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Implementation of Transfer Learning Models in Microaneurysms Detection from Fundus Images

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Abstract: Diabetic Retinopathy (DR) is a significant vision-threatening condition in diabetic individuals, mostly caused by damage to the retinal blood vessels. Microaneurysms, small red patches on the retina, are among the first indicators of DR. If left untreated, they can lead to serious vision problems or even blindness. Consequently, early and precise identification of microaneurysms is essential for efficient treatment and the prevention of disease progression. This research introduces an innovative deep learning framework for the automatic identification of microaneurysms in retinal fundus images with a Frozen-based VGG19 model. The suggested method has two main steps: pre-processing and classification. During preprocessing, lighting changes are corrected, and image scaling is applied to facilitate feature extraction. The modified Frozen-based VGG19 model is used in the classification phase to quickly identify microaneurysms without segmenting vessels. We tested the proposed technique on three benchmark datasets: E-ophtha, ROC, and DIARETDB1. We also compared it with existing transfer learning architectures such as VGG16 and VGG19. The experimental results show that the proposed model achieves 93.4% detection accuracy on the E-ophtha dataset, 88.3% on the ROC dataset, and 83.5% on the DIARETDB1 dataset. The work emphasises the capabilities of sophisticated deep learning models for early diagnosis of diabetic retinopathy, facilitating prompt clinical intervention and improving patient outcomes.

Keywords: Diabetic Retinopathy (DR); Transfer Learning; Benchmark Datasets; Fundus Images; Deep Learning; Enhancing Patient Outcomes; Feature Extraction; Blood Vessels.

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1. Introduction

The number of diabetics in India, which is commonly recognised as the diabetes capital of the world, is expected to increase by 2025 to 70 million and by 2030 to 80 million. The primary reason for diabetes reaching epidemic proportions is that one-third of the population is unaware of the impact of the disease, which may lead to several complications, including Diabetic Retinopathy, Diabetic foot, Diabetic Nephropathy, etc. Diabetic Retinopathy (DR) is a common eye-related symptom of diabetes. It particularly affects patients who have lived with diabetes for a long duration. Damage to retinal blood vessels can

cause many eye diseases. If it is not detected early, it can lead to blindness. All over the world, diabetes is the fifth leading cause of blindness due to high sugar levels in the blood vessels that damage the retina. It is noticed by retinal thickening, new abnormal retinal vessels, vascular closure, increased vascular permeability and leaky blood vessels. Diabetic Mellitus (DM) is a major metabolic disease characterised by improper insulin secretion or action in the human body. Prolonged hyperglycemia leads to microvascular complications in the eye, known as Diabetic Retinopathy (DR). Based on retinal signs, DR is classified into proliferative DR (PDR) and non-proliferative DR (NPDR). In the current scenario, the major cause of vision loss among diabetic patients is due to DR. According to the International Diabetes Federation (IDF), approximately 451 million people worldwide had diabetes in 2017. This is expected to reach 693 million by 2045 if no effective preventive measures are implemented [1]. In addition, this progressive increase in DM leads to microvascular abnormalities in the eyes, resulting in vision loss. Diagnosis of DR is based on fundus and Optical Coherence Tomography (OCT) images. As per the Early Treatment of DR Study (ETDRS), in the initial stage of NPDR, retinal capillaries are damaged due to Hyperglycaemia, which weakens the capillary walls and appears as a small circular red spot with a diameter less than 125 micrometres, termed as Microaneurysms (MA). Therefore, it is crucial to conduct regular screenings and diagnose blindness early.

The subsequent screening of DR, however, is costly and time-consuming [2]. As a result, much research has been conducted on the automated detection of Mas [4]. Conceptually, many Artificial Neural Networks and Deep Learning networks rapidly become promising methods in medical imaging analysis. In particular, Deep Learning methods have performed well as classifiers in medical imaging applications. It recognises complex structures in large datasets by implementing the backpropagation algorithm to compute each neural network layer. In particular, a Convolutional Neural Network (CNN) automatically generates high-level and mid-level abstractions from raw input images. Therefore, CNNs are considered powerful tools for various computer vision tasks [3]. Many MA detection algorithms achieve low accuracy due to poor-quality input images, varying sizes of MA lesions, a low number of pixels per MA, and the presence of MA lesions near retinal blood vessels. During learning, the classifier generates unbalanced data. In this study, an MA identification method based on a CNN is presented to address the above challenges by increasing detection accuracy and handling imbalanced data in fundus images [5]. Early on, there may not be any symptoms, particularly if the core region of the retina is unaffected. Some symptoms include distorted vision, floaters resembling cobwebs, tiny threads, or black dots, and eye bleeding, which may lead to unexpected or long-term vision loss. In some patients with diabetic retinopathy, blood vessels may enlarge and leak fluid. On the retinal surface, aberrant new blood vessels form in others. Two main stages of DR are NPDR and PDR, where NPDR refers to the development of macular oedema that may result from blood vessel leakage, impairing vision. The proliferative stage causes bleeding into the vitreous when new, fragile blood vessels form or proliferate, leading to significant vision loss. This paper presents a method for detecting microaneurysms using transfer learning. Moreover, freezing the selected convolutional layers reduces the network's complexity [6].

