Edge Alterations as Predictive Biomarkers in Diabetic Retinopathy: A Deep Learning Approach

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Data Analytics

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Edge Alterations as Predictive Biomarkers in Diabetic Retinopathy: A Deep Learning Approach

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Abstract

Diabetic Retinopathy (DR), is a serious complication of diabetes mellitus and poses a major threat to the vision of a patient. The early detection and accurate prognosis of DR severity plays a vital role in effective management and treatment. This research presents a novel deep learning-based method to assess the correlation between DR severity levels and changes in retinal edges. Using a dataset of fundus images, a convolutional neural network (CNN) was used that focuses on the edge features within the retina. Some of these features include variations in vascular structure, microaneurysms, and hemorrhages, these features are critical indicators for DR progression. The implemented model was trained to classify images into multiple DR severity levels based on the International Clinical Diabetes Retinopathy scale. To validate the accuracy of the model, comparative analysis is done with another neural network model. Both models are evaluated based on an evaluation matrix containing precision, recall, and f1 score. This model adds to the expanding field of research on artificial intelligence in healthcare by emphasizing the true power of deep learning in improving diabetic retinopathy diagnosis. The techniques that are available at the moment are precise but expensive and need skilled personnel. The clinical significance of this research is to try to improve the management of Diabetic retinopathy.
Keywords- Diabetic Retinopathy (DR), Deep Learning, CNN, Fundus, Edge Alteration, Hemorrhages, Microaneurysms.

1 Introduction

All aspects of the human body hold huge significance, however, the sense of vision is considered the most pivotal sensory system due to its capacity to detect roughly 80 other sensory organs cease functioning. In such instances, it is a visual system that assumes the responsibility of protecting against potential danger. A patient may be affected by more than one ocular condition if they have an ocular disease. Illness related to vision rarely exhibits symptoms until they reach a late stage, at which point there is little chance of recovery, and that is why it is highly recommended to undergo periodic eye examinations as frequently as possible to avoid this outcome Ueda et al. (2019). Diabetic retinopathy is one of the most intricate complications of diabetes mellitus, a prevalent condition that affects people worldwide. If left undiagnosed or untreated, this complication may result in severe vision loss or in some cases permanent blindness. A rise has been seen in the rise of cases of diabetic retinopathy and the resulting issues that come with the illness, showing an urgent need for effective and efficient preventive interventions Thomas et al. (2019).

DR is a slowly progressing disease that majorly affects the eye, especially the blood vessels located in the retina. Initially, Diabetic retinopathy may first cause minor issues related to vision or no symptoms at all but might lead to significant visual impairment. The diagram in Figure 1 shows many areas that could be indicative of DR. The delineated regions serve as early indications since they can be identified by distinctive patterns in retinal images. [1] The retina may change as a result of diabetic retinopathy, especially if small red lesions or microaneurysms and dot hemorrhages start to appear. These small aneurysms create balloon-like bulges in the blood vessel walls which results in vision loss. The retina is located on the right side of the eye and is the crucial component that aids in capturing light and transmitting visual signals to the brain.

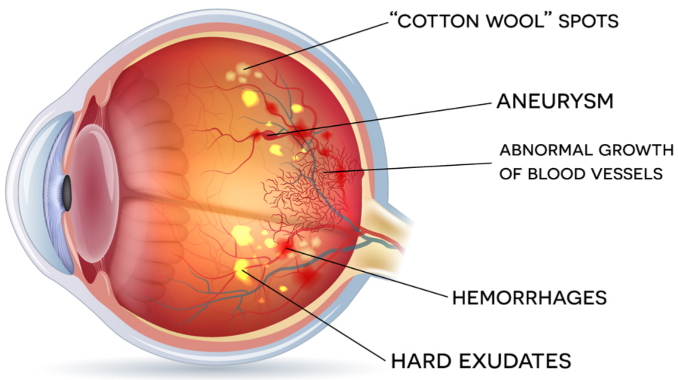

Figure 1: Diabetic Retinopathy Side View

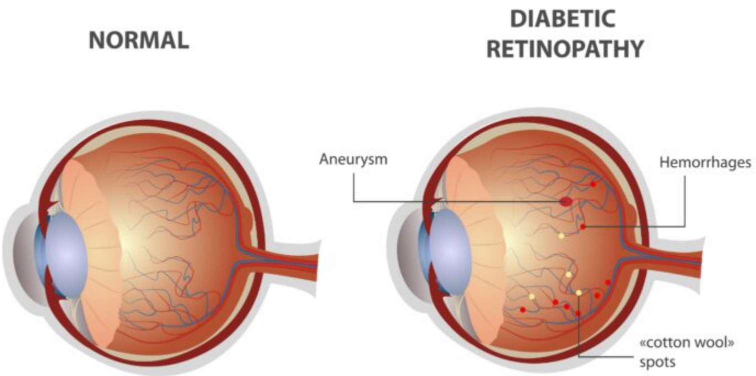

Figure 2: Comaprison of Normal Retina and Infected Retina

The diagram in Figure 2 shows a comparison of the retina affected by DR and one not affected by DR. The vascular network in the healthy state is seen to be uniformly spread overall and guarantees clear vision, but on the other hand, the retina affected by the DR it is seen that the vascular network is disrupted due to prolonged high sugar levels. The existing screening methods depend on the ability of the ophthalmologist to manually evaluate retinal scans, which sometimes might not be feasible concerning time and

