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Original Article

A Novel Approach for Enhancement in Detection of Diabetic Retinopathy Using Customized DenseNet121

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***Abstract** - One of the leading causes of vision loss is Diabetic Retinopathy (DR), highlighting the importance of early diagnosis and treatment to prevent vision loss. Since professional diagnosis requires a careful examination of the retina, early detection of DR is important for effective treatment and prevention of blindness in the future. Traditional diagnostic methods suffer from accuracy and performance problems because they rely on human interpretation of medical images. Compared to traditional methods, this article presents an alternative that uses machine learning algorithms to determine diabetic retinopathy better. To demonstrate the effectiveness of the proposed method, this work uses the APTOS 2019 Blindness Detection dataset, which contains large-scale images of the retina using a variety of images, including eight different types of eye diseases. Circular cropping and two variations of the DenseNet121 model were employed for image Preprocessing. The accuracy of the customized DenseNet121 model surpasses that of the conventional version, highlighting the effectiveness of the proposed enhancements. The results are promising. These technologies will reduce the cost of DR-related blindness by promoting early diagnosis and prompt care and ushering in a new era of patient recovery. Thus, this study not only expands DR diagnosis with new methods and findings but also influences the field's future direction and encourages early intervention to reduce DR-related blindness and improve behavior.*

***Keywords** - Diabetic Retinopathy, CNN, DenseNet121, Machine learning, GAN, Image preprocessing, Customized DenseNet121.*

1. Introduction

A potentially fatal condition called diabetic retinopathy affects the eyes of people with diabetes. To avoid blindness, early identification of this illness is crucial. Machine learning models have recently shown good results in detecting diabetic retinopathy from retinal images. Traditional methods and models diagnose the diabetic retinopathy stage based on analysis of retinal images; however, machine learning models have shown greater efficiency and performance in delivering the same. Such models can be trained on diverse datasets related to optical data in order to develop accurate and reliable diagnostic aids. Machine learning models for vision detection will enable doctors to develop a better early diagnosis for diabetic Retinopathy, lowering the risk of patients going blind due to diabetes. Automated diagnostic machine-learning models can improve accuracy and efficiency and allow doctors to identify and treat patients sooner, potentially minimizing the undiagnosed risks associated with this disease. With diabetic retinopathy being an ongoing research avenue, this work hopes to help by providing machine learning models for the diagnosis.

For the purpose of training, we will access the specific learning model and customize it for optimization to recognize diabetic Retinopathy utilizing retinal images in diabetic patients. This paper will evaluate the model's sensitivity, specificity and accuracy against manual review by an ophthalmologist.

The objective is to realize the benefits and constraints of utilizing these devices in diabetes diagnosis, which may assist doctors in managing and providing treatment for diabetic Retinopathy, increasing the diagnosis's correctness and enhancing the diagnosis's accuracy.

Diabetic Retinopathy goes through many stages and worsens. The four main stages are shown in Figure 1. For the purpose of Model Training, the APTOS 2019 dataset was classified into five labels, 0 to 4.

Machine learning models have been increasingly applied to detecting diabetic Retinopathy, offering a more efficient and scalable approach compared to traditional manual examination by ophthalmologists.

Machine learning models, including deep learning models such as Convolutional neural networks, can examine large datasets of retinal images to learn patterns of diabetic retinopathy and all truth. This approach takes advantage of features learned from one domain and applies them to another, often improving results and reducing learning time. scaling) can be used to enhance the diverse nature of training data and improve the model's generality. Combined methods such as bagging and boosting generally perform better than one model. The model focuses on the most important part of the image, especially on activities where understanding the relationship between the eyes is important, such as classifying diabetic retinopathy.

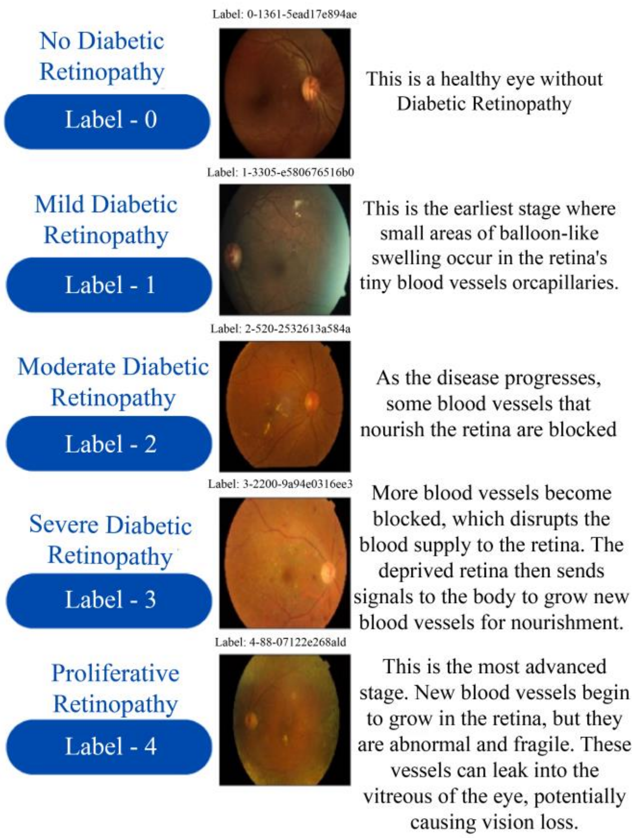

Fig. 1 Stages of diabetic retinopathy

1.1. Contribution to this Research Work

The purpose of this study is to categorize and contrast different machine learning techniques for diagnosing diabetic retinopathy. The performance of these models in terms of sensitivity, specificity, and overall accuracy will be analyzed. This paper also discusses potential obstacles and limitations in applying this model to real-life clinical settings. The goal of this work is to augment the accuracy and reliability of the diagnosis even further by utilizing a combination of these models' benefits to support decisions that lead to improved health outcomes for diabetics. This allows for the leverage of limited data, the building of various training models, and an understanding of differences across disease outbreaks.

