Industry Oriented Mini Project Report

on

DETECTION OF DIABETIC RETINOPATHY USING MACHINE LEARNING

Submitted in partial fulfillment of the requirements
for the award of degree of

BACHELOR OF TECHNOLOGY

in

Information Technology

by

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(NAAC ‘A’ Grade & NBA Accredited- ECE, EEE, CSE & IT)

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CERTIFICATE

This is to certify that the Project report on **"Detection of Diabetic Retinopathy Using Machine Learning "** is a bonafide work carried out by **B. Vagdevi (20WH1A12A1), S. Niharika (20WH1A12A9), T. Sujatha (21WH5A1208)** in the partial fulfillment for the award of B.Tech degree in **Information Technology , BVRIT HYDERABAD College of Engineering for Women, Bachupally, Hyderabad** affiliated to Jawaharlal Nehru Technological University, Hyderabad, under my guidance and supervision. The results embodied in the project work have not been submitted to any other university or institute for the award of any degree or diploma.

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DECLARATION

We hereby declare that the work presented in this project entitled **"Detection of Diabetic Retinopathy Using Machine Learning"** submitted towards completion of in IV year I sem of B.Tech IT at "BVRIT HYDERABAD College of Engineering for Women",Hyderabad is an authentic record of our original work carried out under the esteemed guidance of **Mr. P. Krishna Kishore, Assistant Professor**, Department of Information Technology.

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This project report is dedicated to my beloved Family members and supervisor for their limitless support and encouragement and to you as a reader

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ABSTRACT

Diabetic Retinopathy (DR) is a leading cause of vision impairment and blindness among individuals with diabetes. Early detection and timely intervention are crucial to prevent irreversible vision loss. This study involves the collection of a diverse dataset consisting of retina photographs from both individuals diagnosed with DR and those with healthy retinas. These images are used to train a deep neural network, optimized for the accurate detection of retinopathy. The primary objective of this project is to evaluate the system's ability to determine the presence or absence of DR with a high degree of accuracy, sensitivity and specificity. The proposed system aims to facilitate early diagnosis, allowing healthcare providers to intervene promptly and initiate appropriate treatment plans. This not only improves the prognosis for individuals with DR but also contributes to significant healthcare cost savings by reducing the need for extensive, late-stage interventions. Furthermore, the automated nature of the system holds the potential to enhance the accessibility of DR screening, particularly in underserved and remote regions. It can serve as a valuable tool for primary care physicians and optometrists, enabling them to identify patients at risk of DR more efficiently and refer them to specialists when necessary.

Keywords: Neural Networks, retina, sensitivity, specificity, prognosis

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Chapter 1

Introduction

Diabetic retinopathy (DR) stands as a critical complication of diabetes, impacting the eyes and potentially leading to vision impairment or even blindness if left untreated. Early detection is key to effective management and prevention of severe outcomes. Machine learning (ML) has emerged as a promising tool in this realm, offering a non-invasive and efficient method for DR diagnosis.

ML algorithms, particularly deep learning models, analyze retinal images to identify characteristic signs of DR, such as microaneurysms, hemorrhages, and exudates. These algorithms learn patterns from large datasets of annotated retinal images, enabling them to classify images into different stages of DR with impressive accuracy.

The application of ML in DR detection has the potential to revolutionize screening processes by automating the assessment, reducing reliance on manual evaluation, and accelerating diagnosis. This technology not only expedites the identification of DR but also aids in directing timely interventions and treatment strategies for patients at risk.

However, challenges persist in ensuring the reliability and generalizability of these ML models across diverse populations and imaging conditions. Addressing these challenges is crucial to establish robust, scalable, and accessible solutions for widespread implementation in clinical settings.

