Diabetic Retinopathy Detection Using an Advanced Deep Learning Trinet Model

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Abstract. Diabetic retinopathy (DR), a progressive eye disease caused by diabetes, affects more than 100 million people worldwide, leading to a substantial risk of blindness if not detected early. This paper presents an innovative approach to DR detection using a fine-tuned Trinet model, designed to enhance diagnostic accuracy and efficiency. The Trinet model, a combination of three state-of-the-art models, ResNet-50, DenseNet-201, and VGG16 was refined to leverage the strengths of individual models and significantly enhance overall performance. Our model was trained on a comprehensive dataset divided into five classes: No DR, Mild, Moderate, Severe, and Proliferate DR. The architecture of the Trinet model was meticulously designed to improve its performance. Data preprocessing and key augmentation techniques were used to improve model robustness and generalization. Fine-tuning the Trinet model to significantly enhance accuracy involved the integration of advanced layers, dropout, batch normalization, and Adam optimization. The model achieved an accuracy of 96.47%, significantly surpassing individual models and benchmarks. Precision, recall, and F1 score values of 95.91%, 96.44%, and 96.17%, respectively, underscore the model's reliability in correctly diagnosing various stages of diabetic retinopathy and minimizing misdiagnoses. The proposed Trinet model demonstrates substantial potential for large-scale usage in healthcare, facilitating prompt diagnosis and intervention, thereby improving patient well-being.

Keywords: Diabetic Retinopathy (DR), Deep Learning, Trinet Model, Healthcare Technology, Retinal Image Analysis.

1 Introduction

Diabetic retinopathy (DR) is a significant global health issue and a leading cause of preventable blindness among adults, particularly affecting those with diabetes mellitus (DM). As diabetes prevalence continues to rise, DR poses increasing challenges for public health systems worldwide. In 2019, the International Diabetes Federation estimated that approximately 463 million people were living with diabetes, a number projected to reach 700 million by 2045. Globally, the prevalence of DR among individuals with diabetes is estimated at around 22.27%, which translates to approximately 103.12

million adults affected by the condition as of 2020. This figure is expected to grow to 160.50 million by 2045. The increasing incidence of diabetes and its complications, including DR, necessitates effective screening and management strategies to mitigate the risk of vision loss and improve patient outcomes.

Retinopathy (DR) is a severe complication of diabetes mellitus, marked by progressive retinal blood vessel damage due to prolonged high blood sugar levels. This damage weakens and compromises the vessels, causing fluid leakage and abnormal new vessel growth in advanced stages. If not diagnosed and managed promptly, DR can lead to significant vision impairment and complete blindness. Manual examination of retinal images by ophthalmologists is labor-intensive, time-consuming, and prone to human error. The availability of trained specialists is limited, particularly in rural and underserved areas, where access to comprehensive eye care services is often lacking [2]. In these regions, the burden of diabetes-related eye diseases is exacerbated by the shortage of healthcare infrastructure and resources. Consequently, many cases of DR remain undiagnosed and untreated until they reach advanced stages [8]. Deep learning models, trained on large datasets of retinal images, can identify subtle patterns and features indicative of DR with high accuracy. These models enhance diagnostic efficiency and hold the potential to make DR screening more accessible and affordable, particularly in resource-constrained settings [7].

However, implementing deep learning models in clinical practice necessitates careful consideration of several factors. Firstly, the quality and diversity of the training dataset are paramount. Retinal images used for training must encompass a wide range of DR stages and exhibit various pathological features to ensure the model's robustness. Secondly, integrating these models into clinical workflows must be seamless, providing healthcare professionals with intuitive tools that enhance, rather than hinder, their diagnostic processes. Lastly, the models must be validated rigorously in real-world settings to establish their reliability and generalizability across different populations and imaging conditions [9][12].

