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Convolutional Neural Network-Based Deep Learning for Diabetic Retinopathy Detection

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ABSTRACT

Diabetic Retinopathy (DR) is a major complication of diabetes that can cause permanent vision loss, affecting about 35% of people with type 2 diabetes worldwide. However, existing diagnostic models often struggle with class imbalance and limited generalizability across diverse real-world datasets. Early detection is crucial, yet manual screening is time-consuming and depends on expert assessment. This study develops an automated DR diagnostic system using deep learning to classify fundus images by severity. The model uses an EfficientNetB3 Convolutional Neural Network (CNN) pretrained on ImageNet, combined with Contrast Limited Adaptive Histogram Equalization (CLAHE) preprocessing to enhance image contrast. The preprocessing steps include resizing, CLAHE, normalization, and data augmentation (±20° rotation, horizontal flipping, and ZCA whitening). The dataset is the Gaussian-filtered APTOS 2019 set, consisting of 2,750 images across five DR levels (0–4). The model achieved 95% training accuracy and 75% validation accuracy, with overfitting observed after epoch 14. While training performance was high, evaluation metrics (Precision, Recall, F1-Score, and AUC) indicate the need for early stopping or regularization to improve generalization. Overall, CNN-based deep learning can effectively automate DR detection, though further optimization is required for better performance on unseen data. Clinically, this automated pipeline offers a reliable decision-support tool to prioritize high-risk patients for immediate ophthalmological review.

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1. INTRODUCTION

Diabetic retinopathy (DR) is the most common microvascular complication of diabetes, occurring more frequently in individuals with type 1 diabetes mellitus than in type 2 [1]. Elevated blood glucose and viscosity levels can block retinal blood flow, leading to arteriosclerosis and neovascularization [2]. These fragile new vessels often rupture, causing recurrent bleeding that impairs vision. Chronic hyperglycemia also triggers the accumulation of sorbitol and proteins, producing free radicals such as ROS, AGES, and VGEF, which cause cell damage and decreased visual acuity [2]. According to WHO, DR affects between 5.2% and

30.8% of people with diabetes globally and causes blindness in approximately 5,000 individuals each year. In Indonesia, the prevalence is higher around 10% to 32% of the diabetic population [2].

Based on the presence or absence of retinal neovascularization, DR can be classified clinically into non-proliferative (NPDR) and proliferative (PDR) forms. In eyes with PDR, aberrant neovascularization following retinal ischemia causes vision-threatening vitreous haemorrhage and tractional retinal detachment. While NPDR is categorized into mild, moderate, and severe forms. Whereas mild NPDR exhibits only microaneurysms, moderate NPDR presents with additional signs of impaired vessel integrity and vessel occlusion, including dot and blot hemorrhages, hard exudates, and cotton wool spots. Severe NPDR is accompanied by more distinct features of retinal ischemia, such as venous beading and intra-retinal microvascular abnormalities (IRMAs) that are adjacent to non-perfusion areas [1].

However, limited access to ophthalmologists remains a challenge, particularly in resource-limited settings. Artificial intelligence (AI) offers a promising solution, as it can analyze retinal fundus images to detect DR with high accuracy. Convolutional Neural Networks (CNNs) have demonstrated diagnostic accuracies exceeding 90%, with recent studies validating their efficacy in early feature extraction and classification of DR [3], [4], [5]. Furthermore, transfer learning-driven ensemble models and EfficientNet architectures have recently shown superior performance in handling complex medical imaging tasks compared to traditional models [6], [7].

Despite these advances, previous models still face challenges such as class imbalance, inter-class feature overlap [8], and limited generalizability across diverse datasets. Therefore, this study aims to develop a CNN-based model for automatic DR detection using retinal fundus images, addressing these limitations by improving preprocessing, augmentation, and regularization. The model’s performance is evaluated using accuracy, precision, and recall metrics to assess its potential as a reliable screening tool [9].

