An Improved Deep Learning Model for Classification of Retinal Optical Tomography Images

By

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A thesis submitted in partial fulfillment of the requirements for the degree of Masters of Science in Software Engineering (MSSE)

In

Military College of Signals (MCS),

National University of Science and Technology (NUST),

Islamabad, Pakistan.

(Aug 2023)

THESIS ACCEPTANCE CERTIFICATE

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Dedication

This Thesis is dedicated to my beloved Parents, Children and my beloved Wife, who all have been my endless source of love, encouragement, and strength. Your unwavering beliefs in my abilities, countless sacrifices, and relentless support have been the foundation upon which I built my academic pursuits. Without their love and support this research work would not have been made possible.

Abstract

A well-known eye disorder called diabetic retinopathy (DR) is linked to elevated blood glucose levels. Cotton wool spots, confined veins in the cranial nerve, AV nicking, and hemorrhages in the optic disc are some of its symptoms, which often appear later. Serious side effects of DR might include vision loss, damage to the visual nerves, and obstruction of the retinal arteries. Researchers have devised an automated method utilizing AI and deep learning models to enable early diagnosis of this illness. This research gathered digital fundus images from renowned Pakistani eye hospitals to generate a new "DR-Insight" dataset and known online sources. A novel methodology named Residual-Dense System (RDS-DR) was then devised to assess diabetic retinopathy. The RDS-DR system is trained on the collected dataset 9,860 fundus images. The projected RDS-DR categorization method demonstrated an impressive accuracy of 97.5%. These findings show that the model produces beneficial outcomes and may be used by healthcare practitioners as a diagnostic tool. It's important to emphasize that the system's goal is to augment optometrists' expertise rather than to replace it. In terms of accuracy, the RDS-DR technique fared better than cutting-edge models VGG19, VGG16, Inception V-3, and Xception. This emphasizes how successful the suggested method is for classifying diabetic retinopathy

Key Words: Machine Learning, DiabeticRetinopathyh Disease, Classification Models, E-Healthcare

Acknowledgments

In the name of Allah (S.W.A), the Creator and Sustainer of the Universe, to whom belongs all glory and power. He alone has the authority to elevate and humble individuals as He pleases. Truly, nothing can be accomplished without His will. From the moment I stepped foot into NUST until the day of my departure, it was by His divine blessings and guidance that I was able to navigate the path of success. His unwavering support and the opportunities He bestowed upon me were instrumental in completing my research journey.

I humbly acknowledge that no words or actions can fully express my gratitude for the countless blessings He has showered upon me throughout this research period. I am indebted to His boundless bounties and am forever grateful for His divine intervention in my academic pursuits. To Allah (S.W.A), I dedicate this thesis as a humble tribute, recognizing His infinite wisdom and benevolence. It is through His mercy that I have reached this milestone, and I pray that my work may be of benefit to others and serve as a means of pleasing Him.

I would also like to express my heartfelt appreciation to my thesis supervisor, **Asst Prof Dr. Nuaman Ali Khan**, for his unwavering support and guidance throughout my thesis. His knowledge, expertise, and dedication to his field have been a source of inspiration to me, and I am grateful for the time and effort he invested in my success. Whenever I encountered any difficulties, he was always available to offer his assistance and provide me with insightful feedback.

In addition, I extend my gratitude to my GEC member, **Brig ® Assoc Prof Dr. Fahim Arif** and **Assistant Professor Dr. Yawar Abbas Bangash**, for their continuous availability for assistance and support throughout my degree, both in coursework and thesis. His expertise and knowledge have been invaluable to me, and I am grateful for his unwavering support and guidance.

Lastly, All praises and thanks be to Allah (S.W.A), the Most Merciful and the Most Gracious.

Ijaz Bashir

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List of Abbreviation

ML	--------------------	Machine Learning
DR	--------------------	Diabetic Retinopathy
DNN	--------------------	Deep Neural Network
SVM	--------------------	Support Vector Machine
FFA	--------------------	Fundus Fluorescein Angiography
OCT	--------------------	Optical Coherance Tomography
BNN	--------------------	K-Nearest Neighbor
DCNN	--------------------	Deep Convolutional Neural Network
MSR	--------------------	Multi-Scale Retinex
ANN	--------------------	Artificial Neural Network
AB	--------------------	AdaBoost
PA	--------------------	Proposed Approach
GA	--------------------	Genetic Algorithm
TP	--------------------	True Positive
TN	--------------------	True Negative
FP	--------------------	False Positive
FN	--------------------	False Negative
ACC	--------------------	Accuracy
LASSO	--------------------	Least absolute shrinkage selection operator

CHAPTER 1

INTRODUCTION

1.1 Overview

Diabetic retinopathy (DR) is a severe complication that arises from diabetes and can lead to vision impairment or even blindness if left untreated. With the rising prevalence of diabetes worldwide, early and accurate detection of DR has become increasingly crucial to prevent irreversible damage to patients' vision. Traditional diagnostic methods heavily rely on manual examination by ophthalmologists, which can be time-consuming, subjective, and prone to human error. As a result, the application of machine learning (ML) algorithms has emerged as a promising approach to automate and improve the accuracy of DR classification. The thesis aims to investigate the utilization of machine learning algorithms for the multi-classification of diabetic retinopathy, allowing for early identification and categorization of DR severity levels. By employing ML algorithms, we can harness the power of computational techniques to analyze vast amounts of retinal images and extract meaningful features, aiding in the objective and efficient diagnosis of DR.

To accomplish these goals, we will utilize a comprehensive dataset comprising retinal images collected from diabetic patients/hospitals, along with corresponding annotations indicating the severity level of DR. This dataset will serve as the foundation for training and evaluating a range of ML algorithms, including but not limited to convolutional neural networks (CNNs), support vector machines (SVMs), random forests (RFs), and deep learning architectures. By assessing the performance metrics such as accuracy, sensitivity, specificity, and area under the receiver operating characteristic curve (AUC-ROC), we can objectively evaluate and compare the efficacy of each algorithm in classifying DR.

The main objective and inspiration behind this research is to construct an effective model to detect accurately and precisely as possible. Fig. 1.1, represent the block diagram of proposed hybrid model and the required steps followed in this research are summarized as follow:-

- Five Datasets are combined to prepare an effective and mature dataset
- Data Preprocessing techniques CLAHE and MSR used for normalizing and Class balancing of data
- A Comparison of results is drawn which indicates the difference between without and with preprocessing techniques applied on dataset
- Various ML algorithm like VGG16, VGG19, Xception and Inception V-3 are used

- After preprocessing of data, all five datasets were tempted with proposed algorithm to achieve better results. Proposed Hybrid Model outperforms in achieving accuracy.
- To endorse efficacy and performance, recommended model is applied to another disease Hypertensive Retinopathy dataset having 5290 images.
- A comparison of results is drawn with existing results of former researchers

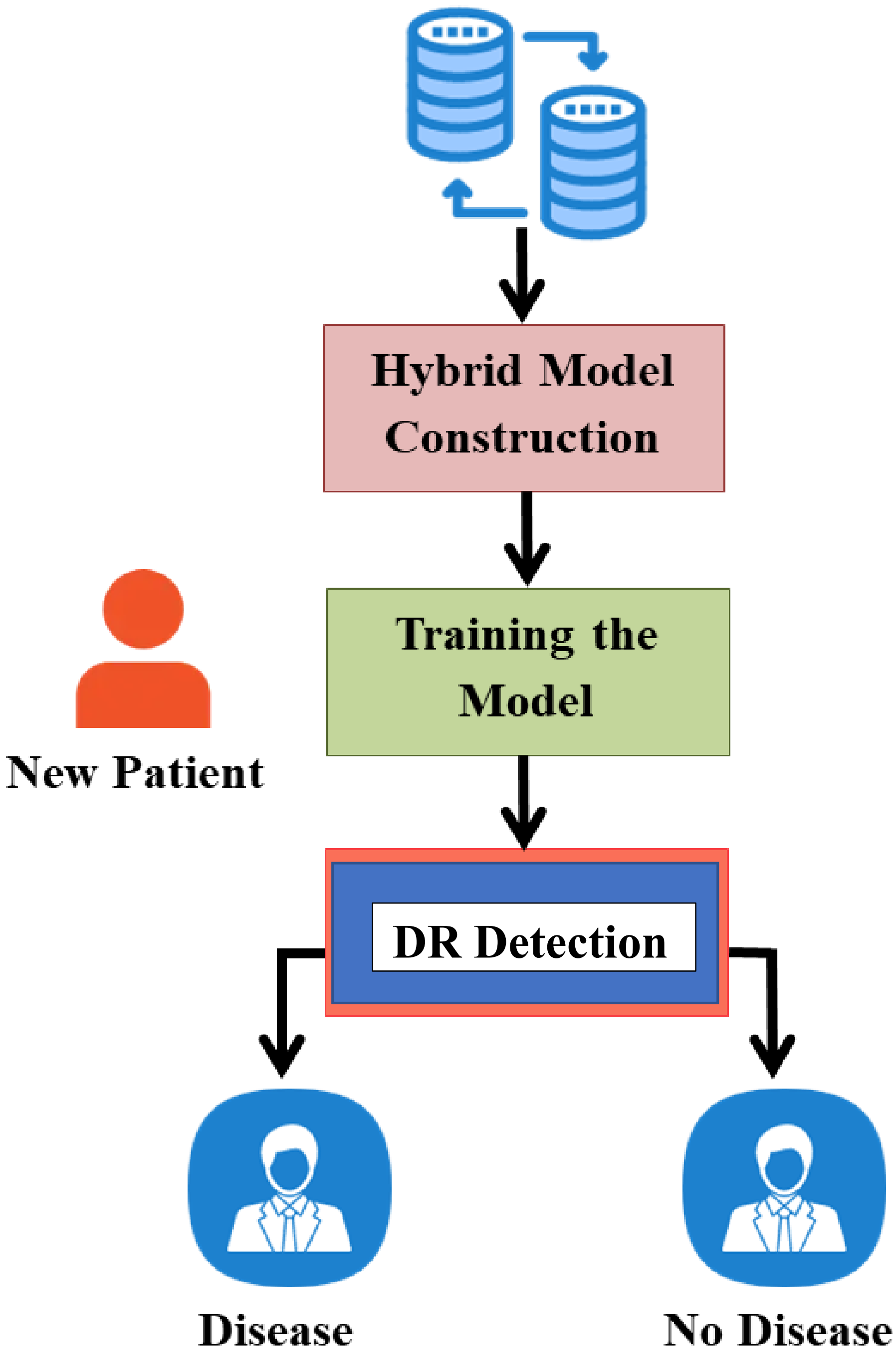

Figure 1. 1: Block Diagram of Model

1.2 Motivation

The main reason why people suffer blindness is because of an eye condition known as diabetes-associated retinopathy (DR). It is a diabetic condition that can damage the vasculature of the retina. Patients only learn they have this quiet condition when they start having visual issues. But this happens when retinal changes have advanced to a point where vision loss is more likely and therapy is challenging. In diabetic people, this illness is incurable and results in blindness. Early DR discoveries, however, could help doctors stop its development in diabetic patients. To detect the illness early and stop its spread, several researchers are driven to create automatic detection methods for DR. DR damages the retinal vasculature, and retinal damage results from the micro-blood vessel loss brought on by high blood pressure, resulting in vision impairments. 350 million people will get diabetes globally over the next 25 years, predicts the World Health Organisation (WHO) [1]. According to the National Eye Institute Database, diabetes significantly contributes to vision impairment in individuals between the ages of 20 and 74.

Both industrialized and developing countries are seeing an increase in diabetes cases. Diabetes is more common in underdeveloped nations than in developed nations. Seventy-five percent of those who have DR reside in poor nations. This is a result of inadequate care and poor healthcare administration. Before receiving therapy, diagnosing a patient's illness is difficult.

The recommended approach provides a trustworthy and efficient technique to spot DR early on, according to the comparative study discussed above. DR images were preprocessed in this investigation using the CLAHE and MSR techniques to improve the image contrast. Dimensionality reduction has been done using the ResNet model, which employs a basic CNN model as a feature extraction technique, and efficacy is improved using DenseNet blocks. To simplify the complexity and cost of the training procedure, SVM has finally been used as the classifier. The newly developed framework of this proposed model supports the claim that this inquiry is novel. The dataset is not large enough. The performance of the model may differ with a sizable dataset, which is not considered in this study. After all, the effectiveness of the model is significantly influenced by the quality of the photos and the preprocessing techniques employed. The DR images used in this experiment are quite good quality. This study is not focused on the model's performance in photos of low quality. In the future, the performance of the model may be examined using a huge data set that includes both low- and high-quality pictures.

1.3 Problem Statement

Diabetic Retinopathy (DR) is a significant global health concern, contributing to a high number of blindness and vision loss worldwide. Timely detection and intervention are crucial for improving patient outcomes and preventing the progression of DR. The utilization of ML classifiers has become increasingly significant in the field of DR identification, presenting an opportunity to support healthcare professionals in achieving precise and efficient diagnoses. This research project aims to investigate the efficacy of diverse DL algorithms, encompassing SVM classifiers, in accurately detecting DR. The performance of algorithms will be assessed using various metrics, including accuracy, sensitivity, specificity, and area under the curve (AUC). The outcomes of this study have the potential to contribute towards the development of more dependable and precise tools for the recognition and diagnosis of DR at early stage.

1.4 Research Objectives

The main objectives of this research work are:-

- A comprehensive examination of ML techniques for accurate detection of DR disease.
- Evaluation of various supervised ML classifiers using DR datasets.
- Investigation of feature selection techniques to identify relevant features for analysis.
- Implementation of a proper training and testing methodology for the proposed model, ensuring separation of training and testing data.
- Comparison of different ML classifiers to determine the highest accuracy in predicting heart disease.
- Development of a recommended model that delivers optimal results across diverse datasets.

1.5 Relevance to National needs

The implementation of multiple ML techniques can aid in prediction of DR disease, potentially saving the lives of individuals with DR conditions. The proposed technique has the potential to identify various DR issues at an early stage.

1.6 Area of Application

Application of this ML technique can aid to following areas for DR detection :-

- Hospitals either private or Government.

- Healthcare Centers
- Research and Development

1.7 Advantages

Followings are the advantages of our research work :-

- Early detection of DR problems to prevent potential risks.
- Minimizing the risk of vision loss by identifying issues at an early stage.
- The proposed system will help doctors and optometrists to identify DR in the early stages.
- The proposed system will reduce the time and cost.
- System aims to provide objective and consistent assessments of diabetic retinopathy severity.
- The proposed system will be able to handle large datasets efficiently, making them scalable for population-level studies and screening programs.
- The findings of this research hold significant potential for Medical Healthcare Centers, particularly in Pakistan, in the field of eye-related issues. The application of the proposed model can assist medical organizations in making prompt decisions regarding heart patients by utilizing various strategies derived from this method. This work aims to provide valuable insights and tools that can aid in the quick assessment and treatment of individuals with diabetic retinopathy conditions, ultimately benefiting the healthcare sector in Pakistan.

