

# Automated Diabetic Retinopathy Detection and Severity Assessment

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**Abstract:** This article demonstrates a revolutionary deep- learning approach for automated diabetic retinopathy (DR) detection using convolutional neural networks (CNNs). With the help of datasets from the Diabetic Retinopathy Detection 2015 and APTOS 2019 Blindness Detection competitions, our model attempts to accurately classify retinal images into two categories: No DR and Proliferative DR, based on the severity of macular degeneration. We enhance the quality of the dataset and the robustness of the model by carefully preprocessing and augmenting it using various approaches like rotation, flipping, shearing, rescaling, translation, brightness correction, and normalization. We train two models: a regression model and a deep learning model. With an 88% validation accuracy, we demonstrated that our deep learning technique performs better than the regression model. In order to properly determine and classify DR severity levels, this study presents a robust and noise-tolerant system that evolves the field of automated DR detection. Our approach enables early detection and intervention by combining cutting-edge CNN architectures with sophisticated preprocessing techniques, which may lessen the strain of DR- related blindness on healthcare systems. We also demonstrate out drawbacks and suggest areas for additional investigation, such as analyzing ensemble learning and using a variety of datasets to improve the generalizability of the model. As we wrap up, our study emphasizes the potential of deep learning techniques to transform DR diagnosis and treatment, with the goal of enhancing the quality of care for diabetics globally.

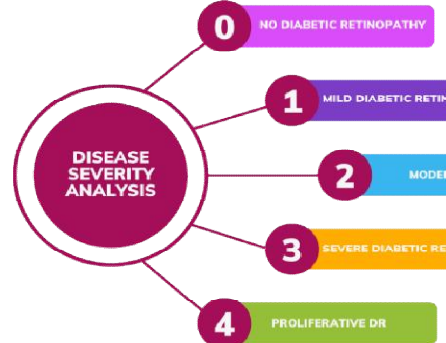
**Keywords:** diabetic retinopathy, deep learning, convolutional neural networks, image classification, data preprocessing, data augmentation, model training, model evaluation, validation accuracy, ensemble learning, dataset integration, healthcare outcomes, early detection, intervention, automated diagnosis, machine learning, image analysis, retinal images, model performance, future research

## I. INTRODUCTION

In light of the vascular damage triggered by chronic diabetes mellitus, diabetic retinopathy (DR) is a notable global health concern [1, 2]. Due to its increasing prevalence and the growing number of diabetic patients globally [2, 5], early detection and intervention are becoming more and more important. The initial stages DR frequently shows no symptoms, which delays diagnosis and causes irreversible lack of vision [1, 2]. On the other hand, enhancements in computer-aided diagnosis systems present feasible remedies to this conundrum, offering effective and precise screening techniques to reduce the tendency toward blindness [3, 5]. Automated systems utilize advanced algorithms to evaluate retinal visuals, quickly identifying distinguishing abnormalities such hemorrhages, exudates, and microaneurysms [1, 3]. These technologies have the potential to greatly lessen the burden of DR-related blindness on global healthcare systems by enabling timely intervention.

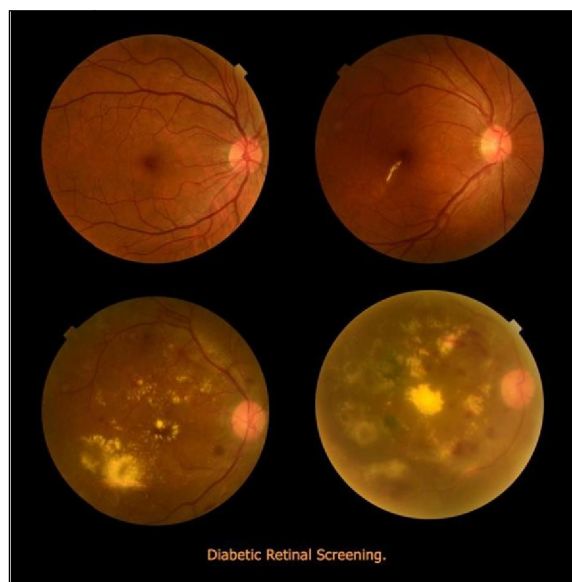
Chronic and uncontrolled diabetes significantly increases the danger to the microvasculature of vital organs, such as the eyes [2, 4]. Diabetes-related retinopathy is characterized by a number of abnormalities that arise from the damage to the retinal blood vessels [2, 4]. Even though patients might not notice early signs like microaneurysms, it is indispensable that they are discovered quickly to start therapy and stop the medical condition from getting worse [2, 4]. The efficacy of screening efforts is restricted by the arduous and time-consuming nature of traditional diagnostic techniques that rely on manual image analysis [3, 5]. On the other hand, computer-aided methods present an attractive opportunity to

expedite this procedure, allowing for the quick and precise identification of diagnostic characteristics that indicate the severity of DR [3, 5]. Through the improvement of healthcare professionals abilities, these technologies foster prompt intervention and ultimately lead to safer patient outcomes.



