



e-ISSN: 2319-8753 | p-ISSN: 2347-6710

IJRSET

International Journal of Innovative Research in
SCIENCE | ENGINEERING | TECHNOLOGY

INTERNATIONAL JOURNAL OF INNOVATIVE RESEARCH

IN SCIENCE | ENGINEERING | TECHNOLOGY

Volume 13, Issue 5, May 2024

ISSN INTERNATIONAL
STANDARD
SERIAL
NUMBER
INDIA

Impact Factor: 8.423

9940 572 462

6381 907 438

ijirset@gmail.com

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Diabetic Retinopathy Detection using Efficient Net

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ABSTRACT: The term Diabetic Retinopathy (DR) is used to describe the damage to blood vessels in the eye's retina. Blurriness, difficulty in vision, and possibly blindness are some of the symptoms associated with DR. Over time, the blood vessels in the eye's retina have been damaged, affecting the ability to see. In the contemporary world, this is a cumulative problem. There are five stages of diabetic retinopathy, including no diabetic retinopathy, mild, moderate, severe, and proliferative diabetic retinopathy. Early diagnosis is essential to lessen the complications of diabetic retinopathy. Thus, it is possible to identify the early stages of diabetic retinopathy with the use of artificial intelligence and image processing. The EfficientNetB1 model was utilized. For both patients and ophthalmologists, this results in quicker and simpler disorder screening.

KEYWORDS: Artificial Intelligence, Diabetic retinopathy detection, Earlier Prediction, EfficientNet.

I. INTRODUCTION

Diabetic retinopathy (DR) is a major global cause of vision impairment and blindness, making it a difficult problem in the fields of ophthalmology and public health. This disorder, which develops as a consequence of diabetes mellitus, has a severe negative impact on those who have it, decreasing their quality of life and adding a heavy load to healthcare systems across the world. The defining feature of diabetic retinopathy is the gradual destruction of the retina's fragile blood vessels, which, if ignored, can eventually result in blindness. The need to address diabetic retinopathy identification and management is becoming more and more urgent as the incidence of diabetes rises, especially in light of rising rates of obesity and sedentary lifestyles.

The emergence of deep learning, a kind of machine learning that uses multi-layered neural networks, has opened up new avenues for the identification of diabetic retinopathy. Driven by massive volumes of annotated retinal pictures, deep learning algorithms have shown to be extraordinarily adept at identifying subtle indicators of diabetic retinopathy and assessing the severity of the condition with previously unheard-of precision. One prominent competitor among the several deep learning architectures suggested for DR detection is the EfficientNetB1 model, which is well-known for its efficacy and efficiency in managing image classification tasks.

The current major project aims to contribute to the developing field of AI-driven diabetic retinopathy detection against this backdrop of innovation and technical improvement. Through the use of complementary image processing techniques and the EfficientNetB1 model, our study aims to establish a scalable and reliable system for the early diagnosis of diabetic retinopathy. We hope to develop a tool that will not only improve diagnostic accuracy but also make DR screening more accessible and affordable, especially in places with limited resources, by utilizing the advantages of deep learning and the abundance of data available from retinal imaging investigations.

By working together, we hope to make a significant contribution to the corpus of knowledge about the identification of diabetic retinopathy, opening the door to better patient outcomes and more effective healthcare delivery. We are unwavering in our resolve to use artificial intelligence (AI) to improve global eye health and stop vision loss from diabetic retinopathy as we set out on this voyage of research and discovery.

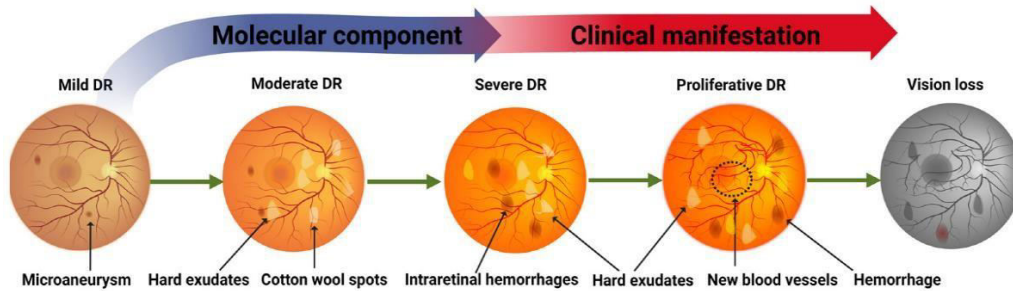


Fig. 1. Stages of Diabetic Retinopathy (Source: <https://www.mdpi.com/1422-0067/24/5/4408>)