[1] https://www.exetereye.co.uk/eye-conditions/diabetic-retinopathy/exeter-eye-diabetic-retinopathy-side-view-of-eye-diagram/

money. The current methods are commendably precise, but the process is lengthy and difficult due to the limited availability of skilled and experienced personnel. The above-mentioned challenge highlights a significant gap in our healthcare system's potential to provide screenings for the rising number of diabetic patients at risk for DR. Because of such challenges it is crucial to impede the advancement of the rate of diabetic retinopathy and lower the risk of visual impairment Ford et al. (2021). In the presence of this important issue, this research offers a framework based on deep learning techniques intending to identify and diagnose diabetic retinopathy and try to co-relate it with changes in edges, to discover if is it possible that change in edges is directly correlated to severity of diabetic retinopathy. This is achieved by employing advanced image processing algorithms on retinal scansKandhasamy et al. (2020). The study has a dual character, to pinpoint and rectify the current shortfall in DR detection by employing a quick, affordable, and readily deployable solution, secondly, this study tries to examine the relationship between the change in retinal edge features and severity levels of diabetic retinopathy.

1.1 Background and Motivation

As per the records of WHO, the leading cause of blindness in adults in the age range of 20-72 is diabetic retinopathy Kropp et al. (2023). In the US, around 7.7 million people were diagnosed with diabetic retinopathy in the year 2010, based on this number the projected growth is 11.3 million by the year 2030. As per records, it is seen that approx. 90% of people with type 1 diabetes will be diagnosed with diabetes retinopathy. Based on the above-mentioned statistics it is estimated that one-third of people with diabetes might be affected with diabetic retinopathy Shukla and Tripathy (2023).

In a lot of parts of Africa and South America, there has been a sudden increase in the rate of diabetic retinopathy in the local population. The major reason for this is the very limited access to the healthcare facility, the limited access relates to diabetic patients not receiving the necessary treatment in a timely manner due to economic constraints. The economy plays a major role in the healthcare sector, a lot of patients are losing their eyesight because of this disease and there are not enough medical professionals to provide the treatment Pastakia et al. (2017).

Facts like these call for an increase in affordable medical care and the promotion of awareness and education of the disease. This includes creating effective, effective methods for screening that are cost-effective and don't require a highly skillful medical professional to give out a diagnosis, doing so will eventually bring down the cost of healthcare and might save the vision of a lot of people.

1.2 Research Question and Aim.

Research Question:- How can alterations in retinal edge features be used as predictive biomarkers for Diabetic Retinopathy, and how effectively can a deep learning approach enhance their detection and accuracy?

By investigating the above research question, this project aims to contribute to the existing information in the field of diabetic retinopathy treatment and offer a novel approach to the management of diabetic retinopathy. Through this approach, the research seeks to enhance the current standard for this condition. In short, this study aims to improve the screening and management of diabetic retinopathy by means of deep learning techniques. The goal is to shorten the gap between the current screening techniques and the healthcare facility, by doing so, hopefully, this research could help reduce visual impairment and lead to better eye care for everyone. The "Introduction" section is followed by the section titled "Related Work", which provides a thorough review of previous research and the diagnosis of Diabetic retinopathy. After reviewing the prior literature, the "Methodology" and "Design Specification" sections explain the procedure that was used and include the research design, and analytical techniques that were employed. Additionally, the "Evaluation" section provides a thorough examination of the project's findings and outcomes.

2 Related Work

It is important to acknowledge the contribution of previous research in gaining deep knowledge about ocular complications and healthcare in general. Studies and research in these areas focus on the importance of deep-learning algorithms for detecting and classifying diseases. The foundation of this study is influenced by the following research and contributed significantly to understanding the complexities in this field.

2.1 Health Care

This section of the related work discusses the benefits and drawbacks of various diseases identified by employing deep learning and by utilizing images or scans of affected areas.

Deep learning has been playing a crucial role in classifying human illnesses, especially in the medical field, where there is a lot of data containing scans, images, and diagnoses. A research Chandrasekar et al. (2020) was proposed with the objective of investigating the duration of implementation, the evaluation matrices, and the precision of detecting human diseases. The findings from this research show that the categorization done by the deep-learning-based models are very close to accurate which results in improved accuracy while assessing the severity of the diseases.

Recently research was carried out Khan et al. (2020). where five different models with classifiers like random forest and SVM, and three deep learning networks, namely VGG16, Inception V3, and Resent. This research was carried out on MRI scans of patients' brains to classify the brain tumor and segment it from the healthy cells. In this research, it was seen that the deep learning models outperformed the machine learning algorithms and achieved a thrashing accuracy of 90%. The researchers suggested that this accuracy can even be improved if different optimizers and cross-validations are implemented.