The arena of medical diagnostics endured a radical transformation with the implementation of machine learning (ML), especially with regard to diabetic retinopathy [4, 5]. Techniques involving deep learning are used by ML-based automated systems to assess retinal visuals at a speed and accuracy that has never been achieved before [4, 5]. By means of the amalgamation of convolutional neural networks (CNNs) and sophisticated image processing methodologies, these systems are knowledgeable in the identification and categorization of DR severity, predicated on the distinctive lesions discernible in fundus images [4, 5]. Healthcare professionals can improve their diagnostic abilities and enable early diagnosis and treatment of diabetic retinopathy by utilizing machine learning (ML) [4, 5]. These technologies are especially useful in areas with limited resources where access to specialist healthcare services may be restricted since they are scalable and accessible [5].

The exigency for effective and highly accurate diagnostic instruments is growing as the incidence of diabetic retinopathy remains elevated [1, 2]. An encouraging approach to this problem is the use of automated retinal image analysis apparatus, which have the potential to enhance patient outcomes and lessen the strain on healthcare systems [3, 5]. These technologies enable medical personnel to provide prompt therapies that can greatly reduce the risk of visual impairment and blindness associated with diabetic retinopathy by integrating easily into current clinical workflows [3, 5]. The field of automated retinal visual analysis continues to blossom as a result of continuous research and development activities, and future developments in the identification and treatment of diabetic retinopathy are anticipated to be substantially greater [4, 5].



## II. LITERATURE SURVEY

Regarding the arena of diabetic retinopathy (DR) detection, several studies have been undertaken with the goal of utilizing advancements made in deep learning (DL) and machine learning (ML) methodologies. A comprehensive examination of the literature demonstrates how DL models—in particular, deep convolutional neural networks, or CNNs—have evolved in the process of examining retinal visuals for indications of DR [4]. Further studies evaluating the comparative effectiveness of vintage machine learning algorithms have been conducted in this domain as well as their integration [4]. By emphasizing the benefits and drawbacks of various methods, this amalgamation of research paves the way for the emergence of the best practices for diagnosing DR in healthcare environments [4].

Despite these innovations, consideration is also given to the hurdles in using manual DR screening techniques and the possibility of using automated systems to address these drawbacks [2]. Scalable viable solutions are desperately needed, as exhibited by the resource limitations and interobserver variability seen in conventional screening procedures [2]. The revolutionary potential of DL and ML technologies in evolving DR diagnosis and therapy is made readily apparent by contrasting human and automated screening methodologies [2].

On top of that, the review of the research explores the more general effects of socioeconomic factors on the affordability of DR screening, emphasizing inequalities in the provision of healthcare, especially in underprivileged areas [6]. Considering how technology is evolving within the broader healthcare system clarifies potential AI-driven solutions might enhance accessibility and equity in DR care [6]. This comprehensive knowledge reinforces how important it is to have fair and inclusive DR screening programs that use AI technology to close gaps in healthcare delivery [6].

Research on automated methods for identification has shown promise in the search for better diabetic retinopathy screening and diagnosis [7]. These initiatives seek to eradicate the drawbacks of manual screening, especially its high expense, low sensitivity, and tedious tasks [7]. Researchers are working to improve the efficacy and precision of DR detection by utilizing sophisticated techniques such ensemble-based frameworks, pre- processing, and enhancement algorithms [7]. This supervised drive for automation highlights the group's goal of using technical innovation to lessen the consequences of DR [7].

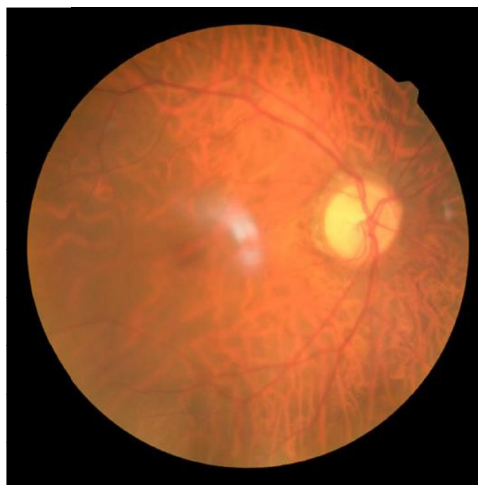
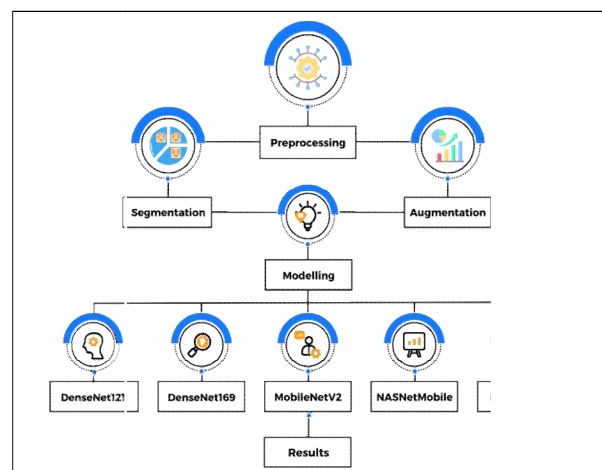