- Using image processing techniques along with machine learning models to detect Diabetic Retinopathy. This would ensure improved accuracy and reliability of diagnostic tools to benefit diabetes patients.
- Using GANs in diabetic Retinopathy, synthetic images similar to real retinal images can be produced with and without the underlying problem. This facilitates the augmentation of limited datasets, generation of diverse training samples, and understanding of variability in disease presentation. By leveraging the power of DenseNet121, enhancements are integrated to increase the accuracy and sensitivity of diagnostic tools while helping improve treatment outcomes for people with diabetic Retinopathy. There are several important steps in the study of diseases: Systematic data review: In reviewing data, it is important to search, select and combine the results of various studies to understand the current status and progress of the field. In short, research using machine learning models to diagnose diabetic Retinopathy covers many topics, including datasets, machine learning, modeling, performance evaluation, challenges and future directions, implications for healthcare and spending, and collaboration with similar providers. This evidence provides broad insight into using machine learning models to diagnose diabetic Retinopathy.

The article is structured in the following manner:

Section 2 outlines the study's methodology. Section 3 examines a related work and gives a concise overview of the research work.

In section 4, a proposed methodology is proposed. Section 5 centers on the experimental analysis and presents the findings. Finally, Section 6 encompasses the conclusion and offers future paths for this research.

2. Research Methodology

Research methodologies for developing machine learning algorithms to detect diabetic Retinopathy involve several key steps:

2.1. Systematic Literature Review

In a thorough review of literature, it is crucial to methodically explore, choose, and integrate the results from a diverse range of studies in order to understand the current status of the field and its potential future impact.

This review illustrates an extensive overview of the literature that has been done on ML-trained models for assessing the severity of DR with emphasis on data sources, ML methods, model architecture, performance metrics, clinical translation and future challenges, potential cost-effective use in clinical settings, and comparison with the ophthalmologist.

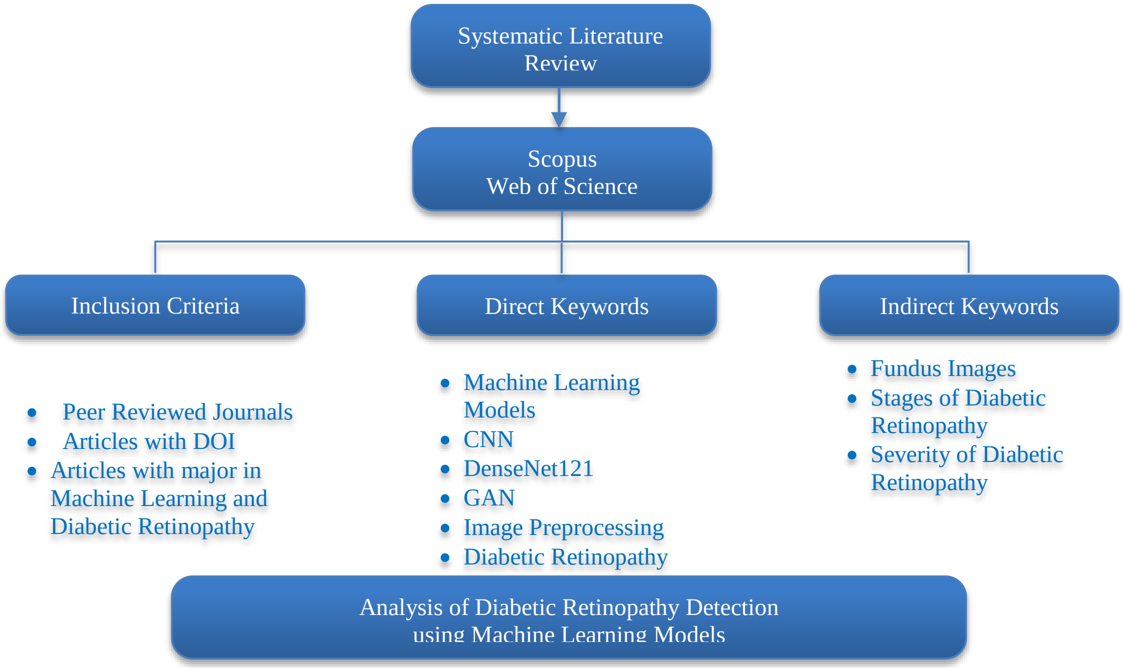

Fig. 2 Systematic literature review parameters

2.1.1. Data Collection

A large dataset of retinal images of patients affected with diabetic Retinopathy and without diabetic Retinopathy is collected and annotated by expert ophthalmologists. APTOS 2019 is the dataset considered in this study

2.1.2. Data Preprocessing

Clear and format the information for tests, including improving picture quality, wiping out commotion, and normalizing pictures. For image preprocessing, circular cropping was applied.

2.1.3. Model Selection

Choose an appropriate machine learning model, such as convolutional neural networks known for their ability to detect patterns in images.

2.1.4. Training

Feed the preprocessed data into the chosen model to identify features associated with diabetic Retinopathy through parameter adjustments.

