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Research Article

Improving Diabetic Retinopathy Detection Using Fine-Tuned ResNet50 and Data Augmentation Techniques

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ABSTRACT

This study introduces a novel deep convolutional neural network (CNN) framework inspired by the fine-tuned ResNet50 model. DR is categorized into four unique stages: mild DR, moderate DR, proliferative DR, and severe DR. This innovative model was crafted to promote feature reuse and guarantee an adequate gradient flow by integrating dense connections among layers. These dense connections are strategically designed to make the model harness data from all earlier layers, thus fostering more in-depth feature representation and spurring learning efficiency. It was performed and evaluated on a sizeable dataset filled with specifically numbered retinal images. Each image was meticulously labeled to indicate the severity of diabetic retinopathy. The findings revealed that this unique model significantly trumped previous methods, yielding an impressive classification accuracy of 99%. Additionally, the model exhibited meaningful progress in recall and F1-score across all classes, reinforcing its reliability in discerning different stages of diabetic retinopathy. The insights from this study suggest that this custom ResNet50 model frame has excellent potential as a vital tool for the precise and early detection of diabetic retinopathy. This could be instrumental in safeguarding individuals with diabetes against vision loss, thus providing a reliable solution for the future.

Keywords: Deep convolutional neural network, Diabetic retinopathy, Fine-Tuned ResNet50, Data Augmentation Techniques

1. INTRODUCTION

The significance of detecting diabetic retinopathy raises essential discussion points, given its global influence on public health. Diabetic retinopathy (DR), a significant complication of diabetes, is a leading cause of blindness, making early detection a global health priority [1]. As diabetes rates rise worldwide, the number of people affected by this sight-threatening consequence is also increasing [2]. Early detection plays a crucial role in managing diabetic retinopathy. Symptoms such as blurred vision appear when it advances, and some damage is often irreversible [3]. Regular eye screening can identify early signs, and appropriate treatment can prevent severe visual loss in up to 98% of cases. Hence, early identification can significantly reduce the risk of blindness. The burden of DR on the public health system cannot be ignored. However, with the potential of the proposed model as a vital tool for the precise early detection of diabetic retinopathy, there is hope for a future with reduced treatment costs, loss of productivity due to impaired vision, and associated psychological distress. Thus, Public health strategies need to focus on effectively managing this ailment. The importance of detecting diabetic retinopathy lies in preventing vision loss, improving the quality of life of those suffering from diabetes, and reducing pressure on global health systems[3]. Regular eye examinations and early detection, which are closely linked to efficient diabetes management, are powerful tools for reducing the incidence of this devastating complication[4].

The crux of the problem revolves around the challenges associated with the multiclass classification of diabetic retinopathy [5]. A crucial issue thrown into the limelight concerns data imbalance. In biomedical informatics, the absence of a balanced dataset is a prodigious setback for medical professionals using artificial intelligence [6], machine-learning enthusiasts[6], and data scientists striving to curate a versatile and realistic model of disease diagnosis [7]. Data imbalance implies that the frequency of manifested varying stages of diabetic retinopathy in the dataset is disconcertingly disarrayed; certain stages are over-represented, whereas others are gravely underrepresented. This uneven distribution of data significantly affects the predictive power of the models [8]. Furthermore, delving into intricacies involves difficulty in feature extraction related to the task. Identifying, selecting, and extracting appropriate and potentially beneficial features from large, complex, and multidimensional databases have proven to be a considerable technological challenge [9]. Because the condition is an intricate disease affecting the blood vessels at the back of the eye, the classification model needs to consider diverse factors, including, but not limited to, patient history, stage of disease, and a multitude of image-defined characteristics.

