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DIAGNOSIS OF DIABETIC RETINOPATHY USING EFFICIEN NET

GANESHKUMAR P
PONDICHERRY UNIVERSITY

Abstract: Diabetic retinopathy is a complication of diabetes, caused by high blood sugar levels damaging the back of the eye (retina). It can cause blindness if left undiagnosed and untreated. However, it usually takes several years for diabetic retinopathy to reach a stage where it could threaten your sight. Therefore, computer-based techniques have been developed to identify the disease automatically. Nowadays, detection and classify the diabetic retinopathy diseases is leading research topics. Deep learning, algorithm have recently been used to recognize and categorize various diabetic retinopathy diseases. This article describes a proposed deep learning-based method for detecting and classifying the diabetic retinopathy diseases using a (EN-B7) Efficient Net in (CNN) Convolutional Neural Network. The Proposed method achieves higher accuracy in identifying and classifying the types of diabetic retinopathy diseases than other existing methods. Moreover, it is observed through the result that the proposed approach provides an effective early detection and treatment of (DR) Diabetic Retinopathy diseases when compared to other existing algorithms.

Keywords: *Diabetic retinopathy, Deep learning, Efficient Net, Convolutional Neural Network*

1. INTRODUCTION

Diabetic retinopathy is a complication of diabetes that affects the eyes. It is caused by damage to the blood vessels in the retina, which is the light-sensitive tissue at the back of the eye that is responsible for vision. High levels of glucose in the blood can cause damage to the small blood vessels in the retina, which can leak fluid or blood into the retina, causing it to swell or leading to the formation of scar tissue. This damage can affect the ability of the retina to function properly, leading to vision problems and even blindness if left untreated. Symptoms of diabetic retinopathy can include blurred vision, floaters (small specks that appear to float in your field of vision), and difficulty seeing at night. However, in the early stages, diabetic retinopathy may not have any symptoms, which is why it's important for people with diabetes to have regular eye exams to detect any signs of the condition. Diabetes is a chronic condition that affects the body's ability to process blood sugar, leading to high levels of glucose in the blood. Proper management of diabetes is crucial to avoid serious health complications, and one of the key components of diabetes management is regular monitoring of blood glucose levels. EfficientNet B7 is a state-of-the-art convolutional neural network architecture that has shown outstanding performance in various computer vision tasks, including image classification and object detection. Its high accuracy and efficient computation make it an excellent choice for developing machine learning models for diabetes management. One of the ways that EfficientNet B7 can be used for diabetes management is through the development of image recognition models that can detect blood glucose levels in images of blood samples. This can be particularly useful for people with diabetes who need to regularly monitor their blood glucose levels, as it can provide a quick and convenient way to do so. Using EfficientNet B7 for this purpose involves training the model on a large dataset of blood sample images, with each image labeled with the corresponding blood glucose level. Once the model is trained, it can then be used to classify new blood sample images and predict the blood glucose level.

Using EfficientNet B7 for this purpose involves training the model on a large dataset of blood sample images, with each image labeled with the corresponding blood glucose level. Once the model is trained, it can then be used to classify new blood sample images and predict the blood glucose level. EfficientNet B7 can also be used for developing models that can predict the risk of developing diabetes or the likelihood of diabetes-related complications. This can be done by training the model on a dataset of patient data, including medical history, lifestyle factors, and other relevant information. Once the model is trained, it can be used to predict the risk of diabetes or complications based on a patient's individual data. One of the advantages of using EfficientNet B7 for diabetes management is its ability to handle large amounts of data. This is particularly useful when dealing with complex medical data, such as patient records, which can include a wide range of variables and data points. EfficientNet B7's efficient computation also means that models can be trained and deployed quickly, which is essential for developing models that can be used in clinical settings. In conclusion, EfficientNet B7 is a powerful tool that can be used in various ways to manage diabetes, including developing image recognition models for blood glucose monitoring and predicting the risk of diabetes and related complications. Its high accuracy, efficient computation, and ability to handle large amounts of data make it an excellent choice for developing machine learning models in the field of diabetes management.