2. Literature Survey

Among the variety of literature available in the field of DR, only a few literatures that matches the problem of MA detection are discussed in this section. Eftekhari et al. [7] proposed a two-step Deep Convolutional Neural Network method for detecting MAs. The performance is tested on the e-optha and Retinopathy Online Challenge datasets, achieving a sensitivity of 0.8 and an average false-positive count greater than 6. Moreover, Xia et al. [8] developed a technique for MA detection that uses a multi-scale residual network for segmentation and a Multi-Scale Efficient Net for classification. The results are validated with the e-optha dataset and reached an average sensitivity of 0.75. Furthermore, Long et al. [9] presented a machine learning algorithm, called Directional Local Contrast, to detect MAs in fundus images. Here, the blood vessels are segmented after enhancing through the eigenvalues of the Hessian matrix. Two publicly available datasets, e-optha and diareddB1, are used to achieve AUC values of 0.87 and 0.86, respectively. Likewise, the FROC scores shown are 0.374 and 0.210 for the corresponding datasets. In addition, Liao et al. [10] highlighted a novel Deep Convolutional Encoder Decoder-based network for microaneurysm detection. In which a smooth disc loss is considered, focus on the misclassified MAs and the activation function is framed to create the probability map. This method reduces running time by 100 times compared to existing microaneurysm detection methods. Furthermore, Qureshi et al. [11] discussed an Active deep learning-based CNN model that automatically extracts handcrafted features. In particular, a label-efficient CNN is implemented using an active learning method called Expected Gradient Length.

The evaluated performance metrics are 98% accuracy, 92.20% sensitivity, 95.10% specificity and an F-measure of 93%. Moreover, Yadav et al. [12] highlighted a MA detection scheme using a colour locus detection method. In which shape, grey-scale and GLCM-based features are extracted and fed to seven different classifiers. The classification algorithms, including Logistic regression, SVM, kernel SVM, KNN, Naïve Bayes, Random Forest, and Decision tree, achieved accuracies of 69.7%, 68.75%, 76.04%, 76.04%, 58.33%, 83.33%, and 73.95%, respectively. According to Usman and Almejalli [13], a new intelligent method for automatic detection of MAs in colour fundus images has been developed. In which Genetic Programming is applied to extract 28 selected features. Previously, the fundus image was pre-processed to improve the quality of the input. Through the binarisation of fitness scores, optimal mathematical expressions are evolved for classification. Three publicly

available datasets, namely MESSIDOR, diareddb1, and e-optha, were tested, achieving sensitivities of 93.62% and 98%, and specificities of 94.6% and 96% for diareddb1 and MESSIDOR, respectively. Furthermore, Sun et al. [14] discuss a novel deep learning model, the Magnified Adaptive Feature Pyramid Network (MAFP-Network), for automatic MA detection. The advantage of this model is that no pre-segmented patches are required to train the CNN network. This model is tested on the IRDID dataset, and the evaluation metrics show a sensitivity of 83.55% and a false-positive rate per image of 8. Similarly, Wang et al. [15] introduced a novel method for automated detection of MAs in Fluorescein Fundus Angiography (FFA) images through an improved FC-Dense Net. Here, FFA images are initially preprocessed to improve image quality using histogram stretching and Gaussian filtering. Later, MA regions were detected using the improved FC-Dense Net, which was compared with other Dense Net models. Likewise, Wang et al. [15] developed a detection procedure for early MAs using a hybrid feature-embedding technique in pre-trained CNNs, particularly VGG-19 and Inception-V3. The performance of this approach is evaluated using publicly available datasets such as e-optha and diaretdB1, and the obtained accuracies are 96% and 94%, respectively.

3. Proposed Method

3.1. Data Preprocessing

Before extracting features and classifying an image, preprocessing is an important step due to various problems in raw images, such as incomplete vision, fuzzy vision, inadequate colour vision drift, or negative colour vision drift. Preprocessing is essential. Otherwise, it may lead to confusion in the outcomes of feature extraction and classification. The proposed strategy, however, used noisy data to boost sensitivity and accuracy, thereby overcoming these obstacles. The proposed flow diagram for transfer learning-based MA detection is shown in Figure 1. The significant steps for preprocessing are enumerated below:

- To minimise the impact of lighting conditions, the input image data is first converted from RGB to grayscale.
- To expedite training and reduce memory requirements, the image is scaled to 224×224 pixels.