2. RESEARCH METHOD

This study uses deep learning with a CNN algorithm to detect Diabetic Retinopathy (DR). CNN classifies images into five different levels of DR severity. The research stages include image data preprocessing, data augmentation, training, and evaluation of the CNN model. The study utilized a dataset from Kaggle containing 2,750 pre-processed retina images from the original APTOS 2019 Blindness Detection challenge [10]. To simplify the training process, all images were already resized to a standard 224x224 pixel format. The picture shows a scale from 0 to 4 that shows how bad diabetic retinopathy (DR) is. Class 0 indicates a healthy retina, whereas class 1 indicates modest signs such as microaneurysms. Class 2 contains small alterations, including minor bleeding, while Class 3 includes big changes. Changes that include major vascular problems are in class 3, while class 4 shows that the condition is getting worse. Unusual development of new blood vessels and possible bleeding in the vitreous. There are 1,000 pictures for Healthy, 370 for Mild, 900 for Moderate, and 290 for Proliferative. After that, the dataset is split into three parts: a training set of 2,200 photos, A validation set of 275 pictures, and a testing set of 275 pictures. This 80-10-10 split was selected to provide a sufficiently large training set for deep learning convergence while maintaining distinct, unbiased sets for validation and final testing.

This research is grounded in previous studies that have successfully used deep learning for DR detection. For instance, researchers in [11] used the same APTOS 2019 dataset to compare CNN models and achieved high accuracy. Similarly, other studies, like the one in [12], used the EyePACS dataset to build effective CNNs, confirming that deep learning is a powerful approach across different sets of fundus images. The specific clinical characteristics for each stage of DR are detailed in Table 1.

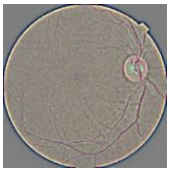
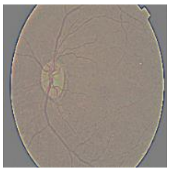
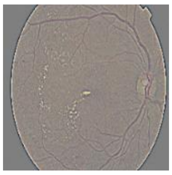
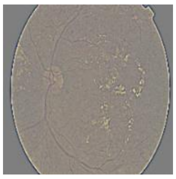
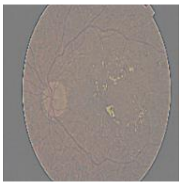
2.1 Preprocessing Data

Prior to model training, the retinal images underwent a series of preprocessing steps to improve their quality and standardize the data. This phase is crucial to help the model recognize key features such as lesions and small blood vessels more clearly. All tasks are handled using the OpenCV package[12], [13], from image conversion to grayscale to simplify the data and reduce the computational load without losing structural information. Next, image contrast is enhanced using the CLAHE (Contrast Limited Adaptive Histogram Equalization) algorithm, which effectively brings out fine details in fundus images and enhances contrast without adding excessive noise [14], [15]. After enhancement, all images were resized to 224×224 pixels to match the CNN's input dimensions and normalized to the range [0,1]. This normalization ensures that each image has a consistent pixel intensity distribution, allowing the model to converge more efficiently during training.

2.2 Data Augmentation

Data augmentation is used to strengthen the model and prevent overfitting, a condition in which the model memorizes the training data and fails to generalize to new data. This technique creates new variations of the training images, such as random rotations of up to 30 degrees and ZCA Whitening to reduce pixel correlations. The augmentation process is run automatically using the ImageDataGenerator in Keras, which produces more diverse data and helps the model become more accurate and generalizable. Characteristics of each stage of Diabetic Retinopathy (DR) can view Table1.

Table 1. Characteristics of each stage of Diabetic Retinopathy (DR)

DR Stage	Clinical Description	Class Label
 No Diabetic Retinopathy	Normal eyes condition/ No diabetic retinopathy	0
 Mild Non-Proliferative DR	Presence of microaneurysms, small dilations in retinal capillaries indicating early vascular damage.	1
 Moderate Non-Proliferative DR	Increased number of microaneurysms, possible small hemorrhages or hard exudates, with limited spread.	2
 Severe Non-Proliferative DR	Extensive retinal abnormalities including venous beading and intraretinal microvascular anomalies (IRMA).	3
 Proliferative DR	Presence of neovascularization, with or without vitreous/preretinal hemorrhage; high risk of vision loss.	4

