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Deep Learning Based Identification and Classification of Diabetic Retinopathy

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Abstract

A major factor contributing to blindness in diabetic people is diabetic retinopathy (DR). Early detection and classification are crucial for preventing vision loss. This study investigates the efficacy of deep learning models for identifying and classifying DR in retinal images. We deployed 9 different pre-trained models and one developed CNN model. The pre-trained models include ResNet 18,ResNet 50, DenseNet 121, DenseNet 169,, DenseNet 201, EfficientNet B5, MobileNetV2, InceptionV3, and Xception and CNN model was developed with 64,32 dense layers for binary classification differentiating DR and those without (non-DR). The models are trained and validated, evaluated on a retinal image dataset labelled for DR presence. The study analyses the accuracy of both the training, validation, and test datasets for each model in identifying DR. Notably, MobileNetV2 achieved the highest accuracy, outperforming the remaining models with an accuracy of 98 percent on test dataset.

Keywords: *Accuracy; Binary Classification; Convolutional Neural Networks (CNN'S); Diabetic Retinopathy; Deep Learning; MobileNetV2.*

1. Introduction

Diabetic retinopathy (DR) stands as a significant complication for individuals with diabetes, posing a substantial risk to vision. When diabetes mellitus persists for an extended period, it damages the blood vessels in the retina. This damage weakens the vessels over time, leading to leakage, swelling, and the development of aberrant blood vessels. The importance of early detection and precise classification of DR severity levels cannot be overstated, as they are pivotal for timely intervention and preventative care [1]. Diabetic retinopathy is classified into two main types: Proliferative DR (PDR) and Non-Proliferative DR (NPDR) based on various phases of the disease's evolution. NPDR, an early stage, is characterized by damage to blood vessels, including the formation of microaneurysms and vessel blockages, affecting the retina's blood supply. NPDR severity is graded as mild, moderate, or severe based on observed vascular abnormalities during eye examinations. On the other hand, PDR represents an advanced stage, marked by the abnormal growth of new blood vessels (neovascularization) on the retina's surface or optic nerve head. The detrimental effects of PDR emphasize the urgency of effective intervention and management. This study focuses on leveraging the transformative capabilities of deep learning, particularly convolutional neural networks (CNNs) architecture, Specifically, it explores the application of deep learning methodologies for the identification and classification of diabetic retinopathy [2]. The study's innovative approach involves preprocessing retinal images using various techniques to enhance the effectiveness of deep learning algorithms [3]. By addressing gaps in current diagnostic methods, this research aims to contribute to the enhancement of early detection and classification of diabetic retinopathy into DR or No_DR. The subsequent sections will delve into the specific methodologies employed and the potential impact of utilizing deep

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learning in medical image analysis for diabetic retinopathy diagnosis [4].

1.1 Literature Review

1. Ayesha Mehboob [5] presented three deep learning frameworks for automated diabetic retinopathy (DR) grading, utilizing large fundus image datasets. These frameworks, employing convolutional neural networks (CNNs) for feature extraction and classification, achieved an impressive accuracy of 83.78%, surpassing baseline models like VGG16 and ResNet-50.
2. Ms. Madhuri V. Kakade [6] proposed a machine learning system encompassing image pre-processing to classification, employing a pre-trained deep neural network model for enhanced detection accuracy and feature extraction. With a total accuracy of 96.66%, this model's simplicity, high recognition rate, and speed make it well-suited for deployment in healthcare.
3. Jaafar et al. [7] introduced an automated algorithm utilizing top-down segmentation and a polar coordinate system to grade hard exudates' severity. Despite a small dataset of 236 fundus images, the algorithm achieved a notable sensitivity of 93.2%.
4. In Osareh et al.'s study [8], a fuzzy C-means clustering segmented color retinal images, and an artificial neural network classifier achieved a sensitivity of 93.0% in classifying regions into exudates and no exudates.
5. Asha Gowda Karegowda [9] improved the performance of the Backpropagation neural network classifier for exudate detection by identifying significant features through Decision tree and GA-CFS methods, achieving a sensitivity of 96.97%, specificity of 100%, and an accuracy of 98.45%.