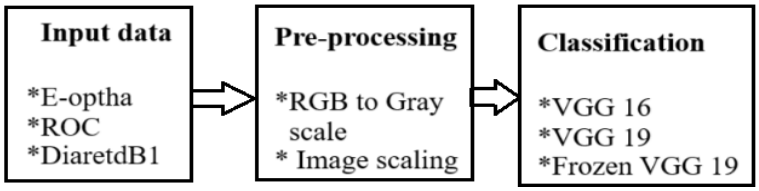

Figure 1: Flow diagram of proposed transfer learning-based classification of MAs

3.2. Transfer Learning Based Model

Transfer learning is the process of classifying data from big datasets using previously learned DNN models. This approach uses a source database to train the network's weights and a destination database to assess the outcomes. The training and test accuracies increase, and low-level feature extraction improves when combined with a pre-trained model. The pre-trained model provides the initial weights, and by updating the weights with the best prediction-related values, it may then extract features from a training set, such as colour and size. Transfer learning is so named because it can be applied to a much larger training set for the target task, which is one of its most significant advantages. Transfer learning is possible when the task model's creator is already skilled. Correct use of Transfer Learning can result in greater asymptotic accuracy, faster convergence, and higher initial accuracy for the training data. The construction of machine learning models benefits greatly from transfer learning. The primary advantages of Transfer learning in developing new models are increased effectiveness and resource savings. The motivation behind TL is multifaceted and is enumerated below:

- Training data of any size can be collected for each new model.
- The model's complexity is reduced.
- To increase the effectiveness of the machine learning tool for different models.
- TL can be trained using simulations rather than real-time data.
- It utilises various techniques in a broad problem-solving approach to address new problems.
- Generalisation is a key feature of TL.
- The models are not highly tied to the training data, but they are general.
- Typically, transfer learning is used to improve efficiency in machine learning applications that require substantial resources, such as image classification or natural language processing.
- To use pre-trained models to compensate for an organisation's lack of labelled training data.

3.3. Implementation of VGG 16

The proposed research work uses a pre-trained VGG-16 architecture for Transfer Learning to classify DR. The architecture of VGG16 consists of four layers, with a kernel size of 3x3. In Convolution 2D, the kernel size is kept at 3x3 across all layers. A sequential layer and a 224x224 input image are used to start the model. The depth of the first 2D convolution layer is 64. The kernel's dot product with each filter produces the feature maps. There will be 64 feature maps generated since there are 64 filters. The 'ReLu' activation function and batch normalisation are described in the Convolution layer, and the Max-pool 2D layer follows it. A 2x2 pool size is used in the max-pool layer. A 2D convolutional layer with 128 filters follows the 2D max pooling layer.