2.1.5. Validation

Test the algorithm's performance on a separate portion of the dataset not used in the training stage to assess its effectiveness.

2.1.6. Evaluation

Assess the model's performance using accuracy metrics like sensitivity (true positive rate) and specificity (true negative rate).

When designing this study to evaluate machine learning algorithms for diabetic Retinopathy, the following important considerations kept in mind include;

- Data quality and quantity,
- Ground truth annotations by experienced ophthalmologists,
- Ethical data collection,
- Comparison of different model performances,
- Justified preprocessing techniques evaluation of performance metrics using robust validation techniques,
- Assessing generalizability on external datasets statistical analysis clinical relevance consideration regulatory requirements post-deployment monitoring.

Patient privacy and consent measures and compliance with relevant industry standards and guidelines are also considered.

3. Related Work

In the study [1], authors Prioritize data to find missing values and results, select features from data acquisition, use CatBoost to create a diabetic retinopathy risk model and use the SHAP model to define the output model in comparative model testing. The factors connected to DR in direct and inverse proportion were discussed. The factors with no impact on DR were also covered.

Convolutional Neural Networks (CNNs) are useful in many areas, and progress has been made in diagnosing diabetic retinopathy using this network [2]. The fact that the ability to prevent the formation of a blind spot is in the recognition period shows the need for a reliable screening process. New methods can classify different stages of diabetic retinopathy, with the aim of improving diagnosis and reducing errors that plague existing models. This study aims to review the literature on diabetic retinopathy in India; these include four categories: Microaneurysm (MA), Soft Exudate (SE), Hard Exudate (EX), and Hemorrhage (HE). An accuracy of 90.4% was achieved using the VGG16 model for extraction and the logistic regression classifier for classification.

This study [3], through a Systematic Literature Review (SLR), discusses the history of diabetic retinopathy, its main causes and pain-related problems in detecting DR, and solutions for early diagnosis of DR. It also provides an in-depth review of current technologies and models used in DR diagnosis, based on SLR, artificial intelligence, machine learning, and recently developed deep learning. Additionally, this research will help the research community learn about the latest methods used for DR analysis and their key issues and limitations.

The DiaCNN model [4] showed consistent accuracy, with 1 in training and 0.98 in testing. These numbers represent a huge jump in the classification of retinal fundus images compared to current diagnostic methods. These developments show how this new technique can increase the accuracy of diagnosing DR and other eye illnesses, which bodes very well for the future. This approach, which promotes early detection and timely intervention, will reduce the incidence of DR-related blindness and thus initiate a new era in the patient's development.

The use of computer-assisted analysis is described in this study [5], which determines the high severity of diabetic retinopathy by evaluating the fundus picture in various lighting conditions and fields of vision using a neural network model in machine learning.

In the paper [6], the authors proposed a hybrid deep learning approach by training multiple deep learning models, using a 5-fold cross-validation process, and combining their predictions into the final score. This hybrid model increases the robustness of the results by showing where each model performs best and where it does not perform well.

This work [7] demonstrates the dual hierarchical integration of four Convolutional neural networks. The proposed method has been tested on the Kaggle APTOS dataset, outperforming other methods announced at the event to test their technology.

They proposed an end-to-end deep learning approach [8] based on separating dark colors from light patterns in the retina for automatic DR grading (5 weights). Using simple image markers, this method makes a significant addition by enabling the generation of independent descriptive maps for red and bright lesions.

The study [9] plans provide greater classification and performance than previous studies. The APTOS dataset was used to train the ResNet-50 DL model, and the EyePACS dataset was used for testing.

By using the appropriate image in advance and improving the process, the problems of classification of small classes and inconsistent data discovered through many experiments can be overcome.

The results in the work [10] show that single-mode DenseNet121 and InceptionV3 are the most efficient but less accurate. Regardless of which model is used, the fusion method outperforms the single-method treatment of two datasets because the first model provides more information about the fundus.

In this study [12], the SCL method, a two-stage training method with failure rate monitoring, is proposed for the first time to determine DR and its severity from Fundus Images (FI) using the APTOS Phase 2019 Annual blind detection data.

The hybrid deep AMDNet23 model [13] proposed successfully detected AMD eye disease more accurately. Additionally, the system's performance was evaluated against 13 other preexisting CNN models, demonstrating its superiority in AMD eye disease in the field of fundus imaging datasets. This overall comparison demonstrates the great potential of this approach and confirms its place at the forefront of determining eye health.

This work [14] presents the methodology of a deep learning algorithm and presents the results of running it on a dataset of 5000 fundus images. The VGG-19 deep learning model makes more accurate predictions than the VGG-16 and CNN models when dividing the virus into two different groups.

The authors of this work [15] used two GPUs to design, build, and analyze parallel pipelines in DDL and then analyze their performance. The authors work on the classification of diabetic retinopathy based on the study of DDL use.

This review [21] summarises an overview of how AI is currently being used in ophthalmology, explains the concerns that must be addressed before AI can be used in the clinic, and discusses the process required to translate these systems into the field of ophthalmology.

4. Proposed Methodology

Image preprocessing is very important for Diabetic Retinopathy (DR) detection because it helps make images better and boosts how well machine learning models work. DR is a condition linked to diabetes that harms the blood vessels in the retina, which can cause vision problems or blindness if not found early. This analysis needs good-quality retinal images taken with methods like fundus photography or Optical Coherence Tomography (OCT). However, these images can have problems with lighting, contrast, and noise problems, so enhancements in preprocessing steps to make them better are needed.

