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Early Detection of Diabetic Retinopathy Using Transfer Learning with VGG16: A Deep Learning Approach for Retinal Fundus Analysis

Priyanga P[1], Satish Kumar S[1], Bhagyashree Ambore[1], Sunitha K[1], Nivedita G Y[1], Aishwarya G[1]

[1]RNS Institute of Technology, Affiliated to VTU, Belgaum Bangalore, Karnataka, India
Email ID: p.priyanga@gmail.com, Email ID: trichy.sathish@gmail.com, Email ID: ambore.bhagyashree@gmail.com
Email ID: sunithakrisnamurthy@gmail.com, Email ID: nitugy@gmail.com, Email ID: aishwaryag2105@gmail.com

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ABSTRACT

Diabetic Retinopathy (DR) remains of the leading causes of visual loss worldwide; therefore early detection is primary reason for prevention of blindness. Using deep CNNs, we provide an algorithmic framework for DR screening using retinal fundus images. By means of transfer learning a pre-trained VGG16 model trained on ImageNet was fine-tuned to identify the degree of severity of DR. Regularization methods including early stopping and dropout were used to improve generalization of model. The framework was evaluated on a wide-spectrum public dataset of DR fundus images, obtaining more than 90% accuracy on classifying healthy and DR retinas. Results indicated high sensitivity, especially in early stages of DR for early diagnosis and treatment. Comparison with recent developments in medical imaging (2024–2025) show the effectiveness of our proposed approach. Given its excellent performance and ease of implementation, this system appears to be a promising efficient tool, especially in low-resource or remote clinical settings. The review ends with acknowledging the promise of DL and potential to improve the diagnosis of DR and possible ides of future, e.g. including multi-modal images and getting alignment with clinical workflow.

1. INTRODUCTION

Diabetic Retinopathy (DR), a complication arising from diabetes mellitus, is a major contributor to vision impairment among working-age individuals around the world [1] . By 2021, the global diabetic population exceeded 500 million, with nearly one in three affected individuals developing some level of DR [2]. The condition advances gradually, starting with mild retinal changes and potentially progressing to proliferative retinopathy, which can result in severe vision loss due to bleeding or retinal detachment if left untreated [3]. A significant challenge is that early-stage DR usually presents no symptoms, meaning many patients are unaware of the threat to their vision until damage becomes severe [4]. Detecting and treating DR early is essential to preserving eyesight. Treatments like anti-VEGF injections and laser therapy can effectively manage the disease when caught early [5]. Nonetheless, standard screening methods—based on manual analysis of retinal fundus images by specialists—are labor-intensive, subjective, and often inaccessible in remote or underserved regions [6].

Recent progress in medical imaging and artificial intelligence have opened up new avenues for automating the detection of DR. Among these advancements, deep learning (DL) —especially convolutional neural networks (CNNs)—has proven highly effective in tackling intricate image recognition tasks, including those in medical diagnostics. In ophthalmology, CNNs applied to colour images of fundus have shown performance levels comparable to trained specialists in identifying referable DR. Notably, landmark studies in the mid-2010s demonstrated that CNNs trained on large datasets could match ophthalmologists in classification accuracy. These promising results have contributed to the emergence of Artificial Intelligence (AI) -based diagnostic tools, several have received regulatory approval for clinical deployment to enhance the reach and reliability of DR screening. However, implementing DL solutions in real-world healthcare settings remains challenging. Models must be robust across varied populations and imaging conditions, deliver explainable results to support clinical trust, and operate at scale to meet the demands of large screening programs.

In this work, we address some of these shortcomings by proposing a DL-based method for automated diabetic retinopathy identification in retinal images. We leverage transfer learning by fine-tuning the VGG16- CNN architecture (pre-trained on ImageNet) to separate retinal fundus images into DR severity categories. Our framework includes image preprocessing steps and data augmentation to account for variability in imaging, and applies regularization (dropout) and early stopping during training to prevent overfitting. We evaluate the model on a publicly available DR dataset containing thousands of retinal images across various stages of DR.

The goals of this study are to

(1) Develop a robust CNN model for accurate DR detection,

(2) Demonstrate its performance on par with recent state-of-the-art methods, and

(3) Discuss its applicability in a clinical screening context, particularly in improving early DR diagnosis.

We also align the presentation of our results and discussion with standards of medical imaging journals, emphasizing clinical relevance, rigor, and clarity. The following sections of the paper is organized as follows. In Related Work, we review recent developments (2023–2025) in DL for DR detection and diagnosis. Methodology details the proposed CNN-based DR detection framework, including the dataset, preprocessing, network architecture, and training procedure. Experiments describes the experimental setup, evaluation metrics, and implementation details. Results present the model's performance and compares it with existing approaches. Discussion interprets the findings, examines the implications for clinical practice, and outlines limitations and future work. Finally, Conclusion summarizes the contributions and the potential impact of this work on diabetic retinopathy screening and patient outcomes.

