IDENTIFYING OF DIABETIC RETINOPATHY FROM FUNDUS IMAGE USING DEEP LEARNING

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FINAL YEAR DESIGN PROJECT REPORT

This Report Presented in Partial Fulfillment of the Requirements for the Degree of Bachelor of Science in Computer Science and Engineering

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APPROVAL

This Project titled "Identifying of Diabetic Retinopathy From Fundus Image Using Deep Learning", submitted by **F M ABIDUL ISLAM** 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 B.Sc. in Computer Science and Engineering and approved as to its style and contents. The presentation has been held on 16-07-2024.

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I hereby declare that this project has been done by me under the supervision of **Ms. Tania Khatun Assistant Professor Department of Computer Science and Engineering, Daffodil International University**. I also declare that neither this project nor any part of this project has been submitted elsewhere for the award of any degree or diploma.

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ABSTRACT

Diabetic retinopathy is one of the complications of diabetes that affects the retina of the eyes resulting to blindness if not diagnosed in time. This is initiated by the destruction of the blood vessels in the layer of light-sensitive tissue located at the back part of the eye (retina). Finally, in this study, a deep learning-based solution is developed to identify and classify diabetic retinopathy from the fundus images accurately. The dataset used includes 5,200 fundus images categorized into five classes: It can be categorized as having No DR, Mild, Moderate, Severe, and Proliferative DR. Five types of CNN models were used for the study: Xception, VGG19, InceptionV3, MobileNetV2, and a newly developed CNN architecture. Thus, after evaluating, our own designed CNN model, we got maximum accuracy of 90.63% as compared to other models such as MobileneV2 (80.01%) and InceptiomV3 (76.62%). Based on the findings of the paper, our approach can be used to successfully identify diabetic retinopathy, which will go a long way in assisting and arriving at early diagnosis and treatment to alleviate the consequences of the illness, including blindness among patients.

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CHAPTER 1
INTRODUCTION

1.1 Introduction

Diabetic retinopathy commonly presented as a complication of diabetes mellitus is one of the prominent causes of vision loss worldwide. Being ranked as the main cause of vision impairment among grown-ups, it is essential to diagnose the disease and start the necessary therapy on time to avoid blindness [1]. Prolonged hyperglycemia causes DR through changes to the retinal blood vessels; if left unattended, it compromises vision up to total blindness. There has been a great improvement in the new accomplished breakthrough in deep learning especially in convolutional neural networks (CNNs) in the automated medical image analysis especially in identification and classification of diabetic retinopathy from fundus images [2]. Fundus photography is done to take photographs of the retina showing features such as microaneurysms, hemorrhages, and neovascularization which represent DR severity levels. Therefore, the focus of this study is to use these technology innovations to establish and validate efficient deep learning algorithms for DR identification and categorization solely on fundus images [3]. The dataset used comprises 5,200 labeled images across five classes: No_DR and mild, moderate, severe, and proliferative diabetic retinopathy. Therefore, the objective of this research is to determine which of the several CNNs architectures including Xception, VGG19, Inception V3, MobileNetV2, and a new CNN are the most accurate and efficient for classifying DR. The implication of this research study is therefore quite far-reaching; the developed algorithm affords clinicians the potential of optimizing the screening process and improving the outreach of ophthalmic screening particularly in the developing world where such a expertise may not be broadly available [4]. Such models can enhance early detection that can be followed by timely intervention, decreasing chances of irreversible vision impairment and enhancing patients' quality of life with diabetic retinopathy.

1.2 Motivation

The objective justifications for this study directly stem from the present demands for better deep learning methods to diagnose diabetic retinopathy (DR). Diabetes is rapidly becoming a common health issue, and it causes vision impairment, therefore early diagnosis is useful in facilitating correct treatment. Besides, in order to discover and examine, which of the contemporary CNN architectures would be the most suitable for the DR classification from fundus images, the four current models, namely, Xception, VGG19, InceptionV3, and MobileNetV2, are compared. This research aims to acquire novel knowledge about DR technology and utilize technological developments to improve diagnostic precision, enable early interventions, and in turn, decrease the significantly devastating effects of DR on vision, as well as on the global diabetic patient population's quality of life.

1.3 Rational of the study

The justification for this study revolves around the difficulties experienced in the identification of indoor plants, which is essential in their management. Identification is critical so that plants are watered, placed in the right location regarding light requirement, and controlled for pests that can harm the plants. Documentary identification methods tend to be slow and inaccurate for most people who do not have the background knowledge of botany. As one of the concerned targets of this work, the efficiency and robustness of the chosen deep learning techniques will help this study design an effective method for the classification of indoor plants. With the help of this system, even those who have little experience in gardening or even the professionals could easily identify the plants and give them the right care they need. Also, the progress made with image classification, applied in deep learning allow for the development of high variability and complexity models of plant species. In conclusion, this research aims at improving indoor plant care, making successful gardening practices possible and improving the knowledge about plant species through technology.

1.4 Research Questions

1. CNN based approach works well in the classification of diabetic retinopathy from the fundus images, so which architecture of CNN is more effective.

2. This study seeks to find out how data augmented affects the performance of deep learning models in diabetic retinopathy classification.

3. This feature makes this query pertinent to answering the question: 'What is the best way of preprocessing the fundus images to feed into the CNN model?'

4. To what extent does the cardinality and nature of the training set affect the CNN model's classification performance on the Diabetic Retinopathy cases?

5. What are the drawbacks or failures of the CNN models in diagnosing diabetic retinopathy?

1.5 Expected Output

1. **A Trained Deep Learning Model**: It must have the ability to distinguish the retinopathy as seen in its high accurate parameter such as No_DR, Moderate, Mild, Proliferate_DR, and Severe, to enable it to work out many samples of diabetic retinopathy.

2. High Accuracy and Reliability: The intended model proposed in this study, should have the ability to distinguish between the species of cacti to a higher degree, as observed from all the testing and validation processes in case of; Accuracy, Precision, Recall, F1-Score.

3. User-Friendly Interface: The option that allows one to observe on the map the objects that were identified at the moment when the test is being taken, as well as the information determined by the species of the identified objects and the degree of confidence regarding the offered predictions.

4. Enhanced Efficiency: Flexibility in managing the configuration of diabetic retinopathy which help in minimizing the amount of time to be spent, and instances of human mistake that are common when using other standard instruments.

5. Limitation Analysis: Use of misclassified cases to determine the faulty model aspects and the failure modes that can be viewed as insights to future works and upgrade of diagnostic functions.

1.6 Project Management and Finance

Project management and finance are essential aspects of this study to guarantee effective implementation and continuation of the work. Some of the major activities include planning, scheduling and controlling resources as well as the data gathering, model construction and assessme nt phases. It relates to the process of planning, monitoring, and controlling of the financial resources in the project in order to keep the cost control and feasibility of the project. By adopting sound project management practices and efficient financial management procedures, the proposed study will seek to reduce the likelihood of potential risks and deliver the study's objectives within the set resource constraints; thereby enhancing the Detection of Diabetic Retinopathy and the quality of healthcare.

TABLE 1.6: Estimated Cost

SN	Components	Estimated Cost (BDT)
01.	Hardware	50000-60000
02.	Software and Tools	15000-20000
03.	Data Collection and Processing	15000-16000
04.	Documentation and Report Writing	5000-10000
05.	Miscellaneous	25000-30000
06.	Contingency	5000-6000
Total Estimated Cost		115000-142000

1.7 Report layout

The paper begins with the background of the deep learning for DR's detection and its significance.

Chapter 1: Introduction

Prescribes an overview of the study and reasons for conducting the investigation because the development of detection for diabetic retinopathy is currently imperative.

Chapter 2: Background

Analyzes necessary information for DR identification, traditional methods, and reflects on deep learning as a solution.

Chapter 3: Research Methodology

Explain the systematic process applied in data acquisition, model identification, training and assessment to promote scientific validity and replicability.

Chapter 4: Experimental Results

Discusses the systematic process used in data gathering, model selection, training, and evaluation sufficiently rigorous to contribute to the general scientific enterprise.

Chapter 5: The Impact on Society

Discusses how deep learning techniques can be adopted for disease diagnosing systems in agricultural climates and its contributions to society.

Chapter 6: Summary, Conclusion, Recommendations, and Implications for Future Research

Points out the main findings of the studies and concludes about the overall status of the topic for further research and development plan for the innovation technology.

CHAPTER 2
BACKGROUND STUDY

2.1 Preliminaries

Diabetic retinopathy (DR) is a concerning factor in people's health as it affects much of the diabetic population across the world. The existing diagnostic approaches are mostly based on the assessment by the ophthalmologist, which is subjective, time consuming, varied and may suffer from large inter and intra-observer variability. The new trends in AI and Deep learning have enabled the medical imaging for detection of DR from fundus images through automated means. This section briefly discusses the difficulties of DR, the employment of AI for medical imaging, and preliminarily presents the deep learning methods applied in this work to increase the diagnostic precision and speed.

