International Multidisciplinary Journal of Science, Technology, and Business

Volume No: 03 Issue No: 02 (2024) https://doi.org/10.5281/zenodo.13889475

AICDR: Automatic and Improved Classification of Diabetic Retinopathy using deep Learning

Maria Abbas[1]

Email: mariaabbas1011@gmail.com

Abstract: *Diabetic retinopathy detection is time-consuming and challenging because resources and knowledge are needed to establish whether the disease is present. It is one of the main causes of blindness and is brought on by alterations in the retina's blood vessels. Diabetic retinopathy primarily results from diabetes. A manual diagnosis of diabetic retinopathy includes expert clinicians, resources, and specialized equipment. This process is costly and is not accessible wherever it is most needed. The goal of this research is to develop an automated, reliable, and cost-effective method for the high-accuracy identification of retinopathy. Physicians and patients can examine diabetic retinopathy more easily thanks to automated detection of the condition utilizing digital color retinal imaging. The retina extraction function can help determine the severity of the disease. This work uses multiple deep learning algorithms to automatically diagnose and categorize retinal pictures into five classes: severe non-proliferate DR, proliferation DR, mild DR, moderate DR, and no-DR. APTOS 2019 is a dataset used for deep convolutional neural network training. Accuracy was enhanced via transfer learning on deep convolutional neural networks that had previously been trained using ImageNet. In our study, the best deep learning models Resnet-18 and Resnet-50 achieved 88.2% and 92% accuracy on the validation range, generating 96% and 97% sensitivity on 100 test images from the same dataset, respectively. Results are described with the error rate, precision, sensitivity, and specificity using the confusion matrix, which describes errors explicitly in model misclassification.*

Keywords: *Diabetes, convolutional neural network, deep learning, diabetic retinopathy, Image Classification, Confusion Matrix, Transfer Learning*

Introduction:

In diabetes, people have high blood sugar due to an insufficient amount of insulin. Diabetic retinopathy is the result of elevated blood sugar, which harms the blood vessels in the retina. When retina blood vessels get affected, fluid leaks or starts bleeding, which affects eye vision as well? The bleeding from vessels is called hemorrhage. In the next stages, it will exceptionally reach proliferative abnormality of blood vessels. This can lead to spots on the retina, blurred vision, and, ultimately, vision loss. After diabetes, diabetic retinopathy commonly becomes part of it. It is a widely spread eye disease that severely causes vision loss after damaging the blood vessels. Diabetic retinopathy chances increase in middle and older diabetes patients. The time duration between the initial stage (no diabetic retinopathy) and the last stage (proliferative diabetic retinopathy) is almost15 years or more [1].

Due to this slow rate, there's a lot more chance to detect and care about diabetic retinopathy at early stages. Diabetic retinopathy progresses and the next stages of development are based on the control of diabetes and its duration. Symptoms of this disease showed only in the advanced stage. The only identifiable sign is total vision loss suddenly at the advanced stage. But in some cases, diabetic retinopathy shows some other symptoms, which are blurred vision, dark spots at the sight center, and finding it tough to see at night.

There are four stages of this disease, from no DR to proliferative DR.

- No DR – A stage where no diabetic retinopathy symptoms are found in patients having diabetes. Mild diabetic retinopathy (Non-Proliferative) – Initial stage of the disease where the occurrence of micro aneurysm was found. These micro aneurysms are swelling in blood vessels, which are like small regions of the balloon.
- Moderate diabetic retinopathy (Non-Proliferative) – In the second stage, blood vessels is blocked that sustain the retina. They may get distortion and swelling in it.
- Severe diabetic retinopathy (Non-Proliferative) – In this stage, blockage in blood vessels increases, and blood supply stops in multiple regions of the retina.
- Severe diabetic retinopathy (Proliferative) – In the last stage, blood vessels increase because of the acknowledgment triggered by the retina to the body for retina sustenance. These new blood vessels are breakable and are more likely to bleed. These blood vessels don't lead to vision loss or disease symptoms, but if blood leaks from them, it may cause vision loss and permanent blindness [2].

Literature Review:

Approach	Year	Method	Algorithm	Performance Evaluation
C. Zhang et al.et al. [3]	2022	STFL (source-free Transfer Learning)	ResNet50	83.2%
Vijayan T et al. [4]	2020	Transfer Learning	ResNet50	86.2%
Gazala Mushtaq et al. [5]	2020	CNN	DenseNet-169	90%
Teja s et al. [6]	2021	CNN	VGG-19	74%

Promising developments have been made recently in the use of deep learning in medical imaging, specifically in the identification of diabetic retinopathy.