In this paper, we investigate the application of advanced deep learning architectures, including DenseNet201, ResNet50, and VGG16, for detecting diabetic retinopathy. We propose a comprehensive Trinet approach that leverages the distinct strengths of these models to enhance detection accuracy and efficiency. DenseNet201, known for capturing intricate image details, excels in identifying subtle features indicative of diabetic retinopathy [6]. ResNet50, with its deep residual networks, effectively addresses the vanishing gradient problem, enabling the training of very deep networks that improve feature learning and classification performance [1]. VGG16, characterized by its simplicity and depth, offers robust solutions for detailed feature extraction through its use of small convolutional filters [4]. By integrating these models into a unified framework, we aim to develop a powerful and accurate system for the early detection and management of diabetic retinopathy.

2 Literature Review

The advent of deep learning models has revolutionized DR detection, enabling more accurate and timely interventions. This section reviews studies that have employed deep learning techniques for DR detection and classification. Dasari et al. [1] address the limitations of manual DR detection, which is labor-intensive and prone to misdiagnosis in large populations. Their study fine-tunes the ResNet50 model using transfer learning on the APTOS2019 dataset, achieving superior classification accuracy, precision, recall, and F1 score. Reddy and Narayanan [2] proposed a CNN and data analysis method to classify DR based on clinical data, predicting diabetes presence and identifying its stage. This approach aims to optimize performance using various datasets and clinical lesion images, emphasizing the potential of deep learning algorithms in early DR detection.

Raman et al. [3] utilized the EfficientNet-B7 model on the Aptos2019 dataset to detect diabetic retinopathy (DR), achieving a classification accuracy of 94% through hyperparameter tuning and augmentation. Shrabony and Ejaz [4] conducted a systematic review, highlighting the effectiveness of deep learning methods in automating retinal screening and improving early DR detection. Lakhera and Garg [5] employed a ResNet-18-based CNN, optimized with the Slime Mould Algorithm (SMA), for DR classification, achieving 98.79% accuracy, 98.94% sensitivity, 98.60% specificity, and a 97.05% F1-score on the Kaggle dataset. Gurthula et al. [6] addressed diagnostic challenges in diabetic and hypertensive retinopathy, finding that the Xception model outperformed others, with 98% accuracy on Messidor-2 and 89% on ODIR-5K datasets.

Pandey et al. [7] review AI and machine learning approaches for DR detection, highlighting the superior performance of CNNs and RNNs. Automated solutions assist medical practitioners by analyzing retinal images and providing severity classifications, enhancing DR screening and diagnosis reliability and affordability. Nandhini et al. [8] introduce the DiaNet Model (DNM) for DR detection, incorporating a Gabor filter for enhanced blood vessel visibility and PCA for dimension reduction. The DNM model achieves a mean classification accuracy of 90.02%, demonstrating significant improvement over existing methods and reducing computational burden. Joshi et al. [9] explore a multistage transfer learning approach using diverse datasets to enhance DR diagnostic accuracy. Evaluated on the APTOS 2019 dataset, their model achieves 0.99 sensitivity and specificity. Shapley Additive exPlanations (SHAP) enhance model interpretability, providing a robust framework for clinicians.

Zanelli et al. [10] explore photoplethysmography (PPG) technology for diabetic retinopathy (DR) detection, achieving 80% sensitivity and specificity with a LightGBM-based model, offering a cost-effective alternative to traditional methods. Mayya [11] presents an automated DR diagnosis pipeline using deep learning, combining retinal image preprocessing, transfer learning with Inception, U-Net segmentation, and a custom CNN, achieving 88.7% accuracy on APTOS 2019 and DRIVE datasets. Khanapur and Patil [12] address challenges in DR detection, focusing on machine learning applied to fundus images, particularly with limited training datasets and manual segmentation. Ayesha Jabbar et al. [13] propose a hybrid deep learning model combining GoogleNet

and ResNet with an adaptive particle swarm optimizer (APSO), achieving 94% accuracy in classifying DR severity. Huma Naz et al. [14] introduce the Robust Fuzzy Local Information K-Means Clustering algorithm, improving the classical K-means approach and attaining 94.4% accuracy with an average execution time of 17.11 seconds. These studies highlight the significant advancements deep learning technologies bring to DR detection.

