International Journal of Advanced and Applied Sciences, 9(12) 2022, Pages: 135-144

Contents lists available at Science-Gate

International Journal of Advanced and Applied Sciences

Journal homepage: http://www.science-gate.com/IJAAS.html

Comparative study on early recognition and identifying diabetic retinopathy with different layers in CNN

Gorli L. Aruna Kumari [1, *], Poosapati Padmaja [2], Jaya G. Suma [3]

[1]*Department of CSE, Gitam School of Technology, Gitam Deemed to be University, Visakhapatnam, India*
[2]*Department of IT, Anil Neerukonda Institute of Technology and Science, Visakhapatnam, India*
[3]*Department of IT, College of Engineering, Jawaharlal Nehru Technological University, Kakinada, India*

A R T I C L E I N F O

Article history:
Received 10 March 2022
Received in revised form
9 June 2022
Accepted 7 September 2022

Keywords:
Deep neural network
Classification
Convolution neural network
Data mining
Diabetic retinopathy

A B S T R A C T

Diabetes is the most prevalent condition worldwide, and diabetic retinopathy (DR) is a subsequent condition caused by acute diabetic cases. It causes severe degeneration of the retina. The compounding blood vessels bloat and often burst, causing fluid leaks in the aqueous humor. This, in turn, causes the creation of undesirable nerve fiber infractions from the occlusion of arteries. Diagnosis requires a manual retinal examination that can often be inconsistent and deliberate with potential flaws in the diagnosis. Early detection through an ophthalmologist is paramount to prevent the prognosis of severe vision loss. Considering the current leap of machine learning in the field of healthcare, early detection of DR can be potentially made efficient with intelligent systems. This research proposes methodologies to fine-tune the existing pre-trained architectures, attaining the classification accuracies of 98% to classify the ocular fundus images which identify early prediction of diabetes. Additionally, this study presents an exposition of other equally scrutinized approaches to ultimately showcase a deep neural network architecture that can precisely classify normal fundus and degenerated fundus from the lowest to the most severe hierarchy. Among several layers in the CNN model pre-tuning and post-tuning exception layers outperformed with good results.

1. Introduction

Diabetes historically referred to as diabetes mellitus, is a common disease observed in most people that can cause high sugar or glucose levels in a person's blood (Lee et al., 1997). It is caused by food habits or can be inherited from ancestors. Diabetes is characterized primarily by type 1 and type 2 diabetics (Cnop et al., 2005). Type 1 diabetes mellitus is a chronic condition where the body produces no insulin because the immune system of the body targets insulin-producing pancreatic cells (Katsarou et al., 2017). Type 2 diabetes mellitus occurs when the body is unable to produce enough insulin (Ozougwu et al., 2013). Although both forms of diabetes seem to be the same, they have significant differences. The distinction between the two is what causes them, how they are managed, and affect the entire body. Diabetes affects more than 420 million individuals globally. Type 2 diabetes affects 90-95 percent of diabetics, while type 1 affects approximately 5-10 percent. Because of diabetes, our body loses some of its control over its senses, it primarily affects the eye; this primary condition of vision is called Diabetic Retinopathy (DR) (Nakayama et al., 2005). DR can result in total blindness. DR is a gradual condition, so medical professionals recommend that patients with diabetes be tested at least twice a year for signs of the illness. Detection is essential because, in contemporary clinical diagnosis, the visual scientist will study the fundus's color image. This detection is time-consuming and tiresome, and it can also result in a significant error.

Substantial progress has been achieved in artificial intelligence and machine learning that had a wide-ranging influence on many research and engineering disciplines. The medical definition is one of the disciplines that has benefited the most from these advances. Researchers were able to systematize the diagnosis of numerous illnesses thanks to new and enhanced machine learning algorithms. Scientists have been attempting to

* Corresponding Author.
Email Address: agorli@gitam.edu (G. L. A. Kumari)
https://doi.org/10.21833/ijaas.2022.12.017
Corresponding author's ORCID profile:
https://orcid.org/0000-0002-8856-5465

accomplish the same for DR diagnosis. Several effective solutions have been developed and implemented in this area thus far. Practical DR diagnosis is based on retinal pictures obtained through a method known as fundus photography. The retina and its contents are captured in exquisite clarity in these photos. State-of-the-art algorithms based on convolutional neural networks (CNNs) perform well on clean DR pictures. Existing DR identification algorithms differ in many ways, including the source of the retinal pictures, pre-processing image methods, the type of characteristics collected from retinal images, and the machine learning algorithm used. To deal with retinal image collections, most researchers employ deep learning approaches.

2. Literature review

DR is a serious concern that has enthralled the entire globe. Diverse researchers' efforts to find an effective approach for the early identification of this disease have been stymied. This section depicts a survey of several research efforts in DR. Acharya et al. (2009) used SVM to extract characteristics such as exudates, arteries, and microaneurysms among 331 fundus pictures with greater than 80% of accuracy. Mir and Dhage (2018) used machine learning and data mining approaches to predict several diabetic-associated disorders, notably skin cancer including conditions related to diabetic retinography.

Chetoui et al. (2018) presented a machine learning approach for DR using SVM accompanied with features such as LTP and LESH, where LESH provided better accuracy results at 90.4%, compared to LBP abbreviated as Local Binary Pattern. The field of medical science, particularly DR, is disclosing many potentials to preclude dreadful diseases. In terms of deep learning's manual feature extraction. Orlando et al. (2018) suggested a CNN using hand-crafted features to identify red lesions in the retina of an eye. The study by Kumaran and Patil, (2018) focused on segmentation algorithms that give a detailed approach for diagnosing DR.

Calleja et al. (2014) employed a two-staged technique for feature extraction and Machine Learning, notably SVM and Random Forest, for classification. The Random Forest outperformed the SVM in terms of accuracy, scoring 97.46 percent. Sadda et al. (2020) developed a quantitative strategy for identifying unknown characteristics for diagnosing proliferation DR while assuming that the extent of lesions might improve demand forecasting. Voets et al. (2019) used a Kaggle dataset to detect DR in retinal fundus pictures. This study is a reimplementation of previously published work but on a new dataset.