All these studies show that deep learning has the ability to automate the diagnosis of diabetic retinopathy; nevertheless, issues like data imbalances and the requirement for huge, annotated datasets still need to be further investigated. Although deep learning models have demonstrated remarkable outcomes in drug discovery, extant literature indicates that further development is necessary, especially in the domains of generalization and resilience to fluctuations in data.

Methodology:

In this dataset, data preprocessing, data augmentation, hardware/software, and models' descriptions are described for recognizing diabetic retinopathy and its stages at early stages.

APTOS 2019 dataset available at Kaggle is used in this research. It is employed in the deep learning process to train and validate the suggested models. A portion of the dataset's photos were kept so that the trained models could make predictions. It includes many retinal photos taken in different lighting conditions utilizing color fundus photography. An expert ophthalmologist labeled this dataset according to the diabetic retinopathystages on a scale of 0 to 4:

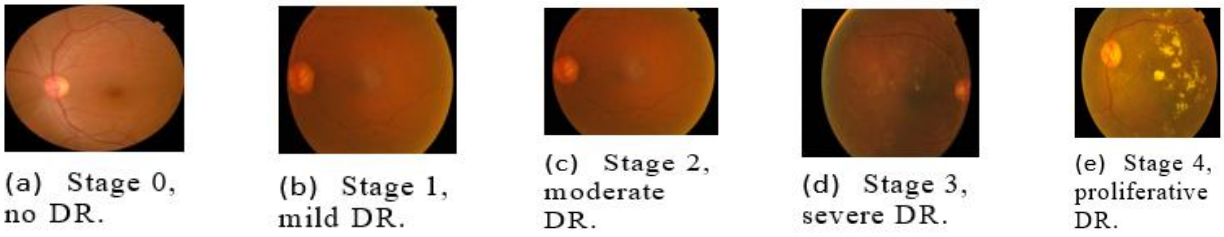
0-No diabetic retinopathy

1- Mild diabetic retinopathy

2- Moderate diabetic retinopathy

3- Severe diabetic retinopathy

4-Proliferative diabetic retinopathy

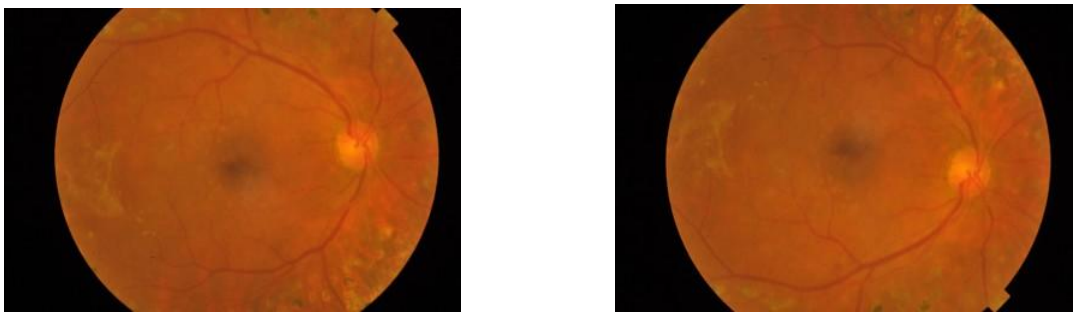


(a) Stage 0, no DR. (b) Stage 1, mild DR. (c) Stage 2, moderate DR. (d) Stage 3, severe DR. (e) Stage 4, proliferative DR.

Figure 1: Dataset images with all DR stages

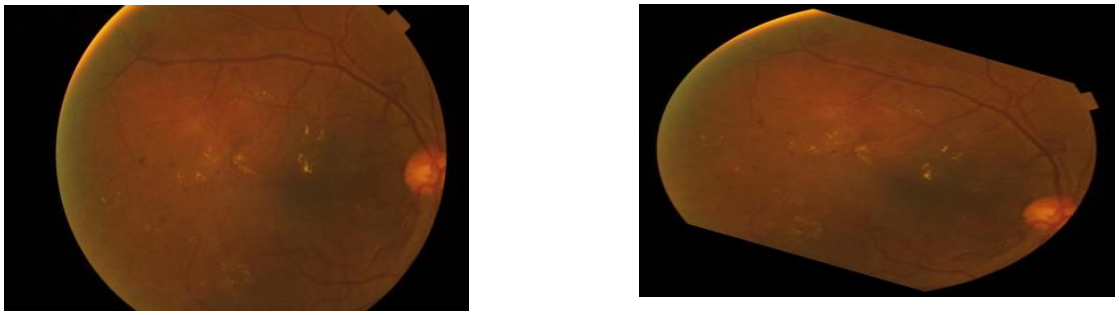
Data Augmentation:

In order to balance the datasets and enhance the model's generalization across various images, data augmentation was essential. Rotating, flipping vertically, and flipping horizontally were some of the augmentation strategies that produced more photos and improved the training dataset. The dataset was divided into 80% for training and 20% for validation after it was expanded [7].