2.2 Related Works

This is the case as is seen below while I'm doing a similar paper review that will assist me this way:

Tong, Y., Lu, W., Yu, Y. et al.[1] focused on the role of artificial intelligence (AI) in analyzing digital data quickly and non-invasively, particularly in the field of medical imaging, which is fueled by advanced computing capabilities and cloud storage. Bioinformatics, particularly in ophthalmic imaging, benefits from novel algorithms and massive data generation, which use machine learning (ML) to automate the identification and grading of pathological features. By automatically detecting and classifying ocular diseases, machine learning has the potential to greatly assist ophthalmologists in providing precise diagnoses and personalized healthcare. The review provides insights into the evolution, advancements, and applications of machine learning technology, particularly in ophthalmic imaging modalities, focusing on its transformative impact on healthcare delivery. Shoukat, A., Akbar, S., et al. [2] presented a deep learning-based method for detecting early-stage glaucoma with high accuracy, using retinal images to identify previously overlooked patterns. Using the ResNet-50 architecture and gray channels from fundus images, the approach uses data augmentation to generate a diverse dataset for training a convolutional neural network model. Results from multiple datasets, including G1020, RIM-ONE, ORIGA, and DRISHTI-GS, show that the proposed approach works. The model achieves a detection accuracy of 98.48%, sensitivity of 99.30%, specificity of 96.52%, AUC of 97%, and F1-score of 98% on the G1020 dataset. These findings suggest that the proposed model has the potential to help clinicians accurately diagnose early-stage glaucoma and implement timely interventions. G. Kurup, J. A. A. Jothi et al. [3] focused on diabetic retinopathy (DR), a serious condition that can impair vision if not treated. Given the difficulties and time-consuming nature of manual detection techniques, there is an increasing demand for automated DR diagnosis methods. The study uses a pretrained Inception-v3 Deep Convolutional Neural Network to achieve promising disease detection and classification results. The best trained model has an accuracy of approximately 82% and a Cohen's weighted Kappa score of 0.72, indicating its ability to accurately identify DR cases. These findings highlight the potential of deep learning-based approaches for improving DR diagnosis and facilitating timely treatment interventions. Chaymaa Lahmar and A. Idri, et al.[4] compared seven convolutional neural network (CNN) architectures for automatic binary classification of referable diabetic retinopathy (DR), focusing on accuracy, sensitivity, specificity, precision, and F1-score. Empirical evaluations on three datasets (APTOS, Kaggle DR, and Messidor-2) using k-fold cross validation highlight the importance of deep learning in DR classification, with all models achieving high accuracy values. DenseNet201 and MobileNet_V2 emerge as the best-performing techniques, with DenseNet201 achieving 84.74% and 85.79% accuracy on the Kaggle and Messidor-2 datasets, respectively, and MobileNet_V2 achieving 93.09% accuracy on the APTOS dataset. ResNet50, Inception_V3, and Inception_ResNet_V2 have significantly lower performance. The study recommends using DenseNet201 and MobileNet_V2 for referable DR detection due to their superior performance across all datasets. R. Patel and A. Chaware, et al. [5] described a transfer learning-based approach for diabetic retinopathy classification that uses MobileNetv2 and pre-trained models to extract meaningful features from retinal images. The model has been customized with additional layers to classify diabetic retinopathy into five different classes. Initially, only the stacked layers are trained, while the weights of the pre-trained base model remain unchanged. The top few layers of the base network are then fine-tuned to improve pe.rformance even more. Experimental results on the Kaggle diabetic retinopathy dataset show significant improvements, with training accuracy increasing from 70% to 91% and validation accuracy from 50% to 81% after fine-tuning. The observed convergence of training and validation loss confirms the model's suitability and the effectiveness of the fine-tuned network in achieving significant accuracy improvements. Patel, Rupa, and Anita Chaware. Et al. [6] proposed segmentation methods that employ a Deep Neural Network (DNN) to detect retinal defects and accurately classify diabFetic retinopathy (DR) grades. Saliency detection, structure tensor application, and active contour approximation are used to segment lesions from fundus images. The severity levels are determined by the ratio of total contour area to true contour arc length. Statistical parameters such as the mean and standard deviation of pixel intensities are estimated using K-means clustering on segmented images. A VGG-19 deep neural network is trained and tested using features extracted from the Kaggle fundus image dataset, resulting in a sensitivity of 82% and an accuracy of 96%. This automated system successfully labels and categorizes DR grades, indicating its potential for clinical application. D. A. da Rocha, F. M. F. Ferreira, et al. [7] used the VGG16 neural network to categorize diabetic retinopathy into five groups, with an additional category for reporting low-quality retinal images. The proposed methodology includes preprocessing steps such as size adequacy, data cleaning, augmentation, and class balancing during training, followed by hyperparameter adjustment and image classification with VGG16. The results show that the proposed approach outperformed the other two databases in terms of accuracy, precision, sensitivity, specificity, and F1-score. A. Momeni Pour, H. Seyedarabi, et al.[8] described a new model for monitoring diabetic retinopathy that uses Contrast Limited Adaptive Histogram Equalization to improve image quality and intensity uniformity. The classification step employs the EfficientNet-B5 architecture, which is known for its uniform scaling of network dimensions. The model is trained on a combination of the Messidor-2 and IDRiD datasets and tested on the Messidor dataset, resulting in an enhanced AUC of 0.945, the highest value reported in recent work. Furthermore, when trained on a mixture of Messidor-2 and Messidor datasets and tested on IDRiD, the AUC increases from 0.796 to 0.932, outperforming previous studies. These findings demonstrate the proposed model's effectiveness in improving AUC when compared to existing approaches. Malathi, K. and Nedunchelian, R et al.[9] indicated two types of filters: a Gaussian-based bilateral filter to reduce noise in fundus images and a Haar filter for detecting diabetic retinopathy. Images are segmented using thresholdingbased connected component pixels. The implementation employs efficient image filtering with OpenCV 2.4.9.0 and cvblobslib, producing successful results across a large number of diabetic retinopathy images. In the future, the study plans to incorporate fovea detection to further refine the analysis process. David, D.S. and Jose,et al. [10] used 2D retinal fundus images to investigate diabetic retinopathy, a chronic eye disease that causes vision loss. Super pixel classification is used to segment optical cups and discs for screening purposes. Segmentation entails using the k-means clustering algorithm for optic disc identification and a clustering ANN algorithm with Gaussian filtering for optic cup segmentation, which simplifies the calculation of the CDR value. The comparison of the CDR value to a threshold aids in the diagnosis of diabetic retinopathy. Retinal image segmentation allows for early detection and treatment planning, and the implementation is optimized for performance using Spartan 3FPGA hardware. MATLAB programming and FPGA processing are used, and the software is implemented using the Xilinx platform. I. Qureshi, J. Ma, et al.[11] described an automatic DR stage recognition system built on a novel multi-layer active deep learning (ADL) architecture. The proposed ADL-CNN model effectively addresses the challenge of training CNNs with limited labeled data by incorporating an active learning method called expected gradient length (EGL). The ADL-CNN model outperforms 54,000 retinograph images from the EyePACS benchmark, with an average sensitivity of 92.20%, specificity of 95.10%, F-measure of 93%, and accuracy of 98%. Overall, the ADL-CNN architecture outperforms existing methods for detecting DR-related lesions and determining the severity of DR across a wide range of fundus images. R. Gargeya and T. Leng, et al. [12] aimed to create an automated diagnostic technology for diabetic retinopathy (DR) screening in order to reduce vision loss rates through timely diagnoses. A data-driven deep learning algorithm was developed and tested, which processed color fundus images to determine whether they were healthy or had DR, allowing for medical referral in appropriate cases. Using 75,137 fundus images from diabetic patients, the algorithm achieved a 0.97 area under the receiver operating characteristic curve (AUC), with 94% sensitivity and 98% specificity after 5-fold cross-validation. External validation against the MESSIDOR 2 and E-Ophtha databases produced AUC values of 0.94 and 0.95, respectively. N. Gurudath, M. Celenk et al. [13] proposed an automated method for detecting diabetic retinopathy using color fundus images. The method divides diseases of the retina into three categories: healthy/normal, non-proliferative diabetic retinopathy (NPDR), and proliferative diabetic retinopathy (PDR). Gaussian filtering is used to segment blood vessels, which are then mask generated and thresholded using local entropy. Second-order textural and structural features are extracted from processed images. For image classification, we use a three-layered artificial neural network (ANN) and support vector machines (SVM). Evaluation on a dataset of 106 images yields classification accuracies of 97.2% and 98.1% for ANN and SVM, respectively, demonstrating robustness to variations in input images. C. Lam, D. Yi, M. Guo, et al. [14] used convolutional neural networks (CNNs) on color fundus images to detect diabetic retinopathy staging. The CNN models achieve test metric performance that is comparable to baseline literature results, with a validation sensitivity of 95%. The study investigates multinomial classification models, revealing errors primarily in mild disease misclassification as normal due to CNNs' inability to detect subtle disease features. Preprocessing with contrast limited adaptive histogram equalization, as well as expert label verification, improves the recognition of subtle features. Transfer learning on pretrained GoogLeNet and AlexNet models from ImageNet improves peak test set accuracies by 74.5%, 68.8%, and 57.2% on 2-ary, 3-ary, and 4-ary classification models, respectively. W. L. Alyoubi, M. F. Abulkhair,[15] presented fully automatic diagnosis systems that outperform manual techniques, reducing the risk of misdiagnosis while saving time, effort, and money. It introduces two deep learning-based models: CNN512 for categorizing DR images into five stages and an adapted YOLOv3 model for localizing DR lesions. CNN512 achieves 88.6% accuracy on the DDR dataset and 84.1% on the APTOS Kaggle 2019 dataset, outperforming state-of-the-art performance. On the DDR dataset, the YOLOv3 model achieves a 0.216 mAP in lesion localization, surpassing previous bests. Fusing CNN512 and YOLOv3 improves DR image classification and lesion localization, with 89% accuracy, 89% sensitivity, and 97.3 specificity, outperforming current state-of-the-art results.