Similar research was conducted in 2018 by a group of small researchers Fuse et al. (2018), where the main aim of the research was to detect if the patient had Alzheimer's or not. For this, they acquired data of brain scans of patients, and with the help of a Supervised Vector Machine model extracted features. The feature extraction was done with the help of a P-type Fourier Descriptor and image slicing. This research was able to achieve an 87% accuracy on two of six intracranial volumes.

In the year 2016, Riri et al. (2016), research was conducted to detect and classify the dental problems of patients using deep learning and decision trees. This research was carried out on the scans of dental molds, intra-oral, extra-oral, and other radiological images. Although the model was able to achieve good results but could have achieved more efficiency with it was trained and tested on a larger dataset, as the dataset used by the researchers was of only 50 patients.

In the year 2020, Serte and Serener (2020), a couple of researchers conducted a research study to detect the different types of pneumonia in patients, namely, mycoplasma pneumonia, viral pneumonia, and bacterial pneumonia. In this study, they employed multiple deep-learning models to detect and classify different types of pneumonia. Amongst the deep learning models, VGG outperforms the rest of the model by attaining an accuracy of 87%, specificity of 71%, and sensitivity of 94%. Although the models achieved a decent number in the results, they could have done better if the data had been augmented.

A study was conducted Carreira-Perpinan and Hinton (2005) based on the central nervous system in the field of biomedical neuroscience. Many diseases like brain tumors, strokes, and Alzheimer's are rapidly increasing. This study proposed a machine learning model that implemented a region-based contour method for the detection of the cancerous area and for segmentation using a fuzzy mean algorithm. This model yielded decent results while separating cancerous cells from non-cancerous cells.

A review was conducted in the year 2021, where the researchers did a thorough investigation of twenty-two deep learning-based models that were implemented for human disease detection, subtype classification, and prediction. Based on the review conducted it was seen that the reviewed model outperformed many machine-learning models which shows that there is still potential that these models can be used in clinical settings. However, the actual application and implementation in the real-life scenario are still far from reality due to insufficient interpretability, this shows that there is still room for improvement in both machine learning and deep learning models to be used in real life situations Nguyen et al. (2021).

In the field of pulmonology, Saleh et al. (2021), similar research was conducted where the researchers used a hybrid machine-learning algorithm to detect and classify different diseases related to the lungs. This research was conducted on a dataset of 5103 CT scans of patients. This data was taken from the data repository of the National Institute of Health. The implemented model was able to achieve a sensitivity of 97.70% and a specificity of 99.32%. These studies done in the domain of healthcare could have been better with diverse datasets, proper hyperparameter tuning, and data augmentation.

2.2 Ocular Diseases

In the field of ophthalmology, there are several diseases that come under this field and much research is done in this field. In a research Zhang et al. (2018), an automated system was developed to aid with diagnosing and recommending treatments to handle them. This automated system takes images of the eye sorts them into five groups and analyzes them using the knowledge it has on the anatomy of the eye. This automated system completely works on deep learning architecture and is capable of figuring out the exact disease 79%-98% of the time. The system has achieved an accuracy of 95% in identifying and providing remedies for a condition called Pterygium.

In a study conducted by researchers Khan et al. (2020), they implemented a model based on VGG-19 to classify whether the human has any eye disease or not with the help of a dataset that consists of human fundus images. This proposed model achieved the highest accuracy for normal versus myopia, which was 98.10%, and also attained a 94.03% accuracy for the normal versus cataract class. Furthermore, the model was able to classify a normal eye form a glaucoma eye with a 90.94% accuracy rate.

A researcherYang et al. (2013) has proposed an ensemble-based learning algorithm that uses Random Forest for classifying the fundus images based on the severity of the cataract. The main intention behind using Random Forest with ensemble learning is to improve the accuracy of the model during the classification process. The model achieved a decent accuracy of 75% but it could have been better if necessary image preprocessing techniques were used.

A research paper titled "Classification of Cataract Fundus Images Based on Deep Learning" Dong et al. (2017)presented a cutting-edge methodology that is based on deep learning to identify and categorize cataracts automatically. This proposed method categorizes the retinal scan into four groups based on their severity levels and labels them as normal, minor, medium, and severe. The researchers have employed a Caffe-based deep learning network to extract unique features from the fundus images, they have done image preprocessing using the maximum entropy method. In result, it is been seen that the deep learning model produces higher accuracy when used with the Softmax activation function than the conventional method. This research showcases how efficiently and accurately a deep learning network can identify and classify cataracts and contributes to the efficient diagnosis in ophthalmology.

The prior work done above shows the significant advancements in the domain of ophthalmology with the implementation of deep learning and machine learning models. Overall, these previously done is work collectively highlights the expanding influence of high-level computational methods toward improving diagnostics outcomes in ophthalmology.

