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Detection of Diabetic Retinopathy Using Deep Learning

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Abstract

Eyes are the main organs in the human body for sight and are among the most important sensory organs, using a large portion of brain processing power. Diabetes Mellitus (DM) has been a long-lasting condition that devastates the way the body processes glucose in various organs and tissues. DM is a chronic condition that eventually affects the body as a result of excess sugar in various part of the body. It has the potential to cause complications in microvascular areas, such as cerebral hemorrhage and coronary heart disease . The worrisome concern is retinopathy, which can lead to vision loss in severe cases. Due to the irreversible nature of the disease phases, timely screening and detection are vital. This research sets itself apart from previous studies by offering new insights and addressing important limitations in diabetic retinopathy (DR) detection. While many studies focus solely on the accuracy of their models, we took a broader approach. We evaluated our model using multiple metrics, such as F1 score, AUC, precision, recall, and sensitivity. This comprehensive evaluation ensures our model is not only accurate but also reliable in various real-world scenarios.

To improve our model's performance, before deploying the pre-trained model, we perform data augmentation on the images in order to make the images ready and effective for training. We then used a pre-trained model called MobileNetV2; this model was already trained on a large dataset of images, giving it a strong starting point. We then fine-tuned this model specifically for DR detection, making it even more effective for medical diagnosis

Categories: Computer Vision, Image Processing and Analysis, Deep Learning
Keywords: diabetes mellitus (dm), diabetic retinopathy, vision loss, early detection, retina

Introduction

The estimated number of diabetics in India was 691 million as compared to 18 million in 1995. According to All India Ophthalmology Society's pan-India prevalence study of diabetic retinopathy at 194 centers, 21.8% of diabetics had manifested diabetic retinopathy (DR). There are two types of DR: Proliferative Diabetic Retinopathy (PDR) and NPDR. The severity of NPDR is related to the number of microaneurysms, hemorrhages, cotton wool patches, and vein beading present, with PDR representing its natural outcome. Neovascularization is an inherited attribute of PDR [1]. As a result of medical advancement, the incidence and prevalence of diabetes mellitus (DM) and its complications have paradoxically risen in the last decades. Diabetes is becoming more common in the industrialized world due to a variety of factors such as longer life expectancy and a change in eating habits leading to overweight. Thereby, ocular consequences often range from impairment or loss of an eye due to DR and early cataracts to reduced visual acuity. It is also worth noting that despite the fact that DR can be adequately treated, it still the most common causes of blindness among working-age individuals in the industrialized world [2]. Nevertheless, frequent eye tests can deter sight-threatening levels caused by DR and related problems. Regular screening by an eye specialist is important for early detection and treatment of DR [3].

The world prevalence of diabetes from all age group was estimated at 2.8%, and it is forecast to increase to 4.4% by 2030. The number of individuals who are forecast to be diabetic-positive is expected to rise from 171M in the year 2000 to 366M in 2030. However, there is a shortage of ophthalmologists to screen all diabetic patients. Existing methods often require the identification of retinopathy by highly trained and expensive personnel, presenting challenges to the healthcare system. Therefore, there is an urgent need for a more cost-effective screening method that does not rely on ophthalmology specialists. Uncertainty is common and challenging in the field of medicine, particularly when patients' symptoms are ambiguous, making a definitive diagnosis difficult. Consequently, efforts to minimize uncertainties and support medical diagnosis, decision-making, and predictions are widespread. We seek to demonstrate how AI can help reduce medical uncertainties and establish new certainties [4]. An entirely automated method utilizing fundus image analysis by a computer could offer instant classification of retinopathy without requiring specialist evaluations. Automated results from the computer are crucial for decreasing the screening workload and improving accuracy [5,6].