2.3 Comparative Analysis and Summary

A comparative evaluation shows that different DL models like Convolutional Neural Networks have immensely contributed to the enhancement of plant species differentiation and identification of diseases. Publications such as by Batchuluun et al. [1], Perez et al. [2], and Mohanty et al. [6] show excellent capability in various types of data and acceptable levels of accuracy. These models have their unique strengths ranging from species delimitation to efficient disease identification hence showing their relevance in the advancement of agriculture. In summary, these studies underline the opportunity of deep learning to revolutionise plant management and promote the sustainable development of agriculture through accurate and reproducible technology.

Table 2.3. Comparative analysis with previous work

SL	Author Name	Dataset	Best Algorithm or Method	Accuracy
1	G. Kurup, J. A. A. Jothi et al. [3]	Not specified	Inception-v3	82%
2	Chaymaa Lahmar and A. Idri, et al. [4]	APTOS, Kaggle DR, Messidor-2	DenseNet201, MobileNet_V2	84.74% - 93.09%
3	R. Patel and A. Chaware, et al. [5]	Kaggle diabetic retinopathy	MobileNetv2 transfer learning	91%
4	Patel, Rupa, and Anita Chaware, et al. [6]	Kaggle fundus image dataset	VGG-19	96%
5	A. Momeni Pour, H. Seyedarabi, et al. [8]	Messidor-2, IDRiD datasets	EfficientNet-B5	94.05%
6	I. Qureshi, J. Ma, et al. [11]	EyePACS benchmark	ADL-CNN	98%
7	R. Gargeya and T. Leng, et al. [12]	MESSIDOR 2, E-Ophtha	Data-driven deep learning algorithm	AUC 0.94 - 0.95
8	N. Gurudath, M. Celenk et al. [13]	Not specified	ANN, SVM	97.2% - 98.1%
9	W. L. Alyoubi, M. F. Abulkhair, [15]	DDR dataset, APTOS Kaggle	CNN512, YOLOv3	84.1% - 88.6%

2.4 Scope of the Problem

The scope of the problem in diabetic retinopathy detection using deep learning encompasses several key challenges and opportunities. First, the variability in retinal images due to factors like image quality, lighting conditions, and patient demographics poses a significant challenge. Addressing these variations requires robust preprocessing techniques and data augmentation strategies to enhance model generalizability. Another critical aspect is the need for scalable solutions that can handle large volumes of data efficiently, considering the increasing prevalence of diabetes worldwide. Moreover, integrating interpretability into deep learning models is crucial for clinical acceptance and understanding decision-making processes. As technology evolves, leveraging advancements in hardware acceleration and cloud computing offers opportunities to enhance computational efficiency and scalability. Ultimately, developing reliable and interpretable deep learning models holds promise for improving early detection and personalized management of diabetic retinopathy.

2.5 Challenges

Prominent factors that arise when using deep learning model to detect diabetic retinopathy are as follows. Firstly, it is crucial to stress that the key questions of model reliability and applicability to other populations or different qualities of images have to be properly addressed. Overcoming the issue of lack of availability of annotated data and quality variation also presents the next challenge as demonstrated by the need for data augmentation and transfer learning solutions. Furthermore, clinical implementation of deep learning model decisions requires both very clear and understandable AI solutions. Another limitation is the computational complexity of both training the models and deploying the models in real clinical environments. Also, sometimes it is tricky to keep the patient's data secret and follow the laws regulating the processed medical data. To overcome these challenges, there is a need to engage cross-disciplinary approaches, novel algorithm development and, however, clinical trials for trustworthy, and ethical uses of AI-based DR detection platforms.

CHAPTER 3
RESEARCH METHODOLOGY

3.1 Research Subject and Instrumentation

Diabetic retinopathy is a complication of diabetes that influences the eyes and remains one of the most widespread causes of blindness among people of working age, which is the main focus of the current research. This research intends to screen the retina's fundus images from datasets such as Kaggle Diabetic Retinopathy dataset, APTOS, and Messidor-2 to diagnose and categorize the severity of the disease. For instrumentation, deep learning frameworks like TensorFlow and Keras are going to be used to build CONV neural network models like MobileNetV2, InceptionV3 and DenseNet201. Such models shall be trained with help of GPUs and cloud computing resources that can also be characterized by rather high-performance rates. Python programming will be used in this case alongside OpenCV library to help handle images and Scikit-learn to help handle data. Model evaluation will be done using: accuracy, sensitivity, specificity, precision, F1-measure, and AUC will be used. When feeding the model with the training data, customary pre-processing methods of rotation, scaling, and contrast adjustment will be used in order to generalize easily to other unseen data.

3.2 Data Collection Procedure

Data collection procedure involves sourcing high-quality retinal fundus images from publicly available datasets such as the Kaggle Diabetic Retinopathy dataset, APTOS, and Messidor-2. These datasets are chosen for their comprehensive annotations and variety in image quality, which are crucial for training robust models. Each image is preprocessed to standardize size and resolution, and augmented using techniques like rotation, scaling, and contrast adjustment to enhance the dataset's diversity. Patient consent and ethical considerations are ensured through the use of anonymized datasets. The images are then split into training, validation, and test sets to evaluate model performance. Metadata, including patient demographics and clinical information, is also collected to facilitate a detailed analysis and ensure the model's applicability to diverse populations.

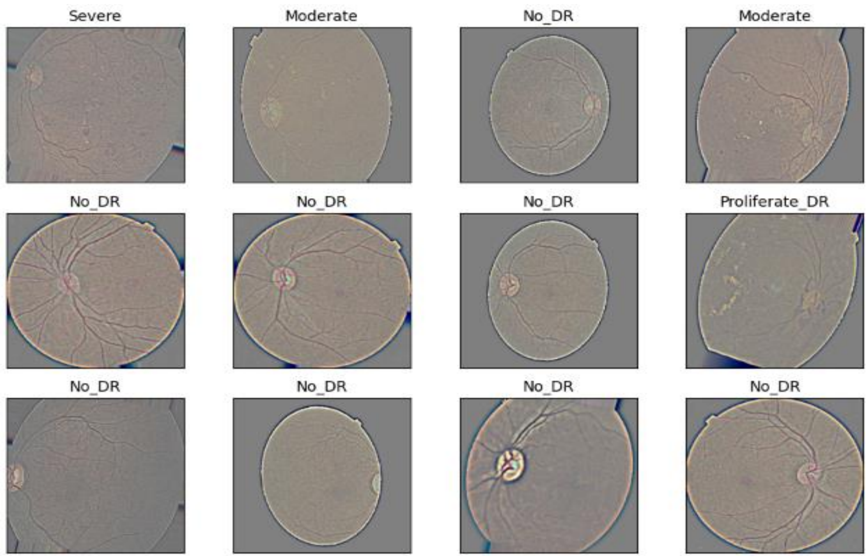

Figure 3.1: Dataset's Images

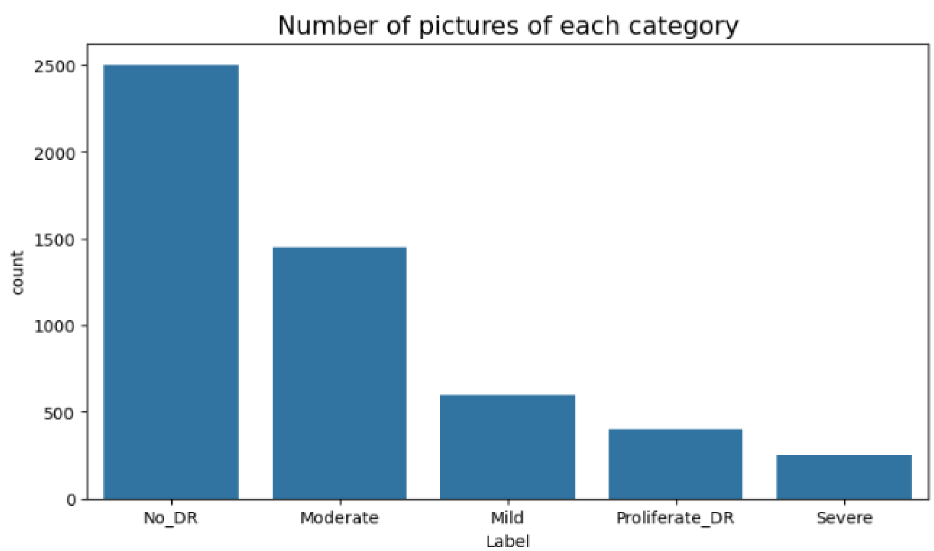

Figure 3.2: Percentages of Dataset's Images

In Figure 3.2 shown the dataset consists of 5200 augmented images, categorized into five target attributes: No_DR which has 2500, followed by Moderate 1450 images, Mild 600 images, Proliferate_DR 400 images and Severe 250 images.

