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Deep Learning–Driven Automated Grading of Diabetic Retinopathy Severity Using Transfer Learning and Web-Based Deployment

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Abstract

As one of the most prevalent microvascular complications of diabetes, diabetic retinopathy (DR) remains a leading cause of vision loss that is largely preventable." Early detection of DR is critical to prevent permanent loss of vision"; however, traditional screening methods are labour-intensive, subjective, and heavily dependent on the availability of trained ophthalmologists. This study addresses these challenges by presenting a deep learning–enabled framework for automated DR severity classification from retinal fundus images, designed for smooth integration into a web interface. The proposed model employs transfer learning by fine-tuning the ResNet-50 architecture, enhanced with data preparation strategies like normalisation, cropping, and data augmentation to improve robustness and generalisation. Experiments were conducted on the APTOS 2019 Kaggle dataset, which consists of high-resolution, labelled retinal images spanning five DR severity levels. The model achieved a training accuracy of approximately 90% and a validation accuracy of 71%, with balanced precision and recall across multiple classes. A lightweight web application was further developed to enable real-time predictions, providing users with DR grading and confidence scores. Results indicate that the proposed system can serve as an efficient, low-cost, and scalable approach to DR screening, making it particularly valuable in under-resourced healthcare settings. Future directions include the integration of explainable AI, multilingual accessibility, and clinical validation.

Keywords

Diabetic Retinopathy, Deep Learning, Transfer Learning, ResNet50, Fundus Image Classification, Automated Screening, Healthcare AI Deployment

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1. Introduction

DR remains a critical issue in the context to eye health. Left unchecked, it can completely steal your sight. High blood sugar basically wrecks those tiny blood vessels in the retina over time. Vision starts to decline gradually. What's scary is how fast this condition's spreading as a blindness cause of blindness, especially among folks still in their working years. Catching it early makes a huge difference. Most vision loss can actually be prevented. [1] The problem is that traditional screening needs eye doctors to check manually. That process is time-consuming, costly, and relies on human judgment. Places short on specialists really feel the strain. Here's where AI comes into play these days. Deep learning, particularly in medical imaging, holds significant promise. [13]

1.1 Background and Motivation

As a progressive complication of diabetes, DR contributes significantly to preventable blindness among working adults worldwide. The International Diabetes Federation (IDF) indicates that more than 537 million adults at this time have diabetes, and the number is expected to increase to 783 million by 2045, with almost a third having both diabetes and DR [1]. The disease develops in stages, with mild and non-proliferative ones being the initial stages, and severe proliferative ones, which can lead to unforeseen and irreversible loss of vision. Although other treatment options like laser treatment and anti-VEGF injections are available, early symptomatic detection has served as one of the leading causes of optical dysfunction and the attendant socioeconomic disasters. Traditional DR screening is based on the manual analysis of the retina fundus by ophthalmologists; this method is highly accurate but time-consuming and will likely remain dependent on the presence of specialists. This is worsened by the shortage of healthcare infrastructure in resource-limited areas. Subsequently, financing automated, cost-effective, and scalable DR detection approaches has been developed as an emergency concern in healthcare [5].

1.2 Role of Artificial Intelligence in Medical Imaging

Recent advancements in artificial intelligence (AI) and deep learning (DL) have demonstrated remarkable success in medical image analysis [6]. Convolutional neural networks (CNNs) are capable of extracting hierarchical features from images, making them highly effective for disease classification and segmentation tasks. Several studies have shown that CNN-based models can achieve ophthalmologist-level accuracy in DR detection [7], [8]. Transfer learning has further improved performance by adapting pre-trained models such as ResNet, DenseNet, and Inception from large-scale datasets like ImageNet to medical images [9]. This strategy minimizes training time and mitigates the challenge of limited labelled datasets, which is a common issue in medical imaging [10]. Additionally, techniques such as data augmentation and normalisation enhance model robustness by addressing variability in fundus image quality and acquisition devices [11].

1.3 Research Gap

Despite the success of AI-driven DR detection systems, several limitations remain:

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- Deployment Limitations: Most models are confined to research environments and lack real-world usability through user-friendly clinical interfaces [13].
- Stage-Wise Classification: Although detecting the presence of DR is common, accurate grading of all five severity levels remains challenging [14].
- Resource Constraints: Lightweight and scalable solutions suitable for low-resource healthcare settings are underexplored, hindering adoption [15].

