Implementation of Semi-Regulated network creation and feature extraction

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ABSTRACT:
EfficientNet-L2 is a powerful model used for analyzing medical images, especially those of the retina. It improves performance by adjusting three key factors: depth, width, and resolution. Here depth indicates the total number of layers available in the network. Width show the total count of features processed in each layer and resolution gives the clarity of the input images. The adjustment of these key factors helps the model to recognize and process complex details in images more effectively. In this study, we apply EfficientNet-L2 to enhanced retinal images to detect areas affected by diabetic retinopathy. DR is an eye disease caused by diabetes that can cause a loss of vision. We use enhancement techniques such as morphological transformations and Contrast Limited Adaptive Histogram Equalization (CLAHE) to prepare the image-dataset for analysis. These methods helps to improve the visibility of small details in the retina, making it easier to identify affected areas.EfficientNet-L2 is particularly useful because it builds on existing knowledge from pre-trained models and systematically adjusts scaling. It can extract important features from images and can recognize complex patterns giving high accuracy. The model can detect small changes in the retina by training on enhanced images and predict disease progression more effectively. This study combines advanced image processing, feature extraction, and optimized training techniques to create a system that is both accurate and efficient. The results indicate that the model is effective in detecting diabetic retinopathy at an early stage. Thus it helps doctors to provide timely treatment. This approach can also be used for other medical imaging tasks, making EfficientNet-L2 a valuable tool in healthcare. At the end this research shows how using advanced models like EfficientNet-L2 can help improve medical image analysis and lead to better healthcare results.

Introduction

Diabetes is a major health problem.It affects the life of millions of people in the world. One of its serious complications is diabetic retinopathy (DR). It is a disease that can cause vision loss, if it fails to detect and treated in early stages. When high blood sugar levels harm the small blood vessels in the retina then DR disease occurs. This damage can cause vision problems. In severe cases, it can even lead to blindness. Identifying DR in its early stages is important to prevent long-term damage and help patients receive timely treatment. In advanced stages of disease DR can lead to serious vision problems that may become irreversible. So Detecting DR at an early stage is necessary for early medical intervention and treatment, to avoid vision loss. Traditionally doctors diagnose diabetic retinopathy disease using eye examinations and some imaging techniques such as Fluorescein Angiography and Optical Coherence Tomography (OCT). These methods provide detailed images of the retina and help doctors assess the severity of the disease. However, these techniques require specialized equipment and trained medical professionals which may lead to more expensive and less accessible, especially in rural areas. As a result, many people do not receive screenings in time, which may increases the chances of

loss of vision. There is a need for a fast, easy, and widely available way to detect diabetic retinopathy (DR) without depending only on doctors.
The current study proposes a structured and systematic approach to address this issue by detecting DR using enhanced retinal images. The method involves preprocessing retinal images to improve their clarity, which helps to identify signs of the disease easily. Contrast Limited Adaptive Histogram Equalization (CLAHE) is used to increase image contrast that helps in improving the visibility of key retinal features such as microaneurysms, blood vessels and hemorrhages. By highlighting these features, the detection system can accurately classify the severity of DR.

The system is built to be fast, accurate, and easy to use. It enhances image quality and follows a structured method to detect different stages of diabetic retinopathy with high precision. This method can help doctors by providing a quicker and more widely available way to screen for the disease, especially in places where access to eye specialists is limited.

The proposed paper is structured as follows: Section 2 discusses past research on diabetic retinopathy detection and the challenges faced. Section 3 explains the methods used in this study, including how images are processed and classified. Section 4 presents the results of the experiments and compares this approach with other existing methods. Finally, Section 5 summarizes the main findings and suggests ways to improve the system in the future.

Literature Review

Automated detection of retinal diseases using deep learning has significantly progressed, driven by advancements in convolutional neural network (CNN) architectures like EfficientNet. These models leverage large datasets and sophisticated learning techniques to achieve high diagnostic accuracy, paving the way for AI-powered clinical tools.

