# Research Proposal

on

Classification of Diabetic Retinopathy (DR) with its stages Using Transfer learning and image recognition technology

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MSc Data Analytics – 2018/9

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July 31, 2019

**Abstract**

One of the leading illness conditions of oncology is Diabetic retinopathy which may cause vision loss for the working age people across globe. The main reason behind this illness is the damage of blood vessels of retina and leakage of blood in it and this may be me due to one of the reasons like high blood glucose level, different extent of microstructures, such as micro-anuerysms, hard exudates, and neovascularization, could occupy the retina area. Early detection is very costly, and time taking and also includes lot of human effort. By this paper we propose a method to detect DR and its stages using CNN architecture which examines the photos taken in colour fundus format. Our main aim is to improve sensitivity and specificity over the entire model accuracy through this architecture. In this we use GoogLe Inception V3 Architecture and we removed the layers of classification and attached a pre-processing stage, hyperparameter optimization and save the data as a cache file, which is used as an input for the further convolution layers. This saves time and computing power. We use transfer learning technique where we can use the Inception V3 CNN architecture. After saving the cache file, it is transferred as an input to the neural network where it consists of convolution layers and activation functions like leaky ReLU, a maxpool layer, which summarizes the output of Convolution layers and passes to the next layer and classification layers like softmax. We can implement this proposal in Google AI cloud platform because of its requirement of computation power.

**Keywords:** Image Classification, Keras, Tensorflow, R, Diabetic Retinopathy, GoogLe's Inception V3, Transfor learning

## Contents

# 1 Introduction

## 1.1 Background

One of the major issues of Human eyes are recognizing the attack of Diabetic Retinopathy Farquhar et al. (2019) shortly called as DR. the cause of this disease inappropriate care taken by a Diabetic positive (person who is suffering from DR) for a long duration. DR causes serious problems like damage of minute blood vessels in the retina and this causes the leakage of blood and different fluids of eye on to the retina. The person who is suffering from DR will not witness any symptoms or visual abnormality at initial stages, but the DR positive person will notice that his/her power of eye site is decreasing, and it may cause vision loss if this is continued (Afrin & Shill (2019).)

This recognition of visual abnormality requires the high qualified doctors with a keen observation of the eyes of patients to confirm the illness and its stages which is costly and time consuming. The DR is classified broadly into two stages, they are NPDR (Non-proliferative Diabetic Retinopathy), PDR (Proliferative Diabetic Retinopathy). This stage of DR is classified based on different microvascular lesions found onto the retina.

If different indications like Microaneurysms (MAs), Haemorrhages (HMs) and Exudates (EXs) has found eye, then it is said to be a NPDR, an early stage of DR and along with these indications if the abnormal increase of blood vessels and lesions is found then it is said to be PDR which is advanced (Afrin & Shill (2019), Wang et al. (2018))

## 1.2 Problem Statement

At this stage Accuracy and perfection plays a major role and also many times its also impossible for the patients to go for the frequent check-ups due to many reasons (Abràmoff et al. (2016)). According to some reports of WHO, nearly four hundred and twenty million people across the world has been found this disease which is advanced stages which is called as diabetes mellitus in medical terminology, Out of them most of them are at the age of 25-79 (Afrin & Shill (2019)). The recognition and occurrence of this disease has become twice in the past 30 years and it tends -to be increased day by dayAdem (2018). Although this disease has been found across the world, but it is more severe in Asia. According to WHO Reports approximately one-third are expected to be diagnosed with diabetic retinopathy (DR) of those who are diagnosed as a diabetic patient. DR is a complicated eye disease that can cause a permanent eye damage or vision loss if it is not detected in early stages or havent took complete care. Early detection will reduce the chance of vision loss which includes a skilled Doctor and even it is a costly because it required keen observation of retinal blood vessels which is a time taking process. This area where the skilled people are lack off in medical environment and also, due to the manual detection of DR, there is a chance of errors taken place by the medical practitioners in detecting the exact stage of DR. this point where the technology can help the medical practitioners to increase their prediction accuracy and treat their patients more effectively. therefore, a statement is clear that technology plays a major impact in detecting, diagnosing and even preventing the cause of DR which is more cost efficient and less time barrier than manual methods and increases the quality of life. The detection of DR based on Image recognition has been improved a lot in recent years (Garside et al. (2019))

With the use of machine learning and artificial intelligence technologies, the methods of deep learning like binary classification in general and convolution neural networks (CNN) has got the top most error reduction rate when compared to other manual feature extraction methods. from different architectures like GoogLeNet, ResNet, AlexNet, VGGNet, ResNeXt, RCNN, SqueezeNet etc. Whereas multi-stage classification results are less accurate, particularly for early-stage detection Chalakkal et al. (2018). At this stage of detecting DR Sensitivity and specificity is much more than Accuracy. To improve these results, a new architecture of CNN with combination of GoogLeNet Inception V3 architecture and different hyperparameter optimization techniques like Bayesian Lévesque (2018), Ant colony optimization (Sreng et al., 2019), particle swarm optimization Adem et al. (2019) is proposed, the results are compared and only one algorithm is concluded as a best Hyperparameter optimizer. Which hopes to improve its sensitivity and specificity over its accuracy based on its state-of-the-art technological papers.

## 1.3 Purpose of Study

The main intention of this study is to increase the sensitivity, specificity and accuracy by using advanced technologies like Convolution Neural Networks, transfer learning, and image recognition technology. By use of Technology we hope that the cost and the time for detecting Diabetic retionopathy for a person will be decreased.

## 1.4 Research Question

The following research question has been formulated Based on the problem stated above,

*"With the use of Transfer learning method and Hyperparameter Tuning feature extraction method in inception V3 architecture, can this improve sensitivity and specificity over its accuracy in detection of Diabetic retinopathy?"*

## 1.5 Scope of Study

The stated Research Question is answered by taking 452 thousand images of retina which is the combination of people who are effected with DR and without DR. The data is taken from the links of Kaggle [1]

## 1.6 Structure of Project

**Chapter 2:** This section will tells us about the State-of-the-art work in the field of classification of images on detecting DR with its stages. This section also provides literature work about the topics called Image Classification, Keras, Tensorflow, Diabetic Retinopathy, GoogLe's Inception V3, Transfor learning at the end of each sub-section.

