Enhancing Diabetic Retinopathy Classification Using Geometric Augmentation and MobileNetV2 on Retinal Fundus Images

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***Abstract*—Diabetic retinopathy (DR) ranks among the foremost contributors to blindness worldwide, particularly affecting the adult demographic. Detecting DR at an early stage is crucial for preventing vision loss; however, conventional approaches like fundus examinations are often lengthy and reliant on specialized expertise. Recent developments in machine learning, especially the application of deep learning models, provide a highly effective option for classifying diabetic retinopathy through retinal fundus images. This investigation examines the efficacy of geometric data augmentation methods alongside MobileNetV2 for the classification of diabetic retinopathy. Utilizing augmentation techniques like image resizing, zooming, shearing, and flipping enhances the model's ability to generalize. MobileNetV2 is selected for its impressive inference speed and computational efficiency. This analysis evaluates the effectiveness of MobileNetV2 in relation to InceptionV3, emphasizing metrics such as accuracy, precision, sensitivity, and specificity. The findings show that MobileNetV2 attains exceptional performance, achieving an accuracy of 97%. These findings highlight the promise of employing efficient models and augmentation strategies in clinical settings for the early identification of DR. The findings highlight the critical need to incorporate advanced machine learning methods to enhance healthcare results and avert blindness caused by diabetic retinopathy.**

***Keywords*—Diabetic retinopathy; data augmentation; InceptionV3; MobileNetV2; transfer learning**

I. INTRODUCTION

Diabetic retinopathy is a significant complication linked to diabetes mellitus, contributing significantly to the global incidence of blindness. The International Diabetes Federation (IDF) indicated that in 2019, around 463 million individuals globally were diagnosed with diabetes mellitus (DM), with projections suggesting a significant increase to about 700 million by 2045. Diabetic retinopathy (DR) remains a prevalent complication linked to diabetes, posing a significant health issue as it stands as a primary cause of preventable blindness, especially within the adult working-age demographic worldwide [1]. The condition is characterized by impairment of the retinal blood vessels, leading to potential leakage, bleeding, and the development of scar tissue. These alterations may ultimately result in diminished visual acuity or potentially irreversible blindness [2], [3]. It is essential to achieve a more profound understanding of the fundamental mechanisms of diabetic retinopathy and to create more effective approaches for its early detection to avert more severe outcomes.

Identifying diabetic retinopathy at an early stage is essential to prevent additional harm to the eyes. The application of early interventions, including the management of blood glucose levels and the arrangement of routine eye examinations, has been shown to decrease the likelihood of blindness [4]. This research suggests that through prompt identification and effective management, individuals with diabetes can preserve their ocular health and hinder the advancement of the condition. Nonetheless, a considerable obstacle remains, as numerous patients do not recognize the existence of diabetic retinopathy until symptoms become evident [5]. This research highlights the necessity for creating more effective approaches for the classification and detection of the disease.

Technological developments in retinal imaging and deep learning have pioneered new avenues for boosting the precision of diabetic retinopathy diagnoses. Conventional diagnostic techniques for identifying diabetic retinopathy, such as eye examinations by an ophthalmologist, are regularly laborious and rely on a physician's experience and acumen. Machine learning algorithms and imaging processing methods can heighten the effectiveness and exactitude of the categorization process. Convolutional neural networks (CNNs) are inspired by the structure and function of brain neurons with image input [6], [7]. The use of CNN has evidenced proficiency in detecting diverse medical conditions from medical visuals [8], [9],[10].

Numerous previous studies have attempted to classify diabetic retinopathy using Convolutional Neural Networks (CNN). State-of-the-art CNN architectures, such as VGG, ResNet, and Inception, have been applied for feature extraction, significantly improving the sorting process [11]. Additionally, investigations combining CNNs with preprocessing strategies like Contrast Limited Adaptive Histogram Equalization (CLAHE) have indicated enhanced model productivity and accuracy [12]. Furthermore, examination by [13] has proposed hybrid approaches that integrate machine learning and deep learning methods, for example, merging Support Vector Machines (SVM) and Random Forests with CNNs to further optimize categorization performance. Moreover, transfer learning has been employed to utilize pre-trained models, minimizing the need for large data sets and reducing computational demands [14].