Contrast enhancement, brightness change, noise cut down, and circle cropping are the main preprocessing methods applied to retinal pictures to make the images clearer and emphasize important parts of the retina, such as the optic disc and macula. The contrast enhancement makes the targeted structures more visible by either brightening or dimming certain pixels with high or low values, while the noise cut minimizes artifacts that might affect a diagnosis. Circular cropping eliminates irrelevant regions, so the models pay attention to only the relevant parts for diagnosis. The work was motivated by the desire to use these preprocessing techniques and Machine Learning (ML) models to enhance diagnostic accuracy and assist in the early detection of diseases and prompt treatment. The above study approaches two key parameters, which are adjustment for contrast and cancellation of unnecessary LED space in the image data set to assist the model. Automated processing systems are consistent across large volumes of data, making diabetic retinopathy tests faster and more dependable-and, by extension, resulting in healthier outcomes.Also known as a circular crop, it can help a lot while processing the image, which can scrape and be focused only on some of the retinal parts, which is beneficial for analysis. It improves diagnosis by reducing background noise. Circle crop focuses on important areas like the iris, anterior chamber, and lens vault, which is critical for looking at eye maladies like angle-closure glaucoma. This crop differs from traditional rectangular cropping, which may retain extraneous areas. This technique allows machine learning systems to learn from the best data, increasing accuracy and efficiency.

4.1. Image Preprocessing

Image Preprocessing in Diabetic Retinopathy is a crucial method that includes pre-analysis processes such as retina image enhancement, analysis, and interpretation between retina images for diabetic Retinopathy detection and disease progression detection. Diabetic retinopathy is a complication of diabetes that affects retinal blood vessels, resulting in vision impairment or complete blindness if not treated. Important methodologies include taking high-quality images with fundus photography or Optical Coherence Tomography for diagnosis, improving image visibility by adjusting contrast, brightness, and noise reduction, using circular cropping to focus on specific areas such as the optic disc or macula, and eventually integrating imaging processing with automated algorithms to facilitate early detection and the grading of the disease. Such automated systems are helpful in cost-effective screening, which in turn results in timely treatment. Perfectly processed images are very important for detecting and monitoring diabetic Retinopathy.

Fig. 3 Proposed architecture of the research work

Additionally, this study also will focus on the use of image preprocessing techniques that are integrated with machine learning training and models to diagnose the severity level of diabetic retinopathy. This component focuses on the latter two elements.

- The object removal stage (image denoising) is necessary to eliminate the negative impacts of lighting conditions from the dataset. It assists in maintaining the object's integrity while minimizing errors in biological judgment.

In image processing, cropping out unused areas is crucial as it involves removing anything that isn't needed, repetitive images, or files without information one needs to focus on. This creates an elegant cropped image that centers on its subject and makes the image stronger and more impactful. There are different approaches that may be used in the process, from simple edge detectors for cropping to high-end models that analyze the salience and aesthetic qualities of the image. It is crucial to consider computational complexity and efficiency while opting for the circular cropping technique.

4.2. Circular Cropping

In image processing for diabetic retinopathy, circular cropping refers to cutting out a circular region of an image, unlike rectangle cropping, which is a very popular and more common cropping method. This rectangular cropping could be used for emphasizing a region of interest in the image or for aesthetic reasons, for example generating profile photos for social networks. However, circular cropping allows us to take the following anatomical measurements of an eye: iris area, iris width, iris volume, anterior chamber volume, and lens vault.

These parameters have great potential in diagnosing angle-closure diseases and may contribute to increasing the accuracy and objectivity of diagnosis.

The general procedure for circular cropping a fundas image from the APTOC 2019 dataset as a part of image processing is as follows:

- Circle crop detection - Find the center point (x, y) and the radius.
- Create a circular mask that defines the beneficial area during analysis and training.
- Apply this mask to the image so that only the pixels within the circular mask are retained, while the rest are usually set to a background color (often black or transparent).

4.2.1. Circular Cropping Steps

To apply a circular mask to an image for the purpose of circular cropping, here are the common mathematical operations involved:

i. Circle Equation: Use the standard equation of a circle to define the region of the mask:

$$[(x-a)^2+(y-b)^2=r^2] \tag{1}$$

Where *(a,b)* is the center and *r* is the radius. This will check if each pixel falls inside this circular region.

ii. Binary Mask Creation: Iterate over the image, and for each pixel located at *(x, y)*, calculate the value using the circle equation:

Inside circle:

$$[(x-a)^2+(y-b)^2\le r^2] \tag{2}$$

Outside circle:

$$[(x-a)^2+(y-b)^2> r^2] \tag{3}$$

Based on these conditions, create a binary mask of 1s for pixels inside the circle and 0s for pixels outside.

iii. Element-wise Multiplication: Apply the binary mask to the image with an element-wise multiplication operation:
  - Processing grayscale images involves combining the binary mask with the image matrix. This method enables a more accurate analysis and understanding of anterior segment images, assisting in distinguishing between various mechanisms of angle closure in different populations.
  - Color images with multiple channels, like RGB, require the binary mask to have matching dimensions as any of the color channels. One can duplicate the mask for each channel or employ broadcasting if supported by the library (e.g., NumPy). Utilizing these image-processing techniques could potentially improve healthcare professionals' capability to precisely diagnose angle-closure diseases and distinguish between various mechanisms of angle closure in diverse populations.

iv. Alpha Channel for Transparency: If you need transparency outside the circle, you must create an additional alpha channel and apply the binary mask, setting pixel values to 255 (opaque) within the circle and 0 (transparent) outside.

v. Combine Channels: If an alpha channel is used, the resulting cropped image must combine the original RGB channels with the new alpha channel so that the final image has the circular region visible and the outside region transparent.