**Chapter 3:** This section introduces the methodological approach to the research of detecting DR with its stages. This also provides the information about the steps that proposed in the new methodology including data prepossessing steps, how the data is transformed from raw format to a fully classified format. this section will also provide complete information about the proposed algorithms and technology used to achieve or answer the above stated question.

**Chapter 4:**To check the performance of the proposed model, this section will provide information about model evaluation techniques. It consists of mathematical expressions to evaluate the results.

**Chapter 5:**Ethical aspects plays an important role in preserving the confidential information of people. in this section this is majorly concentrated.

[1] https://www.kaggle.com/c/aptos2019-blindness-detection/data
https://www.kaggle.com/c/diabetic-retinopathy-detection/data

**Chapter 6:**Planing of any project is very important before its started. this section is concentrated on planing and deadlines of the project.

# 2 Literature Review

From the last few decades, deep learning and machine learning areas are majorly focused by most of the technological researchers. In this areas image classification and recognition and classification has also began its impact and shown its importance in different areas of the business world, in some or the other way this helps common person to increase their stage of living. to classify and recognise the images with a maximum accuracy, the algorithms which are employed, should be powerful. to build an image classification there are lot of predefined models available in the present world.

This section will explains about the different Predefined models which are trained and ready to classify the images. To improve the power of algorithms the architecture of the models are changed with some advanced techniques which helps in improving the classification and detection power of the images and tries to identify which method can be considered the best among all. Different architectures of CNN are explained in this section.

## 2.1 Machine Learning Algorithms

In recent years the examining of medical images and detection of diseases by using machine learning technology has been in a rapid pace. In the same way Diabetic Retinopathy (DR) is also a serious condition that needs to be addressed as soon as possible because there are lot of people around the globe who are suffering from this defect. To recognize that illness, type-2 fuzzy regression is used by Shafaei Bajestani et al. (2018). Shafaei Bajestani et al detected DR using features like HbA1c, TSDR, MHbA1c and many more and achieved 82% accuracy, but in his paper he is not concentrated on Sensitivity and specificity which are effective metrics in health care industry. The reason behind of his choice f fuzzy regression is because of its uncertainty and ambiguity in the data of medical research. In 2015, (Arenas-Cavalli et al. (2015)) Arenas-Cavalli et al., has proposed a web based platform for Automated DR Screening using diverse computational intelligence techniques, because the population will be huge for healthcare. So, to decrease the cost and increase the optic examination area, authors have used a web-based tool and in this features user interfaces for healthcare professionals, ophthalmologists and also an Automated DR detection frame work to reduce their workload. In this paper (i.e.,Arenas-Cavalli et al. (2015)) it is given that the values for sensitivity and specificity are 92% and 65% where the sensitivity is very low. In healthcare industry identifying the sickness in a positive result patient is as important as identifying the negative result patient (Chalakkal et al. (2018)). So, the specificity should be concentrated in this paper. According to Afrin & Shill (2019) the chance of blindness for the patient who is suffering from DR, if it is not detected in an early stages is 95%. For this detection of DR in retina images they (i.e., Afrin and Shill) has used Fuzzy classification on images from STARE, DIARETDB0 and DIARETDB1 databases where they have used only a

400 images to detected and classify the stages of DR and achieved an overall accuracy of 95.63%, sensitivity of 95.77% and specificity of 94.44% .which gave better results.

Researchers Shafaei Bajestani et al. (2018) have used pure statistical models like linear regression, logistic regression, ANOVA by considering some specific features which are explained above. But Afrin & Shill (2019) have used machine learning algorithm after extracting the features because of which the accuracy improved. This improvement is due to the image classification, integrating of statistical and machine learning algorithms after feature extraction. According to Iglovikov et al. (2017)the size of the dataset also effects the performance of the algorithm and Lalkhen & McCluskey (2008)tells that sensitivity and specificity are most important aspects to be considered while assessing any medical or clinical analysis because they deal with the actual and the predicted values of the algorithms by considering True positives, false positives , true negatives and false negatives. In Afrin & Shill (2019) papers they are failed to determine about sensitivity and specificity which plays a major role in clinical examinations and also authors said that the cost for the tests may be a considerable point .

## 2.2 Pixel-Wise Detection

In 2017 pixel level segmenting of images based on features like micro aneurysms, hemorrhages, exudates, cotton wool spots which are combinedly called as lesions has been done by the Quellec et al. The researchers have classified the images on 3 lesions and achieved an accuracy of 95.4% where as there is detection of various stages of DR in their paper. A research that has been carried out by Meng et al. (2018)on Classification of DR images based on few features of Retina. Features that has been considered for this research are circularity and area of micro aneurysms. The datasets used by the author for his research are DRIVE, ROC, and DIARETDB. After conducting the experiment by the author, the results are fascinating for them and authors achieved 94.44% and 87.5% sensitivity and specificity respectively. He used principal component analysis (PCA) as a classification algorithm to differentiate between the images of optic disk of patients eye from the fundus images. The author of this research paper has achieved about 20-40% of increase in the detection probability of exudates which is said to be an area that surrounds the optic disk in the retina images of patients by using enhanced MDD classifier. This achievement is based on the state of art at that particular period of time. The dataset of 39 images have been taken by the researcher to execute the algorithm of classification. the algorithm has classified the fundus images into 2 categories where 4 of them are normal and remaining 35 are classified as with exudates. The below image will explain clearly about the features used by most of the state of the art authors.

Researchers like Bhatia et al. (2016)and Maher et al. (2015)used algorithms like SVM (support vector machine), Bayesian method, and PNN for classifying the phases of DR. They are defined as NPDR (Non-proliferative Diabetic Retinopathy), PDR (Proliferative Diabetic Retinopathy). For this research they (authors) have used the images of retina from the fundus dataset which is publicly available and also, they have used DIARETDB0 data which consists of 130 images. The features like portions of blood vessels, exudates, and haemorrhages have been extracted from the retinal images and examined by using the propose algorithms and achieved an accuracy of 87.69%, 95.5%, and 90.76% respectively.

