Eye Disease Detection in Retinal Images using Deep Transfer Learning Techniques

RAJALAKSHMI S[1]
JASSEM M[2]
AMAAN MEER[2]
ANGEL DEBORAH S[1]

[1] Department of Computer Science and Engineering
[2] Department of Electrical and Electronics Engineering
Sivasubramaniya Nadar College of Engineering,
Chennai - 603110, Tamil Nadu, India
[1]{rajalakshmis,angeldeborahs}@ssn.edu.in
[2]jassem193001046@eee.ssn.edu.in,

Abstract. Image processing with the help of machine learning algorithms is breaking barriers in various fields of study, especially in the medical field. Deep learning image classification algorithms have made disease detection based on images in an easy manner thus assists the medical professional to taking quick decisions. This paper discusses various deep learning algorithms and transfer learning methods used to classify various eye diseases. Kaggle Eye dataset is used for this purpose. We compared four deep learning algorithms, namely EfficientNetB3, Inception V3, VGG 19 and Convolutional Neural Network models. Various categories of eye diseases, namely Cataract, Diabetic Retinopathy, Glaucoma are considered for classification with normal eye with the help of the scanned images. The strengths and weaknesses of these models are compared based on Precision, Recall, Accuracy and F1 score. In an identical testing environment, EfficientNet B3 outperforms the other algorithms and provides better accuracy for the classification of eye diseases.

Keywords: Image Processing, Deep Learning, Retinal Disease, Convoluted Neural Networks, Transfer Learning, EfficientNet B3, Inception V3, VGG 19, Cataract, Diabetic Retinopathy, Glaucoma

(Received December 12th, 2023 / Accepted June 28th, 2024)

1 Introduction

Computer Vision has penetrated almost all fields of study. Computers can now identify the things that we think as unimaginable with the help of computer vision and artificial intelligence. It can detect even the minutest of details in images that even humans cannot see with naked eyes [6]. Image processing with machine learning involves the usage of algorithms and models to analyze and manipulate digital images. This can include tasks namely object detection, image classification, image enhancement, image regeneration etc. Deep learning algorithms are trained on large datasets of labeled images in a supervised manner to learn the features and patterns that are important for a specific image processing task [49, 45]. Once the model is trained using the input images, the model is then applied to new images to perform the desired image processing task, such as identifying objects within an image or classifying the images into several categories. Deep Learning (DL) has been increasingly used in image processing tasks such as image classification, object detection, segmentation, and enhancement [37, 35]. One popular approach is to use Convolutional Neural Networks (CNNs), which has been shown to be effective in analyzing images and identifying patterns in visual data.

Recently, Transfer Learning (TL) plays a vital role in deep learning classification techniques [17, 16, 36, 31, 9, 10, 26]. As developing the model from the scratch for a particular problem takes large amount of time and needs large amount of data to learn in a perfect manner, we can take a pre-trained model and fine tune the model for our specific task with a limited amount of data and time. By this way we can transfer the knowledge occurred by the pre-trained model in a different domain to another specific domain [18]. We use Kaggle Dataset containing various images of eyes with diseases namely Cataract, Diabetic Retinopathy, Glaucoma, and normal eye that have been labelled and classified for this purpose [24].

Usage of machine learning and deep learning models in medical field plays a vital role in the early detection of diseases in an accurate manner [25]. Eye being an important organ of the human body, early detection of the diseases that lead to loss of sight or reduction in sight needs to be taken care of. This eye problem causes severity in all the age groups from young children to old aged people. Hence we have worked on the eye images to assist the medical professionals in detecting the eye diseases in the early stage.

This work involved the usage of modified versions of transfer learning image recognition algorithms namely EfficientNet B3 [41], Inception V3 [8], VGG 19 [7], ResNet [30] and a DL model (CNN) [47] to detect and classify a random image of the eye under the four categories. After fine tuning the algorithms based on the dataset's requirements, we compare the models and reach a conclusion of the best model for the eye disease classification task based on their F1 Score, Accuracy, Recall and Precision values. Section 2 discuss about the related works and dataset is described in section 3. Need for deep learning and transfer learning are described in sections 4, 5 and 6. Sections 7 to 12 illustrate the various deep learning models used for eye disease detection. Results are discussed in section in 13 and section 14 concludes with the future work.

2 Literature Survey

Gulshan et al., reported a groundbreaking work that established the viability of employing CNNs for diabetic retinopathy identification with excellent accuracy and sensitivity. This study [13] served as a platform for further research and created the foundations for employing neural networks in eye disease diagnostics. Furthermore, AbrÃ moff et al., broadened the integration of deep learning with classical machine learning methods in order to gain improved performance in diagnosing diabetic retinopathy [1].

Zhang et al., expanded the use of deep learning to categorise a wide range of eye illnesses beyond diabetic retinopathy, demonstrating the potential for multi-class classification challenges [49]. Prasad et al., developed a multi-label deep network paired with a polar transformation strategy for precise optic disc and cup segmentation in the context of certain eye disorders essential in glaucoma diagnosis [27].

Furthermore, the Kaggle Diabetic Retinopathy Detection Challenge drew a large number of researchers who proposed unique neural network designs and image processing approaches for the categorization of eye diseases [27]. This competition gave insightful information about several neural network techniques and their performance on benchmark datasets [29, 22].

Sarki et. al., demonstrated the benefits of employing deep learning models in the detection of diabetic retinopathy [33]. Venhuizen et al., also focused on the identification and characterization of intra retinal cysts in OCT images using deep learning, revealing the potential for neural networks in OCT-based disease diagnostics [1].

Furthermore, Gargeya and Leng demonstrated the benefits of utilizing deep learning models in identifying diabetic retinopathy are demonstrated in [18], while Rajalakshmi and Subashini complete assessment of current breakthroughs in diabetic retinopathy diagnosis using deep learning techniques are given in [43]. Venhuizen et al., focused on the identification and characterization of intraretinal cysts in OCT images using deep learning, revealing the potential for neural networks in OCT-based disease diagnostics [1].

