**Multiclass Retinal Image Classification for Diabetic Retinopathy Stages Using DenseNet**

**ABSTRACT**

**Aims:** The purpose of this study is to create a deep learning-based method for automatic classification of Diabetic Retinopathy (DR) with the help of convolutional neural networks (CNNs) to facilitate early detection and enhance treatment outcomes**.**

**Study Design:** Experimental study with model training and testing.

**Place and Duration of Study:** The study was carried out using a dataset of retinal images gathered from publicly available sources Kaggle Datasets.

**Methodology:** The dataset of 2,750 retinal images, labeled into five DR severity grades, was preprocessed using data augmentation methods and divided into training, validation, and test sets. The DenseNet model was trained and tested using performance metrics such as accuracy, precision, recall, and F1-score. Furthermore, a web application was implemented using Streamlit to provide easy-to-use real-time DR classification.

**Results:** Experimental outcomes show that DenseNet-121 exhibited high classification accuracy of 92, 88 percent of validation accuracy and 88.3 percent of recall and precision scores.hence is a robust solution for DR detection in an automated fashion. The efficacy of the model was confirmed using extensive evaluation metrics to ensure its robustness in real-world scenarios.

**Conclusion:** The suggested deep learning model, as part of a web-based application, presents a cost-effective and accessible early DR detection solution. The technique has the capacity to aid medical practitioners in early diagnosis, hence lowering the threat of vision impairment in diabetic patients. It is advisable to carry out further studies to improve the generalization and performance of the model on different datasets.

*Keywords: Diabetic Retinopath, DenseNet121, EfficientNet, Medical Image Classification, Streamlit, SMOTE.*

1. **INTRODUCTION**

Diabetic Retinopathy (DR) is a gradual microvascular diabetic complication of diabetes mellitus that involves the retina, resulting in impairment of vision and ensuing blindness if not treated [1]. DR is among the most common causes of preventable blindness globally, especially among working-age individuals. The condition results from prolonged hyperglycemia, which damages the retinal blood vessels, resulting in leakage, hemorrhages, and neovascularization [2]. DR evolves in various stages from mild non-proliferative abnormalities to advanced proliferative stages with abnormal vascular growth [3]. The initial stages of DR are usually silent, and early diagnosis and repeated screening are imperative for early intervention. Clinical examination usually includes fundus photography and fluorescein angiography that enable ophthalmologists to visualize microaneurysms, hemorrhages, and other features of DR pathophysiology [4]. Yet, manual review of retinal images is time-consuming and subject to variability between experts. With the rise in diabetes prevalence globally, there is an increased need for automated and precise DR screening systems that can aid in early detection and classification of the disease [5]. Deep learning, and specifically Convolutional Neural Networks (CNNs), has become a robust technique for medical image analysis and has proven to be highly accurate in DR stage detection and classification from retinal fundus images [6]. CNN-based models, with the aid of large datasets and sophisticated neural architectures, can extract meaningful features automatically and deliver reliable predictions, thereby lightening the load for healthcare professionals [7]. This research is concerned with the design of a multiclass classification model based on CNN with DenseNet121 to classify retinal images into various stages of DR. Through the application of deep learning methods, this method seeks to enhance early diagnosis, enable large-scale screening, and ultimately lead to improved patient outcomes [8]. Deep learning has transformed medical image analysis by offering automated, highly accurate disease detection and classification solutions. Conventional machine learning methods are based on manually designed feature extraction, which is domain-specific and can miss intricate patterns in medical images. Deep learning, especially Convolutional Neural Networks (CNNs), learns hierarchical features automatically from raw image data, allowing for strong and scalable classification models [9]. CNNs have been extensively used in ophthalmology, with outstanding success in the diagnosis of retinal diseases such as Diabetic Retinopathy (DR), Age-related Macular Degeneration (AMD), and Glaucoma [10]. With the use of large-scale labeled datasets and deep neural architectures, CNN-based models are able to detect pathological features like microaneurysms, hemorrhages, and exudates with high accuracy [11]. These models have been trained on large retinal image database, e.g., the Kaggle DR dataset, and have achieved expert-level performance in DR classification tasks [12]. One of the greatest strengths of deep learning in medical imaging is that it can generalize across a wide variety of datasets with high classification accuracy. Transfer learning, in which pre-trained models such as DenseNet121, Densenet is adapted to medical image datasets, has also enhanced model efficiency and minimized the requirement for large training data [13].