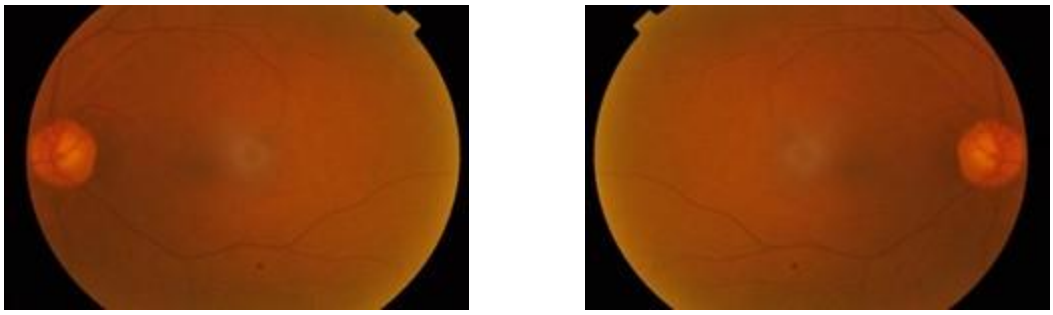
(a) Original Image. (b) Vertically flipped image.

Figure 2: Vertically flipped image of the original dataset.



(a) Original Image. (b) Rotated image.

Figure 3: Rotated image of original dataset image.



(a) Original Image. (b) Horizontally flipped image.

Figure 4: Horizontally flipped image of original dataset image.

Deep Learning Models

Two deep learning models were employed in this study: The two models are ResNet-18 and ResNet-50 which are both convolutional neural networks most effective in image classification. These models were trained on the image net database and transfer learning was used for the tuning of the models for the specific task of the classification of retinal images [8].

ResNet-18: As the name suggests, this model has 18 layers and incorporates residual connections to reduce the gradient vanishing issue that occurs during model training [9].

ResNet-50: ResNet-50 has 50 layers and is designed to learn more specific features and patterns within the images as compared to ResNet-18 [10].

Model Training and Optimization:

Using the previously indicated larger dataset, 800 photos were used for training and the remaining 200 images were for validation during the models' training. The training process involved two optimizers: The training process involved two optimizers:

Stochastic Gradient Descent with Momentum (SGDM): This optimizer enhances the rate of convergence and raises the model's likelihood of being generalized with the momentum for decreasing oscillations at the time of training [11].

Adaptive Moment Estimation (ADAM): ADAM represents a recent extension of stochastic gradient descent, which was obtained from the combined features of AdaGrad and RMSProp in which; it provides an adaptive learning rate for each parameter [12].

Following several epochs of training for both models, the models with the best validation F1 score, accuracy, precision, sensitivity, and specificity were chosen.

Results:

Each model results are explained with a confusion matrix. The model prediction results on a classification problem are represented in tabular form. It is helpful to illustrate the prediction of correct and erroneous results with numbers for each class. It included details regarding the various kinds of mistakes that might be made by classifiers. As in this research, the dataset has four classes of problemsso the confusion matrix size was 4x4. After creating a confusion matrix for each model results are evaluated.

Configurations of the model's training are given below:

Models Configurations

- The dataset was split into 80% and 20% for each model's training and validation respectively.
- Each Model has a batch size that is different according to model requirements.

Models	Batch Size	Optimizer	Learning Rate	Epoch
ResNet18	4	50	ADAM	40
ResNet50	4	64	ADAM	30
ResNet18	2	70	ADAM	40
ResNet50	2	70	SGDM	40

Resnet-50 & Resnet-18

Model Training Graph

Figure 3 shows the training and validation loss of the Resnet-50 and Resnet-18 models with four classes, along with thecalculated accuracy of the learning model.