Additionally, one of the central concerns is the scale and reliability of the classification accuracy [10]. As this factor often serves as the defining aspect of diagnostic models, its significance cannot be understood. The precision of identification and subsequent categorization of the disease assists doctors in prescribing the most appropriate and immediate treatment course and drastically influences patient outcomes [11]. Therefore, improving the accuracy of such diagnostic models is of utmost importance. There are three significant challenges in the multiclass classification of diabetic retinopathy: an imbalanced dataset, complexities of feature extraction, and the requirement for an elevated level of classification accuracy [12]. These issues pose formidable hindrances, leaving room for enhanced research methodologies and innovative diagnostic solutions.

Figure 1. depicts the various severity levels of Diabetic Retinopathy (DR) through retinal images. Each image highlights distinct pathological features corresponding to different DR stages.

i. **Mild DR (a):** This stage is characterized by microaneurysms or hemorrhages, small blood spots caused by weakened blood vessels in the retina. These early signs of DR indicate minimal damage.

ii. **Moderate DR (b):** At this stage, the damage becomes more pronounced with microaneurysms, or haemorrhages accompanied by cotton wool spots, which are signs of retinal nerve fiber layer damage.

iii. **Severe DR (c):** This advanced stage shows more significant damage, including hard exudates and new blood vessel formation in the optic disc. These features indicate a high risk for progression to more severe vision-threatening stages.

iv. **Proliferative DR (d):** This is the most advanced stage, where blot hemorrhage, hard exudates, and new abnormal blood vessels (neovascularization) are evident. Untreated left eye can lead to a high risk of vision loss.

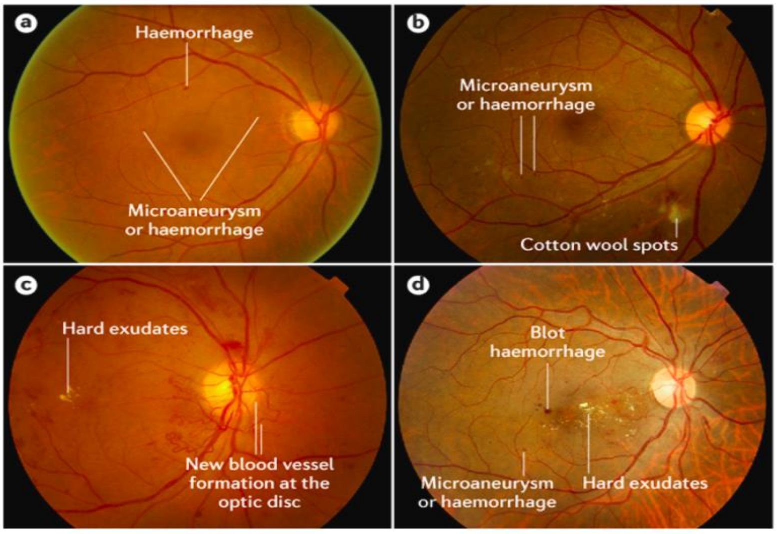

Fig.1 Severity levels of DR - (a) Mild DR (b) Moderate DR (c) Severe DR (d) Proliferative DR[13]

The proposed endeavour is structured to examine and fashion a model using a dataset from Kaggle. This dataset is composed of 7220 images that are categorized into four distinct classes[14]. The primary objective of this study was to ascertain the disease stage by employing Fine-Tuned ResNet50 and additional Data Augmentation Techniques. A key tool that will be utilized to assess the success and effectiveness of the trained model is the Confusion Matrix. The performance retrieved from this model was analyzed and contrasted with the outputs of other machine learning algorithms. This comparative exercise will provide more insights into the efficacy of various approaches and invigorate the pursuit of better models in the field.

1.1 Literature review

Deep Neural Networks, notably Convolutional Neural Networks (CNN), have proven to be highly efficient in classifying images. The methodologies used to discern and categorize Diabetic Retinopathy (DR) severity using Deep Learning tactics can be grouped into several types, such as binary and multi-class classification, lesion-based classifications, and vessel-based categorizing techniques. This section will explore a handful of the current multi-classification methods used to discern DR presence.

