Early Detection of Curable Diabetic Retinopathy From Retinal Images

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***Abstract*—Diabetic Retinopathy just like the term suggests is a complication caused to the retina because of diabetes. Those with either diabetes type I or diabetes type II, with no control on their blood sugar are more prone to this disease which ultimately leads to vision impairment. Previous researchers made use of conventional handcrafted methods for feature extraction which was time consuming as well as computationally complex. This work explores the implementation of automated feature extraction making use of Convolutional Neural Networks with transfer learning to detect Diabetic Retinopathy in the retinal images. The retinal image dataset is acquired from Kaggle. The images are classified into 5 classes. CLAHE along with other techniques are used for pre-processing. The implementation results provided a model classification accuracy of 89% meanwhile adhering to reduced computational complexity and processing time thus providing a robust and efficient model to the practitioners to effectively detect Diabetic Retinopathy.**

***Index Terms*—Images Classification, Convolutional Neural Networks, Diabetic Retinopathy, Transfer Learning**

I. Introduction

The consequences of having Diabetes can be seen in several parts of the body out of which Diabetic Retinopathy (DR) is one of the impacts on eyes and is considered as a major cause of blindness in the world which is curable if detected in the early stages. Diabetes as known, is a condition where the body does not maintain the insulin levels which leads to diverse effects on various organs. If not diagnosed at the early stage, it affects the nerves and blood vessels of the retina which results in loss of vision gradually leading into blindness which is termed as Diabetic Retinopathy [1]. The estimated count of adults suffering from Diabetes is 72 million from which nearly one-third of the population is likely to develop a problem of DR. Around 370 million people are estimated to be diagnosed with Diabetes by the year 2030 which also raises the risk of DR which in turn would increase the pressure on the medical department to strategize and detect DR appropriately [2]. It is also observed that there are many areas where access to medical resources and technologies is limited for diagnosis thereby leading to irreversible vision loss and total blindness [3].

This research focuses on a category of DR called Non-Proliferative Diabetic Retinopathy (NPDR) which can further be categorized into different phases like mild, moderate and severe. Diagnosis from a human interpretation depends on the experience of the doctor or clinician, an inexperienced clinician may lead to the wrong diagnosis of a patient which can have serious effects at a later stage, whereas a computer-aided diagnosis might cause faster and efficient detection of the DR by making use of Neural Networks to classify the retinal images of diabetic patients. An effort has been made by using Convolutional Networks and transfer learning techniques to help identify different stages of diabetic Retinopathy. CRISP-DM was followed as a part of the method which helped in better data understanding and identifying the business needs in it.

A. Motivation

There are millions of retinal cases in the pathology labs to be examined and diagnosed based on reports. This makes it time-consuming particularly for the patients who have diabetes. Patients need to get their retinas checked on regular intervals to treat the occurrence of Diabetic Retinopathy. The reports were assessed under human expertise by examining the fundus images. This approach had a tremendous workload, hence to reduce human intervention computer-aided detection algorithms were created. In order to improve the performance, multiple instance-based algorithms were created where least human interference was needed and work on large data sets [4]. Clinicians find it difficult to monitor and make a rational decision on the huge data being generated by the modern medical appliances. Various classification methods were implemented to evaluate the risk of having Diabetic Retinopathy. Different classification algorithms like J48, BayesNet, ID3 and neural network were applied where neural network achieved the highest accuracy in order to evaluate the risk of DR [5].

Another approach in the study for detecting the blood vessels and red lesions for diagnosing Diabetic Retinopathy by using fundus images were implemented using extreme machine learning. A novel approach by using tetragonal local octal patterns (T-LOP) particularly intended for fundus images was used to extract the features from the data. The evaluation of the model was done by using k-fold cross-validation. A high accuracy, precision and recall values of 99.6 percent,0.991 and 0.993 were achieved respectively [6]. Hence, a different approach has been made to classify the images efficiently with minimal amount of time and complexity as compared to the traditional methods and attain commendable results to answer the research question.

B. Research Question

Can utilization of histogram equalization and CNN along with transfer learning significantly reduce the model learning time and improve the performance of classifying retinal images corresponding to detection of Diabetic Retinopathy?