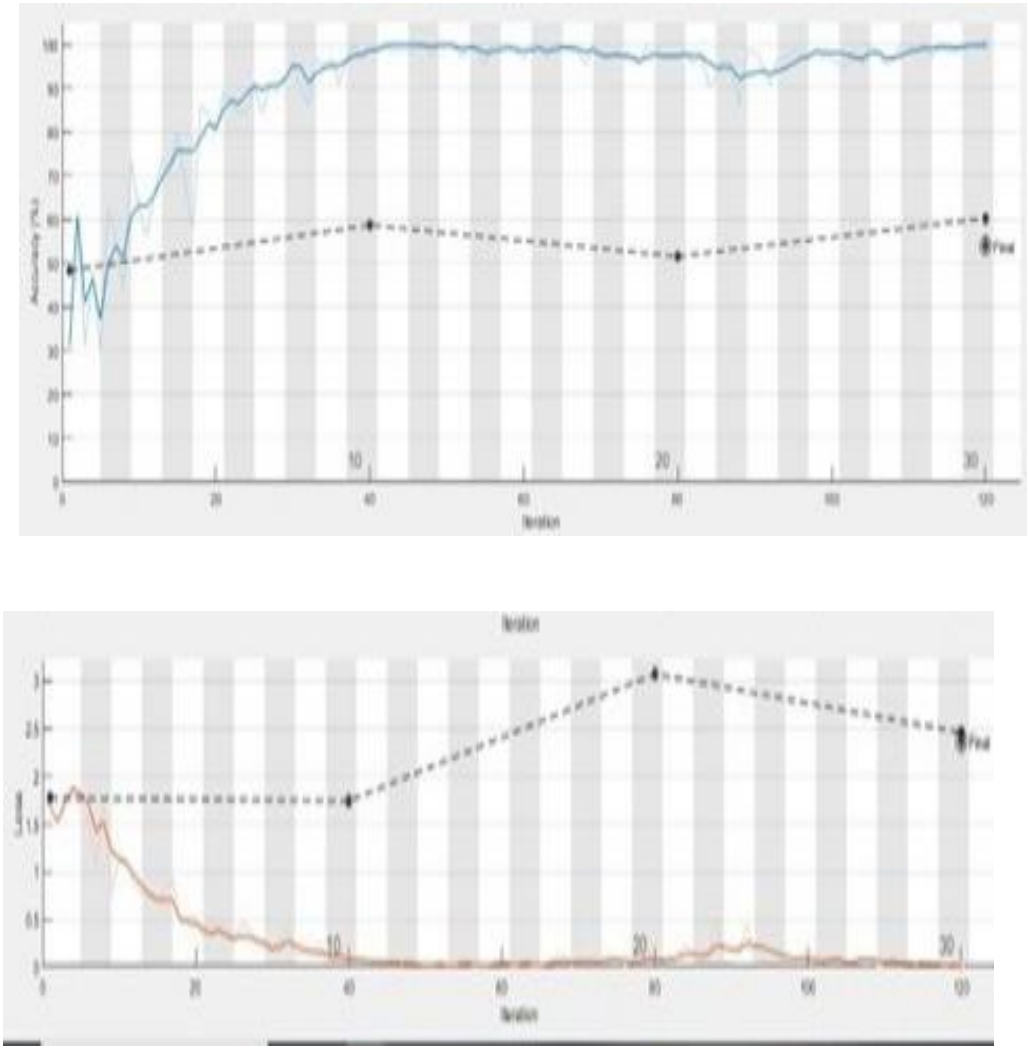
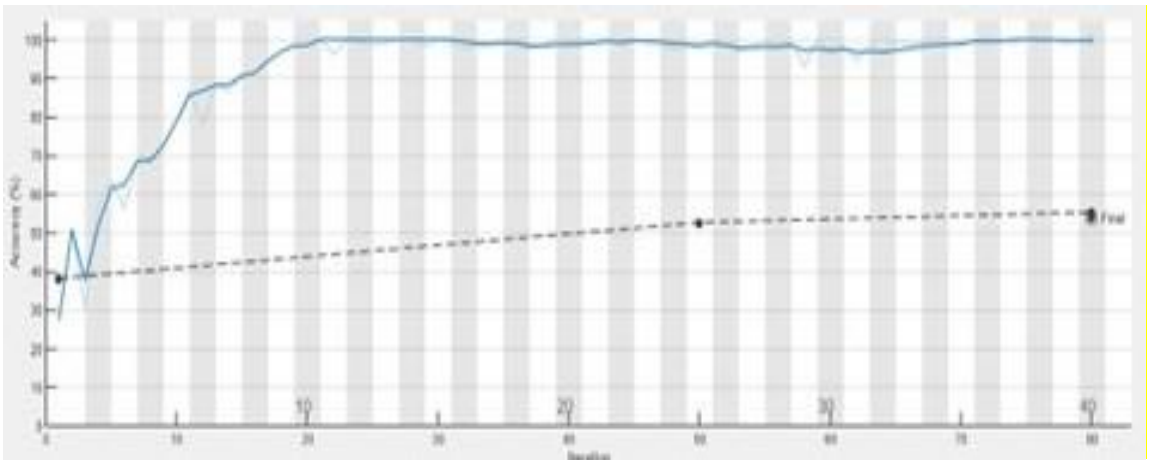


Figure 3: Accuracy and loss Rate of Resnet-50 with 4 classes.