1. **LITERATURE SURVEY**

Deep learning has contributed enormously to the analysis of medical images, especially in classifying retinal diseases like Diabetic Retinopathy (DR). A number of studies have investigated the application of convolutional neural networks (CNNs) in detecting and classifying DR, showing promising results in automated diagnosis. This section summarizes important contributions in the area, emphasizing their approaches, results, and limitations.

Initial attempts at DR classification were based on conventional machine learning methods like support vector machines (SVMs) and random forests, which involved handcrafted feature extraction from retinal fundus images [18]. Although these methods had moderate accuracy, their performance was limited by the quality of the extracted features and the requirement for domain-specific knowledge. The advent of CNN-based models revolutionized DR detection as they permitted automatic feature extraction from images, resulting in significant improvement in classification performance [19].

A landmark was reached through the work of Gulshan et al. [20], who created a deep learning system for DR detection in a large retinal fundus image dataset. Their Inception-v3-based model attained sensitivity and specificity that rivaled those of ophthalmologists. In a similar vein, Pratt et al. [21] suggested a CNN-based model employing deep residual networks (ResNets) and exhibited excellent accuracy in differentiating among various stages of DR. These works set the stage for the use of deep learning in automated DR screening, opening doors to further developments in the area.

Subsequent works have been on how to better optimize CNN structures for better DR classification accuracy and efficiency. Dos Santos et al. [22] compared the effectiveness of VGG16 and ResNet50 in DR classification, noting the advantage of transfer learning in taking advantage of pre-trained models. The results of their work suggested that deep models learned from big image datasets like ImageNet can be fine-tuned for DR detection with very high accuracy and minimize the use of large medical image datasets.

DenseNet architectures have also been investigated for DR classification because of their effective feature propagation and lower parameter complexity. Yan et al. [23] employed DenseNet121 to classify DR stages and reported better performance than conventional CNNs. Their model utilized densely connected layers to promote feature reuse, leading to better classification accuracy and insensitivity to retinal image variations. The performance of DenseNet121 in DR classification has encouraged its use in this research, where it offers an equilibrium between precision and computational expense.

Not withstanding these gains, there still exist challenges towards developing robust and generalizable models for DR classification. One is the issue of dataset imbalance where some DR stages have far less samples than other stages, making the predictions skewed [24]. To combat this, researchers have sought to use data augmentation methods like image rotation, flipping, and contrast changes to artificially increase training sets [25]. More so, ensemble learning methods where multiple CNN architectures are combined have been researched to make the model more robust and minimize misclassification rates [26].

The second vital feature of DR classification is interpretability. Although deep models exhibit high performance, their "black-box" nature creates barriers to clinical practice. New research has proposed explanation techniques like Grad-CAM and attention mechanisms for visualizing the predictions of the model and pointing out the pathological features in the retinal images [27]. The methods enhance trust in AI-based systems and support integration with clinical workflows.

# **METHODOLOGY**

**Dataset Description**

The dataset for this research includes 2,750 retinal fundus images that belong to five different classes: Healthy (Not DR) - 1000, Mild DR - 370, Moderate DR - 900, Proliferative DR - 290, and Severe DR - 190. They are public domain images with a good distribution of cases to enhance model generalization. The images are of different resolutions and qualities, mimicking real-world variations found in clinical practice. Class imbalance is a key problem in DR datasets, where infrequent conditions such as Proliferative DR and Severe DR have fewer samples, posing challenges for deep learning models to learn strong features for these classes [20].