Efforts continue to refine and optimize ML algorithms, aiming to enhance their sensitivity, specificity, and interpretability while integrating them seamlessly into existing healthcare frameworks. Ultimately, the integration of machine learning in the detection of diabetic retinopathy holds immense

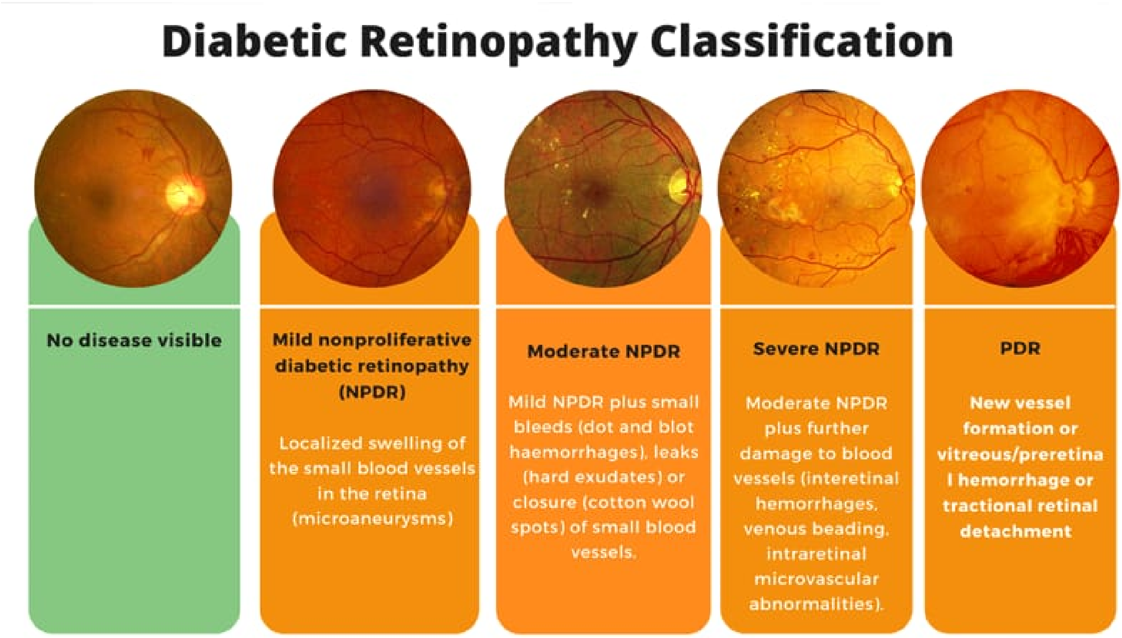

Figure 1.1: Different stages of DR: (a) no DR, (b) mild, (c) moderate, (d) severe, and (e) PDR

promise in improving patient outcomes and combating vision loss associated with this condition.

1.1 Motivation

The motivation behind using machine learning for diabetic retinopathy detection stems from the urgent need for early diagnosis and intervention in diabetic patients at risk of vision impairment. Traditional screening methods often rely on manual assessment, which can be time-consuming, subjective, and prone to human error. Machine learning offers a transformative solution by automating this process, enabling quicker and more accurate identification of retinal abnormalities associated with diabetic retinopathy.

The scalability of machine learning models allows for the analysis of large volumes of retinal images, facilitating population-wide screening programs. This scalability is vital in addressing the growing prevalence of diabetes and its associated complications, ensuring timely detection and management of diabetic retinopathy for a larger number of individuals.

Moreover, the potential of machine learning to detect subtle changes in retinal images that might go unnoticed by the human eye enhances the sensitivity of diagnostic tools. This capability opens doors to early intervention, potentially preventing the progression of diabetic retinopathy to more severe stages and reducing the risk of irreversible vision loss.

Machine learning-driven diagnostics also offer a cost-effective approach, streamlining the screening process and optimizing healthcare resources. By improving the efficiency of screening programs, these technologies have the potential to make eye care more accessible to underserved populations and remote areas, reducing disparities in healthcare access and outcomes.

