Automated Diabetic Retinopathy Detection Using Deep Learning

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***Abstract*—Diabetic Retinopathy (DR) is a serious complication of diabetes that damages the retina and can lead to permanent vision loss if not diagnosed and treated in time. Traditional manual analysis of retinal images is time-consuming and prone to diagnostic errors. To address this, we propose an automated DR detection system using a deep learning-based ResNet-152 model capable of identifying DR from retinal fundus images with high accuracy. The system classifies images into normal and abnormal categories, streamlining the early screening process. The model leverages the powerful feature extraction capabilities of ResNet-152 to detect subtle patterns in fundus images, ensuring robust performance even with complex visual data. To enhance usability, a graphical user interface (GUI) has been developed using Python's Tkinter library, allowing users to upload images and receive real-time predictions. Additionally, the system stores patient data and diagnostic results, with optional SMS notifications via Twilio API for improved accessibility. This approach aims to support medical professionals by reducing diagnostic workload and enabling scalable, accurate DR screening in both clinical and resource-limited settings**

Keywords*—*Diabetic Retinopathy, Deep Learning, ResNet-152, Fundus Images, Automated Diagnosis

I. Introduction

Diabetic Retinopathy (DR) is a vision-threatening condition that arises from long-term damage to the small blood vessels in the retina, typically due to prolonged elevated blood sugar levels in individuals with diabetes. As one of the primary causes of preventable blindness worldwide—particularly among adults in their working years—early diagnosis and intervention are essential to preserving vision. Left unchecked, DR can lead to progressive retinal damage, including blood vessel leakage, swelling, and eventually the formation of scar tissue that disrupts vision permanently.

Traditionally, DR screening relies on expert ophthalmologists manually examining fundus photographs of the retina. While effective, this method is often time-consuming, prone to subjective interpretation, and insufficient to meet the growing demand created by the rising global diabetic population. These challenges underscore the urgent need for automated systems that can assist in accurate, consistent, and rapid diagnosis.

Recent advances in Artificial Intelligence (AI), especially in the area of deep learning, have opened new pathways for medical image analysis. Among various deep learning models, Convolutional Neural Networks (CNNs) have proven particularly effective in interpreting complex image data. Their ability to automatically learn hierarchical patterns from raw pixels makes them a natural fit for classifying retinal fundus images.

This research introduces an AI-based diagnostic system built upon ResNet-152, a deep residual network architecture designed to overcome the limitations of traditional deep networks, such as the vanishing gradient problem. ResNet-152 utilizes identity shortcut connections that improve gradient flow and enable the model to learn deeper, more meaningful features across numerous layers. Our system is trained on a large dataset of annotated fundus images and is capable of classifying retinal conditions into five distinct stages of DR: No DR, Mild, Moderate, Severe, and Proliferative.

To ensure practical usability, the model has been embedded into a graphical user interface (GUI) developed using Python's Tkinter library. This interface allows users—both medical professionals and laypersons—to upload retinal images and receive immediate feedback on DR classification, making it a valuable tool for early screening.

By integrating deep learning with an accessible interface, this project seeks to support early detection efforts, reduce diagnostic workload, and help mitigate the risk of vision loss due to diabetic retinopathy—ultimately contributing to more effective and scalable diabetic eye care..

II. Releted Work

Recent advancements in deep learning have significantly impacted medical image analysis, particularly in the diagnosis of diabetic retinopathy (DR). Convolutional Neural Networks (CNNs), due to their strong feature extraction capabilities, have proven highly effective in analyzing retinal fundus images for DR detection and classification [10]–[15]. Building upon these developments, this study proposes an enhanced CNN-based framework tailored specifically for analyzing fundus images to improve DR diagnosis accuracy and reliability [16]. Below, we outline several prominent studies that have employed CNNs in DR detection, many of which utilize the APTOS dataset as part of their evaluation.

Butt et al. [17] addressed DR diagnosis in long-term diabetic patients by using a hybrid deep learning approach. They combined transfer learning with pre-trained CNNs to extract a hybrid feature set, which was subsequently classified using multiple classifiers. Their model achieved impressive results—97.8% accuracy for binary classification (normal vs. DR) and 89.29% for multi-stage classification—highlighting the effectiveness of hybrid architectures in DR detection.