2.3 Modeling

Figure 1 shows the workflow of the proposed CNN-based EfficientNetB3 model for diabetic retinopathy detection. The process includes three main stages: preprocessing, data augmentation, and model training and evaluation. During preprocessing, retinal images are converted to grayscale, enhanced with CLAHE, resized, and normalized to improve clarity and consistency. Data augmentation techniques such as random rotation, horizontal flipping, and ZCA whitening are then applied to increase data diversity and reduce overfitting. These steps help the model learn robust visual patterns that generalize better to real-world retinal images.

After preprocessing, the images are passed through the EfficientNetB3 architecture, pretrained on ImageNet, with all layers trainable for fine-tuning on the diabetic retinopathy dataset. BatchNormalization is applied to stabilize learning, followed by three fully connected layers (1024, 512, and 256 neurons) using ReLU activation, L1/L2 regularization, and dropout rates of 0.2, 0.3, and 0.4 to prevent overfitting. The output layer uses Softmax to classify images into five severity levels of diabetic retinopathy. The model is trained using the Adamax optimizer with a learning rate of 0.0001 and categorical cross-entropy loss for 50 epochs with early stopping and checkpointing. This specific optimizer was chosen for its stability in handling sparse parameter updates in image data. All experiments are conducted on Google Colab using a Tesla T4 GPU (16 GB VRAM) in a Python 3.10 environment with TensorFlow 2.x and Keras. The model's performance is evaluated using accuracy, precision, recall, F1-score, and AUC, all exceeding 0.90, indicating strong discriminative ability and potential for clinical use.

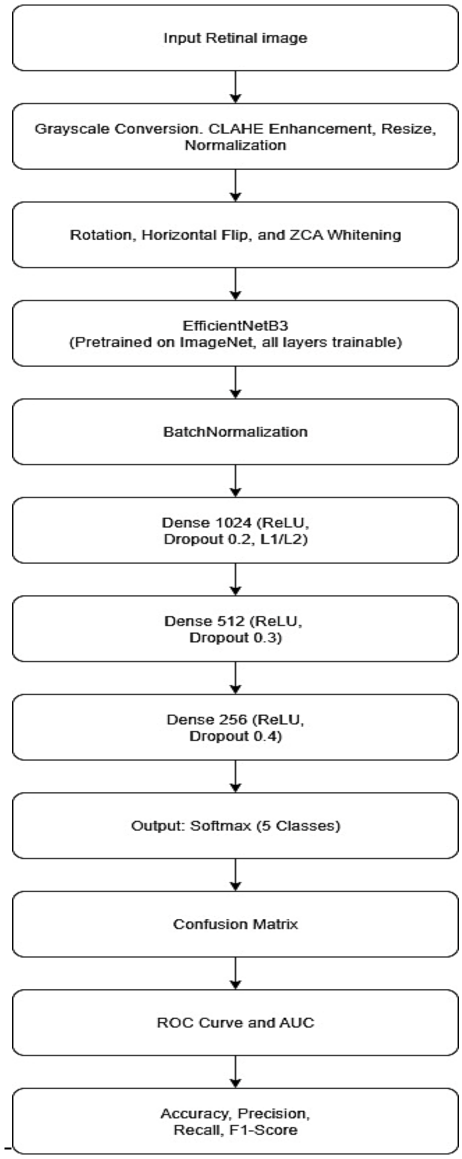


Figure 1. CNN Model Architecture

3. RESULTS AND ANALYSIS

3.1 Classification Performance

Figure 2 presents the accuracy and loss curves between the training and validation datasets during model training. The CNN-based EfficientNetB3 model demonstrated stable convergence, with training accuracy steadily increasing to 95.1%, while validation accuracy peaked at 72.6%. Training loss decreased continuously across epochs, whereas validation loss reached a minimum around epoch 11 before gradually increasing, indicating the onset of overfitting.