Overall, the motivation behind employing machine learning in diabetic retinopathy detection lies in its capacity to revolutionize screening methods, enhance accuracy, enable early intervention, and ultimately preserve vision and improve the quality of life for individuals affected by diabetes.

1.2 Objective

Our project aims to combat the rising threat of diabetic retinopathy, a leading cause of blindness, by developing a cutting-edge machine learning model for its early detection. This model, trained on a massive dataset of retinal images, will analyze key features like microaneurysms and hemorrhages to accurately diagnose DR at various stages. By enabling early intervention and optimizing resource allocation, we hope to improve screening efficiency, reduce healthcare costs, and ultimately prevent vision loss in countless diabetic patients. This project harnesses the power of technology to tackle a global health challenge head-on and make a meaningful contribution to the well-being of millions.

1.3 Problem Definition

The project aims to address the critical need for efficient and accurate detection of diabetic retinopathy using machine learning techniques. Diabetic retinopathy, a prevalent complication of diabetes, poses a substantial risk to vision if not identified and managed promptly. The problem entails creating a reliable system capable of autonomously analyzing retinal images to detect signs of retinopathy, enabling early intervention and personalized care. Challenges include the complexity of analyzing diverse retinal patterns, the need for robust feature extraction from images, and developing machine learning models capable of discerning subtle variations indicative of retinopathy stages. The project seeks to bridge this gap by leveraging machine learning algorithms to enhance diagnostic accuracy, streamline screening processes, and empower healthcare providers with a tool that efficiently identifies diabetic retinopathy, thereby aiding in the preservation of vision and improving outcomes for individuals with diabetes.

Chapter 2

Literature Survey

The authors in [1] detail the architecture and configuration of the CNN employed in the study, outlining the convolutional layers, pooling layers, and fully connected layers. They discuss the rationale behind the chosen architecture and highlight the significance of convolutional operations in capturing hierarchical features at different levels of abstraction. The training process, including the choice of optimization algorithms, learning rates, and data augmentation techniques, is thoroughly explained to provide insights into model development.

This paper [2] conducts a thorough review of methodologies for detecting diabetic retinopathy through fundus image analysis. The comprehensive nature of the review encompasses both traditional image processing techniques and contemporary machine learning approaches. The authors aim to provide a valuable resource for researchers and practitioners seeking insights into the evolution, challenges, and advancements in diabetic retinopathy detection.The authors transition to a comprehensive analysis of contemporary machine learning techniques applied to diabetic retinopathy detection. They cover a wide array of methodologies, including but not limited to, supervised learning, unsupervised learning, and semi-supervised learning. Specific algorithms such as Support Vector Machines, Random Forests, and k-Nearest Neighbors are discussed in the context of their applications to fundus image analysis.

This paper [3] conducts a comparative analysis of transfer learning techniques for diabetic retinopathy detection, aiming to leverage pre-trained models for improved performance. The study explores various pre-trained models, including VGG, ResNet, and Inception, and compares their effectiveness in adapting to the specific task of detecting diabetic retinopathy.

The authors address the growing interest in transfer learning and its potential to enhance the efficiency and generalization of deep learning models in medical image analysis.

This paper [4] focuses on the application of ensemble learning techniques for diabetic retinopathy classification. Ensembling involves combining multiple classifiers to enhance overall predictive performance. The authors aim to provide a comprehensive understanding of how ensemble methods, such as bagging and boosting, can be effectively utilized to improve the accuracy and robustness of diabetic retinopathy classification models.The paper also discusses the evaluation metrics employed to assess the performance of the ensemble models. Common metrics such as accuracy, precision, recall, and F1-score may be highlighted, and the authors may justify their selection based on the specific requirements of diabetic retinopathy classification. A comparison with baseline models or individual classifiers may be included.