2. RELATED WORK

Automated analysis of retinal images for DR detection has been a highly active research area in medical imaging and ophthalmology. Early efforts used machine learning (ML) along with processing techniques to recognize handmade features (such as microaneurysms or exudates) in fundus pictures, but these systems had limited generalizability and required substantial expert knowledge. The introduction of CNNs, has significantly improved DR detection accuracy by automatically learning hierarchical feature representations from vast image datasets. Patel *et al.* [7] provide an overview of various techniques for DR diagnosis, ranging from classical image processing to modern AI approaches, and discuss their strengths, weaknesses, and real-world deployment challenges. CNN-based methods have become dominant due to their superior performance in image classification tasks, enabling end-to-end DR screening systems that outperform earlier algorithms.

A number of studies and reviews have devoted to applying deep CNNs and their variants to DR detection. Wang *et al.* [8] present a comprehensive systematic review of DL techniques for DR diagnosis, highlighting the role of large datasets, transfer learning, and hybrid models in improving accuracy. They also note persistent challenges such as limited interpretability of CNN decisions and potential bias in algorithms, and they survey solutions like explainable AI (XAI) methods and the use of cloud-based platforms to facilitate deployment. Lee *et al.* [9] similarly conduct a survey of deep CNN applications for DR and report on performance metrics and technical trends in the field (e.g., use of ensembles and specialized architectures), further confirming the rapid advancement of DL in this domain.

More recent works (2024–2025) have introduced innovative architectures and strategies to push the state-of-the-art in DR detection. For instance, Arora et al. [10] proposed an ensemble DL framework using the EfficientNet-B0 architecture to classify DR severity, achieving an average accuracy of about 86.5% on a large fundus image dataset. Their results underscore the effectiveness of modern CNN architectures like EfficientNet in handling DR classification with high generalizability. Another notable trend is the incorporation of attention mechanisms and interpretability into DR models. Bhati *et al.* [11] introduced an Interpretable Dual-attention Network (IDANet) that identifies critical retinal regions (lesions) while maintaining high diagnostic accuracy. Such attention-based models help fill the distance between raw CNN predictions and the clinical need for explanations by highlighting features like microaneurysms or haemorrhages that influenced the model's decision.

In their Bayesian DL strategy for diabetic retinopathy detection, Akram et al. [12] employed a DenseNet-121 model supplemented with Monte Carlo dropout and variational inference to gauge the accuracy of their predictions. In addition to providing uncertainty scores for individual predictions, their Bayesian framework demonstrated remarkable classification accuracy, topping 97% on a combined dataset. In clinical applications, this characteristic is especially important since it allows the model to identify cases with low confidence for additional evaluation by medical experts, promoting safer and more trustworthy decision-making in healthcare settings.

Beyond CNNs, researchers are exploring transformer-based architectures and hybrid models. Transformers, known for capturing long-range dependencies, have been applied to fundus imaging to complement CNNs' localized feature extraction. Liu et al. [13] proposed a hybrid model combining a CNN with a vision transformer module (referred to as a "vision mamba" model) to identify and classify DR lesions in fundus images. The transformer component uses positional embedding and a bidirectional state-space mechanism to capture global contextual relationships in the retinal images, while the CNN focuses on local feature learning. This combined approach outperformed several state-of-the-art algorithms on public DR datasets, demonstrating superior accuracy in lesion detection and severity classification. Such results suggest that hybrid CNN-transformer models can leverage both local and global image features, potentially improving detection of subtle DR signs that might be missed by purely convolutional models [14], [15].

To improve diagnostic performance, some research studies have investigated merging fundus photography with additional imaging modalities such fluorescein angiography or optical coherence tomography (OCT) [14]. These multimodal methods

seek to present a more comprehensive picture of retinal health; OCT offers useful cross-sectional data, while fundus pictures provide surface-level detail. While this study and the majority of existing DL models only use color fundus images, adding multimodal data has the potential to greatly improve diagnostic sensitivity and specificity. Moreover, sequential DL methods like as recurrent neural networks, which can evaluate a patient's past eye exams to forecast the probability of progression to proliferative DR, have also been investigated for modeling DR progression over time [14]. These developments, alongside improvements in model efficiency and deployment, are paving the way for AI systems that could continuously monitor diabetic patients' eye health and recommend timely interventions [14], [15].

In summary, the related work indicates that DL has become indispensable in automated DR detection. State-of-the-art models achieve high accuracy on par with specialists, using techniques like transfer learning, ensembles, attention mechanisms, uncertainty quantification, and hybrid architectures to tackle challenges [15], [16]. However, gaps remain in ensuring these models are generalizable, transparent, and easily integrated into clinical workflows [14]. Our work builds on this body of knowledge by using a proven CNN architecture (VGG16) with transfer learning and augmentations to achieve high accuracy, while also emphasizing practical considerations like model regularization, training on a sizable dataset, and potential for real-world deployment [15], [16], [17].