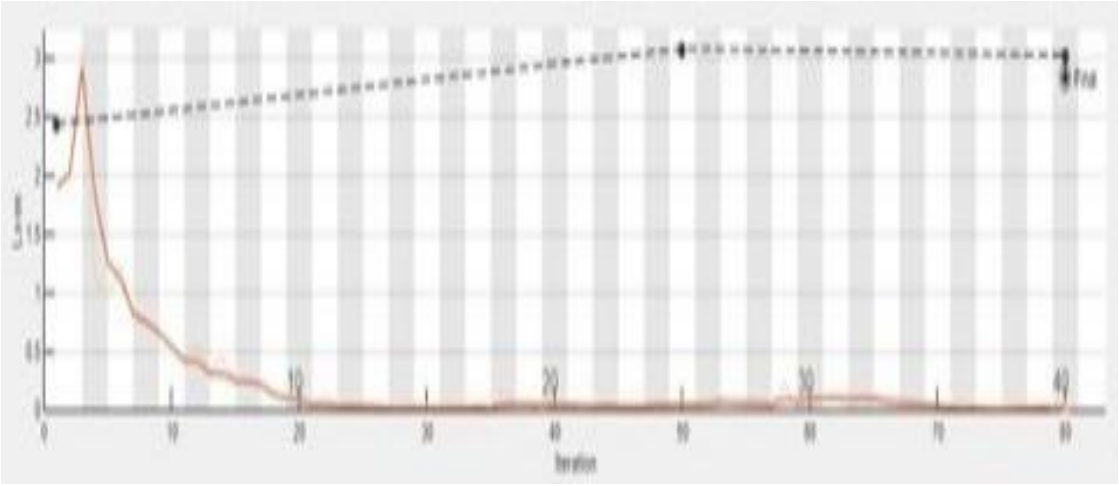


Figure 4: Accuracy and loss Rate of Resnet-18 with 4 Classes

Model Training and Prediction

The accuracy and rate loss of the Resnet-50 model are 53% and 54% respectively as it correctly predicts 54 images of 100 from test dataset images. And ResNet-18 has an accuracy of 54.6% and a loss of 58.7%.

Confusion Matrix of Resnet-50 & Resnet-18

The diagonals in the confusion matrix table display the true positive values for each class, the false negative values are represented by the row excluding the diagonal value, and the false positive values are represented by the column omitting the diagonal value. The total of all values, excluding the class row and column, is the true negative. The average values of false positives and false negatives are displayed in Table 1.

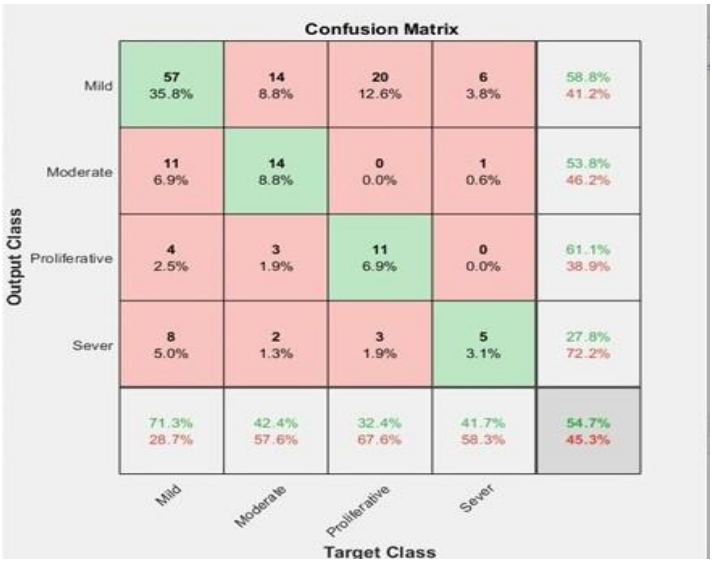


Table 1: Resnet-50's confusion matrix with four classes.