Fig: Infected Retina

YEAR	TITLE	MODEL / METHO D	ALGOR ITHM/ ARCHI TECTU RE	DATA SET
2023	Diabetic Retinopat hy detection based on CNN	Increment al Modular Networks (IMNets)	CNN (MCNN)	IDR.ID, MESSI DOR, APTOS
2023	Analysis of Diabetic Retinopat hy based on the Deep Learning	Neural networks, Alex Net, Deep CNN, ResNet-101	SVM with numerous kemats Ant colony for core features	APTOS, Fundus images
2023	Detection & grading of Diabetic Retinopat hy using digital retinal images	C-means Clustering	SVM, KNN, Decision Trees	Kaggle
2022	Detection of Diabetic Retinopat hy using DCNN on mobile devices	MobileNet Efficient Net B7, B0 (Confusion matrix)	DCNN	Kaggle

### III. PROPOSED METHODOLOGY

In this study, we stipulate a novel approach to develop a robust, noise-tolerant system for diabetic retinopathy receiving a diagnosis. Leveraging deep learning methods, our method correctly classifies retinal visuals according to the prevalence of diabetic retinopathy, that varies from No DR to Proliferative DR. To improve the data quality and reduce noise artifacts, a number of preprocessing processes were carried undertaken before feeding the illustrations into the neural network. A vital aspect of our research was training two different models: the regression model for comparison and the suggested deep learning model. In experiments of diabetic retinopathy categorization, the recommendation for deep learning model outperformed the regression model as far as of accuracy. This result demonstrates how well our deep learning-based method distinguishes between different phases diabetic retinopathy severity levels.



### 3.1 DATA SOURCE:

Two well-known datasets—Diabetic Retinopathy Detection 2015 and APTOS 2019 Blindness Detection—both acquired via Kaggle contributed data for our investigation. The accumulation of thousands of retinal images taken in different settings offer a rich and varied resource for assessment and training. Two visuals, one for each subject's left and right eye, are included in the datasets. It's crucial to remember that the photos come from a variety of sources, including different cameras and models, which introduces noise and unpredictability that calls for rigorous preprocessing.

Each image's accompanying diabetic retinopathy is rated from 0 to 4, with 4 denoting the severity of the condition:

0: No Diabetic Retinopathy (No DR)

1: Mild Diabetic Retinopathy

2: Moderate Diabetic Retinopathy

3: Severe Diabetic Retinopathy

4: Proliferative Diabetic Retinopathy

Through the use of this grading system, retinal anomalies can be precisely classified and characterized, affording crucial clinical insights into the course and severity of diabetic retinopathy. The objective of this project is to create and assess deep learning models that can precisely identify and categorize diabetic retinopathy according to severity levels by using this annotated data. We aim to fully utilize these datasets to advance the science of diabetic retinopathy diagnosis and improve clinical decision-making and patient care through rigorous preprocessing and strong model training.

### 3.2 DATA PREPROCESSING

We meticulously organize the file places for retinal images and the labels that go with them into a structured dataframe as part of our data preprocessing regularity. This methodical approach guarantees effective data administration and makes a breeze to integrate into the subsequent steps of the model building process. We simplify data access and manipulation by enclosing image paths and labels within a dataframe, providing a strong basis for reliable model training and assessment.

The dataframe is subsequently divided into separate subsets for training, validation, and testing using a train-validation-test split methodology. By leveraging the `train_test_split` function, we may maintain the distribution of diabetic retinopathy severity levels among several partitions while guaranteeing the integrity of every subset. This deliberate division reduces the possibility of overfitting and safeguards the trained model's capacity for generalization by facilitating thorough model assessment and validation.

The configuration of Image Data Generator objects that are suited for both training and testing data is a cornerstone of our data preprocessing workflow. These generators are essential for executing preprocessing operations to the retinal images, like scalar normalization. We improve the model's robustness to modifications in input data by normalizing image intensities and improving data consistency, which helps to promote accurate and dependable diabetic retinopathy detection.

