DESIGN OF AUTOMATED COMPUTER AIDED DIAGNOSIS SYSTEM TO PREDICT DIABETIC RETINOPATHY BASED ON EFFICIENTNET

A PROJECT REPORT

Submitted by

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BONAFIDE CERTIFICATE

Certified that this project report "**DESIGN OF AUTOMATED COMPUTER AIDED DIAGNOSIS SYSTEM TO PREDICT DIABETIC RETINOPATHY BASED ON EFFICIENTNET"** is the bonafide work of **V. RAGUVARAN (810017205066), K. VIGNESH (810017205093),** who carried out the project work under my supervision.

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INTERNAL EXAMINER

EXTERNAL EXAMINER

DECLARATION

We hereby declare that the work entitled "**DESIGN OF AUTOMATED COMPUTER AIDED DIAGNOSIS SYSTEM TO PREDICT DIABETIC RETINOPATHY BASED ON EFFICIENTNET"** is submitted in partial fulfilment of the requirement for the award of the degree in B. Tech, in University College of Engineering, BIT Campus, Tiruchirappalli. It is the record of my own work carried out during the academic year 2020 - 2021 under the supervision and guidance of **Dr. S. SATHIYA DEVI** professor, Department of Information Technology, University College of Engineering, BIT Campus, Tiruchirappalli. The extent and source of information are derived from the existing literature and have been indicated through the dissertation at the appropriate places.

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LIST OF ABBREVIATION

DR	Diabetic Retinopathy
CNN	Convolutional Neural Networks
AAO	American Academy of Ophthalmology
KNN	K – Nearest Neighbor
SVM	Support Vector Machine
DL	Deep Learning
BDR	Background Diabetic Retinopathy
PDR	Proliferative Diabetic Retinopathy
NPDR	Non Proliferative Diabetic Retinopathy
GPU	Graphics Processing Units
BCNN	Bayesian Convolutional Neural Networks
ReLU	Rectifier Linear Unit
GMM	Gaussian Mixture Model
VGGNet	Visual Geometry Group Network
SVD	Singular Value Decomposition
PCA	Principal Component Analysis
DenseNet	Densely Connected Neural Network
FPOPS	Floating Point Operations Per Second
XGB	Extreme Gradient Boosting
GBM	Gradient Boosting
CAD	Computer Aided Diagnosis

DESIGN OF AUTOMATED COMPUTER AIDED DIAGNOSIS SYSTEM TO PREDICT DIABETIC RETINOPATHY BASED ON EFFICIENTNET

ABSTRACT:

Healthcare is an important field where image classification has an excellent value. A rising healthcare problem recognized by the WHO that the world suffers is Diabetic Retinopathy (DR). DR is a global epidemic which leads to vision loss, if left untreated. In this project, an automated Computer Aided Diagnosis (CAD) System for DR is implemented based on the convolutional deep learning model called EfficientNet. Initially, image preprocessing is to be performed by smoothing it with median filter and converting into gray scale image for better contrast. Then size normalization and shape normalization are to be performed. In order to increase the volume of the dataset for processing with a deep learning model, data augmentation is carried out. The following operations are performed. Flip the image horizontally, Flip the image vertically, Randomly rotate the image in the range of [-25, 25] degrees, Randomly zoom in or out in the range of [0.85, 0.95] and Randomly distort the image. The CAD system diagnoses the severity levels of DR from fundus images. There are 5 class labels that are 0-normal,1-mild,2-moderate,3-severe,4-proliferative. The efficiency of the CAD system is improved by incorporating the XGBoost classifier. Performance of Xgboost Training accuracy is 80 %, testing accuracy 46%, validation accuracy 46%, precision 0.94, recall 0.88, F-score 0.92.

1. INTRODUCTION

Diabetes is a disease which occurs when the pancreas does not secrete enough insulin or the body is unable to process it properly. According to International Diabetes Federation estimates, presently, the global number of individuals affected with diabetes is 463 million and it may rise to 693 million by 2045 [1]. Diabetic retinopathy is an eye condition that occurs due to diabetes. It can arise as a result of the high blood sugar level that diabetes causes. Over time, having too much sugar in the blood can damage blood vessels and leak fluid in the retina.

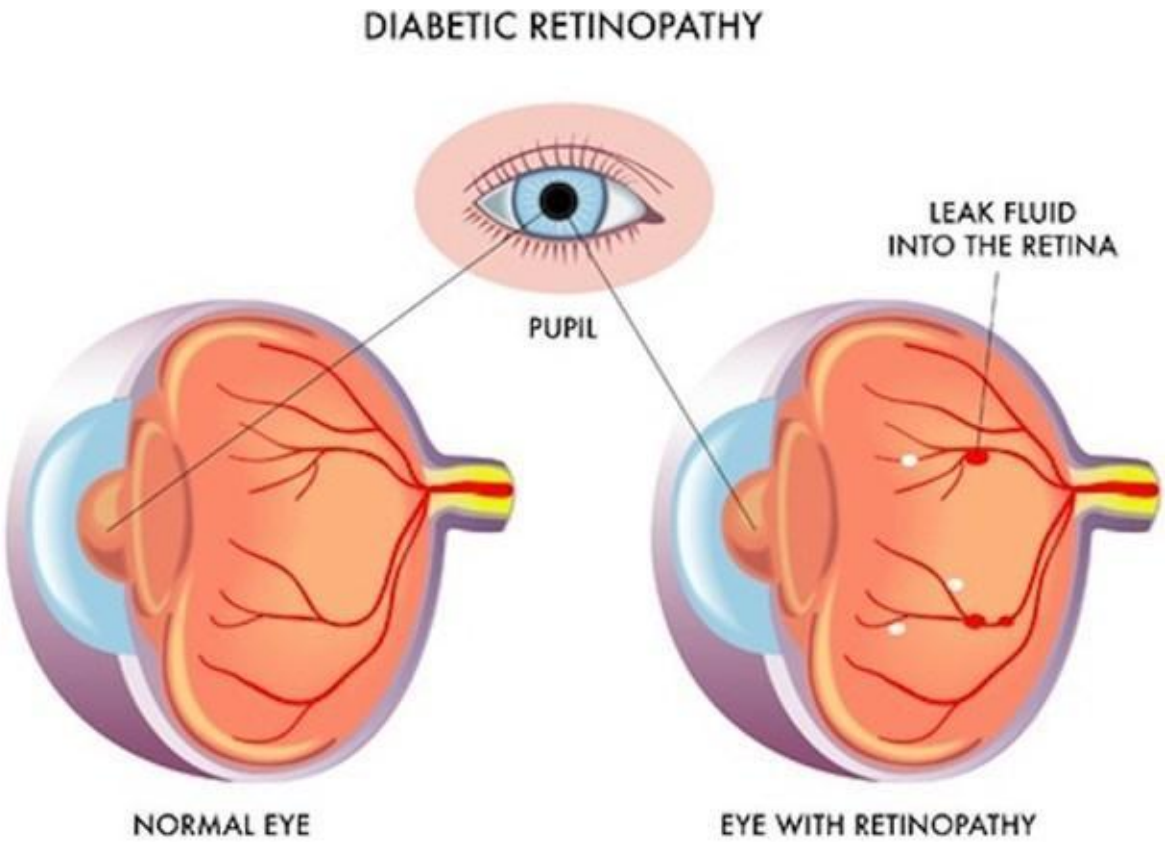

Figure 1. Diabetic Retinopathy

The patients who have either type 1 or type 2 diabetics for 15 years, one out of three patients is estimated to have some form of DR and one in ten is prone to severe visual impairment [2]. Along with diseases leading to blindness, such as cataracts and glaucoma, DR is one the most frequent ailments among the people of

working age in India, making it the world's diabetic capital. Early diagnosis and treatment of DR can prevent vision loss. Hence, diabetic patients are typically referred for retinal screening once or twice a year [3].