1.8 Thesis Organization

The research work has been organized and distributed in the following chapters:-

- **Chapter 1**: A brief introduction is given. Research objectives are listed. Relevance to National need is highlighted followed by area of application, its advantages and justification for selection of the topic is elaborated.
- **Chapter 2**: Describes related works carried out of various DR databases related to DR prediction system. A comparison is drawn to observe existing work by various researchers.
- **Chapter 3**: Discuss the overall research methodology including, Overview of Proposed model followed by the application and implementation of proposed model.

- **Chapter 4**: This Chapters presents the results and objective achieved by our proposed model
- **Chapter 5**: This Chapter sums up the research with conclusion drawn and provides direction for future work
- **Chapter 6**: Includes References

  Figure 1.2 gives overview of thesis toxonmoy

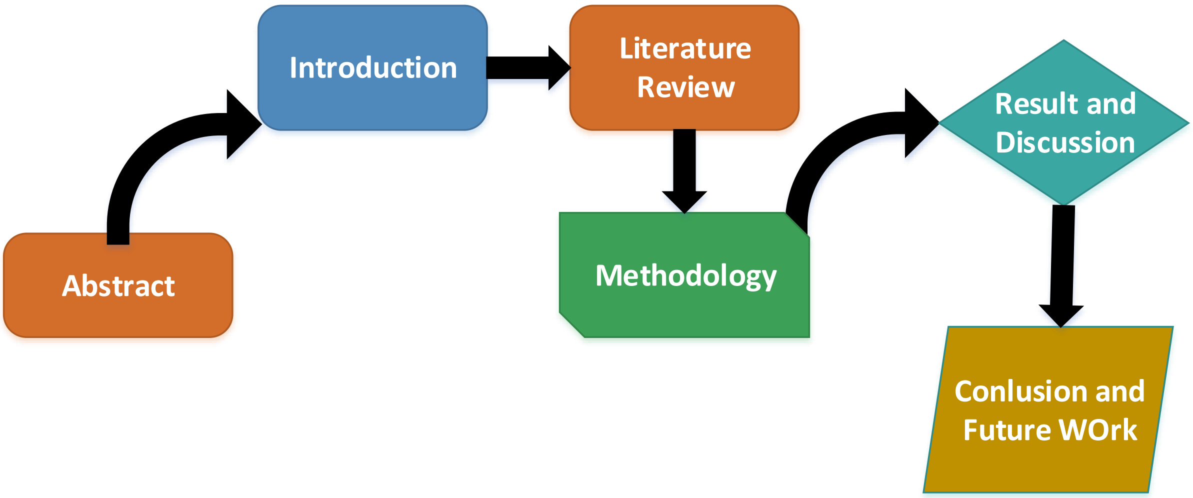

Figure 1. 2: Taxonomy of Thesis

CHAPTER 2

LITERATURE REVIEW

2.1 Introduction

Over the past 20 years, there has been significant growth in the number of people living with diabetes. the International Diabetic Federation(IDF) [1] estimates that about 500 million individuals of every age are facing a diabetes diagnosis. This is anticipated to mount to 700 million by the year 2045. It affects people all across the world, according to the IDF, one out of every third individuals suffering from diabetes will get diabetic retinopathy (DR) by the end of the year 2040.

Diabetic retinopathy is termed as the presence of ruptured vessels at the back of the retina. Color fundus retinal imaging can reveal DR symptoms including Microaneurysm (MA), Exudate (HE), Hemorrhage (HM), and Cotton Wool Spot (CWS) [2]. Figure-2.1 shows all possible symptoms that can be appeared on a fundus image.

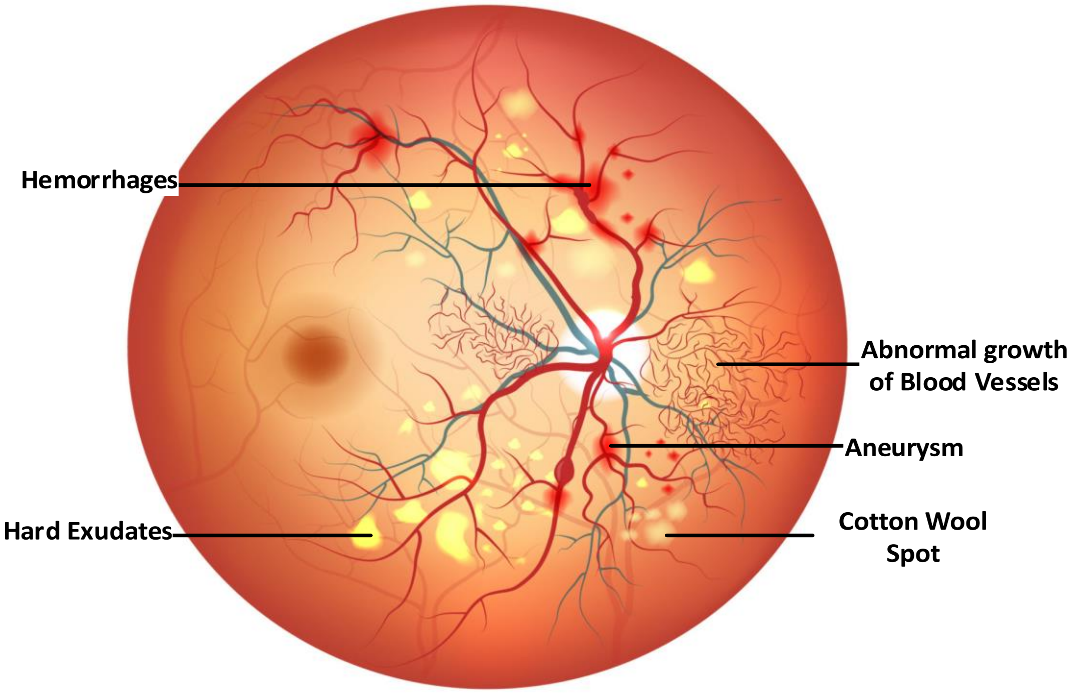

Figure 2. 1: Diabetic Retinopathy Symptoms

A microaneurysm is a blood vessel growth in the retina where veins appear as a red patch with a sharp edge on the retinal layer. Exudates, which look like yellowish areas in the retina, are the result of the breakdown of proteins from microscopic venous vessels of the retina. Hemorrhages are developments that bear a resemblance to red areas with irregular borders and are brought on through leakage of fragile blood capillaries [3]. Table-2.1 sums up the clinical findings of DR.

Mainly, DR is categorized into two basic classes: proliferative(PDR) and non-proliferative (NPDR), which is further distributed based on severity into 4 progressive levels: mild, moderate, severe, and PDR depending upon retinal findings as shown in figure-2.2. The mild stage is the very first level of DR in which microaneurysms (red dots of various sizes) are present only. Lesion progresses to moderate NPDR with signs of hemorrhage and exudates. Hemorrhage size increases considerably with definite beading in severe NPDR level. PDR is the stage where blindness occurs due to neovascularization that causes blood leakage [4]. Table 1 presents symptoms against each classification level of DR.

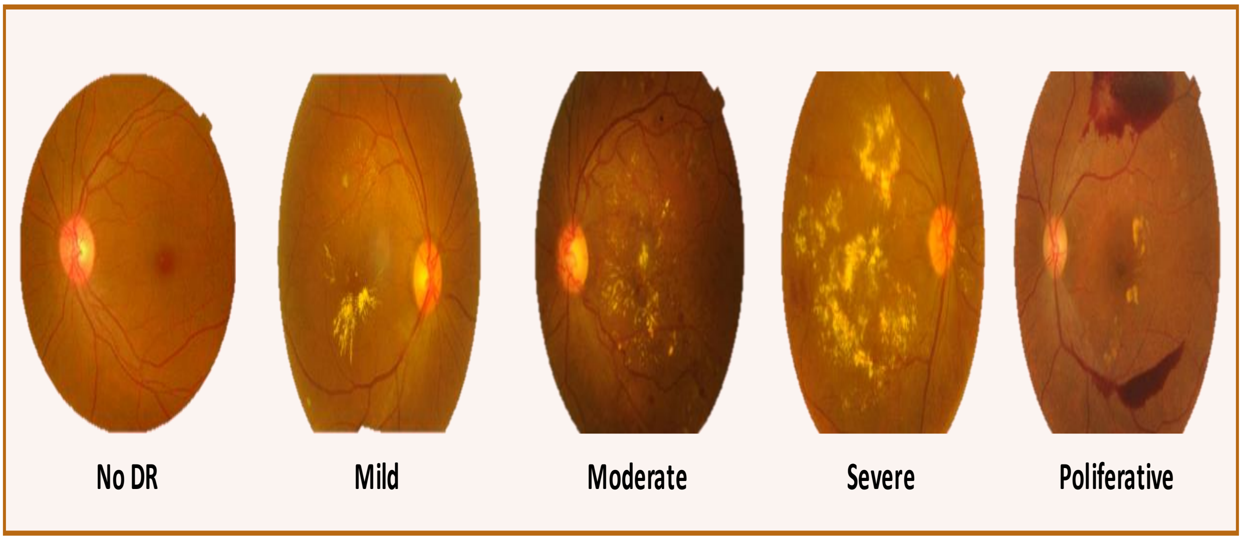

Figure 2. 2: Categorization of DR images According to Severity Level

Table 2. 1: Number of DR Symptoms as per Severity Level

No of Symptoms	Retinal Image Analysis	DR Level
1	Micro aneurysms (MAs) only	Mild
1	Hemorrhages	Moderate
2	Microvascular Abnormalities	
3	Hard Exudates	
4	Soft exudates	
5	Venous Beading	
1	>20 intra-retinal hemorrhages	Severe NPDR
2	Retinal vein occlusion	
3	Noticeable Intra-Retinal MA	
1	Neovascularization	PDR
2	Vitreous/pre-retinal hemorrhage	

It is critical to address this as if it remains undiagnosed for a long period, it might lead to major consequences such as blindness and vision loss. Diabetic retinopathy is a major contributor to blindness worldwide. Loss of eye vision mainly occurs at advanced stages of DR. Keeping in view the severity level, the importance of early detection becomes manifold. Therefore, for the betterment of the patient thorough inspection and monitoring is necessary at an early stage with accuracy and precision, so that proper diagnoses and in-time treatment of DR can be executed to avoid loss of vision.

Currently, ophthalmologists merely employ manual methods for the identification of diabetic retinopathy. They assess the degree of DR severity by observing the color of retinal photos. Typically, inspection and screening of clinical DR through colored fundus images obtained via optical coherence tomography (OCT) and fundus fluorescein angiography (FFA) are in practice. OCT Fundus images proved to be a more effective and efficient way of diagnosis and screening because of ease of availability and because it provides in-depth high resolution. Provision of pathological variations can easily be obtained through FFA [4]. However, this approach is quite time-consuming, susceptible to mistakes, and intricate. It is also dependent on ophthalmologist expertise and experience. Secondly, about the real number of patients, this costs a lot of time, and there isn't enough availability of doctors. These factors contribute to the fact that many patients do not get medical attention on time. Even though diabetic individuals are urged to have frequent clinical assessments of fundi, however still numerous patients go undiagnosed until the condition gets worse [5]. Therefore, having a computer-assisted diagnosis system that will support in the screening of diabetic retinopathy is necessary. Early DR identification is essential for avoiding irreversible blindness. Accuracy remains critical during diagnoses and screening of DR.

Many learning techniques such as machine learning (ML) and deep learning (DL) algorithms for DR detection have evolved in recent years to overcome these issues. These methods automate the detection process using cutting-edge algorithms and models, offering a more effective and precise solution. Deep neural network-based techniques for retinal imaging are a recent research area in ophthalmology. Numerous studies are being conducted to improve the diagnostic precision of DR scanning. The CAD system's accuracy has increased over time because of the integration of AI-based technology. Modern medical scanning utilized cutting-edge deep-learning techniques to categorize retinal images.

Deep learning algorithms produce better and more desirable results for DR detection. Using a hybrid approach that combines image processing and computer vision is another adaptive choice for building CAD systems with high accuracy. Computer-aided diagnoses proved to be the future of medical science [8].

Many learning techniques such as machine learning (ML) and deep learning (DL) algorithms for DR lesion recognition have evolved in past few years to overcome these issues. These methods automate the detection process using cutting-edge algorithms and models, offering a more effective and precise solution. Deep neural network-based techniques for retinal imaging are a recent research area in ophthalmology. Numerous types of research are presently in progress to improve the diagnostic precision of DR scanning. The CAD system's accuracy has increased over time because of the integration of AI-based technology. Modern medical scanning utilized cutting-edge deep-learning techniques to categorize retinal images.

DL algorithms produce improved and desirable results for DR identification. Using a fusion approach that chains image processing and computer vision is another adaptive choice for building CAD systems with high accuracy. Computer-aided diagnoses proved to be the future of medical science.

2.2 Related Work

There have been considerable developments in the field of automated diabetic retinopathy pathology screening in the near past. The efficacy and accuracy of identifying lesions in the retina have been improved by several deep learning and machine learning-centered methodologies suggested in the literature.

In one noteworthy work, Akram et al. [6] employed a mixed ensemble classifier built with the Gaussian mixed Model (GMM) and Support Vector Machine (SVM) to identify DR lesions. The researchers combined intensity characteristics with shape-enhanced features to increase the model's classification precision. Similar to this approach, Akram et al. [7] adopted an identical technique to increase classification accuracy by combining an ensemble classifier with a variety of techniques, including k-Nearest Neighbors (k-NN), AdaBoost, SVM, and GMM. Effectiveness in identifying diseased images and healthy images was assessed by these classifiers. In a different research, a hybrid feature retrieval approach was used to extract pertinent characteristics from retinal pictures [8]. This method concentrated on removing details from the retinal pictures, such as the location of exudates, The positioning of veins and arteries, points of division, texture, and level of disorder. The researchers yearned to increase the precision of lesion identification by adding these variables to the classification process.

The previously stated strategies may be subject to performance constraints since they rely on conventional classification techniques that might not be effective in properly differentiating between intricate data such as lesion and non-lesion pictures. In addition, these methods frequently involve human feature engineering and domain expertise to extract pertinent data from the incoming data. CNNs, in particular, have shown to be extremely effective in solving classification issues related to DR and have substantially helped the field of automated DR diagnostic screening.

DL algorithms are capable to recognize mild variations from retinal pictures without the assistance of an individual or domain knowledge. Gulshan et al. [9] deployed the Inception-v3 model for DR detection. To test the approach, 9963 quality images were employed from both the EyePACS-1 dataset and the Messidor-2 dataset. They concluded that their proposed model is accurate and reliable for DR diagnosis. A CNN algorithm was proposed to categorize images into five severity levels and their technique was able to identify clinical findings of DR in another work by Pratt et al. [10]. Utilizing the Kaggle EyePACS dataset, the projected algorithm was trained. The researchers used data augmentation techniques to boost the quantity of data to address issues like overfitting and unbalanced datasets. The proposed CNN architecture comprised three fully linked layers and 10 convolutional layers. The model attained 75% accuracy, 30% sensitivity, and 95% specificity.