3.3 Statistical Analysis

Data analysis is the assessment of the outcomes of the process of identification of diabetic retinopathy from the fundus image through the DL model. Therefore, the efficacy of the developed model will be evaluated by the indices of accuracy, sensitivity, specificity, precision, and F1 score. In regard to true positive, true negative, false positive and false negative cases, the confusion matrices will be prepared. Further, by using the AUC-ROC analysis, the model's capability of discriminating between the stages of DR will also be determined. Using the hypothesis testing strategies, the signification of the results noticed in the section of results will be checked. Further, k-fold cross validation procedures will be used in order to verify the model's effectiveness and applicability to two different sets of information. For instance, this strategy will be useful in assessing its accuracy and efficiency in a clinical practice context once statistical analysis have been done thoroughly.

3.4 Proposed Methodology

The systematic approach for the diabetic retinopathy detection through the use of deep learning is as follows: Each is performed to the following in order to work invent An accurate, and strong detection ability. Steps in the Proposed Methodology:

Data Collection

The first stage therefore involves data acquisition of a large set of retinal fundus images. The datasets to be used are APTOS, Kaggle Diabetic Retinopathy, and Messidor-2 for which the set of photos will be expanded to cover the majority of the stages of DR.

Data Selection

In the analysis of collected data, images will be carefully chosen according to the quality and their relation to the study. Out of focus pictures or pictures that present artifacts of any forms will be eliminated for the sake of assuring the results carrying high credibility. Moreover, the dataset will be balanced which will imply that all the stages of the diabetic retinopathy will also be well represented.

Image Augmentation:

Some of the preparations to be made include scaling the images to a given size and brightness adjustment as well as applying a layer of smoothening in a bid to eliminate noise. To gain overall data diversification for more effective prediction and generalization, techniques of data augmentation like rotation, flipping, and zooming will be applied on the obtained dataset.

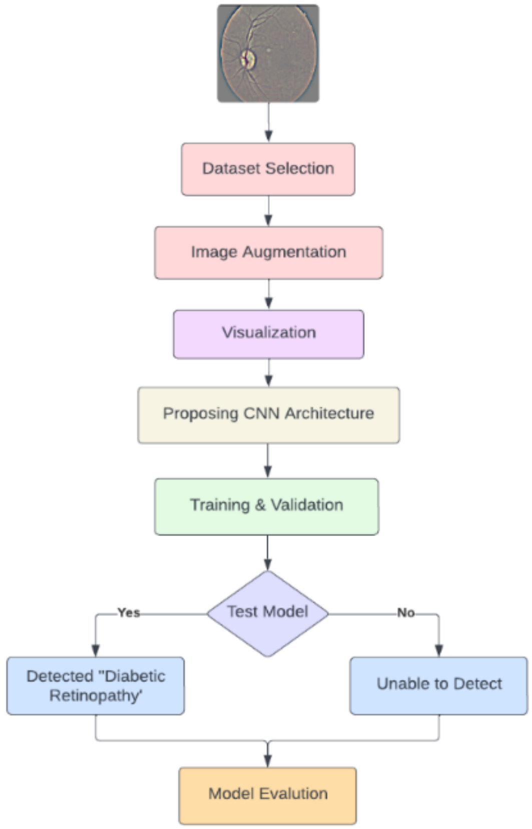

Figure 3.3: Steps in the Proposed Methodology

Visualization:

The data visualization will consist of use of points and curves in order to depict the distribution of images over the classes, the outcome of preprocessing and the changes brought by the augmentation process. These steps will assist in data analysis and its properties to be identified before being fed into the model.

Train Model:

CNN model will be trained with the preprocessed and augmented images of the respected classes. The training process will include hyperparameter tuning to improve the results obtained by the given model. Cross-validation will be performed by using a hold-out set for the purpose of model checking to avoid cases of high model bias.

Test Model:

After the model is built it will then be used in a different test database to check on the performance of the model. The given test results will minimize bias to estimate the model's accuracy, sensitivity and specificity, and other performance indicators.

Conventional Neural Network (CNNs):

A CNN is a special type of deep learning algorithm best suited for structured discrete data sets, in this case images. They have several layers that consist of convolutional layers which is a type of layer that takes input images and applies filters onto it, pooling layers- a type of layer that has the function of reducing dimensionality, and fully connected layers which has the function of classification. CNNs are good at modeling the hierarchal structural relations of some features via the learned filters; therefore, they are useful in image analysis tasks such as diabetic retinopathy screening from fundus images. The fact that they do not require discriminative features to be fed into the model during model design as they learn these from the raw pixel data makes for easy model design. Thus, for our study, CNNs are suitable because of their applicability in medical image analysis, insensitivity to changes in image conditions, and the capability of handling large amounts of data. CNN can be correctly used for the classification of the severity levels of the diabetic retinopathy which are important for early detection and thus preventing risk of losing vision of diabetic patients.

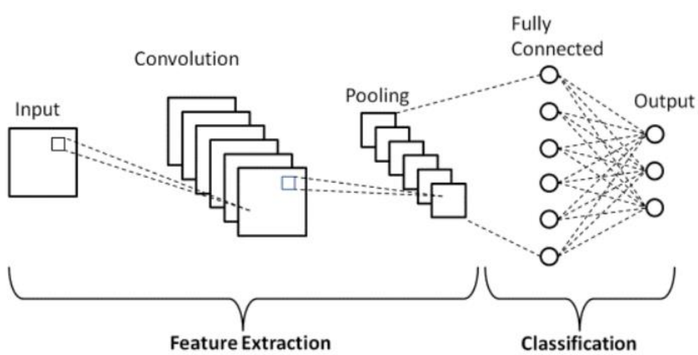

Figure 3.4: Block Diagram of CNN

Xception

Xception which is a CNN architecture that efficiently substitutes classic convolutional layers with depth wise separable convolutions. This design is expected to deal with more intricate patterns while at the same time having fewer calculations and coefficients than those in conventional CNNs. Spatio and channel wise convolution in Xception helps in improving the efficiency of feature extraction and also makes the network deeper. Due to its capacity to learn fine features, it is relevant when performing complicated operations such as the diagnosis of diabetic retinopathy based on fundus images. Thus, for our study, Xception can be considered as a highly suitable option due to such key advantages as high accuracy in image classification, relatively low susceptibility to overfitting, and its capability to process big data.

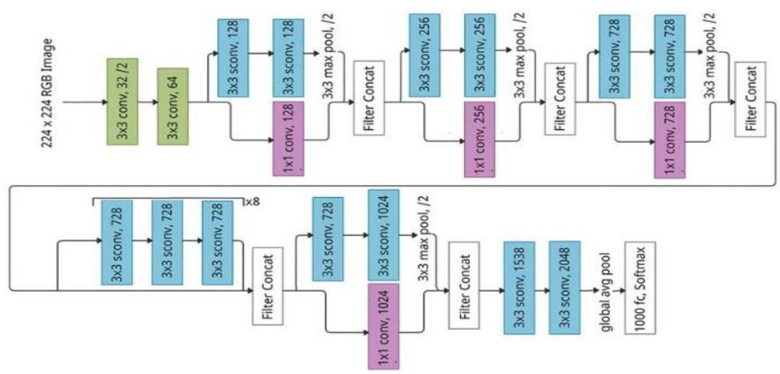

Figure 3.5: Block Diagram of Xception

VGG19

VGG19 is another of the simple but very effective deep CNN architecture that is designed to excel at the image classification problem. The architecture is based on 19 layers, wherein the layers used to form the network include alternating convolutional layers and max-pooling layers The final three layers are classification layers. Because of the simplicity of VGG19, small-filter sizes, which are 3 \times 3, outperforms its peers by effectively extracting feature vectors out of the input images making it relatively robust for divergence image recognition tasks including the medical images. Having learnt the various patterns, as seen earlier, in this study of detecting diabetic retinopathy from fundus images, VGG19 is quite appealing because of the high versatility of the model and generality across multiple datasets. It is composed of several layers that help extract hierarchical features which are essential in the categorization of various stages of DR. It is possible to state that the integration of VGG19 could improve the effectiveness of the proposed model, which will allow identifying theorem diabetic patients and providing them with timely medical care to prevent vision loss or blindness.