The DR is mainly dependent on the number of ophthalmologists and necessary health care infrastructure [4-5]. In the Indian subcontinent, ophthalmologist to population ratio is 1:107,000, however, in urban regions this ratio is 1 : 9000 whereas in rural parts there is only one ophthalmologist for 608,000 inhabitants [6]. By 2045, India alone is projected to have approximately 151 million people with diabetes and one-third of them are expected to have DR [1]. So screening such a large population for DR confronts issues related to implementation, management, availability of human graders, and long-term financial sustainability. The identification of DR at an early stage is also a challenge for the ophthalmologist. The efficient computer aided diagnosis tools are required to address the challenges and issues of DR and also to reduce the burden of ophthalmologists. The retinal images are used in the diagnosis system to predict the severity levels of DR. The retinal images acquired through fundal cameras with back mounted digital cameras provide useful information about the consequence, nature, and status of the effect of diabetes on the eye [7].

1.1 TYPES OF DR

DR is classified according to the presence or absence of abnormal new vessels in the retina as:

- Non-proliferative (background/pre proliferative) retinopathy
- Proliferative retinopathy

Each has a different prognosis for vision. The International American Academy of Ophthalmology (AAO) classification, DR progresses with four stages and its fundus images (*Figure 2.*) are given below :

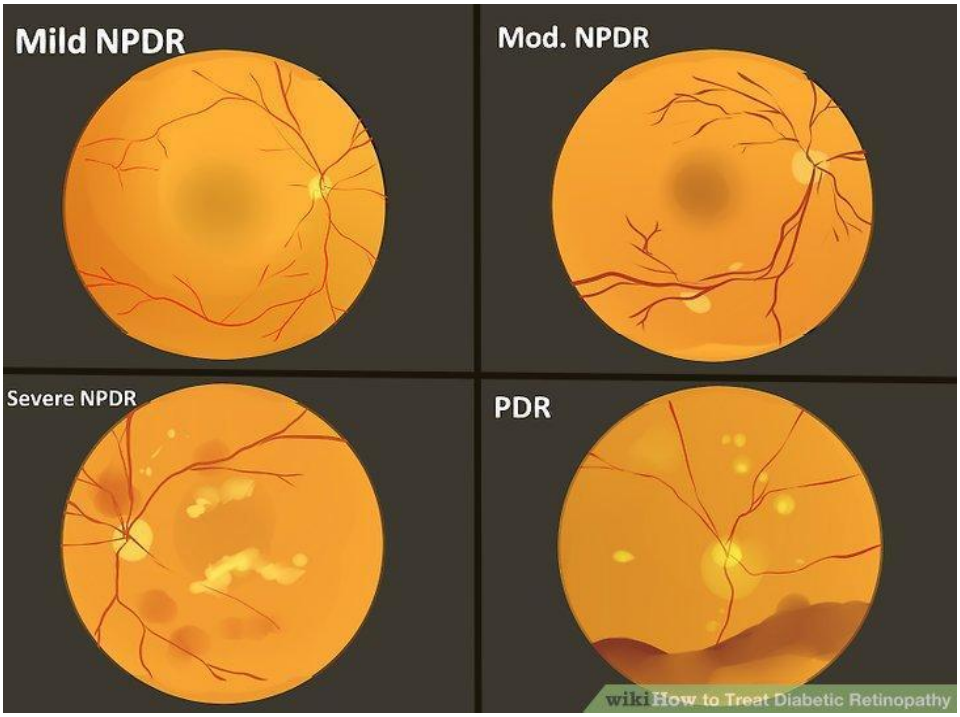

Figure 2. Type of DR

(i). Mild non proliferative retinopathy (Level 1), the earliest stage, where only microaneurysms can occur;

(ii). Moderate non proliferative retinopathy (Level 2), a stage which can be described by losing the blood vessels' ability of blood transportation due to their distortion and swelling with the progress of the disease;

(iii). Severe non proliferative retinopathy (Level 3), results in deprived blood supply to the retina due to the increased blockage of more blood vessels, hence signaling the retina for the growing of fresh blood vessels;

(iv). Proliferative diabetic retinopathy is the advanced stage, where the growth features secreted by the retina activate proliferation of the new blood vessels, growing along the inside covering of retina in some vitreous gel, filling the eye.

1.2 SYMPTOMS

Anyone can have diabetic retinopathy and not know it. This is because it often has no symptoms in its early stages. As diabetic retinopathy gets worse, you will notice symptoms such as:

- seeing an increasing number of floaters,

- having blurry vision,
- having vision that changes sometimes from blurry to clear,
- seeing blank or dark areas in your field of vision
- having poor light vision and
- noticing colors appear faded or washed out
- losing vision.

Diabetic retinopathy symptoms usually affect both eyes.

1.3 TREATMENT

Laser treatment:

Scatter laser surgery, or panretinal photocoagulation, takes place in a doctor's office or an eye clinic. A doctor uses targeted lasers to shrink blood vessels in the eye and seal the leaks from abnormal blood vessels.This treatment can either stop or slow down the leakage of blood and the buildup of fluid in the eye. People may need more than one session.Laser treatment comes with certain risks, such as a loss of peripheral vision, color vision, and night vision. A person can talk to their doctor about the relative benefits and risks of this treatment.

Injections:

Certain medicines can reduce swelling and minimize leakage from blood vessels in the eyes. Medicines may include anti-VEGF drugs and corticosteroids.Eye injections involve the doctor taking the following steps:

- placing numbing medicine on the eye
- cleaning the eye to help prevent infections
- placing the medicine in the eye using a very small needle

People may need to get regular injections, but over time, they usually require injections less frequently.After removing the cloudy or bloody vitreous, the surgeon will insert a clear liquid or gas in its place. The body will absorb the liquid or gas over time and create new vitreous in its place.