1.4 Objectives and Contribution

To address the above challenges, this study proposes a DL–based framework for automated grading of DR severity with real-time web deployment. The main contributions are:

- Model Development: Fine-tuning of the ResNet50 architecture, with preprocessing steps (normalisation, cropping, augmentation) to improve generalisation.
- Performance Evaluation: Multi-class evaluation using accuracy, precision, recall, F1-score, and confusion matrix analysis to ensure robustness.
- Web-Based Deployment: Integration with a Flask-based web application, enabling users to upload retinal fundus images and receive immediate predictions with confidence scores.
- Practical Relevance: Focus on system usability in resource-constrained healthcare settings, bridging the gap between laboratory research and clinical application.

1.5 Paper Organisation

The rest of this manuscript will be presented as follows. The next section provides an extensive overview of the available literature on diabetic retinopathy classification using artificial intelligence and deep learning tools, highlighting key findings and inherent shortcomings. The following section outlines the development of the research problem and the proposed procedure, including preprocessing strategies, model framework, and workflow framework. The following section outlines the framework of the experiment and presents the findings, comparing them to state-of-the-art methods. The second-to-last section is a discussion of the findings with the strengths, limitations, and practical implications components of the proposed system. Lastly, a conclusion section concludes the paper, defining the research areas of interest for future clinical validation, scalability, and implementation in real-life healthcare settings.

2 Related Work

The referenced works have been systematically classified to illustrate their thematic contributions to DR detection. The graph IN Figure 1 presents a comprehensive bifurcation of the selected articles, grouping them into categories such as foundational CNN-based studies, ResNet and feature extraction approaches, ensemble and hybrid models, multimodal techniques, lightweight frameworks for resource-constrained environments, systematic reviews, and deployment-oriented research. This structured visualisation not only highlights the distribution of prior research efforts but also underscores the dominant trends within the domain.

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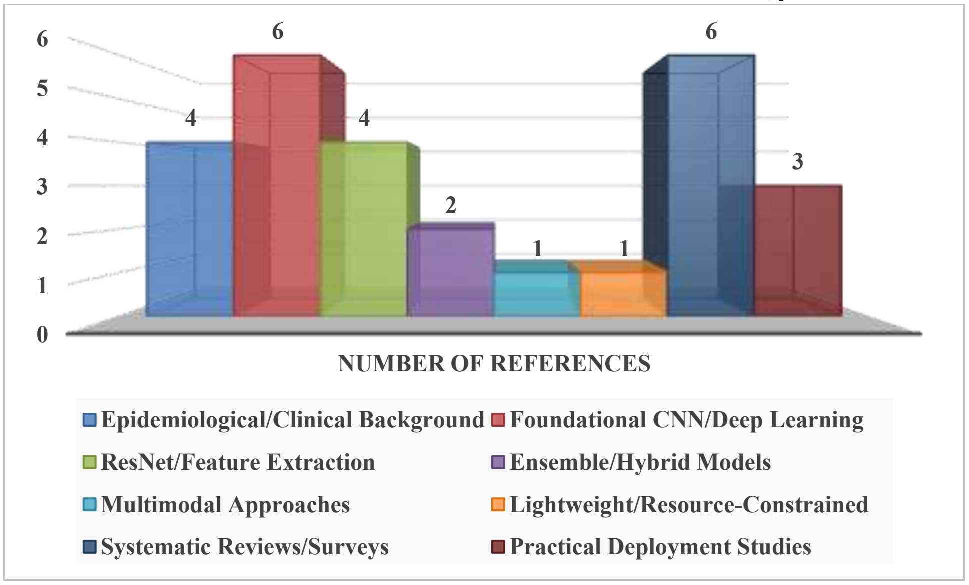

Fig. 1 Article bifurcation based on technology

Complementing this, Table 1 provides a detailed breakdown of the references, explicitly mapping each article to its respective contribution area. Together, the graphical and tabular representations offer a coherent overview of the existing body of knowledge, thereby setting a clear context for the subsequent critical analysis and positioning of the present study.