4.3. Proposed DenseNet121

DenseNet121 has become prominent in the realm of medical image analysis, particularly in detecting diabetic Retinopathy. Its capacity to discern detailed features within retinal images allows for more accurate identification of pathological changes linked to diabetic Retinopathy.

The DenseNet121 model is used for feature extraction with pretraining from big datasets like ImageNet. The customized version of the DenseNet121 Model keeps this base but adds important enhancements. For preprocessing, the original does basic resizing and cropping, while the adjusted one uses circular cropping and resizes to 224×224 pixels, targeting key areas in Diabetic Retinopathy (DR) images better. Also, the original lacks specific regularization techniques, but the customized model has these layers to reduce overfitting and boost generalization. Another major improvement is including fully connected layers in the customized version that enhances feature extraction beyond what was in the standard classifier of DenseNet121. Lastly, while DenseNet121 classifies severity levels directly, the updated model involves extra processing steps with new fully connected layers that likely improve accuracy and robustness in detecting severity levels. These changes overall enhance how well the model works for the classification of DR severity levels.

This makes the proposed DenseNet121 achieve better generalization, improvement in feature learning and more accuracy in Severity Detection of Diabetic Retinopathy.

The analysis begins with collecting retinal images from individuals diagnosed with diabetic Retinopathy. This dataset will encompass a diverse array of images depicting various stages of the ailment. These images will be used to train and validate the performance of the machine-learning models. Training is applied to the upper layers and hyperparameters of the selected architecture; in this case, they use a DenseNet 121 model pre-trained on ImageNet weights to achieve better accuracy.

Sensitivity, specificity and total accuracy will be used to evaluate model performance. Moreover, computational efficiency and scalability elements - significant for real-world implementation - will also be accounted for.

DenseNet121 has densely connected layers, allowing for more efficient communication among layers, which can be beneficial when analyzing images with subtle anomalies, such as retinal images. Such an architecture has performed exceptionally well in respectively classifying images, making it a great candidate for diabetic Retinopathy detection.

The DensNet121model proposed has the below includes

- Pretrained weights proposed with DenseNet121 are helpful for training on image datasets of hundreds of thousands of images and significantly improve the overall capacity of the model. In the detection of diabetic Retinopathy, where accurate and reliable predictions are paramount for early intervention and treatment, this factor is important.
- This research mainly analyzes the success of improved regularization methods available for denseNet121. In particular, it aims to determine the impact of different regularization techniques, including batch normalization, dropout and weight decay, on improving the performance of DenseNet121. These methods introduced within the framework of deep learning were supposed to solve a common problem, such as overfitting during the training model of deep neural networks. Additionally, the pertained models were considered to see their effectiveness in accuracy. For this, the comparison is made of the DenseNet121 with and without adopting these regularization techniques on different datasets.

By capitalizing on the advantages offered by DenseNet121, the goal is to improve the accuracy and sensitivity of diagnostic tools, ultimately leading to better outcomes for individuals at risk of diabetic Retinopathy.

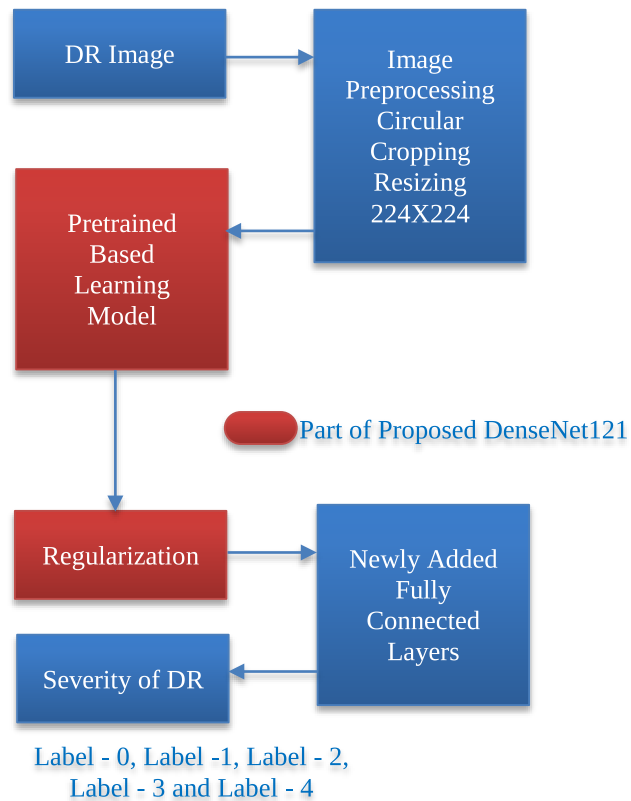

Fig. 4 Customized DenseNet121 model

4.4. GAN

Two neural networks (the discriminator and the generator) compete with each other during training, creating Generative Adversarial Networks. The role of the generator is to take in a random noise vector as input and generate data that are as similar as possible to the valid data instances.

For example, within the diabetic Retinopathy domain, it would try to generate images similar to real images of human retinas having diabetic Retinopathy. Conversely, the discriminator serves as a jury, deciding if every data instance is authentic (from the data set) or counterfeit (made by the generator). Thus, it is important to learn to correctly predict real and downvote fake.

During training, GANs try to make the generated data more realistic while increasing discrimination between fake and real datasets within them until they become nearly indistinguishable from each other. They are useful as they can simulate any kind of μ and σ, which can greatly help , especially in cases like diabetic Retinopathy detection with limited datasets.

