy, using retinal fundus images. The study leverages deep learning to automatically learn features indicative of abnormalities, eliminating the need for manual feature extraction. The methodology includes using a deep CNN classifier to predict the presence of diseases in retinal images after learning from a training set that includes features of abnormalities present in the retinal images. The proposed method was implemented in MATLAB and evaluated using normal and abnormal diabetic retinopathy images from the IDRID, ROC, and local datasets, achieving high performance metrics such as a sensitivity of 98.2%, specificity of 98.45%, accuracy of 98.56%, and an average area under the receiver operating characteristic curve of 0.9. These results outperform several existing methods, demonstrating the efficacy of the proposed deep learning approach in the automatic detection of retinal abnormalities [20].

V. Sathananthavathi, et. al. presents a methodology for detecting microaneurysms and hemorrhages in retinal fundus images, crucial for grading diabetic retinopathy levels. The proposed approach utilizes dynamic shape features alongside an SVM classifier to differentiate between lesions and non-lesions. The process begins with candidate detection through pixel classification, separating vasculature and potential red lesions, followed by the training of an SVM classifier with these detected candidates. The method was tested on the Diaretdb1 and STARE databases, demonstrating an accuracy of 90% and 80% respectively. This study underscores the importance of accurate lesion detection in automated diabetic retinopathy grading systems, offering a significant step forward in the development of automated telemedicine solutions for diabetic retinopathy screening [21].

O. S. Khan et. al. outlines a novel approach for classifying multiple retinal diseases using an ensemble of deep learning models, specifically EfficientNetB4 and EfficientNetV2S. This research leverages the RFMiD dataset, one of the first to offer a broad range of 45 ophthalmic disease classes, to develop a Multi Retinal Disease Classification Model (MRDCM) aimed at achieving higher accuracy than previous methods. The methodology includes preprocessing, data augmentation, and the application of ensemble and transfer learning techniques to create a model capable of identifying 27 main disease classes from the dataset. The ensemble model demonstrated promising results, achieving an Area Under the Curve (AUC) score of 0.973, surpassing existing literature and providing a lighter, more efficient model architecture suitable for clinical decision support systems. This work highlights the potential of combining deep learning and ensemble learning for multi-disease classification in retinal images, contributing significantly to the advancement of automated diagnostic tools in ophthalmology [22].

S. A. Thomas and G. Titus focuses on developing an automated system for detecting retinal diseases using a novel, low-cost, portable retinal fundus camera compatible with smartphones and an advanced convolutional neural network (CNN) algorithm. The system is designed to automatically detect and classify retinal diseases such as Diabetic Retinopathy (DR) and Age-related Macular Degeneration (AMD), including their severity levels, aiming to enhance accessibility and efficiency in rural and under-resourced areas. The study evaluated the system using images from various databases and real-time samples captured with the developed camera, achieving high performance metrics with an accuracy of 95.83%, sensitivity of 0.93, and specificity of 0.97. The proposed solution addresses the need for affordable, efficient, and accessible retinal screening tools, potentially reducing the risk of blindness through early detection. However, the system currently focuses on two retinal disorders, and expanding its capabilities will require additional computational resources due to the need for retraining the model for new diseases or severity stages [23].

T. Yamuna and S. Maheswari presents a method for identifying and classifying diabetic retinopathy-related abnormalities in retinal images, emphasizing microaneurysms. Utilizing preprocessing techniques such as illumination equalization and contrast-limited adaptive histogram equalization, the approach aims to enhance image quality for more accurate abnormality detection. Morphological operations are employed for candidate extraction, focusing on features like area, mean, standard deviation, and entropy. The classification of abnormalities into categories like normal, mild, and severe is achieved using the Adaptive Neuro-Fuzzy Inference System (ANFIS), leveraging its ability to handle the fuzzy nature of medical images. The methodology demonstrates a structured approach to automate the screening process for diabetic retinopathy, potentially aiding early diagnosis and treatment to prevent vision loss. The paper underscores the significance of advanced image processing and machine learning techniques in medical diagnostics, particularly in ophthalmology [24].

2.3 Comparative Analysis

Comparative analysis of the literature review is presented in Table 1.