II. EXISTING AND PROPOSED SYSTEM

In the existing model, the training image items are the system's primary focus. To distinguish the objects in the foreground from the background, methods similar to picture segmentation are probably employed. This aids the model in focusing on the key components of every picture. Next, these isolated objects are blurred using a Gaussian blur. By doing this step, the training process is less affected by minute details, allowing the model to learn from larger shapes and characteristics. Following this preprocessing phase, a deep learning model built on the ResNet50 architecture is fed the photos. A popular convolutional neural network (CNN) architecture for image recognition applications is called ResNet50. The model gains the ability to recognize patterns and characteristics that differentiate across various item categories by processing the images through this CNN. The image's lower section shows how the model's performance is evaluated by the system. For this assessment, an additional collection of pictures—referred to as testing data—is utilized. These testing images are likewise run through the ResNet50 architecture, much like the training data. Lastly, the system determines the "ground truth" by comparing the model's predictions on the testing data with the actual labels of the images. The system may compute a number of metrics based on this comparison, which indicate how well the model can identify images. All in all, this downsized image offers an insight into how a deep learning model for image classification is trained.

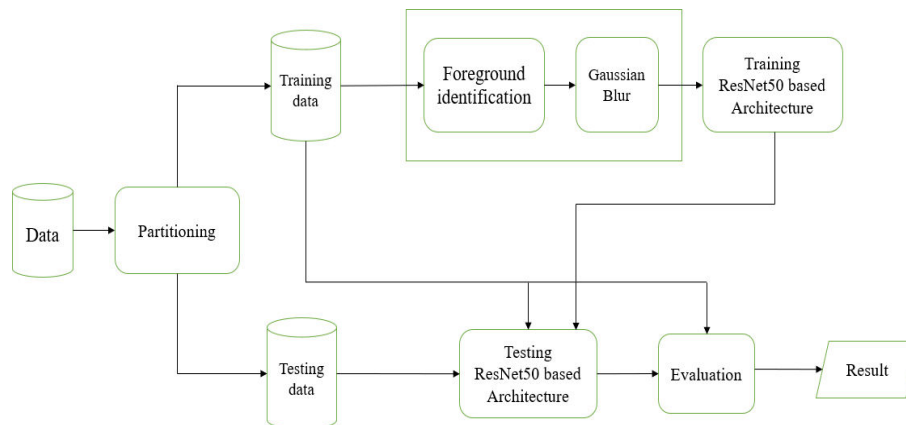


Fig. 2. Existing System

The proposed model initially, the unprocessed data used to train the model. This data may come from several sources in data mining, and it may need to be preprocessed before it can be utilized for modeling. At this stage, data preparation and cleaning take place next. To guarantee a smooth training process, this may entail resolving missing numbers, fixing formatting errors, or eliminating outliers from the data. To generate more training examples, the data is then artificially altered. Augmentation techniques include random cropping, flipping, and rotating the data. This lessens the possibility of overfitting on the initial training set of data and aids in the model's learning from a greater range of data variances. The data is utilized to train a deep learning model built on the EfficientNet architecture following preprocessing and augmentation. A class of CNN models called EfficientNet is renowned for its ability to recognize images accurately and efficiently. The model's performance during training is then visualized. These visualizations could be graphs or charts that show metrics over time, like as accuracy or loss, so that the model's development can be tracked. Lastly, a more thorough evaluation of the model's performance using untested data is conducted during the evaluation stage.

Validation data is a different set of data that is used in the evaluation process. The ground truth, or the actual labels on the data, is compared against the model's predictions based on this data. We can evaluate the model's generalizability and pinpoint any areas that require development by comparing the two.

III. DATA PREPROCESSING AND MODEL SELECTION

The dataset that was gathered has 3662 images in it. To identify diabetic retinopathy, the images are made up of retina scan images that have been Gaussian filtered. To make them compatible with a wide range of deep learning models that have already been trained, these photos have been scaled to 224 by 224 pixels. Using the 'train.csv' file, every photograph has already been saved into the appropriate folder based on the degree or stage of diabetic retinopathy. We have the corresponding images in five directories:

0 – No DR, 1 – Mild, 2 – Moderate, 3 – Severe, 4 – Proliferate DR

At the stage of preprocessing: There are multiple steps to it. The dataset is loaded by the code from a comma separated value (csv) file. The file paths to the photographs and their related labels are included in the csv file. Next, the code uses a dictionary to translate the category labels to numerical values. This mapping gives several types of eye illnesses numerical values and transforms the categorical labels into binary labels. The code makes sure that each class has an equal number of samples to address class imbalance. To create a balanced dataset, samples are either replicated or sampled at random. Using 'train test split', the preprocessed dataset is divided into training (80%), validation (10%), and test (10%) sets. The validation set is used to track training progress and stop early, the test set is used for final assessment, and the training set is used for training models. Pixel values in an image are normalized to fall between [0, 1]. Normalization promotes convergence and stabilizes the training process.