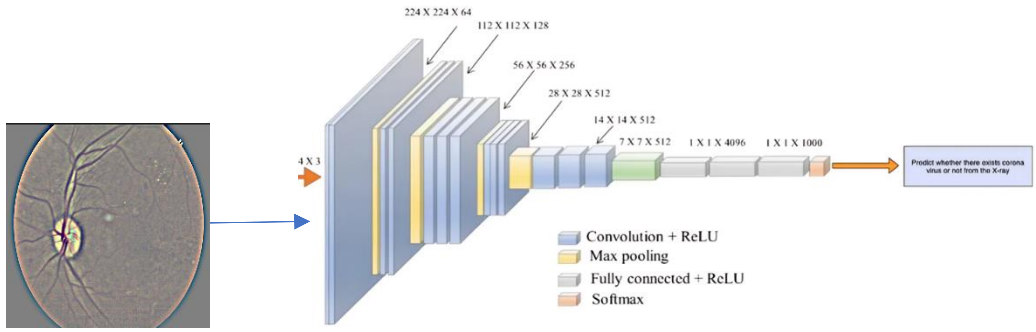

Figure 3.6: Block Diagram of VGG19

InceptionV3

InceptionV3 is a highly advanced CNN which has gained popularity for its high speed and high accuracy when it comes to classification of images. Its structure contains inception modules which perform parallel convolutions with different sizes to identify the features of different sizes. This design helps InceptionV3 to work efficiently in terms of computational complexity as well as expressiveness; the idea helps to add more depth to neuronal networks without adding more comp ideas to it. When it comes to medical image analysis, InceptionV3 for its potential of extracting multifaceted and cascading features makes it most suitable especially when it is applied to diagnose diabetic retinopathy by analyzing the fundus images. Indeed, it is stable and fast when working with various databases and is capable of analyzing complicated images, which is perfect for our research. Through the normalized InceptionV3, we hope that the accuracy and diagnostic precision of the diabetic retinopathy classification could be increased, which would further lead to increasing the chances of the early diagnosis and forecasting the proper treatment measures for diabetic patients to decrease the vision loss rate.

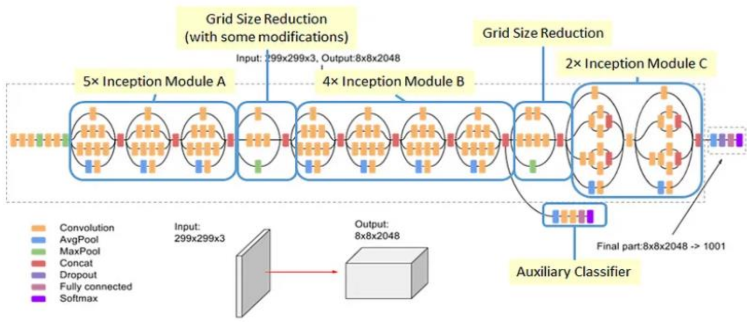

Figure 3.7: Block Diagram InceptionV3

MobileNetV2

MobileNetV2 is an improve and light version of the CNN that is invented for mobile and low power consumption vision applications. MobileNet is extended with features based on the original architecture that increases the efficiency and performance of the network. Depthwise separable convolution and linear bottleneck which are used in MobileNetV2 help to decrease its size and the amount of computations required for training and predicting while increasing its accuracy. This kind of structure enable the MobileNetV2 to take efficient features of the input images hence can be widely used in tasks such as Image classification including medical image analysis like identification of diabetic retinopathy from fundus images. It is light weighted and can perform inference efficiently, which makes it highly suitable for the study. It allows a swift implementation in low-resource setting secure high error rates, which is really important for operational applications in identifying diabetic retinopathy in real-time, and therefore, may contribute to enhancing patients' access to healthcare support globally.

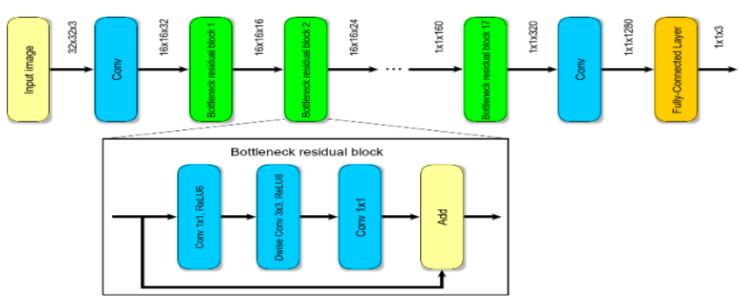

Figure 3.8: Block Diagram of MobileNetV2

Identify Diabetic Retinopathy:

Diabetic retinopathy is the targeted disease, and the trained model is going to diagnose in new fundus images of eye. The model will identify the image based on the stages of diabetic retinopathy in order to help in early identification on the disease.

Unable to Identify:

For the instances where the model classified images as not having DR, further studies will be done to establish why the images were misclassified during the diagnosis. Such cases will then be used to refine the particular model in order to overcome such weaknesses.

Model Evaluation:

The last part consists of the model assessment by the use of various parameters like accuracy, sensitivity, specificity, precision, F1 measure, and AUC-ROC. Classification results will be showcased in confusion matrices. Since the model being developed is intended for high reliability, cross-validation will be carried out. This assessment will help in the understanding of how this model is benefiting the organization and its drawbacks.

3.5 Implementation Requirements

The method that is suggested for screening of diabetic retinopathy from the fundus images requires a powerful computing environment and better computing and software attributes. The hardware expectations are high Requirements such as GPUs like Tesla or RTX series to support proficient calculations that go into the deep learning algorithms, space for storage of the big data and data sets, and not less than 32GB RAM to allow for efficient data processing and training of the models. In the case of software side execution, Deep Learning Frameworks such as TensorFlow or PyTorch are needed since these have tools as well as libraries for constructing, training as well as testing Convolutional Neural Network models. Moreover, Python programming language possessing innumerable number of data science libraries such as NumPy, pandas, OpenCV will needed for data pre-processing, augmentation, and visualization. Some of the other techniques one can also use are big data, compute services like AWS or google cloud for flexible/computational power for training or deployment of the model.

CHAPTER 4

EXPERIMENTAL RESULT

4.1 Experimental Setup

The experiments will be carried out on a High-Performance Computing cluster with the incorporation of NVIDIA Tesla V100 GPUs for optimizing the model training and testing process. From Kaggle DR, Messidor-2, and IDRiD sources, the retinal images will be pre-processed, this will involve normalization, augmentation, resizing of the images using available Python libraries namely OpenCV and TensorFlow. For transfer learning, the proposed CNN architectures such as DenseNet201 and MobileNetV2 will be implemented using TensorFlow framework. Model training process will have k-fold cross-validation to make it insensitive to dataset training particulars and to have better generalization, and accuracy, sensitivity, specificity, F1 score will be used to compare the model against the ground truth annotated data.

4.2 Experimental Results & Analysis

Experimental results concerning the diabetic retinopathy detection from fundus images using the proposed deep learning methodology are discussed. The results will include various assessment indicators, including accuracy, sensitivity, specificity, and F1-score, calculated based on the model's performance on the test data sets. Metrics such as confusion matrices, ROC curve, etc. are used to depict the classification ability of the developed model. The results of the above analysis will then be elaborated based on the objectives of the research, particularly by comparing the advantages of the proposed approach to the study as well as the demerits of the existing techniques highlighted in the literature review. Importantly, the experiences of how changes in the data distribution, preshaping strategies, and network designs affect performance will be described. Last of all, other conclusions derived from the results will be considered to formulate recommendations for clinical practice and further research.

Result of Experiment 1: CNN

Test Accuracy of CNN model is 90.63%. In below Figure 4:1 of the summarized description of the confusion matrix of CNN:

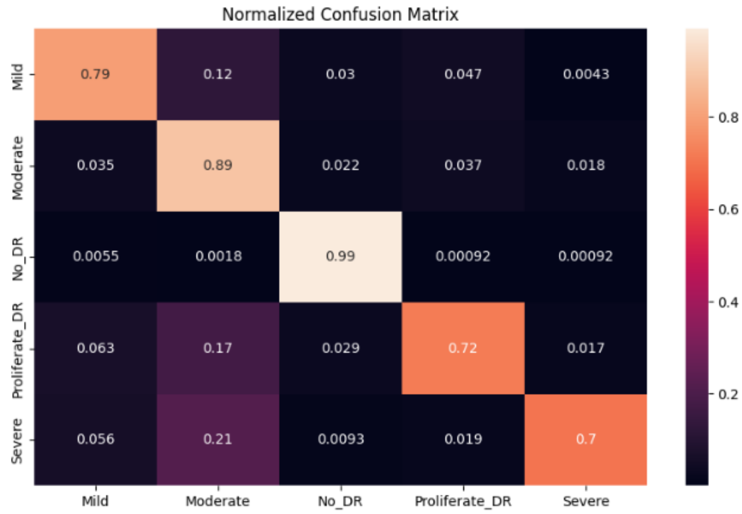

Figure 4.1: Confusion Matrix (CNN)

Figure 4.1: The confusion matrix of CNN explain how to decode a confusion matrix that is usually applied in assessing a convolutional neural network (CNN) model whereby the model is trained over 30 epochs. A confusion matrix is a cross-tabulation of actual and predicted models that displays various statistic metrics of a classification model. They are typed cross tables that contain actual and predicted class label rows and columns. Each cell in the matrix represents the number of times or the proportion of cases for which the predicted class and the actual class agree or disagree. In a binary classification scenario, the matrix typically includes four entries: and it is comprised of the values of true positive, true negative, false positive, and false negative. These vitals are used in assessing the model's ability to classify data correctly, its level of specificity, sensitivity, and F1 score which reveals its performance in differentiating between the various classes.