The objective of the present study aims,

1) To efficiently identify the early signs of Diabetic Retinopathy in patients retinal images with the help of machine learning methodology.
2) To understand the overall impact on model performance by using the Contrast Limited Adaptive Histogram Equalization(CLAHE) in image pre-processing with CNN and transfer learning.

C. Paper Outline

This study on Diabetic Retinopathy using transfer learning is divided into different sections where the previous researches are studied in the literature review to understand the procedure and steps taken to attain the aim in section II. The answer to the research question, that is, the process or approach is discussed in detail in section III. After implementing the methods, section IV explains the evaluation, the obtained results are reviewed with different techniques. The research was concluded and the future work is proposed in section V

II. Literature Review

Deep learning techniques like Convolutional Neural Network has shown significant potential in classification modelling using image processing. Various research in the field of medical retinopathy identification is executed using CNN. [3] Convolutional Neural Network (CNN) was applied to detect DR with different architectures like AlexNet, VggNet, GoogleNet, and ResNet. Data pre-processing was performed on the data set with normalisation schemes, data augmentation techniques and the fundus images were cropped to remove the noise content from data. To achieve better results and handle overfitting, techniques like transfer learning and hyper-parameter tuning were applied to classify the fundus images. The evaluation of these models was measured with different parameters like accuracy, specificity, and AUC. The VggNet model resulted in an accuracy of 95.68 percent. In a similar approach [7], a VggNet model with transfer learning technique was applied which gave the highest accuracy. Another approach with customized CNN model classifies DR images using AlexNet, VGG-16, and SqueezeNet [3]. Out of 5 layers in the CNN model, 2 are used for feature extraction and the rest 3 for classification. The outcome of this proposed method was measured with specificity 98.94 and accuracy of 97.87 percent [8] . The author [9] uses 4 Convolutional layers for CNN. MESSIDOR, a publicly available dataset was used for identifying lesions in the images, indicating a side effect of Diabetic Retinopathy, an accuracy of 82.51 percent was achieved. Increase in the training data would have contributed much more to the prediction accuracy as expected.

In [10], the author has made use of transfer(migration) learning using Keras library in order to fine-tune the dataset on Diabetic Retinopathy downloaded from Kaggle. Pre-processing techniques namely contrast adjustment, flipping, data amplification, and folding were performed on the dataset followed by the usage of pre-trained models VGG19, Inception V3 and Resnet50. The neural networks were trained already using ImageNet dataset. The images were classified in 5 categories based on their degree of seriousness. Various combinations and producing complexity in the structure, contributed to higher accuracy of 60% by Inception V3, with 300 rounds of training(epochs) and 0.0001 learning rate. It was observed that the learning rate and the epochs highly influenced the prediction accuracy. Another approach with a VggNet model with a transfer learning technique was applied with considerable accuracy [3] using fine-tuning a pre-trained CNN for feature extraction.

In [11], the author uses a dataset comprising of the images of the retina of both the eyes. Various pre-processing techniques were carried out, to augment the detecting capacity of the Diabetic Retinopathy process. The performance of various CNN architectures is also explored. It was observed that VGG19 provided the highest accuracy of 76.9% among all other architectures, namely VGG16 and Inceptionv3. It was concluded that even though the accuracy provided by Inceptionv3 is relatively less, it seems to be a better predictor of cases with Diabetic Retinopathy. The increase in the number of layers contributed highly to the time taken for training but was positively linked with performance, that is the performance increased with the increase in Convolutional layers. While in [12], state of the art deep learning models are employed for detecting Diabetic Retinopathy, basically for the lesion detection, segmentation, and the classification. A fundus image dataset was used for this purpose. The models used for RCNN, YOLO, and SSD, Caffe framework was used for the implementation along with fine-tuning of weights and pre-training of the dataset. Even though deep learning technologies are potential enough in todays medical field, they possess some limitations. The models were said to do well for classification but perform fairly for lesion detection and segmentation. Author [13], has tried evaluating the identification and classification of DR using CNN and tried to address data mining features like CNN architecture, Fine Tuning, Class data Imbalance and data pre-processing. The author has tried to explore three CNN based architecture Viz- AlexNet, ResNet and VGG-16. The class imbalance is resolved using resampling and incase of overly represented class, random sampling is performed, the model is trained based on Caffe protocol.