3 Proposed Methodology

In this section, we present the proposed methodology for detecting diabetic retinopathy using deep learning by integrating three advanced convolutional neural networks (CNNs): DenseNet201, ResNet50, and VGG16. This combined Trinet framework aims to enhance detection accuracy and efficiency by leveraging the strengths of each model.

3.1 DenseNet201

DenseNet201, with its dense connectivity, is particularly effective at capturing intricate details in retinal images, such as microaneurysms, hemorrhages, and exudates. The architecture ensures that each layer receives inputs from all preceding layers, which promotes feature reuse and mitigates the vanishing gradient problem, making it well-suited for identifying subtle and complex patterns in medical images. This model excels in situations where fine-grained features are crucial for distinguishing between different stages of diabetic retinopathy, such as early signs of microvascular damage or advanced retinal lesions. **DenseNet201** is best suited for cases where fine details are critical, such as identifying early microaneurysms or distinguishing subtle changes in the retinal vasculature.

3.2 ResNet50

ResNet50 addresses the degradation problem in deep networks by using residual learning and shortcut connections. This architecture is highly effective in learning deep and complex features, which is critical for distinguishing between different severities of retinal abnormalities. ResNet50 is particularly good at capturing deep hierarchical features that represent different levels of abstraction, from low-level textures to high-level structures. These features are essential for detecting a wide range of diabetic retinopathy manifestations, including both early and advanced stages. ResNet50 is ideal for capturing both fine details and complex, high-level features, making it highly effective for distinguishing between different stages of diabetic retinopathy across a wide spectrum.

3.3 VGG16

VGG16 is known for its simplicity and uniform architecture, comprising 16 weight layers with small 3x3 convolution filters and a consistent arrangement of convolution

and max-pooling layers. This design allows VGG16 to capture hierarchical features across multiple abstraction levels, making it effective at detecting global patterns and structural changes in retinal images. VGG16 excels at identifying broad manifestations of diabetic retinopathy, such as large areas of retinal thickening or significant hemorrhages, which may not require as deep a network as ResNet50. VGG16 is effective in scenarios where global patterns and structural changes are the primary indicators, such as in detecting more obvious and widespread retinal damage.

3.4 Trinet Model

The Trinet model shown in Fig.1 combines the strengths of DenseNet201, ResNet50, and VGG16 to create a comprehensive solution for diabetic retinopathy detection. Each model is initially employed independently for feature extraction and pretrained on the dataset to capture a wide array of visual features. During fine-tuning, only the higher-level layers are trainable, allowing the models to adapt to the specific characteristics of the diabetic retinopathy dataset while retaining their foundational feature extraction capabilities.

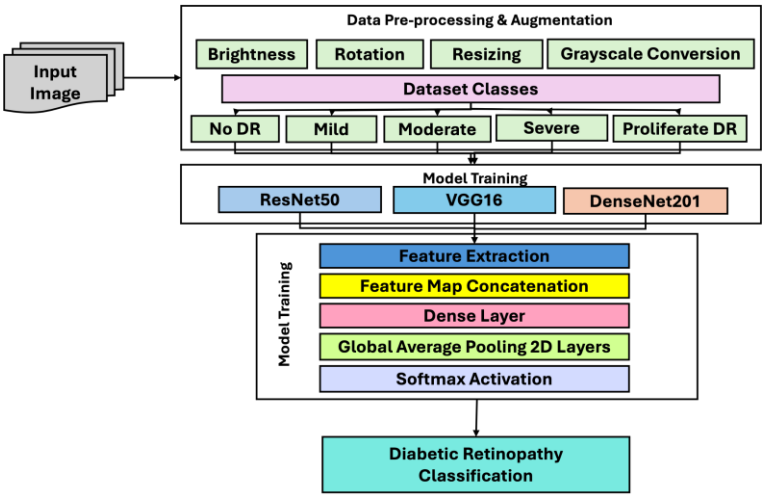

Fig. 1. Architecture of the proposed Trinet Model for Diabetic Retinopathy detection.