It even specifically discusses methods in GANs that can help battle challenges such as the mode collapse or convergence problem for small-scale medical imaging datasets. Additionally, it emphasizes the advantages of employing GANs for diabetic Retinopathy detection to tackle threshold data availability issues by augmenting and generating diverse synthetic images similar to those suffering from this disease. To sum it up, using GANs to identify diabetic retinopathy helps overcome the limitations of scarce dataset resources by synthesizing realistic-looking retina images with this disease while also improving the performance of machine learning models overall.

5. Experimental Analysis

This section provides a summary of the research experiments conducted in order to understand the performance of the proposed single-modal deep feature representation DenseNet121. In the context of the blind detection research work, this study used the APTOS 2019 dataset, composed of plenty of retinal images captured by fundus photography methods across different imaging modalities. Images are labeled on a scale of 0-4 to indicate disease severity (where 0 means no DR and 1-4 shows the magnitude of severity). Details on the distribution of retinal images at different intensity levels can be found in Table 1 of this dataset. 80% of the data is used for training and 20% for validation for each experiment.

5.1. DR Identification

This study identifies retinopathy in diabetic patients using DR images. Loss is measured using binary cross-entropy loss, and the objective function is optimized using Adam optimization. Five categories are used, producing 1857 good and 1805 terrible normal images.

Table 1. Dataset analysis

Severity	Count
Label - 0	1805
Label - 1	370
Label – 2	999
Label - 3	193
Label - 4	295
Total	3662

5.2. DR Severity Estimation

In this study, weight analysis is used as a separate task by dividing the retina's image into one of five weight levels (Label - 0 to Label - 4).

5.3. Image Preprocessing

The aim of this investigation was to identify diabetic retinopathy and its severity through the analysis of fundus images. The application of Circular Cropping has yielded the expected outcomes. Figure 5 displays the results obtained from applying circular cropping transformation to fundus images, presenting two variations in gray and colour which are advantageous for this research.

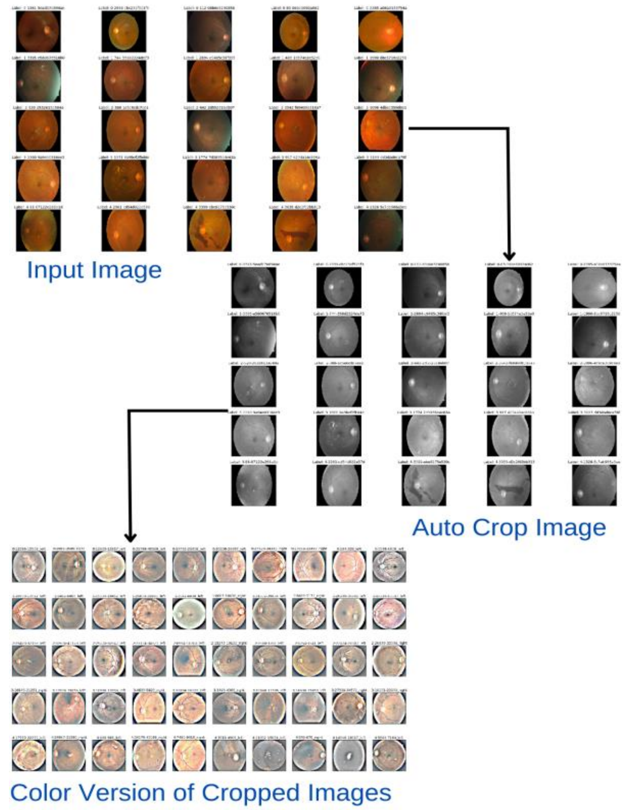

Fig. 5 Image preprocessing using circular cropping

5.4. DenseNet121

DenseNet121 model performs well in the current research work with the given dataset. It reached a 79% accuracy rate.

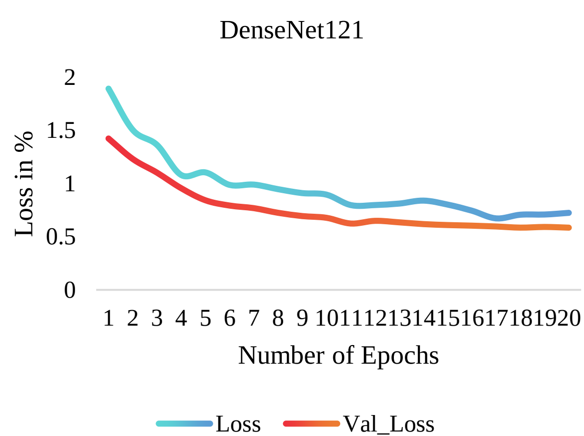

Fig. 6 Loss in each epoch with DenseNet121

To evaluate the performance of the DenseNet121 model, a comparison of it with other popular models such as ResNet and Inception was done. It was found that DenseNet121 outperformed ResNet and Inception in terms of accuracy, achieving 79% accuracy on the image classification task.

These results indicate that DenseNet121 is a strong candidate for the APTOS-2019 dataset and provides hope for future applications.