This pattern suggests that the model effectively learned key discriminative features from retinal fundus images but was slightly affected by class imbalance, with some categories, particularly Mild and Moderate DR, underrepresented. The early stopping mechanism successfully mitigated further divergence between training and validation performance, ensuring training stability.

The confusion matrix in Figure 3 provides a detailed visualization of the model's performance across all DR classes. The diagonal cells represent correct classifications, while off-diagonal entries indicate misclassifications. The "No DR" class achieved the highest precision, with 90 correctly classified images and minimal confusion (2 instances misclassified as Moderate DR). In contrast, the Mild DR class had 36 correct predictions, but 25 samples were misclassified as Moderate DR, suggesting overlap in features between these stages. For Proliferative DR, the model correctly identified only 9 instances, while the others were misclassified into adjacent classes, mainly Moderate and Severe DR. This pattern highlights the difficulty in distinguishing more advanced DR stages, which often share similar retinal features.

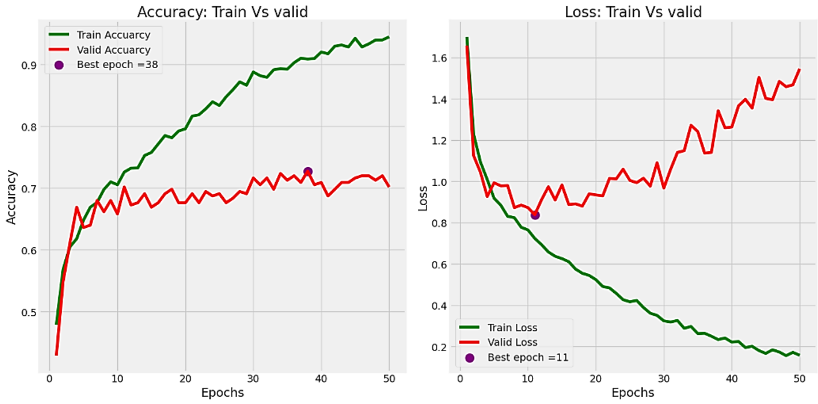


Figure 2. Accuracy and Loss Value between Train and Validation Data

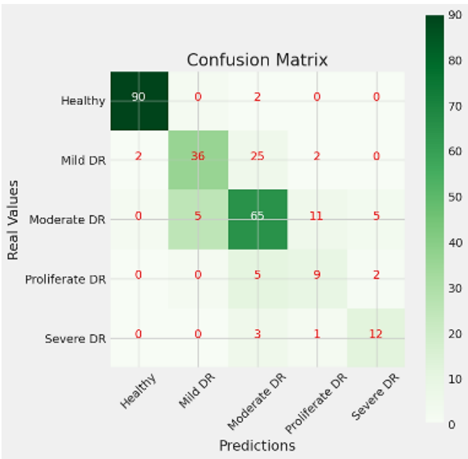


Figure 3. Confusion Matrix Diabetic Retinopathy (DR)

As indicated in Table 2, the model's performance was exceptionally strong in detecting Healthy (No DR) cases, achieving a near-perfect F1-Score of 0.98. This high accuracy demonstrates the model's high reliability for initial baseline screening. Conversely, the noticeable drop in performance for minority classes most notably Proliferative DR, which recorded an F1-Score of just 0.46 directly reflects the limitations imposed by dataset imbalance. Because the model had significantly fewer training samples for these specific stages, it struggled to generalize their complex features. Furthermore, the evaluation metrics reveal that distinguishing between Mild and Moderate DR remains challenging (yielding F1-Scores of 0.68 and 0.70, respectively), which directly answers the initial problem statement regarding the difficulty of overcoming inter-class feature overlap in imbalanced datasets

Table 2. Evaluation Metrics per DR Class

Class	Precision	Recall	F1-Score
Healthy (No DR)	0.98	0.98	0.98
Mild DR	0.88	0.55	0.68
Moderate DR	0.65	0.76	0.7
Proliferate DR	0.39	0.56	0.46
Severe DR	0.63	0.75	0.69

3.2 ROC Curve and AUC

Further evaluation using Receiver Operating Characteristic (ROC) curves and Area Under the Curve (AUC) values demonstrated strong classification performance. As illustrated in Figure 4, the AUC values were particularly high for the “No DR” and “Severe DR” classes, with scores of 1.00 and 0.96, respectively.