Zhou Y. et al., demonstrate the efficacy of the proposed DNN model using the discrete state transition mechanism [50]. When compared to conventional deep learning models and traditional grading systems, the technique delivers higher accuracy in cataract classification.

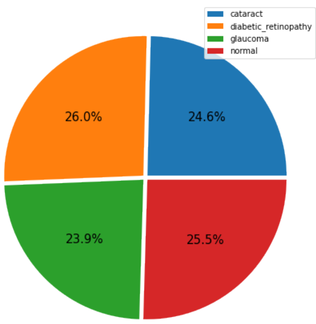
The model's iterative structure allows it to adaptively modify predictions, resulting in increased accuracy and dependability. The researchers also examine the suggested method's practical ramifications, imagining its use in clinical settings to assist ophthalmologists in efficiently assessing cataract severity.

3 About the Dataset

This eye disease dataset contains retinal images of eye diseases namely Cataract, Diabetic Retinopathy, Glaucoma, and a normal healthy eye. Under each class there are roughly 1000 retinal images. This Kaggle dataset [1] contains images collected from various sources such as IDRiD, Oculur recognition and HRF. The distribution of the data across each class is shown in Table 1. Class label 0 denotes cataract, 1 denotes diabetic retinopathy, 2 denotes glaucoma and 3 denotes normal healthy eye. The percentage of distribution across the various categories is shown in Figure 1. The dataset is a benchmark dataset and is removed from noise. Hence we can directly give the image as vectors to the deep learning models. The preprocessing involves only image to vector conversion.

Table 1: Data distribution across different classes

Class label (Eye Disease)	Size
0 (cataract)	1038
1 (diabetic retinopathy)	1098
2 (glaucoma)	1007
3 (healthy eye)	1074
Total	**4217**



Distribution.png

Figure 1: Percentage distribution of Eye image dataset

4 Deep Learning in Image Processing

Deep learning has been extensively used in image processing, detection and classification tasks [38] because of its ability to understand the intricacies of images. Given that they are effective at processing grid-like input of photographs, convolutional neural networks (CNNs) is a common deep learning architecture utilised for these tasks. A common method for categorising photos uses a pre-trained CNN as a feature extractor, where the CNN is trained on a huge dataset of images and the final fully connected layers are removed [21, 48]. The output of the remaining layers, known as feature maps, is then utilised as a condensed representation of the image that may be fed into a classifier like a logistic regression model or a support vector machine (SVM) [23].

In medical image processing tasks like segmentation, classification, and restoration, deep learning has been extensively applied. Fully convolutional neural networks (FCNs), like U-Net, is a popular method for segmenting medical images since they are made to take an image as input and produce a segmentation mask [14]. These networks have demonstrated success in tasks including tumour, organ, and blood vessel segmentation and can be trained on enormous datasets of annotated medical pictures. CNNs are frequently used for medical picture classification. For instance, CNNs have been trained to discriminate between benign and malignant mammograms and to categorise chest X-rays as normal or abnormal.

5 Need for Transfer Learning

Deep learning algorithms such as CNN usually require substantial amounts of labelled data to successfully classify an image. The amount of data available in the real world is usually limited which in turn inhibits the accuracy of a deep learning model [11]. This problem is solved with the help of Transfer Learning (TL) [51, 20]. Just as how humans use their experience in a particular activity to perform another activity in a more efficient manner provided these activities are related or similar, transfer learning is used to improve the accuracy and detection in a particular given dataset or task by training the model in another similar dataset where there is ample number of labelled examples available.

For example, a person who plays a particular racquet sport tends to be faster at learning a new racquet sport in comparison to a person who is new at this since both activities have similarities, that is hand-eye coordination.Hence in transfer learning, information from a related domain is used to increase performance and decrease the amount of labelled data and time required for learning in another domain. It is possible that if the two datasets are far apart or have little in common, it might have either no effect or a negative effect in some cases.Using transfer learning with CNN makes the information transfer occur at the parametric level. When we use TL in combination with CNN, a CNN model that is trained well in the source dataset, the generic features (parameters) that it learns can be leveraged to learn a classification task from the target dataset which has relatively lesser amount of data available.

[1] https://www.kaggle.com/datasets/gunavenkatdoddi/eye-diseases-classification

The different types of transfer learning are:
i. Inductive Transfer Learning
ii. Transductive Transfer Learning
iii. Unsupervised Transfer Learning

In this proposed work, Inductive Transfer Learning is used, and we shall restrict our discussion to that. In Inductive Transfer Learning, the dataset in which the model has been trained is not necessarily similar to the dataset that it is being used in as target. In this type of TL, some amount of labelled data is required in the target dataset. Using the biases that were set in the source dataset, the model tries to improve in the target dataset.

In this paper pre-trained deep learning models were employed for identifying the diseases from retinal images, and different layers were fine-tuned as per the target dataset requirements and made it to categorize the various eye disorders. There are multiple Transfer Learning based DL models that are available such as VGG16, VGG19, EfficientNet, Inception V3 etc. that use TL with CNN to classify images. All the different models discussed in this paper have already been trained in the ImageNet dataset and then have been retrained with the Eye Dataset from Kaggle for transfer learning.

6 Importance of Transfer Learning

Deep Convolutional Neural Networks (DCNN) nowadays are yielding amazing results in the field of computer vision and image processing. The problem lies in the fact that in order to train a CNN, huge amounts of data are required along with a combination of powerful computers with GPUs with the facility of running them for long periods of time. This can be eliminated with the help of transfer learning. Apart from this, designing a CNN is a tremendous task. Hence, by using pre-trained models such as VGG-19, Inception V3 etc., image classification for various tasks can be simplified [39].