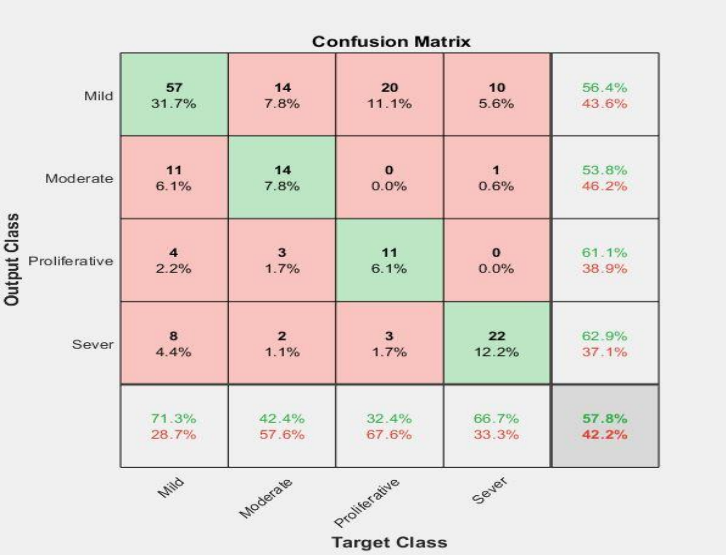
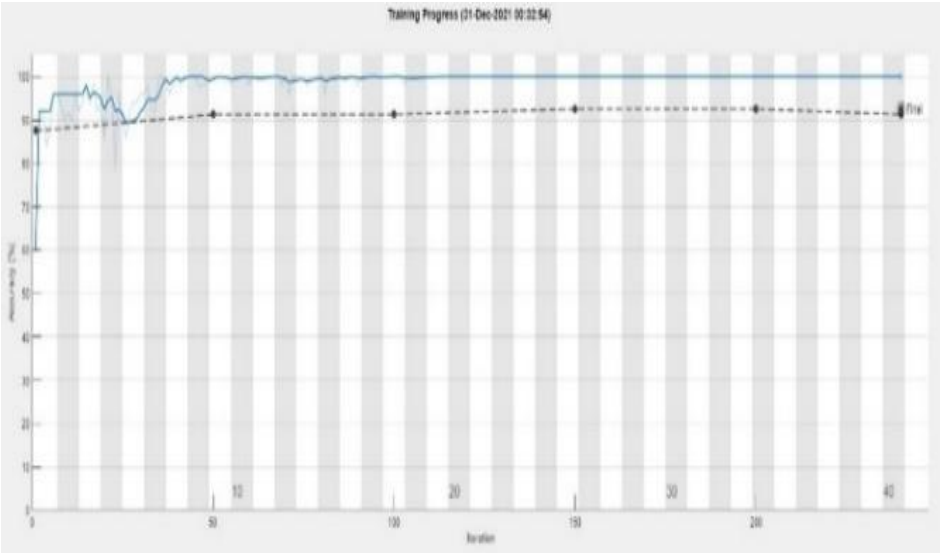


Table 2: Resnet-18's confusion matrix with 4 types

Resnet-50 & Resnet-18

Model Training Graph

Figure 5 shows the training and validation loss of the Resnet-50 and Resnet-18 models with 2 classes, along with thecalculated accuracy of the learning model.