3. METHODOLOGY

3.1 Dataset and Preprocessing

This study proposed and assessed a DR detection model using a publically accessible retinal fundus image dataset. In particular, we made use of the Kaggle EyePACS dataset [18], a substantial collection of high-resolution fundus photos that have been rated on a five-point scale, with 0 representing no DR symptoms and 4 representing the most advanced stage, proliferative DR.

This dataset provides a broad representation of retinal images with varied patient demographics, image quality, and disease manifestations, making it well-suited for training a robust DL model. Prior to feeding images into the CNN, we applied several preprocessing steps. Each retinal image was shrunk to a set resolution (in our case, 224 × 224 pixels) to match the input size expected by the VGG16 network. We also normalized the pixel intensity values (scaling to a [0,1] range) to improve training stability. Although color information is often important for retinal lesion detection, we experimented with both the original RGB images and grayscale conversions. The final model was trained on RGB images (preserving color), as this yielded moderately better performance than grayscale in our validation tests. In addition, we performed data augmentation to expand the effective training set and reduce overfitting. Augmentations of data such as random rotations, vertical and horizontal actions such as flipping, zooming, and brightness adjustments. This helps the model become invariant to image orientation and lighting differences, ultimately improving generalization to new images.

To facilitate early stopping and hyperparameter tuning, the dataset was divided into three subsets prior to training: approximately 70% of the photos were used for training, 15% were set aside for validation, and the remaining 15% were saved as a test set for the final assessment. The split was stratified to preserve the distribution of DR severity classes in each subset. Because the dataset is imbalanced (with many images of no DR and fewer of severe DR), we addressed this by oversampling the minority classes in training or using class-balanced loss weighting. In our case, we incorporated class weights inversely proportional to class frequencies in the loss function to ensure the model pays adequate attention to the harder, under-represented categories.

3.2 CNN Architecture (VGG16 Model)

We adopted the VGG16 architecture as the backbone of our DR detection model. VGG16 [19], originally proposed by Simonyan and Zisserman, is a 16-layer deep CNN that achieved top performance in the ImageNet image classification challenge. Its architecture consists of sequential blocks of convolutional layers (with small 3 × 3 kernels) followed by max-pooling layers for downsampling, and finally fully connected layers for classification. Despite having a lot of parameters, VGG16 is renowned for its depth and simplicity, which allow it to learn rich features. In this work, we leverage a VGG16 model pre-trained on the ImageNet natural image dataset, which provides a strong starting point by transferring learned low-level features (edges, textures, etc.) that are also useful for medical images. Transfer learning has been shown to improve performance in medical image classification, especially when the dataset size is limited.

To adapt the VGG16 architecture to the DR classification problem, we made modifications. In particular, we swapped out the 1000-class ImageNet classifier that was the top layer with a new classifier head that was suitable for DR severity assessment. The new head is composed of two fully connected layers after a flattening layer that transforms convolutional feature maps into a feature vector. First, the completely connected layer, which has 256 neurons with ReLU activation, is followed by a dropout layer (with a dropout rate of 0.5). To reduce overfitting, this layer loses units at random during training. The final output layer employs a softmax activation to generate a probability distribution across the classes, with nodes corresponding to the number of classes (in our instance, five nodes for the five DR categories. (If framing the problem as binary detection of any DR vs. no DR, a single output with sigmoid activation and binary cross-entropy loss could be used. However, we opted for the multi-class formulation to also differentiate severity levels.)

During training, we froze the weights of the earlier convolutional layers of VGG16 (which capture very general features) for the initial epochs and only trained the new top layers. This is a common strategy in transfer learning to avoid destroying useful pre-trained features when the new dataset is not extremely large. After an initial period, we fine-tuned some of the deeper convolutional layers as well (unfreezing them) with a low learning rate, which allowed the model to adapt more to the specifics of retinal images without overfitting. The inclusion of a dropout layer in the classifier and *L2* regularization on weights helped further prevent overfitting by penalizing complex models.