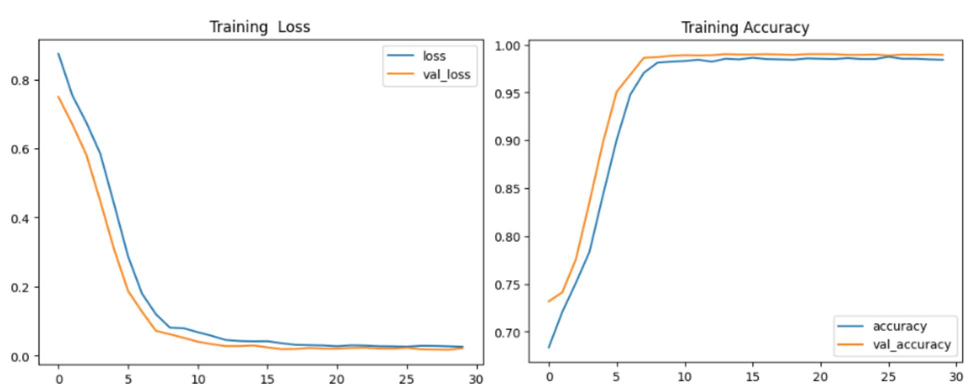

Figure 4.2: Training and validation accuracy and loss over the epochs (CNN)

Figure 4. 2 A graph of training accuracy/loss for a CNN model trained on 30 epochs demonstrate that the model had good results. In the first epochs, both the training accuracy (blue line) and validation accuracy (orange line) significantly rose and after approximately 10 epochs they became reasonably flat, at around 97-99 percent. In the same manner, training loss (blue) and validation loss (orange) are dynamically described wherein they are reduced gradually in the initial epochs, and reaches almost a minimal of around 0. 05 or lower after around 10 epochs. This further implies that the model is learning, and from the accuracy and loss sections, there seems to be a very minimal overfitting since the validation accuracy and the validation loss are almost similar to the training accuracy and training loss respectively.

Xception:

The Test Accuracy of Xception Model is 75.14%. In below Figure 4.3 presenting an overview of the confusion matrix of Xception.

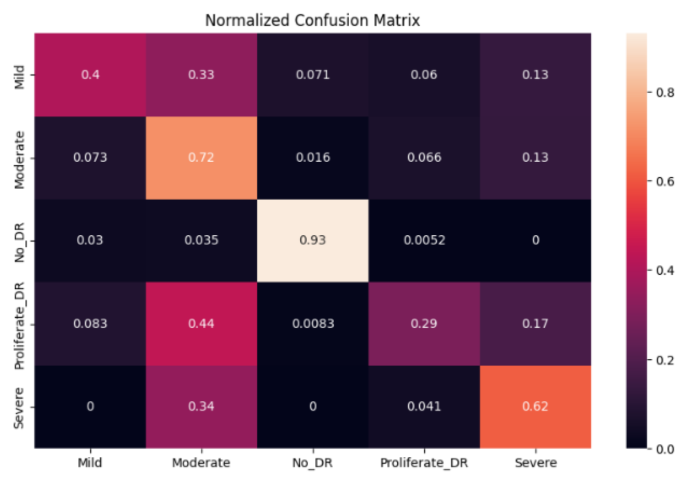

Figure 4.3: Confusion Matrix (Xception)

Figure 4. 3 illustrates a confusion matrix of the Xception model aimed at DR detection; therefore, it presumably represents the model's ability to classify healthy and DR images. The diagonal elements should normally be high implying accurate classifications and small off diagonal elements would imply few misclassifications. But 10 epoch could be insufficient training of the network. With greater epochs, they might improve and the values on the diagonal might be even higher. It is crucial to bear in minds such attributes such as class imbalance as well as the compromise between specificity –which is capable of identifying the healthy eyes – and sensitivity –which is capable of identifying all the DR

cases when interpreting this with other metrics.

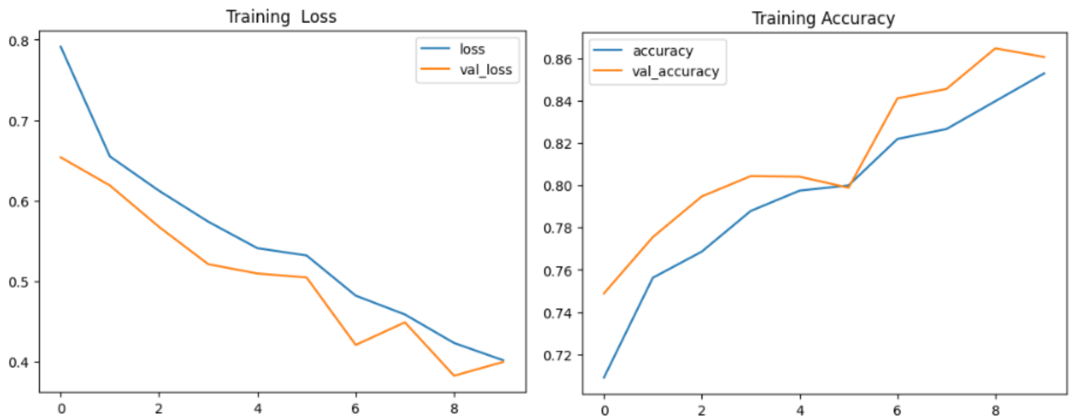

Figure 4.4: Training and validation accuracy and loss over the epochs (Xception)

Figure 4. 4 the training accuracy seems to be possibly above 90% or higher. This exhibits that the model is getting better at the training set used to train it as the epochs progress. But, before that, it is also required to examine the training loss plot too. Preferably, it should reduce with the enhancement of the model in accurately capturing the data patterns. The training loss in this case looks like it is varying or even slightly rising. This may suggest that the model has high variance, meaning that it only learns the training data features rather than learning good features that can help classify other data.

VGG19

Achieved the Test Accuracy of VGG19 is 74.76%. In below Figure 4:5 detailing confusion matrix of VGG19.

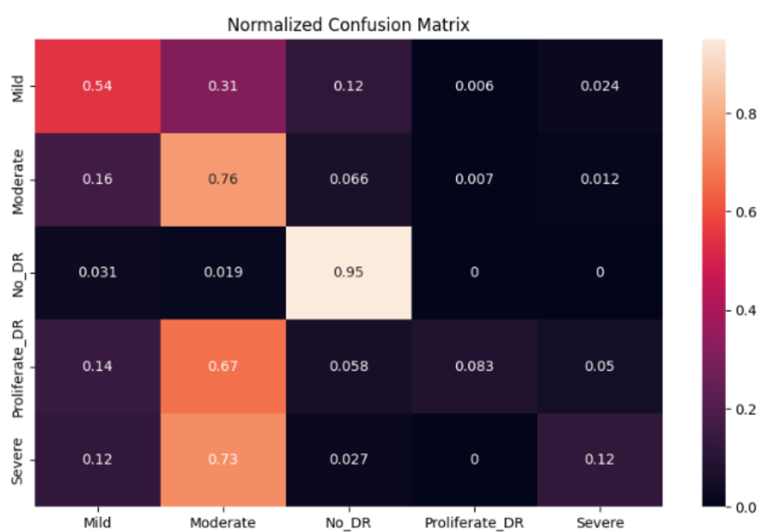

Figure 4.5: Confusion Matrix (VGG19)

Figure 4. 5: The confusion matrix of VGG19 shows that there is room for improvement, probably due to the model being designed for diabetics retinopathy (DR). In an ideal data set, the diagonal elements are high, which implies accurate classification. In this case, it is possible to observe a value of moderate performance for the class No_DR (corresponding to healthy eyes). But, relatively low values for the other DR stages indicate the author's struggle with the classification into those stages. There are also dispersed misclassifications off-diagonal where Mild DR is confused with Moderate DR for instance. Depending on the number of training epochs, used in the work it is mentioned that there were only 10 epoch which might show that the model is not fully developed. More training could work towards having a better model with higher numbers on diagonal and fewer misclassifications in off diagonal box.