We also comprehend that optimizing memory consumption is crucial while testing models. In order to achieve this, we determine a unique batch size for the test generator, guaranteeing effective use of processing power while protecting high throughput. We balance computational economy with model performance, enabling smooth and seamless model inference in practical applications by dynamically modifying the batch size based on memory restrictions. We provide the foundation for the creation of a strong and dependable diabetic retinopathy detection system, intended to have a significant influence on clinical practice, with these meticulous data preparation procedures.

### 3.3 DATA AUGMENTATION

By incorporating a variety of improvements to the retinal images as part of our data augmentation technique, we manage to improve the training dataset and strengthen the resilience of our model. We implement a number of important transformations, such as rotation, shifts in width and height, zoom, flips in both directions, brightness correction, shear transformation, and normalization, by utilizing the Image Data Generator. Through the



implementation of an accurate strategy, it is ensured that a variety of representative training samples will be generated, which will aid in the identification of invariant features for the detection of diabetic retinopathy.

**Rotation:**

To add variation to orientation and allow the model to learn from various angles and perspectives, images are randomly rotated within an agreed-upon angle range ( $0^{\circ}$ – $360^{\circ}$ ).

**Flipping:**

The random usage of horizontal and vertical flips has a probability of either 0 (no flipping) or 1 (with flipping). The model's capacity to generalize to mirrored and inverted representations of retinal visuals is improved by this alteration.

**Shearing:**

To produce distortions that mimic variations in perspective and viewpoint, random shear transformation is used at angles that vary between  $-15^{\circ}$  to  $15^{\circ}$ .

**Rescaling:**

Utilizing a scale factor ranging from 0 to 1, images are arbitrarily resized to accommodate changes in size and magnification while preserving spatial relationships.

**Translation:**

The model can learn robust features regardless of its position varies inside the image by applying random shifts in both vertical and horizontal directions, with a shift range of -10 to 10 pixels.

**Brightness Adjustment:**

The model's tolerances to various lighting circumstances is improved and its performance is ensured across diverse illumination settings by making random adjustments to brightness.

**Normalization:**

To enhance overall stability and performance, the pixel values of the images are normalized to a specific range, often  $[0, 1]$  or  $[-1, 1]$ . This aids convergence during model training.

**3.4 MODELLING**

In the process of implementation, we build a strong model for the identification of diabetic retinopathy by employing the capabilities of deep learning techniques. In particular, we utilize five cutting-edge architectures, each seamlessly incorporated with its analogous TensorFlow Keras application module. NASNetMobile, EfficientNetB3, MobileNetV2, DenseNet121, and DenseNet169 represent a couple of these architectures. The initial performance metric of every algorithm is set to 0, guaranteeing a uniform basis for training and assessment.

**DenseNet121:**

The dense connectivity pattern of DenseNet121, an iconic convolutional neural network (CNN) design, facilitates for effective feature reuse and gradient flow across the network. The tightly interconnected blocks in this architecture allow for efficient feature extraction at various scales. Our DenseNet121 implementation is specifically designed to take into account its natural abilities to capture intricate details found in retinal visuals, which improves the model's discriminative capacity in the announcement of diabetic retinopathy.

**DenseNet169:**

DenseNet169 is a model that relies on the premise of DenseNet by providing greater model depth and capacity, making it possible more complex feature representation and learning. DenseNet169 upgrades model performance by promoting strong feature propagation and gradient flow by conducting the use of densely connected layers. We deploy

DenseNet169's capabilities in our implementation to extract rich hierarchical features from retinal visuals, which elevates the model's ability to detect the subtle symptoms associated with diabetic retinopathy.

#### **MobileNetV2:**

Known for its effective design and lightweight architecture, MobileNetV2 is especially well-suited for resource-constrained settings like embedded and mobile devices. MobileNetV2 performs outstandingly in depict classification tasks given its tiny stature. We take use of MobileNetV2's efficiency in our implementation to achieve quick inference times without affecting accuracy, which makes it an appealing decision for real-time applications that detect diabetic retinopathy.

#### **NASNetMobile:**

Using reinforcement learning strategies to automatically find highly efficient neural network topologies, NASNetMobile marks a breakthrough in neural architecture search (NAS). NASNetMobile represents an appealing choice for a variety of computer vision jobs, including diabetic retinopathy detection, because to its exceptional adaptability and flexible thinking. The effectiveness and capacity of the re improved by our implementation, which makes use of NASNet Mobile's optimized architecture.

#### **EfficientNetB3:**

Especially compared to conventional models, the EfficientNetB3 familyof convolutional neural network layouts achieves state-of-the-art performance with a much less number of parameters. Through the application of a compound scaling technique, EfficientNetB3 produces better results on envision classification tasks by striking a good balance between model depth, width, and resolution. We exploit EfficientNetB3's effectiveness and efficiency in our implementation to improve the precision and productivity of diabetic retinopathy identifying purposes.

