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RetinoCare: A Web-Based Intelligent System for Early Detection of Diabetic Retinopathy Using CNN

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ABSTRACT

Diabetic retinopathy (DR) is a leading cause of preventable blindness, while access to screening in primary healthcare settings remains limited. This study presents RetinoCare, a web-based intelligent system for early DR detection using a deep learning model based on the DenseNet121 architecture. A hybrid dataset combining publicly available fundus images and locally collected retinal images was utilized to address domain shift and enhance contextual relevance. Image preprocessing and augmentation techniques were applied to improve data quality and handle variability in fundus images. The model was trained to classify DR into five severity levels and evaluated using three stratified data split scenarios (70:30, 80:20, and 90:10) and two training configurations (50 and 80 epochs). Experimental results demonstrate that performance improves with increased training data and epochs, achieving the highest accuracy of 87.50% using a 90:10 split at 80 epochs. Accuracy and loss analyses indicate stable convergence and effective generalization, while confusion matrix evaluation shows balanced classification performance across all severity levels, including clinically critical cases. The trained model was successfully integrated into a web-based platform that supports practical screening workflows and referral decision-making. These findings indicate that the proposed system is effective, scalable, and suitable for implementation in resource-limited environments, contributing to improved early detection and prevention of DR-related blindness.

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1. INTRODUCTION

Indonesia's Diabetic retinopathy (DR) is a chronic complication of diabetes mellitus that may lead to permanent visual impairment and blindness if not detected and treated at an early stage. The burden of diabetes and its complications continues to rise globally, and Indonesia is no exception: the high prevalence of diabetes contributes to increasing cases of DR and the urgent need for widespread retinal screening services. Access to comprehensive fundus examinations remains limited in many regions, particularly in primary healthcare facilities (puskesmas and community clinics) that often face shortages of ophthalmologists and lack of standard diagnostic equipment such as fundus cameras. As a result, many diabetic patients are only diagnosed at advanced stages when treatment is more difficult and costly, often after irreversible vision loss has occurred [1]–[3].

The challenges underlying this research are multifaceted and interconnected. First, the unequal distribution of ophthalmologists makes it difficult for remote areas to access standard retinal examinations, leading to delays in early detection. Second, the acquisition and maintenance costs of conventional fundus

cameras are relatively high, making them impractical for primary healthcare centers. Third, the manual interpretation of fundus images by specialists is time-consuming, subject to inter-observer variability, and inadequate for large-scale population screening. Fourth, many existing AI-based DR detection models are trained exclusively on public datasets from other countries, making them vulnerable to *domain shift* when applied to Indonesian populations, where image quality, pigmentation, pathological variations, and acquisition conditions may differ. Fifth, the use of smartphone-based portable fundus cameras as a low-cost alternative introduces technical challenges such as inconsistent illumination, capture angles, reflections, noise, and narrower fields of view compared to conventional cameras, which require tailored preprocessing and augmentation strategies. Sixth, the creation of a reliable local dataset requires medical annotation and validation by ophthalmologists, which demands resources, time, and clinical coordination. Finally, operational challenges in real-world deployment—such as internet connectivity, integration with puskesmas workflows, training of non-specialist healthcare workers, and ensuring patient data security—must be anticipated to enable sustainable adoption. These combined technical, clinical, and organizational barriers underscore the urgent need for an integrated solution that combines affordable imaging hardware, locally adapted AI models, and user-friendly digital platforms to reduce preventable blindness due to DR.

To address these challenges, this study proposes the development of a web-based intelligent system for early DR detection that integrates several key innovations. At the image acquisition level, the system employs a smartphone-based fundus adapter, a low-cost optical attachment that enables retinal imaging using standard smartphones. This device provides a practical, portable, and affordable alternative to conventional fundus cameras, making large-scale screening feasible in primary care. At the data level, the system leverages a hybrid dataset combining public fundus image repositories (e.g., Kaggle) with locally collected datasets from Indonesian healthcare facilities, ensuring both diversity and contextual relevance while mitigating domain shift issues. At the algorithmic level, the system implements DenseNet121 architecture, chosen for its feature reuse capability, efficient parameter utilization, and strong performance in medical image classification. Images undergo preprocessing steps such as normalization, contrast enhancement, alignment, and augmentation to address variability from smartphone acquisition. The model is validated using metrics including accuracy, sensitivity, and specificity, and compared against ophthalmologists' diagnoses as the clinical gold standard. Finally, the trained model is integrated into a web-based platform with an intuitive interface that allows healthcare workers in puskesmas to upload fundus images, receive automated DR severity classifications, and obtain referral recommendations. The platform also supports metadata logging, encrypted storage, and optional specialist confirmation, thereby incorporating a *human-in-the-loop* approach for clinical safety and acceptance.