A convolutional neural network alogrithm was proposed by G. Garcia et al. [11] to classify the levels of diabetic retinopathy. Their model performed estimably when tested against the EyePACS dataset, with a 93.65% specificity and an 83.68% accuracy. This shows how well the model can distinguish between various DR levels. In a work by Wang et al. [12], the Kaggle dataset was utilized in testing effectiveness of three pre-trained CNN architectures: Inception-Net V3, Alex-Net, and VGG-16. The objective was to categorize each DR stage. The Inception-Net V3 architecture distinguished between various phases of DR with the best average accuracy of 63.23% across the three models.

Esfahan et al.[13] utilized the Kaggle dataset in combination with the renowned CNN architecture ResNet-34 for DR sorting. The results were 85% accurate overall. The researchers employed multiple types of image preparation methods to improve image quality. Different techniques were also used in preprocessing step including weighted addition, Gaussian filtering, and picture normalization. These techniques helped improve quality of input images before using as input to the CNN, leading to improved accuracy in DR classification.

The Kaggle dataset was utilized in research by Dutta et al. [14] to diagnose and categorize images of diabetic retinopathy into five distinct stages. Researchers assessed the performance of the Convolutional Neural Network, Deep Neural Network (DNN), and Back Propagation Neural Network (BNN) with a collection of 2000 images. Dutta et al. applied several filters to the images before being fed to the network to improve the data. The pre-trained VGG-16 architecture, which comprises three fully connected (FC) layers, four max-pooling layers, and sixteen convolutional layers, was used by the CNN model. The DNN, on the other hand, used three FC levels. Interestingly, the DNN fared better than both the CNN and the BNN in terms of accuracy, obtaining a remarkable accuracy rate of 86.3% for DR classification. Dutta et al. offer important insights into the potential of deep learning methodologies for DR classification by contrasting performance of several neural network designs. The results imply that selecting the right architecture, in this case, the DNN, may considerably affect the precision of DR diagnostic and classification tasks.

C. Lian et al. [15] used three different CNN architectures AlexNet, ResNet-50, and VGG-16, to investigate the categorization of diabetic retinopathy. To improve the precision of DR classification, their study concentrated on network architecture, preprocessing methods, addressing class unevenness, and fine-tuning. On EyePACS dataset, C. Lian et al. obtained results by utilizing these convolutional networks. The achieved accuracy rates for AlexNet, ResNet-50, and VGG-16 were 73.19%, 76.41%, and 79.04%, respectively. C. Lian et al. focused on critical elements such as network design optimization, input data preparation, addressing class imbalance difficulties, and model tweaking throughout their investigation. The leave-one-out approach was applied by Shaban et al. [16] to develop the DR classification CNN model for analyzing retinal images. The model scored fairly well with an accuracy rate of 80.2%, sensitivity of 78.7%, and specificity of 84.6%.

In order to categorize their set of data., Hongyang et al. [17] used three pre-configured architectures: Inception-V3, Inception-ResNet-V2, and ResNet-152. The Adam optimizer modified the CNN models' weights during training. Additionally, the predictions from these models were combined using an ensemble strategy utilizing the AdaBoost framework. The ensemble model with an accuracy of 88.21% was attained. A technique for diagnosing diabetic retinopathy was put out by Wei et al. [18] using a proprietary dataset composed of 13,767 pictures divided into four classifications. They were scaled and cropped to prepare the images for each network's input needs. The authors improved the pre-initialized architectures ResNet-50, Inception-V2, Inception-V3, Xception, and DenseNet for identification of DR. The models were enhanced to provide precise DR detection by tailoring these architectures to the particular objective.

Harangi et al.[19] used the AlexNet architecture with manually built traits for recognition of diabetic retinopathy photos. While the IDRiD dataset was put to use for testing, the Kaggle dataset was utilized for training the CNN model. All five levels of DR were correctly identified by the research with an accuracy of 90.07%. A weighted paths CNN (wp-CNN) was developed by Yi-Peng et al. [20] to recognize DR images. Agumentation technique was used to resize images to 299 x 299 so that class imbalance can be addressed. With numerous convolutional layers using various kernel sizes on weighted channels, the wp-CNN produced very accurate results. The wp-CNN beat pre-trained models like ResNet, Se-Net, and DenseNet, displaying its better ability in recognizing referable DR images, with 94.23% accuracy rate on their dataset and 90.8% on the STARE dataset.

A method for detecting diabetic retinopathy utilizing DCNN ensemble classification used by Qmr et al. [21]. Their ensemble method used the ResNet-50, Inception-v3, Xception, DenseNet-121, and DenseNet-169 models. Evaluating their approach on a publicly accessible Kaggle dataset recommended approach outperformed earlier ones and produced an accuracy of 80%. DR classification method that allocates values to points in the input and hidden spaces was introduced by Jod et al. [22]. This makes it possible for their classifier to explain the results of the classification. On the binary classification portion of the Messidor-2 dataset, their classifier had a 91% accuracy rate. A multitasking deep learning (DL) model for detecting diabetic retinopathy was described by Mjr et al. [23]. A combination of regression and classification models was employed to come up with multitask model. Each model had a unique loss function and underwent separate training. In addition, a multilayer perceptron network was used to do image recognition for diabetic retinopathy within the dataset using input characteristics from the aforementioned models. 82% accuracy On the EyePACS and 86% accuracy rate was achieved using the APTOS Dataset.

By applying fine-tuning on VGG16 and MobileNetV1 models, [24] investigated a transfer learning technique. They attained training accuracy rates of 89.42% for VGG16 and 89.84% for MobileNetV1 using this learning method. Using the APTOS 2019 dataset, a pre-trained and modified DenseNet121 network was used [25]. For evaluating DR severeness level detection, model had a remarkable accuracy of 96.51%. Using fundus fluorescein angiography (FFA) pictures, three CNN were used [26] to automatically identify and classify DR lesions. Area under the curve (AUC) values of 0.8703 for DenseNet, 0.8140 for ResNet50, and 0.7125 for VGG16 were obtained. Table-2.2 sums up above literature in tabular form.

Table 2. 2: Existing work for DR Prediction by various Former Researchers

Ref	Year	Technique Used	Architecture	Data Set	Results
[6]	2013		GMM, SVM	DiaRet0,DiaRet1	
[7]	2014		GMM	DiaRetDB	
[8]	2013	PNN	SVM, Decision Tree		
[9]	2016	DNN	-	EyePACS-1 Messidor-2	ACC 93.4% ACC 93.9%
[10]	Jan 2016	CNN	-	Kaggle EyePACS	ACC 75%
[11]	2017	CNN	-	EyePACS	ACC 83.68%
[12]	2018	DCNN	AlexNet VGG16 InceptionNet V3	Kaggle dataset	ACC 37.43% ACC 50.03% ACC 63.23%
[13]	2018	DCN	ResNet	Kaggle dataset	85%
[14]	2018	BNN, DNN, CNN	VGGnet model	-	72.5%
[15]	2018	CNN	AlexNet, VggNet, GoogleNet, ResNet,	Kaggle	-

[16]	Dec 2018		leave-one-out method	-	ACC 80.2%
[17]	Jul 2019	CNN	Inception-V3, Inception-ResNet-V2, and ResNet-152	-	ACC 88.21%.
[18]	Jul 2019	CNN	ResNet-50, Inception-V2, Inception-V3, Xception, and DenseNet	13,767 images	-
[19]	Jul 2019	CNN	AlexNet	Kaggle dataset IDRiD	ACC 90.07%.
[20]	Aug 2019	CNN (wp-CNN).	Resnet, Se-net, and DenseNet models	-	ACC 94.23%
[21]	2019	DNN	ResNet-50, Inception-v3, Xception, DenseNet-121,Dense-169	Kaggle dataset	ACC 80%.
[22]	2020	CNN	Binary	Messidor-2 data set	ACC 91%
[23]	2021	CNN	a classification and regression model	EyePACS dataset APTOS Dataset.	ACC 82% ACC 86%
[24]	2020	DCNN	VGG16 and MobileNetV1		ACC 89.42% ACC 89.84%
[25]	Apr 2020	DNN	DenseNet121	APTOS 2019 data set.	ACC 96.51%
[26]	Apr 2020	DCNN	Dense Net, ResNet50, and VGG16,		AUC 0.8140 AUC 0.7125

2.3 Importance of DR early Detection

The main reason why people suffer blindness is because of an eye condition known as diabetes-associated retinopathy (DR). It is a diabetic ailment which can damage the vasculature of the retina. Patients only learn they have this quiet condition when they start having visual issues. But this happens when retinal changes have advanced to a point where vision loss is more likely and therapy is challenging [21]. In diabetic people, this illness is incurable and results in blindness. Early DR discoveries, however, could help doctors stop its development in diabetic patients. To detect the illness early and stop its spread, several researchers are driven to create automatic detection methods for DR. DR damages the retinal vasculature, and retinal damage results from the micro-blood vessel loss brought on by high blood pressure, resulting in vision impairments.

2.4 Recent Research on DR Classification

To categorize DR, numerous DL algorithms have been used. In background knowledge, some of the most recent approaches have been covered. In a study referenced as [27], a DenseNET-based architecture is proposed. This architecture classifies all three stages of DR from fundus images using a multitasking deep neural network. The training and evaluation of the model were conducted using the two largest online available datasets of retinal images, EyePACS and APTOS. The results suggest that the new multi-tasking model outperforms the five-step DR classification algorithms that were previously used. However, the size of the datasets used and the lengthy training times required to train a large quantity of data are still limitations of current deep learning models. In [28], a novel deep feature generator patch-based new model is presented. This model has high classification accuracy for DR. To achieve high accuracy in classifying images into three categories (normal, PDR, and NPDR), a new system moved by the vision transformer (ViT) and multilayer perceptron mixer (MLP mixer) techniques was developed. The fundus picture is divided in vertical and horizontal regions, and features are retrieved from both local images and patches by means of a pretrained DenseNet201 model. The newly suggested dataset and the Case 1 dataset inferred from APTOS 2019 dataset both achieved over 90% accuracy.

In reference to [29], the recommended methodology involves using median filtering on fundus images and a adapted approach to eliminate blood vessels. To test the model for training, a multiclass SVM classifier is utilized to retrieve characteristics. The approach was tested using fundus photographs from the year 1928. Results show that on the 'KAGGLE APTOS dataset, the approach had a sensitivity of 75.6% and an accuracy of 94.5%. On the 'IDRiD' dataset, sensitivity was 78.5% and accuracy was 93.3%. An innovative automated deep learning-based technique for identifying severity is presented in [30] using a single-color Fundus picture. An approach that has proven to be highly effective involves utilizing the encoder from DenseNet169 to establish a visual integration. In addition, the Convolutional Block Attention Module (CBAM) is utilized to further enhance the model's performance. Throughout the model's training, the cross entropy loss technique is employed in conjunction with data from Kaggle Asia Pacific Tele Ophthalmology Society (APTOS). Because of these efforts, the binary classification test yields an impressive 98.3% specificity, 97% sensitivity, and 97% accuracy.

Notably, the Quadratic Weighted Kappa score (QWK) achieved is an outstanding 0.9455, surpassing that of other advanced techniques.

The researchers in the study [31] developed a technique to enhance picture quality, which they combined with a deep learning-based classification algorithm. They used a method called Contrast Limited Adaptive Histogram Equalization (CLAHE) and rate of accuracy achieved by this technique was 91%, 95%, and 97% on various models such as VGG16, InceptionV3, and EfficientNet, respectively. Another innovative method for detecting diabetic retinopathy (DR) is proposed in [32]. The method involves using an asymmetric DL feature to separate optic nerve. Authors used U Net to extract these features and then used a convolutional neural network (CNN) and a support vector machine (SVM) to categorize DR lesions into four levels: exudates, microaneurysms, haemorrhages, and normal lesions. Two commonly available datasets of retinal images, APTOS and MESSIDOR, were used to test a recommended approach. An innovative two-step process involving SqueezeNet and DCNN was used to create a highly effective and advanced DR classification solution as explained in [33]. In the first step, SqueezeNet was used to distinguish the fundus image as normal or abnormal. The severity of the erroneous images was then determined in the second level decomposition using DCNN. Table 3 shows various techniques that have recently been used for DR categorization.

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Al Antary and Yasmine [34] suggested a multi-scale attention network (MSA Net) for classification of DR. Retinal pictures with mid- and high-level attributes have better resolution thanks to the encoder network, which also embeds them in a high-level representational space. Many distinctive scale pyramids are used to characterize the retinal anatomy in other places. Along with improving top-level representation, a multi-scale attention methodology develops feature visualization and refinement. The model uses cross-entropy loss to classify the level of DR severity. As a side project, the model employs flimsy annotations to discriminate between photos of healthy and sick retinas. This helps the model recognize photos of diseased retinas. The EyePACS and APTOS datasets responded favorably to the proposed method. Table-2.3 presents a summary of the background.

Table 2. 3: Summary of recent work on DR Classification.

AUTHOR	YEAR	METHODOLOGY
Al-Antary	2021	Multi-scale attention network (MSA-Net)
Majumdar	2021	Squeeze Excitation Densely Connected deep CNN
Macsik	2022	Local binary, convolutional neural network (LBCNN)
Saranya	2022	Support vector machine (SVM)
Kobat	2022	DenseNet201
Mohamed M.Farag	2022	DenseNet169+CBAM
Hayati	2023	EfficientNet
Pradeep Kumar Jena	2023	U-net for segmentationCNN with SVM for classification
S. Zulaikha Beevi	2023	Squeezenet, the picture is classed into the normal or abnormal DCNN for severity level.

2.5 Research Work on DR Classification Using SVM Classifier

An innovative automated deep learning-based technique for identifying severity is presented in [30] using a single-color Fundus picture. An approach that has proven to be highly effective involves utilizing the encoder from DenseNet169 to establish a visual integration. In addition, the Convolutional Block Attention Module (CBAM) is utilized to further enhance the model's performance. Throughout the model's training, the cross entropy loss technique is employed in conjunction with data from Kaggle Asia Pacific Tele Ophthalmology Society (APTOS). Because of these efforts, the binary classification test yields an impressive 98.3% specificity, 97% sensitivity, and 97% accuracy. Notably, the Quadratic Weighted Kappa score (QWK) achieved is an outstanding 0.9455, surpassing that of other advanced techniques

Another innovative method for detecting diabetic retinopathy (DR) is proposed in [32]. The method involves using an asymmetric DL feature to separate optic nerve. Authors used U Net to extract these features and then used a convolutional neural network (CNN) and a support vector machine (SVM) to categorize DR lesions into four levels: exudates, microaneurysms, haemorrhages, and normal lesions. Two commonly available datasets of retinal images, APTOS and MESSIDOR, were used to test a recommended approach. An innovative two-step process involving SqueezeNet and DCNN was used to create a highly effective and advanced DR classification solution as explained in [33]. In the first step, SqueezeNet was used to distinguish the fundus image as normal or abnormal. The severity of the erroneous images was then determined in the second level decomposition using DCNN. Table 3 shows various techniques that have recently been used for DR categorization.