7 Convolutional Neural Network Model for Image Classification

7.1 About the method

A CNN consists of multiple layers [32], including:
1. Convolutional layers: These layers apply a set of filters on the images to recognize the important part of the image that is used to extract important features such as edges, shapes etc. The result of the convolution layers is a collection of feature maps, which are compressed representations of images.
2. Pooling layers: These layers are used to shrink the spatial size of the feature maps while keeping the most important data intact. Applying a pooling procedure like max pooling, which chooses the highest value from a narrow window that moves over the feature maps, does this. Pooling layers are frequently employed to simplify the network's computations and increase the features' resistance to subtle input translations.
3. Fully connected layers: These layers use the classification results from the pooling layers to sort the input images. A non-linear decision border between the classes can be taught to fully connected layers, which are like the layers in a conventional feedforward neural network.
4. Activation layers: These layers add non-linearity to the network, allowing it to learn more complex features.

Figure 2 shows the arrangement of the layers in the CNN model. Stochastic Gradient Descent (SGD) and its derivatives, a type of backpropagation algorithm used to train CNNs, are used to alter the weights of the network to reduce the discrepancy between the projected output and the actual output. CNNs have been shown to be accurate in image classification, object detection, and many other image processing tasks. They have also been used in other areas such as natural language processing, speech recognition and even drug discovery. In this proposed work, we have designed a basic CNN from scratch and train it with Kaggle's eye disease classification dataset.

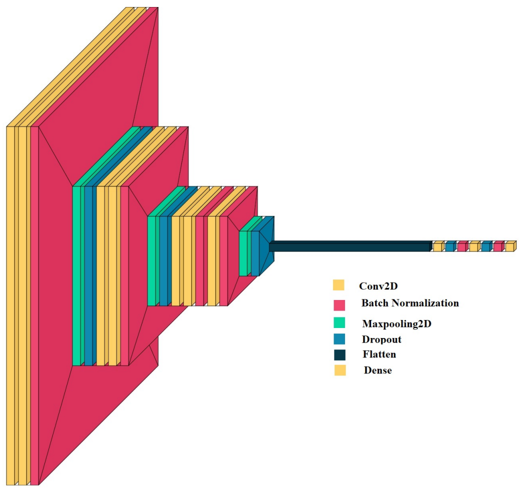


Figure 2: Convolution Layers for CNN

7.2 Results

This section describes the results of working of CNN model on eye disease dataset. Figure 3 depicts the accuracy and loss across the various epochs for training and validating the model. Figure 4 shows the confusion matrix for each target disease classes in the dataset. Table 2 describes the evaluation metrics like precision, recall, F1-score for each class and the overall accuracy of the model and macro average of various metrics.

Histogram.png

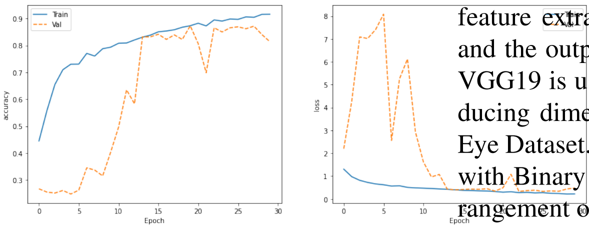
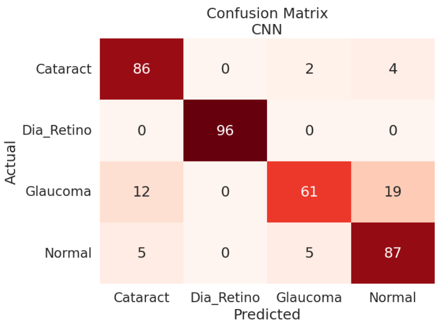


Figure 3: Accuracy vs No. of Epoches & Loss vs No. of Epoches for CNN



CM.png

Figure 4: Confusion Matrix for CNN

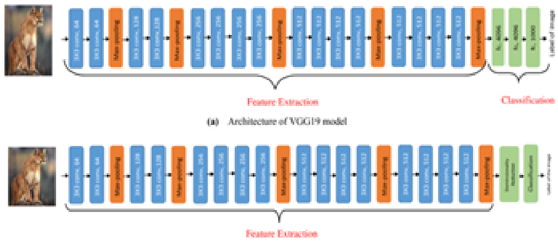
Table 2: Classification Metrics for CNN

Type of Disease	Precision	Recall	F1 Score
Cataract	0.83	0.93	0.88
Diabetic Retinopathy	1.00	1.00	1.00
Glaucoma	0.90	0.66	0.76
Normal	0.79	0.90	0.84
Accuracy	-	-	0.88
Macro Average	0.88	0.87	0.87
Weighted Average	0.88	0.88	0.87

8 VGG-19 Model

8.1 About the model

The VGG-19 network developed in 2014 uses a CNN with 19 layers, including 16 convolutional layers and 3 fully linked layers, to divide the input images into 1000 different object categories [3]. The ImageNet database, which contains a million images divided into 1000 classes, served as the training material for VGG19 [28, 5]. It has gained a lot of popularity due to the inclusion of numerous 3x3 filters in each convolution layer. For feature extraction, 16 convolution layers are used, while 3 layers are used for classification. A max pooling layer is placed after the five groups of segmented feature extraction layers. An image of size 224x224 and the output is the label of the image. In this work, VGG19 is used for feature extraction proceeded by reducing dimensions as per requirements of the current Eye Dataset. The Adam Optimizer has been used along with Binary Cross Entropy. Figure 5 describes the arrangement of layers in VGG-19 network [4].

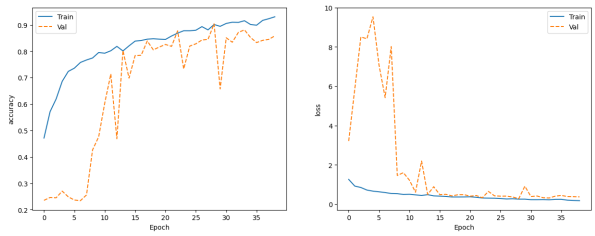


arch.png

Figure 5: Architecture diagram of VGG-19

8.2 Results

This section describes the results of VGG-19 network model for the eye disease dataset. Figure 6 shows the accuracy and the loss for the VGG-19 model for various epochs of training and validation dataset. Figure 7 shows the confusion matrix for the four class labels. Table 3 depicts the evaluation metrics for VGG-19.