The paper [14], have implemented transfer learning and ensemble approach for identification of DR. The paper defines a comparative analysis against various state of art approaches in DR identification and also presents the results using nine different evaluation metrics for validity and reliability. In order to achieve high grading, certain techniques like pre-processing in order to remove invalid areas, data argumentation were used.

For enhancing the performance, the methodology implemented included ResNet50 and InceptionV3 transfer learning model. The paper concluded that stronger the base learner was, higher was the model performance.Author compares the results of different machine learning algorithms assessed on various parameters namely Accuracy, sensitivity, specificity, Area under curve. Methods like IDP,classifier ensemble, supervised classifier CNN and deep learning were implemented. The results prove that efficiency was very high when it comes to the usage of deep learning. The author also comments that the usage of a good image could provide higher accuracy [15].

The author [16] have used dataset provide by EyePacs for identification of Retinopathy using transfer learning. The dataset pre-processing was performed by downsampling the image to a specific radius, subtracting local average color from images, and lastly cropping the image border. The inceptionV3 model was retrained using the dataset, however only the last layer of the model was retrained so that the readily trained weights can be utilized well. The observation showed that the accuracy of the trained model was significantly improved with the increase in the radius of the images and the dataset size aswell. However, the improvement was visible only in the testing dataset and not in the training phase. In paper [17] deep neural network is implemented using GR-Net and Id-Net for identification of detection and classification task. The model is divided into a set of task, first, one which detects cases suffering from ROP using Id-Net and the second task which defines the severity of as minor or major using Gr-Net. The future work identified in the paper included classification of ROP based patient into further classes including plus deceases, zone and stage. On the other hand, In [18], a new novel approach is proposed making use of regions scoring map referred to as RSM used to detect the region of interests. This method uses deep Convolutional Neural Networks along with RSM, The results proved that the model exhibited better performance due to the inclusion of RSM which helped detect the regions which were visibly different from others in the input image. Addition of more units of RSM into the layers of the CNN could provide better accuracy. Precision provided by Resnet18 with RSM was the highest amongst other methods namely, VGG16 and ResNet18.

Another approach with a vggNet model with transfer learning technique was applied which gave highest accuracy [3] using fine tuning a pre-trained CNN for feature extraction and then SVM was used to train the model which showed better results by transferring the knowledge. [7] To identify the red lesions in Micro-Aneurysms(MA) mostly CNN is preferred because of its computational capacity [19], but studies from [20], [21] used SVM for classification. The data pre-processing techniques like median filtering, a non-linear method specifically used for reducing the noise is applied and gaussian filtering were used unlike the cropping of images and normalisation [3]. The implementation was performed in different stages which involved pre-processing, blood vessel extraction and red lesion detection, followed by feature extraction using genetic algorithm. Lastly, the images were classified using support vector machine(SVM) algorithm, a supervised learning technique in to MA and non-MA. The performance is measured using sensitivity and specificity. The evaluation showed 88 percent and 92 percent of sensitivity and specificity, respectively. An approach uses dimensional reduction is performed by using PCA and KPCA to extract the features instead of the genetic algorithm [20], as to increase the computational power. A grid search technique is applied for parameter optimization to bypass the slow operability problem because of large data set. The SVM reaches the accuracy of 98.83 percent with KPCA performing superior than PCA for reducing the dimensionality. [22] The Author [23] tried to identify the root cause of diabetic retinopathy by trying to study medical background, however no specific risks related to DR could be identified. The paper also present treatment and screening details for diabetic retinopathy patients. The paper implemented receiver operating characteristics (ROC) curve in DR patient by using optimal ROC value. This values are evaluated based on SVM with accuracy of 83.9%, Decision tree and Artificial neural network with accuracy of 79.5% . The study has helped to identify that patient having consumption of insulin has a increased probability of DR with 3.56 percent as compared to patient without the consumption of insulin. In contrast, An author made use of SVM, along with decision tree. SVM provided an accuracy of 92.4% [24]. This proposed diagnosis method for Diabetic retinopathy used 400 images of the retina, these images were labelled on a scale of 4 based on the intensity of DR.

III. METHODOLOGY

In this section, we explore, validate and analyze the implementation of Deep learning techniques for Diabetic Retinopathy identification using the retinal images. The experiment is implemented using CRISP-DM methodology. In this methodology, phases are developed keeping in mind the machine learning model so that appropriate level of training for a machine learning model can be executed in the big data project. The phases of CRISP-DM model allows going backward and forward, in both directions and allow the accommodation of the business requirement changes identified in later stages [25].