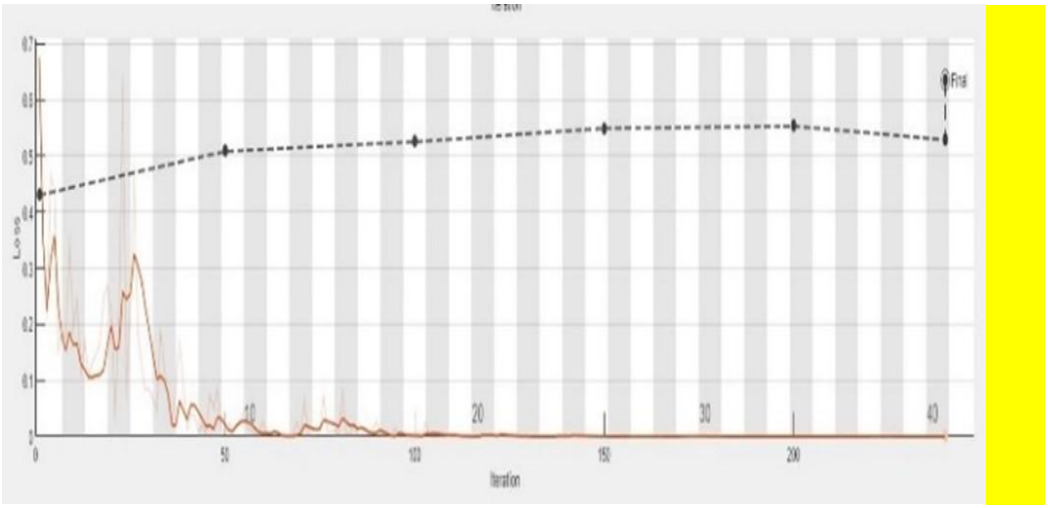


Figure 5: Resnet-50's accuracy and loss rate with 2 classes

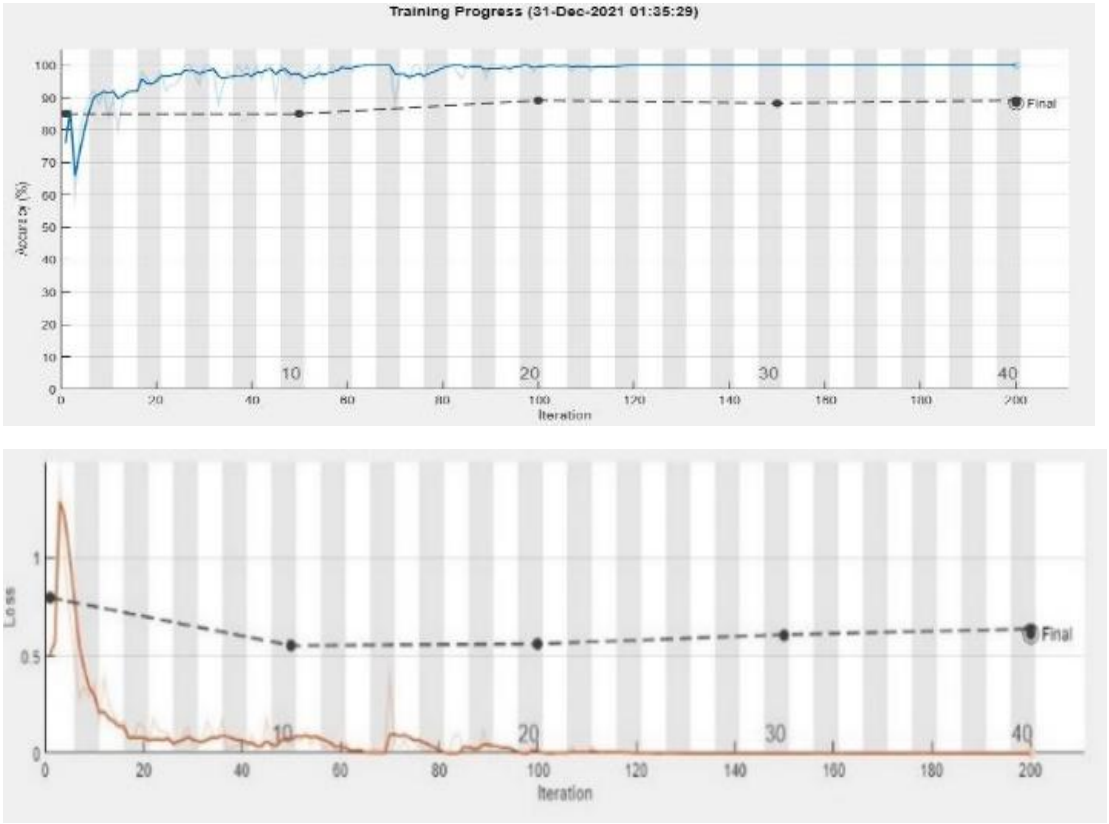


Figure 6: Accuracy and loss Rate of Resnet-18 with 2 Classes.

Model Training and Prediction

The accuracy and rate loss of the Resnet-50 model are 92% and 43% respectively as it correctly predicts 92 images out of 100 from test datasets images. And ResNet-18 has an accuracy of 88.33% and a loss of 79%.

Confusion Matrix of Resnet-50 & Resnet-18

The diagonals in the confusion matrix table display the true positive values for each class, the false negative values are represented by the row excluding the diagonal value, and the false positive values are represented by the column omitting the diagonal value. The total of all values, excluding the class row and column, is the true negative. The average values of false positives and false negatives are displayed in Table 3.

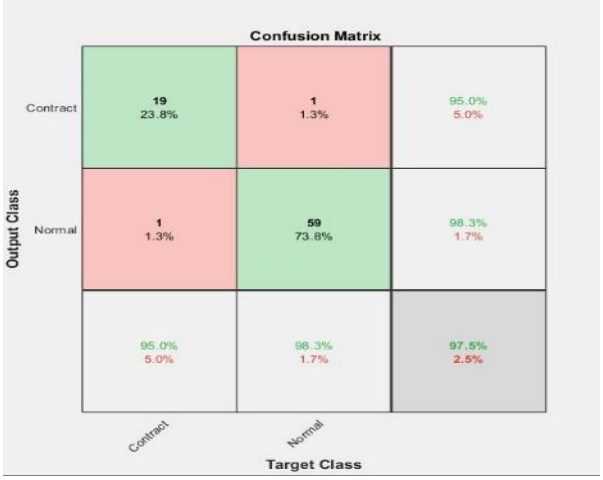


Table 3: Resnet-50's confusion matrix.