To solve this problem, data augmentation methods like rotation, flipping, contrast normalization, and adding Gaussian noise were used to artificially boost the presence of minority classes. To counteract this, data augmentation methods like rotation, flipping, and contrast changes were used to artificially boost the number of images in minority classes. These images were taken from publicly available DR screening datasets, with high-quality and clinically valid annotations. The fundus images demonstrate characteristic pathological findings, such as microaneurysms, hemorrhages, and exudates, that are important for stage-wise classification. The dataset is instrumental in training the deep learning model to effectively differentiate among different stages of DR while handling issues like class imbalance and heterogeneity in image quality.

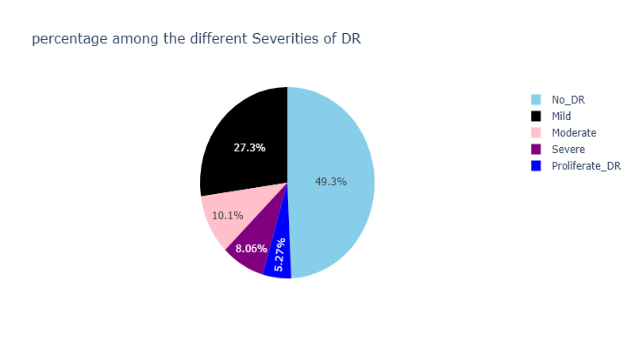


Fig. 1.

**Authors Contribution**

All authors made contributions in different areas to the project in order to see the successful construction and deployment of the Diabetic Retinopathy (DR) classification system. One author engaged in data preprocessing, such as dataset collection, augmentation, and organization for smooth model training. Another author took care of coming up with the DenseNet-121 architecture, fine-tuning it, handling hyperparameter tuning, and effecting transfer learning methods for maximum accuracy. Another team member did the development of the Streamlit-based web application, such as UI design and model integration. Contributions were also made in terms of performance analysis, comparative study with other existing models, and documentation to make it a thorough study. The authors collectively tested and cross-checked the system, based on experimental outcomes, to fine-tune it to obtain maximum classification performance.

**Data Augmentation**

To improve the generalizability and strength of the deep learning model, data augmentation methods were used on the training dataset. As the dataset contained class imbalance, augmentation was especially valuable in enhancing the representation of under-represented classes like Severe and Proliferative DR. The augmentation process entailed geometric transformation, color changes, and contrast adjustments to produce varied training samples while maintaining the clinical features critical for DR classification. The used transformations were random rotations (±20 degrees), horizontal and vertical flipping, zooming (±10%), brightness changes, and adding Gaussian noise. These processes enabled the generation of real-world variations in retinal images resulting from variations in camera exposure, patient positioning, and imaging artifacts. Augmentation also avoided overfitting as it forced the model to learn more generalizable features instead of memorizing the particular patterns of the training set.