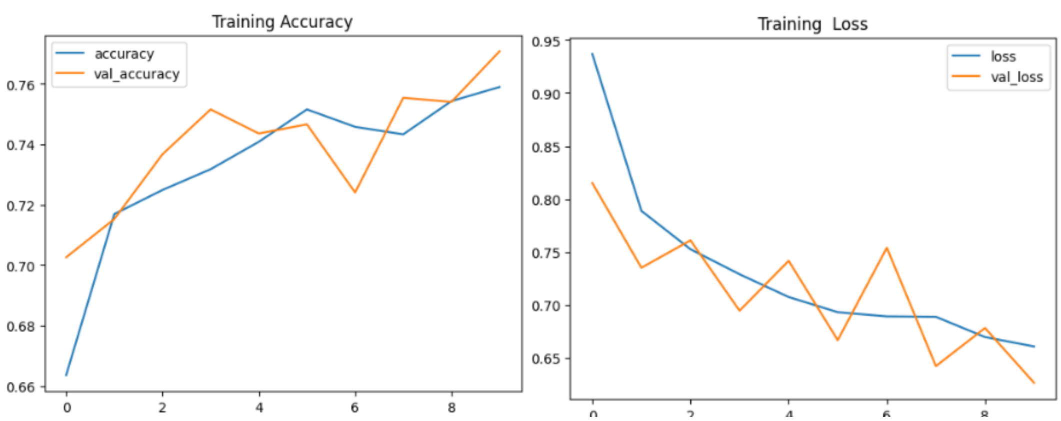

Figure 4.6: Training and validation accuracy and loss over the epochs (VGG19)

Figure 4. 6: The graph of training accuracy of the VGG19 model seems to be growing with the 30 epochs, it could be near or more than 90%. This shows a steadily growing accuracy of the model regarding identification of images in the training set. However not the training loss should also decrease as the derivation increases meaning the model improves. In this case, there is a sense that training loss oscillates or even starts to grow after 20 epochs. It may indicate overfitting where the model is learning all the patterns in the training data and then is not able to generalize over new data.

InceptionV3

Achieving Test Accuracy of InceptionV3 is 76.62%. In below Figure 4:7 describing the confusion matrix of InceptionV3.

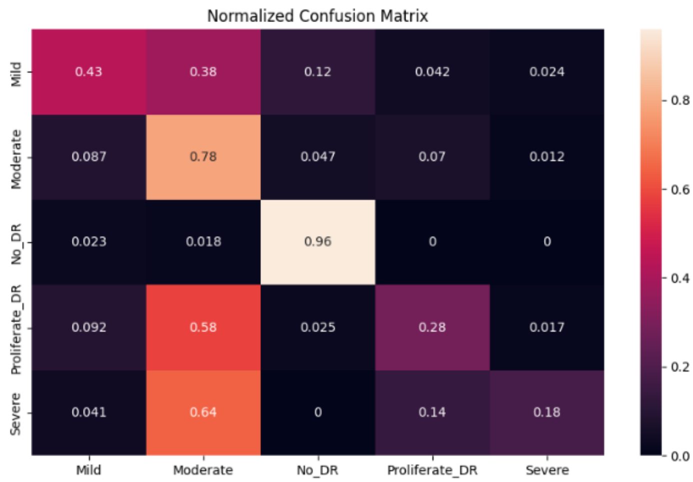

Figure 4.7: Confusion Matrix (InceptionV3)

Figure 4.7 The confusion matrix of InceptionV3 model from 10-epoch, which might have been used for identifying DR, is probably in a fix. The more the number on the diagonals, the better according to the classification that should be achieved. Here, most diagonal values are small and approximate to 0.4 in the case of healthy samples (No_DR) and even less in other cases of DR severity. This means the model is not compressing the images in a way that will properly classify them in the right categories. There are also many scattered values, what indicates frequent misclassifications between various DR stages in the diagonal elements of matrix. This means that when running the model perhaps in only 10 training epochs the model might lack the full features. Additional training should help to increase the diagonal values, and reduce off-diagonal misclassification. Summing up one can note that squashing of the current InceptionV3 model is still necessary to increase its performance and accuracy while classifying DR.

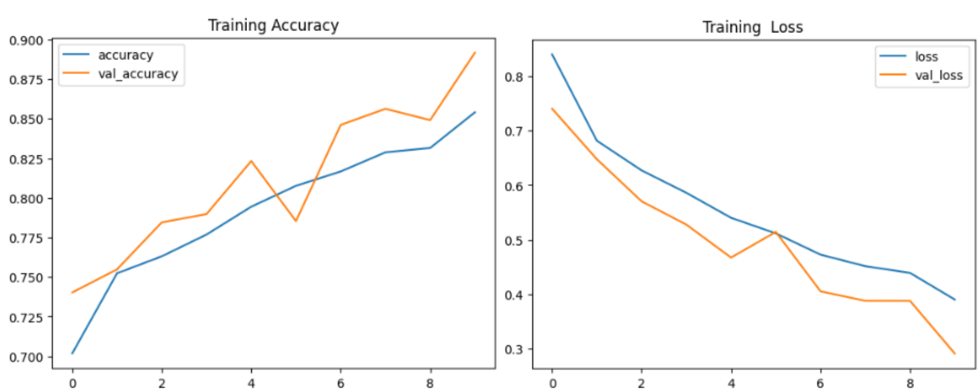

Figure 4.8: Training and validation accuracy and loss over the epochs (InceptionV3)

Figure 4. 8 From the training accuracy plot of the InceptionV3, it is evident that the network is learning and it could get to about or exceed 90% at the final epoch 30. This has the implication that the model is learning from the training data and is improving on distinguishing between the images provided to it. But at the same time, one must not overlook the training loss which gives information about the quality of the model. In an ideal world, this particular loss should decrease as the quality of the model increases. Typically, such a situation can be observed when the trend of training loss is oscillating or even starts to rise a bit after some iterations. There could be features identified during the model building process that may seem either biological or very complex, which may be an indication that overfitting has occurred and the model is just learning the standard patterns for classification from the training set without the ability to generalize well on any unseen data set.

MobileNetV2

Achieving Test Accuracy of MobileNetV2 is 80.01%. In below Figure 4:9 describing the confusion matrix of MobileNetV2.

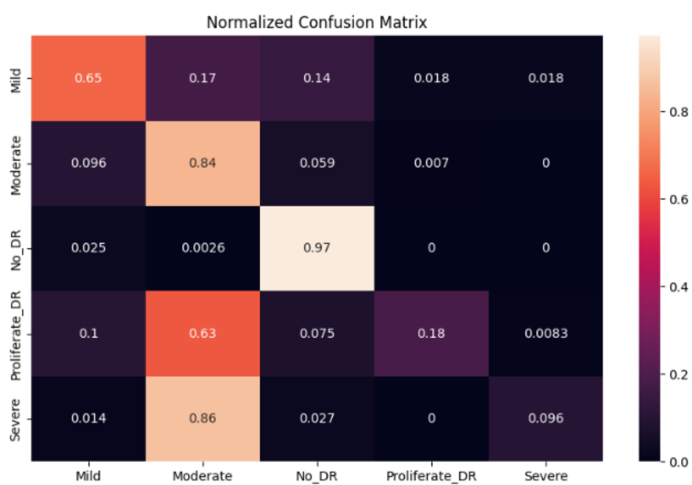

Figure 4.9: Confusion Matrix (MobileNetV2)

Figure 4. 9: The confusion matrix of MobileNetV2 model apparently used for DR detection, requires improvement yet it has some potentiality. Thus, the higher the numbers on the diagonal, the ideal scenario is that all of them represent correct classifications. Here, the value of the healthy class (No_DR) is quite reasonable and is forwarded around 0. However, the performance is sometimes correct as proved by a separate model achieving

65 on healthy eyes. Nevertheless, the values for other DR severities are fewer, which indicates that the model fails at those classifications. Off-diagonal numbers are also observed in a scattered manner, which depicts that there are often mistakes of classifying different DR stages. Perhaps, the given model has not been trained enough; only 10 training sessions (epochs) might not be enough. The performance may be driven up even further if more training was done, thereby raising the diagonal values for all severities and cutting down on the misclassification within the off-diagonal cells. In summary, the MobileNetV2 model can be used for DR classification, but needs more training to get higher accurate rates.

