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DIABETIC RETINOPATHY DETECTION AND CATEGORIZING USING A LIGHTWEIGHT DEEP LEARNING APPROACH

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ABSTRACT

Diabetic retinopathy is an ocular disorder that has the potential to result in visual impairment and complete loss of vision in those diagnosed with diabetes. This illness affects the retinal blood vessels inside the light-sensitive tissue layer at the posterior of the eye, known as the retina. This paper presents a complete approach to diagnosing and categorizing diabetic retinopathy using deep learning models. A lightweight Convolutional Neural Network (CNN) is used to detect diabetic retinopathy in fundus images. This CNN has been developed to have fewer parameters and calculations, making it suited for resource-constrained environments while retaining decent performance. The categorization of diabetic retinopathy is carried out with the help of EfficientNet. This model uses an innovative compound scaling approach to strike a balance between the model's depth, width, and resolution. As a result, it maximizes computing efficiency while preserving high accuracy. The proposed detection model obtained an accuracy of 95%, and the classification model produced an accuracy of 84%.

Keywords: classification, convolutional neural network, detection, diabetic retinopathy, EfficientNet.

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1. INTRODUCTION

DR is a consequential ocular ailment from diabetes, especially in persons with challenges maintaining optimal glycemic control. This disorder is characterized by the adverse consequences of increased glucose levels in the bloodstream on the microvascular network inside the retina, which is the photosensitive tissue situated at the posterior region of the ocular organ. Over a prolonged duration, this detrimental effect might give rise to ocular complications, such as impaired visual acuity, the manifestation of floaters, and, in extreme instances, total loss of eyesight. To efficiently manage and mitigate the occurrence of DR [1], it is essential to undertake periodic ocular examinations and diligently regulate glycemic management. Early identification and management are crucial in mitigating the likelihood of visual impairments in those affected by diabetes.

Identifying and categorizing phases of DR, a vision-threatening consequence of diabetes is a crucial field of study and medical application. By utilizing sophisticated imaging modalities, including fundus imaging, optical coherence tomography, and Machine Learning (ML) algorithms, collaborative efforts between healthcare practitioners and researchers are underway to create automated systems capable of effectively identifying DR [2], differentiating between its different stages (ranging from mild non-proliferative to severe proliferative) [3], and delivering timely interventions. The timely identification and categorization of Diabetes Patients (DP) play a pivotal role in optimizing healthcare interventions and mitigating visual impairment, ultimately leading to enhanced healthcare results.

The detection [4]and classification [5] of DR have great importance due to their pivotal role in promptly diagnosing and treating a severe disease linked to diabetes. DR is a widely seen cause of vision impairment on a worldwide level, mainly affecting those who have been diagnosed with diabetes [6]. This problem's prompt and precise identification is crucial to avoid permanent visual impairment. Through the utilization of sophisticated imaging methodologies, ML algorithms, and Artificial Intelligence (AI) healthcare practitioners can expeditiously discern the ailment's advancement, hence enabling prompt intervention and customized therapeutic strategies. The identification and categorization of DR include various techniques within medical imaging and computer vision [7]. The use of retinal images is a common practice in these methodologies, including the application of conventional image processing methods and sophisticated ML algorithms. Standard methodologies encompass various strategies, such as image pre-processing to enhance the quality of features, the segmentation of blood vessels, the identification of lesions, and the utilization of DL models, specifically CNNs, to automate the evaluation and classification of the severity of DR [8].

The current techniques used in detecting and classifying DR encounter a range of research obstacles that want prompt attention. It is essential to enhance the robustness and accuracy of automated screening procedures since existing algorithms often exhibit deficiencies in sensitivity and specificity. Moreover, incorporating sophisticated DL architectures, such as CNNs and Recurrent Neural Networks (RNNs), with diverse and enormous datasets presents a significant and daunting obstacle.

Furthermore, there is a determined lack of real-time, cost-effective, and easily accessible screening methods, particularly in settings with low resources. This paper presents a DR detection and classification model using DL. Section 1 presents the paper's introduction;

section 2 presents the literature survey, section 3 presents the architectures in the proposed model, section 4 presents the experimental results, and section 5 conclusions and future scope.