Table 1: Comparative analysis of the existing literature reviews

Author	**Model**	**Dataset**	**Accuracy**	**Limitation**
J. Anitha et al.	Back Propagation Neural Network (BPN)	205 images from Aravind Eye Hospital	92%	Dependency on feature selection and parameter settings
R. Saha et al.	SVM, Single-layer perceptron, Naïve Bayes	DIARETDB0, DIARETDB1, 25 dry AMD images	SVM: 97.13%, Perceptron: 95.13%	Over-segmentation, uneven illumination, variability in lesion appearances
S. Giraddi et al.	Decision Tree, KNN	Diaretdb0 and Diaretdb1	KNN: 85%, Decision Tree: 75%	Improvement in classification accuracy
A. Nawaz et al.	Deep CNN	EyeNet dataset	95%	Enhancing model performance and adaptability
M. A. Rodríguez et al.	Transformer-based model	MuReD dataset	7.9% and 8.1% increase in AUC score	Class imbalance, extensive data requirement
H. S. Alghamdi et al.	CNNs	DRIVE, STARE, DIARETDB1, MESSIDOR, etc.	High sensitivity and specificity	Generalization to unseen data
V. Raman et al.	Machine Learning Approaches	Not specified	Not specified	Detection and classification accuracy across datasets
R. Murugan et al.	Deep CNN	IDRID, ROC, local datasets	Sensitivity: 98.2%, Specificity: 98.45%	Not specified
V. Sathananthavathi et al.	SVM with dynamic shape features	Diaretdb1 and STARE	Diaretdb1: 90%, STARE: 80%	Not specified
O. S. Khan et al.	Ensemble of EfficientNetB4 and EfficientNetV2S	RFMiD dataset	AUC score of 0.973	Not specified

S. A. Thomas and G. Titus	CNN with portable retinal fundus camera	Various databases and real-time samples	95.83%	Focus on two disorders, need for retraining for new diseases
T. Yamuna and S. Maheswari	Adaptive Neuro-Fuzzy Inference System (ANFIS)	Not specified	Not specified	Not specified

2.4 Scope of the problem

This retinal model is used to identify eye health and disease of retina. The model is deals with balanced dataset to overcome overfit problem. I also try to focus on diabetes related eye disease called diabetics retinography because based on data from the latest BDHS 2017–18, over one-quarter of individuals aged 18 years and older had diabetes or prediabetes in Bangladesh, representing more than 19 million individuals in 2020 [13]. This can be used to identify retinal abnormality caused by diabetes retinopathy (DR) with 88% accuracy, retinal multilabel disease classification with 97.5% accuracy with less complexity. Two sperate models can be generated by this project work for medical contribution.

2.5 Challenges

Using the deep learning model that it is developed; our goal is to obtain the maximum possible degree of accuracy and precision. It will be more helpful and useful for the domain people to identify eye diseases with less confusion. At first, we require high space GPU to run and evaluate the work smoothly. Secondly we face class imbalance of the dataset. Then a large number of dataset in every class label or disease with a high-quality resulation image for greater acceptance. The fact that our data is collected from mdpi.com website where it has 45 categories disease but maximum has vary few number of images. For that reason, model may be biased and also overfitting problem may occur. So, we have to increase the data contribution and collection of that particular class labels. But our model successfully adopts the challenges and give better results comparing previous work.

CHAPTER 3

RESEARCH METHODOLOGY

3.1 Introduction

In this chapter, we will discuss research methods, tools and techniques to implement the project related thesis work. In this section, data description, its statistical analysis, proposed methodology and model workflow are discussed. Visualization using matplotlib plays a important for visualize the data nature. We use python libraries to analysis and evaluate the data using different models.

3.2 Research Subject and Instrumentation

This research is tried to find out more reliable and suitable approach to detect retinal abnormality using REMiD dataset. We split the whole dataset into train, test, and validation set to overcome overfit problem. But the difficulties arise when we analysis dataset and found the class imbalance and duplication of sample image. Our image is in high resolution but the number of image is not enough satisfactory of each class label. There are several transfer network but the challenge arise in the question of high resolution giant size dataset with few sample in particular labels. To deal with the problem we use under sampling to cope up with data class imbalance. We also try to give a comparative analysis between different models with high accuracy. In further work, comparative analysis between different activation function will be evaluate for more comparison. In the research we use advanced deep learning model EfficientNetB0, ResNet152, VGG16, DenseNet 169 to show comparative analysis to pick a model which can get better result in this type of work. Ensemble approaches are used here to improve results.

3.3 Data Description

By addressing the limitation of medical data availability in publicly, a custom dataset of multilabel retinal eye disease dataset [14]. The purpose of that dataset mentioned by M.A. Rodriguez [15]:

- Large number of eye disease sample for significant analysis
- A certain degree of quality in the images contained in the dataset.