A. Business Understanding

Diabetic Retinopathy is a common causing of blindness among people in age of 20-65 years. The Global Diabetic Retinopathy market is about to touch 10.11 billion by 2020 [26]. However, we can avoid the blindness caused because of DR using early identification of fundus and take appropriate preventive measure. The manual procedure for identification and judgment is a time-consuming process and has high chance of mis-assessment. As a result of which there are issues like lack of follow up and miscommunication. With the advancement in the field of data computation and machine learning the process can be automated. Deep learning techniques, especially CNN, as per the study in II holds great potential to support identification of DR when trained using appropriate dataset. However, in most of the medical cases,

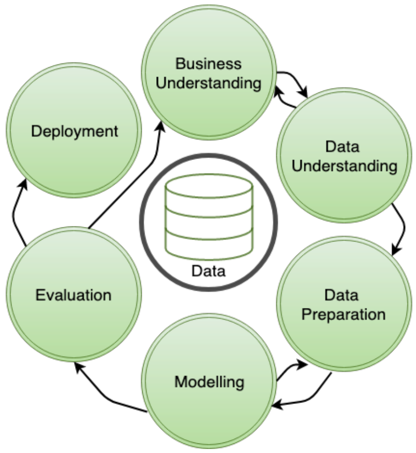

Fig. 1. CRISP-DM made using draw.io

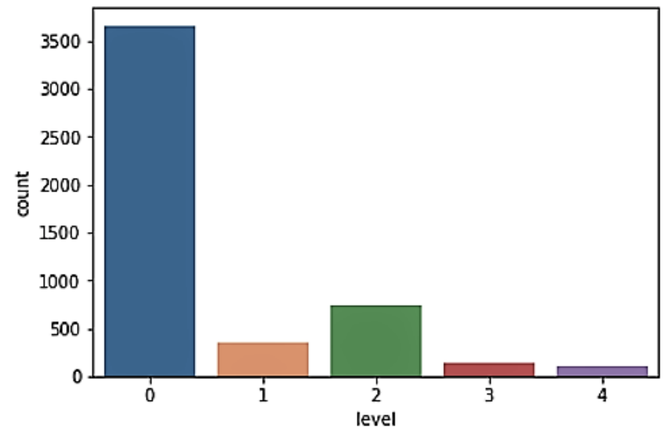

Fig. 2. Class Imbalance Check (Created using Python)

insufficient dataset is the major cause of low accuracy of model prediction. This is due to lack of infrastructure or limited access to medical data source. Transfer learning model can be used to overcome this training the model on actual dataset in order to improve the computational performance.

B. Data Understanding

The dataset used for implementation of the project consist of more than 35k images (82 GB). Out of these total of 35,124 images, 5k images were extracted for training and testing the model. The base dataset is divided into four classes of DR stages, No-DR, Mild, Moderate, Severe, and Proliferative DR. As the images are collected from different sources within the dataset, the images suffer variance in the picture quality. Also, in some scenarios the images represent retina directly and in some cases, images are in format as microscope condensing. We also noticed that dataset contains some level of noise and variation in level of focus on the eyes. The dataset replicates image variation like real time scenario and thus adds to the advantage to help train the model with accuracy and performance precision if implemented in a real world. There are several cases where in only one eye image is provided. We performed a check if all the patients we are going to evaluate in the project have both eyes (left and right) image, if in case both eye images are not provided for an id then those images/labels are not considered in experiment. We also made a check to see if the retinopathy stage of the images is same in case of both the eyes. If in case the retinopathy stage of both the eyes are not same, then those cases/labels were dropped from the experiments. We noticed there is a very large class imbalance present in the dataset. Figure 2 provides a detailed visualisation of the class imbalance. While training the model the issue of class imbalance is addressed by adding extra weights to the minority class.

C. Data Preparation

The following section provides details of the measures that were taken care of while training the model to tackle the challenges.