1.2 Proposed System

The Proposed System (Figure 1) results in Early detection of DR with High accuracy and sensitivity of Classification based on DR stages using deep learning [10]. The proposed system offers several advantages, including automation of the DR diagnosis process, improved efficiency, and potentially higher accuracy compared to traditional manual methods. By harnessing the power of deep learning and image preprocessing techniques, our system contributes to advancing the field of diabetic retinopathy diagnosis and holds promise for enhancing patient care and outcomes.

2. Method

The proposed methodology aims to develop an automated classification system for diabetic retinopathy severity levels using deep learning techniques [11]. Initially, the system preprocesses the Diabetic Retinopathy dataset obtained from Kaggle, utilizing data augmentation methods to augment the dataset and improve model generalization. The dataset is then divided into training, validation, and testing sets to facilitate model development and evaluation. We used different pre trained deep learning models on dataset such as Resnet, Densenet, Xecption, Moblenetv2, Inceptionv3, EfficintNet B5model and custom CNN model with 64,32 filters in convolutional layers on gaussian filtered images 224x224 [12].

2.1 Dataset Description

The Diabetc Retinopathy dataset, sourced from Kaggle and is titled " Diabetic Retinopathy 224x224 Gaussian Filtered" [13]. This dataset consists of 3,662 retinal images divided into 5 folders, each representing different severity stages of the disease.

- "No_DR" containing 1805 images.
- "Mild" containing 370 images.
- "Moderate" containing 999 images.
- "Severe" containing 193 images.
- "Proliferative_DR" containing 295 images.

The dataset includes a CSV file with two attributes: "id_code" for unique image IDs, and "diagnosis" indicating the severity of diabetic retinopathy on a scale from 0 to 4:0 denotes "No_DR",1 denotes "Mild",2 denotes "Moderate",3 denotes "Severe",4 denotes "Proliferative_DR". We merged Mild , Moderate and severe, Proliferative_DR in to DR class for binary classification.