2. LITERATURE SURVEY

Zubair Khan *et al* [9] focused on enhancing the efficacy of training and the convergence of models in identifying various stages of DR by reducing trainable characteristics. A DL model known as VGG-NiN has been devised to accomplish this objective. This model integrates the VGG16 model with the spatial pyramid pooling layer (SPP) and network-in-network (NiN) architecture. This model exhibits strong nonlinearity and scale invariance. Nikos Tsiknakis *et al* [10] presented a comprehensive examination of DL methods across the many stages of the DR diagnosis process, specifically focusing on using fundus images. In this discourse, the authors examine various facets of the pipeline encompassing the utilization of datasets widely employed within the research community. Manisha Saini *et al* [11] conducted a comprehensive comparison study on many advanced techniques used on three benchmark datasets in diabetic retinopathy: Kaggle DR Detection (KDRD), IDRiD, and Diagnose Diabetic Retinopathy (DDR). This research focused on evaluating the performance of these approaches in tasks such as classification, object identification, and segmentation.

Recep E. Hacisoftaoglu *et al* [12] focused on constructing an automated model for detecting DR in smartphone retinal photos. To do this, the authors use a DL methodology, specifically the ResNet50 network. The present work first used the well-recognized AlexNet, GoogLeNet, and ResNet50 architectures, using the transfer learning methodology. Imran Qureshi *et al* [13] presented a novel and advanced multi-layer framework for active DL (ADL) with the primary objective of automating the detection and classification of different phases of DR. The authors used a CNN model to construct the ADL system, automating the feature extraction process instead of depending on manually engineered features. Li Xuechen *et al* [14] provided an automated diagnostic tool for the early detection of DR via Optical Coherence Tomography (OCT) imaging. The proposed method focuses on diagnosing DR in both grades 0 and grade 1.

Mohammad Z. Atwany *et al* [15] comprehensively examined and evaluated the most advanced DL techniques in supervised learning, self-supervised learning, and Vision Transformer setups. The study also introduces a novel application of these approaches for classifying and detecting retinal fundus images. S. Gayathri *et al* [16] introduced an innovative methodology for the automated assessment of DR via the use of DL and ML algorithms. This strategy involves extracting distinctive features from fundus images and then categorizing them based on their respective levels of severity. Jyostna Devi Bodapati *et al* [17] presented a brand-new Deep Neural Network (DNN) architecture in this work that incorporates a gated-attention mechanism. This architecture was primarily designed to make it easier to DDR automatically. In addition, the model includes gated attention blocks, which allow it to maximize attention to the retinal picture's lesion areas and minimize it to the non-lesion portions.

Ramzi Adriman *et al* [18] suggested a comprehensive approach to identifying and categorizing DR. The methodology used in this study consists of two primary stages. Local binary patterns (LBP) extract texture features in the first stage. Subsequently, in the second stage, an in-depth analysis is conducted on contemporary DL approaches for detection and classification tasks.

3. PROPOSED METHOD

Using DL to examine DR signifies a noteworthy progression within medical diagnostics. This novel methodology uses DL methodologies to autonomously identify and evaluate DR, a prevalent and possibly sight-threatening condition associated with diabetes. DL algorithms have shown exceptional accuracy in identifying minor anomalies and classifying the severity of DR by analysing digitized retinal images.

This technique has several significant advantages. First and foremost, this technology facilitates the prompt identification of DR, a condition of utmost importance in promptly intervening and providing therapy to mitigate the risk of visual impairment. Furthermore, DL-based analysis demonstrates a notable level of efficacy, enabling the expeditious examination of a substantial volume of patients within a limited timeframe. In addition to conserving healthcare resources, the quick provision of essential eye care to persons with diabetes is also guaranteed.

3.1 Diabetic Retinopathy Detection

The DDR involves the identification and evaluation of a vision-threatening disorder known as DR, which is associated with diabetes. The framework of the proposed method to detect DR is depicted in Figure-1.