The use of augmentation techniques in image classification has been shown to impact model accuracy [15] significantly. In the realm of diabetic retinopathy classification, augmentation plays a crucial role in enhancing the model's ability to identify significant patterns and features that might be overlooked in the original dataset. In the realm of image data classification, geometric augmentation serves as an essential method for improving both the quality and quantity of training data utilized in machine learning models. Geometric augmentation includes various transformations such as rotation, cropping, and rescaling, which can enhance the learning process by presenting the model with the natural variations found in the data. Augmenting the training data allows us to reduce overfitting and improve the model's generalization, which in turn enhances classification accuracy [16],[17],[18].

Moreover, utilizing transfer learning model architectures like MobileNetV2 and InceptionV3, designed for enhanced efficiency and accuracy in image recognition, can significantly improve the classification ability for diabetic retinopathy [19], [20], [21], [22]. MobileNetV2 provides benefits regarding efficiency and inference speed [23], [24], [25], [26]. In a clinical setting, where the speed of diagnosis is essential, more efficient models can offer considerable benefits. MobileNetV2 demonstrates enhanced inference speed while maintaining a high level of accuracy, positioning it as a compelling choice for practical applications. In scenarios with constrained computing resources, MobileNetV2 emerges as a more viable option.

The comparative analysis and performance evaluation of MobileNetV2 and InceptionV3 in diabetic retinopathy classification reveals that each model has its unique strengths and weaknesses. Choosing the best model necessitates careful consideration of the unique needs of the clinical application, such as accuracy, efficiency, interpretability, and generalizability. Additional investigation is essential to explore the integration of the two models or to create a new model that harnesses the advantages of both.

It is crucial to highlight the importance of early detection and precise classification in diabetic retinopathy. Utilizing the most recent technological innovations in image processing and machine learning presents a significant opportunity to improve diagnosis and treatment results for individuals with diabetes. This study seeks to significantly enhance the prevention of blindness caused by diabetic retinopathy by refining classification accuracy through the application of geometric augmentation techniques and transfer learning models.

II. METHODOLOGY

The study was carried out in multiple phases, starting with the collection of datasets from Dr Sardjito and the APTOS 2019 dataset. The datasets were subsequently partitioned into three separate subsets: training sets, testing sets, and validation sets. The next step in the process involves enhancing the training data and training the model using the MobileNetV2 and InceptionV3 architectures. The last phase consists of assessing the model through a confusion matrix to derive the metrics for accuracy, precision, sensitivity, and specificity. Fig. 1 illustrates the research flow.

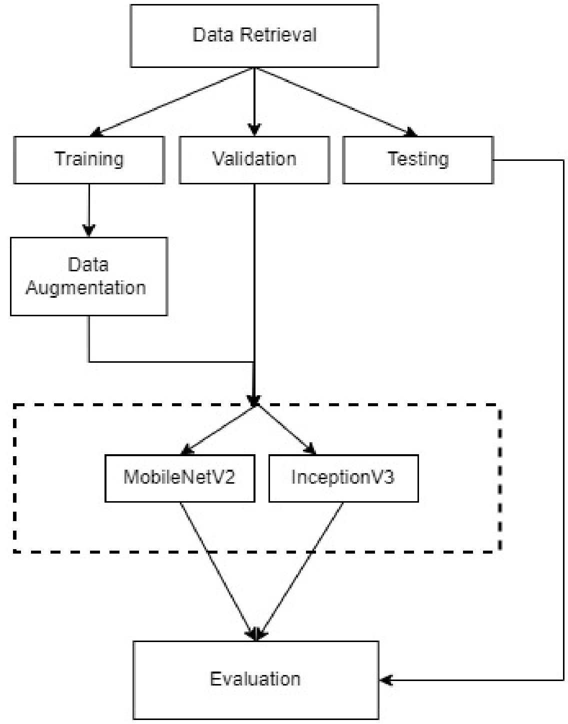

Fig. 1. Research flow.

A. Data Retrieval

The acquisition of data was crucial in this study, especially regarding the classification of diabetic retinopathy. The data for the retinal fundus images was sourced from two main origins. The data were collected from Dr Sardjito Hospital in Yogyakarta and the APTOS 2019 dataset. Dr. Sardjito Hospital stands out as a leading medical institution in Indonesia, featuring an extensive collection of retinal fundus images that covers a wide range of diabetic retinopathy severity. The data holds considerable importance as it accurately represents the condition of patients treated at the hospital, thus improving the relevance and precision of the developed classification model. Fig. 2 presents the exemplar of the retinal fundus image dataset.