In their comprehensive survey [5], Zhang and Wang delve into the application of deep learning techniques for diabetic retinopathy diagnosis. The paper focuses on a variety of neural network architectures, prominently featuring Convolutional Neural Networks (CNNs) and recurrent neural networks (RNNs). This survey provides an extensive examination of recent advancements, challenges, and future directions in leveraging deep learning to enhance the detection and classification of diabetic retinopathy. In their comprehensive survey, Zhang and Wang delve into the application of deep learning techniques for diabetic retinopathy diagnosis. The paper focuses on a variety of neural network architectures, prominently featuring Convolutional Neural Networks (CNNs) and recurrent neural networks (RNNs). This survey provides an extensive examination of recent advancements, challenges, and future directions in leveraging deep learning to enhance the detection and classification of diabetic retinopathy.

Chapter 3

System Design

The system design for detecting diabetic retinopathy (DR) encompasses a multifaceted approach aimed at addressing challenges within the dataset and enhancing the overall efficiency of the classification process. The journey begins with a thorough consideration of preprocessing methods and data augmentation techniques, laying the foundation for robust deep learning models.

In the realm of medical imaging, the quality of input data plays a pivotal role in the accuracy of diagnostic models. To mitigate issues arising from low-quality images, a critical preprocessing step is employed. This involves leveraging the OpenCV library to implement image cropping and resizing. Each input image undergoes a transformation, being cropped to a square shape that encapsulates the most tightly contained circular area of the fundus. This meticulous cropping eliminates undesirable black borders and patient-related annotations, ensuring that the subsequent training data is pristine and focused. Following this, each cropped image is resized to a standardized 300×300 pixels. The rationale behind multiple resolutions lies in the exploration of the impact of input image resolution on classification performance.

The next critical phase in system design involves data augmentation. Deep learning models, particularly Convolutional Neural Networks (CNNs), thrive on large, diverse datasets. However, the availability of such datasets is often limited in medical domains. Data augmentation serves as a powerful strategy to artificially expand the dataset, addressing the challenges of data noise and limitations. The Keras library is instrumental in implementing augmentation techniques such as image rotation, horizontal flipping, scaling, clipping, and translation. These techniques not only introduce diversity into the dataset but also contribute to the model's robustness by inducing rotation invariance and other desirable properties.

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The training process involves feeding the preprocessed and augmented retinal images into the selected CNN models. The models, implemented in Python using TensorFlow, undergo hyperparameter tuning to optimize their performance. Key hyperparameters, such as the number of iterations (set at 4000) and learning rate (0.0005), are fine-tuned to achieve superior classification outcomes. The training dataset comprises 1607 images from Xiangya No. 2 Hospital Ophthalmology, with 1000 healthy images and 607 defective images. The division of the dataset into training and testing sets follows a meticulous strategy to ensure a balanced representation of both classes.

The experimental phase involves rigorous testing of the trained CNN models to evaluate their accuracy in detecting diabetic retinopathy. The evaluation goes beyond simply measuring correct and incorrect classifications; it includes a nuanced analysis of error categories, allowing for a deeper understanding of model performance. The categories of error classification and their respective accuracy scores contribute to a comprehensive assessment of the models.

In conclusion, the system design for diabetic retinopathy detection adopts a systematic and holistic approach. From preprocessing and data augmentation to the selection and training of state-of-the-art CNN models, each step is meticulously designed to enhance the accuracy and robustness of the classification system. The integration of advanced techniques, such as GAN-based data augmentation and residual learning-inspired CNN architectures, underscores the commitment to achieving excellence in medical image classification. The resulting system not only contributes to the early detection of diabetic retinopathy but also serves as a paradigm for leveraging deep learning in medical diagnostics.

Chapter 4

Methodology

The methodology for detecting diabetic retinopathy using machine learning with Convolutional Neural Networks (CNNs) is a multifaceted approach designed to enhance the accuracy and efficiency of automated diagnosis. The process initiates with meticulous data preprocessing to address issues related to image quality and consistency. Leveraging the OpenCV library, images undergo cropping to focus on the most relevant fundus areas, followed by resizing to a standardized 300 $\times$ 300 pixels. Subsequently, data augmentation techniques, including rotation, flipping, and translation, are applied to artificially expand the dataset. The incorporation of Generative Adversarial Networks (GANs) further augments data, overcoming limitations and fortifying the model against noise.