The objectives of this research are to develop and evaluate a prototype of an intelligent web-based DR detection system that leverages Convolutional Neural Networks (CNN) with DenseNet121 architecture and hybrid datasets, while testing the feasibility of smartphone-based fundus adapters in primary healthcare settings. Specifically, the research aims to (1) collect and clinically validate a local DR dataset; (2) design a preprocessing and augmentation pipeline to address smartphone image variability; (3) train and optimize DenseNet121 for DR severity classification; (4) integrate the trained model into a web-based platform tailored to primary healthcare workflows; and (5) evaluate the system's performance and feasibility in real-world settings.

The contributions of this study are fourfold: (i) demonstrating that a combination of smartphone-based fundus imaging and deep learning can provide an economical and context-aware screening solution for Indonesia; (ii) introducing preprocessing methods tailored to smartphone-acquired retinal images; (iii) integrating an AI model into an operational web platform accessible to non-specialist healthcare workers; and (iv) providing practical recommendations for deployment and policy adoption. By combining technical innovation with clinical applicability, this research aims to support national efforts to prevent diabetes-related blindness through scalable, affordable, and locally relevant digital health solutions.

The remainder of this paper is organized as follows: Section 2 reviews related work, Section 3 describes the proposed methodology, Section 4 presents the results and discussion, and Section 5 concludes the study

2. LITERATURE STUDY

2.1. Diabetic Retinopathy

DR is one of the most prevalent microvascular complications of diabetes mellitus and remains a leading cause of preventable blindness globally. The pathophysiology of DR is primarily driven by chronic hyperglycemia, which damages retinal microvasculature and leads to progressive stages ranging from mild non-proliferative DR (NPDR) to proliferative DR (PDR), characterized by neovascularization and potentially vitreous hemorrhage [1], [2]. According to the International Diabetes Federation, over 463 million people worldwide are living with diabetes, with approximately one-third exhibiting signs of DR, and one-tenth facing vision-threatening conditions [3].

In Indonesia, the prevalence of diabetes increased to 10.9% based on the 2018 National Health Survey (Riskesdas) [4], and recent national reports show a continuing upward trend [5]. Despite this, access to DR

screening remains limited, particularly in rural and remote regions where the distribution of ophthalmologists and specialized diagnostic equipment is uneven. Conventional DR diagnosis relies on capturing fundus photographs using standard tabletop fundus cameras followed by manual evaluation by ophthalmologists. However, this process is resource-intensive, subjective, and not scalable to meet the needs of large diabetic populations [6].

The literature highlights several systemic barriers: (i) limited accessibility to fundus cameras due to high cost and maintenance burden [7]; (ii) lack of specialists to interpret images, especially in low-resource areas [8]; and (iii) reliance on manual interpretation, which introduces inter-observer variability and delays in diagnosis [9]. These limitations create an urgent need for cost-effective, scalable, and automated approaches to DR detection that can be integrated into primary healthcare settings.

2.2. Convolutional Neural Networks and DenseNet

Deep learning, particularly CNN, has revolutionized medical image analysis by achieving expert-level accuracy in tasks such as lesion detection, segmentation, and disease classification [10]. CNN are well-suited for retinal image analysis as they can automatically extract hierarchical features from fundus photographs, reducing dependence on handcrafted features traditionally used in computer vision [11].

The landmark study by Gulshan et al. [12] demonstrated that CNN trained on large fundus datasets achieved sensitivity and specificity comparable to ophthalmologists for detecting referable DR, sparking significant research interest. Since then, numerous studies have applied variations of CNN architectures, such as ResNet, Inception, VGG, and DenseNet, achieving high accuracy on public datasets including EyePACS, Messidor, and APTOS [13], [14].