Pao et al. [12] introduced a method for uniquely generating entropy images from grey and green levels in their work. They administered this process skillfully by employing a Bayesian Convolutional Neural Network (CNN) model. This innovative technique provides an intriguing exploration of image processing, focusing mainly on grey and green hues. Their procedure was distinguished by utilizing a CNN model to facilitate essential calculations. In essence, Pao and his colleagues successfully expanded the scope of these models, providing greater depth and flexibility for image processing and analysis. Gayatri et al. [15]proposed a lightweight Convolutional Neural Network (CNN) model that could effectively grade Diabetic Retinopathy (DR) in binary and multiclass settings. Their model aims to simplify the complex DR diagnosis procedure by providing a more streamlined approach. Similarly, Pratt et al. utilized another CNN model to classify DR severity. This model offers a comprehensive analysis of DR stages, guiding doctors in making informed decisions about the treatment needed. These research directions signify noteworthy advancements in the medical field, such as precisely diagnosing and treating DR.

In their research work, S. Dutta et al. [16] aimed to analyze the application of Convolutional Neural Network (CNN), Deep Neural Network (DNN), and Back-Propagation Neural Network (BNN) in the detection and classification of Diabetic Retinopathy (DR) severity. Utilizing these neural network techniques is essential for groundbreaking research. They intended to provide effective and accurate health care solutions. This study focuses on DR, a globally recognized health problem, unveiling mechanisms to assess its severity levels effectively. Therefore, the results of this study highlight the importance of machine learning in the medical field to ensure progressive strides in patient care. The researchers conducted a comprehensive study using 2000 images from the renowned Kaggle dataset[17]. Their innovative approach was based on utilizing Deep Neural Networks (DNN). After careful analysis and scrutiny, it was clear that the DNN performed relatively well when pitted against the other two neural networks employed in the study. The level of accuracy in terms of image recognition was commendable, marking a substantial development in the realm of artificial intelligence research. However, it is also worth mentioning that although the DNN system exhibits certain advantages, it is still comparable in efficiency to the other two systems tested.

Wan et al. [18] broadly used pre-trained CNN, or Convolutional Neural Network (CNN) architectures. Specifically, they turned to well-established models, including VggNet, GoogleNet, and AlexNet for their study. Each of these has made significant contributions to the deep learning field. Modelled on human cognitive structures and processes, these architectures are remarkable in their ability to perform complex tasks and computations. Researchers' utilization of such sophisticated, pre-established structures has allowed them to bypass the time-consuming process of creating new models, thus focusing more on their specific objectives in artificial intelligence studies. Sandhya et al.[19] introduced a mixed methodology that utilizes pre-trained architecture models to identify the severity of Diabetic Retinopathy (DR). Preliminary findings from their research suggest that the hybrid usage of the InceptionV3 and DenseNet169 algorithms leads to reasonably good performance. These results highlight the promising potential of applying deep learning models in healthcare, particularly in detecting and diagnosing severe health conditions, such as DR. This innovative approach not only contributes to the advancement of medical technology but also improves the accuracy and efficiency of disease detection, helping physicians establish an effective treatment plan.

Esfahani et al. [20] employed ResNet, a renowned deep learning tool, to identify different stages of Diabetic Retinopathy, a disease affecting millions globally. Their research paper 32 study indicates that their experiments resulted in a commendable success rate. Specifically, they could classify disease stages with an accuracy rate of 85%. This compelling evidence reinforces the increasing importance of implementing artificial intelligence and deep learning in medical diagnosis, particularly in ophthalmology. However, this pioneering result should encourage further research to increase the limits of accuracy. Nguyen et al. [21] suggested automated classification using specific models. These models include VGG-16, Convolutional Neural Networks (CNN), and VGG-1. This methodology allows for enhanced categorization and increased accuracy in data analysis. These models have been extensively applied in artificial intelligence for many purposes, including image recognition, filtering, and classification. The utilization of VGG-16, CNN, and VGG-1 in automated classification offers the potential for improvement in various facets of machine learning.