Hist.png

Figure 6: Accuracy vs No. of Epoches & Loss vs No. of Epoches for VGG-19

9 Inception V3

9.1 About the model

Inception V3 is a pre-trained deep learning model used for image recognition [46]. It has been trained on the

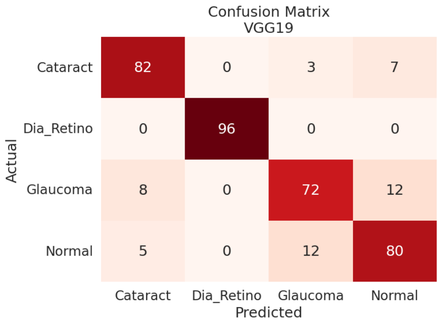
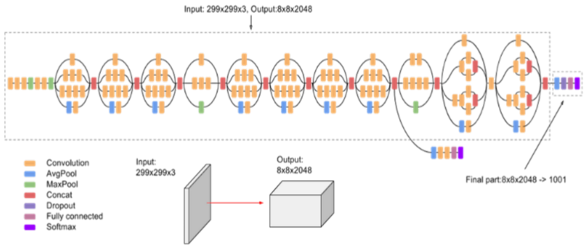


Figure 7: Confusion Matrix for VGG-19



arch.png

Figure 8: Architecture diagram for Inception V3 model

Table 3: Evaluation metrics using VGG-19

Type of Disease	Precision	Recall	F1 Score
Cataract	0.86	0.89	0.88
Diabetic Retinopathy	1.00	1.00	1.00
Glaucoma	0.83	0.78	0.80
Normal	0.81	0.82	0.82
Accuracy	-	-	0.88
Macro Average	0.87	0.87	0.87
Weighted Average	0.88	0.88	0.88

ImageNet dataset, which contains over 1 million images across 1000 classes, and has shown an accuracy of 78.1% on this dataset [42]. It has 48 layers in total and is based on transfer learning, where its layers and dimensions can be modified to suit a specific dataset. This pre-trained Inception V3 model is modified by varying its layers and dimensions to suit the eye dataset.It uses multiple convolution layers in parallel to extract features from an input image. These layers are called Inception modules. These modules are stacked to form a deep network followed by fully connected layers for hierarchical features of an image, it can learn extremely complex representations. The key feature of Inception V3is the use of a variety of convolutional layer sizes and pooling operations, this enables it to be able to recognize very small objects from a given image. The architecture of the Inception V3 model is shown in Figure 8 [40].

V3 Histogram.png

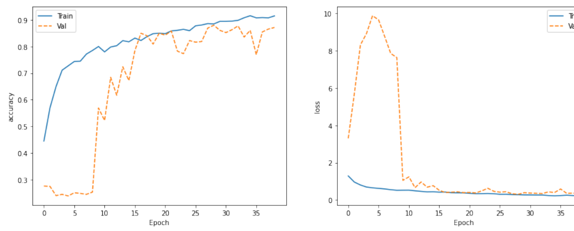


Figure 9: Accuracy vs No. of Epoches & Loss vs No. of Epoches for Inception V3 model

9.2 Results

The results of the Inception V3 model are explained in this section. Figure 9 shows the accuracy and loss graph of various epochs for the training and validation dataset. Table 4 represents the evaluation metrics for the model. Figure 10 shows the confusion matrix for the same.

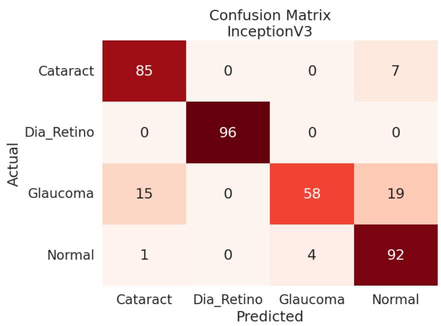


Figure 10: Confusion matrix for Inception V3

Table 4: Evaluation metrics using Inception V3

Type of Disease	Precision	Recall	F1 Score
Cataract	0.86	0.88	0.87
Diabetic Retinopathy	1.00	1.00	1.00
Glaucoma	0.92	0.93	0.81
Normal	0.79	0.93	0.85
Accuracy	-	-	0.89
Macro Average	0.89	0.88	0.88
Weighted Average	0.89	0.89	0.88

10 EfficientNet B3

10.1 About the model

The EfficientNet B3 is a deep convolutional neural network architecture designed for image classification. It used a combination of depth wise separable convolutions and global average pooling to reduce the computational cost of the network while maintaining accuracy. The architecture design makes it very scalable, and it can easily be adjusted to different computational budgets and accuracy targets. The B3 in the name refers to the scaling coefficients applied to the network which determine the size and capacity. This model is also trained on the ImageNet dataset. This model can achieve extremely high accuracy of a variety of image classification benchmarks and is also able to be more computationally efficient than many architectures. This architecture was developed by Google researchers in 2019. Figure 11 shows the architecture of the EfficientNet B3 [41].

B3 architecture.png

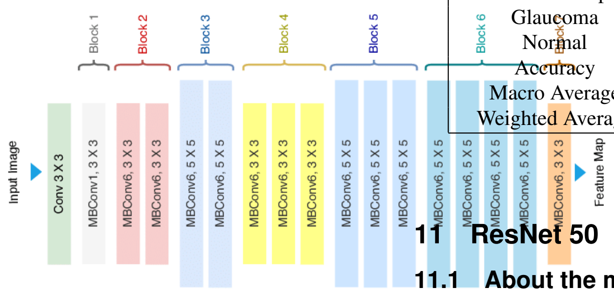


Figure 11: Architecture for Efficient Net B3

10.2 Results

This section describes the results of the EfficientNet B3 for the eye disease dataset. Figure 12 depicts the accuracy and loss graph and Figure 13 shows the confusion matrix for EfficientNet B3 model. Table 5 displays the metrics to evaluate the model on the eye dataset.