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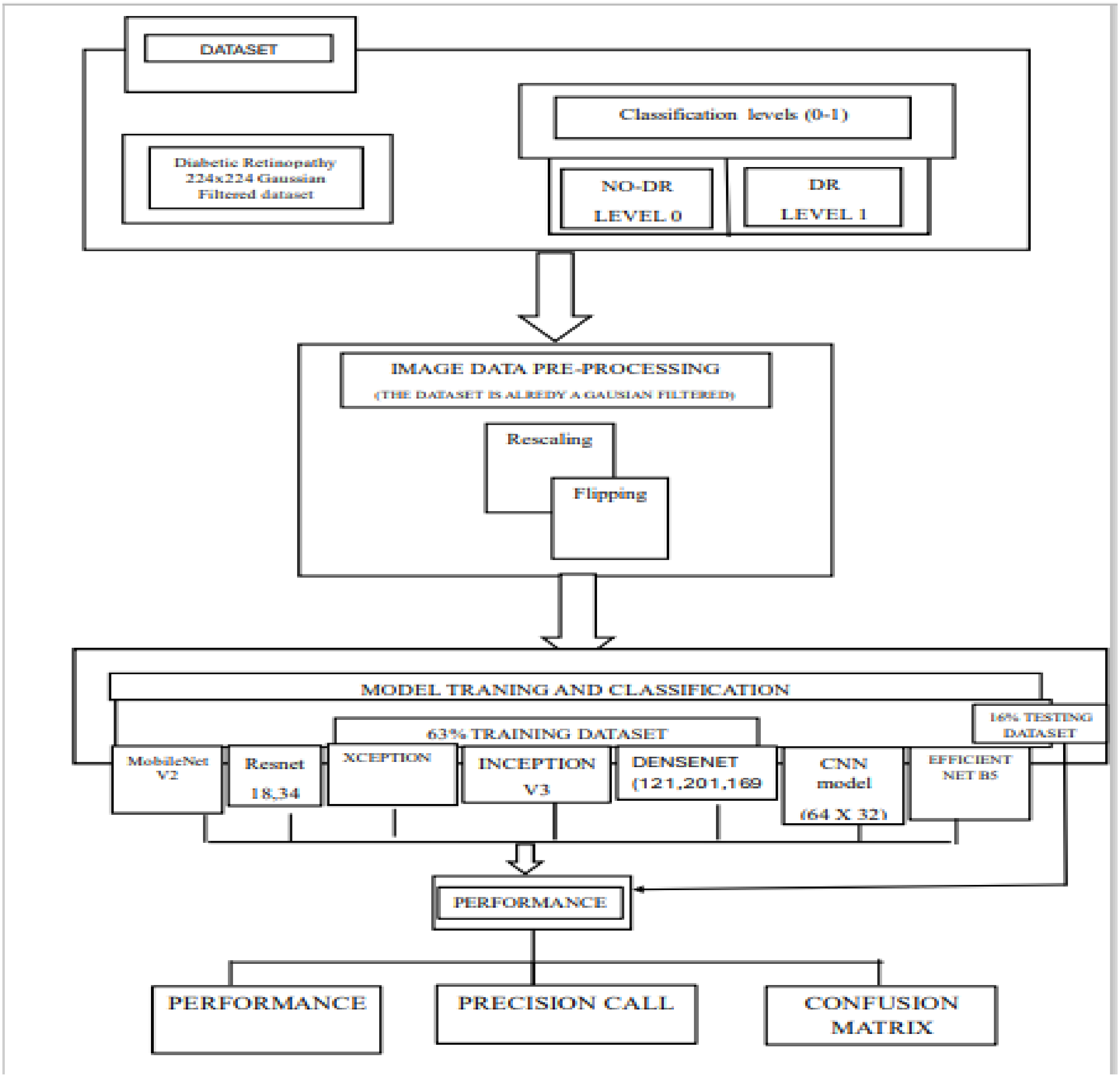

Figure 1 Proposed System

2.2 Preprocessing

We applied a 1/255 rescaling to every image [14]. The image pixel values fall into the interval [0, 1]. Random displacements were applied up to 10% in both directions and rotations of up to 10 degrees are performed to train data. Object forms are changed by shearing transformations, with a maximum shear of 10%. Zooming procedures are available with up to a 10% magnification or decrease. Finally, horizontal flipping involves mirroring the photos horizontally for training data [15]. All datasets (training, validation, and testing) have their photos resized to (224, 224) as a common size. Here we merged the

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classes of Mild, Moderate and severe, Proliferative in to DR class (Figure 2) and remaining class No_DR (Figure 3) is categorized into No-_DR. Further dataset is divided into training, validation with and testing.

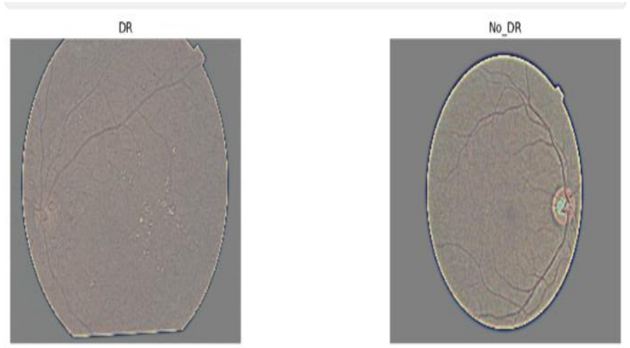

Figure 2 The Above Image Shows Two Different Classes of Dr Before Preprocessing

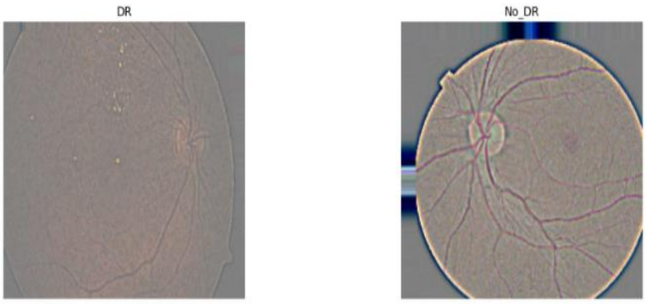

Figure 3 The Above Image Shows Two Different Classes of Dr Images After Preprocessing Techniques Were Applied