The present work presents a unique and fine-tuned ResNet50 model for multiclass diabetic retinopathy classification. The main objective of this architecture is to address the identified limitations of the previous models. A key method used to achieve this is to enhance the reuse of features and create an environment for efficient training through dense connections. Thus, this novel work is centered on improving performance and providing an efficient path for future research in the multi-classification of diabetic retinopathy.

2. METHODOLOGY

Description of the dataset: The dataset utilized in this study comprised 7220 retinal images categorized into four distinct stages: Mild_DR, Moderate_DR, Proliferative_DR, and Severe_DR, representing the progression of diabetic retinopathy [14]. Each image was captured using high-resolution retinal imaging equipment with the desired resolution to provide the necessary details for precise analysis and classification.

The images were thoroughly annotated by medical experts who ensured that each image was accurately labelled according to the severity of the disease. This careful curation process guarantees the reliability and relevance of the dataset for training deep-learning models to detect and classify diabetic retinopathy. The diversity and high resolution of the dataset make it an ideal resource for developing robust models capable of performing well in real-world clinical settings. Additionally, the dataset includes variations in lighting, contrast, and retinal features, further challenging the model to generalize across different conditions and patient profiles effectively.

Classes: The five classes in diabetic retinopathy detection represent different stages of the disease, each with an increasing severity and risk of vision loss. MildDR is the earliest stage, characterized by microaneurysms and small balloon-like swelling in the blood vessels of the retina. ModerateDR showed more significant changes, including blocked blood vessels, which could lead to retinal damage**.** ProliferativeDR is an advanced stage in which new abnormal blood vessels grow on the retina, which can cause severe vision problems if not treated. Severe_DR is the most critical stage, with extensive damage, significant bleeding, and scar tissue formation, often leading to blindness. Detecting and accurately classifying these stages is crucial for timely intervention and prevention of diabetic retinopathy progression.

Preprocessing: Preprocessing is a crucial step in preparing the dataset for training the deep learning model, ensuring that the images are standardized and suitable for analysis. Several pre-processing techniques were applied to the retinal images before they were fed into the model. First, all images were resized to a uniform resolution of 224 × 224 pixels] to ensure consistency across the input dimensions of the dataset. This resizing helps reduce computational complexity while maintaining the essential features required for classification.

Next, normalization was performed to scale the pixel values of the images to a range between 0 and 1. This step is vital because it helps speed up the convergence of the model during training and ensures that all input images have a similar data distribution, reducing the risk of the model being biased by varying the image intensities.

In addition, data augmentation techniques are employed to artificially increase the dataset size and improve the model's generalization capability. Techniques such as rotation, zooming, horizontal flipping, and shifting were randomly applied to the training images. This augmentation helps the model become more robust by exposing it to various possible distortions and variations in the images, thus better preparing it for real-world scenarios in which images may differ significantly.

2.1 Loading and Preparing the Dataset

The process begins with loading and preparing the dataset, a critical step in the machine learning workflow. The dataset, consisting of retinal fundus images, was loaded using the flow_from_directory method provided by TensorFlow's Keras API [22]. This method is particularly effective for handling large image datasets because it enables on-the-fly augmentation and the efficient batching of images during training. Each image was resized to a standard dimension of 224 × 224 pixels, ensuring uniformity across the dataset, essential for the consistency of input data to the convolutional neural network (CNN). Furthermore, the labels were encoded one-hot, converting categorical labels into a binary matrix format. This encoding is essential for multiclass classification tasks, allowing the model to predict the probability distribution across multiple classes.

To address the significant issue of class imbalance within the dataset, random oversampling was employed using RandomOverSampler from the Imblearn library [23]. This technique involves duplicating samples from minority classes until each class contains an equal number of samples. By balancing the dataset in this manner, the model is better equipped to learn equally from all classes, prevent bias toward majority classes, and improve its ability to correctly classify minority classes, which is crucial for achieving robust and fair model performance across all categories.