The accuracy ought to be 95%. Sadek et al. (2017) proposed an automatic DR detection using deep learning, which comprises four CNNs to classify DR. This method achieved an accuracy of 91%-92%. The work offered by Amin et al. (2016) examined various DR methodologies by analyzing the mixed results from detecting exudates, hemorrhages, and blood vessels to give an in-depth understanding of ongoing research. Doshi et al. (2016) presented a method for categorizing the severity degree of retinal pictures into five phases. This method evaluated the outcomes on kappa metrics using three CNN architecture models and a bring a huge of the three. With a rating of 0.3996k, the ensembling approach produced the best results.

Anant et al. (2017) utilized wavelet and texture features for diabetic retinography detection by using image processing and data mining on a database named DIARETDB1 and reached 97.95% accuracy. Kumari et al. (2020) introduced three different techniques for each phase such as missing value imputation using mean value, logistic regression with recursive feature Elimination for attribute selection, and random forest for classification. Padmaja and Haritha (2018) reported that a machine learning algorithm is combined with clustering to find an estimation of effort. The study of Zago et al. (2020) developed a localization model, precisely a convolutional neural network (CNN) approach, to discourse the model's sophistication and enhance performance. A two convolutional networks approach on a Standard DR Database obtained nearly 95% of sensitivity. A proposed technique by Gandhi and Dhanasekaran (2013) detects exudates by an SVM classifier for automatic diabetic retinography detection. Some works integrate manual feature extraction with deep learning feature extraction for diabetic retinography. Kaur et al. (2019) employed MATLAB to give a neural network approach for retinal image classification.

The generated findings were examined using machine learning methods such as SVM, yielding more promising results. Sailasya and Kumari (2021) analyzed the performance of stroke prediction using ML classification algorithms moreover, supervised backpropagation is applied to the training dataset to fine-tune the network. Kumari et al. (2022) presented a novel method for the prediction of diabetes mellitus using deep CNN and long short-term memory. Rajeswari et al. (2019) designed a scheme that relies on Machine learning. The project is adept enough to identify eye infections of the human fundus, which is impacted by diabetes mellitus. Hemanth et al. (2020) proposed a DR detection and classification method using a CNN. It operated with histogram equalization imaging techniques and contrast-limited adaptive histogram equalization and achieved a 94% score. Shankar et al. (2020a) documented a Deep Learning model for diagnosing DR integrating segmentation techniques and image processing, which obtained an accuracy of over 99%. A CNN model with a total of six layers to extract features from fundus images was proposed and introduced by Gayathri et al. (2020). Shankar et al. (2020b) introduced a classification model named-Hyperparameter Tuning Inception-v4 model for DR images. Jebaseeli et al. (2019) proposed a model of SVM based on deep learning for DR categorization.

3. Methodology

This research includes a comparative performance analysis of 6 pre-trained network architectures that classify between Normal and Detorriated Fundi. The Dataset for this research is obtained from the Kaggle repository. The image repository consists of 516 samples, where the class 0, which represents the normal samples, are 361 and 155 for the class of interest, which is defined using 1. Each of the approaches used in this research is trained in two cycles titled Pre-tuning and Post-Tuning as shown in Fig. 1. A conventional procedure is followed in the pre-tuning stage, setting the hyperparameters in place to train the network and freezing the Pre-trained architecture to use the preset weights as foundational knowledge. In the Post-Tuning approach, the initial arbitrary number of layers (empirically devised) is unfrozen, allowing them to tune over the set number of epochs. This streamlined procedure is applied to all the architectures involved and recorded metrics.

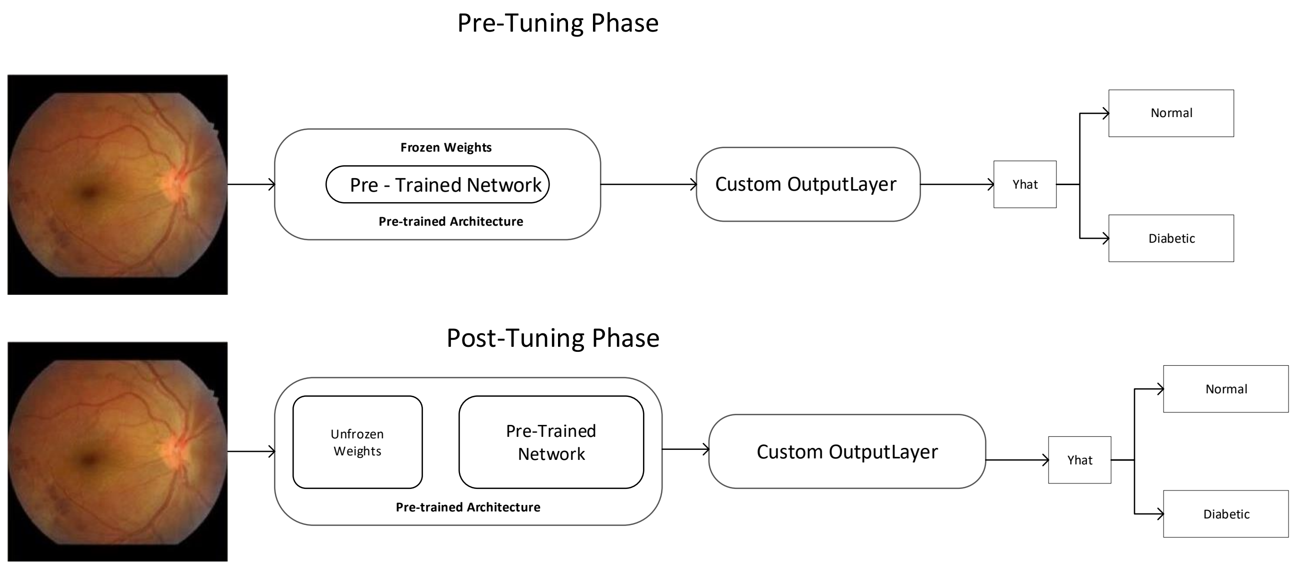

Fig. 1: Pre-tuning phase and post-tuning phases of CNN

3.1. Densenets121

In a standard CNN, each individual convolutional layer gets the results of the previous convolutional layer and generates an output feature map. That output is carried on to the next convolutional layer. As a result, there exist N layers that consist of N direct distinct connections, one connecting each layer to the next. However, when the number of layers in the CNN grows, the vanishing gradient problem emerges as they go further into the layers. This implies that whenever the cycle of information data from the start to end, like the initial input part to the output part layers, gets longer, certain information may 'vanish' or become lost, reducing the network's capacity to train successfully. Dense nets overcome this problem by changing the traditional CNN design and streamlining the layer connection structure. Here in Dense nets, we create short paths from each layer to its previous layers to help train deep networks. Each layer in a DenseNet design is directly linked to every other layer in the network, so it is also known as a densely connected convolutional network as shown in Fig. 2.