Convolutional Neural Network (CNN) architecture EfficientNetB1 is made to perform well in image classification tasks while utilizing very few computational resources and a small model size. It is a member of the EfficientNets model family. The scaling coefficient that establishes the network's depth, width, and resolution is represented by the letter "B1" in EfficientNetB1. Put more simply, it shows the size of the model, with greater coefficients denoting more complicated and larger models. Being one of the smaller members of the EfficientNet family, EfficientNetB1 is appropriate for situations where computational resources are scarce, including on mobile devices or in environments with limited resources. The model has been pre-trained on ImageNet, which entails that it has been trained on a sizable dataset of varied photos from numerous categories. With transfer learning, the model can be refined on a particular dataset or task after learning rich and generalizable features from the data during the pre-training phase. Transfer learning is the process of optimizing a previously trained model on a new dataset so that it can be used for a particular task, like segmentation, object detection, or image classification. EfficientNetB1, comparatively lightweight in comparison to other state-of-the-art models, has shown strong performance on multiple picture classification tasks. Because of this, it is a well-liked option for transfer learning tasks, where users can apply the information that the model has gained by using ImageNet to enhance performance on their own datasets at a low computational cost. All things considered, choosing EfficientNetB1 as the foundational model for transfer learning is a wise decision that strikes a balance between computational effectiveness and accuracy.

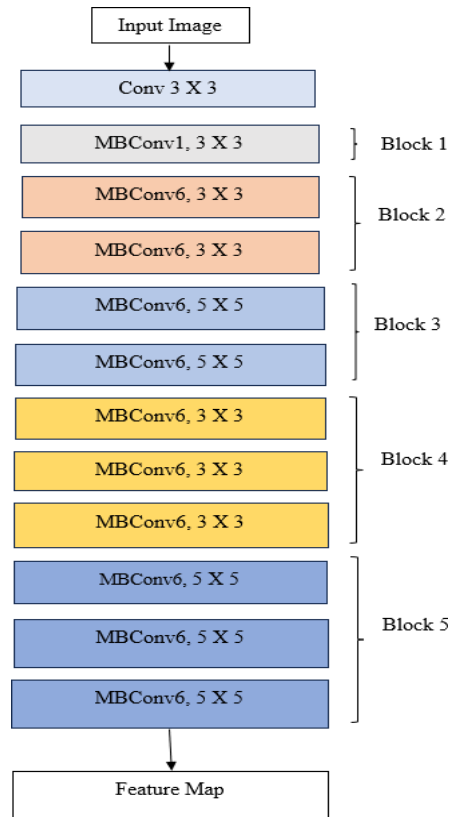


Fig. 3. EfficientNet Architecture

IV. METHODOLOGY

Sorting images into various groups using the given dataset is the main objective. The first step in the procedure is data preparation, which involves loading a CSV file with image file URLs and associated labels. To increase diversity and strengthen the model's capacity to generalize across a range of inputs, this dataset is preprocessed by balancing the classes and enhancing the photos. The model architecture is defined after the data is ready. Using its effective and potent features that were pre-trained on the ImageNet dataset, the EfficientNetB1 architecture is selected as the foundational model for transfer learning. To fine-tune and customize the underlying model for the particular classification task at hand, more layers are built on top of it. After that, the model is compiled using the proper optimizer, loss function, and evaluation metrics to facilitate training.

Using the 'train_test_split' function, the dataset is divided into training, validation, and testing sets as part of the training process. To ensure effective memory use and data augmentation during training, data generators are configured using 'ImageDataGenerator' to load and preprocess images in batches. The 'fit()' method is utilized to train the model by providing the number of epochs, callbacks, validation data, and training data. To improve the convergence and performance of the model, a custom learning rate adjustment ({LRA} callback) is created to dynamically modify the learning rate during training based on certain conditions. Using the 'evaluate()' method, the model's performance on the test set is assessed following training, yielding measures like accuracy. To examine the model's performance in classifying several categories and show its predictions, a confusion matrix is created. Plotting accuracy and loss curves over epochs is another way to examine the training history, which offers insights into the model's training progress and possible areas for improvement.