### **3.5 IMPLEMENTATION**

We implemented anEfficientNetB3 model, which is a state-of- the-art convolutional neural network architecture that has been particularly effective and efficient in consider classification tasks. Commonly used for its advanced architecture, EfficientNetB3 uses the technique known compound scaling to determine a balance between model depth, width, and resolution. This intricate balancing act enables the ideal possible use of computational resources without reducing performance.

Pre-trained weights were rapidly involved into the EfficientNetB3 model in our implementation, with the exception of the top classification layer. EfficientNetB3 expertly brings high-level features from input visuals via the use of these pre-trained weights, which originate from extensive instruction on large datasets such as ImageNet. This builds down the groundwork for reliable and accurate predictions. This architectural strength and its compound scaling techniques highlight EfficientNetB3's ability of accomplishing impressive results with only a few assets.

Our deep learning model was created through a sequential layer assembly, known to be an aspect of the extensible EfficientNetB3 architecture. The model was initiated by importing max pooling for feature extraction, keeping aside the top classification layer, and triggering an EfficientNetB3 base model with pre-trained weights. On the peak of this base, we created more layers to optimize the model's functionality while enhancing its capability to efficiently generalize to novel data.

We integrated regularization techniques into the model aesthetic in order to boost generalization capabilities and avoid overfitting. Specifically, L1 activity regularization, L1 bias regularization, and L2 kernel regularization were explicitly covered. These regularization treatments raise the predictive capacity on unseen data while allowing it recognize relevant features within noisy or extraneous signals.

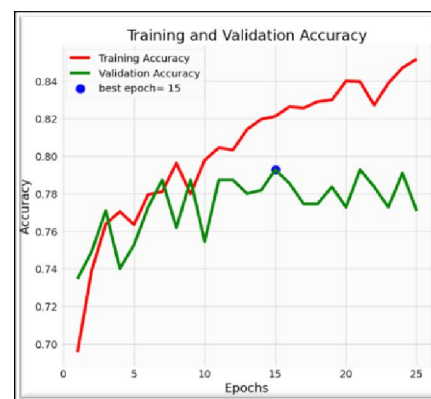
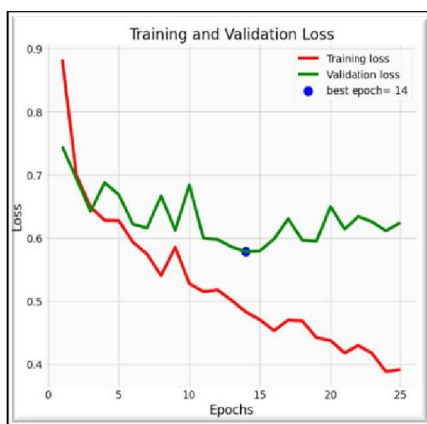
The outcome of our painstaking work was a series of layers for batch normalization, denseness, and dropout. By normalizing layer inputs, batch normalization optimizes training stability and facilitates up convergence. High-level feature representation is possible with dense layers, while overfitting cannot be avoided with dropout layers, which randomly revoke neurons during training.

We employed the Adamax optimizer for training and optimization, which iteratively enhances model parameters by continually altering the learning rate. The completed model is appropriate for training and evaluation due to the has a category crossen tropy loss function and Adamax optimization. The thorough model summary provides significant data on the structure of the architecture, providing a brief description of all the various layer types, output shapes, and the total number of parameters that can be trained.

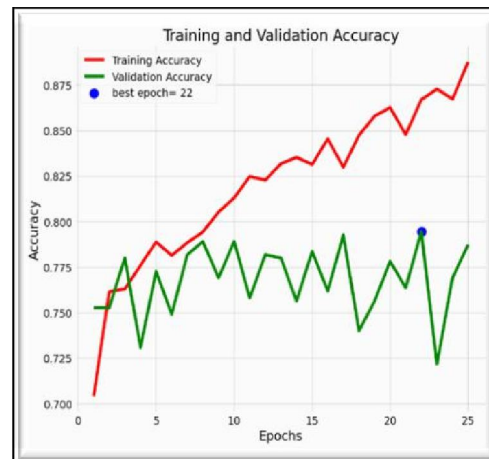
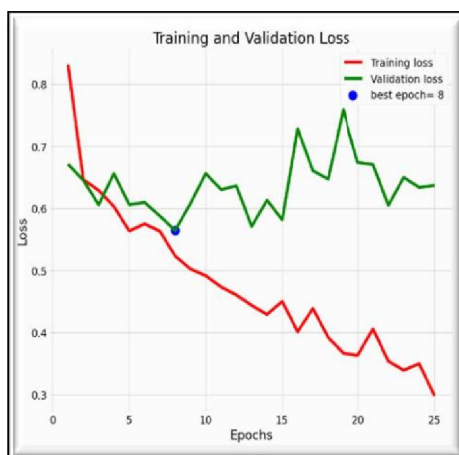
The aim of this project is to generate a durable and efficient deep learning model that is ready to perform better in image classification tasks by meticulously combining the pre-trained EfficientNetB3 architecture and applying extra layers and regularization methodologies.