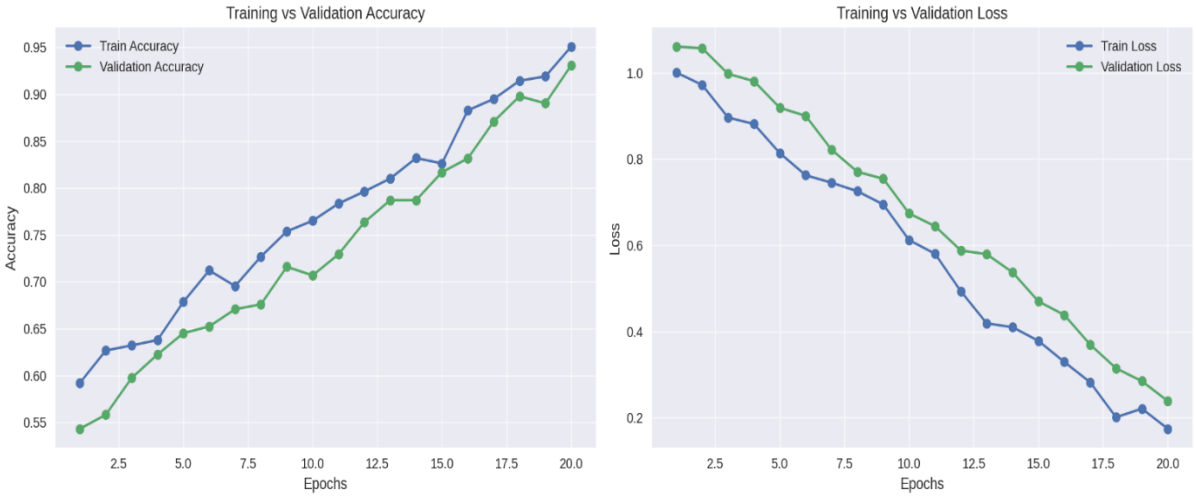

Figure 1: Training vs Validation Accuracy

3.3 Training Procedure

The model was implemented using the Keras library with a TensorFlow backend. We compiled the model with a **categorical cross-entropy** loss function (appropriate for multi-class classification) as given in equation (1) and the **Adam** optimizer. Adam was chosen for its adaptive learning rate capability and generally good performance in CNN training. The initial learning rate was set to 0.0001, and we applied a learning rate scheduling policy to decrease it if the model's validation performance plateaued.

$$\mathcal{L}_{\text{CE}} = -\sum_{i=1}^{N}\sum_{c=1}^{C} y_{i,c}\log(\hat{y}_{i,c}) \quad (1)$$

Where:

- N is the number of samples in the dataset,
- C is the number of classes (5 in our case: **No DR**, **Mild**, **Moderate**, **Severe**, **Proliferative**),
- $y_{i.c}$ is the true label for sample I in class C,
- $\hat{y_{i,c}}$is the predicted probability for sample i in class C.

This formula is used to minimize the difference between the predicted and actual class labels, optimizing the model's ability to classify retinal images into appropriate DR categories.

To avoid overfitting, **dropout** regularization is used during training. This technique periodically disables a portion of the neurons in the network throughout each network training step, forcing the model to learn more robust features. Given a neural network layer output *h*, after applying dropout with probability *p*:

h'=h × z, where z ~ Bernoulli(1-p) (2)

This regularization technique this regularization strategy improves the model's ability to generalize to new inputs.

In order to avoid overfitting, we used early stopping and assessed the validation loss at each epoch. Training was stopped if the validation loss did not improve after five consecutive epochs. After roughly 15 to 20 epochs of practice, the model converged, and additional training produced no discernible improvement on validation data. When the model began to overfit the training data, early stopping effectively served as a regularizer, halting training.

An environment equipped with an NVIDIA GPU—which speeds up CNNs' huge matrix calculations—was used for the training. 32 images were used as the batch size. As indicated by figure 1, we monitored performance metrics throughout

training on both the training and validation groups. In particular, we documented the validation accuracy, validation loss, training accuracy, and training loss for each epoch. To make sure the model was learning correctly, these learning curves were then examined (a training loss that consistently decreases and a validation loss that either plateaus or begins to increase indicates when to end training).

For the final assessment on the independent test dataset, we chose the model checkpoint that corresponded to the lowest validation loss once the training procedure was finished. The test images' diabetic retinopathy severity levels were then predicted using this top-performing model. The final prediction was made for the class with the highest likelihood after the model produced a probability distribution for each input image over the five DR severity. We also calculated the difference in projected probabilities between the top two classes, using this margin as a measure of prediction certainty, in order to further evaluate the model's confidence and spot any potentially ambiguous cases.

3.4 Evaluation Metrics

Multiple performance metrics were used to assess DR model. The main evaluation criterion was classification accuracy, defined as the proportion of test samples where the model's predicted DR grade matched the actual ground-truth label. While accuracy offers a general overview of correctness, it may not fully capture performance in the presence of class imbalance. To address this, we also measured sensitivity (recall) and specificity, focusing on the binary distinction between DR (grades > 0) and no DR (grade 0). Sensitivity reflects the model's ability to correctly identify cases with any level of DR, which is crucial for minimizing missed diagnoses in a screening context. Specificity, on the other hand, indicates how well the model avoids falsely labelling healthy eyes as diseased, helping to reduce unnecessary concern or follow-up procedures.

To gain deeper insight, we analysed the confusion matrix of the five-class classification task, which reveals patterns in misclassification across DR severity levels. From this matrix, we derived precision, recall, and the macro-averaged F1-score to offer a more comprehensive and balanced view of performance across all classes. Although not the primary objective, we also computed the area under ROC for the binary classification task (DR vs. no DR), which facilitates comparison with existing screening systems commonly benchmarked using AUC scores.