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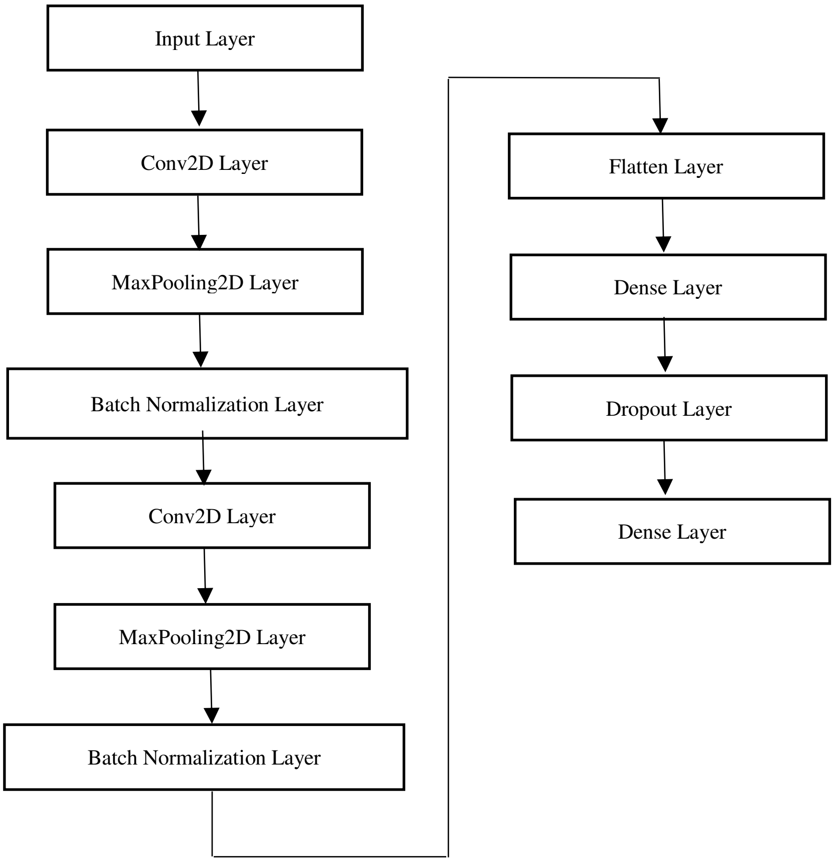

Figure-1. Proposed method structure for DR detection.

The procedure encompasses diverse medical imaging modalities, including retinal photography and Optical Coherence Tomography (OCT), to get intricate visual representations of the retina. Subsequently, healthcare experts or algorithms using Artificial Intelligence (AI) scrutinize these images to detect irregularities, including but not limited to microaneurysms, hemorrhages, and alterations in retinal blood vessels. The earlier identification of DR is essential to mitigate the risk of visual impairment and provide prompt intervention through therapeutic measures such as laser therapy or injections. Ultimately, this improves the overall management of ocular issues associated with diabetes.

3.1.1 Convolutional neural network

CNN is a DNN developed expressly for processing and interpreting grid-like data, such as images photos, and videos. CNNs have seen significant advancements and have emerged as the key components for various computer vision tasks, including image classification, object identification, and image segmentation. CNNs are built with several layers, each of which fulfills a distinct function within the architecture of the network as a whole.

3.2 Diabetic Retinopathy Classification

The classification of DR plays a pivotal role in identifying and managing diabetic ocular pathology. The procedure systematically categorizes the degree and type of retinal damage caused by diabetes, often assessed using various imaging techniques like fundus imagery or optical OCT.

The categorization system often encompasses many phases, including mild, moderate, severe, and proliferative diabetic retinopathy. The existence and intensity of particular retinal abnormalities, such as microaneurysms, hemorrhages, exudates, and neovascularization, determine these stages. This classification system assists healthcare professionals in identifying suitable treatment and monitoring approaches for patients. The framework of the proposed method for the Diabetic retinopathy classification is shown in Figure-2.