2.3 Diabetic Retinopathy

Ophthalmology is a vast field, but diabetic retinopathy is multifaceted and is an increasingly common eye disease linked with diabetes which makes it a global public health issue. To diagnose this complexity multiple research and studies were conducted. One such research was presented in 2017, where the researchers conducted a multistage transfer learning approach to classify the various stages of DR Gargeya and Leng (2017). This research was conducted on human fundus images. With the help of transfer learning techniques combined with different convolutional neural network architectures, the researchers were able to generate high outcomes. Later on, the same model was refined and trained on a dataset, which ultimately gave better outputs as compared to the previous one. Shapely Additive Explanation (SHAP) was suggested in future work to get better performance out of the model.

Very recently new research was conducted in the field of ophthalmology, this research introduced an approach to combine image filtering techniques with deep learning algorithms for the classification of the severity of diabetic retinopathy more precisely. This implementation is effective and accurately distinguishes between different stages of DR. This implementation can be really helpful in early-stage detection and management of the disease Shrimali (2023). Related to the same idea a paper was published in 2019 titled "Convolutional Neural Networks for Mild Diabetic Retinopathy ", in this research the researchers showcased a VGG ImageNet CNN to detect mild diabetic retinopathy. The showcased model was able to achieve a remarkable accuracy of 86% Sarki et al. (2019).

R (2020) Conducted research, research was based on features like hemorrhages, microaneurysms, and exudates. The research has used an amalgamation of classifiers, like SVM, KNN (K-Nearest Neighbor), Random Forest, Logistic Regression, and Multilayer Perceptron to detect and classify diabetic retinopathy. At 90% accuracy, the Random Forest Classifier outperformed SVM and KNN, which both had 68% and 76% accuracy, respectively .

In research, Zhuang and Ettehadi (2020), a new methodology was developed, and a shallow neural network and transfer learning network were compared to get enhanced results. The proposed methods were implemented on human fundus scans. The training, validation, and test set yielded accuracies of 72.35%, 67.05%, and 69.03% respectively for shallow neural networks. However, the transfer learning model outperformed the shallow network by attaining accuracies of 80.85%, 80.60%, and 77.87%.

In 2022, Lim et al. (2022) a review was done to examine the application of interpretability techniques of deep neural networks for analyzing and classifying DR. The review goes deep into various methodologies that aim to interpret decisions that are made by a deep learning network. This review also emphasizes on gaining the trust of clinical specialists or skilled personnel and asks for more research to be done to improve the efficiency and trustability of deep learning in diagnosing DR. Several reviews have been done to showcase the credibility of machine learning and deep learning algorithms.

The above advancements in the field of ophthalmology, especially for diabetic retinopathy have been on a wide scale because of deep learning and machine learning techniques. As seen above transfer learning models and convolutional neural networks (CNNs) have successfully demonstrated their potential in predicting and classifying. These reviews showcase the success of machine learning and deep learning models in diagnosing diabetic retinopathy.

As seen the majority of the prior work that's been done in diabetic retinopathy detection or classification relies on deep learning, showing high accuracy and F1-score. These advanced deep learning techniques come with higher time and space complexities, which leads to an expensive solution. This underscores the possibility of investigating fundamental image processing methodologies, illustrating that the amalgamation of uncomplicated approaches with cutting-edge technologies may result in unexplored advantages.

The reason behind opting for the Inception ResNet v2 is based on its relevance to diabetic retinopathy, successful use in similar fields, and advancement in image processing. The main motive of this project is to show that the foundational image-processing techniques could still significantly impact medical or radiological imaging, ultimately lowering implementation costs.

3 Methodology

This research functions based on the KDD (Knowledge Discovery in Database) methodology. This methodology has five phases which are shown in the figure below.