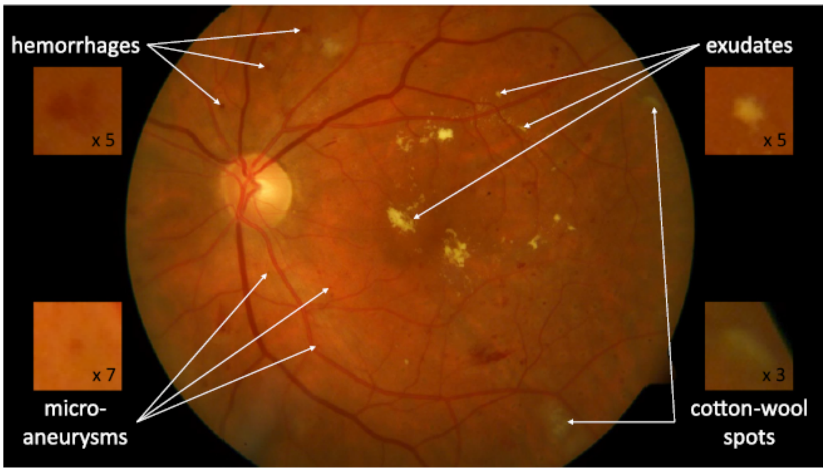


Figure 1: An illustration of the image in Quellec et al. (2017),the image will give the information about some of the important features of retina

Cunha-Vaz, (2002) has used SVM classifier on MESSIDOR, DIARETDB1, and DRIVE datasets and evaluated on their results. He achieved an accuracy of 93% in segregating the images based on their features like exudates and micro aneurysms by the classification of blood vessels images. A research article was published by Garside et al. (2019) where they have used an integration methods of statistics and machine learning classification algorithms to detect DR. the researchers have used the topological Data of retina and considered features like connected components and holes in the images and explained to what extent they exist in the images of retina. These existences of features are then encoded using persistence diagrams and then classified the patients between healthy and effected. The researcher has used a machine learning classification algorithm called SVM for differentiating the patients. In this paper lower star filtration method within the Dionysus 2 software package is used for computing the persistence diagrams for each image of retina. For selecting the variables, SVM have used a method called least absolute shrinkage and selection operator (LASSO). When considering the results of the Garside et al. (2019) work, they have used a very small size of dataset and done multiple times of cross validation tests to reduce the treat of overfitting, the sensitivity and specificity was maintained as 99.1% and 99.3%. they also mentioned that this models accuracy may reduce if the datasets size varies.

## 2.3 Masking Based Detection

Pre-processing of images before they underwent to the CNN process is done to improve the performance of the algorithm and to increase the strength of the algorithm. A common pre-processing of image is to Mask the optical Disk, macula due to the brightening of this characteristic of retinal images there may be a chance of degrading the quality of image which may also affect in the classification of images for DR detection. Masking is a common step that was followed by most of the researchers in the state-of-the-art models for classifying DR and its stages.Adem (2018) has presented a paper on Exudate detection of DR where he used circular Hough transform of optical Disk and canny edge detection. He (Adem (2018)) has used OD masked images to train CNN model and to classify the stages of DR with the help of variating exudate and non-exudate retinal images. When compared with the existing machine learning algorithms and CNN alone models the model which is proposed by the researcher has performed well because of its architecture. It consists of 3 convolution layers with a layer of max-pooling. To detect weather the patient is healthy or not healthy, this architecture has been performed well. So, by this it is evident that the architecture will also perform good enough in binary classification. In Yu et al. (2017) has introduced a CNN model for detecting exudates in pixel wise manner. It is a huge time taking process because the CNN model will apply each pixel of image to the model for classification and because of that the execution time of the whole process will also increase to a huge level. To overcome this problem the researchers, have a new algorithm called ultimate opening. In this process the first step is to illuminate green channel image on the original image so that the optic disk, Inpainting of vessels will be masked up and detection will be easy for algorithm in the next steps. When getting the required fields which are called as seed points with a patch size of 64*64 that is around the seed points is subjected for classification and sent for further stages of CNN. In this paper the data is obtained from E-Optha Ex database for their research.

## 2.4 Image recognition using Neural Network

Abràmoff et al. (2016) has introduced an enhanced deep-learning algorithm for image classification and segmentation of stages of DR like moderate, severe non-proliferative, non-proliferative or macular edema. They have achieved a better results using the dataset which is publicly available called fundus and achieved a sensitivity as 96.8% and specificity as 87% where the data considered for the evaluation is very less and according to the researchers like Maher et al. (2015) and Meng et al. (2018) dataset size will also play a major role in the performance of the algorithm. Gargeya & Leng (2017)has introduced data driven deep learning algorithm model with the use of colour fundus images and classified into only two categories they are 0 or 1 which means weather the healthy or patient has DR. These two researcher have the same model of deep learning and the Abràmoff et al. (2016) has classified more stages of DR than that of Gargeya & Leng (2017) this may be due to the lack of data that has been considered by Gargeya & Leng (2017)

The researcher Omar et al. (2016) has performed an analysis based on a system that works automatically in detecting the exudate by including a texture features of retinal images. These features are extracted from different LBP (local binary patterns) versions by employing machine learning models like ANN classifier. The researchers in this paper have used a publicly available popular image data named DIARETDB0 of colour fundus dataset. The sensitivity is 98.68%, sensitivity is 94.81 and accuracy is 96.73% are the form of results they have got when they run the analysis in ANN classification. The achieved results are also shown by comparing with the existing state of the art results in the similar field of ANN in the paper by the researchers. A smartphone-based device is used to collect the images of retina from 78,685 patients directly and classified them using fundus images dataset. Rajalakshmi et al. (2018) has used an automated cloud-based software called EyeArtTM for detect weather the patient is suffering from DR and if the results are positive then it will also tell the stages of DR. the results which they have obtained are 95.8% of sensitivity and 80.2% of specificity for detecting DR. the researchers have mentioned the name of the cloud-based software but they havent talked about what is the internal functionality used by the software to detect the image.