Histogram.png

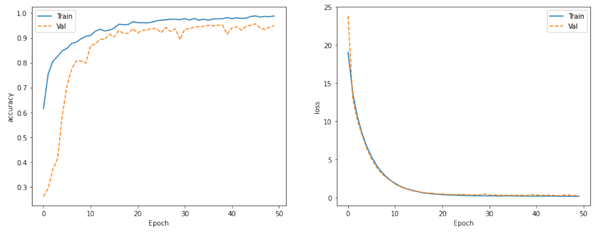


Figure 12: Accuracy vs No. of Epoches & Loss vs No. of Epoches for EfficientNet B3

Net.png

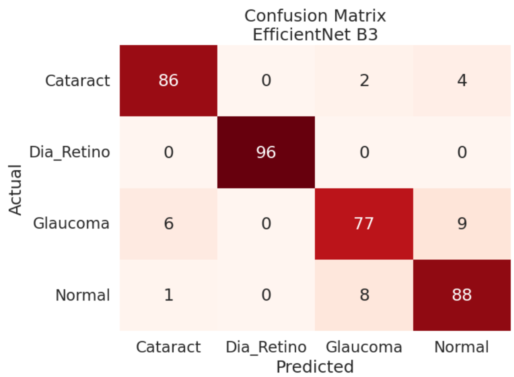


Figure 13: Confusion matrix for EfficientNet B3

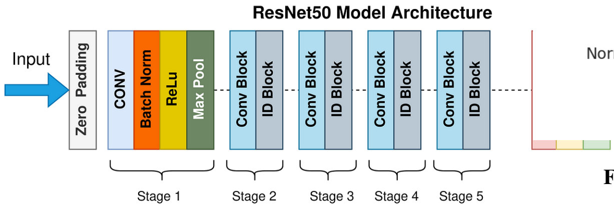
Table 5: Evaluation metrics for EfficientNet B3

Type of Disease	Precision	Recall	F1 Score
Cataract	0.95	0.96	0.95
Diabetic Retinopathy	0.99	1.00	0.99
Glaucoma	0.87	0.92	0.89
Normal	0.91	0.84	0.88
Accuracy	-	-	0.93
Macro Average	0.93	0.93	0.93
Weighted Average	0.93	0.93	0.93

11 ResNet 50

11.1 About the model

This deep CNN architecture is being used for image classification, object detection and computer vision tasks [34, 44]. It was first introduced in 2015 by Kaiming He, Xiangyu Zhang, Shaoqing Ren, and Jian Sun. The most salient feature of this CNN architecture is that it skips or shortcuts connections which help it bypass some deep layers enabling an easier flow of information through the network hence tacking the "vanishing gradient" problem that tends to occur in deep convolutional networks. This architecture has 50 layers making it a very deep mode enabling it to learn complex features and patterns. It has batch normalization improving training speed and stability of the network. It also incorporates a global average pooling to reduce feature map size and create a fixed-length feature vector for each image. Figure 14 shows the architecture of ResNet50 [19].

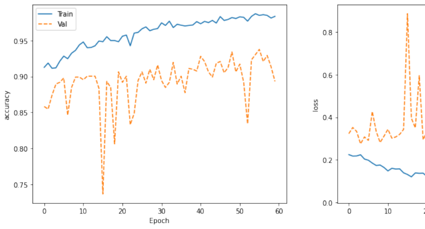


50 arch.png

Figure 14: Architecture for ResNet 50

11.2 Results

The results of ResNet 50 model are described here. Figure 15 shows the accuracy and loss graph for various epochs and Figure 16 shows the confusion matrix for ResNet 50 model. Table 6 describes the precision, recall, F1-score and accuracy values for the model.



50 Histogram.png

Figure 15: Accuracy vs No. of Epoches & Loss vs No. of Epoches for ResNet-50

Table 6: Evaluation metrics for ResNet 50

Type of Disease	Precision	Recall	F1 Score
Cataract	0.93	0.92	0.93
Diabetic Retinopathy	1.00	1.00	1.00
Glaucoma	0.80	0.89	0.84
Normal	0.90	0.80	0.85
Accuracy	-	-	0.90
Macro Average	0.91	0.90	0.90
Weighted Average	0.91	0.90	0.90

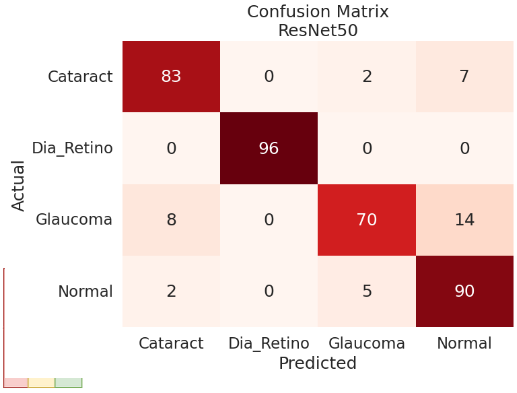


Figure 16: Confusion matrix for ResNet 50

12 Inception-Resnet V2

12.1 About the model

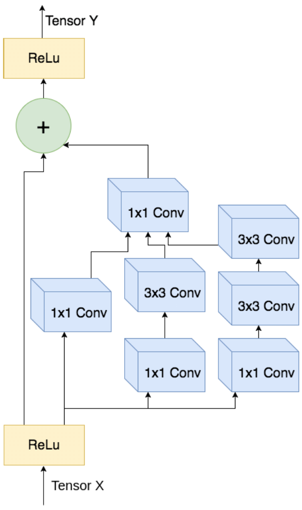
Inception-ResNet V2 is a deep CNN that combines Inception and ResNet architectures to achieve improved accuracy and performance on image recognition tasks [2, 43]. The parallel convolutional filters feature available in Inception also called as Inception modules are used to extract features from input images. This allows the network to capture a wide range of feature sizes and achieve high accuracy on Image recognition tasks. This model also uses residual connections, as discussed before and this reduces the problem of vanishing gradient. This is done by adding the input to the output of each block of layers so that it can learn the residual features instead of the entire mapping. It also incorporates a unique stem architecture that combines convolutional pooling layers to extract features from images. This helps reduce spatial dimensions of the input as well as reduce the number of channels which in turn helps to process images more efficiently. This model has a very deep neural network architecture with over 150 layers in total. This allows it to learn highly complex images leading to improved accuracy [15]. Figure 17 shows the architecture of the model [12].