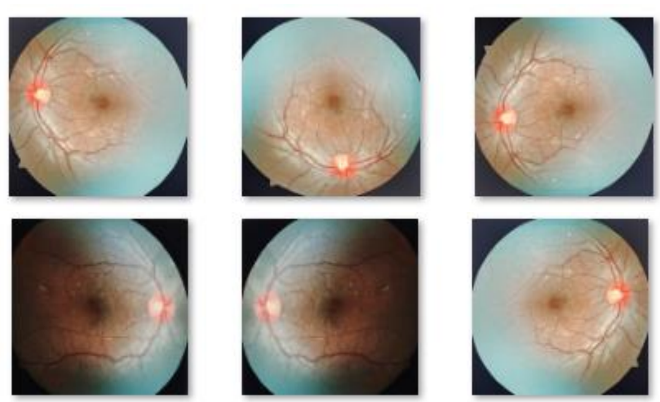

Fig. 2. Retina images dataset.

Additionally, the APTOS 2019 dataset, which is publicly available, was utilized in this study. This study employs a dataset consisting of 3,677 retinal fundus images, categorized into two groups: diabetic retinopathy positive (1,872 images) and average (1,805 images). The use of this dataset allows for model training with a larger volume of diverse data, which is essential for improving model generalization. For additional information concerning the datasets employed in this study, please consult Table I.

TABLE I. DATASET

No	Class	Data
1	Diabetic Retinopathy	1.872
2	Normal	1.805
	Total	**3.677**

Following the collection process, the data is divided into three separate sets: training data, validation data, and testing data. The dataset is segmented into three parts: 80% is allocated for training the model, 10% is designated for validation, and the final 10% is reserved for testing the model's accuracy. The proportional division plays a vital role in guaranteeing that the model learns from the available data while also being able to generalize to previously unseen data. This fact aligns with essential principles of machine learning that highlight the importance of validating models.

B. *Data Augmentation*

Subsequently, the geometric augmentation technique serves as a method to enhance both the quantity and diversity of training data through the modification of existing images. This study utilized various augmentation techniques, such as resizing images to a resolution of 224x224 pixels, adjusting the zoom by a factor of 0.2, applying shear transformations within a range of 0.2, and implementing both horizontal and vertical flip transformations. The application of these techniques is expected to enable the model to learn from a broader array of images, thus improving its ability to generalize in classification tasks.

Images were resized to (224x224) to maintain uniform resolution, an essential factor in training deep learning models. This size was chosen due to its status as a standard dimension commonly utilized in various neural network architectures, such as MobileNetV2 and InceptionV3. Maintaining a consistent size allows for more efficient and effective data processing by the model.

The utilization of a zoom range and shear range facilitates diversity in the viewing angle and perspective of the image. The model can learn to recognize important features of retinal fundus images at various scales through zooming. At the same time, the shear range allows for adaptation to distortions that may occur during image capture. This technique holds considerable importance due to the variability in the angles at which retinal fundus images are captured and the differing lighting conditions present during their acquisition. The implementation of horizontal and vertical flips serves as an essential technique in enhancing data through augmentation. The absence of a fixed orientation in retinal fundus images allows for the use of flip techniques, which helps the model learn from inverted images and improves its ability to recognize essential patterns. This study is especially relevant in the context of classifying diabetic retinopathy, as changes in image orientation can influence the precision of detection outcomes.

The choice of these geometric augmentation techniques is informed by the results of earlier studies that have shown that data augmentation can significantly improve model accuracy in image classification tasks [27], [28], [29]. Data augmentation plays a crucial role in reducing overfitting and improving model performance when working with limited data sets [30], [31]. The application of these techniques is expected to yield a model that demonstrates improved performance in classifying diabetic retinopathy.

C. *Training Model*

The model development process in this study involved training two well-known neural network architectures, specifically MobileNetV2 and InceptionV3. The selection of these two models is based on their proven effectiveness across various image recognition and classification tasks, along with their computational efficiency. MobileNetV2 is tailored for devices with constrained computational capabilities, whereas InceptionV3 provides enhanced depth and complexity, enabling a more thorough examination of the relevant features.

The model underwent training with the dataset that had been previously collected and prepared. The training parameters comprised a dropout rate of 0.2 to mitigate overfitting, a sigmoid activation function for binary classification, and the Adamax optimizer, known for its efficacy in tackling optimization challenges. The learning rate was established at 0.0001, a frequently utilized value to promote stable convergence throughout the training process. The training procedure was planned for 30 epochs, incorporating early stopping to halt the training if there was no enhancement in accuracy over five successive epochs.