Eye surgery:

If a person has problems with the retina or vitreous, they may benefit from a vitrectomy. This procedure is the removal of some of the vitreous from the eye.The aim is to replace cloudy vitreous or blood to improve vision and to help the doctor find and repair any sources of retinal bleeding.If the doctor puts a gas bubble in the eye, the person will need to hold their head in a certain position for a few days or weeks to make sure that the bubble stays in the right place. They will also need to avoid flying and visiting places at high altitudes until the bubble goes away.Surgery is not a cure for diabetic retinopathy, but it may stop or slow the progression of symptoms. Diabetes is a long-term condition, and subsequent retinal damage and vision loss may still occur despite treatment.

1.4 PREVENTION:

Nobody can't always prevent diabetic retinopathy. However, regular eye exams, good control of your blood sugar and blood pressure, and early intervention for vision problems can help prevent severe vision loss.If you have diabetes, reduce your risk of getting diabetic retinopathy by doing the following,

- **Manage diabetes:** Make healthy eating and physical activity part of your daily routine. Try to get at least 150 minutes of moderate aerobic activity, such as walking, each week. Take oral diabetes medications or insulin as directed.
- **Monitor blood sugar level:** Everyone may need to check and record your blood sugar level several times a day — more-frequent measurements may be required if you're ill or under stress. Ask your doctor how often you need to test your blood sugar.
- **Ask a doctor about a glycosylated hemoglobin test:** The glycosylated hemoglobin test, or hemoglobin A1C test, reflects your average blood sugar level for the two- to three-month period before the test. For most people, the A1C goal is to be under 7 percent.

- **Keep blood pressure and cholesterol under control:** Eating healthy foods, exercising regularly and losing excess weight can help. Sometimes medication is needed, too.
- **If you smoke or use other types of tobacco, ask a doctor to help:**Smoking increases risk of various diabetes complications, including diabetic retinopathy.
- **Pay attention to vision changes:** Contact your eye doctor right away if you experience sudden vision changes or your vision becomes blurry, spotty or hazy.

The state of the art methods used to identify the DR is presented in [8 - 11].The traditional machine learning methods such as Support Vector Machine (SVM), K – Nearest Neighbor (K-NN) and Random forest have been utilized to retinal fundus images to detect the DR [11]. These methods provide low accuracy and are time consuming due to manual feature extraction. The feature extraction problem is overcome recently by incorporating the deep Convolutional Neural Network (CNN).

2. LITERATURE SURVEY

W.L. Alyoubi et al [8] discussed about Diabetic retinopathy detection through deep learning techniques. In DL applications to medical image analysis including the classification, segmentation, detection, retrieval, and registration of the images. There are many DL-based methods such as restricted Boltzmann Machines, convolutional neural networks (CNNs), auto encoder, and sparse coding. The performance of these methods increases when the number of training data increases due to the increase in the learned features unlike machine learning methods. Also, DL methods did not require hand-crafted feature extraction. There are different available pre-trained CNN architectures on ImageNet dataset such as AlexNet, Inception-v3 and ResNet. Some studies like and transfer learning these pretrained architectures to speed up training while other studies build their own CNN from scratch for classification.This work did not receive any grant from funding agencies is the ethical statement of this project

K. Günel et. a l[9] discussed regional domination policy as a novel stage to imperialist competitive algorithms. In this work, they proposed to add a new stage to the imperialist competitive algorithm to support passing from imperialism to internationalism. To do so, we have introduced regional organizations (ROs) within a territory defined by hyperspheres. The empires support ROs to dominate the territory. Thus, the weak empires have more chance to compete with the global powers. By this means, the premature convergence of the strongest empire to a local minima may have been prevented. Additionally, the exploration capability of the optimization algorithm is increased by generating different territories in each iteration. The authors declare that they have no conflict of interest is the ethical statement of this project.

K.R. Anil Kumar et. al [10] discussed DR exudates are detected for computer-aid diagnosis. Deep CNN was taken to obtain pixel wise exudate identification achieved accuracy of 91.92%, sensitivity of 88.85% and specificity of 96%. To evaluate changes in retina and determine retinopathy at an early stage they were inspected by multifocal electroretinography (mfERG). For mfERG testing 7 healthy subjects, 16 diabetics with no apparent retinopathy and 9 diabetics with background diabetic retinopathy (BDR) were considered [9].From multifocal ERG record the initial slice from second order kernel (K21) were taken out and added. Three major peaks (P1, N1 and P2) of K21 were assessed. With their amplitude and implicit time linear classification was done. This classifier distinguishes eyes of control, NDR and BDR subjects. The reported accuracy was 99%. Categorized detected DR features into several stages and is pre-processed, then vessel, hemorrhages and exudate were detected, and removed optic discs. The images are grouped as mild NPDR, moderate NPDR, severe NPDR and PDR. The detection percentage for blood vessel & hemorrhages are 98%, and exudates are 100%.

M. Mateen et al [12] discussed Exudate Detection for Diabetic Retinopathy using Pre trained Convolutional Neural Networks. In this work, they used google CoLab's graphics processing units (GPU) runtime to perform their experiments. They used pretrained (Inception-V3, Visual Geometry Group Network-19 and ResNet- 50)models to predict Diabetic Retinopathy. They use a 10-fold cross-validation approach applied for performance evaluation .Their model on DIARETDB1 dataset gives accuracy 98.91%. Although their accuracy is improved, there is a difficulty to discriminate against the mild ,moderate DR.

B. Tymchenko et al.[15] discussed the multistage transfer learning approach and an automatic method for detection of the stage of diabetic retinopathy by single photography of the human fundus used an Ensemble of 3 CNN architectures(EfficientNet4, EfficientNet5, Se-ResNetxt-50) for binary

classification which got 98.6% accuracy. They focused on binary class labels but there are 4 stages in DR. The hybrid model was proposed by M.A. Ahsan et al.[17]. Their model consists of BCNNs (Bayesian Convolutional Neural Networks) and active learning components. It works good on unseen labeled data.

Parvathy et.al.[19] have used CNN to classify the severity level of DR from the color fundus images and also incorporate this technique into the fundus camera.This approach will reduce the time consumption and efficiently diagnose the disease so that there would not be any delay in the treatment. The algorithm will be implemented in the system which is connected to the fundus camera.

Z. Gao et.al.[20] have considered Inception V3 as a base model to diagnose and predict the four levels of DR. They claimed that Inception @ 4 which is the concatenation of Inception V3 with Softmax classifier yields better accuracy when compared with Resnet – 18, Resnet – 101 and VGG – 19. This trained model is deployed in the cloud computing platform and provides pilot diagnostic services to several hospitals via the internet.