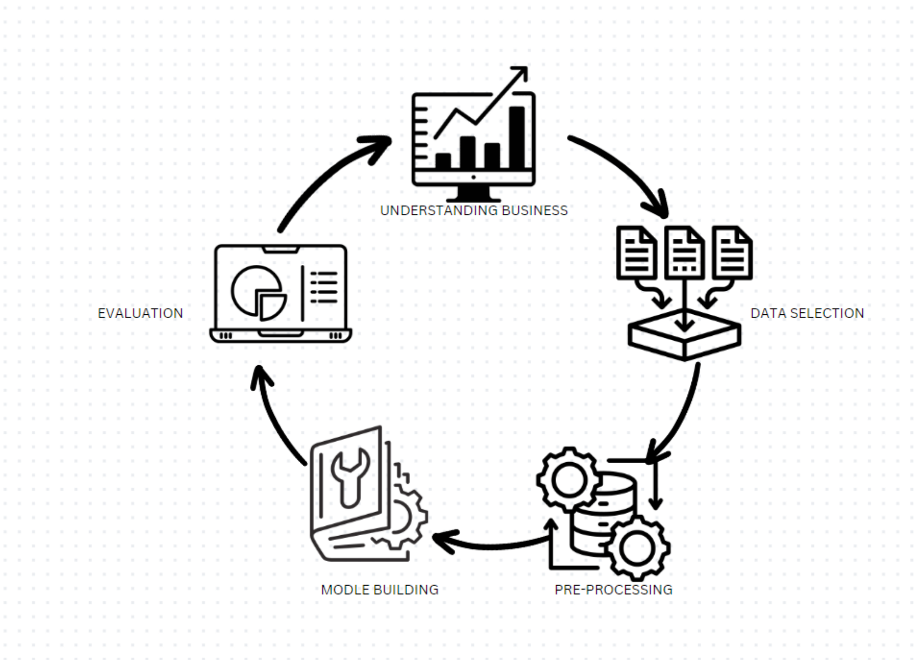

Figure 3: KDD Methodology

The first step is to understand the issues of diabetic retinopathy by taking the needs of the healthcare under consideration so that the management and treatment can be done efficiently and effectively. To do so the viewpoints of patients who suffer from DR and the viewpoints of doctors or health care providers need to be involved, doing so will help us with a better understanding of the challenges that are associated with this disease.

Collaboration between patients and healthcare organizations provides a key to aiming to have a treatment that improves the patient's compliance. Doing so acknowledges the intricacies of DR and disease's impact on quality of life and better treatment strategies. All in all, it calls for the combination of patient's education related to disease and empathetic care. Doing so will benefit the healthcare organizations and businesses that are dealing with diabetic retinopathy.

3.1 Data

3.1.1 Data Selection and Sources

The data used in this research is acquired from two open sources, namely Kaggle and Rotterdam Hospital's ophthalmology repository. Both these datasets contain images of scans of the human fundus. These Images are captured by using a non-mydriatic digital fundus camera shown in the image below. [2]

Figure 4: Non-Mydriatic Digital Fundus Camera

The non-mydriatic camera shown in Figure 4 is normally used for taking high-resolution (up to a 50-degree visual) images of the interior surface of the eye, which includes the retina and the optic disk. These high-resolution images make the examination and diagnosis easy and comfortable for the patients. The Rotterdam Hospital's dataset contains 1236 records, and the Kaggle dataset contributes 3662 images. To maintain consistency, all images were captured at a 45-degree angle. Unique identifiers and grades are present in both datasets, with additional variables incorporated to improve accuracy. Following is a dataset description of the variables present in the data frame. image: This column contains a unique identifier for each fundus image. This could be a number, code, or a combination of letters. grade: This attribute shows the grade of the fundus scans, i.e., the severity level of the diabetic retinopathy. path: This column stores the file path of the images associated with each fundus scan. level_cat: The grade attribute undergoes a transformation and is converted into a one-hot encoded vector. Scans: This attribute stores the respective scans that are allocated to the unique identifier number. These scans are stored in .png format. One-hot encoding was employed to transform categorical variables, representing each grade (Severity Level) as binary vectors stored in the "level cat" data frame. This same data frame, augmented with edge columns indicating the number of edges extracted from each fundus scan, was used for the edge-based methodology. This selected data is then split into train, test, and validation sets.

3.1.2 EDA (Exploratory Data Analysis)

In this phase of the first step, the data is examined thoroughly with the help of common EDA techniques, like visualizing sample images, identifying variations in image sizes, and analyzing the distribution of classes. This was done to get a better understanding of the data so that informed preprocessing techniques could be implemented to get better performance MMed et al. (2016).

[2] `https://www.beye.com/product/trc-nw8f-mydriaticnon-mydriatic-retinal-camera`

3.1.3 Preprocessing

In the initial preprocessing, a pipeline is made involving multiple stages of image augmentation and processing to improve the quality and diversity of data used for training the model. The 'tf_image_loader' is made for loading basic image augmentations like brightness, saturation, flipping, and other adjustments. Doing so increases the dataset's variability, which is crucial when it comes to enhancing the generalization of the capacity of the model.

Further the function 'tf_augmentor' exposes the data to more advanced augmentation techniques, namely random rotation and cropping, this helps in diversifying the dataset. With the help of TensorFlow's Dataset API, this pipeline effectively processes the fundus images and makes sure that a smooth data flow is achieved.

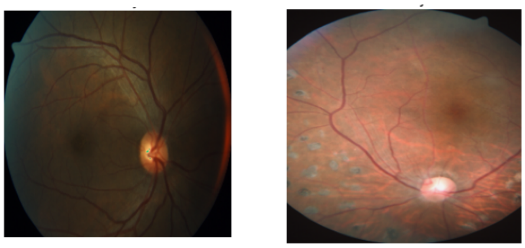

Figure 5: Fundus images after preprocessing

Functions like 'flow_from_dataframe' and 'get_iters_from_df' make sure that there is a continuous supply of augmented images and labels for model training. The training data is subject to a wide range of augmentation but, the validation data is not adjusted too much so that it can reflect the real-world circumstances in a much better way. The images in Figure 5 show the fundus scans after preprocessing. Overall, this framework is used for the analysis of ocular disease and can be used for different image-based machine-learning tasks.