A study was done by El-Baz et al. (2018), and approved by a frontiers in Bioscience in early detection of DR using images from SD-OCT. They have divided the images into layers and based on that layers features they have segmented the images of retina into different categories. The features they have considered like Thickness, Reflectivity, Tortuosity, foveal angles of retinal layers. They have studied on 26 diabetic patients who does not have DR effects and examined the changes of layer changes in retina due to DR. The researchers have used pure statistical models to know the changes and for the feature extraction in the images.Gal et al. (2017) has published a paper based on deep Bayesian active learning in neural networks, where the active learning generally depends on small amount of data to train and perform the test, but it is opposite when it is compared with deep learning.Gal et al. (2017), has combined the active learning and Bayesian deep learning and solved the limitation of data size in Active learning. But the implementation of this complex model takes huge time and computational power whereas theFarquhar et al. (2019) have published a paper based on Radial Bayesian Neural Networks, which is a Robust Variation. According to the researcher Bayesian Neural Networks (BNN) is easy to implement but its drawback is that whenever the data size is increasing then the variance is also increasing and at some point of time it exceeds the mean and gives a wrong result and also getting hard to implement the process. To solve this issue, he introduced a robust model by designing a new posterior distribution he avoided the growth of variance in a theoretically principled way. This method can also be extended to any other fields where the computer vision is necessary. The researchers also used a measuring metrics as Area under the receiver operating characteristic curve (AUC-ROC) for evaluation and got and got a considerable result than that of previous state of the art models.

Pre-processing of images before they underwent to the CNN process is done to improve the performance of the algorithm and to increase the strength of the algorithm. A common pre-processing of image is to Mask the optical Disk, macula due to the brightening of this characteristic of retinal images there may be a chance of degrading the quality of image which may also affect in the classification of images for DR detection. Masking is a common step that was followed by most of the researchers in the state-of-the-art models for classifying DR and its stages.Adem (2018) has presented a paper on Exudate detection of DR where he used circular Hough transform of optical Disk and canny edge detection. He (Adem (2018)) has used OD masked images to train CNN model and to classify the stages of DR with the help of variating exudate and non-exudate retinal images. When compared with the existing machine learning algorithms and CNN alone models the model which is proposed by the researcher has performed well because of its architecture. It consists of 3 convolution layers with a layer of max-pooling. To detect weather the patient is healthy or not healthy, this architecture has been performed well. So, by this it is evident that the architecture will also perform good enough in binary classification.

Xie et al. (2019) has proposed a Randomly wired neural networks which is more diverse set of connectively patterns by its view. To achieve this process, they have used Encapsulated the total network generation process using stochastic network generator and they have got shocking results when compared to the state of art in that area.Xie et al. (2019) have achieved 79% of accuracy in classifying the images under the similar computational cost of ResNet-50. This is the algorithm that have achieved more accuracy than previous ResNet-50 algorithm of 77.1%. Szegedy et al. (2016)

A group of researchers named Chowdhury et al. (2020) has proposed a model to detect DR in Diabetic patients using publicly available dataset from Kaggle and they have used Googles pretrained Inception V3 CNN Classifier and achieved an accuracy of 78.1%. the classifier which they have used in their process is a widely used model in image recognition. This algorithm got a better result than that of the traditional state of art results on ImageNet dataset.

A study on detecting DR by improving its staging and by using artificial intelligence was proposed by Takahashi et al. (2017). In this paper the researchers have taken four images of each persons eyes at Nonmydriatic 45 field colour fundus photographs every year from 2011 to 2015 in a medical university. Prevalence and bias-adjusted Fleiss kappa (PABAK) was used as an outcome measure for 5% of photographs and remaining 95% was trained from modified GoogLeNet using of three additional adjacent photographs by manual modified Davis grading model. The mean accuracy achieved by PABAK was 81%, the authors have mentioned inn their paper that even though the accuracy is lower than most of the existing state of the art models but, the capability their trained set is its two-fold architecture, and this is majorly used in training of single-field fundus images and detecting in stages of DR.

Junjun et al. (2018)has proposed a new approach in detecting DR and its categories based on the scoring the specific regions of retina and the regions are called as regions scoring maps (RSM), with the help of neural networks model. With this proposed model the different scores are allocated to different regions of the retina this is to highlight the discriminative ROIs to detect the level of severity of DR for the patient who is suffering from Diabetic retinopathy. The researcher have taken a dataset from fundus images dataset and the size of the dataset was 300 thousand and among them the model has classified the categories of DR at an accuracy of 78.4% where the sensitivity and specificity are not considered for the evaluation metrics in the paper whereas precision is improved by 30% which is good improvement in the state of art. Shanthi & Sabeenian (2019) have done a proposal using some changes in neural networks and achieved an accuracy in detecting the DR and its categories with an accuracy of 96.6% which is a very huge difference from Junjun et al. (2018). This drastic improvement of accuracy is due to the introduction of Rectified Linear Activation Unit (ReLu) and softmax functions in ANN architecture. ReLu is an activation function which classifies the images either yes or no (0 to 1 or -1 to 1) whereas SoftMax is a smoothing function also called as a classification function in ANN (Agarap (2018)). These introductions of additional layers may also increase the computational time for the model to detect execute and cost for the evaluation is also considerably high according to Lalkhen & McCluskey (2008).

Yip et al. (2019) also used an ensembled ANN model with VGGNet and ResNet-50 which is popular models in tech competitions like ILSVRC. The VGGNet has 16 layers and has designed in oxford in 2014, whereas ResNet has 50 layers of neural networks which ws introduced in 2015 by Microsoft group. By using transfer learning the ResNet was pretrained using ImageNet database. these both models have been ensembled and the results were evaluated using the statistical models called are under the curve model (AUC), sensitivity and specificity which are 0.970, 92.2% and 92.5% respectively. Which has a significant improvememnt over the individual VGGNet and ResNet models. The DensNet is an extension to ResNet where an encemble is required for both the models so that the clinical trials on the medical images will be more accurate and have a huge set of data to detect the diseases even the images are with noise. Now the researchers have been considering the images wich are having low amount of noise and which have less prework by considering Imagenet database but the real world images of retina may not be of such a kind (Yip et al. (2019)).Li et al. (2019) has studied and published a research in 2019 which has given a pour results than that of the state-of-the-art models like VGGNet-16, ResNet-18, DensNet, GoogLeNet, SE-BN-Inception. When the researches Li et al. (2019) have used Caffe (convolutional architecture for fast feature embedding) architecture on the dataset like Fundus Images the performance has been dropped and it clearly tells us that this architecture is not suitable for detection of DR with its stages like moderate, mild, and saviour. Even though the performance has been dropped to 82% of Accuracy in classification of DR but this algorithm has shown even more poor results in detection of lesions in the images of retina. The researchers have also mentioned that working with this algorithm in the future with different dataset is also a challenging part for implementation, the researcher Li et al. (2019) also mentioned in his paper that highest overall accuracy and Kappa score was obtained by SE-BN-Inception network and although this algorithm has a highest overall accuracy but there are huge chances for misclassification for severe DR as a moderate DR so he suggested that DenNet-121 has a good results than others in classifying the DR Classes if it contains a smaller number of samples. By the careful consideration of these two research papers one can say that the CNN is more efficient in classification and detection of lesions by using the architectures like VGGNet-16, ResNet-18, DensNet, GoogLeNet, SE-BN-Inception ect, But according to Li et al. (2019) the research is not only confined to only these architectures and in future more clinical trials may arise for more perfect detection of DR with its stages.