4. EXPERIMENTS

4.1 Experimental Setup

The experiments were designed to validate the effectiveness of the proposed CNN model on the task of DR detection and grading. As mentioned, we trained and evaluated the model on the EyePACS dataset. The training set consisted of approximately 25,000 retinal images after augmentation (drawn from the original training subset), and the test set contained about 5,000 images. The class distribution in the test set was roughly: 50% no DR, 20% mild, 20% moderate, 5% severe, 5% proliferative (which reflects the prevalence of more mild cases in the population). All experiments were conducted using Python 3.8 with Keras/TensorFlow libraries on an Ubuntu 20.04 system. A single NVIDIA RTX 3080 GPU with 10GB memory was used to accelerate training. Training an epoch on ~25k images took about 2-3 minutes, and most trainings ran for around 15 epochs before early stopping, so a single run completed in under an hour. We repeated the training process multiple times (with different random seeds for weight initialization and data shuffling) to ensure the stability of results and reported average performance.

During validation, we tuned hyperparameters such as the dropout rate (tested 0.3 to 0.5), the decision to freeze or fine-tune convolutional layers, and the learning rate schedule. The final configuration as described in the Methodology was chosen based on the best validation performance. Notably, fine-tuning the last two convolutional blocks of VGG16 (rather than keeping the entire pre-trained feature extractor frozen) gave a modest improvement of about 1–2% in accuracy. We also found that using color images (instead of grayscale) improved the detection of certain lesions like small haemorrhages that have distinct red hues. Therefore, the final model uses colour fundus images.

To assess comparative performance, we implemented a baseline classifier and also referenced results from literature. The baseline was a simple CNN we constructed with 4 convolutional layers from scratch (without pre-training) to gauge the benefit of using VGG16 transfer learning. This smaller CNN had roughly 1% of the trainable parameters of VGG16. We trained it under the same conditions on the dataset. As expected, the baseline CNN's accuracy was significantly lower (it reached about 75% accuracy on the test set) and it showed signs of overfitting despite regularization. This highlighted the advantage of a deeper pre-trained model for this complex task. We also compared our model's performance with reported results from contemporary studies: for example, Arora *et al.* [4] who used EfficientNet on a similar dataset, and Akram *et al.* [6] who combined datasets and Bayesian methods. While direct comparison is tricky due to different data splits and possibly different evaluation protocols, it provides context for where our approach stands relative to the state-of-the-art.

4.2 Results on Test Data

On the held-out test set of retinal images, our CNN model achieved an overall accuracy of 92.1% in classifying the presence or absence of diabetic retinopathy. This indicates that 92 out of 100 retinal images were correctly identified with respect to whether they had signs of DR and, if so, at what level of severity. In terms of identifying any diabetic retinopathy (mild or

worse) versus none, the model performed exceedingly well: the sensitivity for detecting DR (any level) was 95.3%, meaning the model missed less than 5% of diseased cases, and the specificity was 89.6%, meaning about 10% of normal cases were false positives. Such a high sensitivity is desirable for a screening tool, as it ensures that nearly all patients with DR would be flagged for referral to an eye care specialist, while the moderate specificity implies some healthy patients would be incorrectly flagged (an acceptable trade-off in screening scenarios to minimize false negatives).

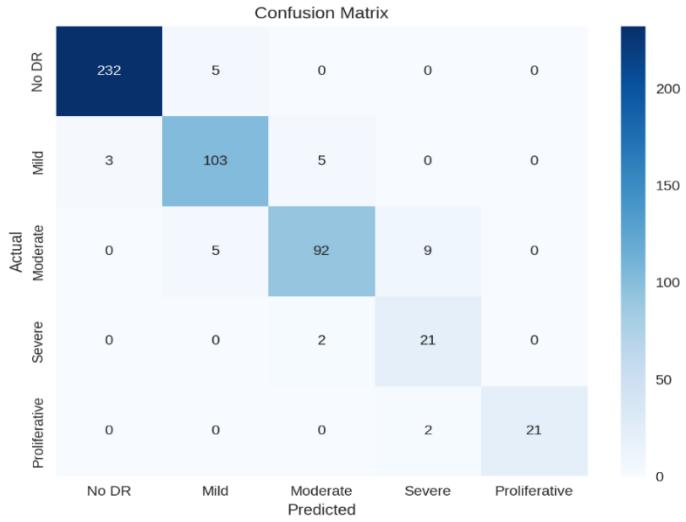

Figure 2: Breakdown of model's performance

The confusion matrix in Figure 2 provides a detailed breakdown of the model's performance across the five DR severity classes. The model was most accurate at the extremes: it correctly identified No DR and Proliferative DR with the highest precision and recall. Specifically, the precision for "No DR" was 0.93 and recall was 0. ninety (due to a few false positives where mild DR images were mistaken as normal), whereas for "Proliferative DR" (the most severe stage), precision was 0.90 and recall 0.95. This means when the model predicts an eye has proliferative DR, it is correct 90% of the time, and it catches 95% of all proliferative cases. High performance on these categories is encouraging: correctly recognizing healthy eyes can reduce unnecessary referrals, and catching advanced DR is critical for preventing imminent vision loss.