*1) **Image Augmentation**:* It is a well-known fact in the field of machine learning, that higher is the size of the dataset for training the model, better is the model performance for predicting the results. Data argumentation is one such technique that uses synthetic data creation procedures for improving dataset size and helping in model generalization. We utilized the Gaussian sampling technique to create sub-sample of the entire dataset, as the original dataset contains more than 35K images, and it is challenging to utilize complete dataset due to the limitation of infrastructure. We implemented the following set of actions as part of image argumentation:

- Zooming & Cropping to Region of Interest (ROI)
  Zooming and image cropping properties are used to extract features from only those parts of the image that holds maximum information. The zoom range parameter was set to 0.3.
- Rotation & Flipping of Image
  Data augmentation technique called flipping is used on the training images to help model create a generalized view of the objects, Ultimately to bring further improvement in accuracy, We have flipped the images vertically for the training model, to give a different view of features.
- Filling Mode
  While augmenting images with rotation, we need to take care of the blank pixel spaces generated in the augmented images. This space is filled using the nearest pixel values in the implementation. The model parameter for filling those white space is set as 'nearest', for filling the colour pixel with the nearest values while processing the images.

*2) **Data Pre-processing**:*

- Histogram Equalization
  We have used Contrast Limited Adaptive Histogram Equalization (CLAHE) technique for improving the colour contrast of the images so that the model can learn well further from the image details. CLAHE technique is used to generate multiple histograms on a different

section of the images and then use it for the light re-distribution. This has resulted in improving the edge definition and also the local contrast of the image. The Figure 3, shows the result of CLAHE processing on retinal images.

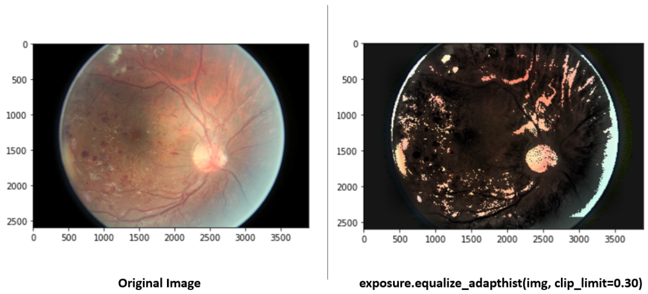

Fig. 3. CLAHE Processed Image Vs Original

- Grayscale
  We have then converted the image to Grayscale in order to help the model learn better with enhanced features of image. The Figure 4 shows a sample representation of tonal re-distribution of images post converting the above images with CLAHE adaptive feature to gray-scale. It also represents the distribution of Grayscale pixel over the entire picture. The advantage of using the Grayscale feature on CLAHE images is the enhancement of the local feature edges.

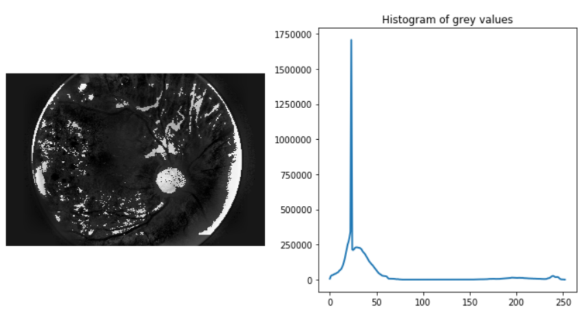

Fig. 4. Histogram of Gray-scale Images Pixel Distribution

- Stratify Splitting & Handling Class Imbalance
  Post data augmentation and pre-processing implementation, dataset is divided into training and testing set, each with 80% and 20% of data size of the images.
  - Stratify: lbl_map_df['level'] (Each class balance is, as it is, kept in split with stratify split based on stage of diabetes)
  - The class imbalances is managed by assigning higher order weights to minority classes. The parameter class_weight is used for passing those weight to model, using the python sklearns class_weight utility.

D. Modeling Architecture

In this section, we present the proposed model architecture and parameter utilized in detail. Figure 5 presents overall project data flow.