2.2 Model Architecture

The model architecture utilized the pre-trained ResNet50 model, which is renowned for its depth and exceptional performance in various image-classification tasks [24]. ResNet50, with 50 layers, is particularly effective owing to its ability to handle complex image features through its deep residual learning framework [25]. In this approach, the original top layers of ResNet50, which are typically used for general image classification, were replaced with a custom dense layer. This ResNet50 model layer was regularized using L2 regularization, which helps prevent overfitting by penalizing large weights within the model, thereby improving the generalization to unseen data. Additionally, a dropout layer was incorporated after the dense layer to combat overfitting by randomly disabling a fraction of neurons during training. The final output layer of the model was modified to include four neurons, each corresponding to one of the four Diabetic Retinopathy (DR) severity classes, and a softmax activation function was applied to produce class probabilities.

Furthermore, the last 50 layers of the ResNet50 base model were unfrozen, enabling fine tuning. This step is crucial, as it allows the model to adjust the pre-trained weights for the DR dataset, improving its ability to detect subtle features unique to this medical imaging task. Fine-tuning these layers ensures that the model leverages the general features learned from the large ImageNet dataset and the specific nuances of the DR images, ultimately enhancing classification accuracy.

2.3 Training Process

During the training process, the model was compiled using the Adam optimizer, known for its efficiency and ability to handle sparse gradients, making it a popular choice for deep learning models[26]The loss function used was categorical cross-entropy, which is well suited for multi-class classification tasks where the goal is to minimize the difference between the predicted class probabilities and the actual class labels. Accuracy was selected as the primary performance metric, allowing for straightforward monitoring of the model's ability to classify images during training correctly[27].

Three essential callbacks are implemented to enhance the training process. The first is early stopping, a technique designed to prevent overfitting by halting the training when the validation loss ceases to improve after a certain number of epochs. This ensures that the model retains its generalization capabilities without becoming overly specialized in the training data. The second callback was model checkpointing, which involved saving the model weights to the point where it achieved the best performance on the validation set. This strategy guarantees that the best version of the model is retained for subsequent evaluation or deployment. Finally, a learning rate reduction on the plateau was employed to dynamically adjust the learning rate when the model's performance plateaued, allowing for finer weight adjustments and potentially overcoming minor local minima, thus improving the overall training outcomes.

3. EXPERIMENTAL RESULTS AND DISCUSSIONS

This section describes the specifics of the dataset characteristics, design of the experimental framework, and metrics employed to assess the (performance efficiency of DR. Additionally, it offers a comparative analytical review of juxtaposing Diabetic Retinopathy (DR) with similar systems or models, furnishing readers with a thorough understanding of its relative efficacy and reliability.

3.1 Implementation details

Dataset: Diabetic Retinopathy (DR) undertakes an experimental analysis on the DR 2019 Data Colored Resized dataset for gauging performance[14]. This dataset contains 1805 snapshots of mild DR, moderate DR, Proliferate_DR, and severe DR. To obtain a comprehensive outlook, the dataset encompasses 7220 retinal fundus images. However, the overall disposition of the images across all classes illustrates an imbalance, indicating that the number of images in each category is not equivalent. Thus, to rectify this imbalanced distribution, an augmentation in the number of images across all classes is suggested to achieve uniformity and balance in data distribution.

3.2 Experimental Setup:

The results or conclusions drawn from the Diabetic Retinopathy (DR) experiments were conducted on a highly advanced system with a core i9/2.4 GHz processor and 32 GB RAM. Additionally, an NVIDIA GeForce GTX 4070 laptop, recognized for its advantages as a graphic processing unit, was used to further optimize the process. This laptop model effectively satisfies the requirements of advanced computational methods. Vital deep-learning software libraries such as TensorFlow and Keras were employed during the experiment. These libraries are ubiquitous for developing and training complex algorithms, adding excellent reliability and accuracy to experimental processes.