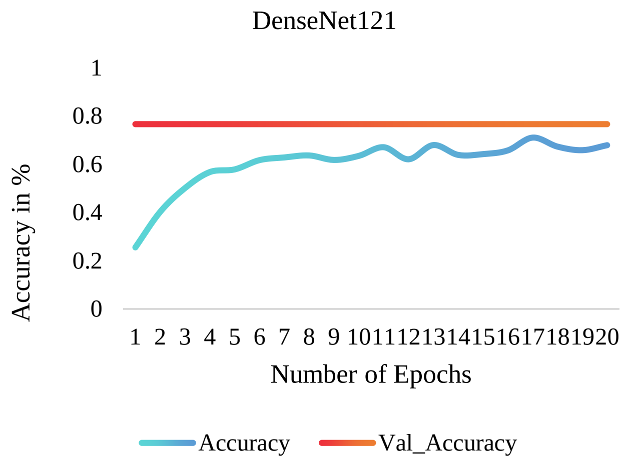

Fig. 7 Accuracy in each epoch with DenseNet121

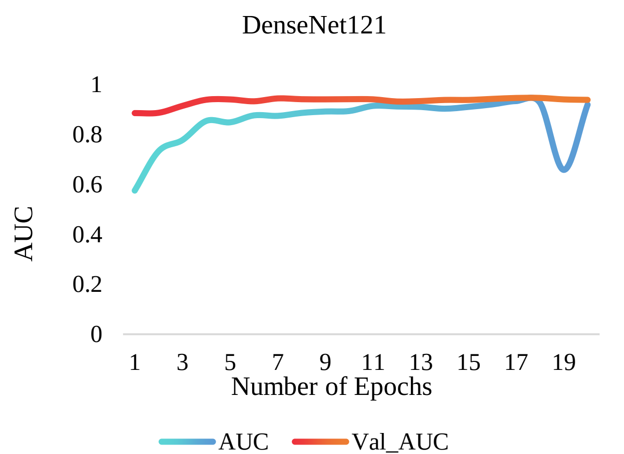

Fig. 8 AUC in each epoch with DenseNet121

5.5. GAN

The GAN has been implemented in 20 epochs, whereas each epoch has 4 batches. The results obtained by GAN are shown in the Figures from 9 to 11.

The best epoch for each of D, G and D(x) are as follows:

- Loss in D is - Epoch # 1 Batch # 2
- Loss in G is - Epoch # 2 Batch # 4
- D(x) is - Epoch # 5 Batch # 1

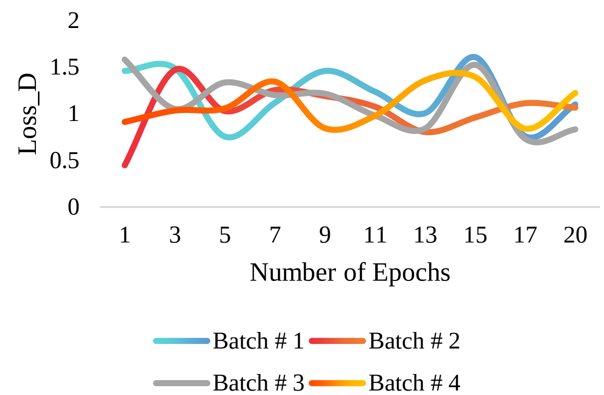

Fig. 9 Batch wise loss_D in each epoch with GAN

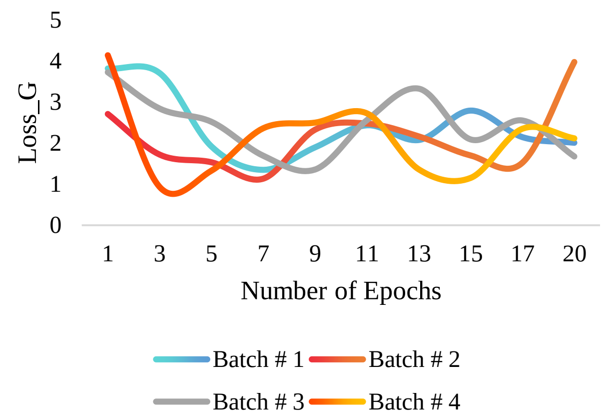

Fig. 10 Batch wise loss in each epoch with GAN

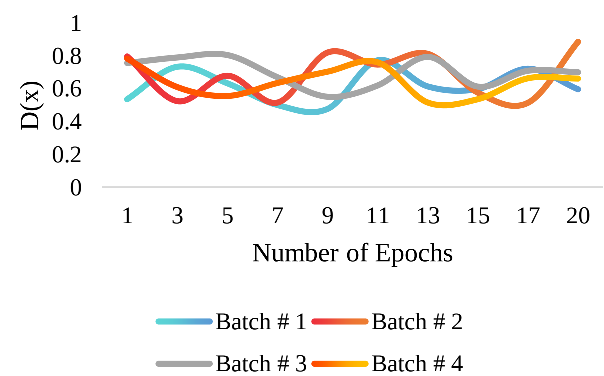

Fig. 11 Batch wise D(x) in each epoch with GAN

5.6. Proposed DenseNet121

The proposed DenseNet121 model performs well on the image classification function of the dataset. Increase accuracy and reduce losses with optimizations such as regularization and hyperparameter tuning. However, as the depth of the network increases, analysis also occurs, and classification accuracy begins to decrease or decrease. It achieved an accuracy of 90.14%. Previous studies have shown that through short-term integration of near-input processes and near-output processes, communication networks can be deeper, more realistic, and more effective for education.