DenseNet, introduced by Huang et al. [15], represents a significant improvement over conventional CNN by introducing dense connectivity between layers, where each layer receives inputs from all preceding layers. This design facilitates feature reuse, alleviates vanishing gradient problems, and improves parameter efficiency. DenseNet-121, in particular, has been widely adopted in medical imaging because it offers strong performance with relatively fewer parameters compared to deeper networks [16]. In the context of DR detection, DenseNet architectures have demonstrated superior generalization and robustness, particularly when combined with transfer learning and fine-tuning [17], [18].

Recent reviews emphasize that DenseNet models achieve competitive accuracy and robustness in DR classification, often outperforming or matching ResNet and Inception variants [19]. Moreover, DenseNet has shown particular strength in handling complex medical images with subtle lesions, such as microaneurysms and exudates, which are critical for early DR detection [20].

2.3. Smartphone-Based Fundus Imaging

Data Traditional tabletop fundus cameras, while highly accurate, are expensive, bulky, and impractical for deployment in primary healthcare centers or rural areas. This has motivated the development and adoption of smartphone-based fundus imaging systems, where an optical adapter is attached to a smartphone camera to capture fundus photographs [21].

Multiple studies report that smartphone fundus adapters provide a cost-effective and portable alternative, enabling wider access to retinal imaging [22]. Research has demonstrated that images obtained via smartphone-based devices are sufficiently high in quality for screening purposes and teleophthalmology consultations, although variability in image quality due to illumination, focus, and operator expertise remains a concern [23].

Malan et al. [24] evaluated smartphone-based imaging devices in rural clinics and found that they facilitated early detection of vision-threatening diseases with acceptable sensitivity and specificity. Moreover, low-cost devices such as DIY adapters and commercial solutions like Peek Retina have gained popularity as feasible tools for screening in low-resource settings [25].

In Indonesia and other developing countries, the affordability and portability of smartphone-based fundus cameras make them particularly suitable for primary healthcare facilities. Nevertheless, the literature stresses the need for rigorous preprocessing and validation when these images are used for automated DR detection, given their susceptibility to noise, uneven illumination, and narrower fields of view compared to conventional fundus cameras [26].

2.4. Preprocessing, Augmentation, and Evaluation

The performance of deep learning models for DR detection strongly depends on the quality of input images and the robustness of the preprocessing pipeline. Fundus images—especially those acquired using smartphone-based devices are prone to illumination artifacts, low contrast, blur, and variable cropping, all of which can degrade model performance [27].

Common preprocessing techniques include contrast enhancement, normalization, histogram equalization, resizing, and artifact removal [28]. Cropping and circular masking are often applied to focus the model on the retinal region while excluding irrelevant background pixels [29]. In addition, image augmentation (e.g., rotation, flipping, scaling, brightness adjustment) plays a crucial role in improving generalization and mitigating overfitting, especially when datasets are limited [30].

Another critical aspect emphasized in the literature is evaluation methodology. Performance metrics such as accuracy, sensitivity, specificity, precision, F1-score, and area under the ROC curve (AUC) are commonly reported [31]. More rigorous evaluations also include agreement metrics such as the quadratic weighted kappa to assess alignment with expert graders [32]. Furthermore, external validation on independent datasets is recommended to evaluate generalization and robustness across domains [33].

Recent works also highlight the importance of domain adaptation strategies to address dataset shift between public repositories and local data. Unsupervised and semi-supervised approaches, as well as federated learning, have been proposed to improve generalization [34], [35]. These methods are especially relevant for smartphone-based fundus imaging, where acquisition conditions may differ significantly from the public datasets on which models are often trained.

Overall, the literature consistently concludes that preprocessing pipelines, tailored augmentations, and rigorous evaluation protocols are critical components for ensuring clinically reliable performance of AI-based DR detection systems.

3. METHODOLOGY

3.1. Data

This study employs a hybrid dataset strategy by combining publicly available fundus image repositories with a locally collected dataset from Indonesian primary healthcare facilities. The public dataset used in this study is the APTOS 2019 Blindness Detection dataset, which provides large-scale, annotated retinal fundus images covering a wide range of diabetic retinopathy (DR) severity levels. The APTOS dataset has been widely used in previous DR studies and enables benchmarking against state-of-the-art classification models [1], [2]. Table 1 shows the distribution of diabetic retinopathy severity classes in the APTOS dataset.