The final convolutional layer features from each model are concatenated into a single feature vector, integrating diverse representations. A Global Average Pooling 2D layer reduces dimensionality, preventing overfitting and enhancing generalization. This pooled feature vector is processed through fully connected layers for final classification, with the last layer using softmax activation to output probabilities for five classes: 0 for 'No_DR,' 1 for 'Mild,' 2 for 'Moderate,' 3 for 'Severe,' and 4 for 'Proliferate_DR.' Data augmentation techniques, including brightness adjustment, rotation, resizing, and grayscale conversion, further prevent overfitting and improve robustness. Crucial modifications included extensive data preprocessing, adding 'GlobalAveragePooling2D'

and 'Dense' layers, and employing dropout and batch normalization to prevent overfitting. The hyperparameters used for fine-tuning the deep learning models were a learning rate of 10^{-5}, a batch size of 15, and training over 20 epochs with the Adam optimizer. The Adam optimizer and feature extraction from three models further enhanced the model's accuracy. The integration of features through a concatenate layer and global average pooling ensures a unified and compact representation of retinal image data, reducing dimensionality and mitigating overfitting. The computational complexity of the Trinet model, executed on 2 T4 GPUs along with 16GB RAM and a generic CPU, is substantial. The fine-tuning process ensures the model is highly specialized, and the fully connected layers enable precise classification.

The Trinet model combines DenseNet201, ResNet50, and VGG16 for enhanced diabetic retinopathy detection. ResNet50 captures deep hierarchical features, DenseNet201 focuses on detailed abnormalities and lesions through dense layer connections, and VGG16 identifies global patterns and structural changes in retinal images to detect diabetic retinopathy.

4 Results and Discussions

The dataset utilized in this study encompasses a total of 3,662 retinal images, each labeled to indicate the severity of diabetic retinopathy. The images are categorized into five classes: 'No_DR' (0), 'Mild' (1), 'Moderate' (2), 'Severe' (3), and 'Proliferate_DR' (4), as shown in Fig. 3. Specifically, the dataset includes 1,805 images labeled as 'No_DR,' representing cases without visible retinopathy, 370 images marked as 'Mild' for early signs of the condition, 999 images categorized as 'Moderate' for more pronounced stages, 193 images classified as 'Severe' for advanced retinal damage, and 295 images under 'Proliferate_DR,' indicating severe complications such as abnormal blood vessel growth. The sampling function effectively visualizes a grid of sample images from various categories as shown in Fig. 2, facilitating easy inspection and comparison across different severity levels of DR. To evaluate and enhance model performance, key hyperparameters include the learning rate, which affects weight updates and convergence; batch size, influencing training stability and efficiency; and the number of epochs, impacting model learning and potential overfitting. For ensemble models like TripleNet, tuning includes managing base model parameters and how features are combined, ensuring optimal performance across accuracy, F1 score, recall, and precision.

ResNet50 addresses the degradation problem in deep networks by using residual learning with shortcut connections, enabling efficient learning of deep features. This is crucial for accurately classifying different severities of retinal abnormalities, with the model achieving strong performance metrics: 0.945 accuracy, 0.940 precision, 0.945 recall, and a 0.942 F1-score. VGG16, with its 16 weight layers and small 3x3 convolution filters, captures hierarchical features across multiple abstraction levels, making it effective in detecting various manifestations of diabetic retinopathy. VGG16's performance includes 0.938 accuracy, 0.925 precision, 0.930 recall, and a 0.927 F1-score, demonstrating its robustness in image classification and suitability for transfer learning in medical imaging. DenseNet201 enhances parameter efficiency and gradient flow,

effectively discerning complex patterns, with performance metrics of 0.942 accuracy, 0.932 precision, 0.937 recall, and a 0.934 F1-score. These results highlight DenseNet201's effectiveness in image classification, particularly in medical imaging. ResNet50 captures deep hierarchical features, DenseNet201 focuses on detailed abnormalities and lesions, and VGG16 identifies global patterns and structural changes in retinal images, making all three models highly effective for diabetic retinopathy detection.