12.2 Results

This section explains the results of Inception ResNet model. The accuracy and loss for the model across different epochs are shown in Figure 18 and the confusion matrix is shown in Figure 19. Table 7 depicts the evaluation metrics for the Inception ResNet model.

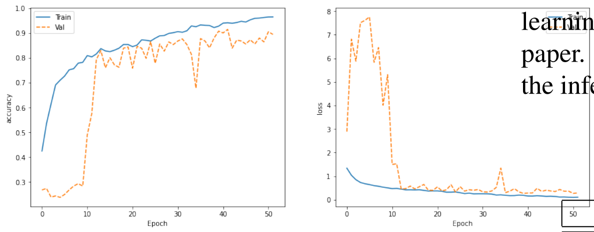
13 Results and Discussion

A comparative analysis of the performance of all the algorithms has been analyzed for eye disease classi-



V2 Architecture.png

Figure 17: Architecture for Inception Resnet V2



histo.png

Figure 18: Accuracy vs No. of Epoches & Loss vs No. of Epoches for Inception Resnet V2

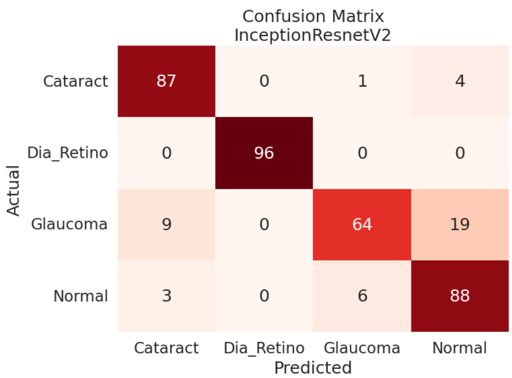


Figure 19: Confusion matrix for Inception Resnet V2

Table 7: Evaluation metrics for Inception Resnet V2

Type of Disease	Precision	Recall	F1 Score
Cataract	0.95	0.93	0.94
Diabetic Retinopathy	1.00	1.00	1.00
Glaucoma	0.90	0.83	0.86
Normal	0.85	0.93	0.89
Accuracy	-	-	0.92
Macro Average	0.92	0.92	0.92
Weighted Average	0.92	0.92	0.92

fication. The EfficientNet B3 algorithm performs the best for overall classification, with an accuracy of 93%. Also, the other transfer learning algorithms like InceptionV3, ResNet50 also performs as close to that of EfficientNet B3 in terms of overall macro average, F1 score and accuracy. Also, the loss function is reduced significantly for the first 40 epochs after that there is no significant improvement in the reduction of the loss function, for EfficientNet B3. So EfficientNet B3 trained for 40 epochs is the optimum for this eye disease classification problem and shows the importance of transfer learning. Table 8 shows the overall comparison of different deep learning and transfer learning techniques used in this paper. This model can be used in the scan labs to give the inferences and interpretations in the lab report.

Table 8: COMPARISION OF ALL MODELS

Algorithm	Prec	Recall	F1	Acc
CNN	0.88	0.88	0.87	0.88
Inception V3	0.89	0.88	0.88	0.89
EfficientNet B3	**0.93**	**0.93**	**0.93**	**0.93**
ResNet-50	0.91	0.90	0.90	0.90
Inception ResNet V2	0.92	0.92	0.92	0.92
VGG-19	0.88	0.88	0.88	0.88

14 Conclusion and Future Work

Our aim is to develop an automatic eye disease detection system for identifying the different types of eye diseases like the cataract, diabetic retinopathy and glaucoma from the normal healthy eye. We have employed the different techniques like CNN, ResNet 50, EfficientNet B3, Inception V3, VGG-19 and InceptionResNet V2 on the Kaggle eye disease dataset to classify the eye images across the four output labels. From the experiments, it is clearly evident that the deep transfer learning technique EfficientNet B3 gives better accuracy than other models and all the other deep transfer learning techniques are close to it. In future we would like to investigate the extraction of features important for eye disease classification and experiment on feature augmentation. Correlation of the eye images with the other clinical details of the patient can be analyzed for prescriptive analysis in future.

References

[1] Abràmoff, M. D., Lou, Y., Erginay, A., Clarida, W., Amelon, R., Folk, J. C., and Niemeijer, M. Improved automated detection of diabetic retinopathy on a publicly available dataset through integration of deep learning. *Investigative ophthalmology & visual science*, 57(13):5200–5206, 2016.

[2] Baldassarre, F., Morín, D. G., and Rodés-Guirao, L. Deep koalarization: Image colorization using cnns and inception-resnet-v2. *arXiv preprint arXiv:1712.03400*, 2017.

[3] Bansal, M., Kumar, M., Sachdeva, M., and Mittal, A. Transfer learning for image classification using vgg19: Caltech-101 image data set. *Journal of ambient intelligence and humanized computing*, pages 1–12, 2021.

[4] Bansal, M., Kumar, M., Sachdeva, M., and Mittal, A. Transfer learning for image classification using vgg19: Caltech-101 image data set. *Journal of ambient intelligence and humanized computing*, pages 1–12, 2021.