3.3 Performance evaluation and comparison analysis

The performance of the Diabetic Retinopathy (DR) was evaluated using the following key metrics: accuracy, precision, recall, and F1-score. These metrics are calculated based on the true positives (w), false positives (y), true negatives (z), and false negatives (the). Accuracy measures the overall accuracy of the model. Precision evaluates the proportion of true optimistic predictions among all positive predictions, whereas recall assesses the ability to identify all relevant instances correctly. The F1-score, a harmonic mean of precision and recall, balances both metrics for a comprehensive performance assessment.

$$Accuracy = z + w\, x + y + z + w \quad (1)$$

$$P\,recision\,(P) = w\, y + w \quad (2)$$

$$Recall\,(R) = w\, x + w \quad (3)$$

$$F\,1 - score = 2 * (R * P) /\, R + P \quad (4)$$

3.4 Performance Comparison

Confusion Matrix: Include a confusion matrix to visualize how well the model performs across different classes.

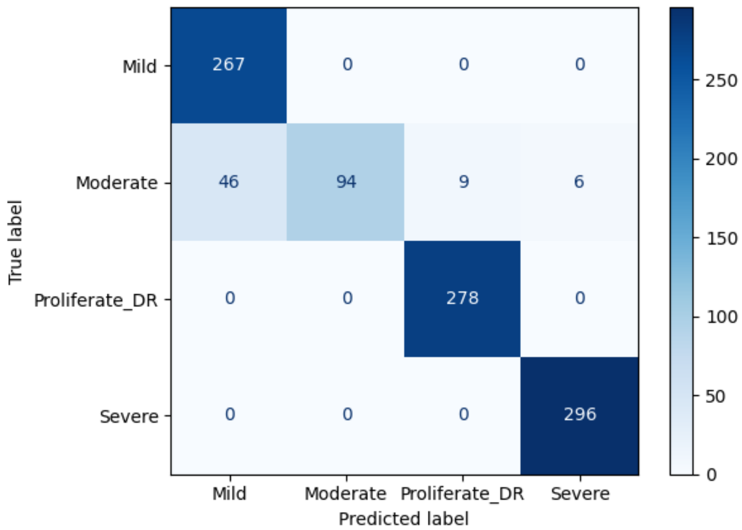

Fig. 2 Confusion matrix

The confusion matrix presented in Fig 2 provides a detailed breakdown of the classification results for four classes: Mild, Moderate, Proliferate_DR, and severe. The figure shows the number of correct and incorrect predictions made by the model.

- **Mild**: Out of 267 images, all were correctly classified as Mild, showing perfect precision and recall for this class.
- **Moderate**: For Moderate images, 94 images were correctly classified, 46 were misclassified as Mild, and 15 as either Proliferate_DR or Severe, indicating some confusion between these classes.
- **Proliferate_DR**: All 278 images were accurately classified, suggesting excellent performance for this class.
- **Severe**: The model correctly identified 296 severe images and achieved perfect classification.

The confusion matrix highlights the model’s strong performance in identifying Proliferate_DR and Severe cases; however, it also indicates that some improvements are needed to distinguish Moderate from Mild cases.

The confusion matrix results (Fig. 2) have significant practical implications for real-world applications of diabetic retinopathy detection systems. The model demonstrated high accuracy in correctly identifying Proliferate_DR and Severe cases, which is crucial in clinical settings where early and accurate detection of severe stages can prevent further deterioration of vision. The perfect classification of these severe cases suggests that the model can reliably support ophthalmologists in identifying patients who require urgent treatment.

However, the confusion observed between the Mild and Moderate classes indicates that the model struggles with less severe cases, which could lead to under-diagnosis or delayed treatment. This limitation may result in patients not receiving timely interventions, potentially allowing the disease to progress to more advanced stages. Addressing this confusion through further model refinement or additional data augmentation can improve the overall robustness of the detection system.

Moreover, the strong performance in detecting Proliferate_DR and Severe classes suggests that the model could be integrated into automated screening programs, particularly in regions with limited access to specialized care, to prioritize patients who need immediate attention. Promptly identifying and treating high-risk patients can significantly reduce the burden on healthcare systems and improve patient outcomes.