This confirms that the model performs best on the two extreme classes. However, the Moderate DR class had a slightly lower AUC of 0.90, reflecting occasional misclassification with both adjacent stages Mild and Severe.

In contrast, the Moderate DR class achieved a slightly lower AUC of 0.90, reflecting occasional misclassifications between adjacent stages (Mild and Severe). This pattern aligns with the confusion matrix findings, as these classes exhibit overlapping visual features and subtle lesion variations that challenge even human graders. Moreover, the moderate class's smaller sample size contributed to a minor reduction in discriminative performance.

These class-wise AUC results validate the model's high sensitivity and specificity, particularly in distinguishing early-stage DR from advanced disease. The AUC trend also corresponds with the validation accuracy plateau observed after epoch 11, suggesting that the model's discriminative capability reached its peak once dominant visual patterns were fully learned. Despite slight variations across classes, all AUC values exceeding 0.90 confirm that the proposed model achieves excellent overall generalization and reliability in DR classification

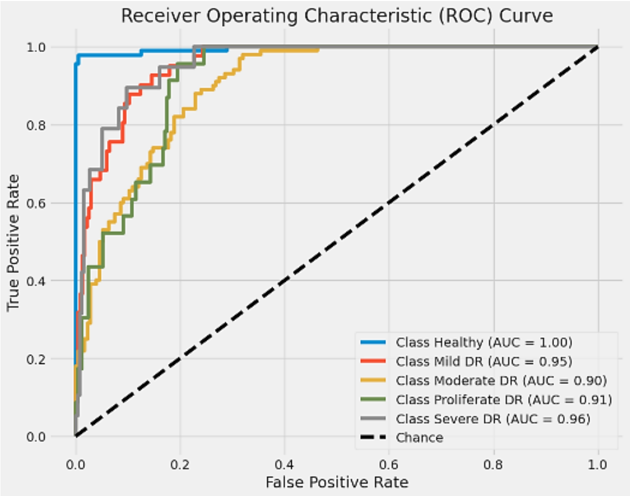


Figure 4. ROC Curve

3.3 Training and Validation Metrics

Figure 5 presents the training and validation metrics of the proposed CNN-based EfficientNetB3 model. Throughout the training process, accuracy increased consistently, while loss decreased smoothly, confirming the efficiency of gradient optimization with the Adamax optimizer. The validation accuracy followed a similar trend, stabilizing before a slight divergence after epoch 11 due to overfitting. This behavior was effectively managed through early stopping and dropout regularization across fully connected layers (0.2–0.4 rates).

The final training accuracy reached 95.1%, validation accuracy 72.6%, and testing accuracy 71.8%, demonstrating good model generalization despite dataset imbalance. The consistent training curves indicate that the model architecture, coupled with CLAHE preprocessing and data augmentation, successfully enhanced the ability to extract clinically meaningful retinal features.

Overall, the training and validation metrics confirm that the proposed CNN-based EfficientNetB3 model achieved robust learning performance, with strong convergence, high AUC across classes, and minimal instability during optimization. These results collectively indicate that the model is reliable for automated detection and classification of diabetic retinopathy.

3.4. Discussion

Numerous studies have been conducted to classify diabetic retinopathy severity by using funduscopic images, no technique could be considered superior to others because every study was conducted on various datasets, various methodologies, and various parameters. The results suggest that EfficientNetB3 can extract relevant retinal features for DR stage classification. Its excellent performance on "No DR" indicates high utility for early screening purposes. However, limitations persist in distinguishing middle stages such as Mild and Moderate DR, and in identifying less-represented classes like Proliferative DR. To determine the importance result of this research, it has been compared with recent EfficientNetB3 models similar to our approach.