The core of the methodology lies in the utilization of three advanced CNN models: VGG-16, ResNet-50, and ResNet-101. These models are chosen for their prowess in image classification and feature extraction essential for diabetic retinopathy diagnosis. Hyperparameters, such as the number of iterations and learning rate, are fine-tuned to optimize the models for the specific dataset. VGG-16's visualization model architecture contributes to efficiency, while ResNet-50 and ResNet-101, with skip connections, address challenges in deep neural network training.

4.1.1 Proposed Methodology

The primary goal of this study is to develop a robust system for diabetic retinopathy detection, employing deep learning to classify severity levels. Through meticulous preprocessing and training two models—an in-house proposed model and a regression model—the study reveals the superior accuracy of our proposed model. This research contributes to diabetic retinopathy diagnostics, potentially leading to early interventions and improved patient outcomes in ophthalmic healthcare.

4.1.2 Data Preprocessing

In addressing the challenge of inaccurate results from low-quality images, this study prioritized preprocessing using the OpenCV library. The dataset's diversity in patient demographics and fundus photography conditions prompted a careful approach. Leveraging OpenCV's functions and noise handling capabilities, the images underwent cropping for focus and resizing to a standardized 300 × 300 pixels. This meticulous preprocessing ensured removal of unwanted annotations, standardized dimensions, and set the stage for robust analysis of resolution impacts on classification, ultimately contributing to enhanced image quality and accurate diabetic retinopathy detection.

- 0 - No DR
- 1 - Mild
- 2 – Moderate
- 3 - Severe
- 4 - Proliferative DR

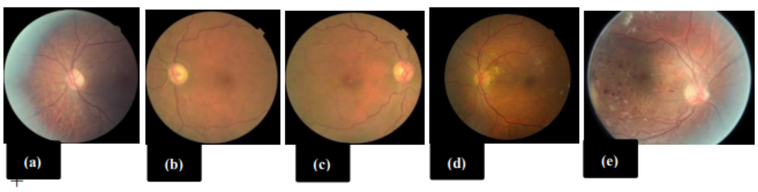

Figure 4.1: Image samples based on severity from dataset

4.1.3 Data Augmentation

The data augmentation process in the provided matter involves utilizing the Keras library's built-in capabilities to enhance the dataset for training deep learning models, particularly convolutional neural networks (CNNs). Various augmentation techniques are applied to generate diverse data and improve the robustness of the model. These techniques include image rotation, horizontal flipping, scaling, clipping, and translation. Additionally, the study incorporates generative adversarial networks (GANs), an advanced approach in data augmentation, to further enrich the dataset. The augmentation aims to address data noise and overcome limitations associated with the available dataset, contributing to the improved performance of the deep learning model in detecting diabetic retinopathy.

4.1.4 Utilizing CNN Models

The essence of the system lies in leveraging three sophisticated CNN models – VGG-16, ResNet-50, and ResNet-101 – for diabetic retinopathy (DR) detection. Selected for their effectiveness and robustness in image classification, these models incorporate convolution, pooling, and activation layers, facilitating automatic feature extraction and efficient computation. The CNN architecture proves pivotal in achieving accurate DR detection. The models' selection is grounded in their notable success across diverse tasks, particularly in the realm of image classification, underscoring their suitability for the DR diagnostic system.