[5] Carvalho, T., De Rezende, E. R., Alves, M. T., Balieiro, F. K., and Sovat, R. B. Exposing computer generated images by eyeâs region classification via transfer learning of vgg19 cnn. In *2017 16th IEEE international conference on machine learning and applications (ICMLA)*, pages 866–870. IEEE, 2017.

[6] Cheng, J., Tian, S., Yu, L., Gao, C., Kang, X., Ma, X., Wu, W., Liu, S., and Lu, H. Resganet: Residual group attention network for medical image classification and segmentation. *Medical Image Analysis*, 76:102313, 2022.

[7] Dey, N., Zhang, Y.-D., Rajinikanth, V., Pugalenthi, R., and Raja, N. S. M. Customized vgg19 architecture for pneumonia detection in chest x-rays. *Pattern Recognition Letters*, 143:67–74, 2021.

[8] Dong, N., Zhao, L., Wu, C.-H., and Chang, J.-F. Inception v3 based cervical cell classification combined with artificially extracted features. *Applied Soft Computing*, 93:106311, 2020.

[9] dos Santos, M. R., Batista, A. P., Rosa, R. L., Saadi, M., Melgarejo, D. C., and Rodríguez, D. Z. Asqm: Audio streaming quality metric based on network impairments and user preferences. *IEEE Transactions on Consumer Electronics*, 69(3):408–420, 2023.

[10] Dos Santos, M. R., Rodriguez, D. Z., and Rosa, R. L. A novel qoe indicator for mobile networks based on twitter opinion ranking. In *2023 International Conference on Software, Telecommunications and Computer Networks (SoftCOM)*, pages 1–6. IEEE, 2023.

[11] Gaur, L., Bhatia, U., Jhanjhi, N., Muhammad, G., and Masud, M. Medical image-based detection of covid-19 using deep convolution neural networks. *Multimedia systems*, 29(3):1729–1738, 2023.

[12] Granger, E., Kiran, M., Blais-Morin, L.-A., et al. A comparison of cnn-based face and head detectors for real-time video surveillance applications. In *2017 Seventh International Conference on Image Processing Theory, Tools and Applications (IPTA)*, pages 1–7. IEEE, 2017.

[13] Gulshan, V., Peng, L., Coram, M., Stumpe, M. C., Wu, D., Narayanaswamy, A., Venugopalan, S., Widner, K., Madams, T., Cuadros, J., et al. Development and validation of a deep learning algorithm for detection of diabetic retinopathy in retinal fundus photographs. *jama*, 316(22):2402–2410, 2016.

[14] Jain, L., Murthy, H. S., Patel, C., and Bansal, D. Retinal eye disease detection using deep learning. In *2018 Fourteenth International Conference on Information Processing (ICINPRO)*, pages 1–6. IEEE, 2018.

[15] Kamble, R. M., Chan, G. C., Perdomo, O., Kokare, M., Gonzalez, F. A., Müller, H., and Mériaudeau, F. Automated diabetic macular edema (dme) analysis using fine tuning with inception-resnet-v2 on oct images. In *2018 IEEE-EMBS Conference on Biomedical Engineering and Sciences (IECBES)*, pages 442–446. IEEE, 2018.

[16] Kaur, M. and Kamra, A. Detection of retinal abnormalities in fundus image using transfer learning networks. *Soft Computing*, 27(6):3411–3425, 2023.

[17] Kim, H. E., Cosa-Linan, A., Santhanam, N., Jannesari, M., Maros, M. E., and Ganslandt, T. Transfer learning for medical image classification: a literature review. *BMC medical imaging*, 22(1):69, 2022.

[18] Kim, H. E., Cosa-Linan, A., Santhanam, N., Jannesari, M., Maros, M. E., and Ganslandt, T. Transfer learning for medical image classification: a literature review. *BMC medical imaging*, 22(1):69, 2022.

[19] Koonce, B. and Koonce, B. Resnet 50. *Convolutional Neural Networks with Swift for Tensorflow: Image Recognition and Dataset Categorization*, pages 63–72, 2021.

[20] Kora, P., Ooi, C. P., Faust, O., Raghavendra, U., Gudigar, A., Chan, W. Y., Meenakshi, K., Swaraja, K., Plawiak, P., and Acharya, U. R. Transfer learning techniques for medical image analysis: A review. *Biocybernetics and Biomedical Engineering*, 42(1):79–107, 2022.

[21] Krueangsai, A. and Supratid, S. Effects of shortcut-level amount in lightweight resnet of resnet on object recognition with distinct number of categories. In *2022 International Electrical Engineering Congress (iEECON)*, pages 1–4. IEEE, 2022.

[22] Kumar, S., Pathak, S., and Kumar, B. Automated detection of eye related diseases using digital image processing. *Handbook of multimedia information security: techniques and applications*, pages 513–544, 2019.

[23] Liu, Q., Yu, L., Luo, L., Dou, Q., and Heng, P. A. Semi-supervised medical image classification with relation-driven self-ensembling model. *IEEE transactions on medical imaging*, 39(11):3429–3440, 2020.

[24] Miranda, E., Aryuni, M., and Irwansyah, E. A survey of medical image classification techniques. In *2016 international conference on information management and technology (ICIMTech)*, pages 56–61. IEEE, 2016.

[25] Nagpal, D., Alsubaie, N., Soufiene, B. O., Alqahtani, M. S., Abbas, M., and Almohiy, H. M. Automatic detection of diabetic hypertensive retinopathy in fundus images using transfer learning. *Applied Sciences*, 13(8):4695, 2023.

[26] Okey, O. D., Udo, E. U., Rosa, R. L., Rodríguez, D. Z., and Kleinschmidt, J. H. Investigating chatgpt and cybersecurity: A perspective on topic modeling and sentiment analysis. *Computers & Security*, 135:103476, 2023.