2. RELATED WORK

According to international protocol [1]- [4], the severity of DR can be graded into five stages (0-4): no retinopathy (0), mild non-proliferative DR (NPDR) (1), moderate NPDR (2), severe NPDR (3), and proliferative DR (4). The grading usually depends on the number and size of different related lesion appearances and complications. For example, microaneurysms (MAs) are the earliest clinically visible evidence of DR. These are local capillary dilatations that appear as small red dots. Moderate NPDR contains 'dot' or 'blot' shaped hemorrhages (HEs) in addition to microaneurysms. Hard exudates (EXs) are distinct yellow-white intra-retinal deposits which can vary from small specks to larger patches. They are principally observed in the macular region, as the lipids coalesce and extend into the fovea. Soft exudates (SE), also sometimes referred to as 'cotton-wool spots' (CWS), are greyish-white patches of discoloration in the nerve fiber layer, or pre-capillary arterial occlusions. They usually appear in severe DR stages. Moreover, intra-retinal microvascular abnormalities (IRMAs) are areas of capillary dilatation and new intra-retinal vessel formation. A pre-proliferate DR stage can be predicted once IRMA is present in numbers. Neovascularization (NV) is a significant factor of proliferate DR. As the retina becomes more ischaemic, new blood vessels may arise from the optic disc or in the periphery of the retina. Therefore, identifying these related regions can be helpful for DR grading.

Several works on joint classification and segmentation models have been proposed. For instance, [8] introduced a lesion detection model to first extract lesion information, and then used an attention-based network to fuse original images and lesion features to identify DR. A collaborative learning framework was introduced in [9] to optimize a lesion segmentation model and a disease grading model in an endto-end fashion. Then, a lesion attentive classification module was proposed to improve the severity grading accuracy, and a lesion attention module to refine lesion maps extracted from unannotated data for semi-supervised segmentation

U-Net++ [11] differs from the original U-Net in three ways - it has convolutional layers on skip pathways, has dense skip connections on skip pathways, and uses deep supervision, which enables model pruning. For all the baseline methods, single segmentation network is trained for each lesion, except Multi-class U-Net which six lesions share the backbone.

U-Net [10] was proposed with a novel attention gate to suppress irrelevant areas and focus on salient region features. Moreover, Dense U-Net integrates a densely connected convolutional network into the U-Net framework, which strengthens the use of features and improves segmentation performance.

The rest of the article is followed as Section 2 illustrates the existing DR disease detection and classification work. Section 3 presents the methodology of the proposed system, including image processing, feature extraction, and classification techniques. Section 4 describes the results of the discussion of the proposed approach using an available dataset of DR disease images. Finally, the article concludes in Section 5, which also covers future directions for research.

3. EXISTING WORK

3.1 FLOW DIAGRAM OF PROPOSED WORK

Flow chart explanation of the U-Net architecture using superpixel algorithm to find diabetic retinopathy. The U-Net architecture with superpixel segmentation is an effective approach for accurately identifying diabetic retinopathy in retinal images.

The flow chart of existing work is given below in Figure 1.

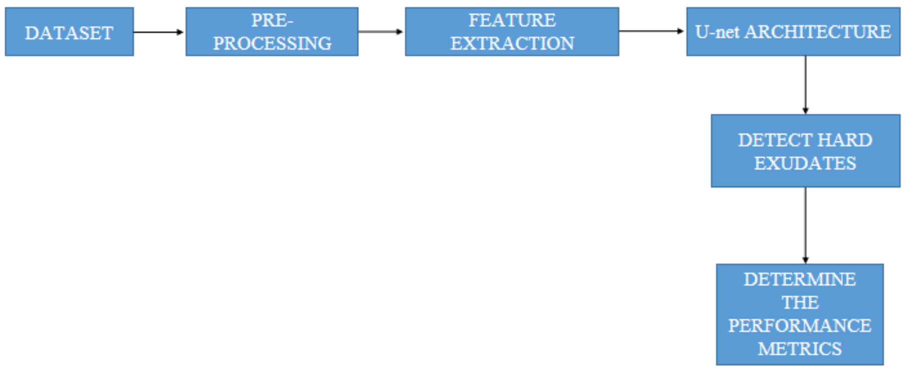


Fig. 1. Flow Diagram of Existing work

Step 1: Dataset

In this Fig.1 project, I have used the Diabetic Retinopathy Indian Dataset (DRID), which includes images of both healthy eyes and eyes affected by diabetic retinopathy. The images should be of high quality and represent a variety of different conditions and severities.