Throughout the training process, evaluations of the model were conducted at consistent intervals to assess its performance. The evaluation described was carried out utilizing a validation data set that was separate from the training data set. This approach allows for the determination of whether the model is showing indications of overfitting. In this situation, the model becomes excessively dependent on the training data and needs to generalize to new data. Should this situation arise, adjustments might be made regarding the training parameters or the augmentation method utilized.

After training the model, the next step involves fine-tuning the chosen architecture. Fine-tuning involves adjusting a pre-trained model by utilizing a more specialized dataset. In this context, the MobileNetV2 and InceptionV3 models, previously trained on a substantial dataset, will be fine-tuned to the dataset of retinal fundus images that have been gathered. This process aims to improve the accuracy of models used for classifying diabetic retinopathy. By implementing a structured approach in model development, it is expected that both architectures will produce the best results in diabetic retinopathy classification. This study aims to enhance classification accuracy while providing an in-depth understanding of the effectiveness of various techniques and architectures in the detection of diabetic retinopathy.

D. Evaluation

The evaluation of the model is a vital step in determining the effectiveness of the created classification system. This study utilized several evaluation metrics, such as accuracy, precision, specificity, and sensitivity. The chosen metrics offer unique insights into the model's effectiveness in classifying retinal fundus images according to the severity of diabetic retinopathy.

Accuracy serves as a crucial metric that reflects the ratio of correct predictions to the overall predictions generated by the model. This metric holds significant value, offering a comprehensive insight into the model's ability to identify images accurately. Nevertheless, depending solely on accuracy needs to be improved, especially in scenarios involving unbalanced datasets, where the quantity of images across different categories can differ significantly. As a result, further metrics, including precision and sensitivity, are also computed.

Precision measures the ratio of accurate positive predictions to all optimistic predictions, while sensitivity evaluates how effectively the model detects actual positive cases. In contrast, specificity measures the ability of the model to identify adverse conditions. The application of a combination of these metrics enables a more thorough understanding of the model's performance in diabetic retinopathy classification.

The testing process was carried out utilizing the previously segregated test data set. Following this, the outcomes of these tests undergo analysis aimed at pinpointing the model's strengths and weaknesses in classification. For example, when the model shows high accuracy yet low sensitivity, it may indicate that the model is more skilled at recognizing images without retinopathy than those that display signs of the condition.

The examination of these findings is essential for advancing model development. If the model shows less than ideal-performance, adjustments can be made to the architecture, training parameters, or augmentation techniques used. As a result, the evaluation of models serves not just as a final step but as a crucial part of the ongoing model development process.

III. Results and Discussion

Diabetic retinopathy is a significant contributor to global blindness, highlighting the critical need for precise classification to facilitate early intervention and effective disease management. This study presents a comparative analysis of two deep learning models, MobileNetV2 and InceptionV3, aimed at evaluating their performance in classifying retinal fundus images to detect diabetic retinopathy. The findings indicate that both models show acceptable performance, yet significant differences are apparent in the evaluation metrics.

MobileNetV2 exhibited higher accuracy than InceptionV3, achieving an accuracy rate of 97%. This result suggests that the model demonstrates enhanced capability in identifying relevant features within retinal fundus images. The accuracy of the MobileNetV2 model is particularly impressive, achieving 97%. This result suggests that the model is highly effective in reducing false positives. On the other hand, InceptionV3 demonstrates an accuracy of 94% and a precision of 97%. Although these values are noteworthy, they indicate that MobileNetV2 surpasses InceptionV3 in terms of overall accuracy. Fig. 3 presents the graph depicting the training accuracy of MobileNetV2.

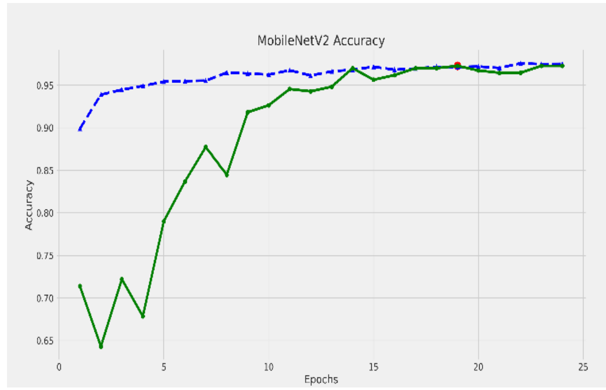

Fig. 3. MobileNetV2 training accuracy.