A paper was published by National Center for Biotechnology Information (NCBI) in 2018 and the researchers are Lam et al. (2018) where they have used transfer learning technique on the pretrained models like GoogleNet, AlexNet. They have used the ImageNet dataset for testing the accuracy of the model on 2-ray, 3-ray, 4-ray classifying the images of DR. even of clear study and focused experimentation the researches could have improved recognization of subtle features, the accuracy they got was 74.5%, 68.8%, and 57.2%, At the same time in 2018 a team of researcher published a paper in IEEE international conference named Wan et al. (2018) on Diabetic Retinopathy Stage Classification Using Convolutional Neural Networks where they have achieved an accuracy of the state of the art. In this paper the researchers have performed optimized hyperparameter tuning in feature extraction and also they have used architectures like AlexNet, VGG 16, and InceptionNet V3, and in this process of research while resizing the images the researcher have mentioned that they have suffered from fidelity and distortion of images and it hasnt been solved across the paper. The Accuracies that has achieved by the researches are 37.43%, 50.03%, 63.23% for AlexNet, VGG 16, and InceptionNet V3 which is very less compared to the state of the art models, whereas Wan et al. (2018) in same 2018 have published a paper on study of detection of DR by using a combination of transfer learning and hyperparameter tuning. With the help of different on-demand architectures in CNN like AlexNet, VggNet, GoogleNet, ResNet and compared the performance with the and without transfer learning and hyperparameter tuning feature extraction methods. The results where they have got is mentioned using a table below.

Classification results with randomly initialized parameters of CNNs model.

| Model | SP | SE | AUC | ACC |
|---|---|---|---|---|
| AlexNet | 90.07% | 39.12% | 0.7968 | 73.04% |
| VggNet-s | 93.98% | 33.43% | 0.7901 | 73.66% |
| VggNet-16 | 29.09% | 86.37% | 0.5512 | 48.13% |
| VggNet-19 | 96.05% | 54.51% | 0.7938 | 82.17% |
| GoogleNet | 86.84% | 64.83% | 0.7756 | 86.35% |
| ResNet | 90.53% | 73.77% | 0.8266 | 0.7868% |

Classification results with hyperparameter-tuning.

| Model | SP | SE | AUC | ACC |
|---|---|---|---|---|
| AlexNet | 94.07% | 81.27% | 0.9342 | 89.75% |
| VggNet-s | 97.43% | 86.47% | 0.9786 | 95.68% |
| VggNet-16 | 94.32% | 90.78% | 0.9616 | 93.17% |
| VggNet-19 | 96.49% | 89.31% | 0.9684 | 93.73% |
| GoogleNet | 93.45% | 77.66% | 0.9272 | 93.36% |
| ResNet | 95.56% | 88.78% | 0.93.65 | 90.40% |

Figure 2: The image shows the results of Wan et al. (2018)

From the above table we can state that the CNN models with transfer learning and hyperparameter tuning given best results rather than that of randomly initialized parameters of CNN. The highest Accuracy is given by VggNet-s with 95.68% and where as its sensitivity, specificity and area under curve are also given remarkable results in this study. So, after the careful consideration of three papers it is said that feature extraction using hypermeter tuning with the use of transfer learning will improve the accuracy of detection of DR in all the architectures of CNN.

## 2.5 Tensorflow

To operate heterogeneous environments and large scale of data TensorFlow is one of the important libraries in deep learning Abadi et al. (2016). It works on dataflow graphs to represent computation, flow and operations. The architecture tensorflow is shown below.

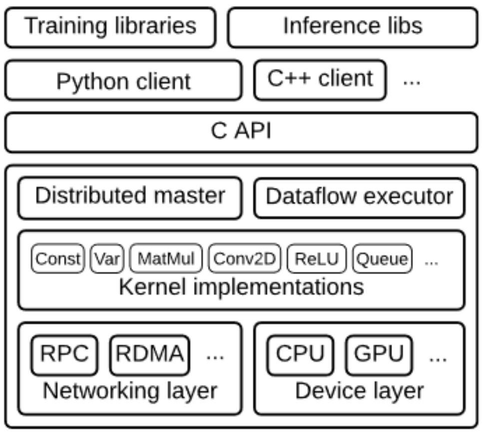


Figure 3: The layered TensorFlow architecture Abadi et al. (2016)

In understanding the working of tensorflow, dataflow graph plays a major role because it is considered as one of the important feature of tensorflow. Wongsuphasawat et al. (2018)

explains the working of tensorflow and TensorFlow Graph Visualizer in his paper very deeply. In Tensorflow machine intelligence platform the TensorFlow Graph Visualizer is a component which helps developers to analyse built models In this the nested structure of their model can be explored by User if required. On the other side, researchers like . Joseph & Geetha (2019) has achieved a grate results. In their paper the researchers used tensorflow library and detected facial emotions of a person. The process in this research begins with enhancing the images using wavelet transform and fuzzy combination. eyemap and mouthmap algorithm has used by the authors to find the facial geometry. By conducting the experiment, researchers has found that the accuracy, decrease of loss and the number of training iterations are directly proportional to each other. Thesize of the data that has been considered in this research is 498 thousand which has given an accuracy of 98.1% at a loss of 0.08, which is considered as a best results when compared with the state-of the art models. Besides researchers names Raghesh Krishnan et al. (2018) has done a research on detection of liver disorders which given a normal result as compared to the previous paper. For classification and detect 9 disorders of liver In this research, authors have used ultrasonography images and built a model tensorflow to achieve the intended results. This model even with the exception of classification of HCC liver disorder, it given a poor results which is explained in the below table. The researchers have proposed that by considering more features may improve the results.