#### IV. EXPERIMENTS & RESULTS

##### Training and Validation Metrics for DenseNet121:

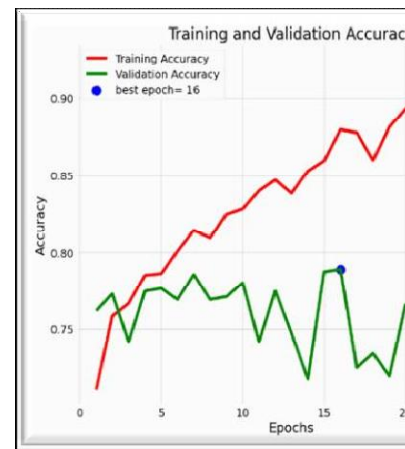
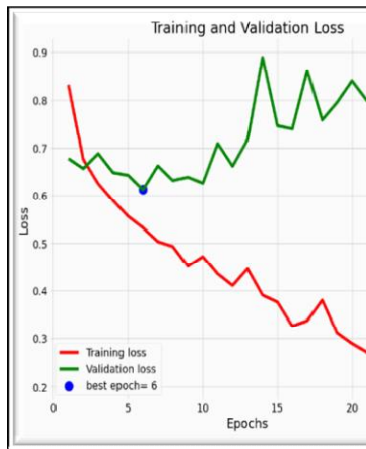


##### Training and Validation Metrics for DenseNet169:



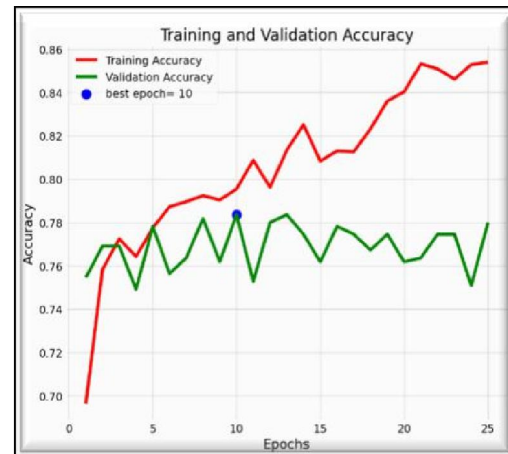
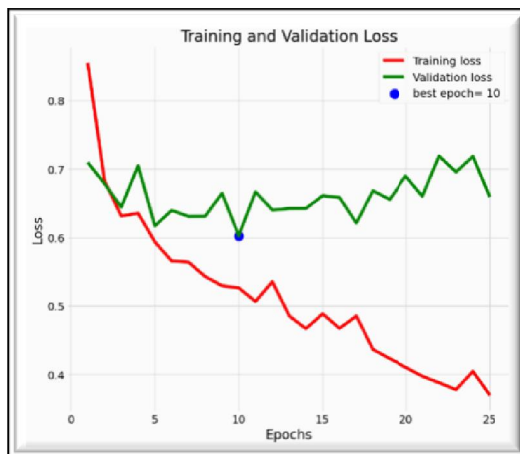