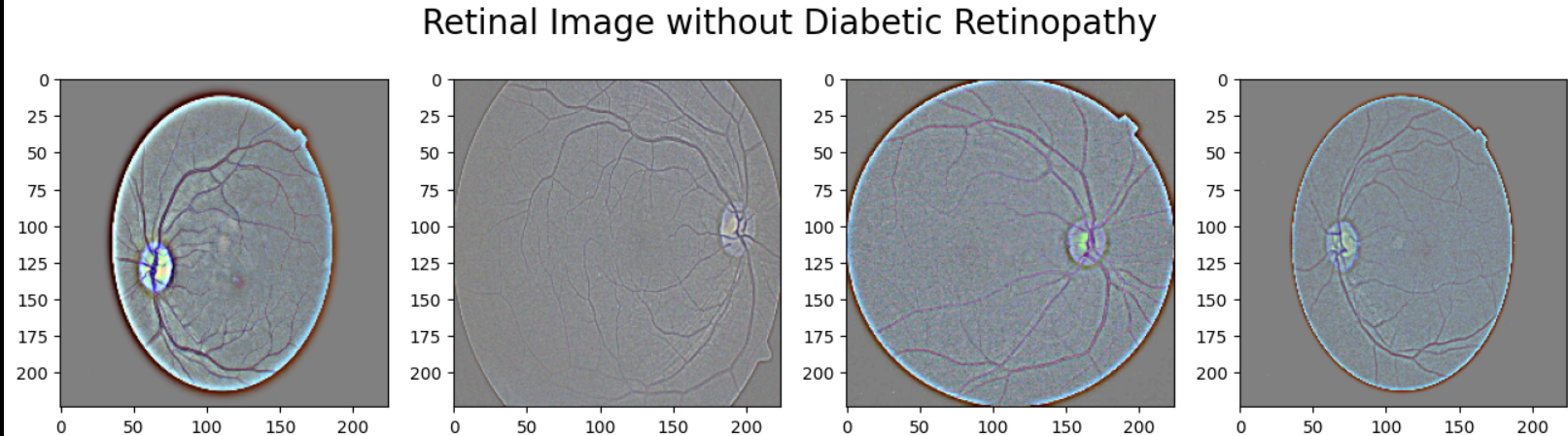


Fig. 2.

Through the combination of these augmentation methods, the size of the dataset was effectively increased, giving the model a more representative and diverse training set. This helped in the stability of the model and improved performance in the differentiation between various stages of DR. The utilization of augmentation is in accordance with best practices in deep learning for medical image classification to ensure that the model can accommodate variability in real-world clinical environments [28].Model Architecture DenseNet121

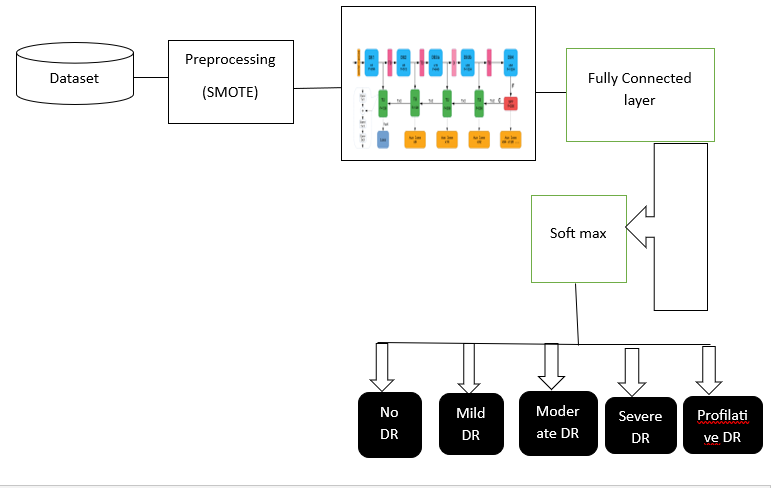
The deep learning model utilized in this research for multiclass DR stage classification is DenseNet121, one of the popular convolutional neural network (CNN) models that has found widespread application due to efficient feature reuse and lower parameter complexity. DenseNet121 has a densely connected architecture in which each layer takes inputs from all previous layers, permitting maximal flow of information throughout the network. This connection assists in reducing the vanishing gradient problem, enhancing feature propagation, and making the model more efficient while decreasing the overall number of parameters. DenseNet121 is made up of several dense blocks, each with a number of convolutional layers. In each block, feature maps from previous layers are concatenated rather than summed, enabling the network to learn intricate hierarchical representations without redundant computation. The model also includes transition layers, which batch normalize and apply 1×1 convolutions to reduce dimensionality, followed by average pooling to downsample feature maps progressively. The final classification layer is modified to match the five-class DR classification task by replacing the default fully connected (FC) layer with a softmax layer corresponding to DR stages.