The Trinet model, combining ResNet50, DenseNet201, and VGG16 architectures, outperforms individual models in detecting diabetic retinopathy across all performance metrics. By leveraging ensemble learning, Trinet reduces errors from individual model weaknesses and captures a broader range of features. This synergy mitigates overfitting, improves gradient flow during training, and enhances the learning of complex features, crucial for accurately distinguishing between different severities of retinal abnormalities. The Trinet model achieves an impressive accuracy of 96.47%, significantly surpassing ResNet50 (94.50%), DenseNet201 (94.20%), VGG16 (93.80%), and other models like Xception and InceptionV3, highlighting the effectiveness of the ensemble approach in improving diabetic retinopathy detection capabilities as shown in Table 1 and Fig. 4. The effectiveness of our approach is highlighted by the significant improvement in performance, due to combining multiple state-of-the-art models to leverage their individual strengths, average out errors, and capture a broad range of features. By integrating diverse feature extraction techniques and learning patterns from different architectures, the Trinet model effectively synergizes their capabilities for superior performance within retinal images, leading to higher DR detection accuracy.

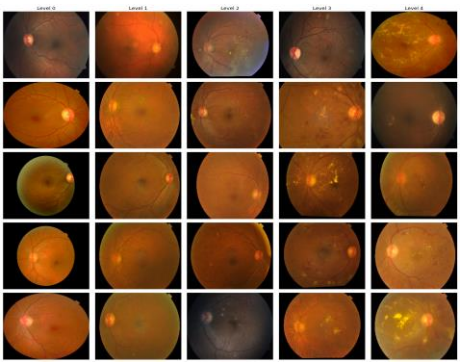

Fig. 2. Sample images from the dataset for various DR classes.

The Trinet model demonstrates strong performance in diabetic retinopathy detection, with precision and recall values of 95.91% and 96.44%, respectively. This indicates the model's robust ability to accurately identify true positive cases while minimizing false negatives. High precision shows the model's specificity in predicting DR, reducing false positives, while high recall ensures it captures nearly all actual positive cases, providing comprehensive screening coverage. The F1 score of 96.17% highlights the model's balanced performance between precision and recall, crucial for accurate medical diagnosis and treatment planning. The confusion matrix (Fig. 5) reveals that Trinet excels in predicting severe diabetic retinopathy, achieving an impressive prediction accuracy of 0.99. This suggests the model can almost perfectly identify severe

cases, ensuring timely intervention and preventing further complications. Trinet also shows high accuracy across all other DR categories, demonstrating reliability in distinguishing between various severity levels. Minor misclassifications, such as moderate DR being occasionally predicted as mild, do not significantly affect overall performance. This comprehensive and precise screening capability makes Trinet an invaluable tool for early diagnosis and effective disease management in diabetic retinopathy.

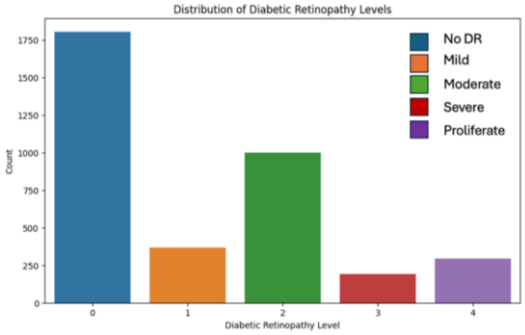

Fig. 3. Distribution of the dataset for various DR levels.

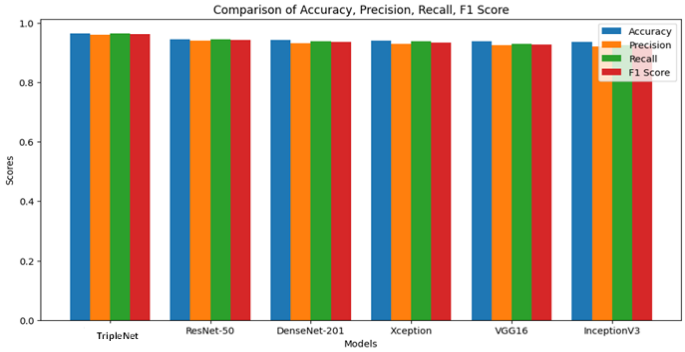

Fig. 4. Comparison of models across metrics.