M. Mateen et. al.[21] have achieved symmetrically optimized solution through the combination of a Gaussian Mixture Model (GMM), Visual Geometry Group Network (VGGNet), Singular Value Decomposition (SVD) and Principal Component Analysis (PCA), and softmax, for region segmentation, high dimensional feature extraction, feature selection and fundus image classification respectively. The optimized Densely Connected Neural Network (DenseNet) for DR classification has been presented in [22].The lightweight CNN for binary and multi class DR classification has been introduced in [23]. In this work, the obtained features are used with different classifiers such as SVM, AdaBoost, Naive Bayes, Random Forest and J48 using images from generic IDRiD, MESSIDOR, and KAGGLE datasets. The J48 outperforms other classifiers for the MESSIDOR, IDRiD, and KAGGLE datasets.

3. PREDICTION OF DIABETIC RETINOPATHY BASED ON EFFICIENTNET

In this project , the CAD is to be designed for Prediction of Diabetic Retinopathy based on EfficientNet. The Flow diagram of the project is shown in Figure 3.

3.1 Flow Diagram:

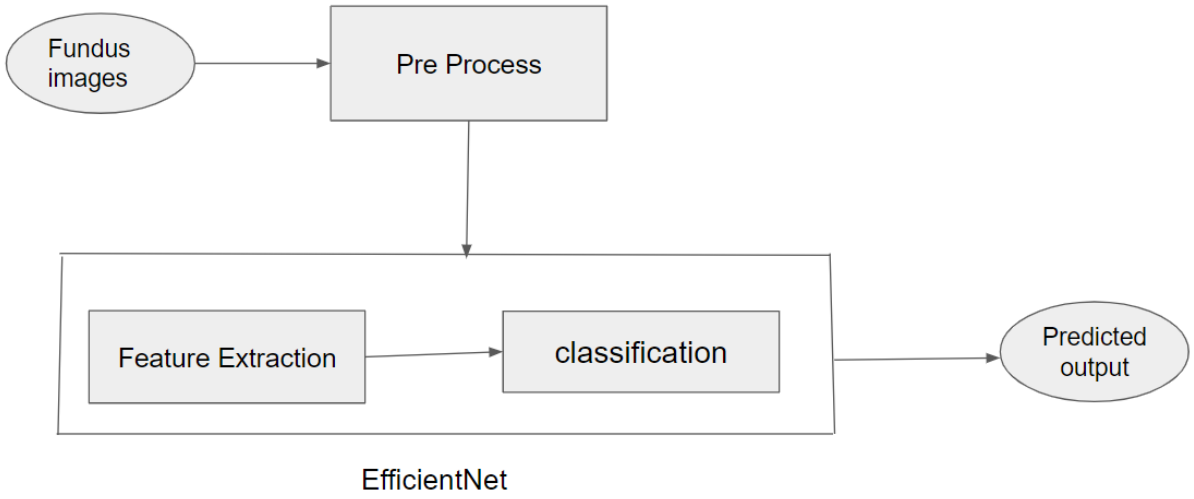

Figure 3. Flow diagram for prediction of DR

The automated CAD system consists of four phases. (i) Preprocessing, (ii) Model setup (consists of feature extraction and classification) and (iii) classification using ensemble learning and (iv). Performance evaluation. Initially the fundus images are undergone to data preprocessing such as rotation and scaling. Then the collected images are given to EfficientNet deep learning model for feature extraction. The extracted features are classified by XGBoost classifier. The phases of the CAD system are explained below in detail.

3.2 Preprocessing:

Initially, image preprocessing is to be performed by smoothing it with

median filter and converting into gray scale image for better contrast. Then size normalization and shape normalization are to be performed. In order to increase the volume of the dataset for processing with a deep learning model, data augmentation is carried out. The following operations are performed. (i). Flip the image horizontally, (ii). Flip the image vertically,(iii). Randomly rotate the image in the range of [-25, 25] degrees, (iv). Randomly zoom in or out in the range of [0.85, 1.15] and (v). Randomly distort the image. All of these methods were combined for augmenting each image, and a probability of 0.5 is used to determine whether or not to perform each of them.

3.3 Model setup (parameter tuning) and Feature extraction:

This project utilizes the latest CNN model "EfficientNet" [17] for feature extraction. Among many CNN models such as Lee Net, Alex network, VGG network, ResNet [32] and Inception network [33] used in the ImageNet dataset since 2012 have become more complex, but many are not effective in terms of computing load. EfficientNet model, which is among the state of the art models by reaching 84.4% accuracy with 66M parameter in the ImageNet classification problem, can be considered as a group of CNN models.

EfficientNet group consists of 8 models between B0 and B7, and as the model number grows, the number of calculated parameters does not increase much, while accuracy increases noticeably. Unlike other CNN models, EfficientNet uses a new activation function called Swish instead of the Rectifier Linear Unit (ReLU) activation function. The aim of deep learning architectures is to reveal more efficient approaches with smaller models. EfficientNet, unlike other state of the art models, achieves more efficient results by uniformly scaling depth, width and resolution while scaling down the model. The first step in the compound scaling method is to search for a grid to find the relationship between the different scaling dimensions of the baseline network under a fixed resource constraint. In this way, a suitable scaling factor for depth, width and resolution dimensions is determined. These coefficients are then applied to scale the baseline network to the desired target network.

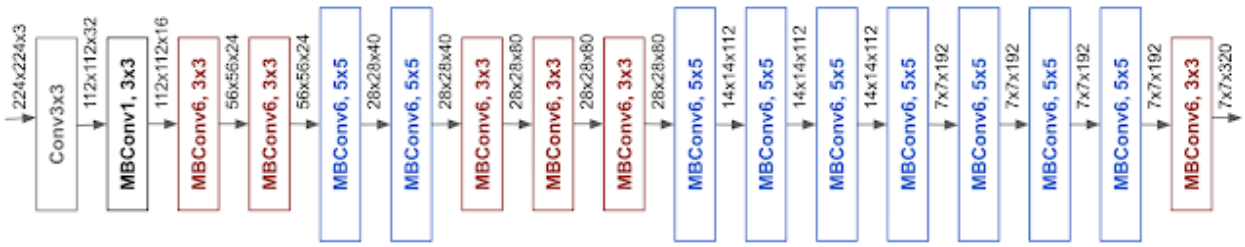

Figure 4. Architecture of EfficientNet B0

The baseline architecture of EfficientNet B0 is shown in figure 4.The main building block for EfficientNet is the inverted bottleneck MBConv, which was first introduced in MobileNetV2 [18], but due to the increased FLOPS (Floating Point Operations per Second) budget, it is used slightly more than MobileNetV2. In MBConv, blocks consist of a layer that first expands and then compresses the channels, so direct connections are used between bottlenecks that connect much fewer channels than expansion layers. This architecture has in-depth separable convolutions that reduce calculation by almost *k2* factor compared to traditional layers where *k* is the kernel size which denotes the width and height of the 2D convolution window [18]. In compound scaling, the compound coefficient φ is used with the principles given in Eq. (1) to uniformly scale depth, width, and resolution.