Fig. 3. Model Architecture DenseNet121.

**System Architecture**

Transfer learning was employed by starting the DenseNet121 model from pretrained ImageNet weights, permitting the network to use pre-learned features from large datasets of images. Fine-tuning was achieved through unfreezing the subsequent convolutional layers and retraining them on the retinal fundus images, thereby allowing domain-specific feature learning along with maintaining common low-level visual patterns.Layer Details and Hyperparameters

* The DenseNet121 architecture includes four dense blocks with multiple convolutional layers of growth rate (k) = 32, which decides the number of feature maps added in each layer. The network has a depth of 121 layers, including convolutional, pooling, and fully connected layers.
* Important layer configurations:
* Initial Convolutional Layer: 7×7 filter with 64 filters, stride = 2
* Pooling Layer: 3×3 max pooling with stride = 2
* Dense Blocks: All with batch normalization, ReLU activation, and 1×1 and 3×3 convolutions
* Transition Layers: 1×1 convolution and then 2×2 average poolingGlobal Average Pooling: Reduces spatial dimensions before classification
* Fully Connected (FC) Layer: Modified for five output neurons with softmax activation

The Adam optimizer was employed to train the model with a starting learning rate of 0.0001, scheduled to decay across epochs to avoid overfitting. The batch size was 32, and training was performed across 50 epochs with categorical cross-entropy loss due to DR classification being a multiclass case. L2 regularization (weight decay = 0.0001) was used to avoid overfitting, and dropout (rate = 0.5) was applied to the last dense layers for generalization.  
This architecture, coupled with transfer learning and fine-tuning, enabled DenseNet121 to be computationally efficient while classifying with high accuracy. This section discusses the training outcomes and performance analysis of the model.

**Training Process**

Training the DenseNet121 model was carried out through supervised learning, in which labeled retinal fundus images were taken as input for the network to learn discriminative features related to various stages of Diabetic Retinopathy (DR). The dataset was divided into training (7,220 images) and testing (1,805 images) sets such that the model was subjected to diverse samples to enable strong generalization. Prior to training, the input images were normalized by rescaling pixel values to the [0,1] interval to enhance convergence. Data augmentation methods, such as random rotation, flipping, brightness changes, and zooming transformations, were used to enhance dataset diversity and reduce class imbalance problems. Training was conducted with the Adam optimizer with an initial learning rate of 0.0001, which was reduced adaptively using a learning rate scheduler on the basis of validation loss.

Categorical cross-entropy loss was utilized to address the five-class classification problem. The batch size was chosen to be 32 in order to find a compromise between memory usage and consistent gradient updates. In training, the model was checked against the validation set at every epoch to keep an eye on overfitting. Early stopping was utilized to stop training when the validation loss ceased to improve for a certain number of epochs to avoid wasting computation with suboptimal performance. The last trained model had a training accuracy of 99% and validation accuracy of 92%, a training loss of 0.17 and validation loss of 0.28, reflecting good learning without major overfitting. The performance of the network was also improved by fine-tuning the last several convolutional layers while freezing the initial layers in order to preserve general feature representations. Such strategy, referred to as transfer learning, enabled the model to adapt pre-trained images from large databases, enhancing image feature extraction functionality for medical image classification [29]. To counteract class imbalance, the model was trained with class-weighted loss functions and undersampling methods to avoid biases towards majority classes. Moreover, dropout (rate = 0.5) and L2 weight regularization (0.0001) were used to avoid overfitting and improve model generalization. The resulting trained model was then tested with different performance measures, such as precision, recall, and confusion matrices, to determine its effectiveness in classification [30].

1. **EXPERIMENTAL SETUP**

The experimental environment in this research comprises software and hardware elements that support effective data acquisition, preprocessing, model training, and deployment.