This dataset is constructed using some of the publicly available datasets, with wide variety of disease. This dataset labeling is in CSV file. It consists of 3200 fundus images captured using three different fundus cameras with 46 conditions annotated through adjudicated consensus of two senior retinal experts[5] [15]. The column name are arranged alphabetic later according are shown a sample in Table 2:

TABLE 2: Sample of column name based on different disease class label of original REMiD dataset of first 9 columns

Disease Name	**Column_Name**
ID: Image Identity Number	A.
Disease Risk: Presence of disease/ abnormality	B.
DR: Diabetes Retinopathy	C.
ARMD: Age-Related Macular Degeneration	D.
MH: Media Haze	E.
DN: Drusen	F.
MYA: Myopia	G.
BRVO: Branch Retinal Vein Occlusion	H.
TSLN: Tessellation	I.

A visual representation of the information that can be found in the CSV file is presented in table 2, with an explanation provided for each column as follows:

Table 2: Sample Csv File of the Dataset

	A	B	C	D	E	F	G	H	I	J	AU
1	ID	Disease_Risk	DR	ARMD	MH	DN	MYA	BRVO	TSLN	....	CL
2	1	1	1	1	0	0	1	0	0		0
3	2	1	0	0	0	0	0	1	0		0
4	3	1	1	0	1	1	0	0	1		0
5	4	1	0	0	0	0	0	0	0		1
6	5	0	0	0	0	0	0	0	0		0

The dataset is divided into three subsets: the training set, which contains 1920 photos, the evaluation set, which contains 640 images, and the test set, which contains 640 images. In the training, assessment, and test sets, the average disease-wise stratification is 60 ± 7%, 20 ± 7%, and 20 ± 5%, respectively. This is consistent across all three sets. The primary objective of this dataset is to consist of a variety of disorders that are encountered in the course of ordinary clinical practice. The labels are provided in three CSV files $RFMiD\_Training\_Labels.CSV$, $RFMiD\_Validation\_Labels.CSV$, and $RFMiD\_Testing\_Labels.CSV$.

Data description based on class label and its amount. Here 1 indicates the 'presence' and 0 indicates 'not presence'. Disease Risk indicates which image has abnormality and which does not. The description of the diseases sample are given below:

```
Disease_Risk
1    1519
0     401
Name: Disease_Risk, dtype: int64
----------------
DR
0    1544
1     376
Name: DR, dtype: int64
----------------
ARMD
0    1820
1     100
Name: ARMD, dtype: int64
----------------
MH
0    1603
1     317
Name: MH, dtype: int64
----------------
DN
----------------
LS
0    1873
1      47
Name: LS, dtype: int64
----------------
MS
0    1905
1      15
Name: MS, dtype: int64
----------------
CSR
0    1883
1      37
Name: CSR, dtype: int64
----------------
ODC
0    1638
1     282
Name: ODC, dtype: int64
----------------
CRVO
0    1892
1      28
Name: CRVO, dtype: int64
----------------
TV
0    1914
1       6
Name: TV, dtype: int64
----------------
```

```
------------------
PT
0    1909
1      11
Name: PT, dtype: int64
----------------
RT
0    1906
1      14
Name: RT, dtype: int64
----------------
RS
0    1877
1      43
Name: RS, dtype: int64
----------------
CRS
0    1888
1      32
Name: CRS, dtype: int64
----------------
EDN
0    1905
1      15
Name: EDN, dtype: int64
----------------
RPEC
0    1898
1      22
Name: RPEC, dtype: int64
----------------
MHL
0    1909
1      11
Name: MHL, dtype: int64
----------------
RP
0    1914
1       6
Name: RP, dtype: int64
----------------
CWS
0    1917
1       3
Name: CWS, dtype: int64
----------------
CB
0    1919
1       1
Name: CB, dtype: int64
----------------
ODPM
0    1920
Name: ODPM, dtype: int64
----------------
PRH
0    1918
```

```
AH
0    1904
1      16
Name: AH, dtype: int64
----------------
ODP
0    1855
1      65
Name: ODP, dtype: int64
----------------
ODE
0    1862
1      58
Name: ODE, dtype: int64
----------------
ST
0    1915
1       5
Name: ST, dtype: int64
----------------
AION
0    1903
1      17
Name: AION, dtype: int64
----------------
----------------
```

```
0    1782
1     138
Name: DN, dtype: int64
----------------
MYA
0    1819
1     101
Name: MYA, dtype: int64
----------------
BRVO
0    1847
1      73
Name: BRVO, dtype: int64
----------------
TSLN
0    1734
1     186
Name: TSLN, dtype: int64
----------------
ERM
0    1906
1      14
```

```
MNF
0    1917
1       3
Name: MNF, dtype: int64
----------------
HR
0    1920
Name: HR, dtype: int64
----------------
CRAO
0    1918
1       2
Name: CRAO, dtype: int64
----------------
TD
0    1917
1       3
Name: TD, dtype: int64
----------------
CME
0    1916
1       4
Name: CME, dtype: int64
----------------
PTCR
0    1915
1       5
Name: PTCR, dtype: int64
----------------
CF
0    1917
1       3
Name: CF, dtype: int64
```

```
BRAO
0    1918
1       2
Name: BRAO, dtype: int64
----------------
PLQ
0    1919
1       1
Name: PLQ, dtype: int64
----------------
HPED
0    1919
1       1
Name: HPED, dtype: int64
----------------
CL
0    1919
1       1
Name: CL, dtype: int64
----------------
2069
```

```
----------------
VH
0    1919
1       1
Name: VH, dtype: int64
----------------
MCA
0    1919
1       1
Name: MCA, dtype: int64
----------------
VS
0    1919
1       1
Name: VS, dtype: int64
----------------
```