### Training and Validation Metrics for MobileNetV2:

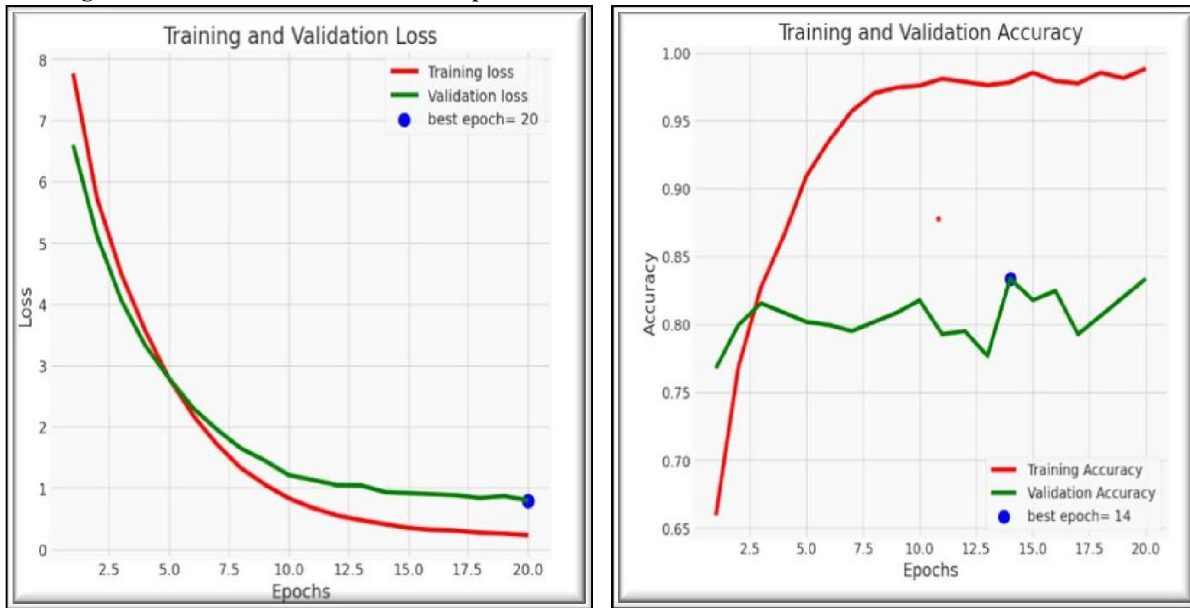


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### Training and Validation Metrics for NASNetMobile:



**Training and Validation Metrics for the Proposed Model:**



**Train Loss:** 0.19413475692272186

**Train Accuracy:** 0.9895833134651184

**Validation Loss:** 0.6448001265525818

**Validation Accuracy:** 0.8802083134651184

Our proposed model demonstrated superior performance compared to all listed models, achieving a validation accuracy of 88%. This result underscores the efficacy of our model for the specified task. It indicates that our model is well-suited for the intended application and offers promising performance when compared to established models such as NASNetMobile, MobileNetV2, DenseNet121, and ResNet101V2, among others.

	Model	Train Accuracy	Validation Accuracy	Training Time (sec)
0	NASNetMobile	0.8423	0.7745	350.68
1	MobileNetV2	0.9297	0.7727	256.49
2	DenseNet169	0.8821	0.7727	398.59
3	ResNet50V2	0.9571	0.7655	328.74
4	ResNet101V2	0.9723	0.7618	439.40
5	ResNet152V2	0.9867	0.7455	689.57
6	DenseNet121	0.8568	0.6782	378.65

## V. EVALUATION METRICS

Several types of measures are used in the evaluation of categorization models in order to determine their effectiveness. Naturally then, the confusion matrix is a crucial instrument that provides an extensive analysis of the model's predictions for various classes. In this study, important evaluation metrics—accuracy, sensitivity (recall), precision, and F1-score—that are obtained from the confusion matrix are explained. By carefully analyzing these indicators, significant information about the model's performance may be obtained, which will help with its improvement and optimization.

### 5.1 CONFUSION MATRIX COMPONENTS

The confusion matrix comprises four fundamental components:

- **True Positive (TP):** Instances correctly identified as belonging to a specific class (e.g., diabetic retinopathy (DR) images).
- **True Negatives(TN):** Negative instances accurately classified as negative.
- **False Positives (FP):** Negative instances erroneously classified as positive.
- **False Negatives(FN):** Positive instances mistakenly classified as negative.

## 5.2 METRICS DERIVED FROM THE CONFUSION MATRIX

**Training Accuracy:** The proportion of correctly classified instances in the training dataset. Achieved a training accuracy of 98.95%, with 24 out of 25 images correctly classified and 2 misclassifications.

**Formula:**  $(TP+TN)/(TP+TN+FP+FN)$

**Validation Accuracy:** The accuracy achieved on the test set. Attained a validation accuracy of 88%, correctly classifying 22 out of 25 images.

**Sensitivity (Recall):** The proportion of correctly identified positive instances.

**Formula:**  $TP/(TP+FN)$

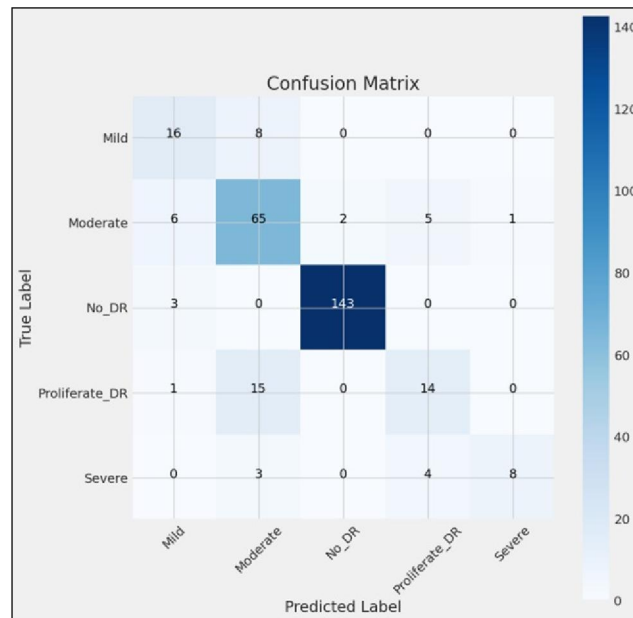
**Precision:** The ratio of correctly predicted positive observations to the total predicted positive observations.