The difficulties in enabling machines to simulate human intelligence using programs in computers. This

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extensive part of software's/application covers specific health management, prevention, detection, and also treatment. Artificial Intelligence (AI) is advancing significantly around various domains, ophthalmology is among the domains, especially in conditions like DR, which depend on image-based diagnostics. AI screenings based on deep learning are employed for identifying numerous visual impairments and sight-threatening ailments, such as DR [7]. In recent years, deep learning (DL) has become a focal point across various academic disciplines due to its capacity to straightly remove important features from training data. DL is currently seen as a promising technology to categorize and detect images and videos. DL algorithms use advanced methods, not limited to data processing and abstraction construction, to enhance performance. In molecular biology, machine learning is widely utilized in uncovering complex relations inside data and generating new insights biologically. Moreover, the continuous widening of molecular biology data needs more powerful DL models to expose deeper insights. DL techniques that are frequently used comprise CNN (Convolutional Neural Networks), LSTM (Long Short-Term Memory), Bi-LSTM (Bi-directional Long Short-Term Memory), DNN (Deep Neural Networks), RNN (Recurrent Neural Networks), and various others [8,9].

This research presents an innovative method for automating DR detection by utilizing Transfer Learning with the MobileNetV2 architecture, resulting in an excellent equilibrium among accuracy and key metrics such as AUC, Precision, Recall, F1-score, Sensitivity, and Specificity. While much of the current literature on DR detection primarily emphasizes model accuracy, other significant evaluation metrics that assess the practical applicability of models in clinical environments, including sensitivity and specificity, are frequently overlooked. This research addresses the existing gap by not only achieving high accuracy overall but also performing exceptionally well in comprehensive metrics, demonstrating the model's ability to distinguish between DR and non-DR cases. Furthermore, this study is motivated by our team's participation in outreach programs centered on general eye health. These initiatives underscored the urgent requirement for cost-effective, precise, and applicable screening methods, especially in areas with scarce ophthalmologists and resources. This study promotes a scalable solution for eye health screening by creating and evaluating a DL model capable of autonomously identifying DR, which has the potential to ease the burden on healthcare systems and enhance access for marginalized populations.

Materials And Methods

The methodology applied in this paper starts with the pre-processing of the dataset in terms of transformations such as resizing, horizontal and vertical flipping, and normalization. This step ensures that the model is invariant to changes in orientation and the scale of pixel values is correct. A transfer learning methodology was utilized, capitalizing on the pre-trained MobileNetV2 architecture. This model underwent fine-tuning for the purposes of binary classification (DR versus No DR) by substituting the classifier layer with a fully connected layer tailored to our dataset [10]. To address the class imbalance in the dataset, transformation was applied to increase the variety of training samples. The training process used an adaptive learning rate scheduler, specifically the function (ReduceLROnPlateau), which dynamically adjust the learning rate based on validation loss, ensuring stable convergence [11].

The model was trained on GPU using the cross-entropy loss function and was optimized using the Adam optimizer. Metrics like accuracy, training loss, and validation loss were monitored and saved at all points during training. Evaluation included confusion matrices, classification reports, and the training curves to note the accuracy as well as loss of the model for epochs.

Dataset preparation

The dataset comprises an extensive assemblage of high-resolution retinal images captured under different imaging conditions.

Each image has undergone the medical professional's evaluation to establish the presence of DR. After the evaluation, the rating has been assigned by using a scale that measures from 0 to 1, which in turn corresponds to the following categories: 0 represents the presence of DR and 1 representing No DR [10]. In diabetic retinopathy detection research, the dataset is essential to training models to recognize patterns across different disease stages. The dataset was divided into training, validation, and test sets. The training set was used for model training, the validation set for hyperparameter tuning, and the test set for final evaluation. Preprocessing and data augmentation were also applied [12]. Raw images were preprocessed to be square, with an input dimension of 224×224 pixels. Besides that, the pixel values were normalized. Other forms of image augmentation have been applied. Normalization scales pixel values from the domain (0, 255) to (0, 1) and also uses mean and standard deviation as used in the super-popular models such as ImageNet. This method ensures faster convergence of models and also enhances its generalization feature [13].

Data Pre-processing

Data exploration: We started by looking at the images to get a better understanding of them. We utilized a tool called Matplotlib to display some sample images and check their size, color, and overall quality. This helped us figure out how we needed to prepare the images for our model, such as resizing them or adjusting their colors.

Image resizing: To ensure consistent input and improve processing efficiency, all images were resized to 128× 128 pixels. This standardization facilitated efficient training and memory utilization.