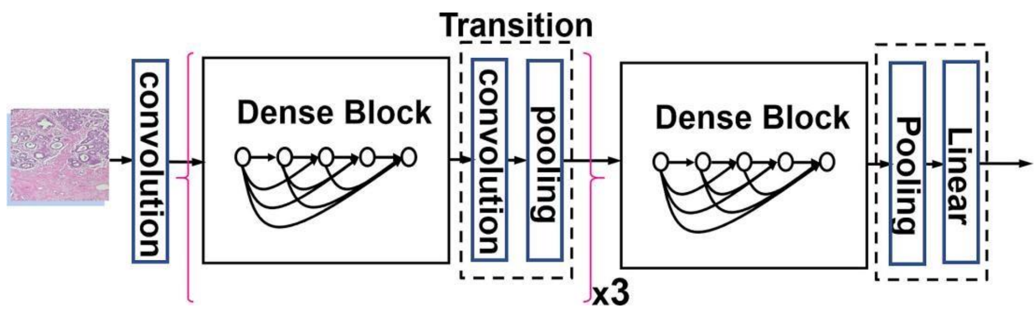

Fig. 2: CNN dense block layer

The main advantages of dense nets are concerned with the use of parameter efficiency, because of a fixed number of output feature maps per layer, only very few kernels are learned per line and also the other advantage was implicit deep supervision and feature reuse, for instance, there is inception that used auxiliary cost function using feature maps from the intermediate layers that improve the learning to be discriminative so as to improve the additional cost function there have been several other approaches, and there is one approach where that take feature maps from the intermediate layers, and give it to an SVM as input, and it does the classification task, and then that error is back propagated however here in this case as the feature maps are concatenated from the preceding layers the activations from the earlier layers have direct access to the error function or the cost function because that these layers are grouped into dense blocks as they call them. The training and validation accuracy and loss are shown in below Fig. 3 and Fig. 4.

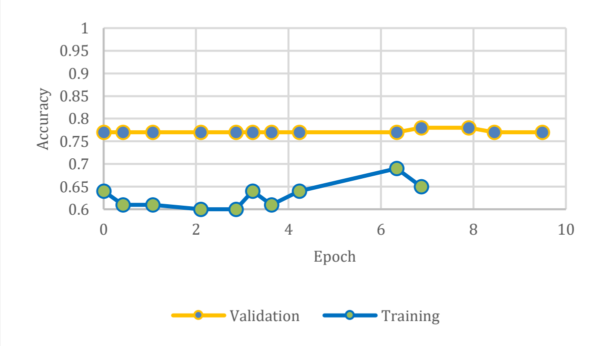

Fig. 3: Training and validation accuracy of Densenet121

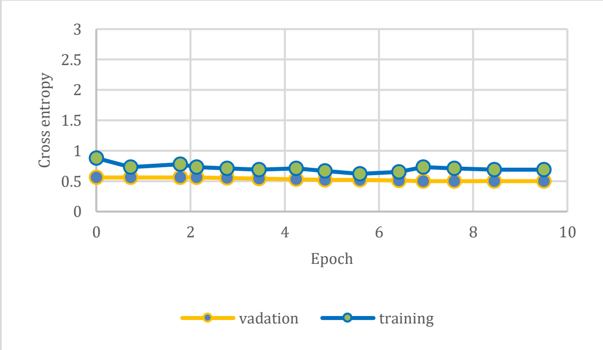

Fig. 4: Training and validation loss of Densenet121

3.2. EfficientNetB2

A scaling approach that uniformly scales the network's depth, breadth, and resolution. It utilized the neural architecture search to create a new baseline system and scaled it up to create the EfficientNets family of deep learning models, which outperform the prior CNNs in terms of accuracy and efficiency. The architecture of efficientNetB2 is shown in Fig 5.

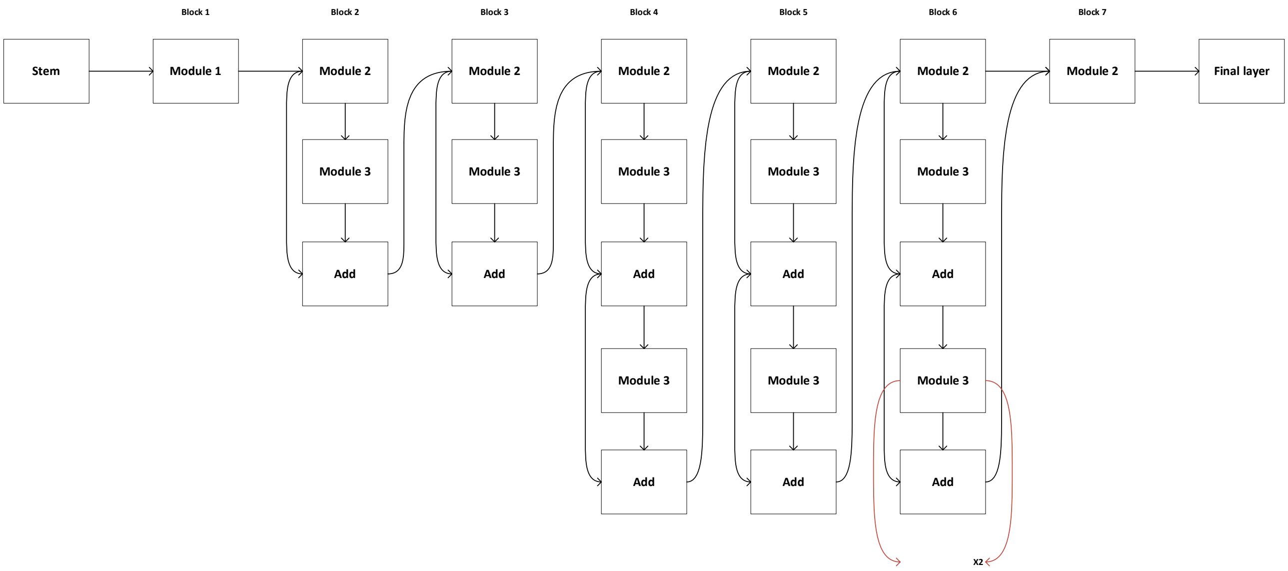

Fig. 5: Architecture of EfficientNetb2

The compound scaling approach is used to scale the network's dimensions. The grid search approach was used to determine the relationship between the multiple scaling dimensions of the baseline network while working with a fixed resource limitation. Using this method, they could determine the proper scaling coefficients for each dimension that needed to be scaled up. The baseline network was scaled by the required size using these factors. Creation of a baseline network using neural architecture search, a technique for automated neural network design. It improves accuracy and efficiency, measured by FLOPS abbreviated as floating-point operations per second. The movable inverted bottleneck convolution is used in this created architecture. Its model architecture is similar to that of the EfficientNetB1 architecture; the only difference is that the number of feature mappings (channels) is variable, which increases the number of parameters.