3.2 Model Building

The preprocessed fundus images were fed as input to the pre-trained model, in this case, Inception-Resnet-v2, so that it could adapt accordingly and provide proper results in classifying the severity of diabetic retinopathy. This neural network was flattened with a dense layer. In the past, several such deep-learning networks have been implemented in the field of radiology to either detect or classify diseases and provide proper diagnoses. Once the model implementation is done, this model will undergo several evaluation metrics to verify and validate the results that are generated by the model. The evaluation of both methodologies is discussed in the evaluation section.

4 Design Specification

The flow chart in Figure 6 showcases the framework that has been used in this research. This framework is structured for data analysis, beginning with Dataset selection. The acquired dataset then is put through preprocessing to make sure that the data is in the correct format and that any irrelevant information is removed. This step is very crucial for proper results.

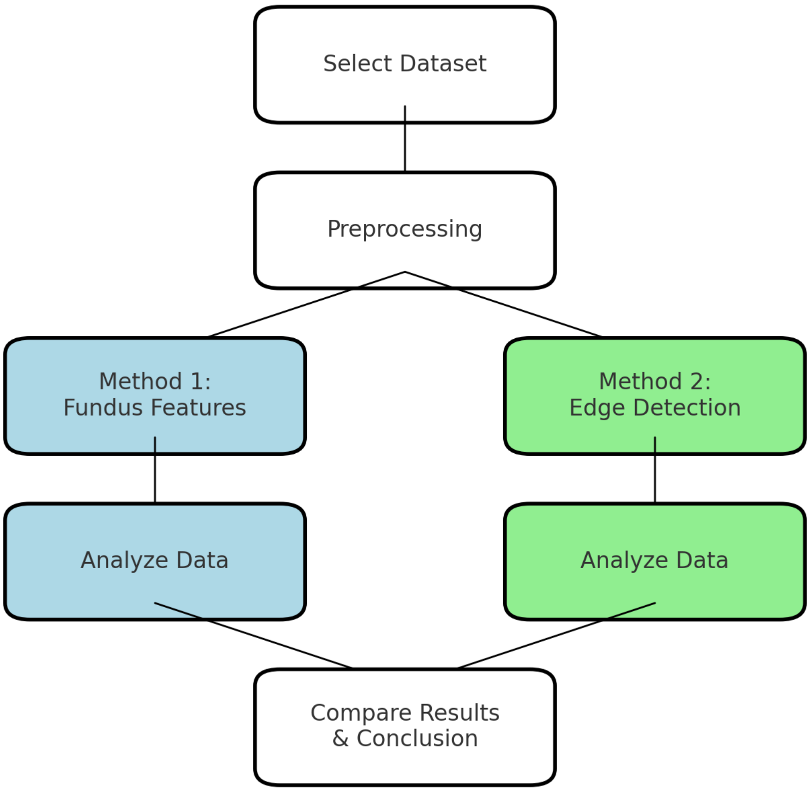

Figure 6: Implemented Framework

Once the preprocessing is done, the employed framework splits into two different methodologies for data analysis. This shows that the framework is designed to evaluate the effectiveness of two different methods based on the same data.
In the "Features based" methodology human fundus images of the eye are analyzed to extract some specific features and then classified into five categories based on the severity of the diabetic retinopathy. In the "Edge Based" methodology retinal edge-based features were extracted from the human fundus images. Later based on these features the images are classified into five severity levels of diabetic retinopathy. Finally, in the last stage, the results from the methodologies are discussed to conclude. The accuracy, efficacy, and appropriateness are analyzed.

4.1 Inception ResNet V2

The flow chart below shows the implementation of Inception ResNet V2. This is a hybrid deep learning model derived from the residual network and inception model with 164 layers. This deep learning model was implemented in the framework for the classification of severity of Diabetic retinopathy. This deep learning model excels in recognizing patterns at various scales within the images and hence was used in research.