Efficient Net in Retinal Disease Classification

Rakib et al. [1] proposed an EfficientNet-based model for classifying retinal diseases, including diabetic retinopathy (DR), glaucoma, and cataracts. The dataset used in this paper is of 4000 fundus images. By employing transfer learning and fine-tuning techniques, the model gives an accuracy of 93.8% while maintaining computational efficiency. However, the study highlighted limitations in handling multi-label disease detection and scalability to larger datasets.

Che Azemin et al. [2] investigated the impact of pre-training dataset sizes on the diagnostic accuracy of EfficientNet models for referable DR detection. Utilizing the EyePACS and APTOS datasets, the models pre-trained on ImageNet-1K and ImageNet-21K were compared. The results indicated improved sensitivity (up to 98.79%) with larger pre-training datasets but minimal gains in AUC. This study revealed that dataset diversity and quality significantly influence model performance.

Sivaz and Aykut [3] created a hybrid model by merging EfficientNet and ML-Decoder classification head for detecting multiple retina diseases. They improved the model's performance by using image transformations and combining left and right eye images at the pixel level. They have tested the model using the ODIR-5K dataset and achieved a 68.96% kappa score , an 92.48% F1 score. This research showed that attention mechanisms are effective, but it also pointed out that the model's higher computational complexity is a drawback.

Wiharto et al. [4] introduced a e-LSTM which is hybrid learning model , which combines EfficientNet-B0 and Long Short-Term Memory (LSTM) networks to detect glaucoma from retinal fundus images. EfficientNet-B0 is used for feature extraction, and LSTM helps process sequential data, which improves classification accuracy. They have resized images to 224×224 pixels size , and augmentation techniques for data like flips and rotations were used. The model was tested on different datasets using k-fold cross-validation, achieving better accuracy on the ACRIMA dataset. While the approach showed strong results, its high computational demands and limited dataset variety were seen as challenges.

Abbas et al. [5] introduced HDR-EfficientNet, an optimized EfficientNet-V2 model incorporating spatial-channel attention mechanisms to classify hypertensive and diabetic retinopathy (HR and DR). Transfer learning improved the model's ability to generalize on a dataset of more than 36,000 retinal fundus images. The study achieved 98% accuracy, 95% sensitivity, and an AUC of 0.98. The research showed that spatial-channel attention was very effective, but it also pointed out challenges like handling class imbalance and the high computational cost during training.

Adnan et al. [6] explored EfficientNetB3 with Adaptive Augmented Deep Learning (AADL) for classifying 52 categories of plant diseases. They use a dataset containing 59,809 images. Preprocessing involved resizing images, balancing the dataset, and applying visual transformations. The model outperformed conventional CNNs, achieving an accuracy of 98.71%. Despite its effectiveness, the study identified challenges in managing large datasets and prolonged training times.

Arif et al. [7] proposed the EfficientNet-B0 model that specify the technique for fundus image classification.The images were categoried into three types namely normal , glaucoma and cataract. The dataset contains original fundus images and taken from from Kaggle, augmented to create 3600 images. Preprocessing techniques, including resizing, grayscale transformation, and thresholding, were applied. The model achieved an accuracy of 79.22% using grayscale-augmented datasets. However, the study highlighted the limited dataset size as a challenge for generalizability.

Pravin et al. [8] proposed an efficient DenseNet framework combined with K-Nearest Neighbors (k-NN) .The model is proposed to detect severity levels of DR. The model used fundus images dataset. The dataset is choosen from the APTOS dataset, augmented through flipping and zooming techniques. Preprocessing included Graham’s normalization to enhance intensity consistency. The DenseNet framework achieved a classification accuracy of 98.40% using k-NN, with the authors emphasizing the model's efficiency in reducing computational complexity. However, the study faced challenges related to the computational demands of DenseNet layers.