The EfficientNet models outperform conventional CNNs regarding accuracy and efficiency while lowering parameter size and FLOPS by order of magnitude as shown in below Fig. 6 and Fig. 7.

3.3. Inception-ResNet-v2

The Inception-ResNet-v2 CNN was trained on over a million photos from the used ImageNet collection. The network of systems has 164 type layers that can identify pictures into many different item categories, including the keyboard, console, mouse, and various creatures. Consequently, for a varied range of images, the network has learned rich feature representations. The network takes a 299-

by-299 picture as input and returns a list of estimated class probabilities as output shown in Fig. 8.

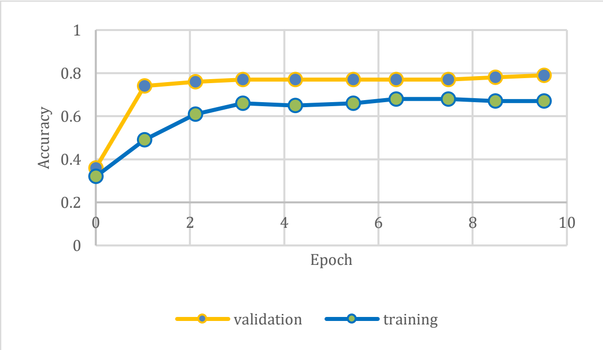

Fig. 6: Training and validation accuracy of EfficientNetb2

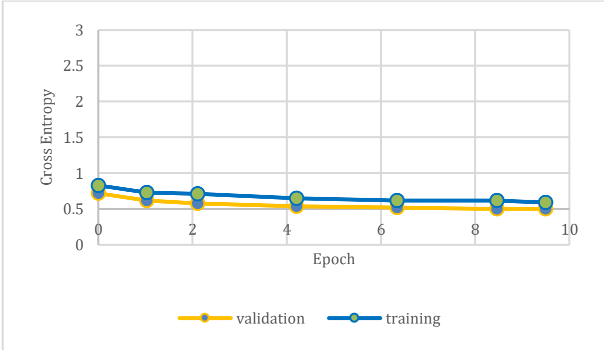

Fig. 7: Training and validation loss of EfficientNetb2

ResNet and Inception have been fundamental to the most significant breakthroughs in the performance of image recognition, delivering excellent results at a reasonable computational cost.

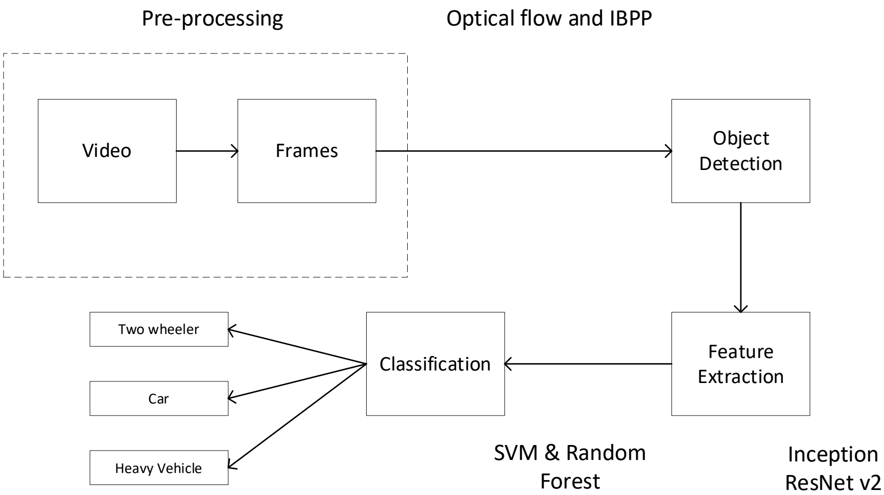

Fig. 8: Architecture of inception-ResNet-v2

Inception-ResNet is a hybrid design that incorporates the residual connections in the Inception architecture. It only uses batch normalization on the top of the standard layers, not on the top position of the summations. It is built on a hybrid of the Residual connections and the used Inception structure. Multiple forms of scaled convolutional type filters are mixed with the residual connections in the Inception-Resnet block. The introduction of residual connections solves the degradation issue caused by the deep structures and shortens the training allocated time are shown in Fig. 9 and Fig. 10.

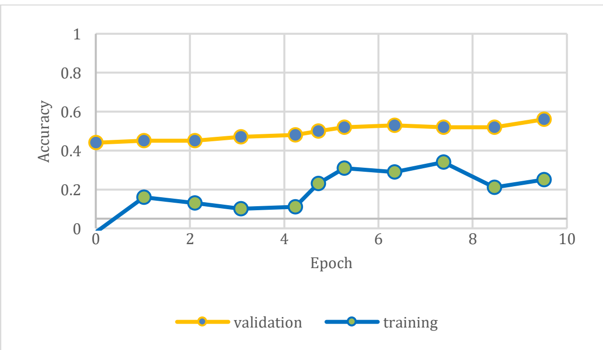

Fig. 9: Training and validation accuracy of inception ResNet-v2

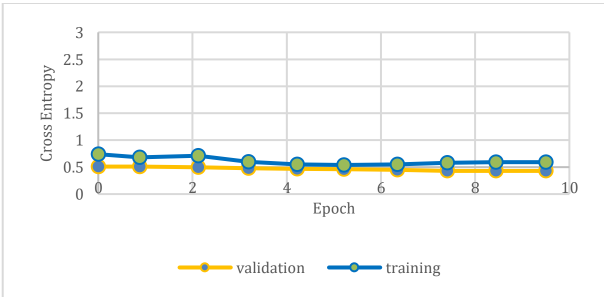

Fig. 10: Training and validation loss of inception ResNet-v2

3.4. Inception V3

The Inception V3 is a model in deep learning for image categorization that is based on CNNs as shown in below Fig. 11. The Inception V3 is an improved version of the fundamental model that is Inception V1, which was launched in 2014 as the GoogLeNet.