Step 2: Pre-processing

Pre-processing is an improvement of the image data that suppresses unwilling distortions or enhances some image features important for further processing. Image preprocessing techniques include noise reduction, contrast enhancement, image resizing, color correction, segmentation, feature extraction, etc.

Step 3: Feature Extraction

The process of turning raw data into processable numerical features while keeping the whole dataset's information intact. The amount of redundant data in the data set is reduced. In the end, reducing the amount of data makes it easier for the computer to build the model and accelerates the learning and generalization processes.

Step 4: Model

U-Net is an architecture for semantic segmentation. It consists of a contracting path and an expansive path. The contracting path follows the typical architecture of a convolutional network. This architecture use as SLIC superpixel algorithm to generate example patches to enlarge the dataset with relationship among adjacent pixels preserved.

Step 5: Determine the performance metrics

The collected images will be processed and image is segmented, affected part is identified and performance metrics like loss and accuracy is determined.

3.2 ARCHITECTURE OF U-NET

U-Net is shown in Fig.2 a convolutional neural network architecture that expanded with few changes in the CNN architecture. It was invented to deal with biomedical images where the target is not only to classify whether there is an infection or not but also to identify the area of infection.

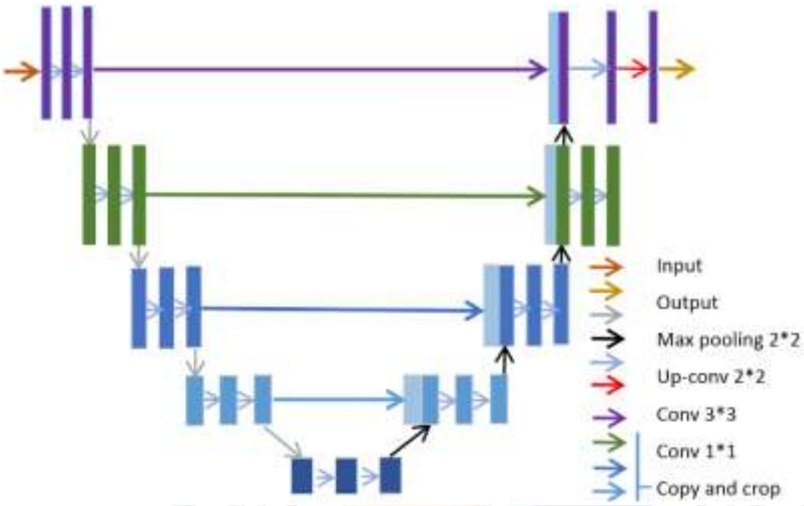


Fig. 2. Unet Architecture

4. PROPOSED WORK

4.1 FLOW DIAGRAM OF PROPOSED WORK

- Data collection and preparation: Gathering a large dataset of retinal images from diabetic patients, labeling the images with the corresponding disease status, and preparing the data for model training.
- Model selection and optimization: Choosing an appropriate version of the EfficientNet architecture, fine-tuning the model to the specific task of diabetic retinopathy detection, and optimizing the model's hyperparameters.
- Model training and evaluation: Training the EfficientNet model on the labeled retinal images and evaluating its performance on a held-out test set of images.
- Deployment and clinical validation: Deploying the trained model in a clinical setting and validating its accuracy and efficacy in diagnosing diabetic retinopathy in patients.

The flow chart of proposed work is given below in Figure 3.