2.6 Summary

The studies reviewed in this literature cover various types of DR datasets used for DR Disease prediction. Various ML algorithms are utilized by numerous researchers to achieve better accuracy of prediction. Multiple data preprocessing techniques were used to normalized data and class balancing of data and furthermore, various feature selection techniques were used mentioned in literature review. Various classifiers like SVM, KNN, RF, DT, GB, ANN, LR and Linear models were also used.

CHAPTER 3

RESEARCH METHODOLOGY

3.1 Introduction

This chapter describes the overall functioning and methodology of proposed model. An overview of proposed model is described with diagram containing workflow of proposed model to be followed for DR detection. Noval approach has been proposed using ResNet-50 with combination of Residual blocks for feature extraction. Extracted feature is then subjected to SVM classifier for classification of DR images. Dataset DR-Insight is used which collected from reckoned Pakistani Hospitals. Next subpart of this chapter, describes the justification of proposed model with co-relation of dataset being utilized. Pseudo code of proposed algorithm is written which easily indicates the flow construction of Hybrid model. A detailed diagram is drawn which tells about how a DR will be detected by using proposed Hybrid model.

3.2 Overview of Proposed Model

The study combines Residual Blocks and Dense blocks to create the Residual- Dense-system(RDS-DR). This approach is used to categorize eye images in five distinct classifications: No DR, mild, moderate, severe, and proliferative. In proposed system the Residual blocks with dense block technique is used to retrieve useful information from the fundus pictures. Transfer learning of the residual blocks is used to successfully train the system on DR-related lesions. Several essential steps are used by RDS-DR method for the diagnosis of retinal fundus pictures and the identification of diabetic retinopathy severity. Figure-3.1 visually represents these steps in the form of a systematic diagram. Throughout the training process, the residual block values are continuously changed. Subsequently, a feature transform layer is incorporated to leverage the combination of features through element-wise multiplication. The activation function of SVM classifier is employed to improve the classification and categorization results.

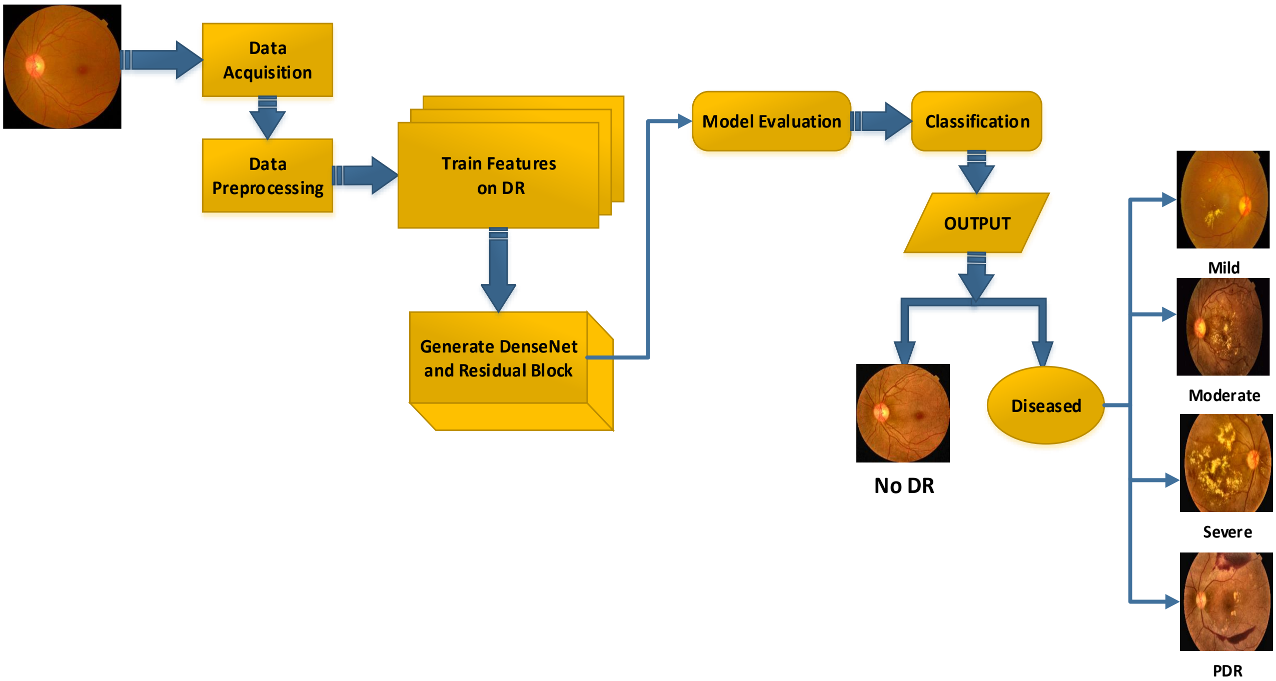

Figure 3. 1: Work Flow of Proposed Methodology

3.3 Residual Network

Deep convolutional neural networks (CNNs) may be trained effectively via residual learning, which provides faster convergence and greater network accuracy. This method requires being familiar with the identity function to skip or avoid some training stages. This strategy offers several benefits. First of all, it enables the information from one layer to be immediately added to another. Equation 1 illustrates an additive process, where the input $x[n-1]$ is added to the output $y[n-1]$ in the following layer:

$$X[n] = y[n] + x[n-1]$$

The final forecast, $x[n] \ - \ x[n-1]$, is produced by deducting $x[n-1]$ from $x[n]$. The network finds it easier to collect and learn the required transformations when residual pictures are learned rather than the actual input images. This simple approach makes the training process more effective. The generic architecture of ResNet-50 is present in figure-3.2.

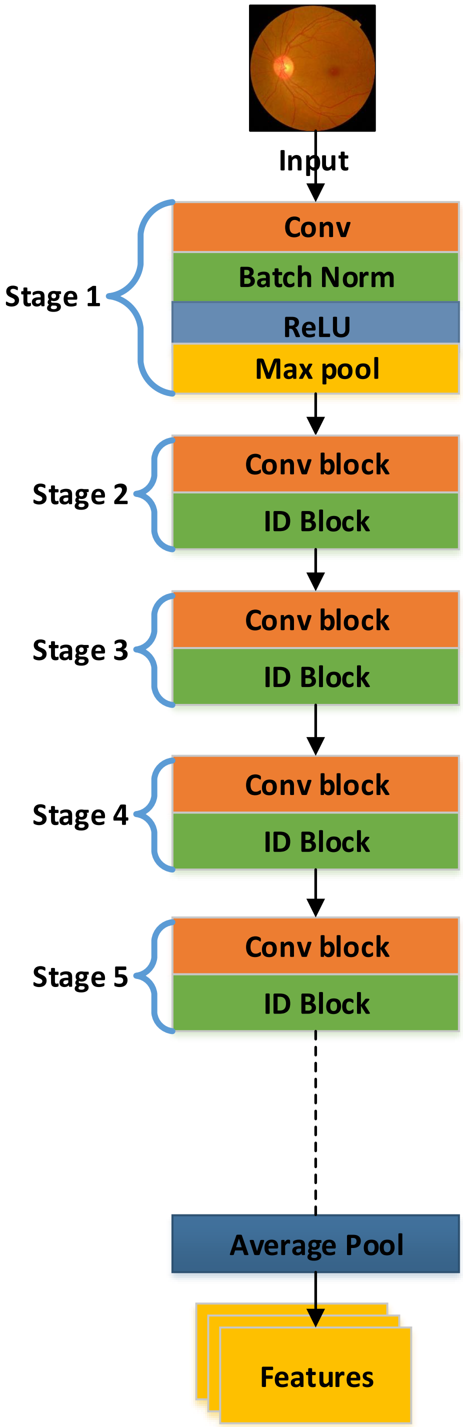

Figure 3. 2: Architecture of ResNet-50

3.4 Dense Blocks

Contrary to conventional designs, DenseNet concatenates, rather than sums, the output of one layer with the input feature maps of the preceding layer. Convolution, pooling, batch normalization, and rectified linear unit activation are some of the transformation procedures that create this relationship, presented in figure-5. DenseNet models have numerous significant characteristics. The network has a lighter, easier-to-understand structure. There are fewer parameters since fewer filters are being used. Additionally, the settings are effective. By reducing duplicate feature maps, DenseNet effectively frees up memory. DenseNet improves classification performance by allowing the final classifier to conclude from all of the feature maps that are available in the network [17]. Each layer of DenseNet may easily access the layers above it, allowing for effective information reuse as of previously calculated feature maps Taken together, xL is the output of Lth layers and TL(xL) represents the nonlinear transformation operations performed on xL. These operations include batch normalization, ReLU activation, and a convolutional layer with a 3x3 filter. The output of the previous layer, xL-1, is used as the basis for these changes. All of the feature maps are joined together during the feedforward phase. Equation 2 can be used to specify the output of xL.

$$xL = TL([xL-1,xL-2,xL-3,\ldots,x0])$$

The transition layer is the layer that lies between each thick block. It comprises an average pooling (AP) layer and a convolutional layer. Feature maps indicated as K, are produced by each TL(XL) procedure for every layer. The number of networks in the input picture determines the first input feature map, K0. K—which indicates the network's growth rate—should preferably be a small integer to reduce computing complexity. As a result, the layer Lth may be determined using the formula Lth = K (L - 1) + k0.

The bottleneck layer is presented in the DenseNet architecture to reduce the quantity of input feature maps. This layer, which has a 3x3 filter, is added before each convolutional layer in the TL (transformational) procedures. Batch normalization (BN), rectified linear unit (ReLU) activation, and a convolutional layer with a 1x1 filter make up the bottleneck layer. The next set of BN, ReLU, and a convolutional layer with a 3x3 filter comes after that.

The bottleneck layer is incorporated into the DenseNet model to increase computational efficiency. DenseNet-B is the name of this model's variation. Using the DenseNet-B architecture, the computational cost may be lowered while preserving the model's representational ability by a factor of four in the number of feature mappings, K.. Figure 3.3 gives generic view of densenet architecture.

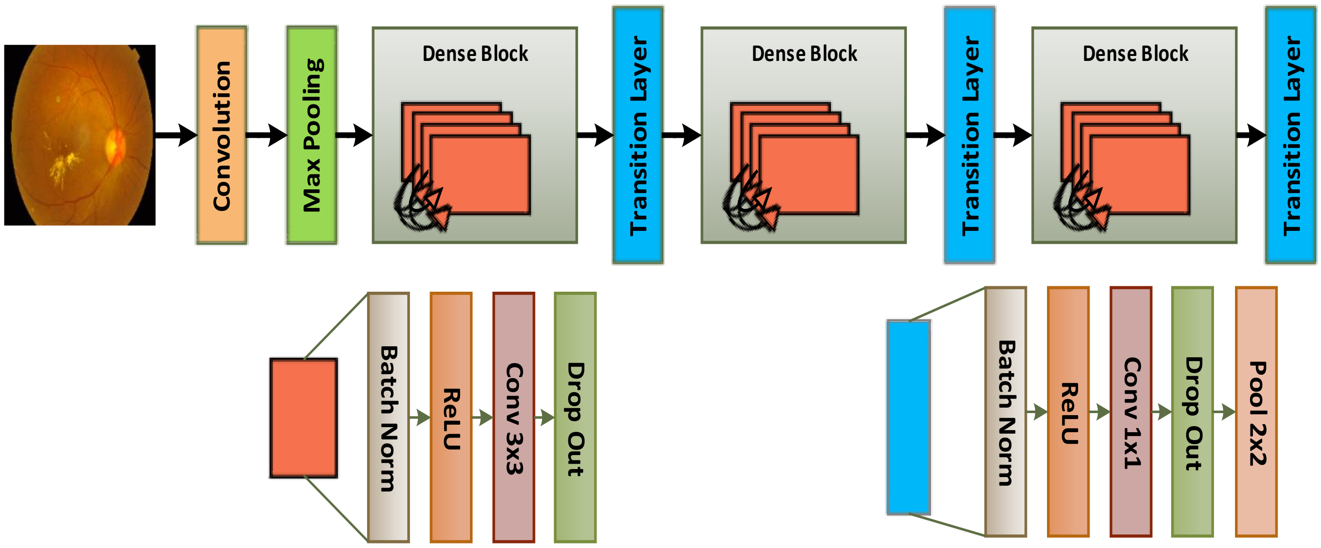

Figure 3. 3: Architecture of DenseNet-121

3.5 Application of Proposed Hybrid Model

The suggested model is proving to be an efficient model once its suitable application is justified and it also aid to deal with real world challenges. Fig. 3.1, illustrates the workflow of our proposed model. This intelligent devised model can be utilized in various health centers to predict DR severity classification in an effective way. The following procedure can be followed to attain prediction of DR.

- DR fundus images is collected and put together to form a dataset
- The main features of will be selected as an input to our proposed model Desne-Residual-Network to perform prediction
- Selected features will be handled in our trained model
- As a result, multi classification output will be generated.
- SVM classifier will be incorporated to classify image as per severity level.

3.6 Justification of Proposed Hybrid Model

The unique hybrid model has been devised by using two various DL models. Consequently, an SVM classifier technique is used to make this model efficient and persistent in achieving results. Data preprocessing techniques used for data normalization and class balancing remains the hallmark difference of former results. After achieving improvements in result in data preprocessing phase, our proposed model was deployed for feature extraction and then SVM techniques is applied as base classifier to achieve accurate classification results. Proposed model was implemented on five different datasets for validation of results. The proposed model came up with excellent results over all five datasets proving to be an efficient model. Results of our model was compared to the state of the art work already conducted on the subject. Better results were achieved as described in later sections.

Various studies have already been conducted by using various ML algorithm that contracts with the same dataset don't produced better results as expected. After an exhausted study we came to a conclusion that some models don't perform well as those systems don't identify most important and highly co-related features.

We tried to make it unique while using our proposed model to another disease, Hypertensive retinopathy along with its own data set. Our model came up with very good accuracy proving the strength of our model. Total of 5490 images of that disease were used for classification. Our model classify these images very accurately giving high accuracy as compare to model already used in that research.

Summary

In this chapter, an overview of proposed model is given followed by a detailed diagram of suggested Architecture of proposed model. The dataset is described along with a comprehensive discussion on dataset is discussed in table 3.1. Application of proposed model in real world is discussed in points. A complete workflow diagram is also appended for better understanding. Furthermore, Justification of proposed model also elaborated supported by co-relation matrix of all 14 features used in this research work followed by pseudo code of proposed model.

CHAPTER 4

IMPLEMENTATION

OF PROPOSED MODEL

4.1 Introduction

In this chapter, the implementation of the proposed hybrid model Dense-Residual-Network is described in details which includes the environment used for this research work, data preprocessing techniques applied. All the ML classifiers utilized for this research are described in details followed by evaluation of parameters.