3.5 Classification matrix

The classification report in Table 1 provides detailed metrics summarizing the model's performance across four classes: mild, moderate, proliferative _DR, and severe. Each metric—precision, recall, and f1-score—gives insight into the model's strengths and weaknesses.

Table 1. Classification report trained model

	Precision	Recall	F1-score	Support
Mild	0.85	1.00	0.92	267
Moderate	1.00	0.61	0.76	155
Proliferate_DR	0.97	1.00	0.98	278
Severe	0.98	1.00	0.99	296
Accuracy			0.94	996
Macro avg	0.95	0.90	0.91	996
Weighted avg	0.95	0.94	0.93	996

Precision measures the accuracy of the optimistic predictions. For example, a precision of 0.85 for the Mild class indicates that 85% of the images predicted as Mild were Mild. High precision across classes, particularly in Severe and Proliferate_DR, indicates that the model generates few false-positive errors, which is crucial for critical classes that require immediate attention.

Recall reflects the model's ability to identify all relevant instances correctly. The recall is perfect for Mild, Proliferate_DR, and Severe, indicating that the model successfully identified all instances of these classes.

However, the Moderate class had a lower recall of 0.61, indicating that 39% of moderate cases were not identified, which could lead to underdiagnosis.

The F1-score balances precision and recall, providing a single metric that reflects both. The high f1-scores, especially for Proliferate_DR and Severe, demonstrate the model's overall solid performance. However, the Moderate class showed room for improvement.

An accuracy of 0.94 indicates that 94% of all predictions were correct, reflecting an overall solid performance. The macro average and weighted average metrics provide an overall performance summary, with the macro average considering each class equally, and the weighted average considering the number of instances in each class. The high scores across these metrics indicate a reliable model, although further improvement is needed for the moderate class to enhance the diagnostic accuracy across all categories.

4. CONCLUSION

Based on these results, several important conclusions can be drawn regarding the effectiveness and performance of the model developed for diabetic retinopathy classification. The model demonstrated a high level of accuracy, particularly in distinguishing between the four classes of DR severity (mild, moderate, proliferative, and severe DR), with an overall accuracy of 94%. The results highlight the model’s ability to correctly classify severe cases, achieving recall and precision close to 100%. This is critical for ensuring that patients with severe conditions receive appropriate attention. However, the model showed some variability in performance across different classes, particularly with the moderate class, where the recall was relatively lower at 61%. This indicates that although the model is highly effective overall, there is still room for improvement in detecting less severe cases of DR, which may require further fine-tuning or the inclusion of more diverse training data. Data augmentation and oversampling techniques are crucial in addressing the imbalance in the dataset, leading to improved generalization and performance across all classes. These results underscore the importance of data preprocessing and model fine-tuning for developing robust AI models for medical image classification tasks.

5. LIMITATIONS

Despite these promising results, this model had some limitations. One significant issue is the lower recall for the moderate class, indicating that the model may struggle to identify cases of moderate diabetic retinopathy correctly. This suggests the potential need for more representative data or further model refinement. Additionally, oversampling helped balance the dataset and introduced noise, leading to less robust predictions. Furthermore, the model's performance could vary on different datasets, necessitating additional validation on diverse populations.

6. FUTURE WORK

Future work could explore several avenues to improve model performance and applicability. First, incorporating more advanced data augmentation techniques, especially for underrepresented classes like Moderate and Severe, could help enhance the model's generalization. Additionally, experimenting with different network architectures or hybrid models that combine the strengths of multiple pretrained networks might yield better results. Including more classes in future studies is crucial for developing a more comprehensive model that can effectively differentiate healthy and diseased eyes. Cross-validation of different datasets from varied demographic backgrounds could ensure the robustness and adaptability of the model to real-world applications. Finally, integrating the model into a clinical decision support system could aid ophthalmologists in diagnosing diabetic retinopathy more efficiently.

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