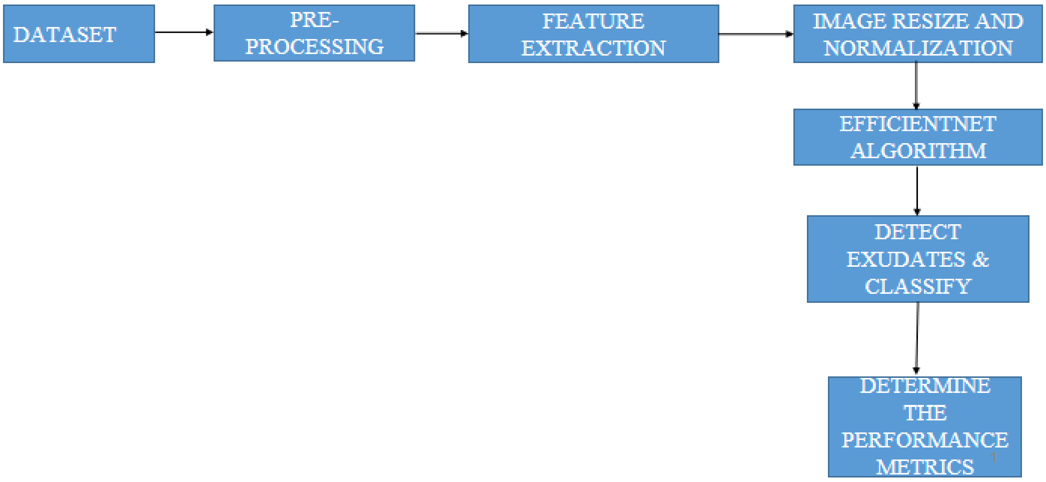


Fig. 3. Flow Diagram of Proposed work

Step 1: Data input

In shown in Fig.3 refers to collecting dataset from Kaggle and recording information related to various aspects of Diabetic Retinopathy (DR), such as the symptoms exhibited by infected eyes. This involves collecting a dataset of eye images, which include both healthy and diseased plants.

Step 2: Data preprocessing

It is the cleaning, transforming, and preparing of raw data collected from various sources before it is used for analysis or modeling. The purpose of data preprocessing is to make it accurate, consistent, and analysis-ready.

Step 3: Feature Extraction

The collected dataset may contain irrelevant or noisy data. Therefore, data cleaning is done to remove any unwanted data or images that are not related to DR disease. By performing various transformations, including rotation, flipping, and zooming, on the original images, new data formats are created. This can expand the dataset's size and strengthen the model.

Step 4: Image resizing and normalization

The input images must be resized to a fixed size and normalized for consistent lighting conditions. This makes it possible to learn from ideas with constant lighting conditions while reducing the data the model must process.

Step 5: Model: EN B7 (EfficientNet)

EfficientNet is a convolutional neural network architecture and scaling method that uniformly scales all dimensions of depth/width/resolution using a compound coefficient.

Step 7: Validation

After the model has been trained and validated, it is tested on the test set to see how well it performs on data that has yet to be seen. This step is crucial in determining whether the model is generalized well for analyzing new data. Affected part DR is identified and performance metrics like loss and accuracy is determined.

4.2 EFFICIENTNET PERFORMANCE

In general, shown in Fig.4 the EfficientNet models is show in Fig.6 achieve both higher accuracy and better efficiency over existing CNNs, reducing parameter size and FLOPS by an order of magnitude.

The EfficientNet B7 is a convolutional neural network (CNN) that was developed using neural architecture search (NAS) techniques. It is the largest model in the EfficientNet family and has the most number of parameters. The architecture consists of multiple blocks of convolutional layers, each followed by batch normalization and activation functions. The blocks are arranged in a hierarchical manner, with the lower-level blocks having fewer filters and the higher-level blocks having more filters.