4.2 Environment

To build and develop the RDS-DR system, a computer with the specification of HP- core i7 CPU with 8 cores, 20 GB of RAM, and a 4 GB NIVIDA GPU was used. 64-bit Windows 11 was installed on a computer system.

4.3 Data Acquisition

To develop and evaluate the efficacy of the diabetic retinopathy model, 9860 retinal fundus images were collected. The dataset was made up of 1000 images of each level: no-DR, mild, moderate, severe, and proliferative DR levels. DR images were obtained from esteemed Pakistani hospitals and well-known web databases. An expert ophthalmologist team painstakingly classified the severity level DR images from multiple existing datasets to produce the training dataset. The five datasets, each with a distinct dimension setting, that were combined to create our training and testing fundus set are listed in Table 4.1. The fundus images were given labels after processing. Data augmentation techniques were used to fulfill the requirement for a balanced depiction of photos with and without the condition. This strategy is intended to guarantee the dataset's impartiality. As part of the preparation stage, the photos from the dataset were downsized to dimensions of 700x600 pixels. The ideal shrinking arrangement was particularly found through experimental research to be this resizing. Instead of expanding smaller photographs, it is sometimes preferable to decrease the dimension of bigger images to equal with that of smaller ones. Deep learning models often demonstrate quicker training on smaller pictures, hence this practice is frequently noticed.

The data collected from Pakistani hospitals during regular testing for diabetes was utilized to train and assess the DR model. 5000 retinal samples were included in this collection, 1000 each of all severity levels of DR, data set is named as DR-Insight. The data were all stored in JPEG format at a size of 1125 × 1264 pixels. Figure 6 displays the composition of datasets.

Table 4. 1: Dataset used for Training and testing purpose

Reference	**Name**	**Normal Image/ NO DR**	**Diseased Image**	**Size**	**No of Images**
[13]	APTOS	600	2090		2690
[19]	DiaReT0	100	100		200
[31]	DiaReT1	100	100		200
Private	PAK-HR	560	1210	(1125 x 1264) pixels	1770
Private	DR-INSIGHT	1000	4000	(1125 x 1264) pixels	5000
		2360	7500	Downsizing: 700 _x 600 pixels	**9860**

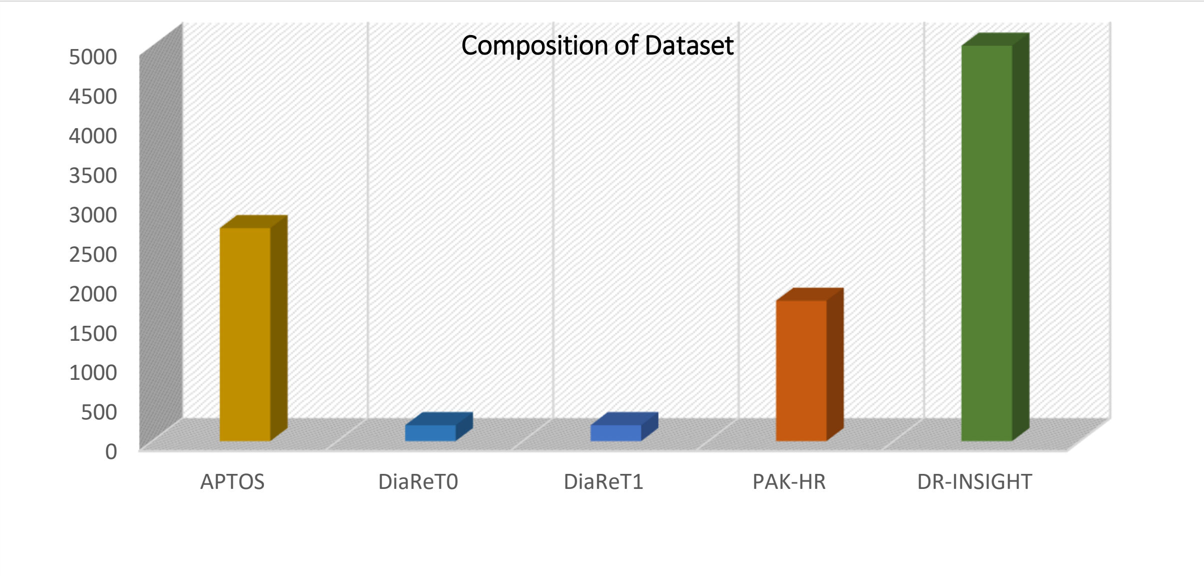

Figure 4. 1:Dataset composition using 5 datasets

4.4 Data Pre-processing Techniques

In this modern era, a large amount of data can be collected via the internet, different valuable experiments and surveys etc. Most of the time data collected for research is noisy data and contain missing or null values. In this case, some popular techniques are applied like deletion and imputation that can deal with missing values. Furthermore, before applying any kind of

ML algorithm data must be normalized or class balancing is executed to make an efficient dataset. We use Clahe and MSR techniques that normalized and balance the dataset. The techniques used for preprocessing of data are described as:

4.4.1 CLAHE

CLAHE (Contrast Limited Adaptive Histogram Equalization) is a popular technique used for image preprocessing in computer vision and image processing applications. It is an extension of the traditional histogram equalization method but addresses some of its limitations. The goal of CLAHE is to enhance the contrast of an image while avoiding the amplification of noise and preventing the generation of unnatural artifacts.

Here's how the CLAHE technique works:

1. **Divide the Image into Tiles**: The input image is divided into small, overlapping tiles or blocks. Typically, a grid of tiles covers the entire image.
2. **Compute Histograms for Each Tile**: For each tile, the histogram of pixel intensity values is calculated.
3. **Apply Histogram Equalization**: The histogram equalization process is applied separately to each tile's histogram. This step redistributes the pixel intensity values in each tile to improve the contrast locally.
4. **Clip the Histograms**: To prevent over-amplification of contrast, each histogram is clipped. This means that pixel intensity values beyond a certain limit are truncated to a maximum value. This limit is often defined as a user-defined threshold or a fraction of the histogram's total count.
5. **Reassemble the Image**: The processed tiles are reassembled to form the final image.

The key advantage of CLAHE over traditional histogram equalization is that it adapts the contrast enhancement locally, ensuring that the details in different regions of the image are preserved without globally over-amplifying the contrast. By applying the histogram equalization on small tiles, the method can capture the local statistics of the image, making it suitable for images with varying lighting conditions and ensuring that smaller details are preserved.

4.4.2 MSR

Multi-Scale Retinex (MSR) is a widely used image enhancement technique in image preprocessing and computer vision. It is designed to improve the dynamic range and appearance of an image by correcting for illumination variations, enhancing local contrast, and preserving important image details. The MSR algorithm is inspired by the human visual system's ability to adjust its sensitivity to light, which helps us perceive objects under various lighting conditions.

The basic concept of MSR involves decomposing an image into multiple scales and then enhancing these scales before combining them back to produce the final enhanced image. The main steps of the Multi-Scale Retinex technique are as follows:

1. **Log Transform:** Convert the input image from the RGB or grayscale domain to the logarithmic domain. This helps to transform the multiplicative illumination variations into additive variations, making it easier to process.
2. **Multi-Scale Decomposition:** Apply a Gaussian pyramid or other multi-scale decomposition technique to the log-transformed image. The pyramid consists of multiple scales, where each scale represents the image at a different level of blurring or smoothing.
3. **Contrast Enhancement:** Perform contrast enhancement on each scale of the pyramid. This can be achieved by applying histogram equalization, adaptive histogram equalization, or other local contrast enhancement techniques.
4. **Image Reconstruction:** After enhancing the individual scales, reconstruct the final enhanced image by combining the enhanced scales.

   The main advantages of Multi-Scale Retinex are its ability to handle images with varying illumination conditions, and its ability to enhance both global and local details, resulting in visually appealing images.

The photos were subjected to several processing steps during the preprocessing phase, including cropping, contrast correction, horizontal flipping, spinning, panning, and boosting utilizing CLAHE AND MSR techniques. Figure 6 illustrates the application of preprocessing techniques being carried on images before being fed to our proposed model. To only keep the desirable areas of the photograph, undesired bits of the image had to be cropped off. Figure 4.1 depicts resuls after implementation of Clahe and MSR technique.

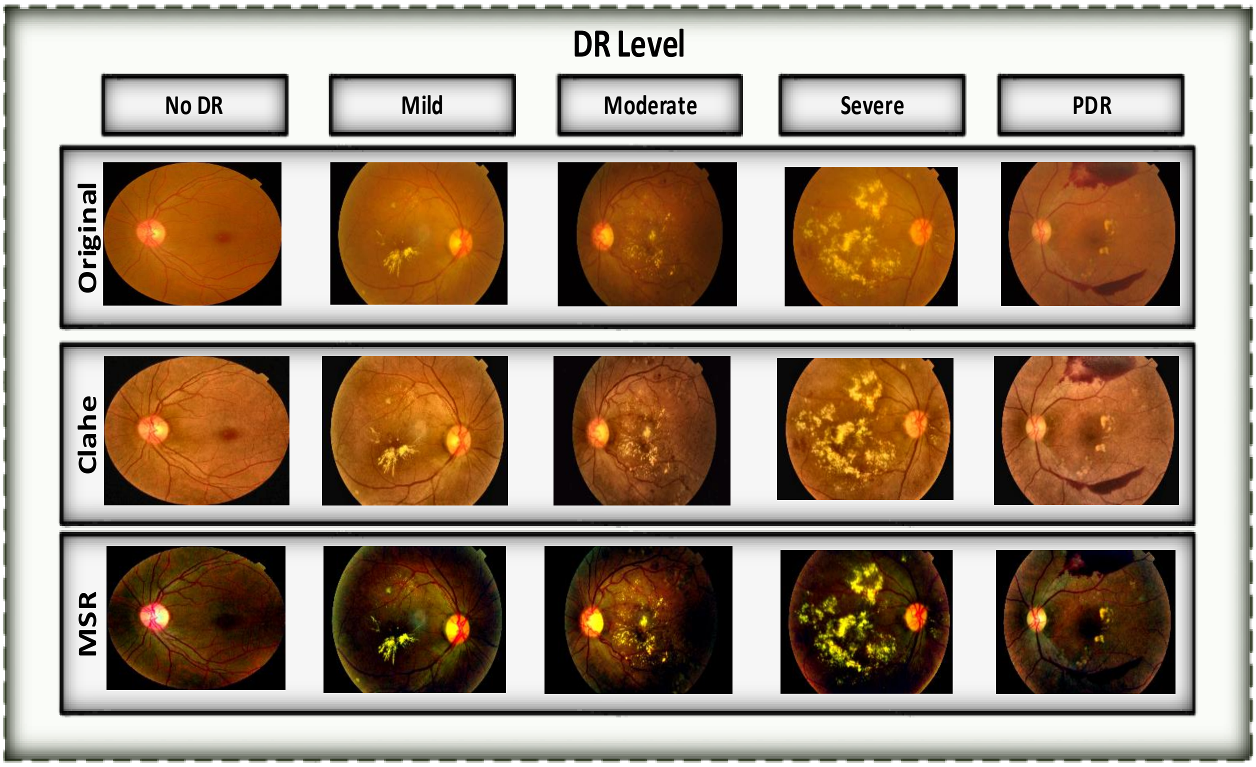

Figure 4. 2: Preprocessed DR images using Clahe and MSR technique

After data preprocessing phase, the data is distributed into 80% of training and remaining 20% into Test data. The algorithms were trained and on training data followed by achievement of results from Test data.

4.5 Data Augmentation

Preprocessing of the fundus photos during this stage involves several processes to clean up the raw data. The photos' raw data was first taken out. The photos were also cleaned using a flip-flop procedure and a variety of techniques to make sure they were ready for processing. This process also included dealing with missing or erroneous pixel values and eliminating outliers from the dataset. This preprocessing stage included feature engineering as well. It involves normalizing data and choosing or developing additional characteristics that would raise the efficacy of the used algorithms. Each of these steps attempted to improve how well the algorithms performed on the dataset. Table 4.2 illustrates the many preparation procedures that were done, including data augmentation approaches, to show how thorough the pretreatment stage was.

Table 4. 2: Augmentation Techniques applied on the dataset

Augmentation Techniques	Value
Width shift range	0.2
Rotation range	15
Zoom Range	0.2
Crop	True
Vertical Flip	False
Horizontal Flip	True

The orientation of the picture along the corresponding axes was changed using horizontal and vertical flips. The use of panning, which involves zooming in or out from a particular area of focus, was made. Additionally, embossing was used, a technique that involves moving pixels up or down to give an image depth and texture. The combined effects of these processes improved classification precision and picture quality. Table 4.2 provides a thorough overview of the precise settings employed during preprocessing by listing the parameters connected with each of these operations.

4.6 Proposed Model: Combination of Residual and Dense Blocks

The proposed architecture for the multiclassification of DR images consists of Residual blocks and Dense blocks, presented in Figure 8. The DR retinal images are accepted as input by the input layer. Each residual unit in the Residual blocks has convolutional layers, batch normalization, and ReLU activation. Due to the residual units' ability to contribute their output to the block's input, identity mapping, and gradient flow are both possible. Within a block, The number of filters in every convolutional layer can be altered, either increasing or decreasing. The number of filters often doubles or grows by a factor of 4 as we move through the blocks. Global average pooling is employed to shrink the spatial dimensions after the Residual blocks. The Dense blocks are then used, each of which comprises dense units. Convolutional layers, batch normalization, and ReLU activation make up each dense unit. Each dense unit's output is combined with the outputs of all preceding dense units in the block. Within a block, The dense blocks consistently contain an equal number of filters.

After the Dense blocks, another round of global average pooling is carried out to further shrink the spatial dimensions. The outputs from the Residual and Dense blocks' most recent global average pooling layers are combined. The completely linked layers, which may be customized based on particular requirements, are then fed the concatenated features. Overfitting is avoided by dropout regularization. The number of output units in the final fully linked layer corresponds to the number of classes used to classify the severity of the DR. Applying a SVM linear activation function yields the class probabilities. The projected probability for each class of DR severity is provided by the output layer. With the help of this architecture, the DL model can accurately envisage the multi-classification of DR severity and extract pertinent features from the input DR photos.