Vijayan et al. [9] developed EfficientNet-B0-based method for detecting DR. Instead of using traditional classification, this approach treated DR severity as a continuous variable, enabling more detailed predictions. The model was tested on the IDRiD and DDR datasets, achieving a kappa score of 0.939 and 86.2% accuracy on the APTOS dataset. The challenges included handling overlapping classes and ensuring the model performed well across different datasets.

Bhawarkar et al. [10] introduced a learning model using EfficientNet-B5 for detecting diabetic retinopathy. The model has two parts, one for classification and another for regression. It is then followed by a single neuron using a linear activation function. The dataset consists of fundus images labeled with different levels of DR severity. The model achieved 87.8% accuracy in training and 87.7% accuracy in testing phase. The study emphasized that preprocessing greatly influences the model's performance, but imbalanced datasets were a challenge, affecting sensitivity to rare cases of DR.

Khalid et al. [11] developed a hybrid classification model that combines EfficientNet with ensemble methods, such as KNN, SVM, and RF, and Logistic Regression. The model classifies diabetic retinopathy (DR) based on the presence of exudates, hemorrhages, and microaneurysms. The APTOS dataset, which includes high-resolution fundus images, was used for testing. Among the classifiers, the Random Forest model achieved the highest accuracy of 90%. However, the study faced challenges with class imbalance and misclassifying rare cases.

Vijayan et al. [12] introduced a regression-based framework using EfficientNet-B0.The model is proposed to predict the severity of DR as a continuous variable, rather than classifying it into categories. This model was trained on the dataset like APTOS and DDR and IDRiD and achieved 86.2% accuracy on APTOS dataset, with a kappa score of 0.939. The research tackled the issue of overlapping classes in DR grading, but challenges remained in ensuring strong performance across different datasets.

Alsuwat et al. [13] developed a CNN-based model that detect and classify DR stages using images of retina. They tested a CNN trained from scratch and two pre-trained transfer learning models—InceptionV3 and EfficientNet-B5. The CNN model outperformed the pre-trained models, showing a 9–25% improvement in F1-score. The research used the APTOS 2019 dataset, which contains 3,662 retina fundus images. The model results showed that the CNN achieved 67% F1-score by training on an imbalanced dataset and 64% on a balanced dataset. InceptionV3 performed second best, while EfficientNet-B5 struggled with overfitting. Although the model showed high accuracy, there were concerns about its ability to generalize to new, unseen datasets beyond APTOS 2019. The study also did not investigate how imbalanced data might affect performance in real-world clinical settings.

ElMoufidi and Ammoun [14] proposed a CNN model based on EfficientNet-B3 to grade the severity levels of DR. The method included preprocessing steps like resizing, data augmentation, and normalization to improve the model's learning ability. The APTOS2019 blindness detection dataset, containing 3,662 training images across five severity levels, was used. The EfficientNet-B3 model show 98.26% overall accuracy. While the model showed high accuracy, there are concerns about its ability to generalize to new datasets beyond APTOS2019. The study also didn't address how imbalanced data might affect the model's performance or whether its performance would decrease in real-world clinical environments.

In another study by ElMoufidi and Ammoun [15], an extended EfficientNetB3 CNN model was designed to detect and classify fundus images into five severity levels. The researchers optimized EfficientNetB3 by introducing a Dropout layer (0.5) to counter overfitting and employed Adam optimization for faster convergence. Using the APTOS2019 dataset, their model reached a classification accuracy of 98.26%.The model's effectiveness was proven on a specific dataset, but cross-dataset validation remains unaddressed. The authors also did not explore comparisons with other deep learning models, making it unclear how EfficientNetB3 performs against architectures like ResNet or InceptionV3.