There are 45 distinct categories that are used to classify retinal pictures.

3.4 Statistical Analysis

As mentioned earlier our dataset is divided into three parts and distribution of the data in each part is shown in Table 3.

Table 3: Distribution of the datasets

Dataset	Number of Data	Percentage
Training Dataset	1920	60%
Validation Dataset	640	20%
Test Dataset	640	20%

The table outlines the division of a dataset for a machine learning project, segregating the data into training, validation, and test subsets. The training data comprises 1,920 entries, accounting for 60% of the overall dataset, and is pivotal in the initial phase where the model learns and adapts to recognize patterns or features specific to the given task. This substantial portion ensures that the model has a diverse and ample range of examples to learn from, which is crucial for the development of accurate and robust predictive capabilities.

In contrast, the validation and test data, each consisting of 640 entries and representing 20% of the total dataset, serve distinct yet complementary roles in the model development lifecycle. The validation data is utilized during the model's training phase to fine-tune its parameters and to prevent overfitting, ensuring the model's ability to generalize well to new, unseen data. Upon completion of the training and validation phases, the test data is employed as a final, unbiased benchmark to assess the model's performance. This rigorous approach, dividing the dataset into specific subsets, underpins the model's ability to make reliable and accurate predictions, reflecting its applicability to real-world scenarios.

3.5 Proposed Methodology

Deep Learning technology is inspired by the deep structure of the human brain [16]. CNN is the most potent and effective DL model [17]. CNN is mostly used in the medical industry, although researchers have expanded its applicability to other disciplines [18]. We used CNN advanced transfer model – Vgg16, Inception V3, RestNet, EffectiveNetB0.

With the use of the CNN based pre-trained model designed for multi label image classification using EfficientNetB0, ResNet152, VGG16, DenseNet 169. Those model are known as advanced Deep learning model with hidden layers that can learn model datset based on pattern and predict its probability. The Convolutional Neural network CNN model works with Convolution + MaxPooling layers act as feature extractors from the input image while a fully connected layer acts as a classifier. In the above image figure, on receiving an image as input, the network will assign assigns the highest probability for it and predict which class the input image belongs to [25].

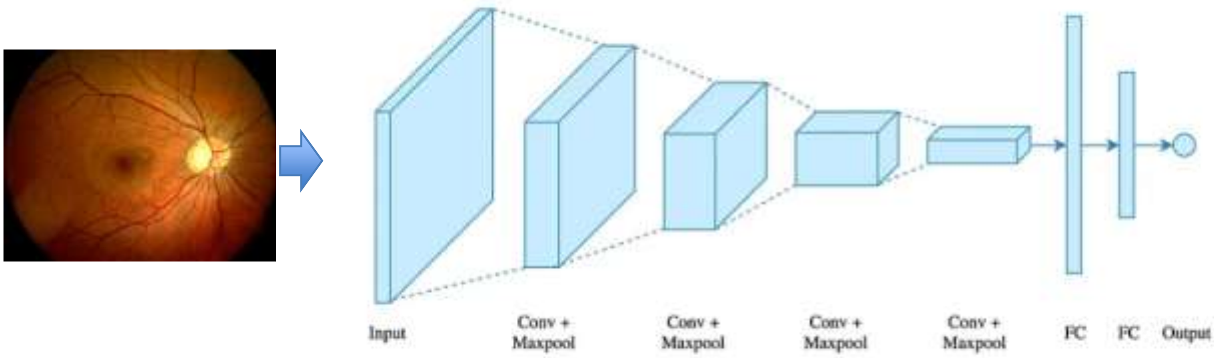

Figure 3.5.1: A simple CNN model used for image classification

Within the model dense layer, that is connected with multi dimensional convolution layer, there was a flat layer that served as a bridge between the them. Rectified linear units (ReLU) are employed as a functional enabler in this approach. Sigmoid, presented as an activation in framework for making predictions based on maximum likelihoods, is one such method. The following is the equation for the SoftMax function:

$$F(x) = \frac{1}{1+e\,^\wedge(-x)} \qquad (1)$$

Here, F(x) sigmoid function, e is eular’s number.