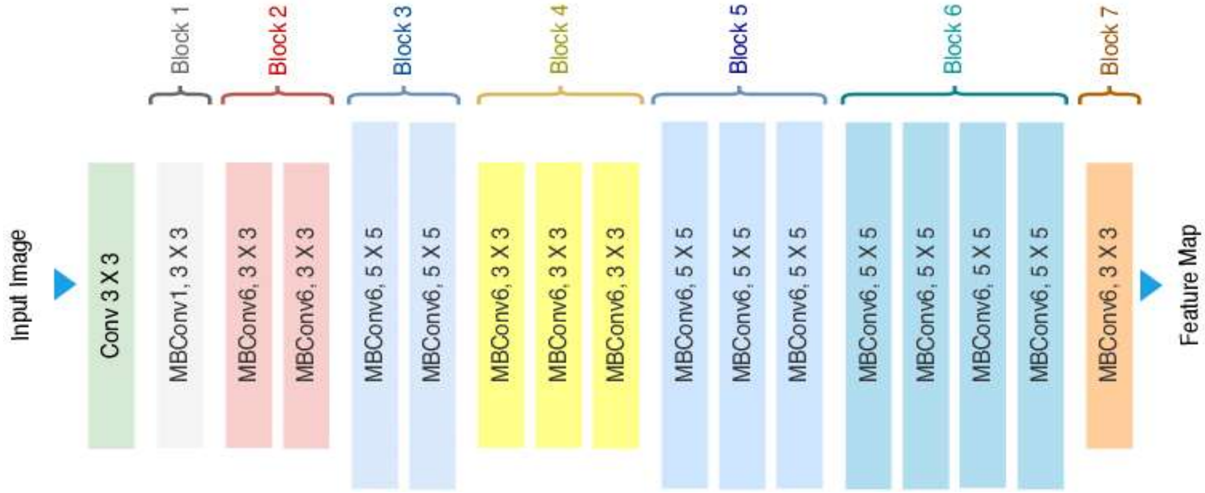


Fig.4. Representation of Efficient Layer

At its core, EfficientNet B7 uses a compound scaling method that optimizes the depth, width, and resolution of the network. This allows the model to achieve state-of-the-art performance on various computer vision tasks while being computationally efficient.

Overall, the EfficientNet B7 architecture has a highly optimized structure that allows it to achieve excellent accuracy while minimizing computational requirements.

5. RESULTS & DISCUSSION

5.1 EXISTING WORK RESULT

A. Experimental Settings

The suggested system has been implemented in Google Collaboratory. A desktop computer with an 10th Gen Intel(R) Core (TM) i3-1135G7 @ 2.40GHz clock speed and 4 GB RAM is used for the experiments. Additionally, this project uses a variety of libraries, including Python, a well-liked programming language. The most commonly used and supported version of Python is 3.7. Open-CV is a free, open-source computer vision and machine learning software library. It gives a variety of algorithms for computer vision tasks like object detection, and the Python Matplotlib plotting library is used for data visualization. It is commonly used for creating graphs, charts, and other visualizations to analyze experimental results. Furthermore, the OS glob library is handy for file and directory manipulation. The training of the neural network with 50 epochs took 8 hours to complete.

B. Dataset

The Largest DR Disease Classification Dataset is collected in Diabetic Retinopathy Indian Dataset (DRID) and designed to evaluate deep learning models for classifying DR diseases. The dataset consists of images of DR captured from lighting conditions.

C. Segmentation of Affected Area using Superpixel Algorithm

Segmentation shown in Fig.5 of shows in affected area using superpixel algorithm involves grouping similar pixels in an image into small regions called superpixels. This process can help to simplify image analysis tasks such as object recognition, image segmentation, and classification.

There are several superpixel algorithms available, and the choice of algorithm depends on the specific application and the desired output. Some popular superpixel algorithms include Simple Linear Iterative Clustering (SLIC), Quick Shift, and Compact Watershed.