The model's sensitivity, characterized by its capacity to identify positive cases, produced some fascinating outcomes. MobileNetV2 showed a sensitivity of 96%, whereas InceptionV3 displayed a sensitivity of just 91%. This result suggests that MobileNetV2 demonstrates greater efficacy in recognizing patients with diabetic retinopathy, which holds considerable importance in a clinical environment where timely identification can avert more severe disease advancement.

The measure of specificity, reflecting the model's ability to identify negative cases correctly, showed similar results for both models, achieving a value of 97%. This result indicates that, even with differences in sensitivity and accuracy, both models demonstrate a similar ability to recognize individuals without diabetic retinopathy. The results indicate that InceptionV3 continues to be a dependable choice for clinical applications.

This study revealed that while InceptionV3 showed similar precision to MobileNetV2, the differences in sensitivity and accuracy suggested that MobileNetV2 performed better in detecting diabetic retinopathy. This results from the enhanced capability of MobileNetV2 to utilize augmentation data used during training, which improves the model's ability to generalize across variations in retinal fundus images.

Furthermore, both models underwent assessment using a varied dataset that included images of patients displaying different stages of diabetic retinopathy. The findings indicated that MobileNetV2 showed enhanced efficacy in detecting the early stages of the disease, which are frequently difficult to identify. This finding highlights the crucial influence that choosing the suitable model can exert on the precision of diagnosis and the management of patients after that. Fig. 4 illustrates the confusion matrix for the evaluation of MobileNetV2.

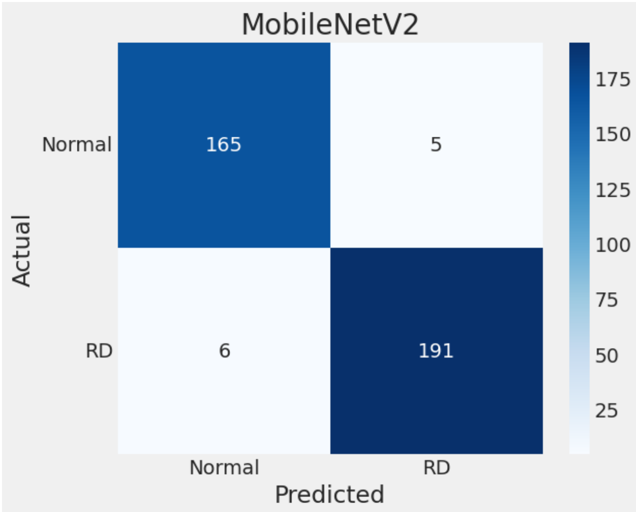

Fig. 4. Confusion matrix.

This study employs various methodologies that significantly diverge from those used in earlier investigations, enabling a more thorough analysis. A previous investigation by [32] utilized CNN to classify diabetic retinopathy, resulting in an accuracy of 75% and a sensitivity of 95%. A separate investigation conducted by [33] utilized ResNet50 to classify the APTOS 2019 dataset, achieving an accuracy of 91%. The findings from this study are thoroughly compared with those of several prior studies in Table II. The comparisons provide valuable insights into the progress and contributions of this study in relation to the current body of literature.

TABLE II. COMPARISON WITH OTHER STUDIES

No	Researchers	Method	Accuracy
1	Pratt	CNN	75%
2	Devi	ResNet50	91%
3	**Our Study**	**MobileNetV2**	**97%**

This study utilizes a range of methods that markedly diverge from those used in earlier investigations, facilitating a more thorough and detailed analysis. A comprehensive comparison of the findings from this study with those of several prior studies is outlined in Table I, emphasizing the differences in methodology, data processing techniques, and model performance across various experiments. The comparisons yield essential insights into the progress and contributions of this study in relation to the current body of literature.

IV. CONCLUSION

This study's findings demonstrate that MobileNetV2 and InceptionV3 serve as two effective models for classifying diabetic retinopathy through retinal fundus images. While both models showed commendable performance, MobileNetV2 revealed enhanced accuracy and sensitivity, positioning it as a more appropriate option for clinical applications. The implications of these findings are substantial for managing and preventing blindness caused by diabetic retinopathy, laying a groundwork for additional exploration in this area.

Future investigations should explore the potential advantages of integrating the MobileNetV2 and InceptionV3 models within an ensemble framework. This method enables the advantages of each model to be utilized, thus improving the overall accuracy and sensitivity. Moreover, it is essential to broaden the datasets employed for training and evaluating the models. Employing more extensive and varied datasets can improve model generalization and decrease the likelihood of overfitting. Additionally, gathering data from diverse geographical areas could improve our understanding of the differences in the clinical manifestations of diabetic retinopathy.

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