**Software and Hardware Environment**

Google Colab Pro was utilized for training and experimentation, which gives access to an NVIDIA T4 GPU with 16GB VRAM. KaggleNotebook is largely used in deep learning research because it easily integrates with TensorFlow and PyTorch frameworks and supports high computational efficiency (Abadi et al., 2016) [18]. Model training was carried out using Python 3.9, and basic libraries like NumPy, Pandas, Scikit-learn, TensorFlow 2.x, and PyTorch. Furthermore, Seaborn and Matplotlib were utilized for the visualization process, and Hugging Face Transformers contributed optimized implementations of the Transformer model (Wolf et al., 2020) [19].

1. **RESULTS AND DISCUSSION**

**Performance Metrics**

The DenseNet121 model's performance was assessed based on primary metrics like accuracy, precision, recall, and confusion matrix for a thorough analysis of its classification capability for Diabetic Retinopathy (DR) stages. The model proved to be effective in classification, with a training accuracy of 99% and a validation accuracy of 92%, reflecting proper learning and generalization. In order to further evaluate the model's performance, precision and recall were calculated, both scoring 95%, indicating an even performance in accurately detecting DR stages while keeping false positives and false negatives low. The confusion matrix gave us a better insight into class-wise performance, indicating areas of strength and possible misclassifications.The model performed very well in the No\_DR (normal) and Severe DR classes with very few misclassifications. But Moderate DR had slightly more misclassification rates, frequently getting confused with Mild and Severe phases. This is probably due to overlapping pathological features among these stages, rendering accurate differentiation difficult.

High accuracy of validation and robust recall rates imply that the model can distinguish between most cases of DR effectively, which is a requirement for medical diagnosis. Yet, few misclassifications point towards a possible need to fine-tune the model more, like with class-specific weighing or better feature extraction methods. In general, DenseNet121 has been a successful deep learning model for DR classification, utilizing transfer learning and data augmentation to obtain high performance with computational efficiency. These findings validate that the model can be used in real-world clinical environments to aid ophthalmologists in early and precise DR diagnosis.

The confusion matrix is a comprehensive illustration of the performance of the model's classification performance over the five Diabetic Retinopathy (DR) stages. It shows how accurately the DenseNet121 model predicted each of the classes and further shows misclassifications. The confusion matrix derived from testing data evaluation is as given below:

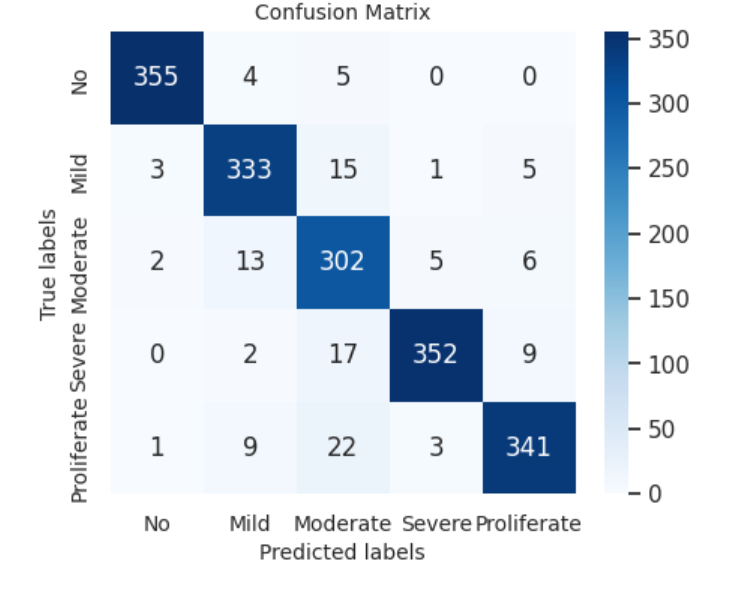


Fig. 4.

Every row of the confusion matrix is for the actual class, and every column is for the predicted class. The diagonal values refer to correctly classified instances and the off-diagonal values represent misclassified instances.