In parallel, a locally collected dataset is obtained from selected primary healthcare facilities in North Sulawesi, Indonesia. This dataset is designed to reflect real-world clinical conditions and capture variations in image quality, patient demographics, and retinal pathological features representative of Indonesian populations. All retinal images in the locally collected dataset are annotated by certified ophthalmologists according to the International Clinical Diabetic Retinopathy Disease Severity Scale, which classifies images into five categories: no DR, mild non-proliferative DR, moderate non-proliferative DR, severe non-proliferative DR, and proliferative DR [3]. Figure 1 presents representative examples of non-DR and severe DR fundus images.

To ensure balanced class representation and reduce potential bias, the combined public and locally collected datasets undergo stratified sampling. Class imbalance is further addressed through oversampling techniques applied during the training phase. The inclusion of the locally collected dataset is particularly important for mitigating domain shift, as it captures imaging characteristics and pathological patterns specific to Indonesian patients.

For model development and evaluation, the balanced dataset is divided using three stratified training–testing scenarios, namely 70:30, 80:20, and 90:10. These split configurations enable systematic evaluation of model robustness while maintaining consistent class distributions across training and testing subsets.

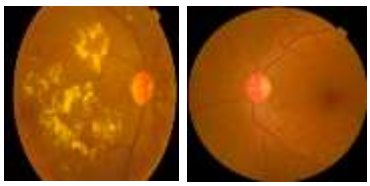

Figure 1. ***Severe and non-diabetic retinopathy fundus images.***

Tabel 1. ***Class distribution of diabetic retinopathy severity levels in the APTOS dataset.***

Classes	Total per Classes
No DR	1805
Mild	370
Moderate	999
Proliferate DR	295

Severe	193
Total	3662

3.2. Proposed Method

The proposed method integrates a deep learning–based diabetic retinopathy (DR) classification model with a web-based deployment framework to support practical and scalable screening in primary healthcare settings. The pipeline is designed to address challenges specific to retinal images obtained from a locally collected dataset, including image variability and dataset imbalance. The overall workflow consists of preprocessing, class imbalance handling, model architecture design, training procedure, evaluation, and system integration.

3.2.1 Preprocessing and Augmentation

The balanced dataset is subsequently prepared through data splitting, normalization, and data augmentation processes to ensure robust model training.

1) Data Splitting

The dataset is divided into three stratified training–testing scenarios: 70:30, 80:20, and 90:10. Stratified splitting is applied to maintain consistent class proportions across both training and testing subsets.

2) Preprocessing

Fundus images are normalized using rescaling by dividing pixel values by 255, constraining the input range to [0,1]. This normalization stabilizes the training process and improves numerical convergence.

3) Image Augmentation

To enhance model robustness and prevent overfitting, image augmentation is applied exclusively to the training dataset. Random transformations are generated using *ImageDataGenerator*, including rotations up to 20 degrees, width and height shifts of up to 20%, shear transformations of 20%, zoom variations of 20%, and horizontal flipping.

4) Data Generator

Data generators are utilized to load images from directory structures, resize them to 224 × 224 pixels, and encode class labels using one-hot encoding, enabling efficient batch-wise training.

3.2.2 Handling Class Imbalance

The diabetic retinopathy dataset exhibits a significant class imbalance, where the *No DR* class dominates the distribution compared to severe categories such as *Severe DR* and *Proliferative DR*. If left unaddressed, this imbalance can lead to biased model predictions and poor generalization on clinically critical minority classes.

To mitigate this issue, Random Oversampling is applied using the *imblearn* library. Minority class samples are randomly duplicated until all five DR classes contain an equal number of images. This process produces a uniformly distributed dataset, which is essential for training an unbiased classifier and improving sensitivity to high-severity DR cases. Table 2 presents the DR class distribution after oversampling.

Table 2. ***Class distribution of diabetic retinopathy severity levels after oversampling across three split scenarios.***

Data Distribution		70:30		80:20		90:10	
Classes	After Oversampling	Train	Test	Train	Test	Train	Test
No DR	1805	1264	542	1444	361	1624	181
Mild	1805	1264	542	1444	361	1624	181
Moderate	1805	1264	542	1444	361	1625	180
Proliferate DR	1805	1264	542	1444	361	1624	181
Severe	1805	1264	542	1444	361	1625	180

3.2.3 Model Architecture

The classification model is developed using a transfer learning approach based on the DenseNet121 architecture.