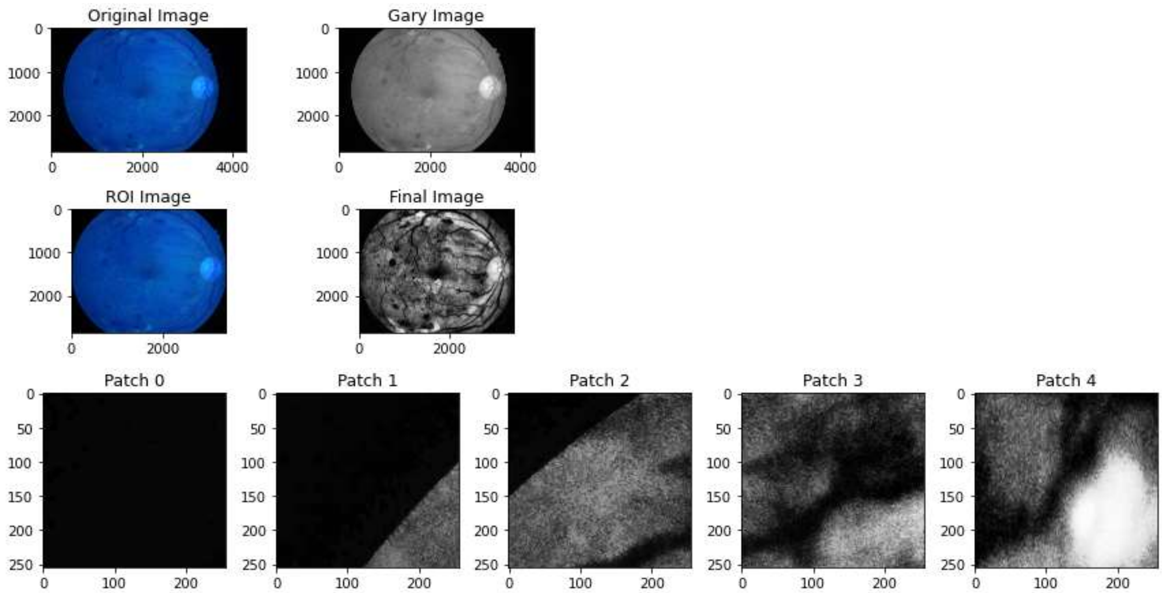


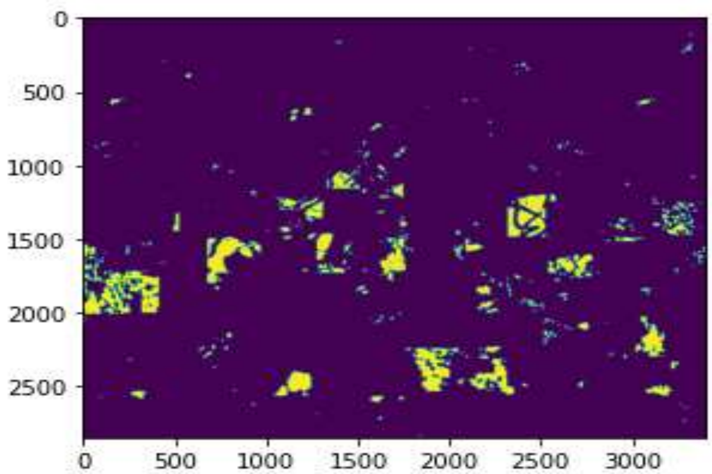
Fig.5. Segmentation of Affected Area using Superpixel Algorithm

To perform segmentation of an affected area using a superpixel algorithm, the following steps can be taken:

- Load the image containing the affected area into the program.
- Apply the chosen superpixel algorithm to the image. This will group similar pixels together into superpixels.
- Use the resulting superpixels to create a segmentation map of the affected area. This map can be used to isolate and analyze the affected area separately from the rest of the image.
- Post-process the segmentation map to remove any small or noisy regions and ensure that the segmented area is smooth and contiguous.
- Extract relevant features from the segmented area, such as color, texture, or shape, for further analysis or classification.

D. Representation of overall affected area

The affected area in DR can be seen as dark or discolored regions in the retinal images, which correspond to areas of damage or abnormalities in the retina. The extent of the affected area can vary depending on the stage and severity of the disease. In the early stages of DR, the affected area may be small and localized, while in more advanced stages, the entire retina can be affected.



Accuracy =75%

Fig.6. Overall Affected Area

5.2 PROPOSED WORK RESULT

A. Experimental Settings

The proposed system is implemented in JUPYTER notebook. Experiments are carried out on a desktop with specifications of 6th Generation Intel® Core™ i3-6200U Processor 2.30 Ghz clock speed and 4GB RAM are installed. Apart from this, different libraries are used for this project which includes Python is a popular programming language used in scientific computing, data analysis, and machine learning. Python 3.7 is a stable release that is widely used and supported, Open-CV is an open-source computer vision and machine learning software library. It provides a wide range of algorithms for image processing, object detection, and other computer vision tasks and Matplotlib is a plotting library that is used for data visualization in Python. It is commonly used for creating graphs, charts, and other visualizations to analyze experimental results. Furthermore, the OS glob library is particularly useful for file and directory manipulation. The training of the neural network with 100 epochs took 6 hours to complete.