**Formula:**  $TP/(TP+FP)$

**F1-Score:** The harmonic mean of precision and recall.

**Formula:**  $(2 \times \text{Precision} \times \text{Recall}) / (\text{Precision} + \text{Recall})$

The heading of the Acknowledgment section and the References section must not be numbered. Causal Productions wishes to acknowledge Michael Shell and other contributors for developing and maintaining the IEEE LaTeX style files which have been used in the preparation of this template.



## 5.3 EXAMINATION OF CLASSIFICATION MEASURES

The precision, recall, and F1-score for each class are shown in the table below:

CLASS	PRECISION	RECALL	F1-SCORE	SUPPORT
Mild	0.62	0.67	0.64	24
Moderate	0.71	0.82	0.76	79
No_DR	0.99	0.98	0.98	146
P_DR	0.61	0.47	0.53	30
Severe	0.89	0.53	0.67	15

## VI.CONCLUSION

In summary upwards, this research introduces a new Deep Learning method employing convolutional neural networks (CNNs) to detect diabetic retinopathy (DR). The CNN architecture of the suggested model has been painstakingly created with the purpose of being exceptionally good in DR detection. After extensive testing and assessment, our model has outperformed other deep learning models, outperforming them with an 88% validation accuracy. This successful outcome highlights the effectiveness and promise of our method for automated DR detection, providing diabetic patients with a useful tool to successfully monitor and manage their medical condition.

Our model demonstrates the ability to extract complex information from retinal pictures by utilizing CNNs, paving the way for precise classification of the severity levels of diabetic retinopathy. Our model's better performance highlights the accuracy with which it can identify minor signs of depression-related rage (DR), which makes early detection and intervention easier. Furthermore, our approach's stability and dependability make it an affordable choice for DR screening programs that are both scalable and effective, meeting the growing need for easily accessible and high-quality medical treatment.

This study's results pave the way for additional investigation and improvement of automated DR detection systems in the decades to come. Subsequent efforts could concentrate upon enhancing the model's predictability for easy interpretation and a smoother integration into clinical workflows. Furthermore, extending the dataset and adding multi-modal imaging data can enhance the model's capacity for generalization and its suitability for practical application. The ultimate aim of our research is to enhance healthcare outcomes for diabetic people globally by advancing automated DR identification technologies.

## VII. LIMITATION AND FUTURE SCOPE

Despite the automated diagnosis of diabetic retinopathy(DR) has advanced tremendously as a result of our study, there are still a number of issues that need to be addressed and directions for future research. First off, certain significant details in the retinal images may be unintentionally missed by the preprocessing and augmentation methods used. Subsequent studies ought to explore sophisticated preprocessing techniques that successfully augmentation data while retaining all relevant its traits.

On top of that, the quantity of pictorial evidence we use for each patient in our study is restricted, which can limit the model's capacity to categorize images reliably. In order to get over this restriction, future research might think about giving each patient numerous photos, which would enrich the dataset and improve the model's capacity to identify minute variants in retinal pathology.

The ongoing development of neural network architectures offers a chance to investigate hyperparameter tuning in depth. To fully realize the promise of deep learning models for DR detection, subsequent investigations could look at cutting-edge pooling techniques and hyperparameter configurations.

Ensemble learning, which combines and trains multiple models, has the potential to boost model performance as a whole. Ensemble approaches have the potential to improve the resilience and generalizability of DR detection systems by utilizing the unique benefits across multiple models.

Furthermore, the reality that we only used two datasets for our study may limit how broadly the results may be implemented. To improve the effectiveness and generalizability of the model, future studies could investigate incorporating or combining different datasets.

Implementing MobileNet or other lightweight convolutional neural networks shows promise in terms of deployment for creating mobile applications for DR diagnosis. Additionally, the creation of online apps that work with many operating systems may make diabetic retinopathy diagnostic tools more widely accessible, which would improve the outcomes and accessibility of healthcare.

In summary, even though our study has advanced automated DR detection significantly, there are still gaps in the field and need for more research. Throughout the resolution of these constraints and investigation of the delineated prospective range, we shall persist in propelling the domain of automated DR proof of identification, ultimately enhancing healthcare results for individuals with diabetes around the world.

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