1) Base Model

DenseNet121, a CNN pre-trained on the ImageNet dataset, is employed as the primary backbone for feature extraction.

2) Layer Freezing

All layers of the DenseNet121 backbone are frozen to preserve the discriminative features learned from ImageNet, while only the newly added classification layers are trained.

3) Classifier Head

A series of fully connected layers is appended on top of the Global Average Pooling 2D output of DenseNet121. This classifier head consists of a Batch Normalization layer, two Dense layers with ReLU activation functions (512 and 256 neurons), Dropout layers with rates of 0.3 and 0.2 for regularization, and a final Dense output layer with five neurons using a Softmax activation function to classify DR severity levels.

4) Model Compilation

The model is compiled using the Adam optimizer with a learning rate of 1×10^{-4} and Categorical Cross-Entropy as the loss function. Accuracy is used as the primary evaluation metric.

3.2.4 Training Procedure

1) Epoch Configuration

The model is trained using two epoch settings, namely 50 epochs and 80 epochs, to evaluate convergence behavior and performance stability.

2) Early Stopping

An EarlyStopping mechanism is implemented as a regularization technique. With a patience value of five epochs, training is automatically terminated if validation accuracy does not improve over five consecutive epochs. This mechanism ensures restoration of the model weights that yield the highest validation accuracy.

3.3 Evaluation

Model performance is evaluated by using accuracy as the primary metric to emphasize overall classification performance across five DR severity levels. Accuracy is chosen due to its interpretability and widespread adoption in prior diabetic retinopathy classification studies, enabling straightforward comparison with related work.

3.4 System Integration

The trained DenseNet-121 model is integrated into a web-based screening platform designed for use by non-specialist healthcare workers. The system architecture consists of several key components. The frontend module provides a simple and intuitive interface for uploading retinal images and displaying classification results. The backend module hosts the inference engine, which preprocesses incoming images and performs DR classification using the trained model. A database module securely stores uploaded images and prediction results, ensuring data integrity and patient privacy.

For cases with severe or uncertain predictions, an optional specialist review mechanism allows ophthalmologists to verify results, thereby enhancing clinical safety.

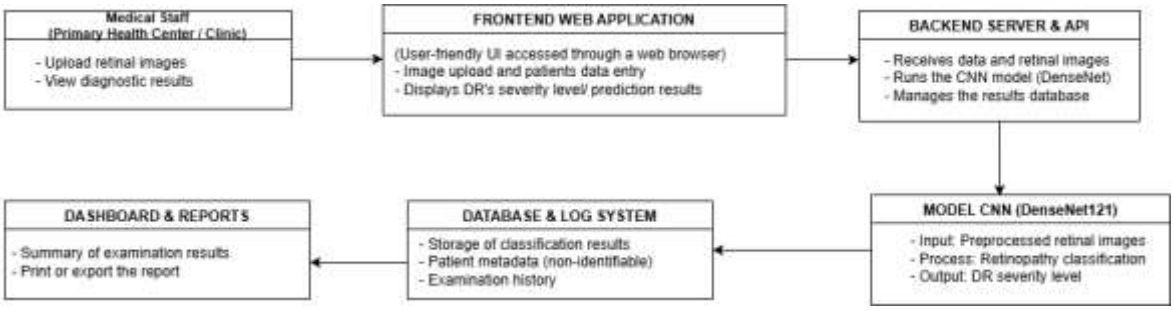

Figure 2. ***High Level Architecture***

Figure 2. depicts the High-level architecture of the proposed web-based diabetic retinopathy severity classification system. Medical staff at primary health centers or clinics upload retinal images and view diagnostic results through a user-friendly web frontend. The backend server and API receive image and patient data, execute the DenseNet121-based CNN for retinopathy classification, and manage the storage of results. The CNN model processes preprocessed retinal images and outputs the diabetic retinopathy severity level. Classification results, non-identifiable patient metadata, and examination history are stored in the database and log system, while summaries and reports are presented to users via an integrated dashboard with options to print or export reports.