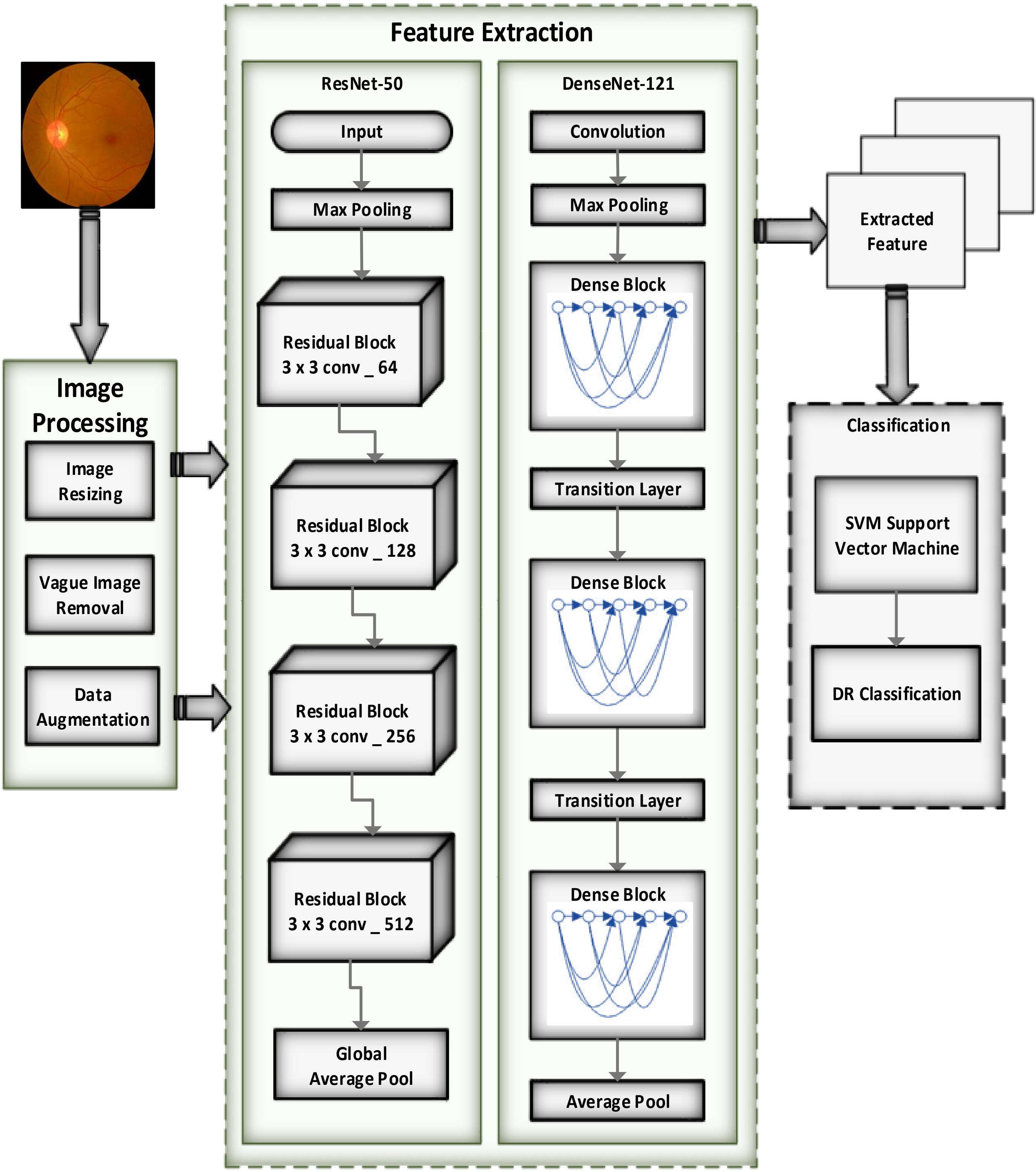

Figure 4. 3: Architecture of Proposed DR Classification System

Algorithm1: Proposed Denset-Residual-Network system with preprocessing steps	
Required	*Fundus Images and Labels (X, Y)*
Step 1	*Dataset acquisition, Fundus images x ε X*
Step 2	*Pre-processing*
	Data Augmentation
	Image enhancement
Step 3	*Load ResNet Mobile Model#*
	ImageNet pre-trained weights
	Convolutional layers
	Pooling layers and Activation functions
Step 4	*Introduction of 4 Dense blocks after layer 9 of the ResNet model*
Step 5	*Introduction of skip connections*
Step 5	*Use of the flattened layer, the feature map x = (x1, x2,……… xn)*
Step 6	*Model evaluation*

Figure 4. 4: Algorithm 1

4.7 Classification Modeling

SVM classifier used in our research. Feature extracted from model are set to SVM classifier for classification

4.7.1 SVM

Extracted features from the model are subjected to an SVM classifier for evaluation. The SVM machine learning classifier automatically classified DR using a 75% to 25% training-test splitting approach. SVM is commonly used due to its great performance and capacity for handling tiny datasets.

SVM is a classification technique that achieves better result as compared to contemporary classifiers and is frequently applied to solve practical problems. SVM was employed in this study to evaluate extracted features into DR. Algorithm 2 outlines each step in detail. We created a Conv2D CNN classifier for image classification issues. It made sense to utilize SVM because we were dealing with multiclassification issues. SVM is used to increase the effectiveness of our method and find the best hyperplane to separate the feature space of diseased and normal retinal images. Typically, an SVM takes a vector $v = (a1, a2, \dots, an)$.

$$Vout = (Weig, Aiv) + c$$

Algorithm 2: SVM Classifier to Recognize hypertensive retinopathy of the extracted features	
Input	*Extracted feature map x = (a1, a2,. !, an) with annotations a = 0,1. Test data A test*
Output samples	*Recognition of hypertensive retinopathy (HR) and normal retinographic*
Step 1	*Primarily, the SVM classifier and Kernel Regularize L2 parameters are defined for optimization*
Step 2	*Classification of normal and abnormal samples*
Step 3	*Depthwise Conv2D was used rather than Conv2D*
Step 4	*Building classifier based on SVM*
	a. The training process of SVM is completed using extracted features
	t = (a1, a2,.., an) by our Algorithm 1. b. For the generation of the hyperplane, use Equation (6).

Figure 4. 5: Algorithm 2

4.8 Evaluation Parameters

On a scale of precision, recall, F1 score, accuracy and ROC-AUC classifiers performance were assessed. If a patient with the condition is anticipated the system determines the person to have DR disease, then the result is a true positive; in other case it's a false negative. Similar to the last example, a prediction that a healthy person will remain disease-free is said to be a true negative; and false positive in other case. These terms are precisely defined below [28]:-

- **True Positive (TP):** Instances correctly identified as positive when they are truly positive.
- **True Negative (TN):** Instances correctly identified as negative when they are truly negative
- **False Positive (FP):** Instances incorrectly identified as positive when they are actually negative.

- **False Negative (FN):** Instances incorrectly identified as negative when they are actually positive
- **Accuracy**: It is a performance parameter that gauges the system's propensity for accurate prediction.

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

- **Precision**: Precision measures the capability of a system to produce only relevant results.

$$\boldsymbol{Presision} = \frac{\boldsymbol{TP}}{\boldsymbol{TP+FP}} \qquad (4)$$

- **Recall:** Recall is the measure of the model's ability to identify all positive instances correctly, indicating the proportion of true positives out of all actual positives.

$$\boldsymbol{Recall} = \frac{\boldsymbol{TP}}{\boldsymbol{TP+FN}} \qquad (5)$$

- **F-Measure**: F-Measure combines results of precision and sensitivity using harmonic mean.

$$\boldsymbol{F1\ Score} = \boldsymbol{2} * \frac{\boldsymbol{Precision*Recall}}{\boldsymbol{Precision+Recall}} \qquad (6)$$

4.9 Summary

Implementation of complete proposed model is discussed in this chapter. Data preprocessing techniques are discussed and how these techniques enhanced the results are discussed in details.

CHAPTER 5

RESULTS AND ANALYSIS

5.1 Introduction

A collection of 5000 retinal images representing all stages of DR used to access training accuracy of the RDS-DR. These images were gathered from reputable Pakistani hospitals (DR-INSIGHT) as well as credible online sources. Images size was reduced to $700\ x\ 600$ pixels so that feature extraction and classification operations could be carried out. A combination of residual blocks and dense blocks is used to create the RDS-DR system. The RDS-DR model underwent training for 100 epochs. The best model with a f1-score of 0.97 was attained at the 30th epoch. Statistical analysis was utilized for assessing the accuracy (ACC), specificity (SP), and sensitivity (SE) scores to evaluate the efficiency of the proposed dense residual network system. The performance of the developed RDS-DR system is evaluated using the above metrics and a comparison is drawn with other systems.

5.2 Performance of Dense-Residual-Network with contemporary methods

In this experiment, Four contemporary comparison methodologies were used to assess the strength of the proposed structure, we trained the VGG16, VGG19, Xcception, and InceptionV3 deep learning models and compared their results to the proposed RDS-DR system. Notably, these DL models were trained with a similar quantity of epochs. Table 5.1 lists the accuracy % comparison between the RDS-DR system and the above models. The comparison reveals the RDS-DR showed superior performance over others. Figure 9 shows the accuracy comparison of different datasets with different deep learning models.

Table 5. 1: Comparision of Accuracy % of state of the Art models with proposed Architecture

Model	F1 Score	Recall	Accuracy
Xception	83	72	84.95%
Inception V3	72	73	73%
VGG-16	79	78	80%
VGG-19	82	79	82.20%
Dense-Residual-Network	97	98	97.5%

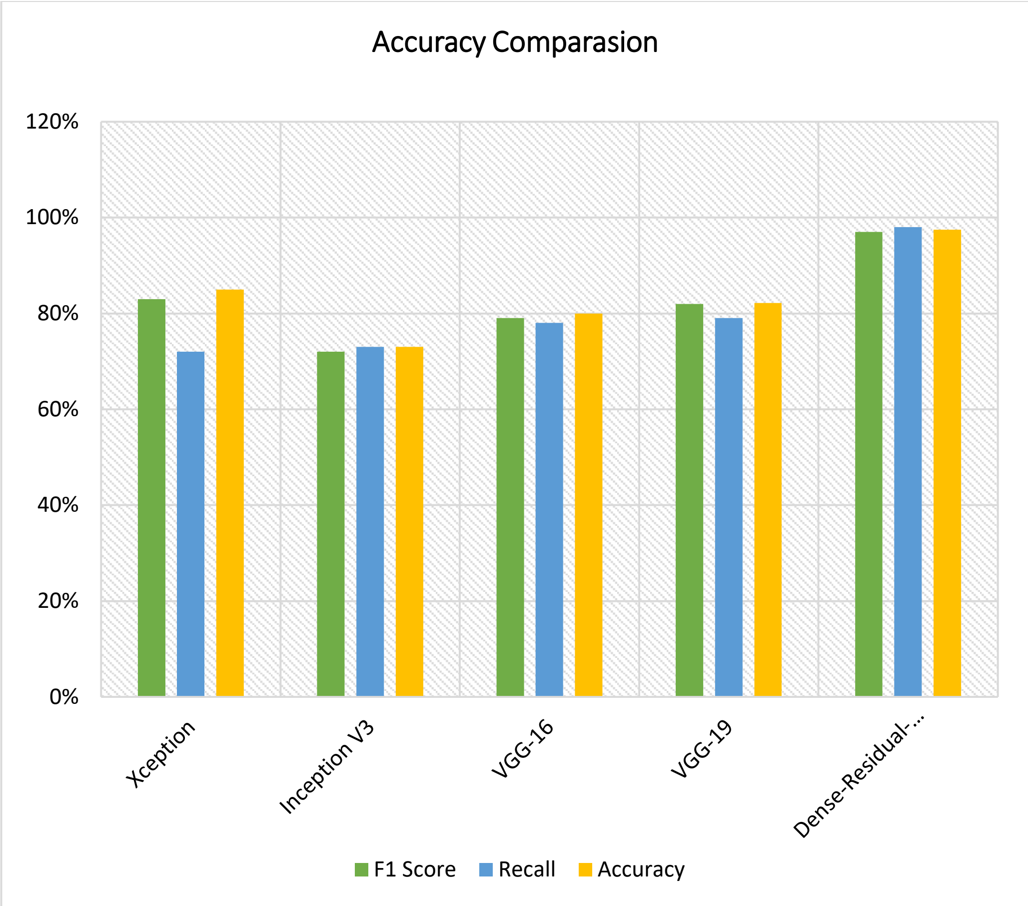

Figure 5. 1: Accuracy comparison between proposed model and state of the art model

5.3 Performance of Dense-Residual-Network on Hypertensive Retinopathy Disease Dataset

The strength of our proposed model was tested on another disease Hypertensive retinopathy with the PAK-HR dataset, utilizing the training and validation accuracy and loss functions. Figure 10 illustrates how effectively our suggested model worked to classify other diseases, needing only ten epochs and reaching 100% training and validation accuracy. Additionally, the proposed model demonstrated success by achieving a loss function below 0.1 for both the training and validation datasets., proving the utility of our model.