The Diabetic Retinopathy dataset is one of the many datasets available on Kaggle. This dataset contains a set of retinal images of patients with diabetic retinopathy, a condition that can cause damage to the blood vessels in the retina and lead to vision loss. The dataset contains a total of 35,126 images, each of which has been graded by ophthalmologists on a scale of 0 to 4 based on the severity of diabetic retinopathy. The images were collected from various sources and were taken with different cameras, so the quality of the images varies. The dataset is provided in two parts: a training set with 28,126 images and a testing set with 7,000 images.The Diabetic Retinopathy dataset on Kaggle is widely used by researchers and data scientists for developing and evaluating machine learning algorithms for automatic detection and classification of diabetic retinopathy. The dataset can be downloaded directly from Kaggle, and it comes with a set of CSV files that contain the corresponding labels for each image.

B. Dataset

The Diabetic Retinopathy dataset is one of the many datasets available on Kaggle. This dataset contains a set of retinal images of patients with diabetic retinopathy, a condition that can cause damage to the blood vessels in the retina and lead to vision loss. The dataset contains a total of 35,126 images, each of which has been graded by ophthalmologists on a scale of 0 to 4 based on the severity of diabetic retinopathy. The images were collected from various sources and were taken with different cameras, so the quality of the images varies. The dataset is provided in two parts: a training set with 28,126 images and a testing set with 7,000 images.The Diabetic Retinopathy dataset on Kaggle is widely used by researchers and data scientists for developing and evaluating machine learning algorithms for automatic detection and classification of diabetic retinopathy. The dataset can be downloaded directly from Kaggle.

C. Classification of diabetic retinopathy

- **No DR:** This stage indicates that there are no visible signs of damage to the retina, and the eye is considered to be healthy.
- **Mild DR:** In this stage, there may be some small changes to the blood vessels in the retina, such as tiny bulges or small areas of bleeding.
- **Moderate DR:** At this stage, there are more significant changes to the blood vessels, including more areas of bleeding and swelling of the retina.
- **Severe DR:** In this stage, there is a high risk of vision loss, as the blood vessels in the retina become blocked or closed off, leading to areas of the retina that are not receiving enough oxygen.
- **Proliferative DR:** This is the most advanced stage of DR, where new blood vessels start to grow in the retina, which are fragile and can leak blood, leading to severe vision loss or even blindness.

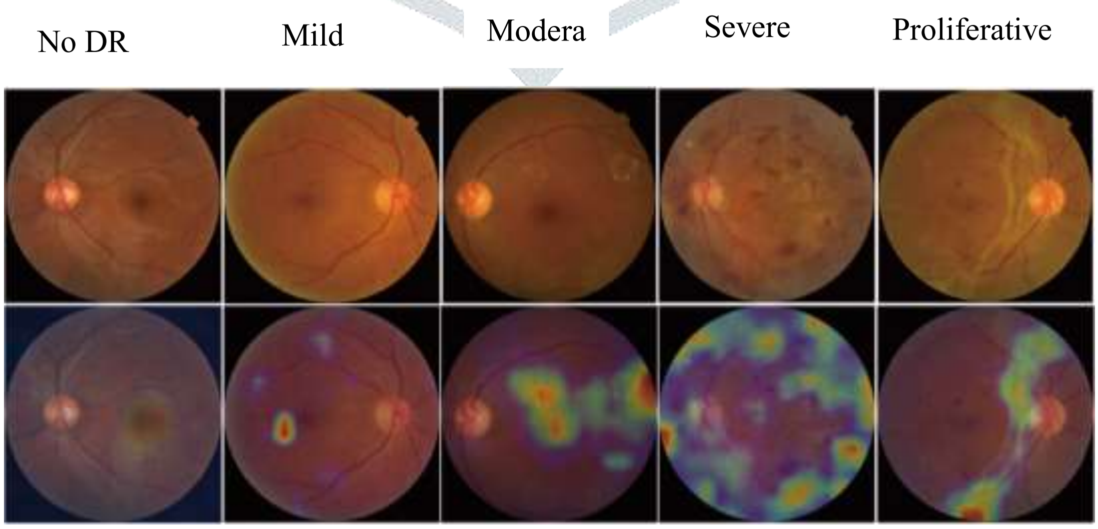


Fig. 7. Classification of diabetic retinopathy on severity of disease

E. CONFUSION MATRIX

A confusion matrix is show in Fig.8 a table summarising how well a classification model performed regarding correct and incorrect predictions. It is a helpful tool for assessing the accuracy of the model's predictions. The matrix consists of four components: True Positives (TP), False Positives (FP), True Negatives (TN), and False Negatives (FN), which are arranged in a table to compare the predicted and actual values. These components can compute several metrics, such as accuracy, precision, Recall, and F1 score, providing valuable insights into the model’s performance. The confusion matrix is frequently employed in binary classification issues but can also be expanded to multi-class problems. The confusion matrix table is given below in Figure.