Data normalization: We gave the images a brightness makeover by scaling their pixel values. This helped the model learn more efficiently and avoid getting confused by images with very different brightness levels.

Label encoding: To ensure compatibility of the DR stages with the model, we transformed them into numerical labels, this conversion enables the model to accurately process the classes.

Data augmentation: To improve the model's capacity to generalize to new data, we implemented data augmentation techniques. By adding variations such as rotation, flip, and zoom effects to the training data, we successfully broadened the diversity of the dataset, this tactic assists the model in learning more resilient features and lessens its likelihood of overfitting.

Data splitting: To make sure our model was accurate, we split the data into three parts, training, validation, and testing. We used the training data to teach the model, the validation data to fine-tune it, and the test data to see how well it worked on new, unseen data.

Augmentation: Many kinds of data augmentations were used to reduce overfit and increase robustness of the model, including random horizontal and vertical flips, rotations, and changes to the brightness at random. This helps to increase diversity in the training dataset, which, in turn, helps the model to acquire more invariant characteristics. Explanatory techniques are often used within the analysis of medical imagery to enhance generalization and to reduce the chance of overfitting.

Transfer learning MobileNetV2

Base Model

The MobileNetV2 architecture was considered as the base model for transfer learning. This model is widely used in medical image analysis due to its efficiency in performance and computational resources, particularly in constrained environments. MobileNetV2 pre-trained on its convolutional layers were retained to leverage learned feature representations (Figure *1*).

Custom Layers

After loading the pre-trained MobileNetV2 model, the last classification layers were removed and replaced with custom fully connected layers specific to DR classification (binary or multi-class based on the task). This allows the model to fine-tune on medical image-specific features.

Freezing and Fine-Tuning

Initially, the pre-trained layers of MobileNetV2 were frozen during training time with the ability for only custom layers to be trained. In achieving a stable training process, the entire model was then released and was fine-tuned. Fine-tuning lets the model have the layers adjusted and well-fit to its new dataset.

Transfer learning is highly effective for medical imaging tasks where annotated data are limited but large pre-trained models are available. This technique has been proven in research to significantly reduce training time and improve model accuracy [14].

Model training and optimization

This study used the objective function that is the ls-entropy loss. Indeed, DR detection happens to be a classification problem. To classify between different classes, it commonly needs a cross-entropy loss function, letting the model minimize the difference between the probabilities calculated and the real class labels [15].

Optimizer

The Adam optimizer was selected due to its effectiveness in training DL models, especially in the context of extensive datasets. Adam integrates the beneficial aspects of both Adagrad and RMSProp optimizers.

Learning Rate Scheduler

A learning rate scheduler, ReduceLROnPlateau, is used to reduce the learning rate if the validation loss plateaus. This ensures that the model converges smoothly without large oscillations in the loss function [16].

The combination of Adam with learning rate scheduling is known as an effective approach for achieving

faster convergence while maintaining stability.

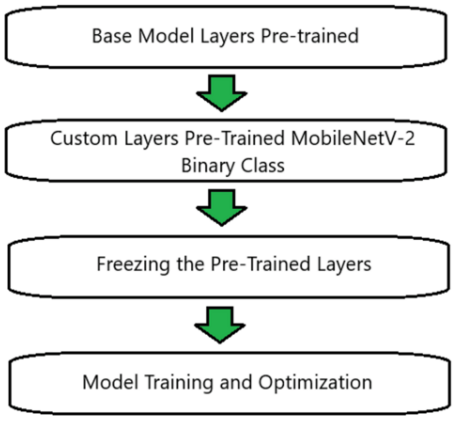

FIGURE 1: Training flowchart

Evaluation metrics

Confusion Matrix and Classification Report

The model's effectiveness was assessed regarding the three phases of diabetic retinopathy following the training process, utilizing a confusion matrix and a classification report. These metrics are valuable for illustrating the model's sensitivity and specificity across different categories.

Accuracy, Precision, Recall, and F1-score

Each of these metrics has been computed to evaluate how accurately the model identified the images. Accuracy reflects the overall correctness, precision indicates the number of correct positive predictions, recall assesses sensitivity, and the F1-score provides a balance between precision and recall.