To sum up, the implementation demonstrates a solid process for creating and honing an image classification model with TensorFlow/Keras and the EfficientNetB1 architecture. The final model exhibits adaptability and scalability for a range of picture classification applications and produces reliable classification results through rigorous data preparation, model customization, and training optimization. Additional examination and adjustment could be carried out to enhance the model's functionality and tackle certain demands or difficulties in practical uses.

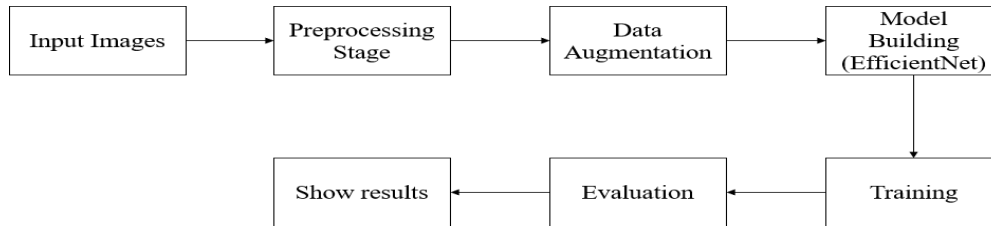


Fig. 4. Methodology diagram

V. IMPLEMENTATION

Several convolutional layers make up the EfficientNetB1 model, which uses the input images to extract hierarchical features. Advanced blocks that efficiently execute feature extraction, like MBConvBlock, come after these convolutional layers. The global max pooling layer at the base of the model reduces the feature maps' spatial dimensions.

Custom Layers: To optimize the model for your particular classification task, we put more custom layers on top of the original model.

BatchNormalization layer: At each batch, it normalizes the activations of the layer before it.

Dense layer with ReLU activation: To account for non-linearity, add a fully linked layer with a ReLU(Rectified Linear Unit) activation function.

Dropout layer: prevents overfitting by regularly setting a portion of the input units to zero during training, thereby regularizing the model.

Output Dense layer with softmax activation: generates the five classes final categorization probability.

EfficientNet model prevents the chance of overfitting, is highly scalable, often used as pre-trained model for transfer learning.

The following is a quick explanation of the steps involved in creating the diabetic retinopathy detection:

- **Input:** The input dataset is a comma separated values file containing the retinal images dataset, which has to be subjected to pre-processing.
- **Pre-processing of input data:** Input dataset is subject to various pre-processing techniques such as normalization, label encoding.
- **Splitting into training and testing dataset:** The pre-processed dataset is then split into training and testing dataset based on the specified split ratio. The split ratio considered in the proposed work is 80:20, which means 80% of the dataset is used for the training the model and the rest 20% is used as test dataset.
- **Testing the data on each of the classifiers:** The testing dataset is applied on each of the classifiers, and the individual class labels are obtained.
- **Model Construction and Evaluation:** The development of the deep learning model for image categorization is the basis of the methodology. EfficientNetB1, a convolutional neural network (CNN) model that has been pre-trained using the ImageNet dataset, serves as the foundational model. The foundation model is extended with further layers to customize it for the particular categorization assignment. For training, the model is assembled using the proper optimizer (Adamax) and loss function (categorical cross-entropy). After training is finished, the performance of the trained model is assessed using validation or test data, which is a different collection of data. Performance metrics including accuracy, precision, recall, and F1 score are computed by comparing the model's predictions with the truelabels.

VI. RESULTS

Experiments were conducted on Kaggle dataset and it has been established that EfficientNet gives the highest accuracy. The EfficientNetB1 architecture, pretrained on ImageNet, is used in the code to create an image classification pipeline. It balances classes, preprocesses image data, and enhances images for training. Additional layers are added to the model, which is then assembled and trained via dynamic learning rate scheduling. Metrics like accuracy are computed after the model has been trained on a test set. The outcomes shed light on the model's functionality and possible areas for

development. All things considered, the pipeline demonstrates how effective and efficient EfficientNetB1 is for image classification jobs.