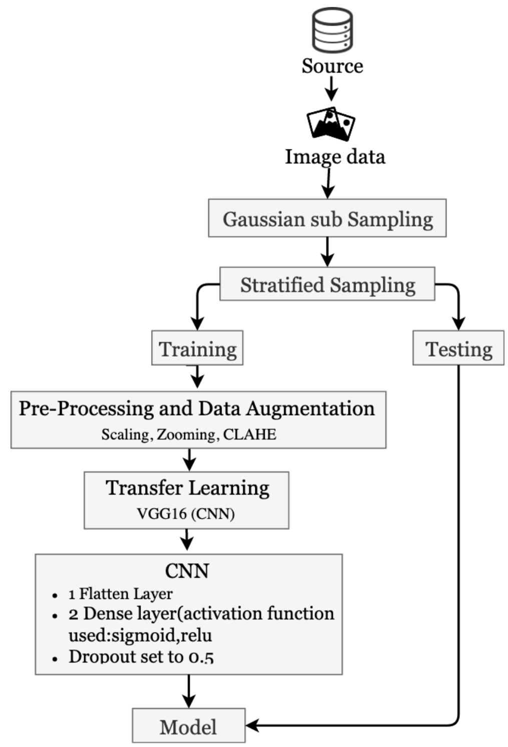

Fig. 5. Data Flow Diagram

*1) **Automated Feature Extraction using Transfer Learning**:* Training a convolutional network over a large dataset is a tedious task. Using transfer learning, we can use the feature weights of the pre-trained model over a large annotated dataset and then train the convolutional model. Transfer learning model has shown significant growth in medical image classification field and the implementation has even been extended to different fields of medical science. As part of this project, we have implemented VGG16 transfer learning model also known as OxfordNet model. The model was first developed by the visual geometry group. The pre-trained model consisted of 20 layer holding features from a dataset of ImageNet. The model takes image input of size 200*200*3 in RGB format. The weights of the layer were transfer to CNN. Figure 6 describes the extracted weight and layers summary of adapted VGG16 model.

*2) **Convolutional Neural Network**:* Extracted feature weights of pre-trained model is used as initial learner for the Convolutional Neural Network to reduce initial learning time and generalized model. CNN is built on top, is consists of one flatten layer and two dense layer.

- Activation Function: It is used as the decision-maker for understanding if the specific neuron should be triggered. We have used Sigmoid and Rectified linear unit function

block1_conv1 (Conv2D)	(None, 200, 200, 64)	1792
block1_conv2 (Conv2D)	(None, 200, 200, 64)	36928
block1_pool (MaxPooling2D)	(None, 100, 100, 64)	0
block2_conv1 (Conv2D)	(None, 100, 100, 128)	73856
block2_conv2 (Conv2D)	(None, 100, 100, 128)	147584
block2_pool (MaxPooling2D)	(None, 50, 50, 128)	0
block3_conv1 (Conv2D)	(None, 50, 50, 256)	295168
block3_conv2 (Conv2D)	(None, 50, 50, 256)	590080
block3_conv3 (Conv2D)	(None, 50, 50, 256)	590080
block3_pool (MaxPooling2D)	(None, 25, 25, 256)	0
block4_conv1 (Conv2D)	(None, 25, 25, 512)	1180160
block4_conv2 (Conv2D)	(None, 25, 25, 512)	2359808
block4_conv3 (Conv2D)	(None, 25, 25, 512)	2359808
block4_pool (MaxPooling2D)	(None, 12, 12, 512)	0
block5_conv1 (Conv2D)	(None, 12, 12, 512)	2359808
block5_conv2 (Conv2D)	(None, 12, 12, 512)	2359808
block5_conv3 (Conv2D)	(None, 12, 12, 512)	2359808
block5_pool (MaxPooling2D)	(None, 6, 6, 512)	0

Total params: 14,714,688
Trainable params: 14,714,688

Fig. 6. Summary VGG16: Transfer Learning

as our activation function. It is commonly annotated as Relu. Relu is difficult at back-propagation training because it is not differentiable at the origin. So instead, a sigmoid function is used, which is again a derivative value of softplus function.

- Neuron Dropout: In order to handle overfitting, a drop out parameter was set to 0.5. The neurons to be ignored are randomly selected using this technique in order to avoid over-relying on few of its inputs.
- Performance Optimization using Adaptive Learning: ADAM has been used as an adaptive optimizer. It is used for individual learning of different parameters used within the projects. ADAM can also be looked as a combination of RMSprop and Stochastic Gradient.
- Loss function: The loss function is used to understand how close the results of the predicted class of the image are from the actual class and then based on that the optimizer functions works to reduce the loss by optimizing the network. We have used cross entropy technique for loss calculation within the network.