| Disease name | Specificity | Precision | Recall | Accuracy (%) |
|---|---|---|---|---|
| Abscess | 0.92 | 0.454 | 0.277 | 81 |
| Cirrhosis | 0.176 | 0.923 | 0.375 | 79 |
| Cyst | 0.991 | 0.882 | 0.312 | 86 |
| Fatty Liver | 0.951 | 0.097 | 0.4642 | 78 |
| HCC | 0.994 | 0.962 | 0.3841 | 91.6 |
| Echinococcosis | 0.982 | 0.733 | 0.0887 | 72 |
| Haemangioma | 0.994 | 0.818 | 0.0545 | 68 |
| Hepatomegaly | 0.994 | 0.6 | 0.0265 | 75 |
| Metastases | 0.981 | 0.631 | 0.060 | 76.8 |

Figure 4: Accuracy of Classification in Raghesh Krishnan et al. (2018) paper

## 2.6 Squeeze-and-Excitation Networks (SENet)

Studies of Hu et al. (2018) have done a remarkable improvement on existing state of the art architectures which has reduced the top- 5 error rate to 2.251% and the researcher also got a relative improvement over the winninh entry of ILSVRC 2016 that is nearly 25%. The changes he has done in the existing architectures. convolution operation has been built based on convolution neural networks which can improve the spatial encoding. The study proposed an architecture that is Squeeze-and-Excitation Networks (SENet) block. In this architecture the SENet recalibrates the features that derives from every channel and remodelling of interdependencies between channels makes the architecture more error free and accurate.

## 2.7 Optimization techniques

### 2.7.1 Bayesian Optimization Technique

One of the efficient optimization techniques in machine learning is Bayesian optimization is said by Shahriari et al. (2016) in his paper on Bayesian Optimization.Zhang et al. (2015) which is long back but had said that this algorithm is a best choice for an expensive objective function. By constructing a probabilistic model, Bayesian optimization targets minimizing or maximizing any given objective function which is also called as a black-box technique. This model has been formed with the combination of the probabilistic model and a loss function. In this model the distribution is specified by objective function f and it is represented in a mathematical specified bellow

$$x_{new} = arg_x \in X^{max/min} f(x)$$

Figure 5: Salama et al. (2019)

From the above mathematical expression x is defined as a design space of interest. This model is also used for making an expertise sampling in which it is also updated in sequential manner. In this Bayesian model the objective function is unknown so that this model treats it as a random function and puts a prior probability distribution over it and it replaced after every iteration by the model (Salama et al. (2019)). The improvement in detection of DR has been in a rapid pace and in this paper, we propose a novel architecture where it is also can be called as extinction to Inception V3

### 2.7.2 Ant colony optimization Technique

In 2018 Ant Colony Optimization Based Exudates Segmentation in Retinal Fundus Images and Classification is published by Hire & Shinde (2018). In their paper it is mentioned that exudates are caused due to DR and they are recognized with microaneurysms very frequently. To detect DR, authors have used fundus image datasets which are publicly available like DRIVE and CHASE. After pre-processing the images, authors have employed ant colony optimization algorithm to segment the exudates. Where in this algorithm it uses artificial ants, which acts as multi-agent methods and they have memory to store knowledge about the optimal path to destination. These segmentation steps are followed by classification stage which is done by KNN algorithm. The results they got like 92.4%, 92.2%, 90% and 90.63%, 89.5%, 87% as Accuracy, sensitivity and specificity.

### 2.7.3 Particle swarm optimization (PTO)

Kaya et al. (2018) has proposed a paper on early detection of DR by using video-oculography signals. In this paper authors have used two machine learning algorithms with a single optimization method called Particle swarm optimization. The used algorithms are HilbertHuang Transform and Discrete Wavelet Transform and proved that when combining are HilbertHuang Transform with Particle swarm optimization will give a best result than that of other pair of methods. In this research, the overall accuracy that has been achieved by this method is 94% overall sensitivity is 90% and overall specificity is 93%. Where PTO searches for the functions global minimum and each particle in the function is influenced by a surrounding best-known position.

# 3 Methodology

### 3.0.1 Data Description

The dataset we used in this research is taken from Kaggle.com which is publicly available. The data consists of 400 thousand images which are divided into 4 test sets and a train set. As the data is publicly available it consists of noise and also data imbalance. Which is shown in below image.The images are of high-resolution retina images, which are taken under different imaging conditions. The data can be downloaded from the links of Kaggle[2]

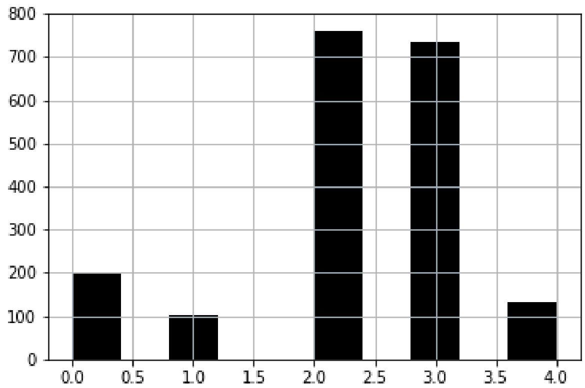


Figure 6: visualization of Data imblance

In the stage of pre-processing this issue of imbalance with the data will be solved using one of the processes like over sampling, under sampling, weight balancing (Shang et al. (2018)) which is proved as an efficient way to solve the imbalanced data. The data consists of two columns they are image serial number and its result of diagnosis which is marked as 0 - No DR, 1 Mild, 2 Moderate, 3 Severe, 4 - Proliferative DR. these images are taken using fundus photography which is an efficient way of taking images of retina.