$$depth : d = \alpha^{\varphi}$$

$$width : w = \beta^{\varphi}$$

$$resolution : r = \gamma^{\varphi}$$

$$\alpha \geq 1, \beta \geq 1, \gamma \geq 1 \qquad \ldots(1)$$

where, $\alpha, \beta, \gamma,$ α, β, γ are constants that can be determined by grid search. φ is a user-defined coefficient that controls how many resources are available for model scaling, while α, β, γ α, β, γ determine how these extra resources are assigned to the network width, depth and resolution, respectively. In a regular convolution process, FLOPS are proportional to *d*, *w2*, *r2*. Since the cost of computing in convolution networks is largely due to convolution operations,

scaling convolution networks as given in Eq. (1) increases the FLOPS of the network by approximately ($\alpha, \beta 2, \gamma 2$) φ ($\alpha . \beta 2 . \gamma 2)\varphi$ in total [17]. Starting from Baseline EfficientNet-B0, the compound scaling method scales this model in two steps [17]:

Step 1: Assuming that there are twice as many resources available, grid search is performed with $\varphi = 1$ and the best values are found for α, β, γ.

Step 2: Obtained α, β, γ values are determined as constant and the baseline network is scaled up to obtain EfficientNet-B1 to B7 using Eq. (1) with different φ values.

The EfficientNet B0 uses Swish activation function instead of Relu, leaky ReLu and Elu. Swish is a multiplication of a linear and a sigmoid activation. which is defined in equation (2) as :

$$Swish(x) = x * sigmoid(x) \quad \ldots(2)$$

The Swish function nullifies negative values and thus derivatives are zero for all negative values and also consistent. The following table 1 and figure 5 summarizes the parameters used in EfficientNet B0.

Table 1. Parameters used in EfficientNet B0 architecture

Stage i	Operator $\hat{\mathcal{F}}_i$	Resolution $\hat{H}_i \times \hat{W}_i$	#Channels $\hat{C}_i$	#Layers $\hat{L}_i$
1	Conv3x3	224×224	32	1
2	MBConv1, k3x3	112×112	16	1
3	MBConv6, k3x3	112×112	24	2
4	MBConv6, k5x5	56×56	40	2
5	MBConv6, k3x3	28×28	80	3
6	MBConv6, k5x5	14×14	112	3
7	MBConv6, k5x5	14×14	192	4
8	MBConv6, k3x3	7×7	320	1
9	Conv1x1 & Pooling & FC	7×7	1280	1

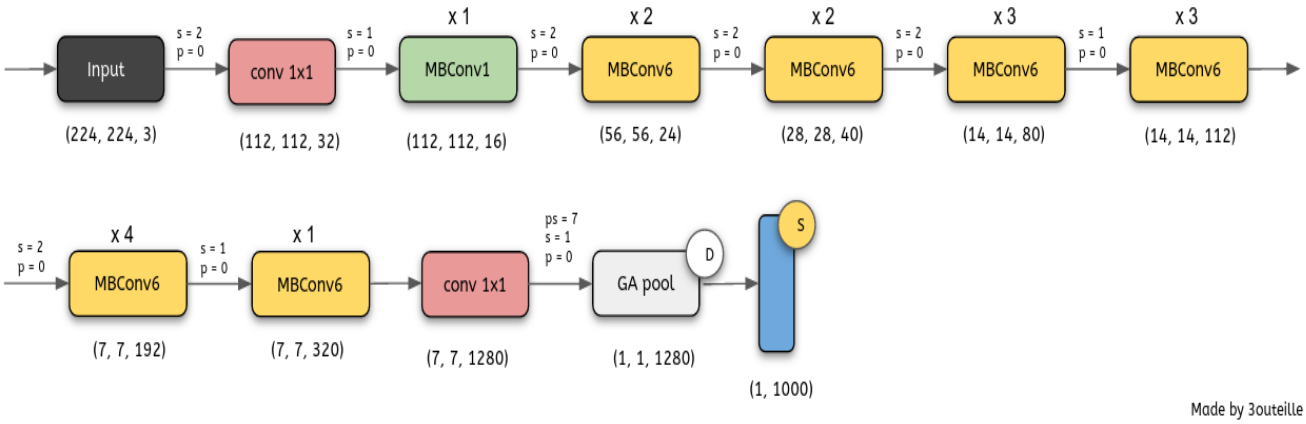

Figure 5. Detailed Architecture of EfficientNet B0

In any network, the architecture starts which is common in eight models and the final layer. The architecture layers are detailed in Figure 6.

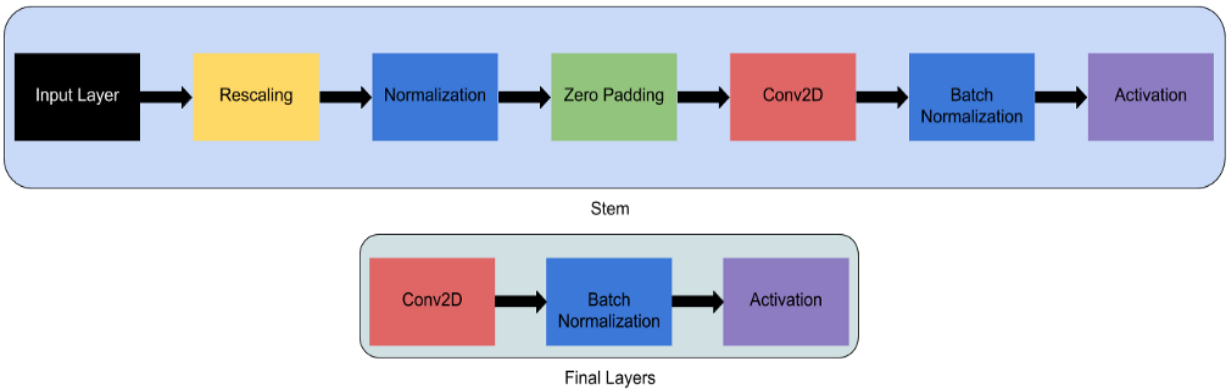

Figure 6. EfficientNet Layer architecture

Each of the layers contains 7 blocks. Then the blocks are divided into sub-blocks whose number is varying from each block.The layers can be made from 5 models that are shown below.

- **Module 1** - This is used as a starting point for the sub-blocks.
- **Module 2** - This is used as a starting point for the first sub-block of all the 7 main blocks except the 1st one.
- **Module 3** - This is connected as a skip connection to all the sub-blocks.