These metrics are widely used in the field of medical image analysis research and gauge the performance of methods when handling imbalanced datasets.

Model saving and deployment

Model Saving

The model's state was saved after training to enable future in testing. Saving the model ensures that the trained weights can be reloaded and deployed without re-training.

Checkpointing

Additionally, model checkpointing was performed to save the best-performing model during training based on validation, ensuring the best version of the model was available.

Saving models and creating checkpoints are standard practices in machine learning experiments to facilitate reproducibility and ensure the best model is preserved.

Visualization

Training Curves

The training and validation loss curves were plotted to track the model's learning process. This is a diagnostic tool to understand if the model is underfitting, overfitting, or training effectively.

Visualizing the learning curves is a well-known practice in DL research to monitor convergence and assess whether additional regularization techniques are required.

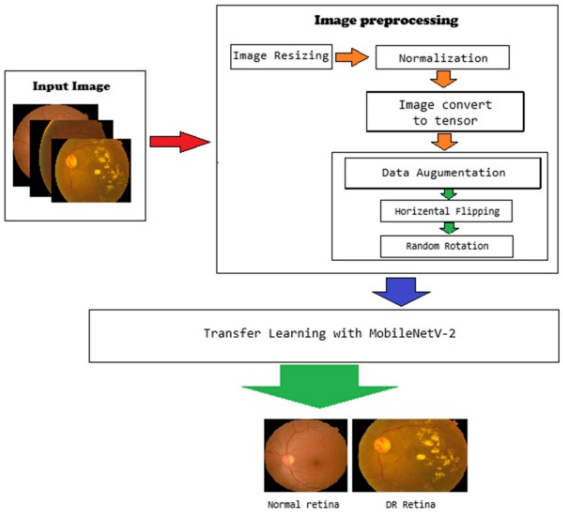

FIGURE 2: Proposed model architecture

Results

Classification report

Precision

The model's ability to correctly identify positive instances (DR; Figure *2*). It scored 0.98 for detecting DR and 0.97 for No_DR, indicating that the model rarely makes false positive predictions (Table *1*).

Recall

The model's ability to find all relevant cases. It achieved 0.96 for DR and 0.99 for No_DR, showing it can effectively detect most DR cases but is even better at identifying No_DR cases.

F1-score

A balanced measure of both precision and recall. The F1-scores are high for both classes, with 0.97 for DR and 0.98 for No_DR, showing excellent model performance.

Overall accuracy

The model achieved an accuracy of 98%, indicating highly reliable detection across both DR and No_DR classes.

Classification Report				
	Precision	Recall	F1-score	Support
DR	0.98	0.96	0.97	245
No_DR	0.97	0.99	0.98	286
Accuracy			0.98	531
Macro avg	0.98	0.97	0.98	531
Weighted avg	0.98	0.98	0.98	531

TABLE 1: Classification report

Confusion Matrix

In Figure 3, confusion matrix shows that the model correctly predicted:

236 out of 245 cases of DR (with 9 false negatives).

282 out of 286 cases of No_DR (with 4 false positives).

This further confirms that the model performs slightly better at detecting No_DR cases but is overall very accurate.

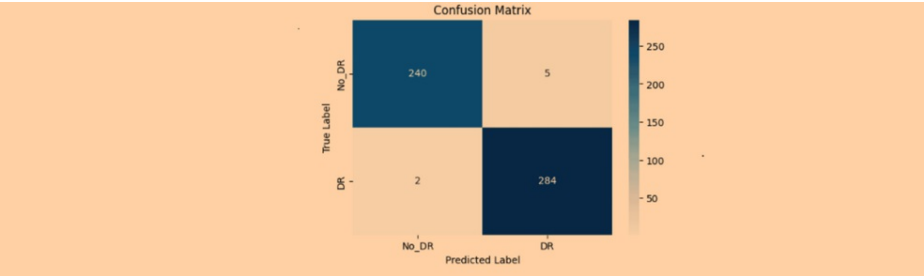

FIGURE 3: Confusion matrix

ROC and Precision-Recall Curves

ROC curve: The ROC curve in Figure 4 has an AUC of 0.9979, which is almost perfect. This means the model can distinguish between DR and No_DR cases with excellent performance.