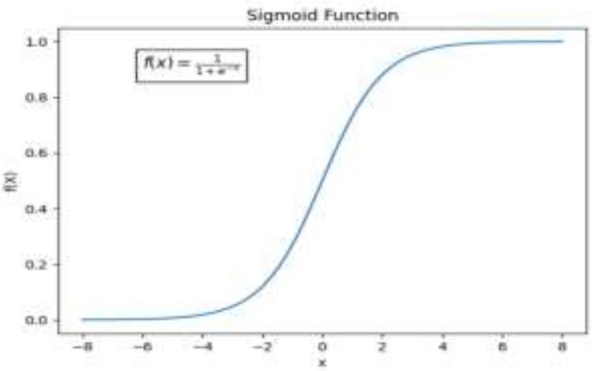

Figure: 3.5.2 Sigmoid function Curve

RMSProp root mean squared propagation is the optimize techniques of machine learning algorithm to train the Neural Network by using different adaptive learning rate. In addition, Adam (Adaptive Moment Estimation) Optimizer which is an iterative optimization algorithm used to minimize the loss function during the training of neural networks. Different analysis will the shown in chapter 04. The Adam optimizer employs a hybrid of two gradient descent methods – modentum, RMSP.

Mathematical equation based on those two methods of Adam Optimizer:

$$m_t = \beta m_{t-1} + (1-\beta)\left[\frac{\delta L}{\delta w_t}\right] v_t = \beta_2 v_{t-1} + (1-\beta_2) * \left[\frac{\delta L}{\delta w_t}\right]^2 \qquad (2)$$

Where, β = Moving average parameter (const, 0.9)

t = time ∂L = Derivative of Loss Function

∂Wt = Derivative of weights at time t

β_1 & β_2 = decay rates of average of gradients in the above two methods. (β_1 = 0.9 & β_2 = 0.999)

3.6 Proposed Model Workflow:

First, we load the dataset and map csv file with our images to label the data. We analysis the images. Figure 3.6 visually represents the working flow of the research work. Due to our one of the goal was to build a model with simplicity and high accuracy we use data augmentation for rescale, rotation, crop and enhance brightness. Then block5_pool, activation function of Relu, sigmoid are used in the dataset withn learning rate 0.0001 with binary cross entropy as loss function. Then apply VGG16, Inception V3, RestNet is used in the datset to predict multi label classification with RMSProp obtimizer. Beside this, adam optimizer is used in the dataset with EfficientNetB0, VGG16, RestNet model with mainly focused on multilabel specially DR, and MH to avoid over imbalance problem to see the variation. At first case, model has overfitting problem and in second case model does not behave without anomalies.

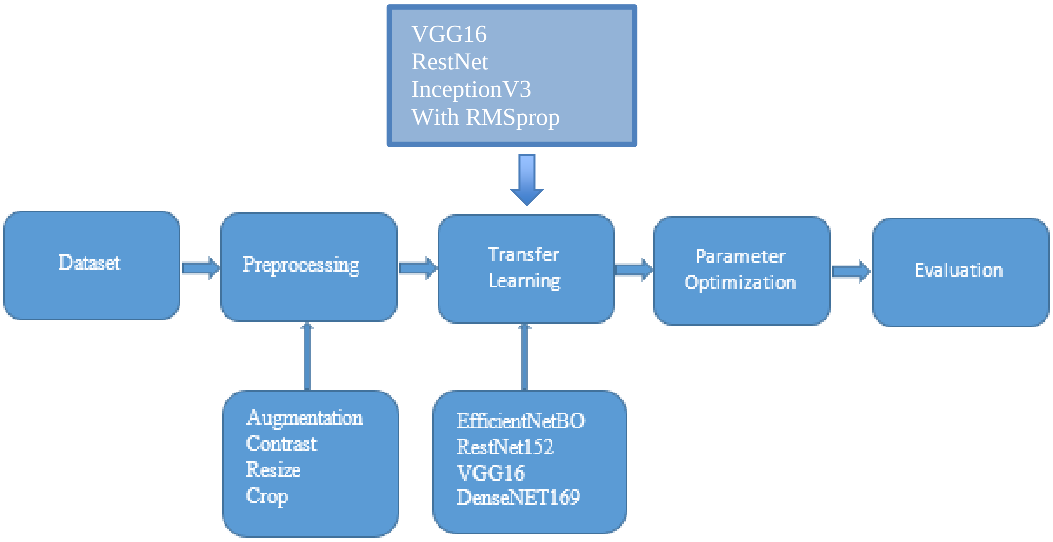

Figure 3.6.1: Proposed Methodology workflow

3.7 Neural Network Used in model

VGG16:

VGG16, or Visual Geometry Group 16, is a renowned convolutional neural network (CNN) architecture designed for image classification. Developed by the Visual Geometry Group at the University of Oxford, VGG16 gained popularity for its simplicity and effectiveness. The model consists of 16 layers, including 13 convolutional layers and 3 fully connected layers.

VGG16 is characterized by the consistent use of small-sized convolutional filters (3x3) throughout the architecture, promoting a deeper understanding of complex visual features. The model's structure and simplicity make it easy to understand and implement, serving as a reference in the field of deep learning.

EfficientNet

EfficientNet represents a family of convolutional neural network (CNN) architectures that focus on achieving optimal performance and efficiency by intelligently scaling model parameters..

The architecture is composed of efficient building blocks, such as Mobile Inverted Bottleneck Convolution (MBConv), which incorporates depth wise separable convolutions. This design choice enhances model efficiency by reducing the number of parameters and computational complexity.

RestNet

ResNet, short for Residual Networks, revolutionized deep learning by introducing a novel architecture to address the challenges of training very deep neural networks.

The key idea in ResNet is the residual block, where the output of a layer is combined with the input through a shortcut connection, bypassing one or more layers. ResNet architectures typically consist of multiple residual blocks organized into stages, with skip connections facilitating gradient flow. This design has become a cornerstone in various computer vision tasks, offering state-of-the-art performance in image classification, object detection, and segmentation. The simplicity and effectiveness of ResNet have influenced subsequent deep learning architectures, solidifying its impact on the field.

DenseNet

DenseNet, short for Densely Connected Convolutional Networks, is a groundbreaking neural network architecture designed to address information flow and feature reuse challenges in deep networks.

DenseNet architecture is composed of dense blocks interspersed with transition layers to control model complexity. Transition layers include batch normalization, 1x1 convolution for dimensionality reduction, and average pooling. DenseNet has shown superior performance on image classification tasks, achieving state-of-the-art results with reduced parameters compared to traditional architectures, making it a prominent choice in deep learning for computer vision.

Inception V6

As of my last knowledge update in January 2022, there is no widely recognized "Inception V6" architecture known. The Inception architecture, also known as GoogLeNet, was introduced by Google in 2014 and has undergone subsequent improvements, but there isn't a specific "Inception V6" that has gained widespread prominence.

The Inception architecture is characterized by the use of inception modules, which incorporate multiple convolutional filter sizes in parallel to capture features at different scales efficiently. This design aims to balance model expressiveness and computational efficiency.

3.8 Implementation Requirements

In this section, a short list of project requirements to implemented the work.

Hardware or Software Requirements

- Windows 10 or above operating system
- Portable or in-built Hard Disk above 300 GB
- Minimum 4 GB RAM
- Google Chrome or Mozilla Firefox
- GPU 20 GB

Developing Tools

- Python with Tensor flow, Keras
- Jupiter / Google Colab with subscription
- Notepad++

CHAPTER 4

EXPERIMENTAL RESULTS AND DISCUSSION

4.1 Introduction

Generally, the descriptive analysis of this image data utilization align with the effect of experimental results which is the primary goal of chapter 04. It is more important to select appropriate method to build a suitable model. Playing with data can retrieve hidden behavior of data which gives us new knowledge and scopes. In this section, experimental results are shown and discussed with models output.

4.2 Experimental Results

The most challenging part to work on the dataset is GPU size. Computer without GPU or free subscription of colab can not work with this 5GB dataset. Also it should be mentioned that the data image has high resolution that increase data loading size. We use different techniques as mentioned in chapter 04. To work with this imbalance and heavy weighted dataset, we go through two different ways to build model and analysis performance. They are:

- Use all class label with class imbalance
- DR and MH class label vs normal health image with balanced data

Now, we highlight the differences between those scenario of the particular dataset. CNN models like VGG, RestNet are commonly used on the dataset.

With imbalance class label, we use RMSprop as optimizer and use ReLu activation functions and run the model. The results is shown in table 05.