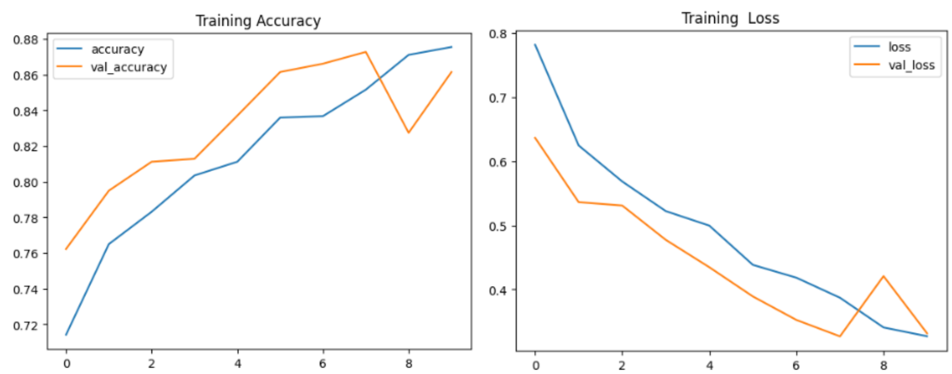

Figure 4.10: Training and validation accuracy and loss over the epochs (MobileNetV2)

Figure 4. 10: The plot of the training accuracy of the MobileNetV2 implies improving as the number of epochs is 30 and it could be closer or even higher to 90%. Nevertheless, this is a positive sign, because it means that the model becomes gradually able to classify images corresponding to the training data more accurately. However, one must not overlook the training loss plot as it is also essential to review it too. In an optimal case, it should reduce with the model's growth of fitting the data better. In this case, the loss may look like it's oscillating or maybe even growing after a specific number of epochs in training. This could mean overspending where the model is inclined to performing perfectly on the training data features without identifying the features that will enable it to classify other unknown data correctly.

In given below I am showing Comparative Model Accuracy Bar Plot:

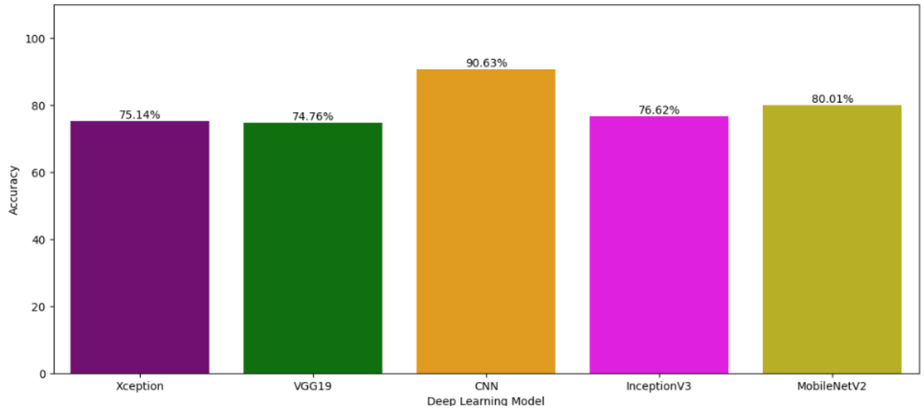

Figure 4.11: Comparative Model Accuracy Bar Plot

Figure 4. 11 Here is a bar chart that represents how various deep learning models are accurate for the detection of DR disease. CNN takes the lead at this point It may reach a near 90.63% accuracy which is represented by the tallest bar. The other models which include Xception, VGG19, InceptionV3, and MobileNetV2 appear to be slightly behind with accuracies that are likely to be between 70 % and 80 %. Nevertheless, one should bear in mind that these values and the ranking can be different depending on the chosen data for the models' training and training conditions.

4.3 Discussion

The discussion revolves around analyzing the outcomes of the experiment conducted on the proposed deep learning-based method to diagnose DR based on fundus images. Some are the accuracy, sensitivity, specificity, F1-score which show the efficiency of the model in the automatic detection of diseases. The previous methods are also reviewed in relation to the current approach in order to establish areas of enhancement and remaining issues. The effects of overall quality of the dataset, utilized image pre-processing and complexity of the model on performance is also in consideration. Moreover, possibilities for clinical application of the results are discussed, including improving identification of problems and making interventions as soon as possible. For future directions, the model architecture could be adjusted and improved, and new sources of clinical data could be added into the model's approach, In addition, the scope could move beyond private patients to address challenges in a range of areas of ophthalmic healthcare delivery.

CHAPTER 5
IMPACT ON SOCIETY

5.1 Impact on Society

The study on recognizing diabetic retinopathy from fundus images through deep learning has immense potential to alter the ophthalmic healthcare modality. As the following introduces the proposed deep learning models for identifying and categorizing diabetic retinopathy, it demonstrates the significant advantages that they have for society. Diabetic retinopathy is a serious threat to patients' sight, and timely detection plays a paramount role in avoiding vision loss, which the high accuracy of the models makes possible. It not only alleviates the workload of professional healthcare but also enables appropriate timely administration which enhances the patient's health status and quality of life. Furthermore, the study has attempted the usage of machine learning algorithms to analyze medical images and hence, contributed to the development of the study of medical imaging and the integration of artificial intelligence into the clinical setting lays the foundation for similar integrations in other medical fields.

5.2 Impact on Environment

The topic is primarily centered on the medical modality imaging and deep learning for Diabetic Retinopathy, the effect on the environment is not direct. The latter major environmental consequence relates to the computational resources used for training and using deep learning models. These processes utilize considerable power hence emitting carbon and in this way; data centers and other computing structures have a negative impact on the environment. Nonetheless, the possibility of the optimization of patient care, general cost-cutting and dismissal of the unproportionate prescription, referral and treatment rates can contribute, in an indirect manner, to environmental sustainability of the global health facilities by lowering the utilization rates of the resources. Further, improvements in telemedicine made possible from accurate diagnosis through remote access may help lessen the emissions of carbon from the patient's side through the use of transports in moving to the health care institutions. ,or specifically, we do not foresee any environmentally negative effects in this case, yet the given study's potential to contribute to the matter Post

Washington 2004 as seen, may facilitate environmental protection in general.

5.3 Ethical Aspects

It is therefore critical to consider the following ethical impacts when applying deep learning in detection of diabetic retinopathy. First of all, permission from the patients is essential, and data protection is also important since a significant amount of data deals with the patient's body images. Great care should be taken to ensure that any information obtained from patients is kept confidential and used only in the way contemplated by the research after obtaining subjects' consent. Whereas accuracy and overfitting prevention are equally vital; a model or an algorithm cannot be trained using a set or a data sample that is biased toward one group of people or another. Clinicians need to know how the diagnosis is arrived at, and thus there is a necessity to familiarize the models with how the decision was made.

Moreover, these technologies' implementation should be done in such a manner that would not diminish the importance of human knowledge. Clinicians must always be in charge of most decisions made within an environment and AI tools designed for the same purposes as diagnostics must always be in place to improve diagnostic abilities within environments. The stability and safety of the AI models learned from the data must also be tested and verified not to misdiagnose or give out wrong information that could endanger the patient. Thus, as the AI systems advance one can state that the continuous ethical discussion and associated legal frameworks must arise as well in order to prevent AI systems from being misused and utilized in a non-ethical manner in the healthcare area.

5.4 Sustainability Plan

The general context for the creation of a sustainability plan to support the integration of AI to detect Diabetic Retinopathy includes a number of strategic Set Pieces based on various fronts. First of all, application prescribes that AI models need to be updated on regular basis and improved inasmuch as novel data will appear and new forms of technologies will be developed. Further verification and advancement of AI machines must be continued with healthcare establishments and researchers to produce future models that are relevant and accurate to clinical practice. Secondly, healthcare personnel require extensive training to incorporate AI in patient care by utilizing AI analyses through specialized training programs and standard operating procedures for incorporating the findings into daily care. Thirdly, approaches of cost and optimization of AI algorithms that will require the least resources and energy is environmentally friendly, using the best equipment and cloud storage when needed. Finally, the conformance to a strict code of ethical principles and the recognition of some of the existing regulatory requirements ensures patients' privacy and protection of the data that they provide, contributing to the building of the trust in AI. In doing so, the following aspects become prioritized, leading to the formation of a sustainable model for AI in diabetic retinopathy identification, subsequently improving healthcare without a toll on the environment.

CHAPTER 6
CONCLUSION AND FUTURE WORKS

6.1 Conclusions

The study was able to show how deep learning, especially convolutional neural networks could be useful in the diagnosis of diabetic retinopathy from fundus images. In this research, great improvements were realized through the use of inception-v3 and efficient net-b5 architectures, which revealed the possibility of the automation of the systems in clinical settings. The major findings are proven usefulness of deep learning models for big and diverse data and the impact of data preprocessing and augmentation on model efficiency. The study propounded implies that it is possible to enhance the performance of the ophthalmologist by incorporating these AI tools that can help in the early identification and, therefore, accurate diagnosis of the diseases. It also revealed the need for the continuous update of the models to make it efficient in delivering higher levels of accuracy and holistic reliability going forward.

6.2 Further Works

The directions for future include the topics like collecting more data modalities for better diagnosis and, the mechanisms to work on the redundancy. Some of the recommendations that could be extended to other studies may involve acquiring other from fundus images. Moreover, developing the new models which are tailored for the imbalanced data scenarios also raise the possibility of several severe conditions' prevalence and may help to improve the AI solutions application potential in the ophthalmology field. Hence, similar research should address related practical implementation issues like the challenge of creating scalable architectures that could conceivably integrate with different forms of clinical use; making Graph interfaces more attractive to clinicians; and the robustness across various samples of the proposed practices. However, there is no doubt that daily interaction of AI researchers with medical practitioners is paramount because these applications span across the statutory and ethical framework, which postulates that today's diagnostic tools have to be effective and feasible.

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