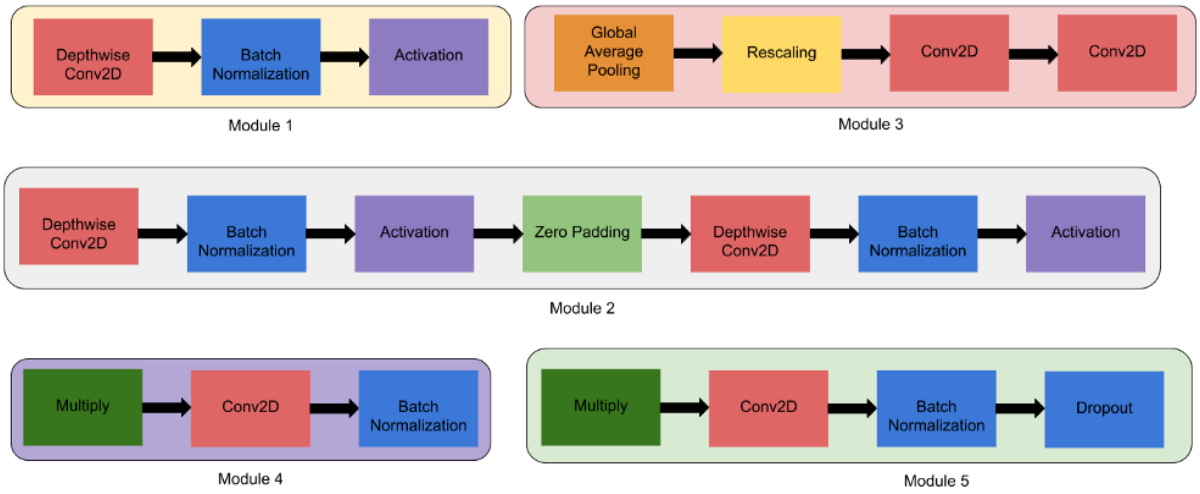

Figure 7. Models used to make the architecture

- **Module 4** - This is used for combining the skip connection in the first sub-blocks.
- **Module 5** - Each sub-block is connected to its previous sub-block in a skip connection and they are combined using this module.

These modules are further combined to form sub-blocks which will be used in a certain way in the blocks.The sub-blocks are clearly explained in Figure 8 that is shown below.

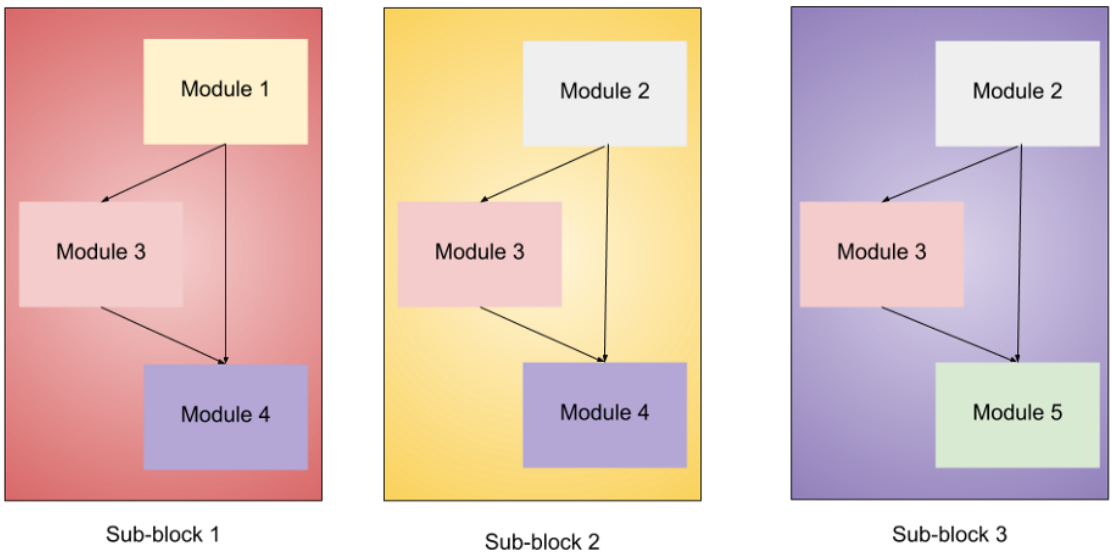

Figure 8. Working of sub-blocks

- **Sub-block 1 -** This is used only as the first sub-block in the first block.
- **Sub-block 2 -** This is used as the first sub-block in all the other blocks.
- **Sub-block 3 -** This is used for any sub-block except the first one in all the blocks.

The architecture of the EfficientNet B0 with respect to models or blocks are explained in Figure 9 shown below.

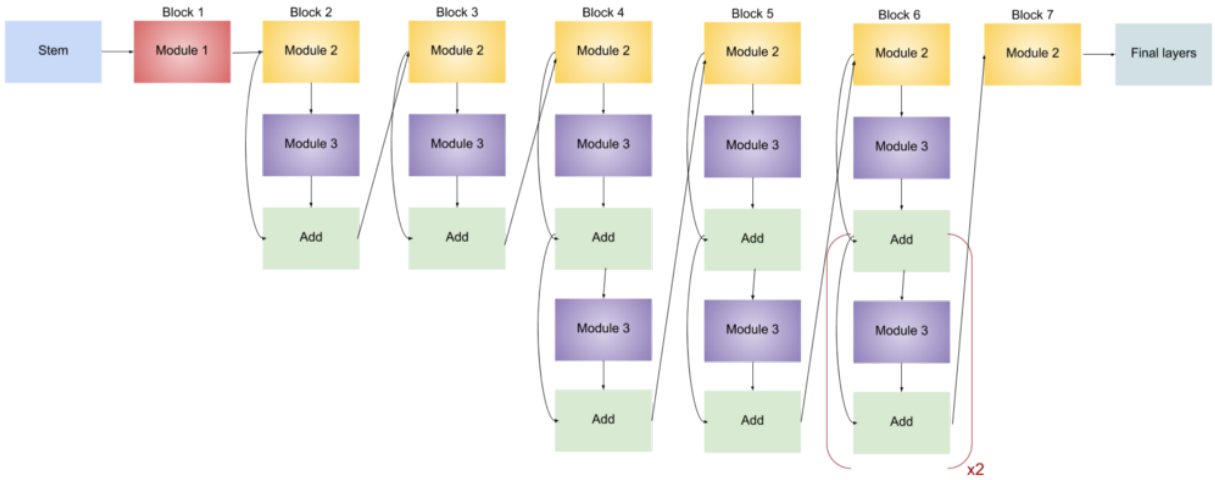

Figure 9. EfficientNet architecture with respect to models

3.4 Classification: This project utilizes ensemble based classifiers called as Boosting (XGboost) instead of Swish which is the built in activation function for EfficientNet.

3.4.1 Ensemble Classifier:

Figure 10. Describes the difference between the workflow of single classifier and Ensemble classifier. Ensemble learning is a way of generating various base classifiers from which a new classifier is derived which performs better than any constituent classifier. These base classifiers may differ in the algorithm used, hyperparameters, representation or the training set.