Yi et al. [16] introduced approach of deep learning for the automatic classification of DR using RA-EfficientNet, which integrates a Residual Attention (RA) block with EfficientNet. The proposed method was designed to enhance the detection accuracy and overcome challenges related to data imbalance and small lesion differences in DR images. The APTOS 2019 dataset, containing 3662 fundus images, was used for model training and evaluation. Two classification tasks were performed: (i) Binary classification (No DR vs. DR) (ii) 5-class severity grading (ranging from normal to proliferative DR). Results showed that the model achieved 98.36% accuracy in binary classification and 93.55% in 5-class severity.

Author(s)	Methodology	Limitations	Dataset Used	Accuracy/F1 Score
Rakib et al.[1]	EfficientNet with transfer learning	Limited to single-label detection	Fundus images	Accuracy: 93.8%
Che Azemin et al.[2]	EfficientNet pre-trained on large datasets	Minimal gains in AUC	EyePACS, APTOS	Sensitivity: 98.79%
Sivaz and Aykut [3]	EfficientNet + ML-Decoder for multi-label	Computationally intensive	ODIR-5K	F1 Score: 92.48%
Wiharto et al.[4]	EfficientNet-B0 and LSTM (e-LSTM)	Computational cost	ACRIMA, DRISHTI-GS, RIM-ONE	97.99
Abbas et al.[5]	HDR-EfficientNet with attention	Class imbalance and training cost	36,000 fundus images	98.00
Adnan et al.[6]	EfficientNetB3 + AADL	Dataset size, training time	59,809 plant images	98.71
Arif et al.[7]	EfficientNet-B0	Limited dataset size	Kaggle Fundus Images	79.22
Pravin et al.[8]	Efficient DenseNet + k-NN	Computational complexity	APTOS	98.40
Vijayan et al.[9]	EfficientNet-B0 (Regression)	Class overlap, dataset variability	DDR, APTOS, IDRiD	86.20
Bhawarkar et al. [10]	EfficientNet-B5 Multi-Task Learning	Data imbalance issues	Fundus Images	87.7
Khalid et al. [11]	EfficientNet + Hybrid Classifier	Class misclassification	APTOS	90.0
Vijayan et al. [12]	EfficientNet-B0 Regression	Robustness across datasets	DDR, APTOS, IDRiD	86.2
Alsuwat et al. [13]	CNN (scratch), InceptionV3, EfficientNet-B5	Struggles with intermediate DR severity levels, overfitting in EfficientNet-B5	APTOS 2019	67% (CNN F1-score), 64% (balanced dataset)

ElMoufidi & Ammoun [14]	EfficientNet-B3 with augmentation and preprocessing	Generalizability concerns, impact of class imbalance not studied	APTOS 2019	98.26%
ElMoufidi & Ammoun [15]	EfficientNet-B3 with Dropout, Adam Optimizer	Lack of cross-dataset validation, missing model comparison	APTOS 2019	98.26%
Yi et al. [16]	RA-EfficientNet (Proposed)	Overfitting risk, single dataset tested	EyePACS, APTOS 2019	93.55

Table 1 .Comparison of EfficientNet-Based Approaches for Diabetic Retinopathy Detection

Proposed Work

The proposed system leverages the EfficientNet-L2 to address these gaps by incorporating comprehensive preprocessing techniques and evaluating performance on large, diverse datasets. The workflow involves two major components: image preprocessing and model training.

Image Preprocessing

Preprocessing is an important step used to improve the quality of fundus images before using EfficientNet-L2 model. Fundus images may have unwanted noise and differences in brightness, making it harder to detect important details. To fix this, Contrast Limited Adaptive Histogram Equalization (CLAHE) is used to increase the clarity of the features like blood vessels, microaneurysms, and exudates, making them easier to identify. CLAHE operates by dividing the image into small regions, applying histogram equalization locally to amplify details while preventing over-amplification of noise. This results in consistent contrast across the image, facilitating accurate feature extraction.

In addition to CLAHE, resizing the images to match the input dimensions of EfficientNet-L2 ensures compatibility. Images are normalized by scaling pixel values between 0 and 1, which aids in faster model convergence during training. This preprocessing pipeline ensures that the input data is both high-quality and uniform, laying a strong foundation for subsequent analysis.