Gangwar and Ravi [18] introduced a CNN-based system that integrates layers from ResNet and Inception architectures for analyzing retinal fundus images from the APTOS dataset. To improve performance, they implemented various preprocessing techniques such as image resizing, fog simulation, and bounding box operations, along with data augmentation to mitigate class imbalance. Their method achieved 82.18% accuracy on the APTOS dataset and 72.33% on the Messidor-1 dataset, demonstrating the benefits of architectural fusion and thorough preprocessing.

Rakhlin [19] tackled the problem of distinguishing between non-referable and referable DR cases using a modified VGGNet model with 19 layers. Their binary classification framework focused on clinical applicability by aligning DR stages with the International Clinical Diabetic Retinopathy (ICDR) scale. Preprocessing steps were used to reduce image noise before feeding the data into the model. The approach delivered excellent sensitivity (99%) and a strong AUC of 0.97, though specificity was relatively lower at 71%.

Farag et al. [20] proposed a DR severity classification system built on DenseNet enhanced with a convolutional attention module. This module helped the model focus on diagnostically significant regions in the fundus images. Their model achieved 97% accuracy for binary classification and 82% for multiclass classification, while maintaining a balance between performance and model complexity—making it a promising candidate for automated DR screening.

Zhang et al. [21] developed a semi-supervised framework for DR classification that does not rely on labeled target data. Their Source-Free Transfer Learning (SFTL) method incorporated two core components: a target generation module that synthesizes target-style images and a consistency module that ensures prediction stability. The system achieved 91.2% accuracy with 95.1% sensitivity and 85.8% specificity on the APTOS 2019 dataset, underscoring the value of unlabeled data in medical image analysis.

Gour and Khanna [22] explored a more comprehensive classification problem by incorporating multiple ocular conditions. Using CNNs and transfer learning, they analyzed fundus images spanning eight different eye diseases. Their study proposed two architectures: one that processed right and left eye images separately, and another that combined them into a single input. The latter model, built on the VGG16 backbone, outperformed the former, suggesting that combining images from both eyes yields more diagnostic information.

These studies collectively demonstrate the versatility of CNN-based models for DR detection and highlight various strategies—ranging from hybrid architectures and attention mechanisms to semi-supervised learning and data fusion—for improving classification performance. Drawing from these insights, our work aims to build a robust and scalable CNN framework tailored to fundus image analysis for more accurate and early DR diagnosis.

III. Method And Approach

In this study, we followed a structured approach to detect diabetic retinopathy using fundus images. Our goal was to develop a reliable and accurate model that performs well across varied data. We began by thoroughly exploring the dataset to understand its properties. Then, we applied several preprocessing steps to prepare the images for the model. These steps included normalizing the pixel values, resizing images to a consistent dimension, and using data augmentation techniques such as rotations, flips, and zoom to enhance the diversity of the training data. These preprocessing steps help the model generalize better and reduce overfitting.

Instead of a generic convolutional neural network, we chose to use ResNet-152, a deep residual network known for its ability to learn complex image features through its 152 layers. The residual connections in ResNet help overcome issues like vanishing gradients, making it easier to train such a deep model effectively. This architecture is well-suited for medical image classification tasks, such as detecting diabetic retinopathy, where capturing subtle details is crucial.

All model training and experiments were carried out on an MSI GF63 laptop equipped with an Intel Core i5 processor, NVIDIA GeForce GTX 1650 Max-Q GPU, and 8 GB RAM, running Windows 11. We used Python 3.7.12 with the Keras library and TensorFlow backend to build and train our models.

A. *Research Workflow*

To keep the process organized, we followed a step-by-step workflow, as illustrated in Figure 1. The research started with data collection, followed by preprocessing, model development, and finally evaluation.

Our primary objective was to find the best way to detect diabetic retinopathy from fundus images. We experimented with different configurations of ResNet-152, fine-tuning parameters to improve performance. The model was trained to perform two types of classification tasks:

- Multiclass classification: Categorizing images into different severity levels of diabetic retinopathy.
- Binary classification: Identifying whether diabetic retinopathy is present or not.