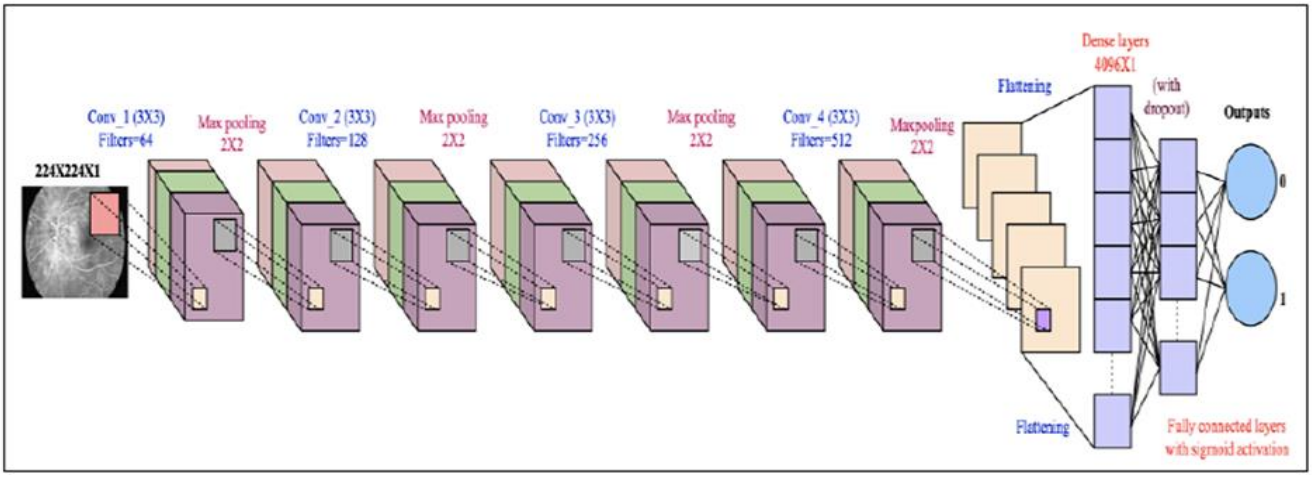

Figure 2: Architecture of VGG 16

Each convolutional layer may double the depth of a typical VGG-16 architecture. As a result, the depth is regarded as 128. A 'ReLu' activation also supports this layer. This layer generates 128 feature maps. A similar procedure is performed by the Max-pooling process, which uses a 2x2 pooling size. After that, a convolution layer with depths of 256 and 512 and the 'ReLu' function is applied, preceded by a Max-pooling layer with the same 2x2 pool size. CNN's feature extraction phase uses convolutional and max pooling layers. CNN classification relies on flatter and denser layers. Data from feature extraction is combined to form a single dimension layer. This was accomplished with the Flatten layer. The dense layer is the second layer that will be used. The 'ReLU' signal activates the dense (fully connected) layer. Each thick layer's input neuron is coupled to an output neuron. The layer's size has been set to 4096. Figure 2 illustrates the architecture of the VGG-16 model.

3.4. Implementation of VGG 19

In VGG-19, a DR fundus image of size 224×224×3 is used as input to the convolutional layer (Figure 3).

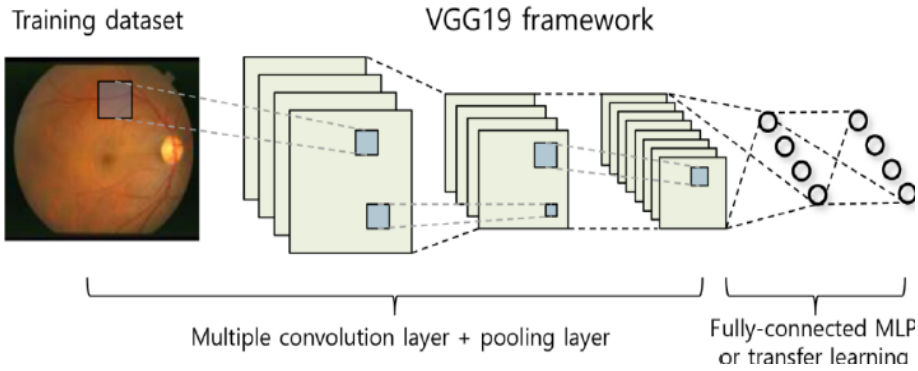

Figure 3: Architecture of VGG 19

The CNN has two layers: one for convolution and one for ReLU. A block that includes two convolution layers, two ReLU layers, a batch normalisation layer, a maximum pooling layer, and a dropout layer comes next. In particular, convolutional

layers were used to extract features during the training phase, and a small number of convolutional layers included max pooling layers to determine the features' dimensionality.

3.5. Implementation of Frozen VGG 19

Deep networks are prone to overfitting and require significant computational resources during training. These methods remove the blocks, layers, nodes and connections from a neural network to make it more regular. During training, deep neural networks stochastically freeze a layer's trainable parameters throughout an epoch. In this research, a novel regularisation technique is proposed for the detection of microaneurysms. This method is applicable for fully connected networks and all varieties of convolutional networks, including VGG-16, VGG-19, etc. For feature extraction, Shabanzadeh and Moghaddam [2] of the Visual Geometry Group (VGG) use a set of 3x3 convolutional filters from the VGG-19 network. This VGG-19 model consists of 16 layers and is particularly suitable for transfer learning. This model uses the ImageNet dataset for training, with max pooling layers to minimise dimensionality. The ImageNet dataset is a collection of 15 million high-resolution natural images, each classified into about 22,000 categories. This challenge is also known as the ImageNet Large-Scale Visual Recognition Challenge (ILSVRC). All pre-trained models were trained on the publicly available ImageNet dataset. Because of its straightforward architecture, VGGNet outperforms existing models. Figure 4 illustrates the proposed frozen VGG19 architecture.