4.1.5 Training Process

In this study, the selection of cutting-edge CNN models, namely ResNet-101, ResNet-V1-50, and VGG-16, stems from their widespread acclaim for effectiveness and robustness. These models are specifically tailored to process retinal images of dimensions 300×300, employing a configuration of alternating convolution and pooling layers activated by the Rectified Linear Unit (ReLU) activation function. The implementation of these state-of-the-art CNN models is carried out in Python using the Tensorflow framework. Crucially, the hyperparameter-tuning method's parameters are not inherently initialized by the network; instead, they undergo meticulous tuning and optimization based on the outcomes of training the diabetic retinopathy (DR) images, a crucial step in enhancing overall performance.

4.1.6 Experiment and Evaluation

The system design encompasses a comprehensive experimental phase, evaluating the accuracy of the trained CNN models in a meticulous manner. The assessment involves a thorough analysis of classifications, with a focus on categorizing errors and appropriately disciplining accuracy scores. By leveraging cutting-edge deep learning techniques and rigorous data preprocessing, the system aims to achieve superior outcomes in the classification of retinal images, contributing to the advancement of diagnostic capabilities in the context of diabetic retinopathy.

Chapter 5

Implemention

The implementation employs Convolutional Neural Network (CNN) models, specifically VGG-16, ResNet-50, and ResNet-101, renowned for their effectiveness in image classification. Data augmentation techniques, facilitated by the Keras library, address data limitations. The CNN models, implemented in Python using Tensorflow, undergo hyperparameter tuning to optimize performance. Training involves iteratively feeding preprocessed images into the CNNs. The experimental phase assesses the accuracy of the models, contributing to a robust diabetic retinopathy detection system through advanced deep learning techniques and meticulous preprocessing.

5.1 Dataset:

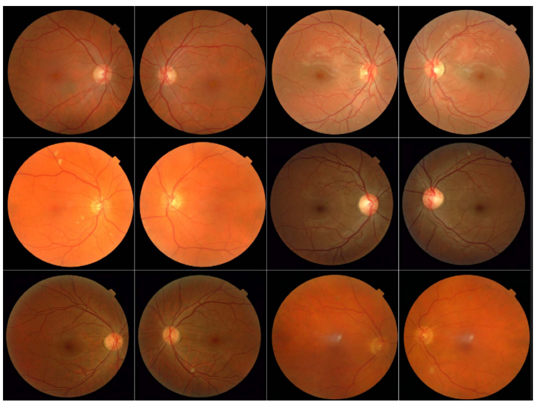

Figure 5.1: Data Set

The dataset plays a pivotal role, particularly when incorporating Gaussian filtered images. Totally it contains 5 divisions namely Mild, Moderate, No-DR, Proliferate-DR, Severe images. Each containing the image count of 370, 999, 1805, 295, 193.

5.2 Code:

```
from google.colab import drive
drive.mount('/content/drive')
```

Figure 5.2: Mounting

```
from tensorflow import lite
import tensorflow as tf
from tensorflow import keras
from tensorflow.keras import layers
import numpy as np
import pandas as pd
import random, os
import shutil
import matplotlib.pyplot as plt
from matplotlib.image import imread
from keras.preprocessing.image import ImageDataGenerator
from tensorflow.keras.metrics import categorical_accuracy, AUC
from sklearn.model_selection import train_test_split

!pip install tensorflow-addons
import tensorflow_addons
from tensorflow_addons.metrics import F1Score, CohenKappa
```

Figure 5.3: Importing Libraries

```
df = pd.read_csv('/content/drive/MyDrive/archive (2)/train.csv')

diagnosis_dict_binary = {
    0: 'No_DR',
    1: 'DR',
    2: 'DR',
    3: 'DR',
    4: 'DR'
}

diagnosis_dict = {
    0: 'No_DR',
    1: 'Mild',
    2: 'Moderate',
    3: 'Severe',
    4: 'Proliferate_DR',
}


df['binary_type'] =  df['diagnosis'].map(diagnosis_dict_binary.get)
df['type'] = df['diagnosis'].map(diagnosis_dict.get)
df.head()
```

	id_code	diagnosis	binary_type	type
0	000c1434d8d7	2	DR	Moderate
1	001639a390f0	4	DR	Proliferate_DR
2	0024cdab0c1e	1	DR	Mild
3	002c21358ce6	0	No_DR	No_DR