When numerous deep layers of convolutions were utilized in a model used, the data was overfitted. To overcome this, the Inception V1 model employs the concept of utilizing many filters of varying sizes on the same type of level. Thus, instead of having deep layers in the inception models, we have similar levels, enabling our system to be larger rather than deeper.

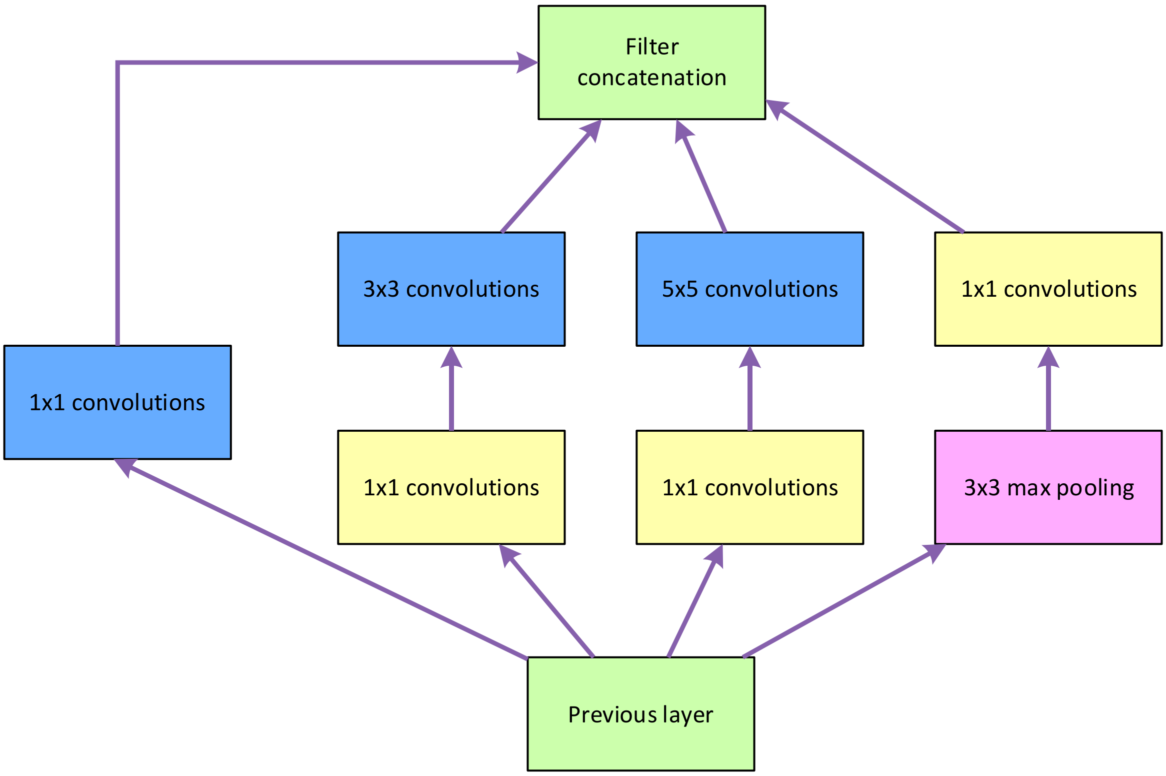

Fig. 11: Architecture of inception V3

The Inception v3 model was published in 2015 and features 42 type layers with a reduced error rate than its used predecessors. Let's have a look at the several improvements that improve the inception V3 type model. Factorization into the Smaller Convolutional layers, Spatial Factorization into the Asymmetric Convolutions, Utility of the Auxiliary Classifiers, and Efficient Grid Size Reduction are the primary adjustments made to the Inception V3 type model. The inception version 3 (V3) model is just an improved and optimized type version of the inception V1 model. It employed several strategies to optimize the network for improved model adaptability. It has superior efficiency of a deeper network than the Inception version 1 (V1) and version 2 (V2) models. Still, its speed is not affected and is computationally made less costly, and it employs auxiliary classifiers as ethical and responsible for its training and validation. Accuracy is shown in Fig. 12. Training and validation loss are shown in Fig. 13.

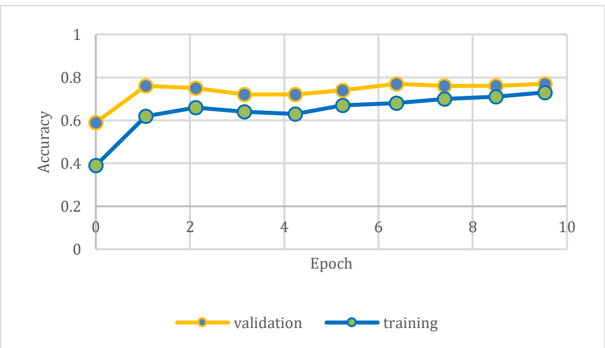

Fig. 12: Training and validation accuracy of Inception v3

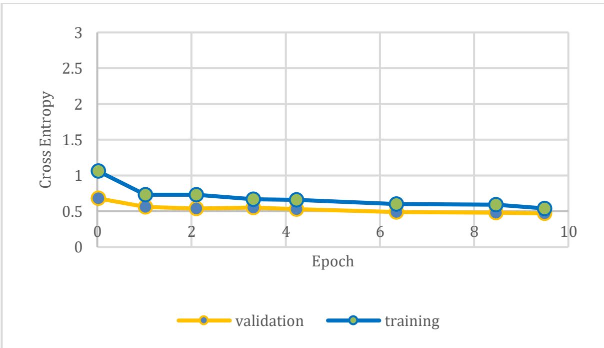

Fig. 13: Training and validation loss of Inception v3

3.5. Mobilenetv2

Mobilenetv2 is based on the depth-wise separable convolutional block that was utilized in the original iteration so this architecture may be regarded as an improved version of mobile net v1. This design includes a new layer module or a new block known as inverted residuals with linear bottlenecks shown in Fig. 14

In Inverted residuals, the given Residual blocks use a type skip link to connect from the beginning and finish of a type of convolutional block. By including these two states, the system has accessibility to prior activations that were not updated in the convolutional layer. This strategy proved to be efficient to create deep networks.