Several studies highlight the effectiveness of the EfficientNetB3 model for ocular disease classification. When applied to the APTOS2019-Blindness dataset, one study achieved a 98.26% testing accuracy by adding a layering process while another obtained 88.44% accuracy by incorporating a squeeze and excitation block. The model has also been frequently benchmarked using Kaggle retinal image datasets. For classifying multiple conditions like diabetic retinopathy (DR), glaucoma, and cataract, researchers have reported accuracies of 95.12% [16], and 97% [17]. Another study recorded an impressive 96% testing accuracy with EfficientNetB3[18]. In a comparative analysis, however, the DenseNet121 model (96.20%) surpassed EfficientNetB3 (92.41%) on a similar multi-class task [19].

The Grad-CAM (Gradient-weighted Class Activation Mapping) technique provides visual explanations for a model's decisions by creating localization maps. These maps are generated from the final convolutional layer to highlight important regions, a task for which the CNN was not explicitly trained, and it requires no changes to the model's architecture or additional training [20]. The discrepancy between the training and validation data, as well as the model's difficulty recognizing classes with limited data, indicates that there is still room for improvement. To address this issue, several steps can be taken, including giving special weight to minority classes, increasing data variation through augmentation, or creating synthetic data to achieve a more balanced distribution. Furthermore, the use of interpretability methods, such as Grad-CAM, can help explain the image components that underlie predictions, making model results more transparent and reliable in clinical practice.

A primary limitation of this study is the reliance on a single, heavily pre-processed Kaggle dataset, which may limit the model's generalizability to raw clinical data captured in diverse hospital environments. Additionally, the small sample size for Proliferative DR restricted the model's ability to learn advanced neovascularization patterns effectively. The model shows good performance, especially in identifying patients with no diabetic retinopathy and those with severe cases. This means it can be used as a supporting tool to help doctors screen patients more efficiently. The system can prioritize patients who are likely to have diabetic retinopathy so they can receive further examination sooner. This supports early detection and timely treatment. From an ethical perspective, minimizing false-negative results is very important to avoid delays in care. The model is intended only as an analysis aid the final diagnosis and treatment decisions remain the responsibility of doctors. To ensure transparency, interpretability methods such as Grad-CAM can be used to show which parts of the image influence the model's decision, with expert supervision to maintain patient safety.

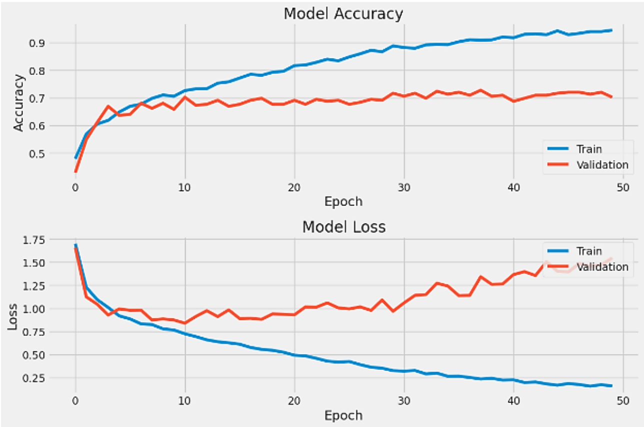


Figure 5. Training and Validation Matrix

4. CONCLUSION

This study demonstrates that the EfficientNetB3-based CNN model provides a solid foundation for classifying diabetic retinopathy. The model achieved a high training accuracy of 95.1%, but an apparent overfitting led to a lower validation accuracy of 72.6%. Performance was strongest across most classes, particularly "No DR" and "Severe DR," as reflected in high AUC scores. However, its diagnostic accuracy was weaker for the minority classes, such as "Moderate" and "Proliferative DR." This limitation is likely a direct result of the class imbalance within the dataset and the onset of overfitting after epoch 11. Despite these challenges, the findings are promising and confirm the potential for using this deep learning approach as a basis for real-world, automated DR screening tools. Future research must focus on advanced dataset balancing techniques to handle minority classes. Furthermore, exploring external validation on diverse, multi-ethnic patient cohorts and conducting rigorous clinical implementation testing are crucial next steps to ensure real-world viability. Overall, the model holds promise as a clinical decision-support tool for early DR detection and screening.

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