4. RESULTS AND DISCUSSION

4.1 Results

4.1.1 Model Accuracy Analysis Across Data Split Scenarios

Table 3 summarizes the classification accuracy achieved under different split scenarios at 50 and 80 epochs. At 50 epochs, accuracy values range from 81.35% (70–30 split) to 82.70% (80–20 split). When the training duration is increased to 80 epochs, accuracy improves across all configurations, with the highest accuracy of 87.50% achieved by the 90–10 split.

The consistent improvement from 50 to 80 epochs highlights the importance of sufficient training iterations for capturing complex retinal patterns. Moreover, the superior performance of the 90–10 split confirms that a larger training dataset significantly enhances model robustness, particularly for multi-class DR severity classification.

Table 3. ***Model Accuracy across three split scenarios***

Split Scenario	Accuracy (%)	
	Epoch-50	Epoch-80
70-30	81.35	85.50
80-20	82.70	87.10
90-10	82.64	87.50

Figure 3 presents the training and validation accuracy of the DenseNet121 model under three different data split scenarios, namely 70–30, 80–20, and 90–10, evaluated at two epoch configurations: 50 epochs (upper plots) and 80 epochs (lower plots).

For the 50-epoch configuration, the accuracy curves across all split scenarios exhibit a consistent upward trend, indicating effective learning during the early training phase. The 90–10 split demonstrates the fastest convergence and the highest validation accuracy among the three scenarios, followed closely by the 80–20 split. This behavior suggests that a larger proportion of training data enables the model to capture more discriminative retinal features, particularly for subtle diabetic retinopathy lesions. However, minor fluctuations between training and validation accuracy are observed, especially in the 70–30 split, indicating limited generalization due to a relatively smaller training set.

In the 80-epoch configuration, the accuracy curves show more stable convergence across all split scenarios. Validation accuracy improves consistently compared to the 50-epoch setting, confirming that extended training allows the model to refine feature representations. The 90–10 split at 80 epochs achieves the highest and most stable accuracy, with minimal divergence between training and validation curves. This indicates that the combination of a larger training dataset and sufficient epochs contributes to improved generalization without significant overfitting.

Overall, the accuracy plots demonstrate that increasing both the training data proportion and the number of epochs enhances model performance, with the 90–10 split at 80 epochs yielding the most reliable results.

4.1.2 Model Loss Analysis Across Data Split Scenarios

Figure 4 illustrates the training and validation loss curves corresponding to the same three data split scenarios at 50 epochs (upper plots) and 80 epochs (lower plots).

At 50 epochs, all split scenarios exhibit a sharp decrease in training and validation loss during the initial epochs, followed by gradual stabilization. The 70–30 split shows relatively higher validation loss fluctuations, suggesting that the model struggles to generalize optimally when trained with fewer samples. In contrast, the 80–20 and 90–10 splits demonstrate smoother loss trajectories and lower final validation loss values. When extended to 80 training epochs, the loss curves become more stable across all split configurations. The 90–10 split again shows the lowest and most consistent validation loss, indicating improved convergence and reduced prediction uncertainty. Importantly, no significant divergence between training and validation loss is observed, confirming that the applied regularization strategies, including dropout and early stopping, effectively mitigate overfitting.

These findings confirm that the DenseNet121 model benefits from both extended training duration and increased training data size, resulting in more stable optimization and improved generalization.