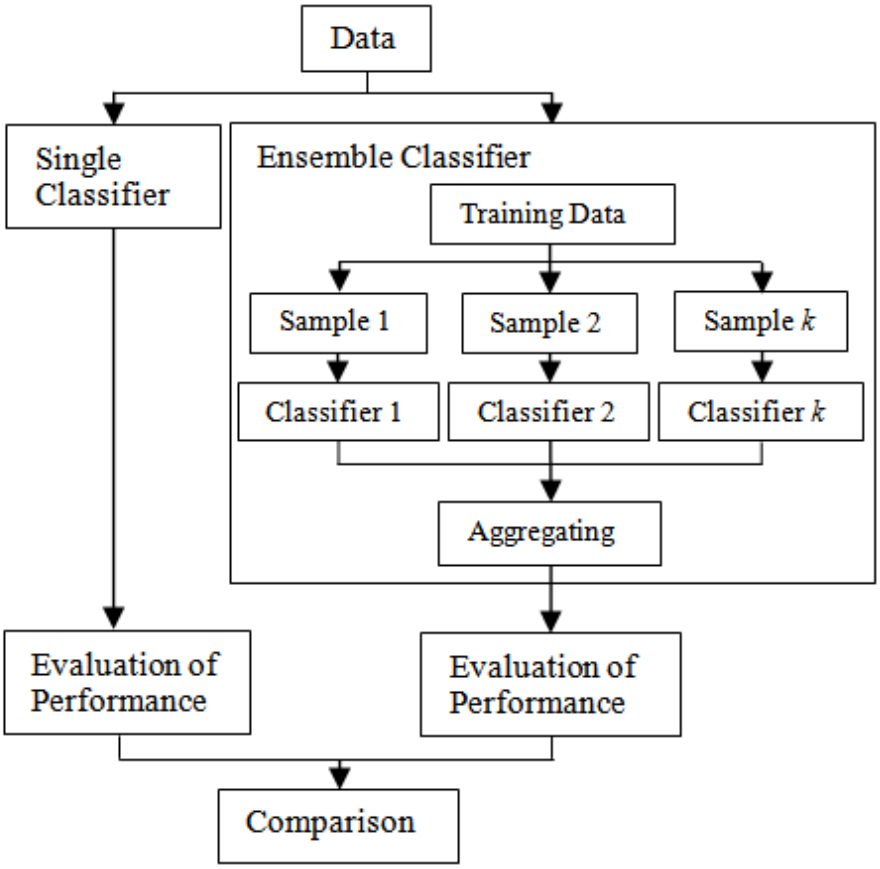

Figure 10. Workflow of single vs ensemble classifier

The ensemble is a Latin-derived word which means ‘union of parts’. The regular classifiers that are used often are prone to make errors. As much as these errors are inevitable they can be reduced with the proper construction of a learning classifier. The key objective of the ensemble method is to reduce bias and variance.Ensemble classifiers pool the predictions of multiple base models. Much empirical and theoretical evidence has shown that model combination increases predictive accuracy. Ensemble learners create the base models in an independent or dependent manner.some of the advanced ensemble classifiers are:

1. Stacking
2. Blending
3. Bagging
4. Boosting

3.4.2 Boosting:

Boosting is a self learning technique. It learns by assigning weights for various items in the data. The boosting technique initially starts with equal weights but after every model, each model is assigned a weight based on its performance. Similarly, after the evaluation of each model, the misclassified data are given more weights so that the next model has more focus on these items.For every iterations,

1. It weights each training example by how incorrectly it was classified.
2. makes a hypothesis.
3. weights the hypothesis.

Thus the final model is derived from various models which focussed on various groups of data, by voting them based on their weights. The final model is averaged by using the weighted average method

$$e=((\sum e_i w_i/*\sum w_i))/n \quad ...(3)$$

Where $e_1, e_2 \ldots e_n$ =base classifier

$w_1, w_2 .... w_n$ =weights

n =no.of models

e =final classifier

some of the boosting algorithms are,

- Adaboost
- GBM
- XGBM
- Light GBM
- CatBoost

3.4.3 XGBoosting:

XGBoost is one of the most popular machine learning algorithms these days. Regardless of the type of prediction task at hand; regression or classification. XGBoost is well known to provide better solutions than other machine learning algorithms. In fact, since its inception, it has become the "state-of-the-art" machine learning algorithm to deal with structured data.XGBoost (Extreme Gradient

Boosting) belongs to a family of boosting algorithms and uses the gradient boosting (GBM) framework at its core. It is an optimized distributed gradient boosting library. XGBoost is free open source software available for use under the permissive Apache-2 license. XGboost has proven to be the most efficient Scalable Tree Boosting Method. It has shown outstanding results across different use cases such as motion detection, stock sales predictions, malware classification, customer behaviour analysis and many more. The system runs way faster on a single machine than any other machine learning technique with efficient data and memory handling. The algorithm's optimization techniques improve performance and thereby provides speed using the least amount of resources. Some special characteristics of XGBoosting are given below.

- **Speed and performance** : Originally written in C++, it is comparatively faster than other ensemble classifiers.
- **Core algorithm is parallelizable** : Because the core XGBoost algorithm is parallelizable it can harness the power of multi-core computers. It is also parallelizable onto GPU's and across networks of computers making it feasible to train on very large datasets as well.
- **Consistently outperforms other algorithm methods** : It has shown better performance on a variety of machine learning benchmark datasets.
- **Wide variety of tuning parameters :** XGBoost internally has parameters for cross-validation, regularization, user-defined objective functions, missing values, tree parameters, scikit-learn compatible API etc.

XGBoosting having some key algorithm implementation features that are,

- Cache optimization.
- XGBoost is used in supervised learning(regression and classification problems).
- Supports parallel processing.
- Can be run on both single and distributed systems(Hadoop, Spark)
- Efficient memory management for large datasets exceeding RAM.
- Has a variety of regularizations which helps in reducing overfitting.

- Auto tree pruning – Decision tree will not grow further after certain limits internally.
- Can handle missing values.
- Has inbuilt Cross-Validation.
- Takes care of outliers to some extent.

.Working steps:

- Calculate the residuals.
- For XGboost some new terms are introdu

λ - regularization parameter

ϒ - for auto tree pruning

eta - how much model will converge

- Calculate the similarity score using the given formula.

Similarity Score(S.S) = (S.R ^ 2)/ (N+λ) …(4)

Here S.R is the sum of Residuals,

N is Number of Residuals

At first let's put λ=0

- Let's make the decision tree using these residuals and similarity scores.
- Calculate the similarity scores for the decision tree.
- Calculate the gain using the given formula.

Gain = S.S of the branch before split - S.S of the branch after the split …(5)

- Find the New prediction based on the formula as below.

*New prediction = previous prediction + Learning rate * Output* …(6)

- Update new residuals and work the above process again.

Model M1 will be trained and residuals will keep on decreasing, which means the loss will be optimized in further models.

4.EXPERIMENT AND RESULT

The experiments are performed on “Google Colab” using graphics processing units (GPUs). The input data are divided into different ratios of training and testing datasets used in the experiments of the proposed methodology. The splitting data are performed in the ratio of 70% for training and 30% for testing.