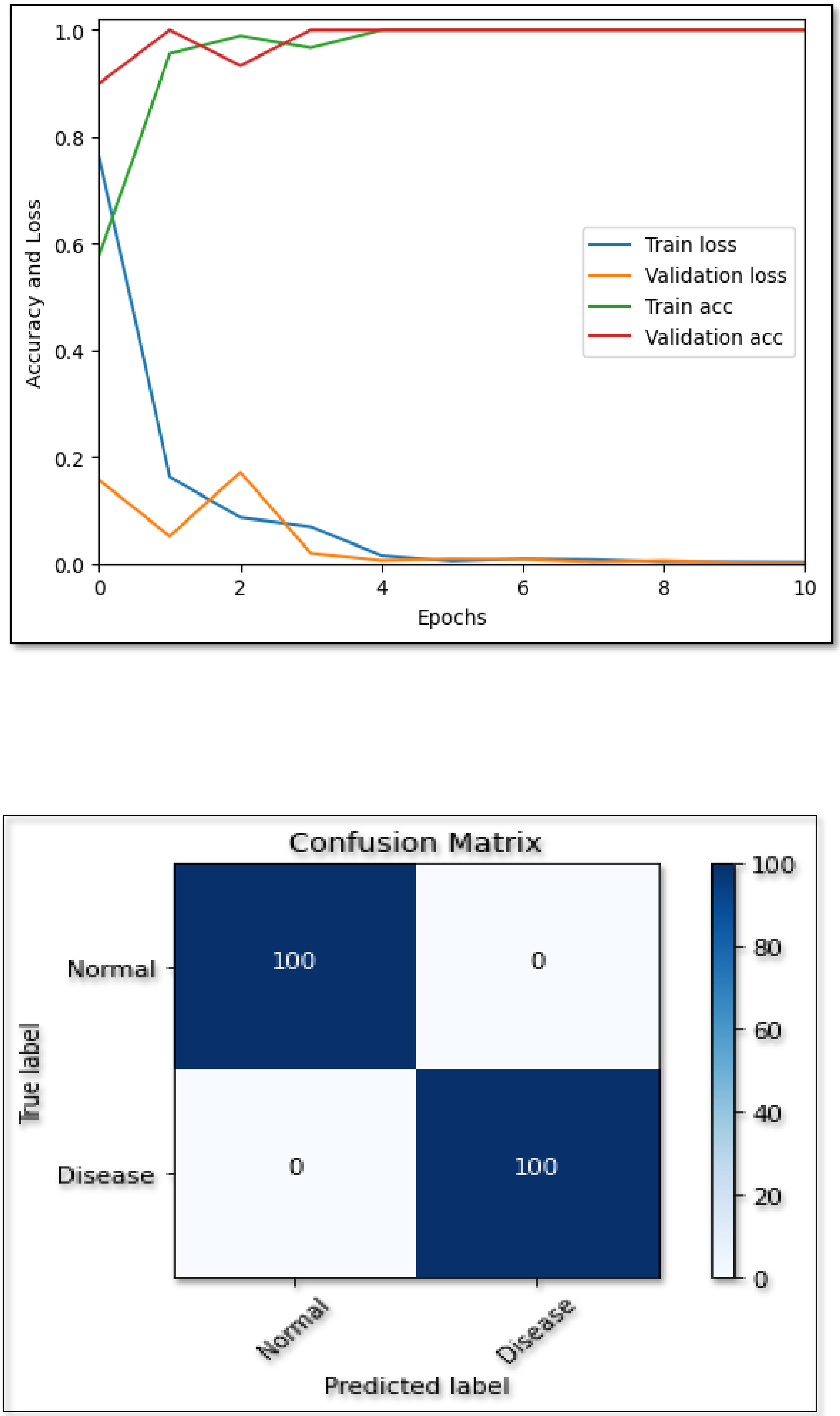

Figure 5. 2: Accuracy loss along with confusion metric with HR-dataset

5.4 Performance of Proposed model on different datasets

In this experiment, a novel dataset (DR-Insights) has been proposed. The five classes that make up the dataset are listed in Table 1. Four different datasets from reliable online sources along with our dataset namely: APTOS 2019, DiaRet0, DiaRet1, PAK-HR, and DR-INSIGHT are used to test the strength of the projected architecture results are presented in figure 5.3, 5.4. This comparison demonstrates how the suggested model performs differently with various data sets. As shown in the Figure 5.3, the suggested model gets the maximum accuracy with the DR-Insight dataset. Figure 14 shows the accuracy comparison of all the datasets which are used in this study. This is due to the proposed dataset's careful organization, which was overseen by qualified ophthalmologists and eye experts. Compared to comparable datasets, this indicates that the proposed Dataset is well-organized and error-free. With the collected dataset, the RDS-DR system achieves an accuracy rate of 97.5%, The maximum accuracy obtained by the proposed model surpasses that of conventional approaches. In the literature, some studies made have used their datasets but the suggested model, however, achieves high accuracy.

Table 5. 2: Comparison of % Accuracy, Recall and F1 Score of Dense-Residual-Network with different Datasets

Datasets	Recall	F1 Score	Accuracy
APTOS 2019	99	99	99.5%
DiaRet0	96	95	95%
DiaRet1	99	98	98.6%
DR-Insight	98	97	98.48%