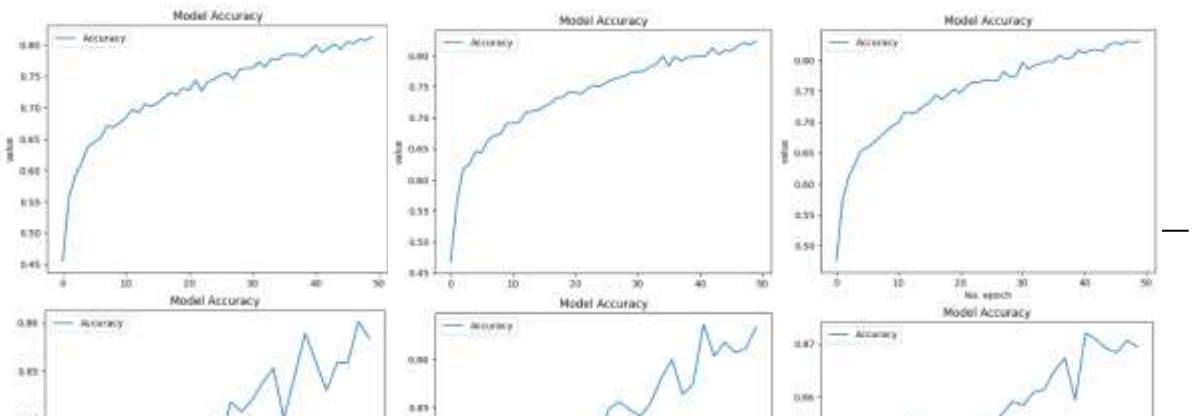

Figure 3. ***Model accuracy across different data split scenarios at 50 and 80 epochs.***

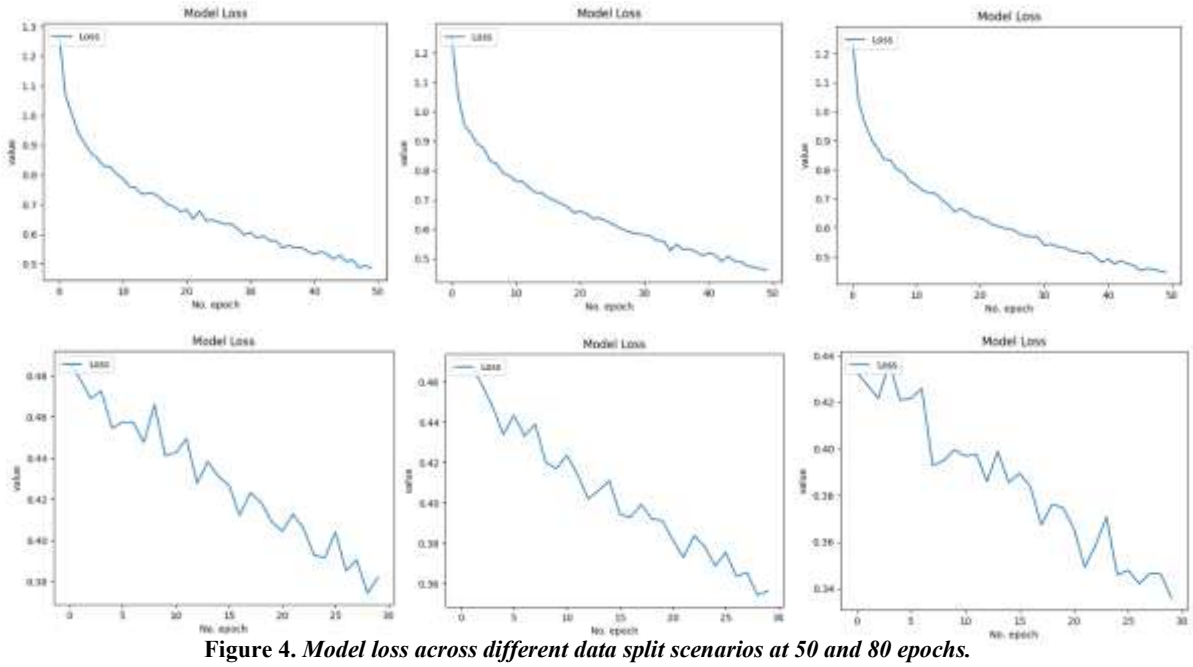

Figure 4. ***Model loss across different data split scenarios at 50 and 80 epochs.***

Figure 5 presents the confusion matrix of the best-performing model, obtained at 80 epochs with a 90–10 training–testing split. The diagonal dominance of the matrix indicates a high number of correctly classified samples across all five DR severity classes.

The model demonstrates strong performance in identifying No DR and Moderate DR classes, which constitute a substantial portion of the dataset. Importantly, clinically critical classes such as Severe DR and Proliferative DR also show improved recognition, reflecting the effectiveness of oversampling in addressing class imbalance. Misclassifications primarily occur between adjacent severity levels, such as mild and moderate DR, which is clinically plausible due to overlapping retinal features.

Overall, the confusion matrix confirms that the proposed model achieves balanced performance across all DR severity levels, supporting its suitability for screening and referral decision support.