Table 1: A detailed breakdown of all the surveyed articles can be seen in the table below:

	Method / Model	Dataset(s)	Major Contribution	Limitation
[5]	Deep CNN (Google AI)	EyePACS	First large-scale validation of DL for DR detection; matched ophthalmologist-level performance	High computational resources; not deployable in low-resource settings
[7]	CNN for DR detection	Local fundus images	Demonstrated feasibility of CNNs for medical image-based DR screening	Small dataset; limited generalisation
[19]	Transfer-Ensemble CNN	EyePACS	Improved accuracy using an ensemble of CNNs with transfer learning	Computationally heavy; no clinical deployment
[20]	Multimodal Fusion (UWF-CFP + OCTA)	Public + hospital datasets	Combined fundus + angiography for robust severity classification	Requires expensive OCTA devices
[15]	Lightweight CNN +	EyePACS, APTOS	Designed resource-efficient models suitable for mobile DR screening	Accuracy trade-offs in constrained devices

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	Knowledge Distillation			

3. Problem Formulation

(DR) is an irreversible but progressive diabetic complication, and as the diseases develop, the impaired retinal circulation leads to retinal endpoints such as visual dysfunction and eventual blindness. Although timely therapeutic intervention can prevent the loss of vision, present-day traditional screening tests, including the gradual viewing of fundoscopic shots by exclusively specialised personnel, cannot be considered less labour-intensive, as their results are prone to human bias, and the presence of qualified personnel primarily determines productivity. This restriction is even more pronounced in resource-strained settings, where healthcare facilities and specialist resources are limited. With the growing national and global statistics over diabetes, an increasing need to design scalable, accurate, and automated diagnosis options is mandated.

A different conceptualisation defines DR detection as a multi-class classification task, whereby retinal fundus images have to be classified into discrete severity scales of diabetic retinopathy, ranging from normal to non-detectable DR and proliferative stages. The main problem is how to identify subtle changes in the retina, which can be related to specific milestones of the disease.

These are additional issues that noninvasively complicate this research process: variation in image quality due to the presence of various acquisition devices, the proportion of classes in datasets, and the necessity to extrapolate the results to a nonidentical population of patients. Even though many modern methods have proven valuable degrees of accuracy with controlled experimentation settings, a significant number of them do not have deployment frameworks that can easily be combined with effective clinical applications. This paper, therefore, suggests the creation and use of a robust deep-learning algorithm to objectively assess the severity of DR. The architecture of transfer-learning is ResNet-50 with available canonical pre-processing methods, namely normalisation, cropping and data augmentation. Going beyond the concept of theoretical constructs, the derived approach focuses on pragmatic applicability, as the model is implemented in a web-based platform. This enables real-time predictions to be made and is applicable in both contexts: to the healthcare community and to patients.

4. Framework Development and Methodology

The framework proposed for the automated detection and classification of DR integrates transfer learning with the ResNet50 model, systematic preprocessing, and a web-based deployment strategy. The methodology is divided into five stages:

1. Data acquisition
2. Preprocessing
3. Model development and training
4. Workflow design
5. Deployment.

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To improve learning effectiveness and achieve better classification performance, the research utilises transfer learning by fine-tuning the ResNet50 architecture, one of the strongest pre-trained deep neural networks. Transfer learning enables the model to leverage features learned from large datasets, such as ImageNet, and transfer them to the DR classification task, even with relatively few labelled medical images. It utilises the publicly downloadable APTOS 2019 Kaggle data, which comprises more than 90,000 high-quality retinal fundus images each tagged by medical doctors according to the DR's stage (see Figure 2 for reference). The significant aspects and research pipeline involve:

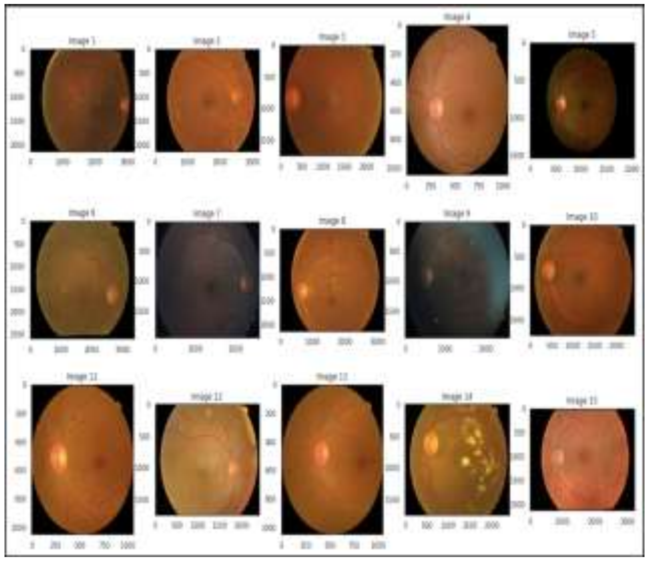

Fig 2. Sample Fundus Images

4.1Technological breakdown

The framework was implemented using a combination of strong software platforms, hardware facilities, and provisioning tools that ensured practical training and realistic deployability. The model has been developed in Python 3.8 and the use of TensorFlow 2.x and Keras was used to implement and further refine the ResNet-50 architecture through transfer learning. The main environment where experimental iterations were performed was a Jupyter notebook, it was a framework, and the functioning Flask was the backend, consuming image inputs and providing infrastructure between the deep-learning model and the web-based interface. Front-end web development was built using both standard web languages: HTML5, CSS3, and JavaScript, with the addition of Bootstrap to ensure compatibility and create an attractive interface across various device types.

The training was conducted in Google Colab, utilising the graphical processing unit (GPU) to train across the massive computational requirements efficiently. Local deployment testing enabled us to utilise systems equipped with at least 8GB of RAM (although 16GB is recommended) and running either Windows 10/11 or Ubuntu 20.04+. The environments used for development included Jupyter Notebook and Visual Studio Code, which were utilised to train the models and integrate them into systems. Interface validation was carried out using web browsers such as Chrome, Firefox, and Microsoft Edge. A storage buffer of 1020GB was considered adequate to store the dataset and model artefact outputs.

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The deployment pipeline itself was intentionally made lean, and Flask enabled real-time inference and two-way communication between the front end and the back end. Scalability was considered, taking into consideration the introduction of cloud inclusion with platforms such as Amazon Web Services or Google Cloud Platform. Moreover, additional aids, such as Ngrok and GitHub, can be incorporated to enhance external visibility and foster a team-building experience. Taken together, this set of technological architectures ensures that the proposed structure offers the highest prediction accuracy and enables effective deployment in a real-world healthcare environment.

4.2 Preprocessing Technique

- Normalising to maintain standard pixel intensity levels
- Crop and Resize to ensure only the area of the retina is observed
- Data augmentation (flipping, rotation, zooming) for decreasing the effects of overfitting

4.3 Model Architecture with Training and Hyperparameters

- Use of ResNet50, which is a 50-layer deep CNN with residual connections to alleviate vanishing gradient issues(figure 3)
- The last layers are modified and tuned to meet the multi-class classification task
- The training is performed using cross-entropy loss and optimised with the Adam optimiser.

conv5_block3_2_bn (BatchNormalizatio…	(None, 16, 16, 512)	2,048	conv5_block3_2_c…
conv5_block3_2_relu (Activation)	(None, 16, 16, 512)	0	conv5_block3_2_b…
conv5_block3_3_conv (Conv2D)	(None, 16, 16, 2048)	1,050,624	conv5_block3_2_r…
conv5_block3_3_bn (BatchNormalizatio…	(None, 16, 16, 2048)	8,192	conv5_block3_3_c…
conv5_block3_add (Add)	(None, 16, 16, 2048)	0	conv5_block2_out… conv5_block3_3_b…
conv5_block3_out (Activation)	(None, 16, 16, 2048)	0	conv5_block3_add…
global_average_poo… (GlobalAveragePool…	(None, 2048)	0	conv5_block3_out…
dropout_4 (Dropout)	(None, 2048)	0	global_average_p…
dense_2 (Dense)	(None, 2048)	4,196,352	dropout_4[0][0]
dropout_5 (Dropout)	(None, 2048)	0	dense_2[0][0]
final_output (Dense)	(None, 5)	10,245	dropout_5[0][0]

Total params: 27,794,309 (106.03 MB)
Trainable params: 27,741,189 (105.82 MB)
Non-trainable params: 53,120 (207.50 KB)

Fig 3. A few layers of the ResNet 50 model

- Model evaluation is conducted using key metrics, including precision, accuracy, precision, F1-score, Recall, and the confusion matrix.
- The above metrics help determine the extent to which the model performs with all five classes

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4.4 System Workflow

- An intuitive web interface was developed to allow users—such as physicians, patients, and healthcare workers for uploading retinal images with immediate prediction results, confidence scores, and DR grading (Figure 4).
- The interface also offers suitable recommendations based on the predicted severity

Fig 4. Web Interface

The system overview and flow are illustrated in Figure 5, which provides a clear breakdown of transfer learning.