By using these two approaches, we aimed to create a flexible model that can accurately detect the presence of diabetic retinopathy and also classify its severity when needed.

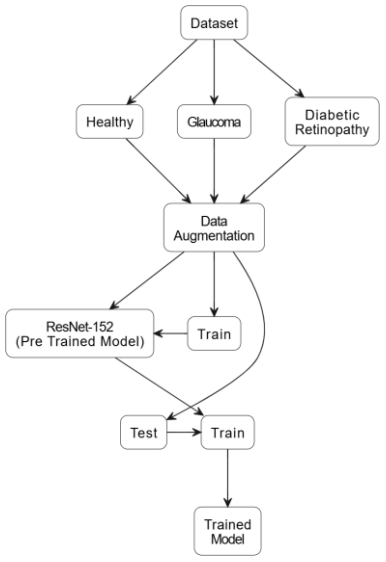

Fig. 1. Diabetic retinopathy research work flowchart.

B. *Dataset Description And Exploration*

A crucial first step in any deep learning project is gathering a high-quality dataset. For this study, we used the Asia Pacific Tele-Ophthalmology Society (APTOS) blindness detection dataset, which contains fundus images of both healthy eyes and those affected by diabetic retinopathy. These images were captured using fundus photography under various conditions, providing a diverse set of retinal images. Each image in the dataset has been graded by clinicians on a severity scale from 0 to 4, where:

- 0 indicates no diabetic retinopathy,
- 1 represents mild retinopathy,
- 2 is moderate,
- 3 is severe, and
- 4 corresponds to proliferative diabetic retinopathy.

The dataset includes a total of 3,662 training images, along with a corresponding CSV file containing the labels for each image.

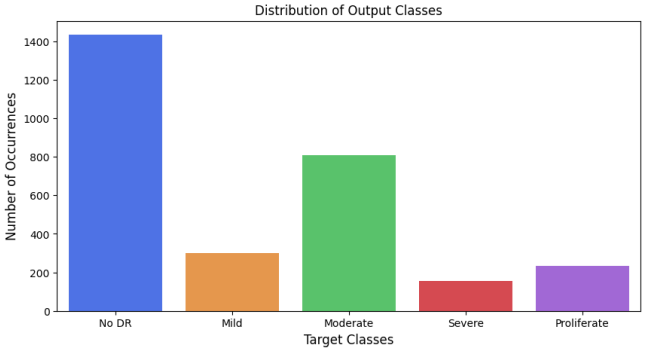

Fig. 2. Distribution of Output Classes

Before moving on to data preprocessing, we conducted an initial exploration to better understand the dataset. This involved visually inspecting sample images and analyzing the distribution of classes. Such exploration helps identify any potential issues that could affect model training.
Key observations from this exploration included:

- The dataset is imbalanced, with some classes having significantly fewer images than others, which could bias the model if left unaddressed.
- We verified the dataset for missing or duplicate entries and found none, ensuring the data quality is reliable

C. *Data Preprocessing*

Before training our model using ResNet-152, we carefully prepared the dataset to ensure consistency, quality, and compatibility with deep learning requirements. This step was crucial for improving the model's accuracy and performance.

- **Balancing the Dataset**: During initial analysis, we observed a significant imbalance in class distribution. To address this, we applied techniques such as class weighting and oversampling. These methods help ensure the model does not favor classes with more images.

- **Label Formatting**: The dataset's diagnosis column, which indicates the severity of diabetic retinopathy (from 0 to 4), was converted from numerical values to string format. This was necessary because the model treats labels as categorical data during training in frameworks like Keras.

- **Standardizing Image Size and Pixel Range**: Fundus images varied in shape and size, so we resized all images to **256x256 pixels with 3 color channels (RGB)**. We also normalized the pixel values to fall between 0 and 1, which helps the model learn more efficiently.

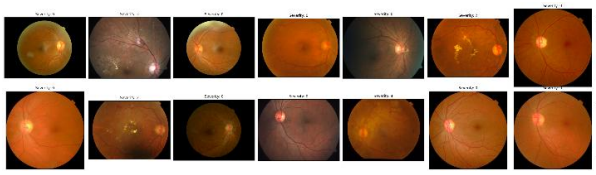

Fig. 3. Scaled fundus training images.