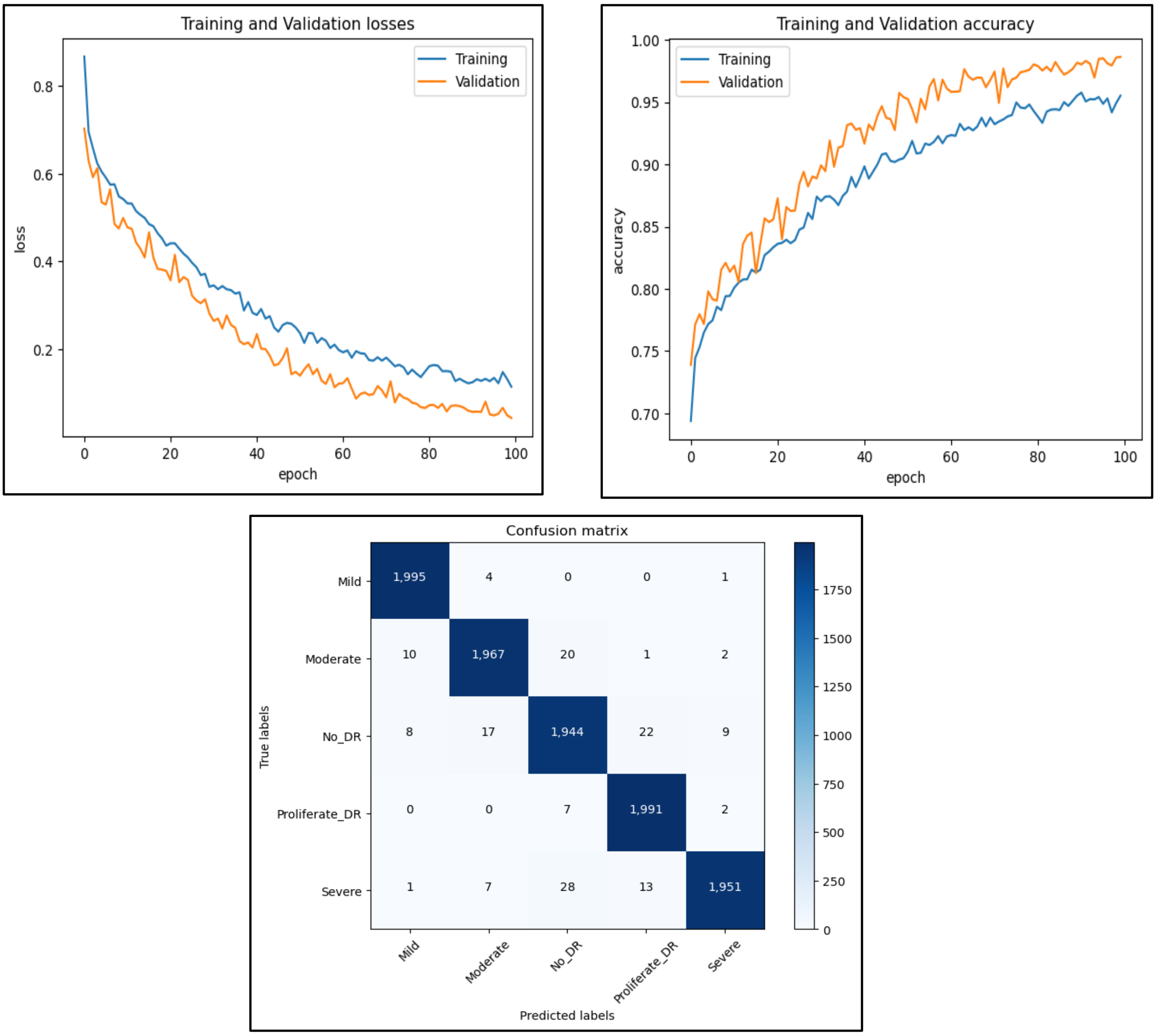

Figure 5. 3: Results with APTOS Dataset

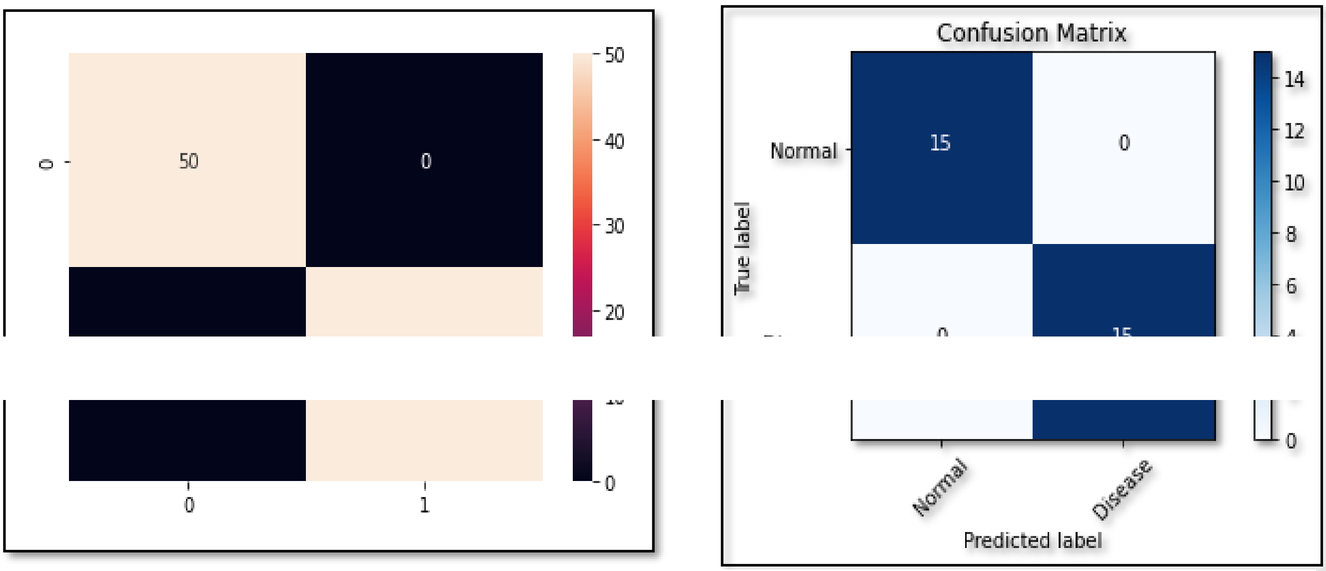

Figure 5. 4: Confusion Metrc Reults of DiaRet0 and DiaRet1 Dataset

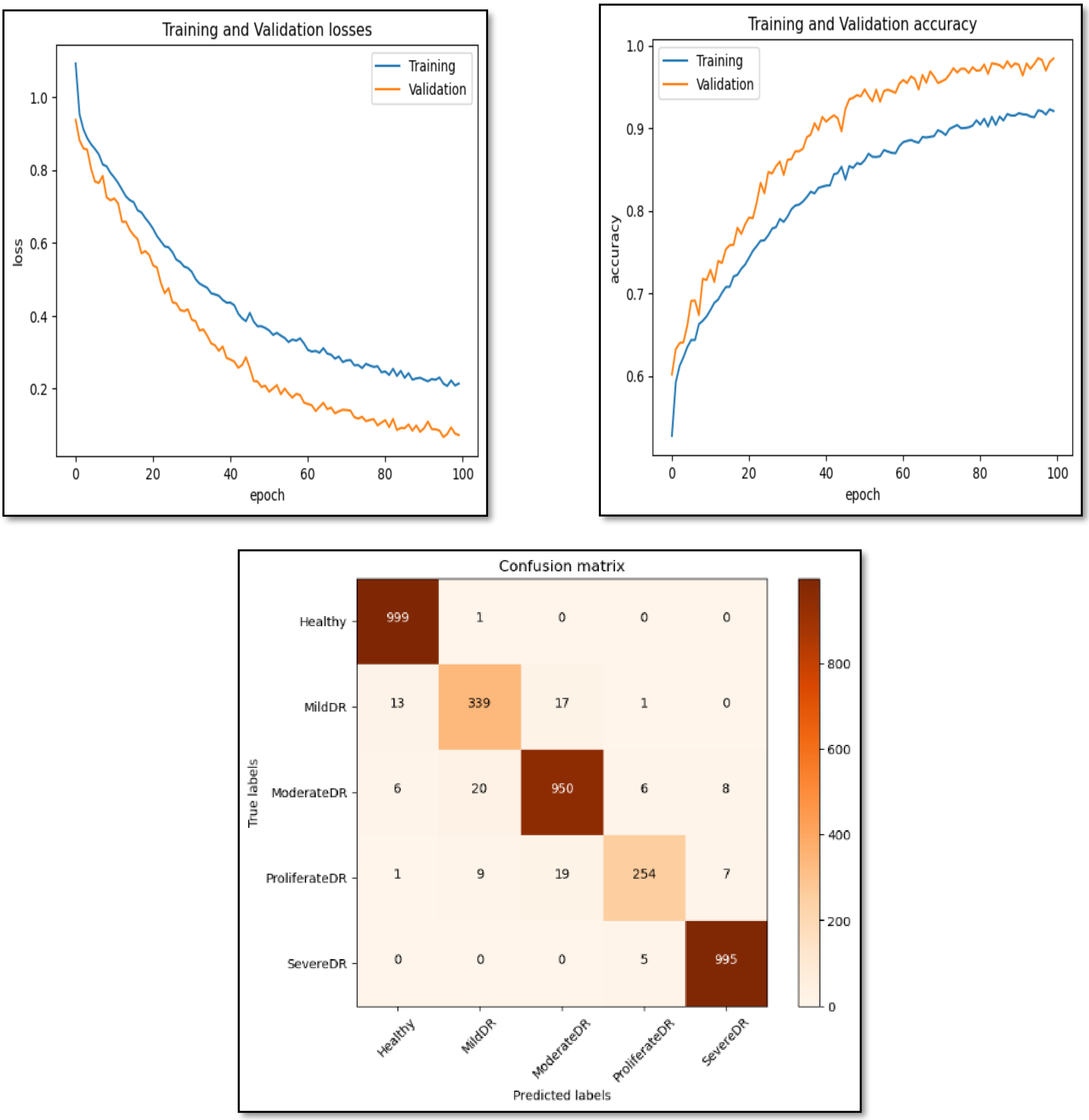

Figure 5. 5: Accuracy and Result of DR-Insight Dataset

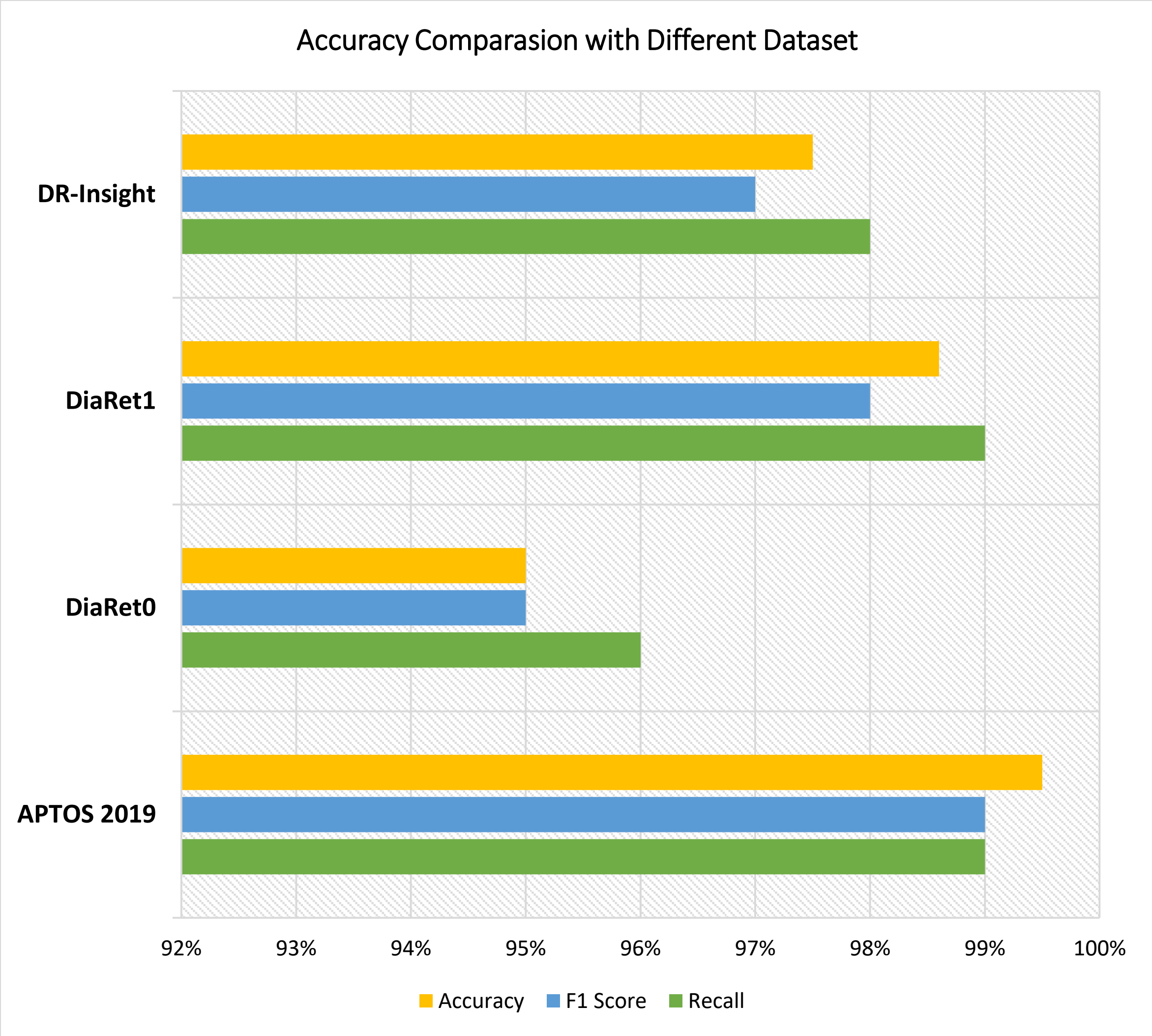

Figure 5. 6: Accuracy comparison of different datasets using Proposed Model

5.5 Comparison of Results with former Researcher Results

Only a limited number of research studies have employed deep-learning techniques to diagnose diabetic retinopathy in retinal images. The studies Multi-Stream DNN [3] and DR-NASNet [36] employ DL to identify DR in retinal images. DR-NASNet is the most current deep-learning model for DR recognition. Table 8 demonstrates that RDS-DR performs better than DR-NASNet. As the primary feature extractors, pretrained DL architectures ResNet-50 and DenseNet-121 are used to create a multi-stream network. The dimensionality of features is reduced by further PCA application. An ensemble machine learning classifier is developed using the AdaBoost and random forest techniques to further improve classification accuracy. The experiment's findings demonstrate up to 95.58% accuracy. To develop the DR NASNet system, the author first utilized a preprocessing technique that takes advantage of Ben Graham and CLAHE to lessen noise, emphasize lesions, and ultimately improve DR classification performance. Taking into account the imbalance between classes in the dataset, data augmentation procedures were conducted to control overfitting. Next, they have integrated dense blocks to improve the effectiveness of classification results for five severity levels of DR. The system was tested using six different experiments. The proposed method achieves 96.05% accuracy with the different datasets. Figure 15 shows the State of the art comparasion with different other research.

Table 5.3 shows Performance comparison between Multi-stream Network, DR-NasNet, and Dense-Residual-Network.

Table 5. 3: Performance comparison between Multi-stream Network, DR-NasNet and Dense-Residual-Network.

Methods	**Accuracy**
Multi-stream Network	95.58%
DR-NasNet	96.05%
Dense-Residual-Network	**97.5%**

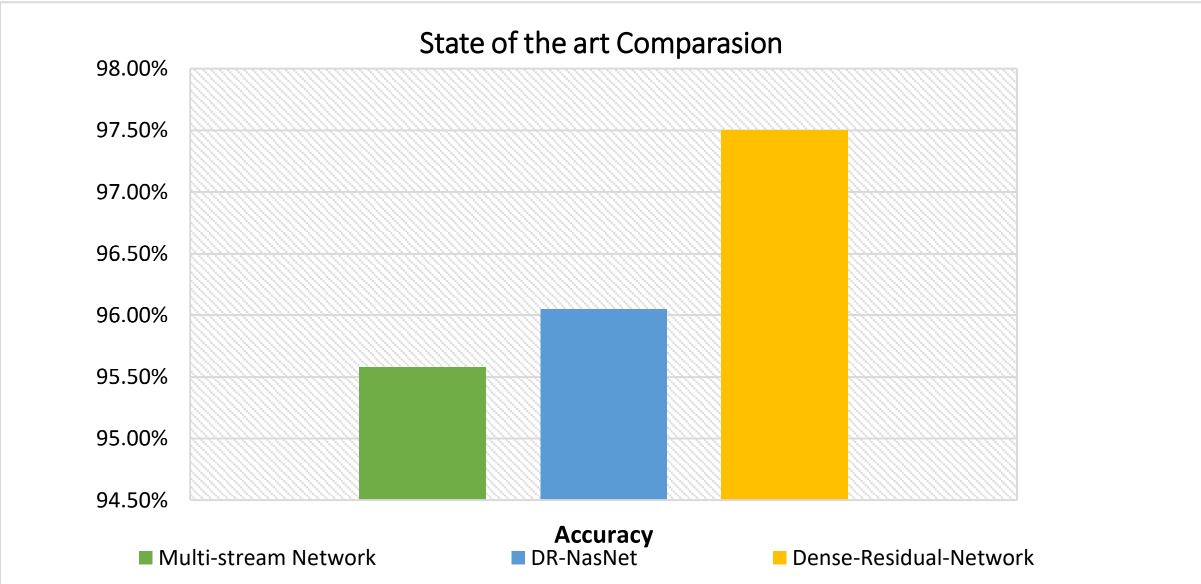

Figure 5. 7: Comparison between proposed model and state of the art models

CHAPTER 6

CONCLUSION

AND

FUTURE WORK

6.1 Conclusion and Objective achieved

Millions of individuals throughout the globe experience DR. Early illness identification facilitates DR prevention. In this study, we proposed the CAD DR detection and classification method, which is completely automated. To attain the highest accuracy, the model is developed utilizing a mix of unique pre-processing steps and deep learning models. The method reduces noise, highlights lesions, and eventually enhances DR classification performance by utilizing CLAHE and MSR image preparation approaches. The innovative image processing technique suggested in this study is the CLAHE and MSR approach, which was utilized to emphasize the areas of DR-affected photos that are particularly crucial in determining their presence. The modified deep learning model of the RDS-DR is also proposed in this research work. The model is assessed using four distinct publicly accessible datasets as well as the authors' dataset (DR-INSIGHTS), which incorporates several datasets gathered from various sources. The most recent comparison demonstrates the suggested methodology's higher performance in contrast to earlier models presented in the literature. It is clear from a comparison of their advantages and disadvantages that the suggested technique performs better than the currently popular methods. The suggested technique has to be tested on a sizable and complicated dataset, ideally one that contains a significant number of potential DR cases, to show its effectiveness.

6.2 Limitations

However, there are several avenues for future work in this area. Firstly, the model could benefit from incorporating additional patient data from diverse populations to improve its generalizability and robustness. This would help ensure that the model performs effectively across different demographic groups and can be widely applicable in real-world healthcare settings. Furthermore, the integration of advanced deep learning methods, such as recurrent neural networks or attention mechanisms, could potentially enhance the model's performance by capturing complex temporal dependencies and extracting more informative features from the data.

6.3 Future Work

Additionally, the model's interpretability can be further explored by incorporating explainable AI techniques, allowing healthcare professionals to understand the underlying reasons behind the model's predictions. This would increase trust and acceptance of the model within the medical community. Lastly, conducting extensive validation studies using large-scale clinical datasets and comparing the performance of the hybrid model against existing diagnostic methods would be crucial for assessing its clinical utility and effectiveness in real-world scenarios. Overall, the improved hybrid model for DR detection shows promise in revolutionizing e-healthcare systems. Future research and development in this field can greatly contribute to advancing early detection and proactive management of DR, ultimately improving patient care and reducing the burden on healthcare systems.

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CHAPTER 7

REFERENCES

[1] IDF Diabetes Atlas 9th Edition. Available online: https://diabetesatlas.org/atlas/ninth-edition

[2] Acharya, U. Rajendra, et al. "Automated screening system for retinal health using bi-dimensional empirical mode decomposition and integrated index." *Computers in biology and medicine* 75 (2016): 54-62.

[3] Mustafa, Hamza, et al. "Multi-stream deep neural network for diabetic retinopathy severity classification under a boosting framework." *IEEE Access* 10 (2022): 113172-113183.

[4] Nair, Anitha T., and Arun Kumar. "Disease Grading of Diabetic Retinopathy using Deep Learning Techniques." *2022 6th International Conference on Computing Methodologies and Communication (ICCMC)*. IEEE, 2022.

[5] Li YH, Yeh NN, Chen SJ, Chung YC. Computer-assisted diagnosis for diabetic retinopathy based on fundus images using deep convolutional neural network. Mobile Information Systems. 2019 Jan 1; 2019.

[6] Akram, M. Usman, Shehzad Khalid, and Shoab A. Khan. "Identification and classification of microaneurysms for early detection of diabetic retinopathy." Pattern recognition 46.1 (2013): 107-116. 2013.

[7] Akram, M. Usman, et al. "Detection and classification of retinal lesions for grading of diabetic retinopathy." Computers in biology and medicine 45 (2014): 161-171.

[8] Mookiah, Muthu Rama Krishnan, et al. "Evolutionary algorithm based classifier parameter tuning for automatic diabetic retinopathy grading: A hybrid feature extraction approach." *Knowledge-based systems* 39 (2013): 9-22.

[9] Gulshan, Varun, et al. "Development and validation of a deep learning algorithm for detection of diabetic retinopathy in retinal fundus photographs." *jama* 316.22 (2016): 2402-2410.

[10] Pratt, Harry, et al. "Convolutional neural networks for diabetic retinopathy." *Procedia computer science* 90 (2016): 200-205.

[11] García, Gabriel, et al. "Detection of diabetic retinopathy based on a convolutional neural network using retinal fundus images." *Artificial Neural Networks and Machine Learning–*

ICANN 2017: 26th International Conference on Artificial Neural Networks, Alghero, Italy, September 11-14, 2017, Proceedings, Part II 26. Springer International Publishing, 2017.

[12] Wang, Xiaoliang, et al. "Diabetic retinopathy stage classification using convolutional neural networks." *2018 IEEE International Conference on Information Reuse and Integration (IRI)*. IEEE, 2018.

[13] Esfahani, Mehdi Torabian, Mahsa Ghaderi, and Raheleh Kafiyeh. "Classification of diabetic and normal fundus images using new deep learning method." *Leonardo Electron J Pract Technol* 17.32 (2018): 233-248.

[14] Dutta, Suvajit, et al. "Classification of diabetic retinopathy images by using deep learning models." *International Journal of Grid and Distributed Computing* 11.1 (2018): 89-106.

[15] Wan, Shaohua, Yan Liang, and Yin Zhang. "Deep convolutional neural networks for diabetic retinopathy detection by image classification." *Computers & Electrical Engineering* 72 (2018): 274-282.

[16] Shaban, Mohamed, et al. "Automated staging of diabetic retinopathy using a 2d convolutional neural network." *2018 IEEE International Symposium on Signal Processing and Information Technology (ISSPIT)*. IEEE, 2018.

[17] Jiang, Hongyang, et al. "An interpretable ensemble deep learning model for diabetic retinopathy disease classification." *2019 41st annual international conference of the IEEE Engineering in medicine and biology society (EMBC)*. IEEE, 2019.

[18] Zhang, Wei, et al. "Automated identification and grading system of diabetic retinopathy using deep neural networks." *Knowledge-Based Systems* 175 (2019): 12-25.

[19] Harangi, Balazs, et al. "Automatic screening of fundus images using a combination of convolutional neural network and hand-crafted features." *2019 41st Annual international conference of the IEEE engineering in medicine and biology society (EMBC)*. IEEE, 2019.

[20] Liu, Yi-Peng, et al. "Referable diabetic retinopathy identification from eye fundus images with the weighted path for a convolutional neural network." *Artificial intelligence in medicine* 99 (2019): 101694.

[21] Qummar, Sehrish, et al. "A deep learning ensemble approach for diabetic retinopathy detection." *Ieee Access* 7 (2019): 150530-150539.

[22] de La Torre, Jordi, Aida Valls, and Domenec Puig. "A deep learning interpretable classifier for diabetic retinopathy disease grading." *Neurocomputing* 396 (2020): 465-476.

[23] Majumder, Sharmin, and Nasser Kehtarnavaz. "Multitasking deep learning model for detection of five stages of diabetic retinopathy." *IEEE Access* 9 (2021): 123220-123230.

[24] Patel, Sanskruti. "Diabetic retinopathy detection and classification using pre-trained convolutional neural networks." *International Journal on Emerging Technologies* 11.3 (2020): 1082-1087.

[25] Chaturvedi, Saket S., et al. "Automated diabetic retinopathy grading using deep convolutional neural network." *arXiv preprint arXiv:2004.06334* (2020).

[26] Pan, Xiangji, et al. "Multi-label classification of retinal lesions in diabetic retinopathy for automatic analysis of fundus fluorescein angiography based on deep learning." *Graefe's Archive for Clinical and Experimental Ophthalmology* 258 (2020): 779-785.

[27] Majumder, Sharmin, and Nasser Kehtarnavaz. "Multitasking deep learning model for detection of five stages of diabetic retinopathy." *IEEE Access* 9 (2021): 123220-123230.

[28] Kobat, Sabiha Gungor, et al. "Automated diabetic retinopathy detection using horizontal and vertical patch division-based pre-trained DenseNET with digital fundus images." *Diagnostics* 12.8 (2022): 1975.

[29] Saranya, P., et al. "Red Lesion Detection in Color Fundus Images for Diabetic Retinopathy Detection." *Proceedings of International Conference on Deep Learning, Computing and Intelligence: ICDCI 2021*. Singapore: Springer Nature Singapore, 2022.

[30] Farag, Mohamed M., Mariam Fouad, and Amr T. Abdel-Hamid. "Automatic severity classification of diabetic retinopathy based on densenet and convolutional block attention module." *IEEE Access* 10 (2022): 38299-38308.

[31] Hayati, Mira, et al. "Impact of CLAHE-based image enhancement for diabetic retinopathy classification through deep learning." *Procedia Computer Science* 216 (2023): 57-66.

[32] Jena, Pradeep Kumar, et al. "A novel approach for diabetic retinopathy screening using asymmetric deep learning features." *Big Data and Cognitive Computing* 7.1 (2023): 25.

[33] Beevi, S. Zulaikha. "Multi-Level severity classification for diabetic retinopathy based on hybrid optimization enabled deep learning." *Biomedical Signal Processing and Control* 84 (2023): 104736.

[34] Al-Antary, Mohammad T., and Yasmine Arafa. "Multi-scale attention network for diabetic retinopathy classification." *IEEE Access* 9 (2021): 54190-54200.