Precision-Recall curve: In Figure 4, the curve shows that the model maintains a very high precision across all levels of recall, which aligns with the strong performance seen in the classification report.

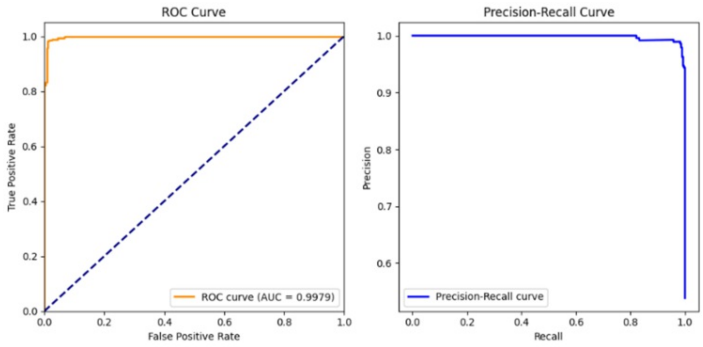

FIGURE 4: ROC and Precision-Recall curves

Validation Accuracy Over Epochs

The model's validation accuracy in Figure 5 consistently improved over 30 epochs, fluctuating around 98%, showing stable learning without signs of overfitting.

The final accuracy in Figure 5 is slightly over 98%, suggesting that the model has learned the patterns well and generalizes effectively to unseen data.

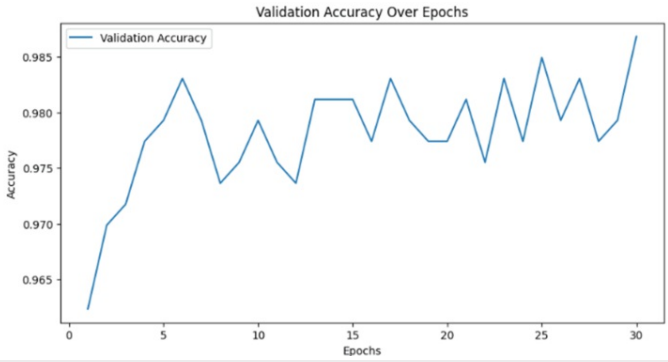

FIGURE 5: Validation accuracy over epoch

Discussion

The work in this thesis has been based on the hypothesis of using MobileNetV2 in transfer learning for the detection of DR, motivated by our extensive experience in outreach programs focused on general eye health, especially in underserved and rural populations [17]. In these communities, we witnessed the difficulties resulting from the absence of prompt and specialized eye care, leaving many individuals vulnerable to the unnoticed advancement of DR. Early identification is vital to prevent blindness, given that DR is the foremost cause of vision impairment among diabetic populations globally. Regrettably, inadequate healthcare infrastructure and a lack of ophthalmologists in these regions frequently obstruct regular eye examinations. This situation underscores the necessity for accessible, affordable, and precise solutions for detecting DR that can reach patients in marginalized areas. Furthermore, this study specifically tackles the shortage of accessible and scalable DR screening tools adapted for low-resource environments. The research enhances existing literature by illustrating that the lightweight structure of MobileNetV2 is particularly effective for DR detection, requiring far fewer computational resources than are generally needed for DL models. This finding supports the implementation of MobileNetV2 in community healthcare programs, where its efficient, automated classification can significantly lessen the demands on limited medical personnel and resources.

To address practical implementation, this research builds upon earlier findings while distinguishing itself by confirming the effectiveness of MobileNetV2 in conditions that closely resemble real-world applications in low-resource contexts. The results indicate that, with adequate training, MobileNetV2 could be incorporated into mobile health units and local clinics, serving as a groundbreaking solution for early DR diagnosis and potentially curtailing the advancement of DR-related blindness in diabetic individuals.

Key objectives

Automation in Screening

The major objective of this research was in attempting to provide a clinician with an automated tool capable of screening DR with high accuracy while using minimal resources to ease the burden on healthcare systems [18], DL model was deployed to bridge the gap in inequality between the underserved community and specialized eye care, enabling timely diagnosis and further treatment [19]. The model must be scalable for regions, languages, and other environmental conditions so that it can provide flexible and fast integration within existing health workflows.