IV. MODEL PERFORMANCE & EVALUATION

The performance of one of the best classifier namely Convolutional Neural networks was evaluated against a large dataset comprising of 5k images, the dataset was split into the training and testing set in the ratio of 80% and 20%. The class imbalance was handled by incorporating weighted training, in which more weight was assigned to the minority class.

*1) **Model Accuracy**:* On a validation set, this parameter explains the percent of classifications done correctly. The formula for computation is given by,

$$^{1}Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

The classification accuracy acquired for the training set as well as the validation set is given below:

- *Training*: In the training set consisting of 80% of the entire data, The model produced an accuracy of 89%.
- *Validation*: Whereas, In the testing data comprising of 20% of the data, the accuracy gained was 88%.

The graph shown in figure 7 depicts the model accuracy when validated on training split and validation split. Gradually rising training and testing accuracy on the line-graph confirms that model is not over-fitting to training dataset. Hence achieving overall generalized model with better accuracy.

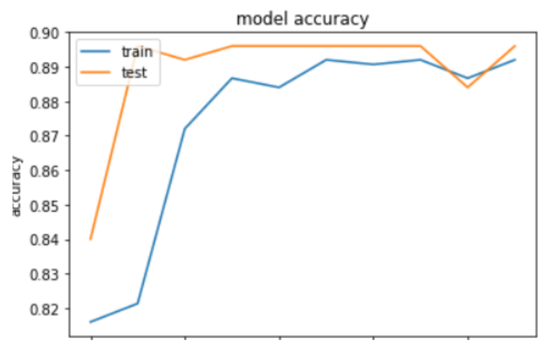

Fig. 7. Model Accuracy

*2) **Model Loss**:* Log loss or to be specific *Logarithmic Loss* is a metric used by the model for evaluation during the each learning iteration. [2]. Binary Cross entropy technique was used for computing the Loss, the formula is provided below:

$$H_p(q) = -\frac{1}{N}\sum_{i=1}^{N} y_i.log(p(y_i)) + (1 - y_i).log(1 - p(y_i))$$

The log loss for Training and validation set is given below:

- *Training:* During the first training iteration, the loss was around 0.9 which was reduced gradually in the final iteration to around 0.2.

[1]https://parasite.id/blog/2018-12-13-model-evaluation/

[2]https://datawookie.netlify.com/blog/2015/12/making-sense-of-logarithmic-loss/

- *Validation:* On the other hand, for the testing data, in the first iteration, the loss was around 0.67 which came down to 0.35 in the final epoch.

Figure 8 provides the visual explanation regarding the model loss over learning iteration.

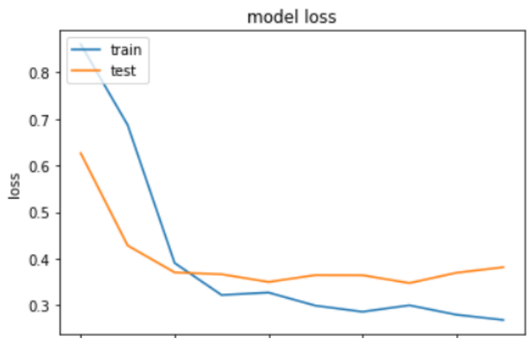

Fig. 8. Model Loss

The loss computation using the Log loss explained that the overall loss was inversely related with the number of iterations. Adam optimizer played an important role in optimizing the performance which could be clearly seen in section IV-2 where the loss is decreasing based on the iterations. It could be inferred that the model learns from the loss and thereby attempts to fix the weights by the observation of the overall loss dropping on increase in the number of training iterations. In other words, we can say that reducing the loss increased the model accuracy since it worked on handling the false classifications by penalizing error causing cases.

V. Conclusion and Future Work

CNN along with transfer learning was used for detection of diabetic retinopathy using the the retinal images which would assist in curing the disease if in the early stage. Various pre-processing techniques like zooming, scaling and CLAHE were employed followed by data augmentation. We made use of VGG16 for transfer learning and made use of 1 flatten layer and 2 dense layers in CNN. We could also observe that, minimal log loss improved the model classification accuracy considerably. It can be inferred from the results that a model accuracy of 89% was acquired while adhering to less computational complexity as well as a reduced amount of time in comparison with the methods used in previous studies. Support vector machine(SVM) along with transfer learning and CLAHE as a pre-processing technique can be utilized in the future.

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