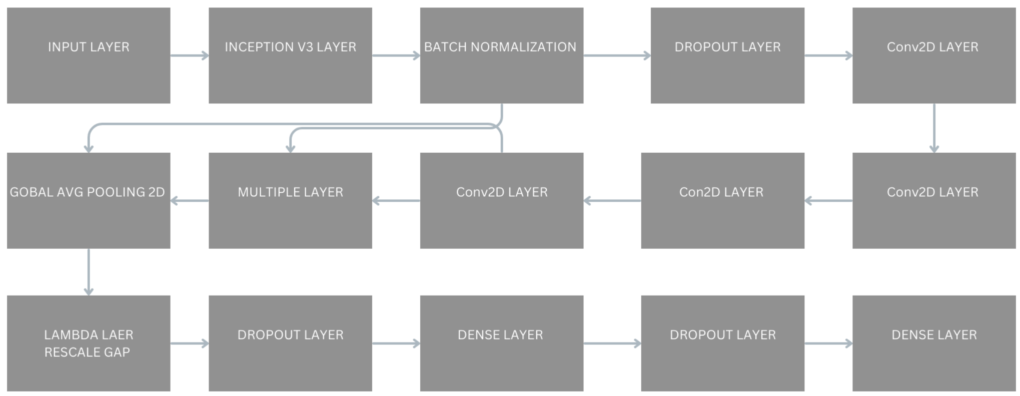

Figure 7: Inception ResNet V2

The architecture of this model shown in Figure 7 starts with an input layer, this input layer then feeds data into the inception v3 layer. This layer is then followed by a batch normalization layer specifically designed so that it can standardize the input to a layer of mini-batch. Doing so adds to the performance of the network by reducing the number of training epochs. After batch normalization comes a dropout layer, which aids in preventing overfitting during the training time. The data from the dropout layer is then passed through a series of convolutional 2D (Conv2D) layers, these layers are used to extract the features from the input.

As seen in figure 7 the architecture features branching, one branch goes to the global average pooling 2D layer, this is used to downsample the input representation. The next branch connects to the lambda layer to rescale the global average pooling and then feed it as input to the dense layer. The last branch goes from multiple layers to Conv2D layers, here multiple filters get applied on the input.

At the end of the architecture, a series of denes layers are connected with the dropout layers. These dense layers are used majorly for recognizing the patterns and analyzing them thoroughly as compared to previous convolutional layers

5 Implementation

This section provides a brief walkthrough of the implementation of the project. Each of the following steps is discussed to provide clarity on the methodology to make understanding of the project easy.

5.1 Programming Language and Platform

Python programming language is used to implement this project because it has extensive libraries and packages that are beneficial for data analysis and machine learning tasks. Jupyter Notebook works as an interactive development environment (IDE) which allows seamless integration of code.

5.2 Data sets

The data for this project is acquired from two open-source datasets, one is from Kaggle[3], and the other is from Rotterdam Hospital's ophthalmic dataset[4]. Both these datasets are stored locally so that managing and organizing datasets gets easier. Both these datasets weren't completely used, but they were merged to some extent to improve the diversity of the dataset. Once the complete dataset was acquired, basic EDA (Exploratory Data Analysis) was done to gain insights into the data. It was seen that the data was imbalanced and was inclining towards one class. Usually data balancing is suggested to avoid false classification or prediction but, in the field of medical images the data depicts real-life scenarios and hence balancing the data is not a good option.

5.3 Data Transformation and Image Processing

With the help of OpenCV, a powerful library majorly utilized in the image processing field data was transformed. A few functions were created to perform basic image preprocessing to attain consistency in images. Cropping and flipping were also implemented to get better fundus images.

5.4 Model Development Using Transfer Learning

A pre-trained model Inception ResNet V2 is employed to execute this project, the reason behind using this pre-trained model is because it is optimal when it comes to images. Transfer learning leverages the existing neural networks to save time and computational resources.

5.5 Correlation Analysis

As this study aims to detect the severity of diabetic retinopathy from the change in retinal edges, the correlation analysis is done to check if the change in edges is a feasible biomarker in predicting the severity level of diabetic retinopathy.

[3] `https://www.kaggle.com/c/aptos2019-blindness-detection/data`

[4] `http://www.rodrep.com/longitudinal-diabetic-retinopathy-screening---description.html`

5.6 Conclusion

The models underwent thorough analysis and evaluation, and the models were assessed for their accuracy, efficiency, and reliability. Various metrics like F1-score, Precision, and Recall are calculated to evaluate the models, more about the evaluation is discussed in the evaluation section. Based on these evaluations a conclusion was drawn.

6 Evaluation

The implemented models are evaluated based on an evaluation matrix containing measures like F1 score, precision, recall, and confusion matrix. Below are some of the formulae for these measures.
The confusion matrix comprises four factors, TP= True Positive, FP = False Positive, TN = True Negative, and FN = False Negative.

$$\text{Precision} = \frac{True\ Positive}{True\ Positive + False\ Positive}$$

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

$$\text{Recall} = \frac{True\ Positive}{True\ Positive + False\ Negative}$$

6.1 Classification Based on Features from Fundus Images

In this experiment, the classification of severity of diabetic retinopathy is done based on the features extracted from fundus images. The detailed evaluation of this experiment is showcased below in the form of an evaluation matrix and a confusion matrix.

Class	Precision	Recall	F1-Score	Support
0	0.94	0.94	0.94	459
1	0.50	0.20	0.29	135
2	0.44	0.67	0.53	162
3	0.00	0.00	0.00	27
4	0.25	0.33	0.29	81

Figure 8: Classification Matrix for the Feature Based System

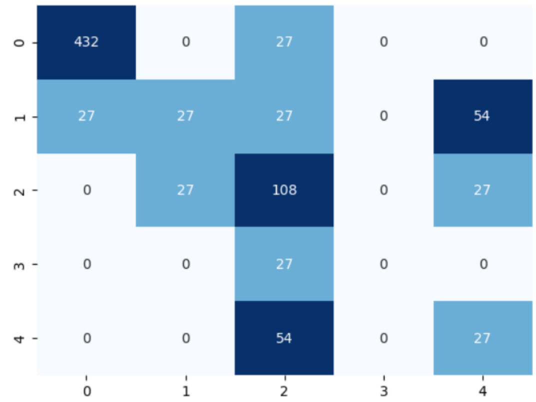

Figure 9: Confusion for the Feature Based System

6.2 Classification Based on Change in Retinal Edges

The categorization of the severity of DR in this experiment is done based on the changes in retinal edges, these changes are analyzed by advanced image processing techniques. The evaluation matrix and confusion matrix below show the results of this experiment.