2.3 Deploying Deep Learning Models

We deployed 9 different pre-trained on ImageNet dataset and one developed CNN model. The pre-trained models include ResNet 18,ResNet 50, DenseNet 121, DenseNet 169, DenseNet 201, EfficientNet B5, MobileNetV2, InceptionV3, and Xception are utilized and CNN model was developed with 64,32 dense layers. We used transfer learning to apply these pre-trained models for DR categorization [16]. the pre-trained model's weights were first loaded. We next added classification layers to the pre-trained base models to fine-tune the models and prevent overfitting. A global average pooling layer and dense layers for classification were added to the final layers of the pre-trained models in each instance. Rectified linear unit (ReLU) activation functions were used after the dense layers. Dropout regularization was used to reduce the possibility of overfitting during training phase. The last layer is composed of a dense layer with two units and a SoftMax activation function [17]. During training, the model's parameters are optimized using the Adam optimizer, which has a learning rate of 1e-5 and loss function, BinaryCrossentropy is used. Accuracy is the metric that is used to track the model's performance throughout the process. The models were trained and validated on epochs of 15 (epochs=15) for better learning and performance. The highest training accuracies of each model were measured on highest epoch accuracy of validation set. Which helps to identify the best accurate model for DR classification [18]. The accuracies result of 10 deep learning models were shown on Table 1.

Table 1 Train, Test, Validation Sets Accuracies Of 10 DL Models

Deep Learning Models	Training Accuracy	Validation Accuracy	Test Accuracy
CNN 64 X 32	84.3	87.9	88.0
RESNET 18	93.30	67.8	51.0
RESNET 50	57.8	88.4	87.0
DENSENET 169	90.0	88.9	91.0
DENSENET 121	88.1	89.0	86.0
DENSENET 201	90.0	90.8	92.0
XCEPTION	94.8	97.0	96.0
MOBILENET V2	96.2	95.7	98.0
INCEPTION V3	94.3	94.9	94.0
EFFICIENT NET B5	62.0	81.8	82.0

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Table 2 Top 5 Models on Test Accuracy Percentage

Deep Learning Models	Train Accuracy	Validation Accuracy	Test Accuracy
MOBILENET V2	96.2	95.7	98.0
XCEPTION	94.8	97.0	96.0
INCEPTION V3	94.3	94.9	94.0
DENSENET 201	90.0	90.8	92.0
DENSENET 169	90.0	88.9	91.0

3. Results

Based on test accuracy results of 10 DL models. After preprocessing the training set images and the models from Table 2 showed better results on training and Validation set, Test set. MobileNetV2 shows significant high results with taring accuracy=96.2 % and validation accuracy=95.7 and test accuracy=98.0% on 15 epochs for Binary classification of DR into DR or Non_DR here model was selected based on Test accuracy.

Conclusion

Based on the test accuracy results of 10 deep learning models, it is evident that the MobileNetV2 exhibited significant improvements in performance [19]. MobileNetV2 achieved a training accuracy of 96.2%, validation accuracy of 95.7%, and an outstanding test accuracy of 98.0% on 15 epochs for the binary classification of diabetic retinopathy (DR) into DR or non-DR categories. These results highlight the efficacy of MobileNetV2 in accurately identifying and classifying DR in retinal images. Therefore, based on the test accuracy metric. In conclusion, the findings of this study underscore the potential of deep learning models, particularly MobileNetV2, in enhancing the early detection and classification of diabetic retinopathy, thus contributing to the advancement of diagnostic methodologies for this critical diabetic complication. Further research can be done in classification of DR in to multi classification Mild,Severe,Moderate.

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