## 3.1 Pre-processing

Pre-processing of images will improve the performance of CNN in a significant manner (Adem (2018)). The steps like decrease noises, non-uniformity and undesired artefacts from the raw fundus images is performed. The process will begin with resizing of original images (IRGB) of fundus into 520*480 pixels to get images which are normalizes. We

[2]https://www.kaggle.com/c/aptos2019-blindness-detection/data
https://www.kaggle.com/c/diabetic-retinopathy-detection/data

will then extract the green channel from the images of fundus because green channel will show the highest contrast between the retinal background and the blood vessels when comparing with the other colours like red or blue channel (Afrin & Shill (2019)). The next step is to remove the errors like salt and pepper, in pre-processing it is done by adjusted the IG and filtered using image adjustment and adaptive median filter techniques while preserving the edges. To see the lesions more clearly, complement operation was performed after removing the errors and noises in the fundus images. The final step in pre-processing is to increase the image contrast and expose the DR lesions. This is done using Contrast Limited Adaptive Histogram Equalization (CLAHE) technique

## 3.2 GoogLeNet Architecture

In recent times GoogLeNet Architecture is the top most CNN Architecture that got the lowest error rate in Training and testing of Images of eyes in detection of DR and its stages. GoogLeNet is a 22 layer architecture and where it consists of convolution, AvgPool, MaxPool, Concat, Dropout, Fully Connected, Softmax layers.Szegedy et al. (2015) says that by using the combination of low-dimensional embeddings and heterogeneous sized spatial filters, this architecture has become the efficient network and also achieved the state-of-the-art accuracy. To achieve the learning of deeper features by the machine, the network has to utilize its internal layers effectively and also increasing of convolution layers will help in feature learning in a deeper manner. This feature classification in DR may be different for different layers, for an instance the initial layer may learn about the edges of the images of retina and the final layer may learn about the core part of the retina in the images. This is a complex architecture where there exists a functional mapping between input and output variables. this functional mapping will be created by convolution blocks with activation on the top layer. A batch normalization block will be introduced for every succession with the increase of number of feature maps.

Maxpooling is introduced to this architecture to decrease the sample size with some mathematical calculations. It is also called as a sample-based discretization process where as it is performed with 3*3 kernal and a stride. In the final convolution block, the network will be straighten to one dimension by this layer called Maxpooling. Due to the usage of huge convolutions in the network the problem of overfitting will be arised in the network. To avoid this issue a researcher called Srivastava et al., in 2014 has introduced Dropout function, where it is performed throughout the network until the final dense five node output layer. This function of dropout uses a softmax activation function to calculate the classification labels probability and with a gradient value of 0.01 a leaky rectified unit linear unit activation was used to mitigate dead neuron bottlenecks at the time of backpropagation (Kazi et al. (2018)). Until now the layers we have discussed where pretrained and by using transfer-learning technique and TensorFlow we train the model and stop at the second node of the five-node layer which is a AvgPool node. From this we get the Transfer values of the input data and which are not completely classified. In our approach these values are then pre-processed and extract the features from those values using Hyperparameter extraction methods like Bayesian optimization technique. Leky ReLu Activation function will be used in our architecture to overcome the issue of dead ReLU, which is said to be a dead neuron problem this may be occurred due to number of epochs.

## 3.3 proposed architectural model

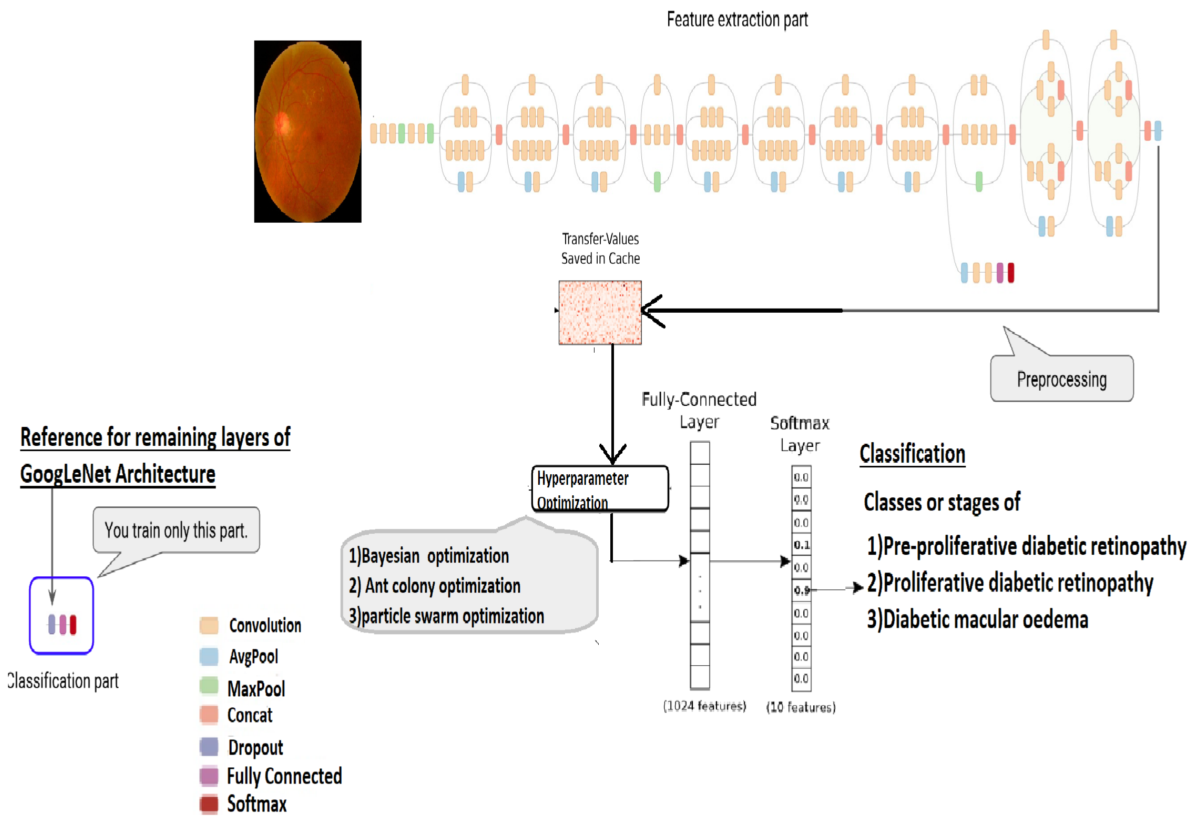


Figure 7: visualization of Data imblance

The reason behind using this architecture is that, based on Wang et al. (2018) paper named "Diabetic Retinopathy Stage Classification using Convolutional Neural Networks" in 2018 has mentioned in his future work that with some changes in the architecture of Inception V3 algorithm, the accuracy can be improved and with the use of Bayesian Hyperparameter optimization method based on Farquhar et al. (2019),(Salama et al. 2019)Lévesque (2018) the sensitivity and specificity of detection of DR is improved. Some additional fully connected layers which is explained in the above architecture is also used based on Takahashi et al. (2017)Lam et al. (2018). By combining all the ideas of those researchers, a new architecture is proposed in this paper to increase sensitivity and specificity over accuracy in detection of Diabetic retinopathy with its stages. After conducting the research, the results are evaluated using Mathematical expressions which are explained in forward sections.