Figure 5.4: Loading the training data

```
train_intermediate, val = train_test_split(df, test_size = 0.15, stratify = df['type'])
train, test = train_test_split(train_intermediate, test_size = 0.15 / (1 - 0.15), stratify = train_intermediate['type'])

print("Train")
print(train['type'].value_counts(), '\n')
print("Valid")
print(val['type'].value_counts(), '\n')
print("Test")
print(test['type'].value_counts(), '\n')
```

```
Train
No_DR             1263
Moderate           699
Mild               258
Proliferate_DR     207
Severe             135
Name: type, dtype: int64

Valid
No_DR             271
Moderate          150
Mild               56
Proliferate_DR     44
Severe             29
Name: type, dtype: int64

Test
No_DR             271
Moderate          150
Mild               56
Proliferate_DR     44
Severe             29
Name: type, dtype: int64
```

Figure 5.5: Splitting the data

```
base_dir = ''

train_dir = os.path.join(base_dir, 'train')
val_dir = os.path.join(base_dir, 'val')
test_dir = os.path.join(base_dir, 'test')
#print(test['type'].value_counts(), '\n')

if os.path.exists(base_dir):
    shutil.rmtree(base_dir)

if os.path.exists(train_dir):
    shutil.rmtree(train_dir)
os.makedirs(train_dir)

if os.path.exists(val_dir):
    shutil.rmtree(val_dir)
os.makedirs(val_dir)

if os.path.exists(test_dir):
    shutil.rmtree(test_dir)
os.makedirs(test_dir)
```

Figure 5.6: Finding path for train, test and validation data

```python
src_dir = '/content/drive/MyDrive/archive (2)/gaussian_filtered_images/gaussian_filtered_images/'
for index, row in train.iterrows():
    diagnosis = row['type']
    binary_diagnosis = row['binary_type']
    id_code = row['id_code'] + ".png"
    srcfile = os.path.join(src_dir, diagnosis, id_code)
    dstfile = os.path.join(train_dir, diagnosis)
    os.makedirs(dstfile, exist_ok = True)
    shutil.copy(srcfile, dstfile)

for index, row in val.iterrows():
    diagnosis = row['type']
    binary_diagnosis = row['binary_type']
    id_code = row['id_code'] + ".png"
    srcfile = os.path.join(src_dir, diagnosis, id_code)
    dstfile = os.path.join(val_dir, diagnosis)
    os.makedirs(dstfile, exist_ok = True)
    shutil.copy(srcfile, dstfile)

for index, row in test.iterrows():
    diagnosis = row['type']
    binary_diagnosis = row['binary_type']
    id_code = row['id_code'] + ".png"
    srcfile = os.path.join(src_dir, diagnosis, id_code)
    dstfile = os.path.join(test_dir, diagnosis)
    os.makedirs(dstfile, exist_ok = True)
    shutil.copy(srcfile, dstfile)
```

Figure 5.7: Training the data

```
train_path = 'train'
val_path = 'val'
test_path = 'test'
print(train_path)
print(val_path)
print(test_path)

train_batches = ImageDataGenerator(rescale = 1./255).flow_from_directory(train_path, target_size=(224,224), shuffle = True)
val_batches = ImageDataGenerator(rescale = 1./255).flow_from_directory(val_path, target_size=(224,224), shuffle = True)
test_batches = ImageDataGenerator(rescale = 1./255).flow_from_directory(test_path, target_size=(224,224), shuffle = True)
```

```
train
val
test
Found 0 images belonging to 0 classes.
Found 0 images belonging to 0 classes.
Found 0 images belonging to 0 classes.
```