4.1 Software and Hardware Requirements:

Software Requirements:

- **Operating System** - Windows 10 / Ubuntu 20.0.4Lts
- **Programming language** - Python
- **IDE** - Google colab
- **Framework -** Pillow, Tensorflow, Keras
- **Browser -**Google chrome

Hardware Requirements:

- **System -** Lenovo
- **Hard Disk -** About 40GB
- **RAM -** 4GB
- **Processor -** AMD Pro

4.2 DATASET:

The Dataset is downloaded from IEEEXport [26] website.The database consists of 413 colour fundus images in Training data.103 color fundus images in Testing Data. There are 5 class labels that are 0-normal,1-mild,2-moderate,3-severe,4-proliferative. Data loaded into X_Data as pickle file,Y_Data as pickle file.

4.3 PERFORMANCE METRICS:

The performance of this project is evaluated in two modes: (i) Subjective evaluation with help of ophthalmologist (ii) based on precision, recall and classification accuracy.

Confusion Matrix:

A confusion matrix is a table that is often used to describe the performance of a classification model (or "classifier") on a set of test data for which the true values are known. The structure of confusion matrix shown in Figure 11.

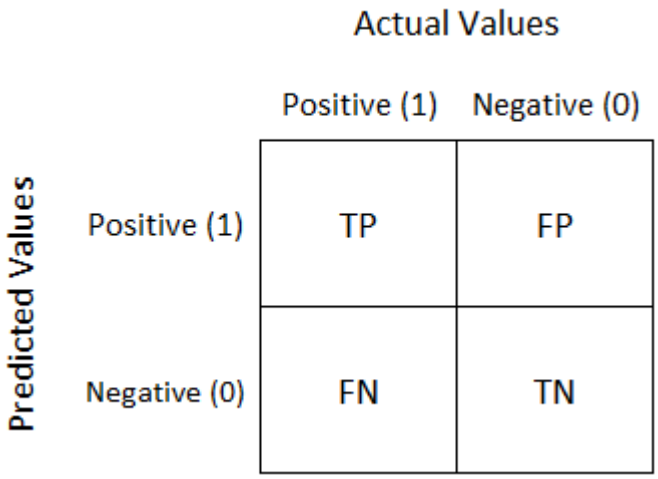

Figure 11. Confusion matrix

True Positives (TP): Outcome where the model correctly predicts the positive class.

True Negatives (TN): Outcome where the model correctly predicts the negative class.

False Positives (FP): It is also called as type 1 error. Outcome where the model incorrectly predicts the positive class when it is actually negative.

False Negatives (FN): It is also called as type 2 error. Outcome where the model incorrectly predicts the negative class when it is actually positive.

4.3.1 Accuracy

Accuracy is defined as the ratio of number of images correctly predicted by the total examples. It is a measure used to evaluate the model effectiveness to identify

correct class labels and can be calculated by the following equation:

Accuracy = (TP + TN) / (TP + TN + FP + FN) ...(7)

Error Rate : 1.00 – Accuracy

4.3.2 Precision

It is also called Positive predictive value. The ratio of correct positive predictions to the total correctly predicted examples.

precision = TP / (TP + FP) …(8)

4.3.3 Recall

Also called Sensitivity, Probability of Detection, True Positive Rate. The ratio of correct positive predictions to the total positives examples.

Recall = TP / (TP + FN) ...(9)

4.3.4 ROC Curve

A ROC curve (receiver operating characteristic curve) graph shows the performance of a classification model at all classification thresholds. It plots two Parameters namely True Positive rate and False positive rate .

True Positive Rate = TP / (FP + TN) …(10)

False positive Rate =FP / (FP + TN) …(11)

4.3.5 F Score:

F-score (F_1 score) is the harmonic mean of precision and recall.

*F score = (2 * Recall * Precision) / (Recall + Precision)* …(12)

4.4 Experiment setup:

To evaluate the performance of the proposed algorithm, the parameters used are followed below.

Table 2.Performance of EfficientNet with different parameters using Softmax classifier

Learning rate	0.001	0.001	0.001	0.001
Batch size	32	32	32	32
No. of epochs	25	25	50	75
Momentum	0.9	0.9	0.9	0.9
Dropout rate	0.2	0.5	0.5	0.5
Weights	Random	Training_Weight_1	Training_Weight_1	Training_Weight_1
Optimizer used	Adam	SGD	SGD	SGD
Train Accuracy	68%	51%	81%	88%
Validation Accuracy	47%	53%	59%	60%

Table 2 also illustrates the output with respective parameters like learning rate, batch size, no.of epoches, momentum, dropout rate, weights and optimizer used.As train our model by random weights with adam optimizer (learning rate 0.001, dropout rate 0.2, momentum 0.9, batch size 32, No of epochs. 25) , Average training accuracy would be 68 %, Average validation accuracy would be 47 % . After the model's weights are saved on the file named as 'Training_Weight_1'. This saved weights loaded to the model ,then changed the models optimizer

algorithm as SGD, dropout rate as 0.5. This model gives average training accuracy 51% for 25 epochs, 81% for 50 epochs, 88% for 75 epochs, average validation accuracy 53% for 25 epochs, 59% for 50 epochs, 60% for 75 epochs. By comparing the Adam boost and SGD classifier, SGD gives better average accuracy 88% over 10 iterations.

Table 3.Performance of EfficientNet with different parameters using XGBoost

Learning rate	0.001
n_estimators	25
K Fold	10
Training accuracy	80%
Testing accuracy	46%
Validation Accuracy	46%
Precision	0.94
Recall	0.88
F-score	0.91

In this proposed model, EfficientNet acts as a feature extractor , It extracts the feature from the images as a feature map . These feature maps are given to the Xgboost classifier with the y trained labels . By change learning rate 0.001, n _estimators as 25, K_fold split as 5, Training accuracy 80%, Testing accuracy 46%,Validation accuracy 46%, precision 0.94, recall 0.88, F-score 0.91. Comparing metrics of softmax classifier and XGboost, softmax classifier is the best classifier.

5. CONCLUSION AND FUTURE WORK

This project for analysis of different types for Diabetic retinopathy and classifying its severity level. In this project, a pretrained convolutional neural network- (CNN-) based framework is proposed for the detection of diabetic retinopathy in fundus images using transfer learning. In the proposed framework, EfficientNet used to extract the features from fundus images, based on transfer learning for the improvement of classification accuracy. Finally, the classification accuracy of the proposed model is calculated. The proposed transfer learning-based framework has been evaluated and outstanding results in terms of accuracy are obtained, instead of training from scratch. In future work, the proposed framework can be modified to discriminate between hard and soft exudates. Moreover, the proposed framework can also be extended to diagnose hemorrhages and microaneurysms for diabetic retinopathy.

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