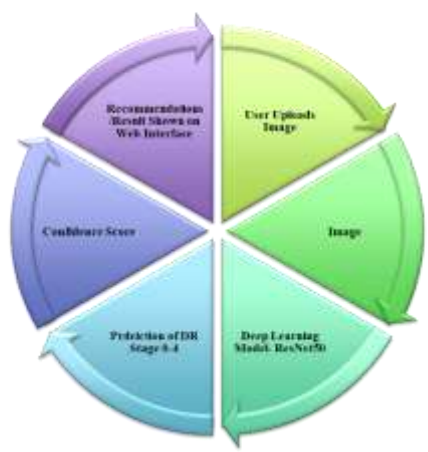

Fig 5. Algorithm for Transfer Learning

1. User Uploads Retina Image- The frontend UI permits users (doctors or patients) to upload retina images.
2. Image Sent to Flask Backend- The image is passed on to the backend Flask API through an HTTP POST request.

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3. Image Preprocessing- The backend normalises and resizes the image to the needed input shape of the trained ResNet50 model (e.g., 128x128x3).

4. Prediction using Trained Model — The processed image is fed into a pre-trained ResNet50 model, which classifies it into one of the five DR categories.

5. Response Sent to Frontend- The prediction outcome is sent back to the frontend and presented to the user with confidence score and visual feedback, for a proper breakdown of the use case of work.

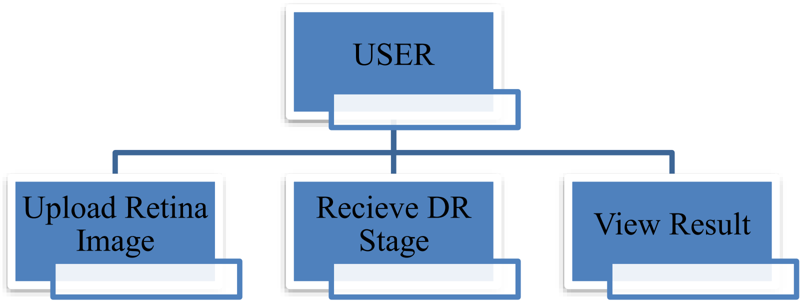

Fig 6. Use-Case Diagram

This illustration depicts the workflow of a web-based ML application. The user sends data to the frontend, which sends a POST request to the Flask server. The server preprocesses the data and passes it to the ML model for prediction. The prediction output is passed back to the server, is JSON-ified, and is returned to the frontend, which then presents the result to the user. Figure 6 illustrates the general use case of the proposed web-based system. The figure depicts how various users interact with the app. A patient or physician initiates by uploading a retinal fundus image via the web portal. The image is routed to the backend system, where preprocessing is performed to normalise size, brightness, and quality. The preprocessed image is then input into the trained ResNet-50 model, which predicts that the picture belongs to one of the five categories of diabetic retinopathy. The result, along with a confidence score, is returned to the user. The diagram illustrates the ease of the process, whereby users need to upload an image, while technical processing takes place automatically in the backend. This application prioritises ease of adoption and accessibility in real-world medical environments.

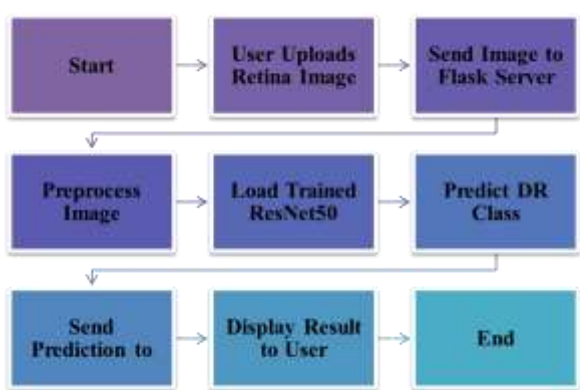

Fig 7. WorkFlow Diagram_1

Figure 7 shows a more descriptive workflow of the system pipeline. It starts with the user uploading a retinal image. The system preprocesses through operations such as resizing, normalisation, and data

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augmentation. These prevent the input image from being in an unexpected format, thereby enhancing the robustness of training. After preprocessing, the image is then propagated to the fine-tuned ResNet-50 model. The model performs deep feature extraction, classification, and severity level prediction of diabetic retinopathy. The output is then prepared for visualisation and propagated to the user via the web interface. This workflow portrays the systematic order of operations from input to prediction.