## 3.4 Proposed Technology and Packages

To achieve this, we use GoogLe Inception V3 architecture and transfer learning technique with TensorFlow library in Python. Keras package of Python is used to conduct the CNN algorithm on the data. Different packages like OpenCV, SimpleCV, Mahotas, scikit-image, NumPy etc will be used in pre-processing of images before conducting CNN operation. Based on the requirement at the time of operation more libraries are used, the provided libraries are limited and given for basic references. The computing power should be very high to conduct this operation so, to achieve cost efficiency and fast execution time, Google cloud platform for AI is proposed . Where we can conduct any operation of CNN with limited cost.

# 4 Evaluation

The performance of the proposed architecture is done using sensitivity, specificity and accuracy. This evaluation parameters will achieve using a confusion matrix table which is mentioned below.

TABLE II. CONFUSION MATRIX

| | | Disease Status | |
|---|---|---|---|
| | | *Positive* | *Negative* |
| **Classifier Result** | *Positive* | TP | FN |
| | *Negative* | FP | TN |

Figure 8: Confusion matrix

From the above table TP-true positive, Tn-True Negative, FP-False positive, FN-False Negative. Where the sensitivity, specificity and accuracy are achieved using below mathematical expressions.

$$Sensitivity = \frac{TP}{TP+FN}$$

$$Specificity = \frac{TN}{TN+FP}$$

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

Results obtained for the ensemble based on above mentioned formulae, will then be compared with **?** because the researchers in this research have also classified blood cells from same dataset just using a CNN and also using high hardware configuration. This research done on classification of healthy and malaria effected blood cells achieved very good output and above mentioned metrics are really good. our aim in this project is to improve sensitivity and specificity over accuracy so it is essential to know about these terminologies. A short explanation is given below,

### 4.0.1 Sensitivity

It is defined as the percentage of People who are affected with DR by who are identified as having DR positive by the algorithm (actual positive/ predicted positive). It is one of the important evaluation metrics that most of the researchers follow while evaluating their models and it is mostly used by the researchers who are working to solve problems of healthcare industry by machine learning.

### 4.0.2 Specificity

It is explained as the percentage of people who are negative with DR and identified as negative by algorithm (actual negative/predicted negative).one of the important metrics of evaluation is Specificity and this gives us an idea that how many people are actually negative towards DR with negative predicted DR.

### 4.0.3 Accuracy

The percentage of correctly identified records and total number of records. The Accuracy is an important metrics which gives the idea about the implementation of selected model in most of the machine learning application fields. whereas it is considered as one of the metrics with sensitivity and specificity.

### 4.0.4 K-fold Cross Validation

Due to the amount of data and number of iterations there will be a problem called overfitting may occur in the model or while optimizing the hyperparameters. To avoid the issue, the k-fold cross validation method is a default process(Lévesque (2018)). The cost of running the K-fold validation is not more than that of running the training algorithm for K times and the k-fold validation test gives the reliable estimate of generalization performance

# 5 Ethical Consideration

the data which is proposed to use in this research is taken from a publicly available website called kaggle and which is open for any analysis. the links to get the data has been provided in the above data description section. so due to is publical availability, the data is free from ethical issues

# 6 Project Plan

Below gantt chart represents how the research will be taken forward in future, where week 1 starts from 1/02/2019 and week ends on 20/06/2019. A gantt chat is provided in the below shows the detailed dead lines of each and every section which starts from September 1st 2019 to 26Th November 2019

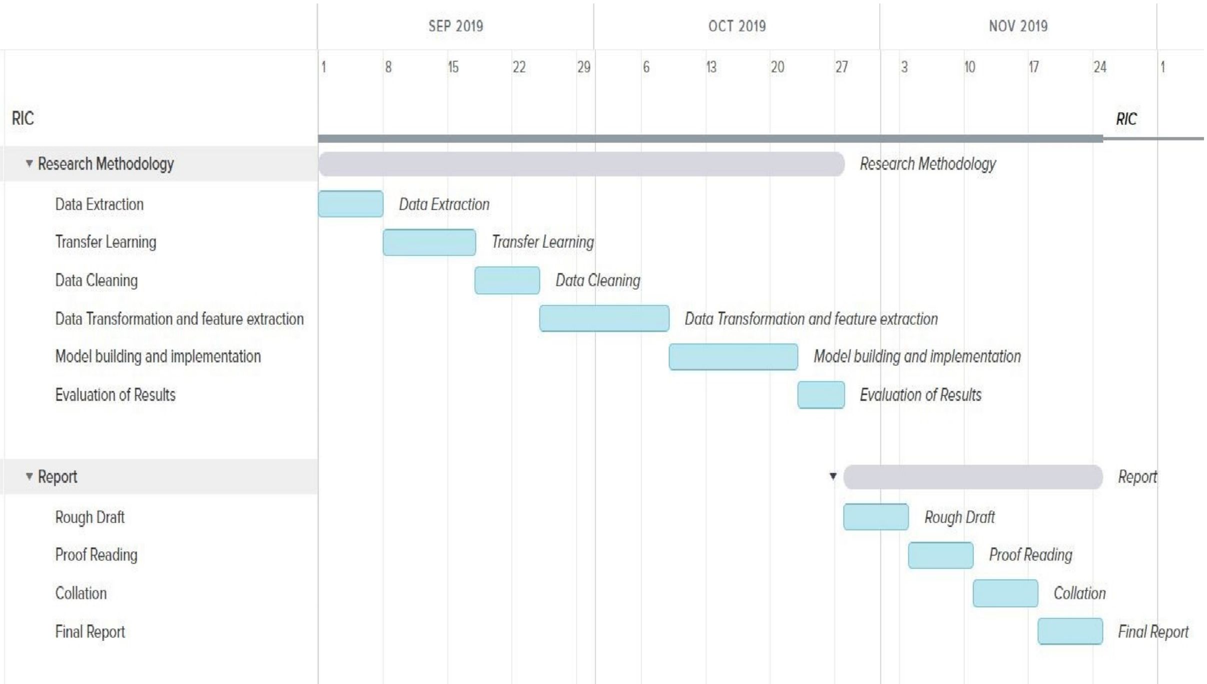


Figure 9: Project plan

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