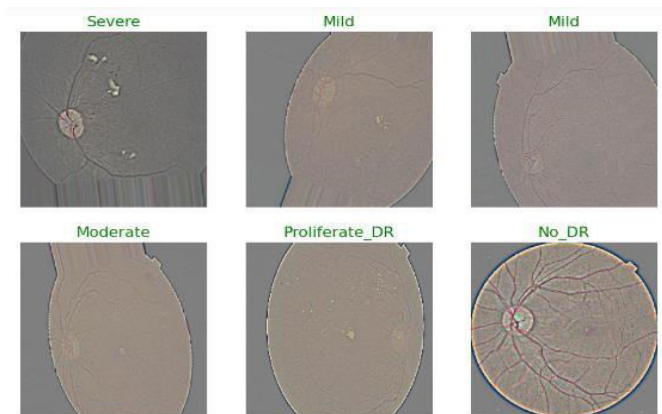


Fig. 5. Sample Images

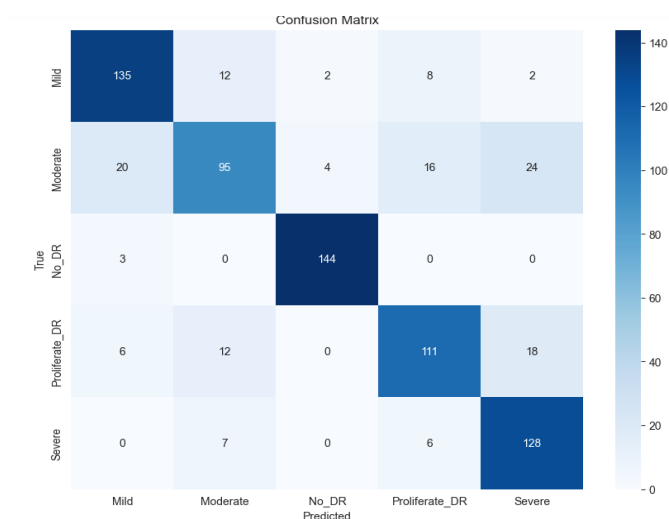
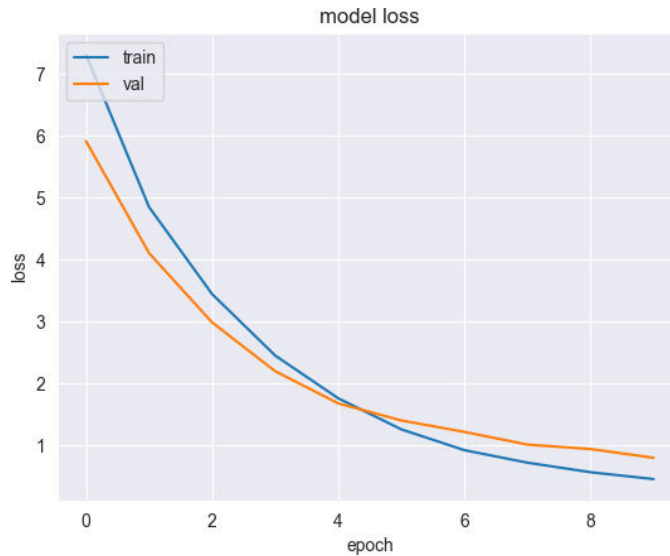


Fig. 6. Confusion Matrix

Classification Report:

	precision	recall	f1-score	support
Mild	0.82	0.85	0.84	159
Moderate	0.75	0.60	0.67	159
No_DR	0.96	0.98	0.97	147
Proliferate_DR	0.79	0.76	0.77	147
Severe	0.74	0.91	0.82	141
accuracy			0.81	753
macro avg	0.81	0.82	0.81	753
weighted avg	0.81	0.81	0.81	753

Fig. 7. Classification Report

**Fig. 8.** Model Loss

VII. CONCLUSION

This experiment illustrates the viability and efficacy of diabetic retinopathy identification from retinal pictures using deep learning, specifically the EfficientNet model. Through the use of transfer learning and data augmentation approaches, we have created a strong model that can reliably categorize the severity levels of diabetic retinopathy. The model's balanced performance across several severity categories and good accuracy point to its potential for clinical use, as indicated by its performance measures. Notwithstanding, many constraints and obstacles persist, including the requirement for more extensive and varied datasets, the interpretability of the model, and validation in real-world scenarios. Notwithstanding these difficulties, the project's achievements demonstrate the promise of deep learning for enhancing patient outcomes and represent a substantial advancement in the diagnosis of diabetic retinopathy. And successfully got an accuracy of 81% as the model performance.

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