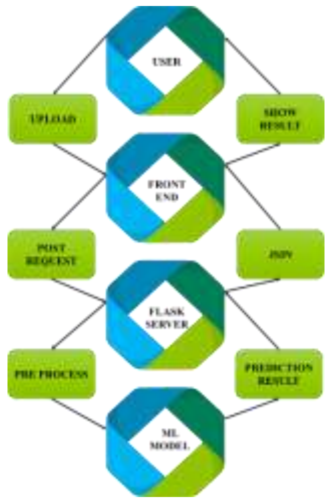

Fig 8. WorkFlow Diagram_2

Figure 8 depicts the interaction among the various components of the system in a more technical sense. It represents the flow of communication from the frontend, where the image is uploaded, to the backend, in which Flask serves as the server—the backend processes preprocessing, model inference, and prediction. The result is then formatted into a JSON response that is sent back to the frontend. On the user's display, this answer is presented as the forecasted class and levels of confidence. This graph illustrates the integration of machine learning with web technologies, demonstrating how artificial intelligence can be applied in a functional and user-friendly application.

5.Results and discussion

The developed system can correctly classify Retinal Fundus Images into five stages of (DR): No DR, Mild, Moderate, Severe Proliferative DR. Eventually, the APTOS 2019 Blindness Detection Dataset was input into and trained with the deep learning algorithm ResNet50, and the results obtained by this system were:

- Training Accuracy: ~90%
- Validation Accuracy: ~71%
- Precision/Recall: Class-specific, better for earlier-stage DR

Once it is successfully integrated with a web frontend, where users upload new images and receive real-time predictions, including the DR stage and model confidence. For the validity check, images 9 and 10

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Data flow and interaction between various components [1]. Flask is an API that serves as a mediator between the front end and the model, performing processing and analysis during inference in the application promptly.