0-No DR	271	5	0	0	0
1-Mild	3	49	10	1	1
2-Moderate	2	26	97	6	2
3-Sever	0	1	10	10	4
4-Proliferative DR	0	3	13	13	23
	0-No DR	1-Mild	2-Moderate	3-Severe	4-Proliferative DR

Fig.8.Confusion matrix

C. PRECISION RECALL AND F1-SCORE FOR CLASSIFIED DISEASE

Precision, recall, and F1-score are commonly used evaluation metrics for classification tasks, including disease classification. These metrics help assess the performance and quality of a classification model. Here's a brief explanation of each metric:

- Precision: Precision measures the proportion of correctly classified positive instances out of all instances predicted as positive. It is calculated as:

  Precision = True Positives / (True Positives + False Positives)

  High precision indicates a low rate of false positives, meaning that the model has a low tendency to incorrectly classify negative instances as positive.

- Recall: Recall, also known as sensitivity or true positive rate, measures the proportion of correctly classified positive instances out of all actual positive instances. It is calculated as:

  Recall = True Positives / (True Positives + False Negatives)

  High recall indicates a low rate of false negatives, meaning that the model has a low tendency to incorrectly classify positive instances as negative.

- F1-score: The F1-score is a harmonic mean of precision and recall. It provides a single metric that balances both precision and recall. F1-score is calculated as:

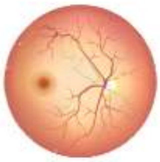
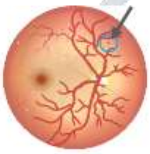
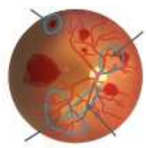
  F1-score = 2 * (Precision * Recall) / (Precision + Recall)

  F1-score is useful when both precision and recall are important, and you want to consider the overall performance of the model.

To calculate precision, recall, and F1-score for classified disease data, you need the following values:

- True Positives (TP): The number of correctly classified positive instances.
- False Positives (FP): The number of negative instances incorrectly classified as positive.
- False Negatives (FN): The number of positive instances incorrectly classified as negative.
- Using these values, you can calculate precision, recall, and F1-score for your classified disease data.

TABLE .1 Performance metrics of proposed method **a**ccording to the disease classification

CLASSIFY DR DISEASES	PRESICION	RECALL	F1-SOCRE
 Normal	0.98	0.98	0.98
 Mild	0.58	0.77	0.66
 Moderate	0.75	0.73	0.74
 Severe	0.33	0.40	0.36
 Proliferative	0.77	0.44	0.56

Accuracy = 82%

D. COMPARISON OF DIFFERENT MODELS

To comparing the accuracy percentages, such as 75% for U-Net and 82% for EfficientNet, it's important to consider the specific dataset and task on which these numbers are based. Accuracy alone doesn't provide a complete picture of a model's performance. Factors like the size of the dataset, class imbalance, data augmentation techniques, and evaluation metrics used can significantly influence the reported accuracy.

Furthermore, U-Net and EfficientNet are designed for different purposes. U-Net focuses on image segmentation, while EfficientNet is primarily designed for image classification. Their architectural differences make them suitable for specific tasks, and their performance can vary depending on the application.

TABLE.2 Performance Metrics of proposed method

ALGORITHM	ACCURACY
Unet architecture	75%
EfficientNet	82%

6. CONCLUSION

In conclusion, the use of EfficientNet B7 for detecting diabetic retinopathy has shown promising results. The model was able to achieve high accuracy in identifying the severity of the condition in retinal images. This has the potential to assist healthcare professionals in diagnosing and managing diabetic retinopathy in patients, particularly in areas where access to ophthalmologists may be limited. However, further research and validation are needed to fully assess the efficacy of this approach and to ensure its safe and effective implementation in clinical settings. Overall, thess use of deep learning models like EfficientNet B7 holds great promise in improving the detection and management of diabetic retinopathy, ultimately leading to better outcomes for patients.

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