TABEL 5: RESULT ANALYSIS OF MULTI-LABEL RETIGANL DISEASE ANALYSIS WITH CALSS IMBALANCE WITH 20 Epochs

Algorithm Name	Loss	Accuracy
RestNet	0.407	0.976
VGG16	0.431	0.976
InceptionV3	0.408	0.977

It is clear that, those models have different loss function but gives similar accuracy. On the other hand to overcome the data imbalance problem, we use those class label (DR) which has the approximate amount of samples with respect to healthy image.

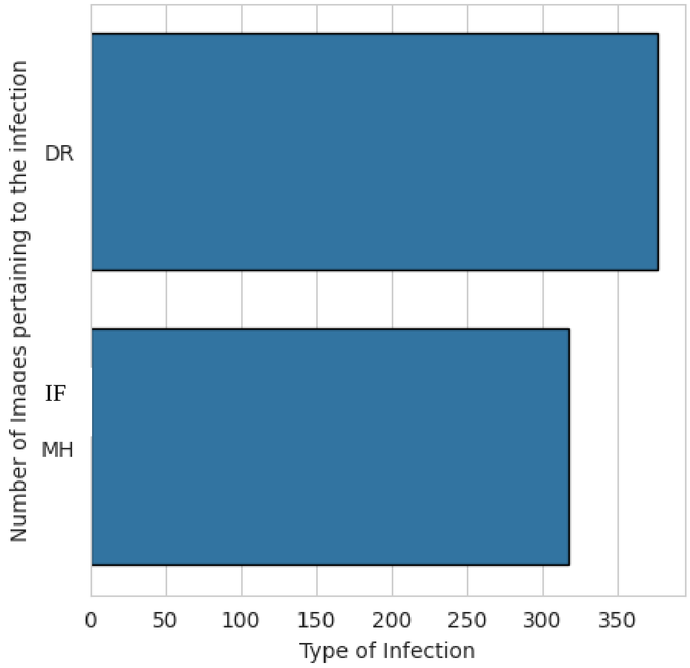

Figure 4.2.1: Class label distribution of the original dataset

In this distribution we are going to binary classification to break down the process to find sustainable model. By using various net model, we get the result Table 05 where infected image is DR image and not infected is normal image. Here, f1 score and accuracy both are same. F1 measure the accuracy of model evaluation in table 06

TABLE 06: MODEL EVALUATION BASED ON BALANCED CLASS WITH WEIGHTED AVG

Algorithm	F1 score	Precision	Recall
EfficientNetB0	0.90	0.90	0.90
ResNet152	0.88	0.87	0.87
VGG16	0.89	0.90	0.89
DenseNet 169	0.90	0.89	0.90

4.3 Discussion

In the mentions result evaluation we can found the maximum 90% accuracy with balanced data and 97% accuracy with highly imbalanced data. To evaluate model accuracy we use f1 score, recall, and precision to calculate accyuracy. F1 score directly indicates the model accuracy based on evaluating models. The model equation and the precision of the classification rate equation:

$$Accuracy = \frac{TP+TN}{TP+FP+TN+FN} \qquad (3)$$

Here, TP= True Positive, TN= True Negative, FN= False, Negative, FP= False Positive.

This research indicates that, the comparison between utilizing all class labels with class imbalance and focusing on a balanced subset, particularly for retinal disease analysis, reveals distinct model performances. While models trained on the imbalanced dataset demonstrate similar accuracies despite varying loss functions, addressing class imbalance by focusing on a balanced subset enhances model robustness, as evident from the higher F1 scores and balanced precision-recall trade-offs. This underscores the importance of handling class imbalance for reliable model performance in medical image analysis tasks.

CHAPTER 5

IMPACT ON SOCIETY, ENVIRONMENT, AND SUSTAINABILITY

5.1 Impact on Society

The development of deep learning model for retinal disease classification holds profound implications for society, revolutionizing the landscape of ophthalmic care and public health. By enabling early and accurate detection of conditions such as age-related macular degeneration, diabetic retinopathy, and glaucoma, these models facilitate timely intervention and treatment, preserving the precious gift of sight for millions worldwide. Through automation of diagnostic processes and integration into clinical workflows, deep learning-based classification systems streamline healthcare delivery, enhancing accessibility and efficiency in resource-limited settings while relieving the burden on healthcare providers. Furthermore, the personalized insights provided by these models support the delivery of precision medicine, optimizing treatment strategies and improving patient outcomes. Beyond clinical applications, the advancement of deep learning in retinal disease classification drives innovation in medical imaging technology and computational methodologies, fostering interdisciplinary collaboration and pushing the boundaries of scientific inquiry. Ultimately, the societal impact of this work extends far beyond the realms of healthcare, shaping the future of public health, research, and innovation for generations to come.