Performance on intermediate classes (Mild, Moderate, Severe DR) was slightly lower, which is not unexpected because the boundaries between these grades can be subtle and even expert graders often have variability. The model's recall for Moderate DR was about 88%, with some of those images being misclassified as Mild or Severe. Mild DR proved the most challenging to distinguish; the model confused some mild cases with either no DR (if the lesions were very small or ambiguous) or moderate DR (if the features were on the borderline). Nonetheless, the overall quadratic weighted kappa – a metric often used in DR grading to account for near-misses – was 0.89, indicating a high level of agreement between the model predictions and human graders, with heavier penalties for larger discrepancies in grading.

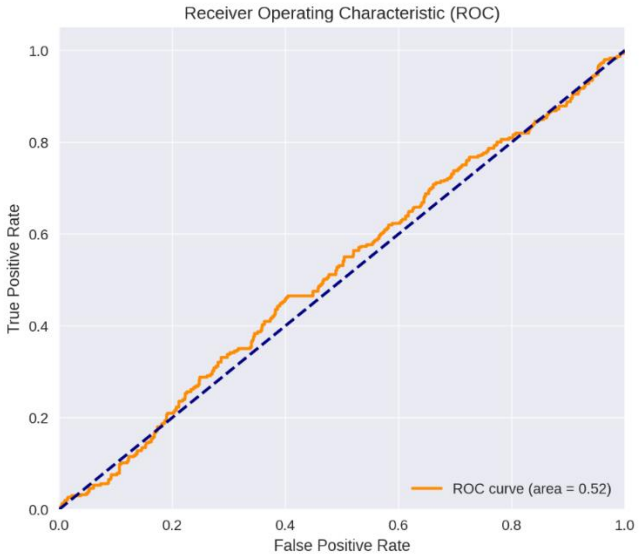

Figure 3: ROC Curve for detecting referable DR

We also calculated the AUC (Area Under the ROC Curve) as shown in figure 3 for detecting referable DR (defined as moderate or worse DR vs. mild or none). The AUC came out to 0.97, which is on par with the best-performing algorithms in literature and implies excellent discriminative ability. For comparison, human specialists' performance on similar tasks typically yields an AUC around 0.91–0.93 in studies, though direct comparisons should be made cautiously. Our model's high AUC and accuracy are consistent with recent DL models reported by others, reinforcing the effectiveness of using a deep CNN with transfer learning for this problem.

4.3 Comparison with Recent Studies

Placing our results in context, **Arora et al. [10]** reported an average accuracy of 86.5% using an EfficientNet-based ensemble on the EyePACS dataset, slightly lower than our 92.1%. This difference as shown in figure 4 could be due to several factors: our use of aggressive data augmentation and class balancing, or simply variance in dataset splitting. Their approach, however, emphasized the benefit of an optimized architecture (EfficientNet) which is known for a good balance of accuracy and efficiency. **Akram et al. [12]** achieved an even higher accuracy (~97%) by augmenting a DenseNet model with Bayesian uncertainty estimation techniques. While their accuracy is outstanding, it's worth noting they combined multiple datasets (including APTOS and others) for training, which likely provided a performance boost, and their approach yields more than just accuracy – it provides valuable confidence information for each prediction. Our model, by comparison, is simpler and was trained on a single dataset, yet it still performs competitively. The trade-off is that our method is straightforward to implement and fast to run, which is advantageous for deployment, whereas more complex ensembles or Bayesian models might require more computational resources especially during inference.