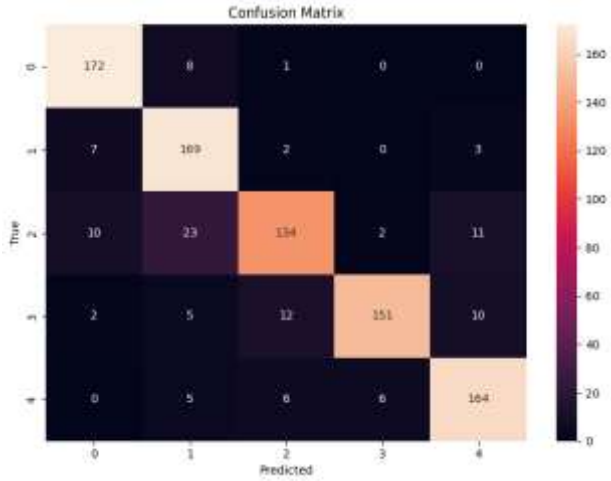

Figure 5. ***Confusion matrix of the model with the highest accuracy.***

4.1.3 RetinoCare Web Application Interface

Figure 6 illustrates the main interface and detection page of the RetinoCare web application. The left image shows the main page, which serves as the entry point of the system and provides basic navigation for healthcare workers to access the screening features. The interface is designed to be simple and intuitive, enabling use by non-specialist healthcare workers in primary healthcare settings.

The right image presents the diagnosis (detection) page, where users upload retinal fundus images captured using smartphone-based fundus adapters. Upon image submission, the system automatically performs preprocessing and diabetic retinopathy severity classification using the trained DenseNet121 model. The predicted severity level and relevant examination information are displayed to support rapid interpretation, screening workflows, and referral decision-making. This implementation demonstrates the practical integration of the proposed deep learning model into a real-world web-based application.

Figure 6. ***Main interface and detection page of the RetinoCare web application.***

4.2 Discussion

The experimental results demonstrate that the proposed DenseNet121-based model achieves reliable performance for multi-class diabetic retinopathy severity classification using a hybrid dataset. The consistent improvement observed across increasing epoch counts indicates that the model effectively learns discriminative retinal features without overfitting, supported by the application of dropout and early stopping mechanisms.

The comparison of different data split scenarios highlights the importance of training data proportion. The 90–10 split consistently outperforms the 70–30 and 80–20 configurations, emphasizing that larger training datasets significantly enhance generalization, particularly in medical image classification tasks involving subtle pathological variations. This finding aligns with prior studies that emphasize data availability as a critical factor in deep learning–based DR detection.

Furthermore, the integration of locally collected Indonesian retinal images with public datasets contributes to improved contextual relevance and robustness. The strong performance on severe and proliferative DR classes is particularly significant from a clinical perspective, as these categories require urgent

referral and intervention. Although some confusion remains between adjacent DR stages, such misclassifications are consistent with clinical diagnostic challenges and are unlikely to compromise the system's utility as a screening tool.

Overall, the results validate the feasibility of deploying a CNN-based DR detection model trained on hybrid datasets and integrated into a web-based platform for primary healthcare settings.

5. CONCLUSION

This study presents RetinoCare, a web-based intelligent system for early detection of diabetic retinopathy (DR) that integrates smartphone-based fundus imaging with a deep learning model based on the DenseNet121 architecture. By employing a hybrid dataset that combines publicly available fundus image repositories with locally collected retinal images from Indonesian primary healthcare facilities, the proposed approach addresses domain shift and enhances contextual relevance for real-world deployment.

Experimental evaluation across three stratified training–testing split scenarios (70–30, 80–20, and 90–10) and two training configurations (50 and 80 epochs) demonstrates that model performance improves with increased training data proportion and extended training duration. The best performance is achieved using a 90–10 split at 80 epochs, yielding an accuracy of 87.50%. Accuracy and loss analyses confirm stable convergence and effective generalization, while confusion matrix evaluation indicates balanced classification performance across all five DR severity levels, including clinically critical severe and proliferative categories.

The trained model is successfully integrated into a user-friendly web-based platform that supports practical screening workflows in primary healthcare settings. The system enables non-specialist healthcare workers to upload retinal images, obtain automated DR severity classification, and facilitate referral decisions, highlighting its potential as an accessible and scalable screening tool in resource-limited environments.

Future research will focus on improving the reliability and clinical trustworthiness of the system by addressing uncertainty in model predictions and further validating performance in real-world screening scenarios.

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