Table 1. Comparison of models across metrics

Model	Accuracy	Precision	Recall	F1-score
InceptionV3	0.935	0.920	0.925	0.9225
Xception	0.937	0.930	0.938	0.934
VGG16	0.938	0.925	0.930	0.927
DenseNet-201	0.942	0.932	0.937	0.934
ResNet-50	0.945	0.940	0.945	0.942
TripleNet	**0.964**	**0.959**	**0.9644**	**0.961**

The ROC curve, as shown in Fig. 6 for the fine-tuned Trinet model highlights its exceptional performance in detecting various stages of diabetic retinopathy (DR).

With an AUC of 0.98 for 'No_DR,' 0.95 for 'Mild' DR, 0.97 for 'Moderate' DR, a perfect 1.00 for 'Severe' DR, and 0.98 for 'Proliferate_DR,' the model demonstrates high accuracy and reliability across all classes. These impressive AUC values indicate the model's robust ability to differentiate between different stages of DR, ensuring early and precise detection. This reliability is crucial for timely intervention, ultimately aiding in preventing severe visual impairment and improving patient outcomes in diabetic retinopathy management. The Fig. 7 and Fig. 8 illustrate the comparison between training and testing accuracy for both the baseline and fine-tuned models. The fine-tuned Trinet model exhibits significantly higher accuracy in both training and testing phases compared to the regular model. This improvement highlights the model's enhanced capability to generalize from the training data to unseen testing data, ensuring reliable performance in real-world applications.

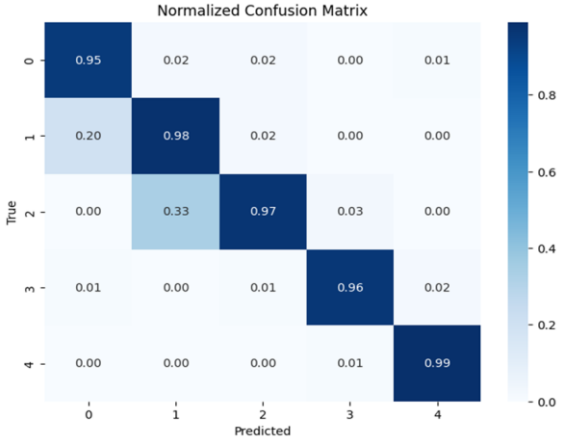

Fig. 5. Confusion matrix illustration of the proposed Trinet model.

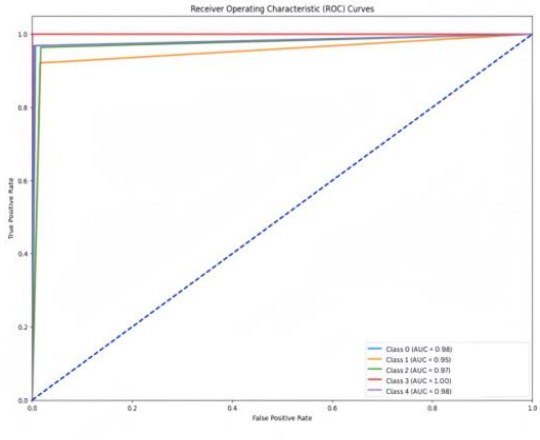

Fig. 6. ROC Curve for the proposed Trinet model.

The fine-tuning process, which involved optimization of various features and incorporating advanced architectural refinements, played a crucial role in boosting the model's accuracy. Additionally, the training and validation loss curves, as shown in Fig. 8 for the fine-tuned Trinet model indicate its stability and effectiveness in learning from the data. The curves demonstrate a steady convergence with minimal signs of overfitting, reflecting the model's ability to maintain a balance between fitting the training data and generalizing to new data. The regular model, by contrast, showed a relatively higher discrepancy between training and testing accuracy, underscoring the importance of fine-tuning in achieving optimal performance.