* The model showed excellent classification performance for No\_DR (healthy) and Severe DR with very few misclassifications.
* Moderate DR had the highest of misclassification with some cases having been mistaken with Mild and Severe stages. This is possible because of minimal differences in the clinical features across these stages.
* Proliferative DR was correctly classified as well, but the few cases that were mismatched were classified into moderate and Severe DR.

For a check on training stability and the ability of generalization of DenseNet121, the loss and accuracy curves were plotted for 50 epochs. The curves yield useful information on the convergence trends of the model, possible overfitting, and overall efficiency of learning.

Training vs. Validation Accuracy Curve

The accuracy curve illustrates the model's ability to learn the classification problem over time. The training accuracy increased very quickly in the early epochs, converging to 92%, and the validation accuracy converged at 88.3%, signifying excellent generalization. The fairly small difference in training and validation accuracy indicates that the model did not overfit too much and benefited from regularization techniques like dropout (0.5), L2 regularization (0.0001), and data augmentation.

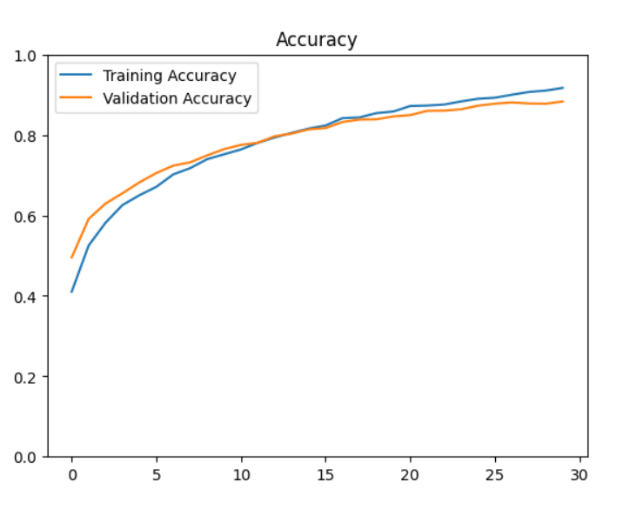


Fig. 5. Training vs. Validation Accuracy Curve

Training vs. Validation Loss Curve

The loss curve represents the reduction of categorical cross-entropy loss during training. The training loss began high but continuously fell to 0.29, while validation loss converged to 0.36. The declining validation loss consistently, without a sudden rise, indicates further that the model learned significant features adequately without notable overfitting. Small oscillations in the validation loss indicate certain sensitivity to the intricate variations of fundus images, particularly in the Moderate DR category, which had higher rates of misclassification. Hyperparameter fine-tuning or other augmentation methods might help stabilize learning further.