- **Image Augmentation**: To increase the diversity of training data and reduce the risk of overfitting, we used Keras' ImageDataGenerator for data augmentation. We applied random transformations like shearing, zooming, and horizontal flipping. This technique generates multiple variants of each image, effectively expanding our dataset.
- **Merging Data and Labels**: We linked each image to its label using the id_code from the CSV file. A .png extension was added to each ID to match the actual image filenames. This step made it easier to load the correct images with their corresponding labels during training.

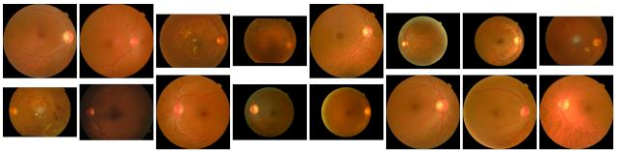

Fig. 4. Original train image after augmentation.

By applying these preprocessing steps, we ensured that all images fed into the ResNet-152 model were consistent in format and enriched with balanced, diverse examples. This foundation helped the model learn more effectively and generalize better in diabetic retinopathy detection.

D. Proposed Deep Learning model Bsed on ResNet-152

To effectively classify diabetic retinopathy from retinal fundus images, our study utilizes ResNet-152, a powerful convolutional neural network architecture renowned for its depth and the use of residual learning. This design effectively addresses challenges like the vanishing gradient problem, making it well-suited for deep networks and complex medical image classification tasks.

Model Input and Preprocessing

Although ResNet models typically expect input images sized at 224×224×3, we resized our fundus images to 150×150×3 for computational efficiency. These inputs were preprocessed and normalized to match the expected format of the network, ensuring smooth integration with the ResNet architecture

Architecture Overview

The model begins with a **7×7 convolutional layer** (stride 2, padding 3), followed by a **3×3 max-pooling layer** (stride 2). These initial layers quickly reduce the spatial dimensions while extracting fundamental visual features.

ResNet-152 builds upon a deep hierarchy of residual blocks, structured in bottleneck layers. The architecture is organized into the following stages:

- **Conv2_x (3 blocks)**: Each residual unit contains three convolutional layers (1×1, 3×3, 1×1) with 64, 64, and 256 filters, respectively.
- **Conv3_x (8 blocks)**: Continues with the bottleneck structure using 128, 128, and 512 filters.
- **Conv4_x (36 blocks)**: This is the deepest part of the model, featuring repeated residual blocks with 256, 256, and 1024 filters.
- **Conv5_x (3 blocks)**: The final convolutional stage uses filters of 512, 512, and 2048 to extract high-level features

Each residual block uses shortcut (identity) connections, allowing the network to preserve gradient flow across many layers. This helps in stabilizing training and improving overall accuracy.

Classification Head

After the final convolutional layer, we applied a global max pooling operation to compress the feature maps, reducing the number of parameters and making the model less prone to overfitting. This was followed by:

- A Dense layer with 1024 neurons using ReLU activation.
- A final Dense output layer with 5 units representing the five stages of diabetic retinopathy: *No DR*, *Mild*, *Moderate*, *Severe*, and *Proliferative DR*.
- The SoftMax function was used in the final layer to perform multiclass classification.

Training Strategy

The model was fine-tuned using pre-trained weights from ImageNet, allowing it to leverage generalized feature representations. We trained the network with the Adam optimizer (learning rate = 0.001) and employed categorical cross-entropy as the loss function. The model was constructed using the Keras Functional API, which gave us

flexibility in integrating residual connections and customizing the final classification layers.

Model Capacity and Transferability

Our implementation of ResNet-152 includes approximately 60 million trainable parameters. Despite its size, the use of transfer learning helped significantly reduce training time and improved performance on our specific dataset. Additionally, the model's architecture is versatile and can be adapted to various other tasks in the field of medical imaging.