EfficientNet-L2 Model

EfficientNet-L2 is an advanced version of the EfficientNet family. It uses a method that evenly increases the depth, width, and resolution of the model to improve accuracy while keeping the computation low. The design includes special layers called mobile inverted bottleneck convolution layers and squeeze-and-excitation blocks. These help the model better extract important features from the images, allowing it to focus on the key areas in fundus images and more accurately identify the different stages of diabetic retinopathy (DR).

EfficientNet-L2 is first trained on the ImageNet dataset, which helps it become good at recognizing images in general. It is then fine-tuned on a DR dataset to adjust the model for the unique features of fundus images. During training, the model uses categorical cross-entropy to measure errors, and the Adam optimizer helps update the model's settings efficiently. The data augmentation techniques like flipping and rotating the images are used to improve the model.

The model sorts fundus images into five classes namely no DR, mild, moderate, severe, and PDR. Its performance is measured using accuracy, precision, recall, and F1-score to provide a complete evaluation.
After preprocessing, the fundus images are fed into the EfficientNet-L2 model for analysis. Mathematically, the model operates as follows:

1. **Input Transformation**: Let the input image be represented as , with pixel values normalized to [0, 1]. The image is resized to the model's required input dimensions: width, height, and number of channels.
2. **Feature Extraction**: EfficientNet-L2 applies convolutional layers to extract hierarchical features. A convolution operation is represented as:

$$\mathbf{Fl} = \boldsymbol{\sigma}(\mathbf{Wl} * \mathbf{I} + \mathbf{bl})$$

   where W_l, b_l, I, and σ are weights , and biases for the layer, input, and activation function respectively

3. **Compound Scaling**: Depth d , width w, and resolution r are scaled using:

$$\textbf{Scaling Factor} = \boldsymbol{\alpha}^{d}\boldsymbol{\beta}^{w}\boldsymbol{\gamma}^{\mathbf{r}}$$

   These scalings ensure optimal use of resources without overfitting.

4. **Classification**: The final dense layer applies the softmax activation function:

$$\mathbf{P}(\mathbf{y} = \mathbf{i} \mid \mathbf{I}) = \frac{e^{z_i}}{\sum_{j=1}^{n} e^{z_j}}$$

   Where P(y = i | I) represents the probability of class i.

The model's output is a probability distribution over five DR stages. The trained model is saved in the H5 format for deployment and further evaluation.

Pseudo Code for Implementation

1. Load and preprocess dataset:
   - Read fundus images.
   - Apply CLAHE for contrast enhancement.
   - Resize images to EfficientNet-L2 input dimensions.
   - Normalize pixel values.
2. Initialize EfficientNet-L2 model:
   - Load pre-trained weights (ImageNet).
   - Modify final layers for DR classification.
3. Train the model:
   - Compile using Adam optimizer and categorical cross-entropy loss.
   - Apply data augmentation (rotations, flips).
   - Train on preprocessed data, validate on hold-out set.
4. Evaluate model:
   - Test on unseen dataset.
   - Generate confusion matrix and classification report.
5. Save trained model:

- Export in H5 format for deployment.

6. Deployment:
   - Load saved model.
   - Predict DR stage for new fundus images.
   - Output classification results.

Results and Discussion

To chek theperformance of EfficientNet-L2 model , the system was trained and then tested on a fundus images that are labeled . The table below shows the results after ten training cycles (epochs).