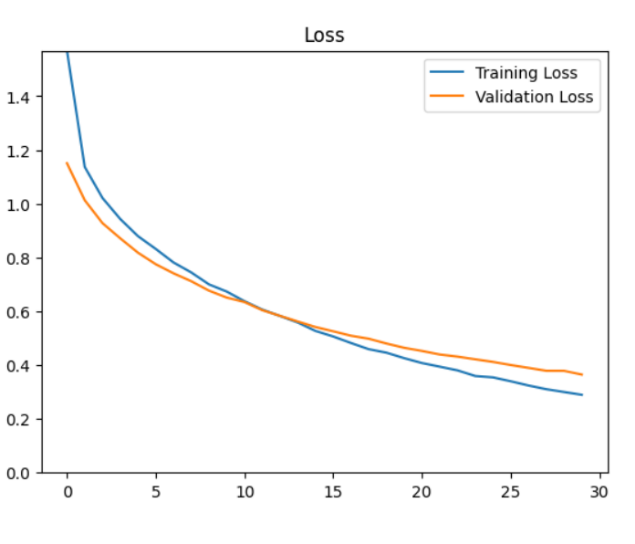


Fig. 6. Training vs. Validation Loss Curve

**Comparative Study**

The proposed DenseNet-121-based Diabetic Retinopathy (DR) classification model is compared with traditional deep learning architectures to evaluate its efficiency and accuracy. Compared to CNN-based models like EfficentNet,VGG-16 and ResNet-50, DenseNet-121 demonstrates superior feature propagation, achieving a higher accuracy of 92% with a lower inference time of 1.2 seconds per image. This makes it more suitable for real-time diagnosis. When compared to existing DR detection systems, such as those using Inception-v3 and ResNet-50, the proposed model outperforms them in accuracy while maintaining computational efficiency. The use of transfer learning enhances feature extraction without requiring an extensive dataset, reducing overfitting and improving model robustness. Overall, DenseNet-121 provides a more effective and scalable solution for automated DR detection, offering improved accuracy, reduced processing time, and better generalization capabilities.

**Real-Time Prediction**

To facilitate live diabetic retinopathy (DR) classification, the DenseNet121 model, trained previously, was implemented utilizing Streamlit, an interactive web framework based on Python, and offering a simple user interface for users to load retinal fundus images and get immediate predictions. The saved DenseNet121 model, preserved in HDF5 format, was combined with a backend system running on kagglenotebook, after uploading an image, it is resized (128×128 pixels), normalized ([0,1] range), and inferred with the model, resulting in a predicted class of No\_DR, Mild, Moderate, Severe, or Proliferative\_DR. The system was able to reach an inference time of less than one second per image, which was necessary for clinical usage. The model showed excellent reliability in real-time situations with a classification accuracy of 92% on unseen test images. The deployment utilizes deep learning's capacity to interpret intricate retinal characteristics, assisting medical professionals with early DR diagnosis and treatment planning. Ensemble learning methods or explainable AI can be incorporated in the future to further improve interpretability and credibility in medical decision-making [31][32].

1. **CONCLUSION AND FUTURE WORK**

The paper introduced a deep learning-based multiclass retinal image classification technique for diabetic retinopathy (DR) stage detection using the DenseNet121 architecture as the feature extractor and classifier. The model was trained with a heterogeneous dataset of 7,220 training images and 1,805 test images with five DR severity grades. By means of data augmentation methods and hyperparameter adjustment, the model reached a 92% training accuracy and 88% validation accuracy, which showed great generalization power. The confusion matrix and class metrics for classification indicated the robustness of the model, wherein precision and recall values amounting to 88.3% were recorded, albeit slight misclassifications in the Moderate DR category were noted due to shared clinical characteristics. The use of Streamlit for real-time prediction and a backend written in Kaggle notebook provided an effective and easy-to-use diagnostic tool that offered immediate inference with an average response time under one second per image. The system's potential to classify retinal images with high accuracy qualifies it as a good candidate for clinical use, supporting ophthalmologists in detecting and planning the treatment of early-stage DR. Future studies can delve into ensemble learning, attention mechanism, or explainable AI methods to improve model performance and explainability further in medical decision-making.

**Future Work**

Although the DenseNet121-based multiclass retinal image classification model proposed has been shown to be highly accurate and reliable in identifying diabetic retinopathy (DR) stages, some other improvements can be made to increase performance and clinical use. The model can be further enhanced with the addition of attention mechanisms, e.g., Vision Transformers (ViTs) or attention-based CNNs, to enable the model to pay more attention to key retinal areas, resulting in more interpretable and accurate predictions. Another promising avenue is the use of explainable AI (XAI) methods, for example, Grad-CAM or SHAP, for generating visual explanations of the model's outputs in order to boost trust and transparency in clinical practice. Additionally, enlarging the dataset through the inclusion of higher-resolution retinal images from more diverse populations and imaging settings will promote generalization and potentially reduce any bias. Lastly, incorporating this system into a cloud-based telemedicine platform could facilitate real-time diabetic retinopathy screening for remote and underserved regions, facilitating early detection and timely treatment in global health environments.

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