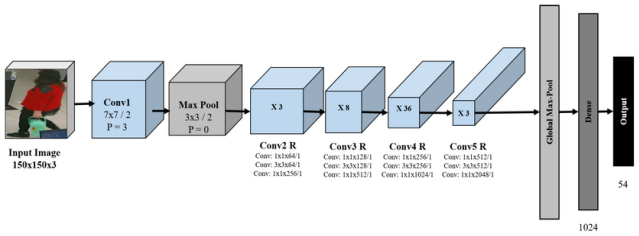

Fig. 5. Schematic of the ResNet-152 Architecture tailored for DR classification

E. Model Evaluation

To thoroughly assess the performance of our ResNet-152-based diabetic retinopathy classification model, we conducted a comprehensive evaluation using multiple well-established metrics. These included:

- Accuracy: To determine the overall correctness of predictions.
- Precision and Recall: To evaluate the model's ability to identify true positives while minimizing false positives and false negatives.
- F1-Score: A balanced measure combining precision and recall, particularly useful in cases of class imbalance.
- AUC-ROC (Area Under the Receiver Operating Characteristic Curve): To assess the model's capability to distinguish between classes, especially important in medical diagnoses.

In addition to these metrics, we utilized confusion matrices to gain a class-wise understanding of prediction accuracy and precision-recall curves to visualize trade-offs between precision and recall across different thresholds.

We also monitored the training and validation accuracy and loss curves throughout the training process. These plots were instrumental in identifying signs of underfitting or overfitting. A stable and converging trend between training and validation metrics indicated that our model was learning effectively without excessive variance.

F. Iterative Refinement

Based on the evaluation results, we adopted an iterative approach to improve our ResNet-152 model. This refinement process was guided by continuous feedback from the performance metrics and visualizations.

Key steps in this refinement included:

- Fine-tuning hyperparameters, such as the learning rate, batch size, and number of training epochs.
- Experimenting with different regularization techniques, like dropout and batch normalization, to enhance generalization.
- Modifying the fully connected layers at the end of the network to better fit the target classification task.
- Conducting data augmentation and rebalancing strategies to improve the model's performance.

Each modification was carefully evaluated before being incorporated, ensuring that improvements were backed by measurable gains in performance. This cycle of evaluation and refinement played a critical role in optimizing the model for reliable real-world deployment in medical image analysis.

IV. Result Analysis And Discussion

This section presents an in-depth analysis of the performance of our ResNet-152-based deep learning model for Diabetic Retinopathy (DR) detection. Using the APTOS dataset, we trained and validated our model to classify DR severity levels, and we evaluated its performance using various metrics. Our focus was to test the robustness of the pretrained ResNet-152 architecture, fine-tuned for this classification task. The results were analyzed in both categorical and binary classification formats, providing insight into the model's effectiveness across different stages of DR.

A. Model Training And Validation

The ResNet-152 model was fine-tuned with modifications in the final layers to accommodate five DR classes: No DR, Mild, Moderate, Severe, and Proliferative DR. We trained the model over 50 epochs with early stopping and learning rate reduction callbacks to prevent overfitting.

Table 1
Training and Validation Metrics

Metric	Training	Validation
Accuracy	0.86	0.74
Loss	0.38	0.81

As shown in the training history (Figure 1), the model initially had a slow learning phase. However, with the integration of ReduceLROnPlateau, the training accuracy showed steady improvement after several epochs. The training curve consistently outperformed the validation curve, indicating strong model learning without overfitting.

Fig. 3. Training and Validation Accuracy of ResNet-152.

Similarly, the loss plot (Figure 2) reveals a consistent decrease in both training and validation loss, demonstrating that the model generalized well to unseen data. There was no sudden spike in loss, which indicates the stability of the learning process.

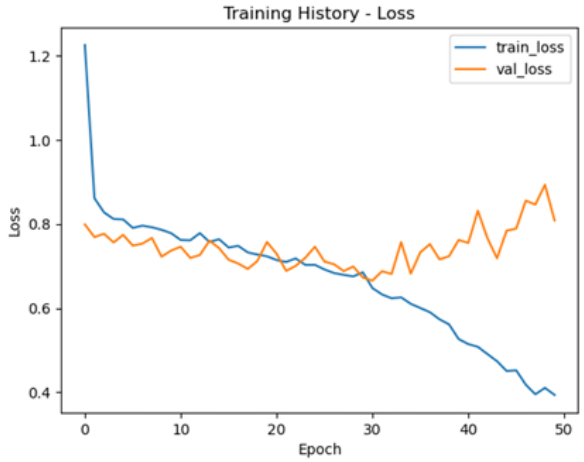

Fig. 3. Training and Validation Loss of ResNet-152.