[27] Prasad, K., Sajith, P., Neema, M., Madhu, L., and Priya, P. Multiple eye disease detection using deep neural network. In *TENCON 2019-2019 IEEE Region 10 Conference (TENCON)*, pages 2148–2153. IEEE, 2019.

[28] Rajinikanth, V., Joseph Raj, A. N., Thanaraj, K. P., and Naik, G. R. A customized vgg19 network with concatenation of deep and handcrafted features for brain tumor detection. *Applied Sciences*, 10(10):3429, 2020.

[29] Ravudu, M., Jain, V., and Kunda, M. M. R. Review of image processing techniques for automatic detection of eye diseases. In *2012 Sixth International Conference on Sensing Technology (ICST)*, pages 320–325. IEEE, 2012.

[30] Reddy, A. S. B. and Juliet, D. S. Transfer learning with resnet-50 for malaria cell-image classification. In *2019 International Conference on Communication and Signal Processing (ICCSP)*, pages 0945–0949. IEEE, 2019.

[31] Rezaie, V., Parnianifard, A., Rodriguez, D., Mumtaz, S., and Wuttisittikulkij, L. Speech emotion recognition using anfis and pso-optimization with word2vec. *J Neuro Spine*, 1(1):41–56, 2023.

[32] Ribani, R. and Marengoni, M. A survey of transfer learning for convolutional neural networks. In *2019 32nd SIBGRAPI conference on graphics, patterns and images tutorials (SIBGRAPI-T)*, pages 47–57. IEEE, 2019.

[33] Sarki, R., Ahmed, K., Wang, H., Zhang, Y., Ma, J., and Wang, K. Image preprocessing in classification and identification of diabetic eye diseases. *Data Science and Engineering*, 6(4):455–471, 2021.

[34] Sarwinda, D., Paradisa, R. H., Bustamam, A., and Anggia, P. Deep learning in image classification using residual network (resnet) variants for detection of colorectal cancer. *Procedia Computer Science*, 179:423–431, 2021.

[35] Sharma, H., Wasim, J., and Sharma, P. Analysis of eye disease classification by fundus images using different machine/deep/transfer learning techniques. In *2024 4th International Conference on*

Innovative Practices in Technology and Management (ICIPTM), pages 1–6. IEEE, 2024.

[36] Silva, D. H., Maziero, E. G., Saadi, M., Rosa, R. L., Silva, J. C., Rodriguez, D. Z., and Igorevich, K. K. Big data analytics for critical information classification in online social networks using classifier chains. *Peer-to-Peer Networking and Applications*, 15(1):626–641, 2022.

[37] Srivastava, S., Divekar, A. V., Anilkumar, C., Naik, I., Kulkarni, V., and Pattabiraman, V. Comparative analysis of deep learning image detection algorithms. *Journal of Big data*, 8(1):1–27, 2021.

[38] Srivastava, S., Divekar, A. V., Anilkumar, C., Naik, I., Kulkarni, V., and Pattabiraman, V. Comparative analysis of deep learning image detection algorithms. *Journal of Big data*, 8(1):1–27, 2021.

[39] Szegedy, C., Ioffe, S., Vanhoucke, V., and Alemi, A. Inception-v4, inception-resnet and the impact of residual connections on learning. In *Proceedings of the AAAI conference on artificial intelligence*, volume 31, 2017.

[40] Szegedy, C., Vanhoucke, V., Ioffe, S., Shlens, J., and Wojna, Z. Rethinking the inception architecture for computer vision. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pages 2818–2826, 2016.

[41] Tan, M. and Le, Q. Efficientnet: Rethinking model scaling for convolutional neural networks. In *International conference on machine learning*, pages 6105–6114. PMLR, 2019.

[42] Wang, C., Chen, D., Hao, L., Liu, X., Zeng, Y., Chen, J., and Zhang, G. Pulmonary image classification based on inception-v3 transfer learning model. *IEEE Access*, 7:146533–146541, 2019.

[43] Wang, J., He, X., Faming, S., Lu, G., Cong, H., and Jiang, Q. A real-time bridge crack detection method based on an improved inception-resnet-v2 structure. *IEEE Access*, 9:93209–93223, 2021.

[44] Wang, M. and Gong, X. Metastatic cancer image binary classification based on resnet model. In *2020 IEEE 20th international conference on communication technology (ICCT)*, pages 1356–1359. IEEE, 2020.

[45] Wang, W., Liang, D., Chen, Q., Iwamoto, Y., Han, X.-H., Zhang, Q., Hu, H., Lin, L., and Chen, Y.-W. Medical image classification using deep learning. *Deep learning in healthcare: paradigms and applications*, pages 33–51, 2020.

[46] Xia, X., Xu, C., and Nan, B. Inception-v3 for flower classification. In *2017 2nd international conference on image, vision and computing (ICIVC)*, pages 783–787. IEEE, 2017.

[47] Yadav, S. S. and Jadhav, S. M. Deep convolutional neural network based medical image classification for disease diagnosis. *Journal of Big data*, 6(1):1–18, 2019.

[48] Zakaria, N., Mohamed, F., Abdelghani, R., and Sundaraj, K. Three resnet deep learning architectures applied in pulmonary pathologies classification. In *2021 International Conference on Artificial Intelligence for Cyber Security Systems and Privacy (AI-CSP)*, pages 1–8. IEEE, 2021.

[49] Zhang, Q., Bai, C., Liu, Z., Yang, L. T., Yu, H., Zhao, J., and Yuan, H. A gpu-based residual network for medical image classification in smart medicine. *Information Sciences*, 536:91–100, 2020.

[50] Zhou, Y., Li, G., and Li, H. Automatic cataract classification using deep neural network with discrete state transition. *IEEE transactions on medical imaging*, 39(2):436–446, 2019.

[51] Zhuang, F., Qi, Z., Duan, K., Xi, D., Zhu, Y., Zhu, H., Xiong, H., and He, Q. A comprehensive survey on transfer learning. *Proceedings of the IEEE*, 109(1):43–76, 2020.