Key observations

Performance of Transfer Learning

We applied MobileNetV2, which allowed us to leverage the pre-trained features. This greatly reduces training time and generalizes well to our relatively small number of images in the dataset.

Differentiating DR from No-DR

The model performance was strongly capable of distinguishing between DR and No-DR images-the accuracy of classification was comparable. The main challenge was detecting the subtle signs arising in the early stages of DR, where the changes are less evident.

Data Augmentation and Normalization

Methods followed in data augmentation include random flips, rotations, and normalizing to prevent

overfitting and improve generalization across diverse images [20].

Challenges and drawbacks

Small Size of Dataset

Despite augmentation, the dataset remained substantially small to train a high-capacity model like MobileNetV2. More data, sourced from a variety of sources regarding ethnicities and image qualities, are required for better generalization.

Computational Constraints

Training on GPUs imposed limits on batch size but mainly model architecture selection, especially when it came to training larger models such as EfficientNetB7.

Class Distribution Imbalance

DR stages are unequally distributed in the dataset since some stages of this particular disease happen to be underrepresented. This made it hard to fine-tune the model for accurate detection at the intermediate stages of DR.

Overcoming challenges

Better Data Acquisition

Outreach programs shall be conducted henceforth to gather more representative and balanced data, such that all DR stages are well represented, and chosen images are representative of different conditions related to lighting and resolution.

Model Optimization

Resorting to smaller yet powerful networks like MobileNetV2 was another key step to strike the right balance between performance and computational cost. Pruning and quantization in future iterations would definitely support deployment on mobile devices and edge computing hardware.

Conclusions

This research successfully established and tested a model for the detection of diabetic retinopathy using MobileNetV2, which was deployed on the Diagnosis of Diabetic Retinopathy dataset. The model performed highly well on all crucial parameters used to evaluate metrics that included, precision, accuracy F1-score and recall, thus suggesting its potential effectiveness in detecting DR. These findings suggest that this model may be of great value in the clinical environment, particularly regarding the early identification of people at risk of vision loss. However, there are some well-known weaknesses such as susceptibility to overfitting and limited diversity in the given dataset. These are reasons why further development is needed; part of which is creating more diversified datasets and seeking external validations.

Future work could concentrate on refining the model-for instance, by the introduction of regularizing techniques for reducing overfitting and validation of the developed approach on larger, real-world populations. The study of applications on mobile platforms may further expand the applicability of the model, especially in less developed areas where healthcare infrastructures are minimal. Although these limitations are apparent, the results provide a good starting point for further AI diagnostic tool design work focused on DR, basis for improved patient outcomes and higher machine learning integration in healthcare. This work shows how extraordinary it is for artificial intelligence to improve both the accuracy and the effectiveness of medical imaging diagnostics.

Additional Information

Author Contributions

All authors have reviewed the final version to be published and agreed to be accountable for all aspects of the work.

Concept and design: Aminu G. Sabo, Swati Sah

Acquisition, analysis, or interpretation of data: Aminu G. Sabo, Swati Sah, Muhammadul Habib Bn Umar, Muttaka I. Yahaya

Drafting of the manuscript: Aminu G. Sabo, Swati Sah, Muhammadul Habib Bn Umar, Muttaka I. Yahaya

Critical review of the manuscript for important intellectual content: Aminu G. Sabo, Swati Sah, Muhammadul Habib Bn Umar, Muttaka I. Yahaya

Supervision: Aminu G. Sabo, Swati Sah

Disclosures

Human subjects: All authors have confirmed that this study did not involve human participants or tissue. **Animal subjects:** All authors have confirmed that this study did not involve animal subjects or tissue. **Conflicts of interest:** In compliance with the ICMJE uniform disclosure form, all authors declare the following: **Payment/services info:** All authors have declared that no financial support was received from any organization for the submitted work. **Financial relationships:** All authors have declared that they have no financial relationships at present or within the previous three years with any organizations that might have an interest in the submitted work. **Other relationships:** All authors have declared that there are no other relationships or activities that could appear to have influenced the submitted work.

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