5.2 Impact on Environment

The adoption of deep learning for retinal disease classification presents an opportunity to mitigate the environmental impact of healthcare by optimizing resource utilization and reducing carbon emissions associated with traditional diagnostic methods. By enabling remote screening and diagnosis through telemedicine platforms, deep learning models minimize the need for patient travel to specialized healthcare facilities, thus decreasing transportation-related emissions. Additionally, the efficiency and scalability of deep learning algorithms contribute to streamlined workflow management and resource allocation within healthcare systems, reducing waste and energy consumption associated with inefficient practices. Overall, the integration of deep learning in retinal disease classification aligns with efforts to promote environmental sustainability in healthcare delivery.

5.3 Ethical Aspects

This thesis based research work respect user’s security & privacy in data collection via website repository with proper citation. No work is copied or does not harmful for any intellectual property. Proper citation is given in the reference sections including image (if any). All statistical data are collected from proper website with citations. The results that is provided is correct. There is no false inappropriate information regarding the work. No animals or humans are harmed during the research. All works are done under the guidance of the supervisor.

5.4 Sustainability Plan

We are concerned that identifying eye abnormality in early stage plays a vital role to have healthy eye with minor treatment. Also, this work helps people to get telemedicine from all over the world. Eye is the most important organ of our body. Blind people are suffering their lives in all works. This work helps patients and also physiologist to deal with blurry vision which is spread majorly all over the work. Specially in Bangladesh, due to diabetes people are getting blind later.

This research work will impact on medical sector, without a shadow of a doubt, endure for a present in this era of technology. In the future, we want to enhance the accuracy od diabetics eye retinopathy classification problem as well as the data range. We also try to collect enough number of images to reduce class imbalance for those shallow number of samples labels. Additionally, higher GPU system helps us for more analysis to find hidden information of the domain that will helps to build more sustainable model.

CHAPTER 6

CONCLUSION AND FUTURE WORK

6.1 Summary of the study

The work on utilizing deep learning techniques to classify retinal abnormalities represents a significant advancement in the field of ophthalmic diagnostics and healthcare. By leveraging convolutional neural networks (CNNs) transformer model network – EffecientNetB0, ResNet152, Vgg16, DenseNet169 with threshold tuning, the study aims to accurately categorize a wide range of retinal pathologies, including age-related macular degeneration, diabetic retinopathy, glaucoma, and retinopathy of prematurity, among others, from medical imaging data such as optical coherence tomography (OCT) scans and fundus photographs. Through rigorous model development and optimization, the research endeavors to address challenges inherent in traditional diagnostic methods, such as interobserver variability and resource-intensive manual interpretation. The integration of deep learning-based classification systems into clinical practice promises to enhance diagnostic accuracy, efficiency, and accessibility, ultimately leading to improved patient outcomes and reduced burden on healthcare systems. Additionally, the study contributes to the broader goal of advancing artificial intelligence in healthcare, paving the way for future innovations in medical image analysis and precision medicine.

6.2 Conclusions

The ultimate goal of our study is to give contribution on medical sector using advanced deep learning techniques to improve disease identification in smart system. Leveraging a diverse array of convolutional neural networks transformer models such as EfficientNetB0, ResNet152, Vgg16, and DenseNet169, coupled with threshold tuning, has enabled accurate categorization of various retinal pathologies, including age-related macular degeneration, diabetic retinopathy, glaucoma, and retinopathy of prematurity, using optical coherence tomography (OCT) scans and fundus photographs. Using literature review, we found the advanced transfer learning methods on deep learning image classification accuracy with its pros and cons. Especially, we focus on retinal disease but it is also a comparative study between multi label and binary classification with balanced dataset sample of retinal abnormality. In binary classification the accuracy is low rather than multi label classification.

Relu is used in multi label classification. The aim of the work is to play a significate role in Bangladesh to give telemedicine in rural area with simple and high accuracy model of machine learning.

6.3 Implication for further study

For the thesis research, artificial intelligence model is generated by deep transfer learning models to deals with a giant size (5GB) of images and also provide better accuracy. Here, DR abnormalities, Macular hole problem is focused separately due to its huge range of patients in Bangladesh. In further, we have a plan to

- Enhance model dataset in lower amount of sample of particular dataset
- Enhance GPU capacity
- Find out the reason of almost same accuracy rate with different loss rate
- Compare with different fine tuning and activation function
- Generate binary classification models of individual diseases with large data
- Increase accuracy for binary classification
- Reduce resolution in convenient amount for overcome time waste

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