Because many matrix multiplications cannot be limited to a single numerical operation, we employ non-linear activation functions in the standard neural networks. It enables us to construct neural networks with several layers that formed. Simultaneously, the activation function of ReLU, which is often used in neural networks, discards values less than 0. This type of loss of information may be solved by expanding the number of connections to enhance capacity of network.

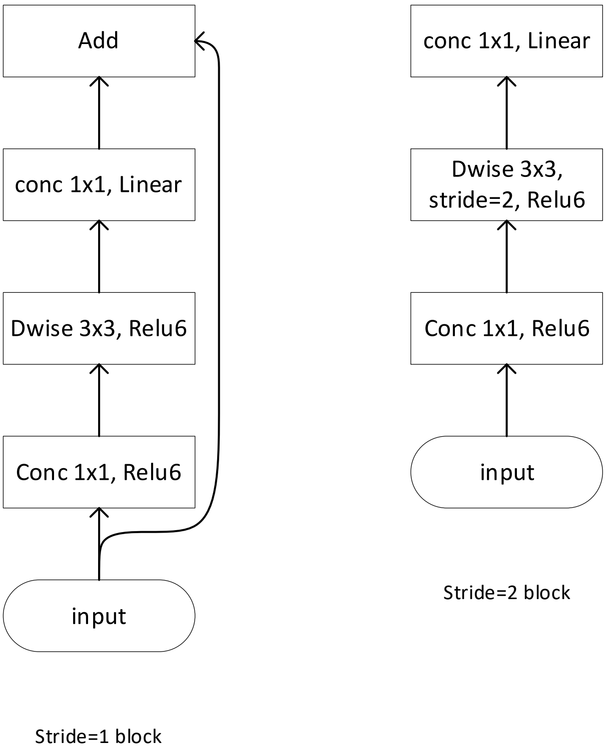

Fig. 14: Architecture of Mobilenetv2

We do the converse with inverted residual blocks, squeezing the layers where the skip connections are coupled. This impacts the performance of the network. The authors proposed a linear bottleneck, in which the final convolution of a residual block has a linear output before it is added to the starting activations.

MobileNetV2 has a narrow-wide-narrow strategy. The initial stage extends the network with a convolution because the ensuing depth-wise convolution already considerably decreases the number of parameters. Following that, another convolution compresses the network to suit the original number of channels. Training and validation accuracy is shown in Fig. 15 and training and validation loss is shown in Fig. 16.

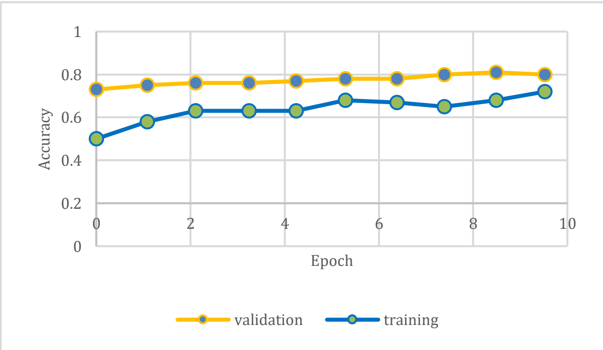

Fig. 15: Training and validation accuracy of MobilenetV2

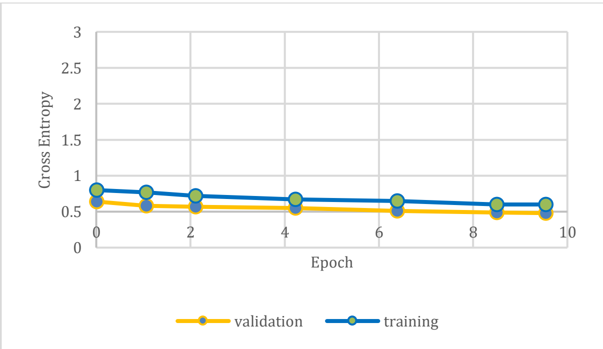

Fig. 16: Training and validation loss of MobilenetV2

3.6. Xception

The Extreme Inception architecture, often known as the Xception architecture, is a CNN design that is composed mainly of depth-wise separable convolution layers. This architecture assumes that mapping cross-channel and spatial correlations in the feature maps of CNNs can be totally decoupled as a primary hypothesis. This hypothesis is a more robust version of the hypothesis supporting the Inception architecture. A linear stack of depth-wise independent convolution layers with remaining connections makes Xception architecture very simple to specify and adjust the architecture as shown in Fig. 17.

Xception is made up of three components they are an injector module that is linked to the target system's kernel. A library with functions and operations can be called from a committed procedure if the raw implementation data is not readily accessible or from a library with processes called from the user application to initiate fault injection. And the primary module that runs on a host machine needs to implement the user experience for fault definition, fault diagnosis injection, and result collection. Training and validation accuracy is shown in Fig. 18 and training and validation loss is shown in Fig. 19. Pre-Tuning and Post-Tuning Results of the above layers are depicted in Table 1.