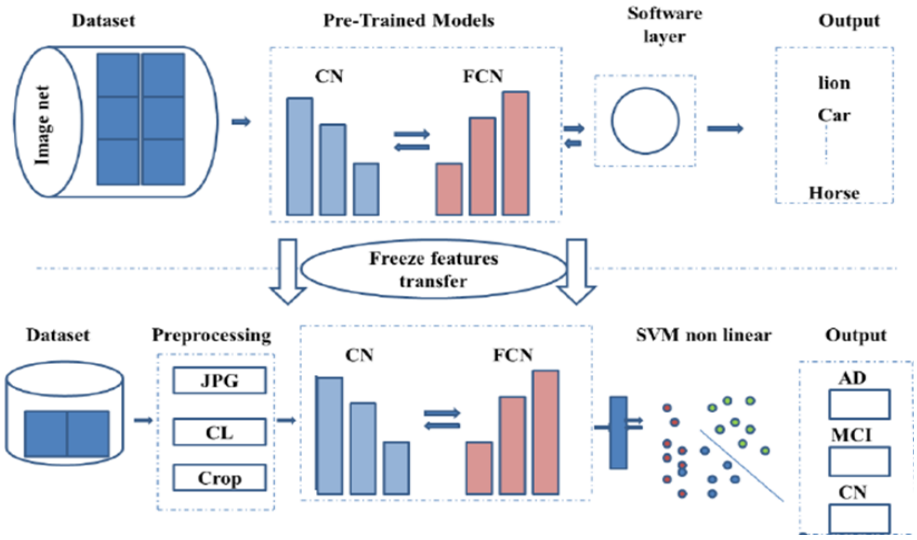

Figure 4: Architecture of frozen VGG 19

The Frozen VGG-19 is a pretrained version of VGG-19. In this pre-trained model, the model parameters are optimised, and the classification process is fine-tuned. Thus, the transfer learning approach is introduced using Frozen VGG-19. In the proposed Frozen VGG-19, most parameters are in the fully convolutional layer. To improve Frozen VGG 19, replace the three fully convolution layers in VGG 19 with one flattened layer and two complete linked layers. The flatten layer is used when a convolution layer cannot be directly connected to a dense fully convolution layer. The proposed model updates the VGG-19 pretrained model by fine-tuning its convolution, pooling, and fully connected layers via transfer learning. The new model incorporates a two-label soft-max classifier, sparse features, dropout, and max pooling. This model fits better in terms of accuracy. The concept of increasing the freezing layers comes from fine-tuning, which enables the model to adjust its pre-trained weights toward the newly added ending layers to complete certain tasks. However, using the same methodology on the alternative model can yield comparable results without adding features. As a result, the other layers were thawed, allowing the flow of new weights and generating diverse characteristics throughout the whole network. As a result, using a combined strategy of weight re-initialisation and fine-tuning, the fused pipeline selected a wide range of different attributes.

3.6. Algorithm

Input: E-ophtha, ROC, and DIARETDB1 datasets
Output: Detected Microaneurysms Begin

Phase I: Preprocessing
Step 1: Load the datasets

Step 2: Preprocess the input images

Phase II: Classification using 3-Layered CNN
Step 3: To extracts the complex features
Step 4: Utilise 3 layered CNN

Phase III: Transfer Learning based Classification using VGG 16
Step 5: Apply Transfer learning VGG16
Step 6: Use four layers with a kernel size of 3x3
Step 7: Activate ReLU activation function

Phase IV: Transfer Learning based Classification using VGG 19
Step 8: Apply VGG19 model with fully connected layer
Step 9: Optimize the model parameters in the convolution layer

Phase V: Transfer Learning based Classification using Proposed Frozen based VGG19
Step 10: To introduce flattened layer
Step 11: To freeze a layer's trainable parameters
Step 12: Generate freeze probability vector
Step 13: Change the dropout values
Step 14: To detect the Microaneurysms

End

4. Results and Discussion

4.1. Dataset Description

Three datasets, E-Optha, ROC, and DiaretdB1, were used in the proposed research:

- **E-Ophtha Dataset:** It contains 381 compressed images, 148 of which are fundus images with MAs, and 233 are fundus images of normal, healthy eyes. 30 French screening facilities provided images at varied resolutions and 45 FOV (Field of view).
- **ROC Dataset:** 50 compressed training and 50 compressed test images. Three separate fundus cameras, with resolutions ranging from 768576 to 13891383 at 45 FOV, were used to take the images. Experts gave all images illness ratings. Thirty-seven images in this collection include MA, whereas the remaining thirteen are clean.
- **DIARETdB1 Dataset:** It contains 61 test uncompressed images and 28 training images collected at a FOV of 50. Four medical professionals carefully annotated each 1500 1152 picture for the presence of MAs and HEs. FPs do not have any MAs; however, the remaining 51 FPs do. In the proposed work, the trained model is verified and evaluated using small DR sets: E-ophtha, ROC, and DIRAT DB1, using performance indicators: accuracy, recall, Precision, and F-measure.

$$\text{Precision} = \frac{\text{TP}}{\text{TP+FP}} \quad (1)$$

$$\text{Recall} = \frac{\text{TP}}{\text{TP+FN}} \quad (2)$$

$$\text{F} - \text{measure} = \frac{2*\text{Precision}*\text{Recall}}{\text{Precision+Recall}} \quad (3)$$