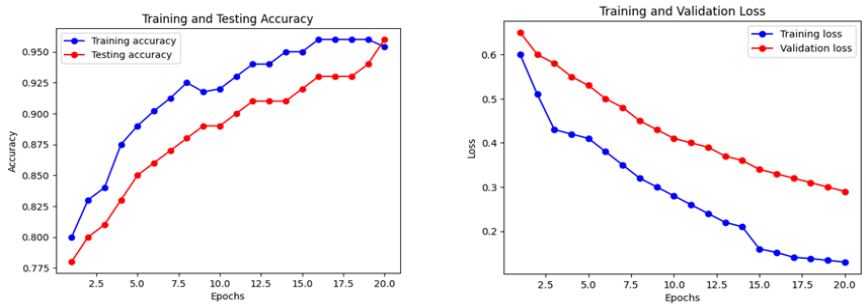

Fig. 7. Training, testing accuracy and validation loss curves for the Trinet model.

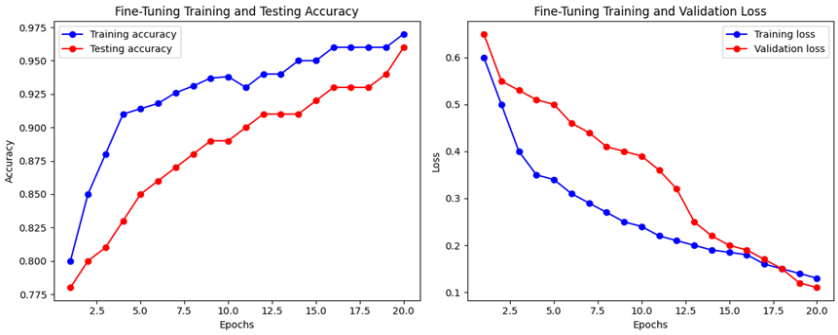

Fig. 8. Training, testing accuracy and validation loss curves for the fine-tuned Trinet model.

The fine-tuned Trinet model presents several avenues for future technical innovations and applications in diabetic retinopathy detection and beyond. One significant direction is the integration of the model into telemedicine platforms, enabling remote screening and diagnosis, especially in underserved and rural areas. This can facilitate early detection and effective management, reducing the burden on healthcare systems and improving patient outcomes. Technical advancements can further enhance the Trinet model's performance. Incorporating multi-modal data, such as patient demographics and medical history, could enhance diagnostic accuracy and enable personalized treatment recommendations. Additionally, the model could be adapted and

trained for other ophthalmic diseases, such as glaucoma or age-related macular degeneration, expanding its utility in comprehensive eye care.

Future work could also focus on the continuous improvement of the model by incorporating more diverse and extensive datasets, ensuring robustness across various populations. Exploring the use of advanced techniques like federated learning can enhance data privacy and security while improving model performance by leveraging distributed data sources. Furthermore, integrating real-time image processing capabilities and developing user-friendly interfaces could facilitate widespread adoption in clinical settings. Ultimately, the adaptability and high performance of the Trinet model position it as a pivotal tool in advancing automated medical imaging analysis and contributing to the broader field of technology in healthcare.

5 Conclusion

The proposed Trinet model for Diabetic Retinopathy significantly outperforms individual models and benchmarks, achieving an accuracy of 96.47% compared to ResNet-50 (94.50%), DenseNet-201 (94.20%), and VGG16 (93.80%). This integration leverages the strengths of each model, enhancing accuracy. The model also boasts precision and recall values of 95.91% and 96.44%, respectively, and an F1 score of 96.17%, demonstrating excellent balance between precision and recall. The confusion matrix reveals high accuracy, with near-perfect prediction (0.99) for severe DR. ROC curve analysis supports these findings, showing an AUC of 1.00 for Class 3, indicating exceptional detection of critical cases. These metrics validate the Trinet model's robustness and potential to improve diabetic retinopathy detection and patient outcomes, marking a significant advancement in the field. Future work will focus on expanding the model's applicability by incorporating additional datasets from diverse demographics to enhance its generalizability. Exploring real-time implementation and integration with clinical workflows could further improve its utility in early diagnosis and timely intervention. Additionally, investigating techniques for model interpretability and explainability will aid in understanding decision-making processes and fostering greater trust in automated diagnostic tools.

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