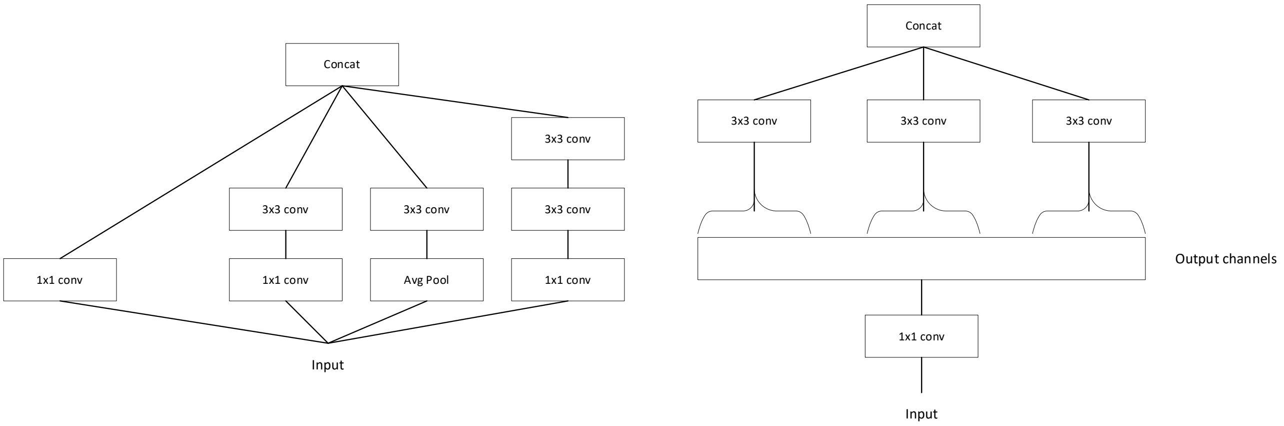

Fig. 17: Architecture of Xception

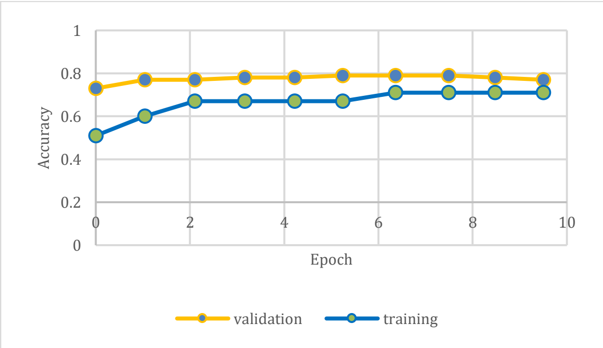

Fig. 18: Training and validation accuracy of Xceptionv2

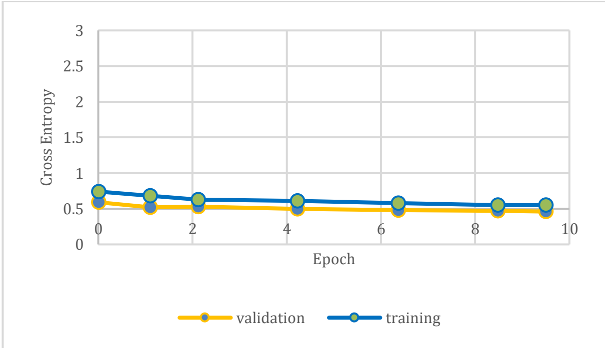

Fig. 19: Training and validation loss of XceptionV2

Table1: Pre-tuning and post-tuning results

Model Name	Pre-Tuning		Post-Tuning	
	Training Accuracy	Validating Accuracy	Training Accuracy	Validating Accuracy
DENSENET121	0.651933	0.772727	0.886740	0.811688
MOBILENETV2	0.715463	0.798701	0.886740	0.850649
XCEPTION	0.734806	0.798701	0.933701	0.896103
EFFICIENTNETB2	0.671270	0.792207	0.889502	0.857142
INCEPTIONRESNETV2	0.698895	0.824675	0.983425	0.863636
INCEPTIONV3	0.723756	0.766233	0.986187	0.876623

4. Conclusion

This research paper presents an approach competent to classify between a normal fundus and degraded retinal tissue because of diabetes. This research aims to facilitate the development of Intelligent Systems that can integrate tightly within the Healthcare ecosystem. Out of all the tested strategies, the observable pattern illustrates that the Deeper Denser Networks such as the Inception Architecture seems to result in efficient scores. The Xception network (Deepest of the lot) outperformed the pack in the pre-tuning and post-tuning cycles as justified by the performance measures used to evaluate in a quantified perspective. The Xception resulted in ~73% and ~79% accuracies in the pre-tuning state but dramatically improved in the post-tuning cycle where it attained ~93% and ~89% accuracy on both training and validation sets, respectively. Additionally, there's significantly less Bias-Variance problem with Inception-based Networks than with the rest, making it an obvious choice for a foundational application. Aim to propagate work extensively and branch it to make state-of-the-art application pipelines using proprietary fine-tuning techniques.

Compliance with ethical standards

Conflict of interest

The author(s) declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

References

Acharya UR, Lim CM, Ng EYK, Chee C, and Tamura T (2009). Computer-based detection of diabetes retinopathy stages using digital fundus images. Proceedings of the Institution of Mechanical Engineers, part H: Journal of Engineering in Medicine, 223(5): 545-553. https://doi.org/10.1243/09544119JEIM486 **PMid:19623908**

Amin J, Sharif M, and Yasmin M (2016). A review on recent developments for detection of diabetic retinopathy. Scientifica, 2016: 6838976. https://doi.org/10.1155/2016/6838976 **PMid:27777811 PMCid:PMC5061953**

Anant KA, Ghorpade T, and Jethani V (2017). Diabetic retinopathy detection through image mining for type 2 diabetes. In the International Conference on Computer Communication and Informatics, IEEE, Coimbatore, India: 1-5. https://doi.org/10.1109/ICCCI.2017.8117738

Calleja JDL, Tecuapetla L, Medina A, Bárcenas E, and Nájera UAB (2014). LBP and machine learning for diabetic retinopathy detection. In the International Conference on Intelligent Data Engineering and Automated Learning, Springer, Salamanca, Spain: 110-117. https://doi.org/10.1007/978-3-319-10840-7_14

Chetoui M, Akhloufi MA, and Kardouchi M (2018). Diabetic retinopathy detection using machine learning and texture features. In the IEEE Canadian Conference on Electrical and Computer Engineering, IEEE, Quebec City, Canada: 1-4. https://doi.org/10.1109/CCECE.2018.8447809

Cnop M, Welsh N, Jonas JC, Jorns A, Lenzen S, and Eizirik DL (2005). Mechanisms of pancreatic β-cell death in type 1 and type 2 diabetes: Many differences, few similarities. Diabetes, 54(suppl_2): S97-S107. https://doi.org/10.2337/diabetes.54.suppl_2.S97 **PMid:16306347**

Doshi D, Shenoy A, Sidhpura D, and Gharpure P (2016). Diabetic retinopathy detection using deep convolutional neural networks. In the 2016 International Conference on Computing, Analytics and Security Trends, IEEE, Pune, India: 261-266. https://doi.org/10.1109/CAST.2016.7914977

Gandhi M and Dhanasekaran R (2013). Diagnosis of diabetic retinopathy using morphological process and SVM classifier. In the 2013 International Conference on Communication and Signal Processing, IEEE, Melmaruvathur, India: 873-877. https://doi.org/10.1109/iccsp.2013.6577181