Table 4: Resnet-18's confusion matrix

Comparison between the performances of the pre-trained models

Dataset	Techniques	Acc.	Precision	Recall	F1-Score	Specificity	Matthews Correlation Coefficient

80-20%	ResNet-18	97.50%	97%	91%	98%	1.00	93.74%
80-20%	ResNet-50	97.50%	98%	98%	98%	98.33%	93.33%

Table 5: Comparison of the pre-trained models' performances

Comparison with Previous Work

Approach	Year	Algorithm	Performance Evaluation
C. Zhang et al.et al. [4]	2022	ResNet-50	83.2%
Vijayan T et al. [5]	2020	ResNet-50	86.2%
Gazala Mushtaq et al. [6]	2020	DenseNet-169	90%
Contract-TL	2023	Resnet-18	88.33%
Contract-TL	2023	Resnet-50	92.50%

Conclusion:

To automatically identify and categorize diabetic retinopathy from digitized retinal images, this work showcased the architectural design and use of trained deep-learning models. These models were trained using data collected from patients with diabetic retinopathy. To determine which deep learning model is the most effective at resolving this issue, several models' training procedures have been compared against one another using a confusion matrix. Every model is trained on the APTOS 2019 dataset for diabetic retinopathy, which contains patient information. The findings presented in the preceding chapter made it abundantly evident that there is a significant disparity between the training of the models and their capacity to extract features for diabetic retinopathy classification problems. When compared to the manual categorization performed by a clinician, the trained models perform significantly better when attempting to identify the disease and its stages. It provided a quick answer to many

images and categorized them according to how difficult they were. The study of a single image or numerous photos from the dataset did not matter to the models; it correctly differentiated between the various stages of the disease regardless of the number of images examined. As a result of comparing these findings, we can deduce that the best model has also functioned correctly in the living environment. This will enable clinicians to speed up the process of diabetic retinopathy detection.

References:

[1] https://modernod.com/articles/2019-june/the-four-stages-ofdiabeticretinopathy?c4 src=article:infinite-scrol

[2] Majumder, S., Elloumi, Y., Akil, M., Kachouri, R., & Kehtarnavaz, N. (2020, April). A deep learning-based smartphone app for real-time detection of five stages of diabetic retinopathy. In Real-Time Image Processing and Deep Learning 2020 (Vol. 11401, pp. 13-22). SPIE.

[3] Zhang, C., Lei, T., & Chen, P. (2022). Diabetic retinopathy grading by a source-free transfer learning approach. Biomedical Signal Processing and Control, 73, 103423.

[4] Vijayan, T., Sangeetha, M., Kumaravel, A., & Karthik, B. (2020). WITHDRAWN: Gabor filter and machine learning-based diabetic retinopathy analysis and detection.

[5] Mushtaq, G., & Siddiqui, F. (2021, February). Detection of diabetic retinopathy using deep learning methodology. In IOP conference series: materials science and engineering (Vol. 1070, No. 1, p. 012049). IOP Publishing.

[6] S. Tesjas, S. Rachana and R. Tejaswini, "Prediction of Cataract and Diabetic Retinopathy using Deep Neural Network", Science and Engineering, vol. 25, 2021.

[7] Shorten, C., & Khoshgoftaar, T. M. (2019). A survey on image data augmentation for deep learning. Journal of Big Data, 6(1), 1-48.

[8] Deng, J., Dong, W., Socher, R., Li, L.-J., Li, K., & Fei-Fei, L. (2009). ImageNet: A large-scale hierarchical image database. 2009 IEEE Conference on Computer Vision and Pattern Recognition, 248-255.

[9] He, K., Zhang, X., Ren, S., & Sun, J. (2016). Deep residual learning for image recognition. Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, 770-778.

[10] Szegedy, C., et al. (2015). Going deeper with convolutions. Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, 1-9.

[11] Kingma, D. P., & Ba, J. (2015). Adam: A method for stochastic optimization. arXiv preprint arXiv:1412.6980.

[12] Ioffe, S., & Szegedy, C. (2015). Batch normalization: Accelerating deep network training by reducing internal covariate shift. arXiv preprint arXiv:1502.03167.