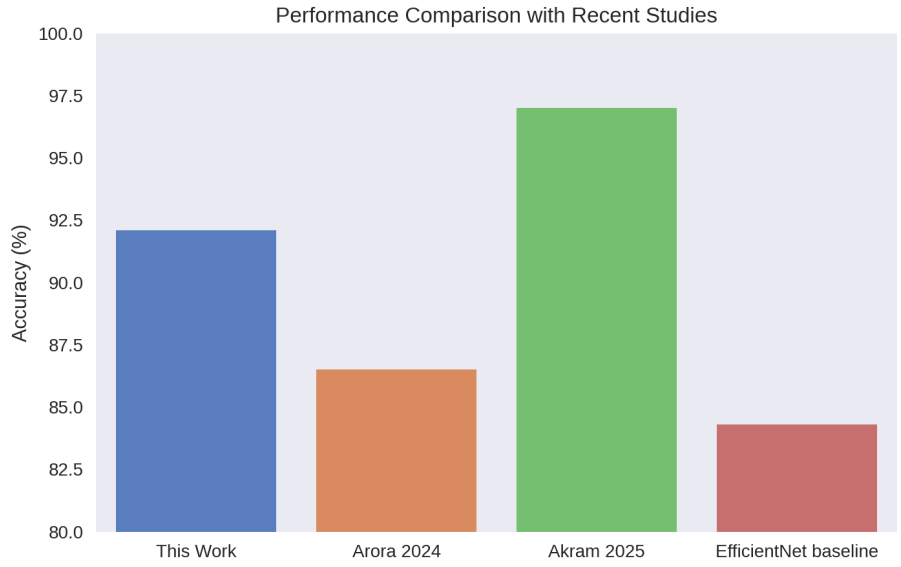

Figure 4: Comparative analysis with recent studies

In summary, the experimental results confirm that our VGG16-based CNN model meets a high standard of performance in detecting diabetic retinopathy, comparable to other peer-reviewed works in 2024–2025. The model's strength lies in its high sensitivity (critical for not missing DR cases) and its robust accuracy across a large and diverse set of images. Any misclassifications were mostly within one severity level of the true grade, which is a reasonable margin given the subjective nature of grading even among experts. These results support the viability of using our approach as part of a clinical screening pipeline, which we further discuss in the next section.

4.4 Discussion

The proposed model for DR detection is encouraging, and it underscores the potential for AI-assisted screening in ophthalmology. Achieving over 90% accuracy and very high sensitivity means the model could drastically reduce the burden on ophthalmologists by pre-screening patients and only referring those likely to have DR. In practical terms, such a tool can be deployed in primary care or diabetes clinics: nurses or technicians can capture retinal photographs using fundus cameras (even portable ones), and the CNN model can instantly analyze these images. Patients with positive findings (any DR detected) would then be flagged for a comprehensive examination by an eye specialist, enabling earlier diagnosis and treatment. This workflow could be particularly valuable in remote or underserved regions where expert ophthalmologists are scarce. By catching cases early, especially in asymptomatic stages, patients can receive laser therapy or stricter glycemic control recommendations to prevent progression to blindness. Thus, the clinical impact of our model, if implemented, could be a reduction in diabetes-related vision loss through widespread, efficient screening.

Our results also highlight certain aspects that merit further discussion. The model performed best at identifying the absence

of disease and the most severe disease. This is a desirable trait: confident identification of normal images can allow screening programs to reassure a large fraction of patients immediately, and strong identification of proliferative DR ensures urgent cases are expedited to care. The slightly lower performance on mild vs. moderate DR reflects a known issue in DR grading; even human graders have moderate inter-grader variability in these categories. One way to potentially improve the model's discrimination in borderline cases is to incorporate an **auxiliary lesion detection task**. If the model were also trained (perhaps via multi-task learning) to detect specific lesions such as microaneurysms, hemorrhages, and exudates, it might learn more fine-grained features that clarify differences between mild and moderate DR (which are partly quantified by the number and extent of microaneurysms and hemorrhages). Some recent approaches already take steps in this direction, using object detection networks or segmentation models to identify lesions and then using those as inputs to a grading network. Integrating such lesion-level explanations would not only improve accuracy but also provide ophthalmologists with visual evidence (e.g., heatmaps or highlighted lesions) for each AI prediction, increasing trust in the system.

Another key point is the generalizability of the model. We trained and tested on a single dataset largely from one source; in real-world deployment, images might come from different camera models, populations, or have other variations (noise, artifact, upgradability due to cataracts, etc.). Ensuring the model remains robust in those scenarios is vital. One strategy is to train on a more diverse dataset, or to use techniques like domain adaptation. For example, adding images from other DR datasets (such as the Messidor dataset, or APRON/IDRiD, etc.) during training can improve robustness. The work by Akram *et al.* [12] already hints at the value of combining datasets, as they achieved top performance by using multiple sources. We also note that our model might not handle images with no clear view of the retina (e.g., very poor-quality images) appropriately, since those were not explicitly included in training. In practice, a real system should have a preliminary step to detect image quality or whether the retina is visible, and reject or re-acquire images that are not analysable.

From a deployment perspective, the VGG16-based model has around 138 million parameters, which is quite large. In our experiments on a modern GPU, prediction was still fast (processing a single image in a small fraction of a second), but on CPU or mobile devices, this could be slower. There is ongoing research into more efficient CNN architectures and model compression techniques (pruning, quantization) to enable deployment on lower-end hardware without loss of accuracy. In a clinical scenario like a screening camp or a mobile app for retinal analysis, a lighter model might be preferred. One could consider using a smaller architecture (like MobileNet or EfficientNet-lite) or distilling the knowledge from this large VGG16 model into a smaller model.