Gayathri S, Gopi VP, and Palanisamy P (2020). A lightweight CNN for diabetic retinopathy classification from fundus images. Biomedical Signal Processing and Control, 62: 102115. https://doi.org/10.1016/j.bspc.2020.102115

Hemanth DJ, Deperlioglu O, and Kose U (2020). An enhanced diabetic retinopathy detection and classification approach using deep convolutional neural network. Neural Computing and Applications, 32(3): 707-721. https://doi.org/10.1007/s00521-018-03974-0

Jebaseeli TJ, Durai CAD, and Peter JD (2019). Retinal blood vessel segmentation from diabetic retinopathy images using tandem PCNN model and deep learning based SVM. Optik, 199: 163328. https://doi.org/10.1016/j.ijleo.2019.163328

Katsarou A, Gudbjörnsdottir S, Rawshani A, Dabelea D, Bonifacio E, Anderson BJ, Jacobsen LM, Schatz DA, and Lernmark Å (2017). Type 1 diabetes mellitus. Nature Reviews Disease Primers, 3(1): 1-17. https://doi.org/10.1038/nrdp.2017.16 **PMid:28358037**

Kaur P, Chatterjee S, and Singh D (2019). Neural network technique for diabetic retinopathy detection. International Journal of Engineering and Advanced Technology, 8(6): 440-445. https://doi.org/10.35940/ijeat.E7835.088619

Kumaran Y and Patil CM (2018). A brief review of the detection of diabetic retinopathy in human eyes using pre-processing and segmentation techniques. International Journal of Recent Technology and Engineering, 7(4): 310-320.

Kumari GLA, Padmaja P, and Suma JG (2020). Logistic regression and Random forest-based hybrid classifier with recursive feature elimination technique for diabetes classification. International Journal of Advanced Trends in Computer Science and Engineering, 9: 6796–6804. https://doi.org/10.30534/ijatcse/2020/379942020

Kumari GLA, Padmaja P, and Suma JG (2022). A novel method for prediction of diabetes mellitus using deep convolutional neural network and long short-term memory. Indonesian Journal of Electrical Engineering and Computer Science, 26: 404-413. https://doi.org/10.11591/ijeecs.v26.i1.pp404-413

Lee M, Gardin JM, Lynch JC, Smith VE, Tracy RP, Savage PJ, Szklo M, and Ward BJ (1997). Diabetes mellitus and echocardiographic left ventricular function in free-living elderly men and women: The cardiovascular health study. American Heart Journal, 133(1): 36-43. https://doi.org/10.1016/S0002-8703(97)70245-X

Mir A and Dhage SN (2018). Diabetes disease prediction using machine learning on big data of healthcare. In the 2018 Fourth International Conference on Computing Communication Control And Automation (ICCUBEA), IEEE, Pune, India: 1-6. https://doi.org/10.1109/ICCUBEA.2018.8697439

Nakayama M, Abiru N, Moriyama H, Babaya N, Liu E, Miao D, Yu L, Wegmann DR, Hutton JC, Elliott JF, and Eisenbarth GS (2005). Prime role for an insulin epitope in the development of type 1 diabetes in NOD mice. Nature, 435(7039): 220-223. https://doi.org/10.1038/nature03523 **PMid:15889095 PMCid:PMC1364531**

Orlando JI, Prokofyeva E, Del Fresno M, and Blaschko MB (2018). An ensemble deep learning based approach for red lesion detection in fundus images. Computer Methods and Programs in Biomedicine, 153: 115-127. https://doi.org/10.1016/j.cmpb.2017.10.017 **PMid:29157445**

Ozougwu JC, Obimba KC, Belonwu CD, and Unakalamba CB (2013). The pathogenesis and pathophysiology of type 1 and type 2 diabetes mellitus. Journal of Physiology and Pathophysiology, 4(4): 46-57. https://doi.org/10.5897/JPAP2013.0001

Padmaja M and Haritha D (2018). Software effort estimation using grey relational analysis with K-Means clustering. In: Bhateja V, Nguyen B, Nguyen N, Satapathy S, and Le DN (Eds.), Information systems design and intelligent applications: Advances in intelligent systems and computing: 924-933. Volume 672, Springer, Singapore, Singapore. https://doi.org/10.1007/978-981-10-7512-4_92

Rajeswari M, Nithya RJ, Santhiya P, and Saranya P (2019). Diabetic retinopathy detection using tensor flow based on machine learning. International Journal of Innovative Research in Science, Engineering and Technology, 8(3): 1729-1733.

Sadda SR, Nittala MG, Taweebanjongsin W, Verma A, Velaga SB, Alagorie AR, and Aiello LP (2020). Quantitative assessment of the severity of diabetic retinopathy. American Journal of Ophthalmology, 218: 342-352. https://doi.org/10.1016/j.ajo.2020.05.021 **PMid:32446737**

Sadek I, Elawady M, and Shabayek AER (2017). Automatic classification of bright retinal lesions via deep network features. ArXiv Preprint ArXiv:1707.02022. https://doi.org/10.48550/arXiv.1707.02022

Sailasya G and Kumari GLA (2021). Analyzing the performance of stroke prediction using ML classification algorithms. International Journal of Advanced Computer Science and Applications, 12(6): 539-545. https://doi.org/10.14569/IJACSA.2021.0120662

Shankar K, Sait ARW, Gupta D, Lakshmanaprabu SK, Khanna A, and Pandey HM (2020a). Automated detection and classification of fundus diabetic retinopathy images using synergic deep learning model. Pattern Recognition Letters, 133: 210-216. https://doi.org/10.1016/j.patrec.2020.02.026

Shankar K, Zhang Y, Liu Y, Wu L, and Chen CH (2020b). Hyperparameter tuning deep learning for diabetic retinopathy fundus image classification. IEEE Access, 8: 118164-118173. https://doi.org/10.1109/ACCESS.2020.3005152

Voets M, Møllersen K, and Bongo LA (2019). Reproduction study using public data of: Development and validation of a deep learning algorithm for detection of diabetic retinopathy in retinal fundus photographs. PLOS ONE, 14(6): e0217541. https://doi.org/10.1371/journal.pone.0217541 **PMid:31170223 PMCid:PMC6553744**

Zago GT, Andreão RV, Dorizzi B, and Salles EOT (2020). Diabetic retinopathy detection using red lesion localization and convolutional neural networks. Computers in Biology and Medicine, 116: 103537. https://doi.org/10.1016/j.compbiomed.2019.103537 **PMid:31747632**