A comparative analysis of deep learning models for retinal image categorisation illustrates the advancing capabilities and constraints of convolutional neural networks (CNNs) in tackling complex medical imaging challenges, especially in the diagnosis of diabetic retinopathy. The models being considered—VGG-16, VGG-19, and Frozen VGG-19—differ in network depth and in their use of transfer learning. Their performance on three benchmark datasets—DiaretdB1, ROC, and E-optha—provides useful insights into how architectural depth and selective fine-tuning affect classification accuracy. Each dataset differs in quality, complexity, and unpredictability, providing a solid basis for assessing the models' generalizability and adaptability.

Table 1: Comparison of proposed frozen VGG-19 with other pre-trained VGG-16 and VGG-19 models

No.	Data set	Model Used		Accuracy (%)
1	DiaretdB1	VGG-16		92.3
	ROC			84.5
	E-optha			73.2
2	DiaretdB1	VGG-19		92.7
	ROC			85.2
	E-optha			81.3
3	DiaretdB1	Frozen VGG-19	Freezing layer1	92.8
			Freezing layer3	93
			Freezing layer5	93.4
	ROC	Frozen VGG-19	Freezing layer1	86.2
			Freezing layer3	87.3
			Freezing layer5	88.3
	E-optha	Frozen VGG-19	Freezing layer1	82.4
			Freezing layer3	83
			Freezing layer5	83.5

This investigation uses VGG-16, a well-known 16-layer convolutional neural network, as a starting point. It has been widely utilised in computer vision applications because it strikes a good balance between speed and feature extraction. VGG-16 achieves strong results on retinal imaging datasets. The DiaretdB1 dataset achieved the highest accuracy of 92.3%. This dataset contains high-resolution images with clear features, making it easier for shallower architectures like VGG-16 to detect microaneurysms and other retinal abnormalities. But when evaluated on more complex and varied datasets such as ROC and E-optha, the accuracy drops to 84.5% and 73.2%, respectively. This large drop shows that the model struggles to handle photos with changing lighting, contrast, and subtle signs of disease. The network's modest depth makes it harder for it to acquire complex hierarchical representations needed to distinguish fine-grained retinal characteristics. In datasets with varying image quality or lesion visibility, deeper feature-extraction layers are essential to ensure consistent performance, a capability that VGG-16 lacks due to its limited architectural capacity. VGG-19 is an improved version of VGG-16 that has three more convolutional layers. It fixes some of these problems by deepening the hierarchical structure. The more layers, the more the network finds more abstract and detailed features, which lets it find patterns that may not be obvious in networks with fewer layers. VGG-19 performs better on all datasets, with accuracies of 92.7% on DiaretdB1, 85.2% on ROC, and 81.3% on E-optha. These findings indicate that deeper designs are superior at capturing the intricate textural and structural changes included in medical imaging data.

The slight improvement in DiaretdB1 over VGG-16 shows that both models perform about the same on datasets with high-quality, well-structured images. But the big gain on E-optha shows how important deeper networks are for generalising to datasets with more noise and variability. The model's capacity to capture multi-level features, from low-level edges and contours to high-level pathological patterns, is especially useful in medicine, where lesions like microaneurysms or exudates can change in size, form, and severity. This improved feature learning enables VGG-19 to better distinguish between normal and pathological retinal areas, thereby improving diagnostic accuracy. The paper further expands this investigation through trials with Frozen VGG-19, which integrates transfer learning and layer freezing techniques to enhance model training. Transfer learning lets a model trained on a large dataset, such as ImageNet, work with a smaller, more specific dataset, such as retinal fundus images. The idea of layer freezing is to save the generic properties learnt in the early layers, including edges, forms, and textures, while fine-tuning the deeper layers to find patterns that are specific to the domain. This method not only reduces the risk of overfitting but also significantly speeds up training time by reducing the number of parameters to update. Freezing the layers of Frozen VGG-19 from the first convolutional layer (layer 1) to deeper layers (layer 5) improves the model's classification performance across all datasets. The accuracy is 93.4% on DiaretdB1, 88.3% on ROC, and 83.5% on E-optha, which is better than both the normal VGG-16 and VGG-19 models. These results show how useful it is to selectively freeze layers in transfer learning, especially for smaller, more complex medical datasets compared to large-scale natural image datasets.