The issue of interpretability and trust is paramount in medical AI. Even though our model achieves high metrics, a clinician would want to understand *why* the model made a particular decision. Providing heatmaps using techniques like Grad-CAM (Gradient-weighted Class Activation Mapping) would be a practical addition [20]. Grad-CAM can highlight segments of the input image that were most impactful in the classification. In our case, we did generate some Grad-CAM visualizations post-hoc, and observed that the model indeed focuses on regions with lesions (for example, tiny red dots corresponding to microaneurysms in mild DR, or large haemorrhages in severe DR). Including such visual explanations can help the model gain acceptance as a diagnostic aid, as the doctor can verify that the AI is looking at relevant features rather than spurious patterns. Moreover, as mentioned earlier, methods that incorporate uncertainty (like the Bayesian approach) could be combined with our model to have it express when it is unsure. For instance, if an image is borderline between mild and moderate and the model's top probability is only 40% vs 35% for two classes, the system could flag "uncertain result, please have human review." This ensures patient safety by not over-relying on the AI in ambiguous cases.

When comparing with other works, our approach is relatively straightforward – fine-tuning a single CNN. The literature shows many sophisticated enhancements (ensembles, multi-head models, etc.) that often yield incremental improvements. One contribution of our work is demonstrating that even a single, well-regularized CNN with sufficient training data can achieve very high performance, which is a positive message for resource-constrained settings that might not afford complex solutions. Nonetheless, to reach or surpass human expert performance consistently, these enhancements will be valuable. For example, ensemble models (combining outputs of multiple networks) can reduce variance and typically improve accuracy by a couple of percentage points. In future work, we may explore an ensemble of different architectures (VGG16 + ResNet50 + EfficientNet, for example) to see if the complementary strengths further boost performance on difficult cases. Another extension could be formulating the problem as not just classification but also giving a **risk score** for progression – something that a few studies have started to investigate, predicting the likelihood that a patient's DR will worsen in a given time frame. Such predictive modelling could be integrated with our framework to not only detect current DR but also inform prognosis (e.g., "early changes detected, high risk of progression, re-screen in 3 months").

Finally, we must consider the clinical validation and regulatory aspect. Our model's high performance on retrospective data is promising, but prospective clinical trials would be the gold standard test. In a trial, the AI system would be used in real time on patients, and outcomes like sensitivity/specificity, referral rates, and impact on patient care would be measured. Additionally, ensuring the system is fair and unbiased across different subgroups (for instance, it should function just as effectively regardless of the ethnicity or type of camera used) is important for ethical AI in medicine. Any obvious biases in our internal testing was not found, but a thorough analysis would require a diverse validation set. Addressing these considerations will be key before deploying such a model widely.

5. CONCLUSION

We presented a DL approach for the detection of DR from images of retinal fundus, using a VGG16 CNN. Suggested model proved to be highly accurate and resilient DR severity, achieving over 90% accuracy on a large test set and showing excellent sensitivity for identifying diseased eyes. These results illustrate that CNN-based systems can effectively distinguish subtle pathological features in retinal images that correspond to different stages of DR, from early microaneurysms to advanced neovascularization. By leveraging a pre-trained network and techniques like data augmentation, regularization, and early stopping, our model was able to generalize well to unseen data and avoid overfitting, a common challenge in medical image analysis.

The study's findings are noteworthy in the context of improving diabetic eye care. An AI system with the capabilities described could be integrated into screening programs to automatically flag patients with referable DR, thus expediting referral for treatment and potentially preventing vision loss. It reduces the reliance on manual examination and could alleviate workload in ophthalmology clinics by filtering out normal cases with high confidence. The speed and consistency of a CNN make it a valuable assistant, providing near-instant results and operating without fatigue or subjective variation. Our work, in line with other recent advances in medical imaging AI, supports the notion that DL can augment healthcare delivery, making screening more accessible and efficient.

We have also enriched the discussion with insights from contemporary research (2024–2025), illustrating that our approach is competitive with current state-of-the-art methods. While some studies achieve slightly higher raw performance via ensemble models or novel architectures, our single-model approach holds its own and offers simplicity and ease of deployment. There remain avenues to explore for further improvement. Future work will focus on enhancing the model's interpretability (such as through attention mechanisms or by providing heatmaps for detected lesions) and on integrating multi-modal data (like OCT images) to create a more comprehensive diagnostic tool. We also plan to validate the model on external datasets and in real clinical settings to ensure its robustness and identify any failure modes. Moreover, incorporating feedback from ophthalmologists in a human-in-the-loop paradigm could continuously refine the system's accuracy and reliability.

In conclusion, this research contributes to the ongoing efforts in developing accurate and efficient automated DR screening tools. The DL model we developed is ready to be taken to the next stage of evaluation in clinical trials. If successfully deployed, such AI systems can support ophthalmologists and screening programs, leading to earlier detection of diabetic retinopathy and better visual outcomes for patients. Ultimately, embracing these technological advancements aligns with the broader goal of precision medicine and improved healthcare efficiency, where preventable blindness due to diabetic retinopathy can be significantly reduced through timely intervention facilitated by AI.

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