B. Test Set Evaluation

The model was evaluated on the same test set, now recategorized into binary labels. A confusion matrix was generated to assess the binary predictions.
The matrix shows:

Correctly predicted “No DR”: 335 out of 349

Correctly predicted “DR”: 357 out of 382

The classifier achieved a 95% accuracy, indicating excellent generalization to new data.

Classification Report:

Class	**Precision**	**Recall**	**F1-Score**
No DR	0.96	0.96	0.96
DR	0.94	0.94	0.94
Accuracy			0.95
AUC-ROC			0.986

The high AUC-ROC score of 0.986 further confirms that the model effectively distinguishes between healthy and DR-affected cases.

C. Summery

The ResNet-152 model, when fine-tuned for the diabetic retinopathy classification task, delivered promising results. While the binary classification setup showed excellent performance across all metrics, the multiclass classification revealed the model’s difficulty in identifying severe and proliferative stages—primarily due to dataset imbalance. Further enhancement can be achieved by balancing the dataset and experimenting with ensemble or attention-based architectures.

V. Conclusion And Future Direction

In this study, we developed and evaluated a deep learning-based approach for detecting diabetic retinopathy using ResNet-152, a powerful convolutional neural network architecture. Our model demonstrated strong performance in binary classification tasks, achieving an accuracy of 95%, which indicates its effectiveness in distinguishing between healthy and affected retinal images. However, when extended to multiclass classification—distinguishing the different severity levels of diabetic retinopathy—the model faced more difficulty, primarily due to the subtle and often overlapping visual cues between classes.

While the results are promising, there is still room for further improvement and refinement. Future research can take the following directions:

- Advanced Data Augmentation: To overcome class imbalance and increase the diversity of training samples, more dynamic and robust augmentation strategies such as synthetic data generation using GANs, or adaptive augmentation based on lesion localization, can be explored.

- Robust Evaluation with Cross-Validation: Integrating k-fold cross-validation in the experimental setup would provide more generalized performance estimates. Additionally, statistical significance testing can be conducted to validate that improvements in accuracy are not due to random chance.

- Incorporating Attention Mechanisms: Attention layers or modules such as CBAM or SE-Blocks can be integrated with ResNet-152 to help the model focus on clinically significant regions in the retinal images. This could not only improve accuracy but

also enhance interpretability for medical practitioners.

- Clinical Evaluation and Expert Review: To move closer to real-world implementation, the model's predictions should undergo validation by ophthalmologists or medical experts. This will ensure that the model's outputs are reliable, clinically relevant, and aligned with diagnostic practices.

- Real-World Integration: A key next step would be to embed the trained model into diagnostic software tools or mobile applications used in clinics and rural health centers. Real-time screening powered by AI could significantly improve early detection and intervention for diabetic retinopathy.

In summary, our implementation of the ResNet-152 model for diabetic retinopathy detection showcases the potential of deep learning in automating medical image analysis. With further improvements and validation, such AI-driven tools could greatly assist healthcare providers in early diagnosis, especially in resource-constrained settings, thereby contributing to the prevention of diabetes-related vision loss.

REFERENCES

[1] Kropp, M., Golubnitschaja, O., Mazurakova, A., Koklesova, L., Sargheini, N., Vo, T.-T. K. S., et al. (2023). Diabetic retinopathy as a major cause of vision loss and an early warning sign for further complications: risk factors and prevention strategies. EPMA Journal, 14(1), 21–42.

[2] Centers for Disease Control and Prevention. (2024). Managing diabetes-related vision problems. U.S. Department of Health & Human Services. Available: https://www.cdc.gov/diabetes/managing/diabetes-visionloss.html

[3] Grauslund, J. (2022). The evolution of diabetic retinopathy screening: integrating artificial intelligence. Diabetologia, 65, 1415–1423. https://doi.org/10.1007/s00125-022-05727-0

[4] Jogin, M., Madhulika, M. S., Divya, G. D., Meghana, R. K., & Apoorva, S. (2018). Feature extraction using deep learning and CNNs. In Proc. 3rd IEEE Int. Conf. on RTEICT (pp. 2319–2323).