The first few layers of a CNN usually capture general visual patterns that work across a wide range of image formats. By freezing these layers, the model preserves the basic visual representations and directs its computational effort toward learning more specific properties unique to the dataset in later levels. This selective adaptation makes the model more stable and generalises better, and it stops overfitting, which is a common problem when training deep networks on small medical datasets. The enhancements observed in the ROC and E-optha datasets demonstrate that transfer learning not only increases accuracy but also enhances resilience in handling images with varying lighting, contrast, and pathological changes. This is especially

useful in medical imaging, where different data types can make it hard for models to be reliable. The comparison of the three models also shows substantial trade-offs among network complexity, computational cost, and generalisation. VGG-16 is easier to compute; however, it doesn't work as well on tough datasets. VGG-19 is deeper, but it requires more computational resources for training and inference, which could make it difficult to use in clinical contexts where processing capacity is limited. The Frozen VGG-19 model, on the other hand, is a balanced solution that leverages pre-trained weights and selective fine-tuning to reduce computational burden without sacrificing accuracy. This balance makes it a great choice for real-world medical diagnostic systems, especially in low-resource or point-of-care settings where both computational efficiency and predicted accuracy are important. Another important lesson from the results is the importance of dataset heterogeneity for testing model resilience. The DiaretdB1 dataset has high-quality, well-labelled images that even the simplest models can perform well on. On the other hand, the ROC and E-optha datasets are better for assessing a model's diagnostic reliability, as they contain more image noise and subtler feature changes. The fact that Frozen VGG-19 performed better on these datasets shows that it can learn representations that are both invariant and discriminative, even when image quality varies.

This capacity is crucial for developing AI-based diagnostic tools that can operate effectively across a wide range of clinical settings, imaging devices, and patient groups. In the broader field of medical image analysis, the results of this comparative investigation support several important ideas. First, the depth of a network is very important for helping models understand complex patterns related to subtle pathological traits. Second, transfer learning and layer freezing are effective ways to customise powerful pre-trained architectures for specific domains without requiring large datasets. Third, better performance on heterogeneous datasets underscores the importance of building models that work well across a wide range of imaging situations, which is necessary for clinical use. These ideas together suggest a hybrid technique that combines deep feature extraction with adaptive fine-tuning to produce diagnostic models that are both trustworthy and scalable. In short, comparative research shows that deeper networks, such as VGG-19, perform better than shallower networks, such as VGG-16, because they can learn hierarchical features more effectively. The Frozen VGG-19 model, which uses transfer learning and selective layer freezing, also performs best overall across all datasets tested. It not only makes things more accurate but also more general and faster to compute. These results show that employing pre-trained deep learning models for medical image analysis is effective, especially for detecting diabetic retinopathy. The combination of transfer learning with deep CNN architectures is a potential area for future research. It could lead to the creation of strong, efficient, and clinically useful AI-driven diagnostic systems. In the end, this study shows that combining architectural depth with strategic model adaptation is the best strategy to balance accuracy, efficiency, and generalisation. This opens the door to advanced and easy-to-use automated retinal screening systems (Figure 5).

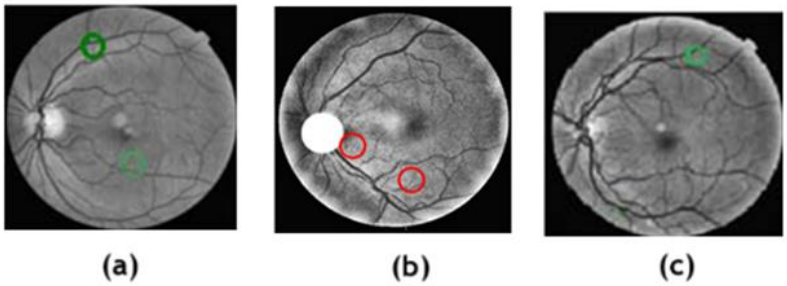

Figure 5: Microaneurysm detected images for three samples (a) DIARETDB1, (b) ROC, (c) E-optha (encircled in green and red)

Here, the proposed Frozen VGG19 achieves better results than the 3-layered CNN and the VGG16 pre-trained model. Table 1 shows that the proposed frozen VGG19 model achieves an accuracy above 80% across all datasets. It is also noteworthy that, given the E-optha dataset, the suggested model performs 10% better than other pre-trained models.