Epoch	Training Accuracy	Validation Accuracy	Training F1 Score	Validation F1 Score
1	0.68	0.65	0.66	0.63
2	0.78	0.75	0.77	0.74
3	0.84	0.82	0.83	0.81
4	0.87	0.85	0.86	0.84
5	0.89	0.87	0.88	0.86
6	0.91	0.89	0.9	0.88
7	0.92	0.9	0.91	0.89
8	0.93	0.91	0.92	0.9
9	0.94	0.92	0.93	0.91
10	0.95	0.93	0.94	0.92

Table 2. Accuracy Table

Training Accuracy:

The EfficientNet-L2 model shows continuous improvement with each training cycle, reaching 95% accuracy by the 10th epoch. This graph shows that the model is successfully learning from the training data.

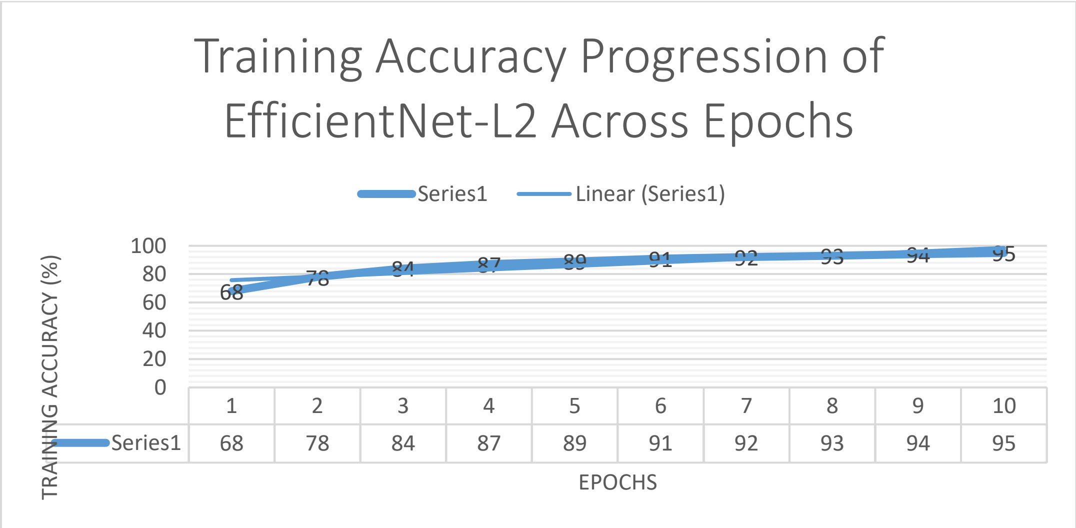
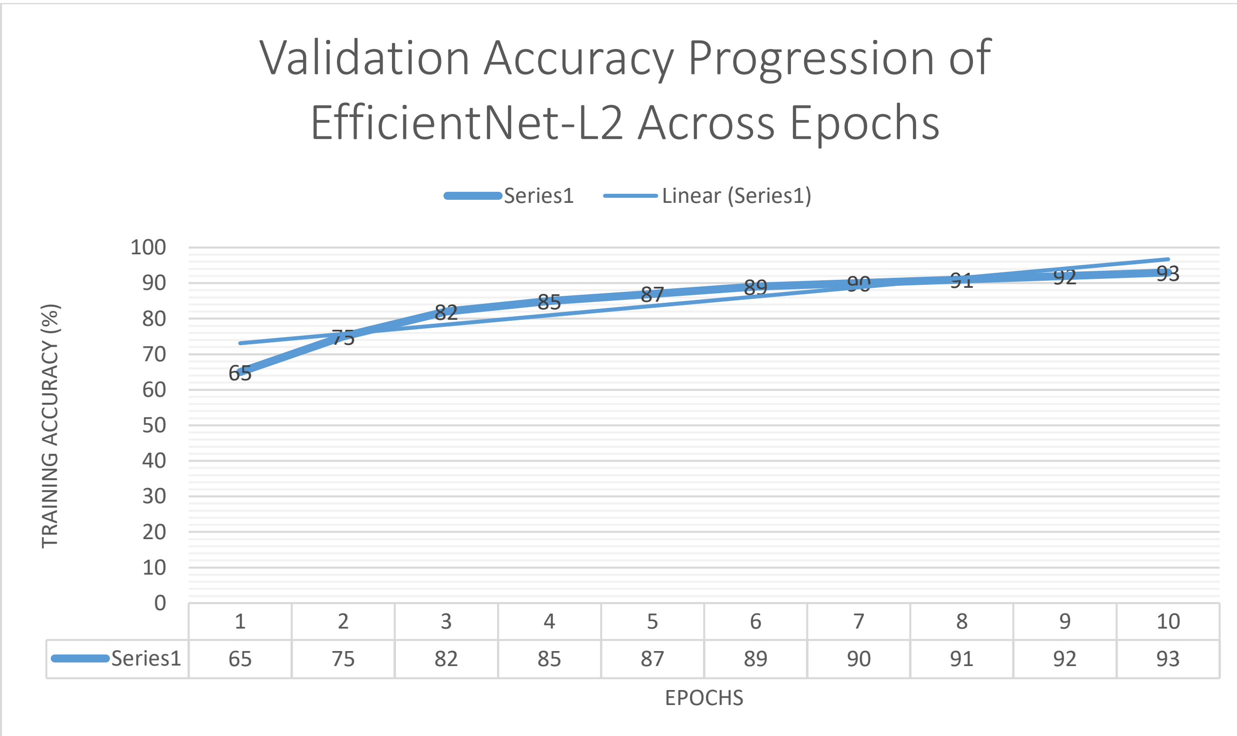