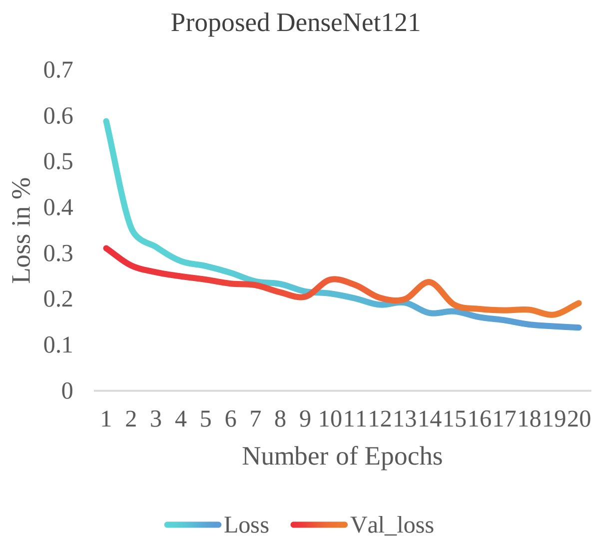

Fig. 12 Loss in each epoch with proposed DenseNet121

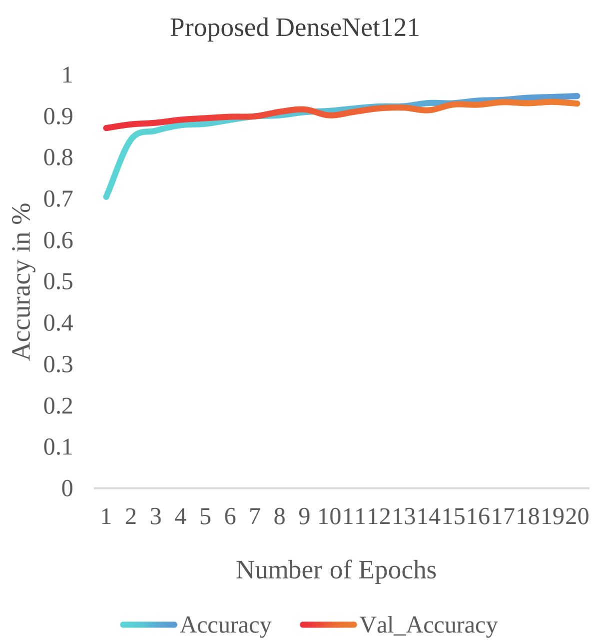

Fig. 13 Accuracy in each epoch with proposed DenseNet121

Table 2 displays the comparative accuracy values of various models found in the research literature, highlighting that this current research has surpassed previous works. Table 3 displays the comparative metrics values of two variants used in this study. This covers various metrics that can give an understanding of how the models behave. The proposed DenseNet121 model does way better than the normal DenseNet121 in all metrics. The accuracy went up from 0.7885 to 0.9014, meaning it classifies things better overall. Precision also got higher, from 0.6880 to 0.8294, which means fewer wrong positives happened, and recall increased from 0.7904 to 0.9002, showing it finds more true cases right. Sensitivity jumped from 0.7340 to 0.8596, so it's now better at spotting diabetic retinopathy cases. Lastly, specificity grew from 0.9474 to 0.9749, proving a lower false positive rate is also there now. These gains show how well the new model finds diabetic retinopathy issues.

Table 2. Different models accuracy with the proposed DenseNert121

Model	Accuracy
Diabetic Retinopathy Detection using Deep Learning [22]	57.2%
Diabetic Retinopathy Detection using Xception [23]	79.59%
Diabetic Retinopathy Detection using InceptionV3 [23]	78.72%
Diabetic Retinopathy Detection using Hdeep [7]	85.30%
Diabetic Retinopathy Detection using DenseNet 121	79.00%
Diabetic Retinopathy Detection using Proposed DenseNet 121	90.14%

Table 3. Metrics of DenseNet121 and the proposed DenseNert121

	DenseNet121	Proposed DenseNet121
Accuracy	0.7885	0.9014
Precision	0.6880	0.8294
Recall	0.7904	0.9002
Sensitivity	0.7340	0.8596
Specificity	0.9474	0.9749

6. Conclusion

This study evaluates and compares single-mode DL models using GAN and DensityNet121 using the APTOS19 public database to divide DRs into used DRs and unused DRs. Additionally, DR is divided into five labels based on severity. There are approximately 3662 high retinal images in APTOS 2019. These are fundus images used to train the learning model to identify different stages of diabetic retinopathy. The presented Preprocessing techniques have been analyzed, and the findings show that circular cropping outperforms auto cropping every time. This result shows how well circular cropping prepares the images for additional processing. The result of this study will be used as evidence of the beneficial effects of this strategy on the entire workflow. In this study, the GAN has shown promising results in generating high-quality images with improved accuracy and realism. In this work, the proposed method used the APTOS dataset and achieved an accuracy of 0.901. The performance is above that reported in the existing literature. This model combination exhibits greater predictive power by providing class predictions close to the correct class even when the image distribution is incorrect, given the uncertainty present in the evaluation data. Image preprocessing methods, like circular cropping, help with DR detection but have challenges. One main issue is differences in how images are taken, such as lighting and camera types, which affect preprocessing results.

While circular cropping targets certain retinal parts, it might miss peripheral info that matters for some diagnoses. Also, even if automated preprocessing makes things more accurate, it still needs adjustments for different datasets to work well across various groups and machines. Future studies should look into smart preprocessing techniques that change contrast, brightness, and selection of areas based on the image's traits. Adding self-supervised learning models could improve feature findings without just using labeled data. Using GANs to create high-quality fake retinal images can help solve data shortages and enhance model generalization. Additionally, looking into multi-modal image fusion-mixing fundus images with OCT or angiography-might give a fuller diagnostic view. By improving these methods over time, one can make automated DR detection more reliable and available, which will ultimately aid early treatment and patient care.

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