5. Conclusion

This study presents a novel automated methodology for identifying microaneurysms, an early sign of diabetic retinopathy, using advanced deep learning techniques. The research introduces a transfer-learning-based model, Frozen VGG19, derived from a pre-trained convolutional neural network (CNN). The main idea behind transfer learning is to leverage the strong feature-extraction capabilities of pre-trained models that have already acquired general visual representations from large datasets. By fine-tuning these networks on retinal images, the model learns to quickly identify disease-specific patterns with less training data. Three publicly available benchmark datasets—E-optha, ROC, and DiaretdB1—were utilised to test the proposed method's effectiveness. These datasets differ in quality, resolution, and feature diversity, offering a solid foundation for evaluating the proposed model's generalisation and stability. The photos in these datasets were divided into two groups: normal and diabetic

retinopathy-affected, with a focus on detecting microaneurysms. During training, different versions of the Frozen VGG19 architecture were tested by freezing different layers to assess their impact on learning speed and accuracy. Freezing the first few layers helped preserve general low-level properties, and fine-tuning the deeper layers enabled the network to better capture high-level disease-specific attributes. The suggested Frozen VGG19 model was evaluated for performance by comparing it with two established CNN architectures: VGG16 and VGG19. The results consistently showed that the Frozen VGG19 model performed better across all three datasets, achieving higher accuracy and improved generalisation. The model's ability to detect subtle retinal aberrations has improved through an optimal combination of transfer learning and selective layer freezing. The suggested method is a reliable, efficient, and scalable approach for detecting early signs of diabetic retinopathy in retinal fundus images.

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Reference

1. T. D. Haskell, "Modeling and Analysis of a Dynamic Voltage Regulator," M.S. thesis, Dept. of Electrical Engineering, *California Polytechnic State Univ.*, San Luis Obispo, California, United States of America, 2013.
2. M. Shabanzadeh and M. Moghaddam, "What is the smart grid? Definitions, perspectives, and ultimate goals," in *Proc. IEEE Power and Smart Grid Conference (PSC)*, Tehran, Iran, 2013.
3. A. Domijan, A. Montenegro, A. J. Keri, and K. E. Mattern, "Custom power devices: An interaction study*," IEEE Transactions on Power Systems*, vol. 20, no. 2, pp. 1111–1118, 2005.
4. A. K. Sadigh and K. Smedley, "Review of voltage compensation methods in dynamic voltage restorer (DVR)," in *Proc. IEEE, Power and Energy Society General Meeting*, San Diego, California, United States of America, 2012.
5. O. P. Mahela and A. G. Shaik, "Topological aspects of power quality improvement techniques: A comprehensive overview," *Renew. Sustain. Energy Rev.*, vol. 58, no. 5, pp. 1129–1142, 2016.
6. K. Chandrasekaran and V. K. Ramachandaramurthy, "An improved dynamic voltage restorer for power quality improvement," *Int. J. Electr. Power Energy Syst.*, vol. 82, no. 11, pp. 354–362, 2016.
7. N. Eftekhari, H. R. Pourreza, M. Masoudi, K. Ghiasi-Shirazi, and E. Saeedi, "Microaneurysm detection in fundus images using a two-step convolutional neural network," *Biomed. Eng. Online*, vol. 18, no. 1, p. 67, 2019.
8. H. Xia, F. Zhu, H. Li, S. Song, and X. Mou, "Combination of multi-scale and residual learning in deep CNN for image denoising," *IET Image Process*, vol. 14, no. 10, pp. 2013–2019, 2020.
9. S. Long, J. Chen, A. Hu, H. Liu, Z. Chen, and D. Zheng, "Microaneurysms detection in color fundus images using machine learning based on directional local contrast," *Biomed. Eng. Online*, vol. 19, no. 1, p. 21, 2020.
10. Y. Liao, H. Xia, S. Song, and H. Li, "Microaneurysm detection in fundus images based on a novel end-to-end convolutional neural network," *Biocybern. Biomed. Eng.*, vol. 41, no. 2, pp. 589–604, 2021.
11. I. Qureshi, J. Ma, and Q. Abbas, "Diabetic retinopathy detection and stage classification in eye fundus images using active deep learning," *Multimed. Tools Appl.*, vol. 80, no. 8, pp. 11691–11721, 2021.
12. D. Yadav, A. K. Karn, A. Giddalur, A. Dhiman, S. Sharma, M. Muskan, and A. K. Yadav, "Microaneurysm detection using color locus detection method," *Measurement*, vol. 176, no. 5, p. 109084, 2021.
13. I. Usman and K. A. Almejalli, "Intelligent automated detection of microaneurysms in fundus images using feature-set tuning," *IEEE Access*, vol. 8, no. 4, pp. 65187–65196, 2020.
14. S. Sun, Z. Cao, D. Liao, and R. Lv, "A magnified adaptive feature pyramid network for automatic microaneurysms detection," *Computers in Biology and Medicine*, vol. 139, no. 12, p. 105000, 2021.
15. Z. Wang, X. Li, M. Yao, J. Li, Q. Jiang, and B. Yan, "A new detection model of microaneurysms based on improved FC-DenseNet," *Scientific Reports*, vol. 12, no. 1, p. 950, 2022.