[5] Alyoubi, W. L., Shalash, W. M., & Abulkhair, M. F. (2020). Review on deep learning methods for diabetic retinopathy detection. Informatics in Medicine Unlocked, 20, 100377.

[6] Dai, L., Wu, L., Li, H., Cai, C., Wu, Q., Kong, H., et al. (2021). A deep learning-based approach for diabetic retinopathy detection across various stages. Nature Communications, 12.

[7] Tsiknakis, N., Theodoropoulos, D., Manikis, G., et al. (2021). A review on AI-based detection and grading of diabetic retinopathy using fundus imaging. Computers in Biology and Medicine, 135, 104599.

[8] APTOS. (2019). APTOS blindness detection challenge. Kaggle. https://www.kaggle.com/c/aptos2019-blindness-detection

[9] Vocaturo, E., & Zumpano, E. (2020). AI advancements in detecting diabetic retinopathy. In IEEE Int. Conf. on BIBM (pp. 1516–1519).

[10] Shah, A. A., Malik, H. A. M., Muhammad, A., et al. (2023). CNN ensemble approach for lung cancer detection. Scientific Reports, 13(1), 2987.

[11] Sharma, P., Nayak, D. R., Balabantaray, B. K., et al. (2024). A review on CNN-based cancer detection: Challenges and research directions. Neural Networks, 169, 637–659.

[12] Gangurde, R., Jagota, V., Khan, M. S., et al. (2023). Efficient cancer detection using CNN and pattern recognition. Biomed Research International, 2023, 6970256.

[13] Das, D., Biswas, S. K., & Bandyopadhyay, S. (2022). Diabetic retinopathy detection using CNN for classification and feature extraction. Multimedia Tools and Applications, 1–59.

[14] Pratt, H., Coenen, F., Broadbent, D. M., et al. (2016). Using CNNs to detect diabetic retinopathy. Procedia Computer Science, 90, 200–205.

[15] Kommaraju, R., & Anbarasi, M. (2024). CNN with residual blocks for diabetic retinopathy detection. Biomedical Signal Processing and Control, 87, 105494.

[16] Senapati, A., Tripathy, H. K., Sharma, V., & Gandomi, A. H. (2024). A systematic review of AI applications in diabetic retinopathy screening. Informatics in Medicine Unlocked, 45, 101445.

[17] Butt, M. M., Iskandar, D. A., Abdelhamid, S. E., et al. (2022). Hybrid deep learning features for fundus image analysis in diabetic retinopathy. Diagnostics, 12(7), 1607.

[18] Gangwar, A. K., & Ravi, V. (2021). Deep learning and transfer learning for detecting diabetic retinopathy. In FICTA 2020 (Vol. 1, pp. 679–689). Springer.

[19] Rakhlin, A. (2017). Deep learning-based framework for diabetic retinopathy classification. BioRxiv, 225508.

[20] Farag, M. M., Fouad, M., & Abdel-Hamid, A. T. (2022). Automatic classification of diabetic retinopathy severity using DenseNet and attention modules. IEEE Access, 10, 38299–38308.

[21] Zhang, C., Lei, T., & Chen, P. (2022). Transfer learning without source data for diabetic retinopathy grading. Biomedical Signal Processing and Control, 73, 103423.

[22] Gour, N., & Khanna, P. (2021). Multi-class ophthalmic disease detection using TL-based CNNs. Biomedical Signal Processing and Control, 66, 102329.

[23] Wong, S. C., Gatt, A., Stamatescu, V., & McDonnell, M. D. (2016). Data augmentation insights for classification tasks. In DICTA 2016 (pp. 1–6). IEEE.

[24] Saproo, D., Mahajan, A. N., & Narwal, S. (2024). Binary classification of diabetic retinopathy using TL-based deep learning. Journal of Diabetes & Metabolic Disorders.