Class	Precision	Recall	F1-Score	Support
0	0.48	1.0	0.65	351
1	0.0	0.0	0.0	68
2	0.0	0.0	0.0	213
3	0.0	0.0	0.0	36
4	0.0	0.0	0.0	65

Figure 10: Classification Matrix for Edge Based System

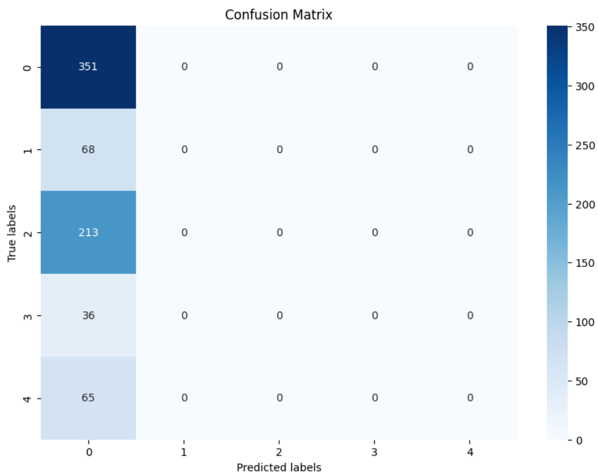

Figure 11: Confusion Matrix for the Edge-Based System

The confusion matrix shown in Figure 11 reveals the outcome of the second methodology which is an edge-based classification of the diabetic retinopathy severity levels (0-4). As seen in the figure this model was excellent at predicting level 0 severity(No diabetic retinopathy) with 351 correctly classified cases. But at the same time, it failed at classifying other severity levels. It is also seen that 213 cases were of true severity level 2 but were classified into severity level 0, this class imbalance could have been easily mitigated by implementing some class-balancing techniques. In this case, the classes weren't balanced to replicate the real-life scenarios. Overall, this model is not accurate and requires additional features for more accurate classification.

6.3 Discussion

This research was conducted to investigate if the change in retinal edges can be a good biomarker in classifying the severity stage of diabetic retinopathy. When compared with other models that used features from fundus scans as parameters for classification it was seen that there was a significant drop in the accuracy of the model which used changes in retinal edges. The accuracy attained by the Inception ResNet V2 model was 69% but the accuracy achieved by the edge model was just 47%, this gap underscores the crucial need for innovation in feature extraction techniques and advanced models and hence based on these findings and prior literature review, the research in the future should look for new methods for extracting features and newer networks for the classification of the severity doing so will ultimately contribute towards the better diagnostic tools for medical research.

7 Conclusion and Future Work

This research was done to investigate the potential correlation between changes in retinal edges and the severity of diabetic retinopathy. The main aim was to check whether the change in retinal edges can be used as a reliable measure for DR progression. Advanced image processing techniques were used and deep learning models were implemented to analyze the retinal changes. Although the models were able to attain a decent accuracy but there is no significant correlation between change in edges and DR severity. This wasn't the anticipated outcome, but it offers crucial insights into the intricacies of diabetic retinopathy, and difficulties in diagnosing it with fundus scans.

Despite the results this research underscores the need for better diagnostic approaches for diagnosing diabetic retinopathy, beyond the analysis of change in retinal edges. Secondly, it highlights the limitations of the existing techniques in monitoring the progression of the disease and the need for better implementation techniques. Although the model achieved decent accuracy, it struggled to showcase a significant correlation between the change in retinal edges and severity levels of diabetic retinopathy. The sole reliance on the edge-based system for comprehensive analysis is not supported, and the inclusion of additional features like thickness and abnormalities in the retina to enhance accuracy is advised. The model's basis towards the absent classes is a major concern for the medical diagnosis, where false negatives could impact the patient's treatment. Overall, the study emphasizes the importance of exploring the diverse retinal features for a more robust and accurate classification of the severity levels.

For future work, this research proposes an investigation of other features that are related to the retina that might correlate with the disease, some of these features are vascular abnormalities or changes in the thickness of the retina. On top of this explore more and never image processing technologies that could provide a more insightful understanding of diabetic retinopathy. The findings from this research do not support the development of a diagnostic tool based on changes in edges but, these findings open doors for the further development and creation of more comprehensive diagnostic solutions. If so these solutions can contribute and impact significantly in offering advanced diagnostic solutions and making the screening process for diabetic retinopathy more effective and efficient.

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