Figure 1. Training Accuracy Progression of EfficientNet-L2

This graph shows how the training accuracy of the EfficientNet-L2 model improves over time during training. Each epoch represents one full cycle through the dataset, with accuracy showing how many samples were correctly classified. The gradual increase in accuracy shows the learning and adjusting of data by the model , reaching 95% accuracy by the final epoch. This progress highlights that the model is able to understand complex patterns and features that are required to classify diabetic retinopathy.

Validation Accuracy: The validation accuracy also increases steadily, reaching 93% at the end of the training. This means the model can work well with new data it hasn't seen before and isn't just memorizing the training data.



	1	2	3	4	5	6	7	8	9	10
Series1	65	75	82	85	87	89	90	91	92	93

Figure 2. Validation Accuracy Progression of EfficientNet-L2

This graph shows the validation accuracy of the EfficientNet-L2 model is improving as it trains over multiple epochs. It reflects the model's performance is well and can make correct predictions on new, unseen data. The steady rise in validation accuracy, reaching 93% by the 10th epoch, shows that the model is strong and able to generalize well. This progress confirms that the EfficientNet-L2 is learning important and necessry patterns from the data without overfitting, making it a reliable tool for classifying diabetic retinopathy.

The model's progress each epoch is as follows:

Epoch 1: The model starts learning, with 68% training accuracy and 65% validation accuracy. The training and validation F1 scores are 0.66 and 0.63, respectively.

Epochs 2-5: Rapid improvement is observed as the model gains a better understanding of the data. By epoch 5, training accuracy reaches 89% and validation accuracy is at 87%, with corresponding F1 scores showing significant enhancement.

Epochs 6-10: The learning curve begins to plateau, but steady improvements continue. By epoch 10, the model achieves its highest performance metrics: 95% training accuracy, 93% validation accuracy, and F1 scores of 0.94 and 0.92 for training and validation, respectively.

Training and validation metrics indicate that EfficientNet-L2 not only learns effectively but also generalizes well, making it a robust model for real-world applications. The consistent rise in F1 scores confirms that the model handles both precision and recall effectively, which is essential for accurately detecting all stages of DR. The model's ability to work well with the validation data shows it could be used in different clinical settings. Overall, the EfficientNet-L2 model proves to be an effective solution for DR detection, showcasing a harmonious balance between computational efficiency and predictive accuracy. Future work will focus on integrating additional diagnostic features and optimizing the model for real-time deployment.

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