Figure 5.8: Preprocessing the images

```
os.listdir('train')
```

```
['Proliferate_DR', 'Severe', 'Moderate', 'No_DR', 'Mild']
```

Figure 5.9: Listing of different classes

```python
plt.subplot(1,2,1)
plt.plot(history.history['acc'])
plt.plot(history.history['val_acc'])
plt.ylabel('acc')
plt.xlabel('epoch')
plt.legend(['train', 'val'], loc='lower right')

plt.subplot(1,2,2)
plt.plot(history.history['loss'])
plt.plot(history.history['val_loss'])
plt.ylabel('loss')
plt.xlabel('epoch')
plt.legend(['train', 'val'], loc='lower right')
```

Figure 5.10: Plotting the results

```python
pred = model.predict(test_batches)
pred = np.argmax(pred,axis=1)

# Map the label
labels = (train_batches.class_indices)
labels = dict((v,k) for k,v in labels.items())
pred = [labels[k] for k in pred]

# Display the result
print(f'The first 5 predictions: {pred[:5]}')
```

```
18/18 [==============================] - 13s 696ms/step
The first 5 predictions: ['Moderate', 'Mild', 'Moderate', 'Moderate', 'Moderate']
```

Figure 5.11: Printing first five results

Chapter 6

Results and Discussions

We trained our proposed model using CNN Model on a dataset called Guassian Filtered Images from kaggle. There was a lot of noise associated with the images provided by the dataset therefore, preprocessing was needed. For preprocessing, we first removed the black border of the images in order to focus more on the fundus image only, black corners of images was also removed, then the images were resized to a standard format of 224*224 of width and height. At last a Gaussian blur was applied to the images in order to remove the Gaussian noise. After preprocessing we analyze that the data is highly unbalanced among the severity classes, majority of data belonged to the class '0'i.e. No DR. in order to address this issue, we used data augmentation, which gives us 3600 images from all classed and made the data balanced. After preprocessing and augmentation of images, data was finally fed to the CNN Model for training the model. After evaluating our model the training accuracy of 0.7272 was obtained, while as validation accuracy of 0.7272 was achieved. We also calculated the Cohen Kappa score which comes out to be 0.5750.

Chapter 7

Conclusion and future works

7.1 Conclusion

Traditional method for detection of DR is prolonged, challenging and costly, thus many researches were brought up to automate the detection process by using machine learning and deep learning approaches. In this work, we presented a comprehensive study of various methodologies for detecting diabetic retinopathy automatically and attempted to propose our own deep learning approach for the early diagnosis of retinopathy by using a CNN Model. Dataset: 'Guassian Filtered Images' from kaggle were used for this study. A lot of preprocessing and augmentation was done to standardize the data in a desired format and to remove the unwanted noise. Our proposed model performed better than the regression model by achieving the accuracy of 72.72 percent

7.2 Future Scope

As there are a number of images taken under different conditions, needs to undergo a lot of preprocessing and augmentation, some features of image might be missed out, so such techniques should be used that not only preserve all the tiny important features but at the same time is able to do a successful pre-processing. Moreover multiple images should be provided with more clarity for every patient which would in turn increase the possibility of classifying the images correctly as more information can be gathered rather than only two images per person. We can improve the performance of the

Model by collecting the more clear images from the opthamalogists directly. The possibility of tweaking hyper-parameters is constantly growing with the emergence of new neural networks through better pooling methods. Such methods can be considered for future work to uncover the possibilities of increasing performance in this area. Furthermore, using different networks for training the model by the process of ensemble can also lead towards the better results. As different model have their own advantages in terms of performance, if tied together, can help in improving overall productivity of a system rather than an individual model. We have used two datasets in our study, using more no of datasets or a combination of various datasets may improve the generalizability. The deployment of such systems can be done by using the MobileNet, which is a convolutional neural network for developing mobile applications. The web applications can be developed that can work for windows, Linux and Android operating systems as a diabetic retinopathy diagnostic tool.

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