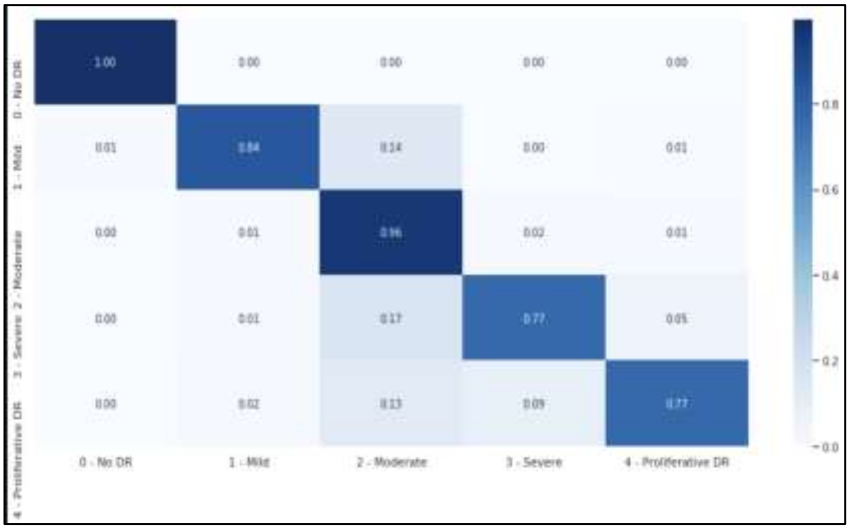

Fig 9. Confusion Matrix

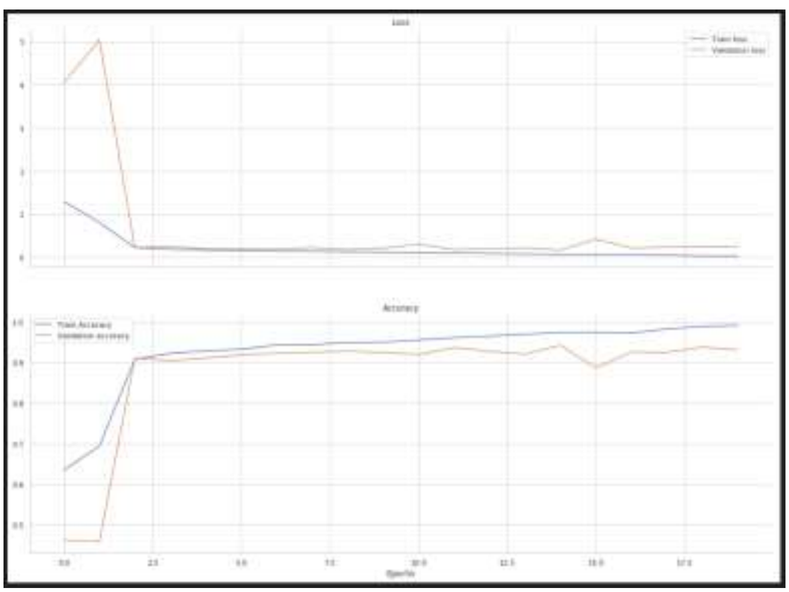

Fig 10. Loss and Accuracy Graph

4.1 Comparison with Existing Studies

The obtained results are consistent with other state-of-the-art DR detection frameworks. For instance, ensemble-based CNNs [19] and attention-augmented ResNet50 [26] have reported improved classification accuracy but at the cost of higher computational complexity. Similarly, lightweight models optimised for

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mobile use [15] demonstrate practical applicability, albeit with reduced precision in advanced stages. Compared to these, this solution delivers a balanced combination of predictive accuracy and deployability, with a unique emphasis on real-time web integration.

4.2 System Deployment Outcomes

Beyond the quantitative performance metrics, deploying the trained model into a web-based diagnostic interface significantly enhances its real-world relevance. Physicians and patients can upload retinal images and receive real-time predictions, confidence scores, and severity grading. This accessibility has the potential to reduce dependence on manual screening, particularly in resource-limited healthcare environments.

4.3 Discussion of Limitations

While the results are promising, several limitations remain. First, the validation accuracy suggests that further improvement is required for robust generalisation across diverse populations and imaging devices. Second, the model exhibits reduced sensitivity in distinguishing between *Severe* and *Proliferative DR*, indicating the need for advanced architectures or attention mechanisms. Finally, the system has not yet undergone clinical validation in a hospital setting, a critical step for regulatory approval and large-scale adoption.

4.4 Implications and Future Directions

The study demonstrates the potential of deep learning combined with web deployment for practical DR screening. Future work will explore:

Integration of explainable AI techniques, such as Grad-CAM, to provide visual interpretability of predictions.

- Use of larger, more diverse datasets to improve generalisation.
- Incorporation of multilingual interfaces and mobile-based deployment for broader accessibility.
- Collaboration with healthcare providers for clinical trials and validation studies.

6. Conclusion:

This study presents a deep-learning-powered method for the automated detection and assessment of (DR) severity, supervised by transfer learning using the ResNet-50 model, along with a basic, economic, web-based interface. The model achieved training and validation accuracies of 90% and 71%, respectively, and performed exceptionally well in early-stage detection. The practical utility of the trained model was also significant, as integrating it into a lightweight web application enabled clinicians and patients to access retinal fundus images and receive instant predictions with confidence scores specified. The key contribution that this project will make to the research is filling the gap between laboratory-based models of DR classification and real-time diagnostic solutions that can be deployed. The combination of effective deep-learning-based methods and an easily accessible interface makes the system less susceptible to scalability and usability issues, particularly in the context of a resource-constrained healthcare environment with limited specialist penetration.

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However, several limitations remain, including reduced classification sensitivity in progressive units of DR and the need for clinical validation in heterogeneous groups. Addressing these weaknesses requires expanding the dataset to cover a broader range of demographic groups, utilising an explainable method of AI to increase interpretability, and conducting large-scale clinical trials to build its robustness in real-life conditions. To conclude, it was found that the suggested system demonstrates the potential for AI-assisted screening of DR to become an integral part of clinical practice. Through their continuous refinement and validation, these frameworks can make particularly significant contributions to early diagnosis, improved therapeutic interventions, and reduced medication costs for vision on an international level.

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