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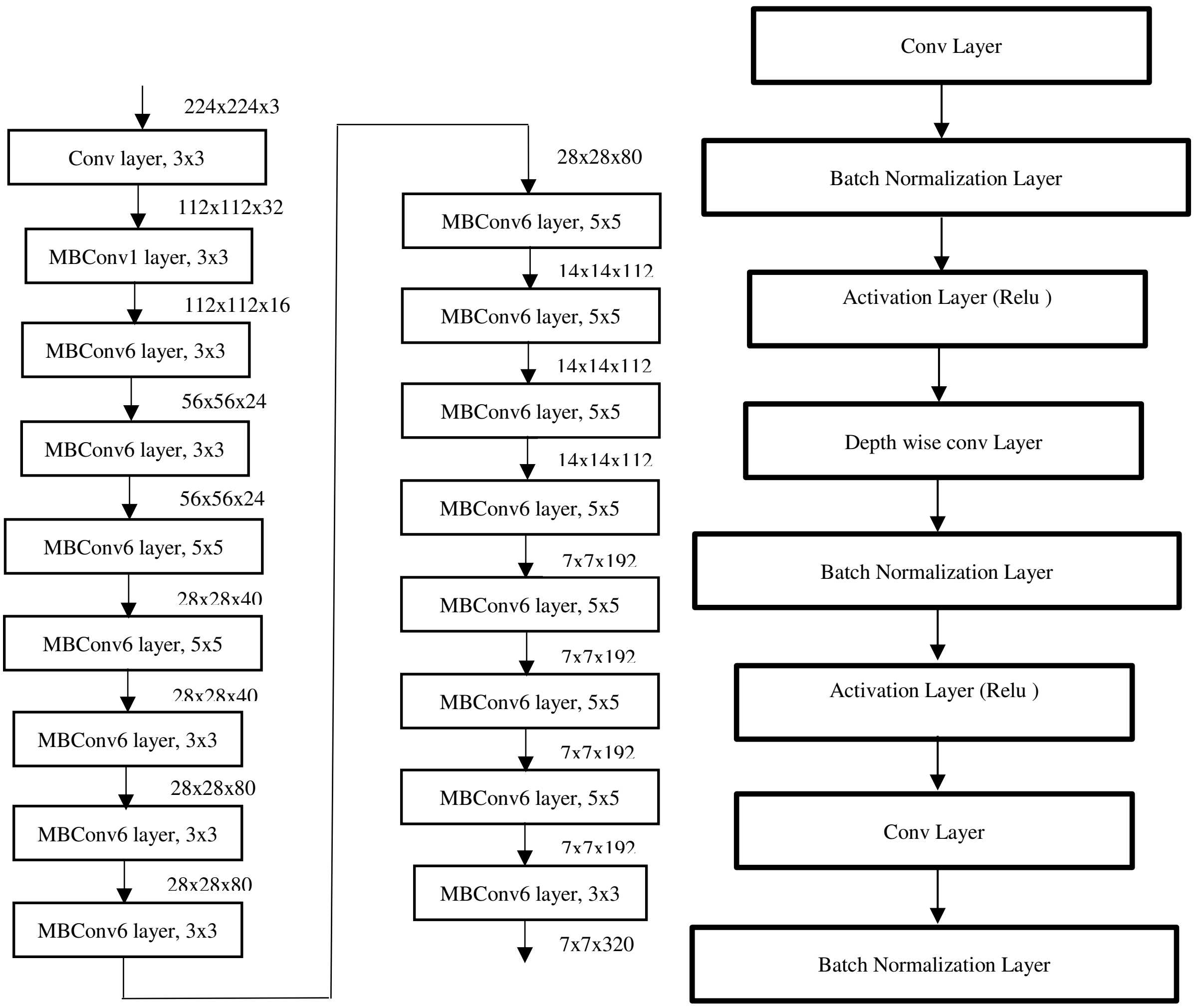

Figure-(a) EfficientNet Architecture **Figure-**(b) MBConv Block

Figure-2. Proposed method structure for DR classification.

3.2.1 EfficientNetB3

EfficientNetB3 constitutes CNN architecture, a constituent member of the EfficientNet model family. The architecture of this system prioritizes excellent efficiency in terms of processing resources and model size while still attaining exceptional performance on a range of computer vision applications. This paper contains a detailed explanation of the stages and components of the EfficientNetB3 architecture.

EfficientNetB3, like other CNN, takes an input image as its initial input. The input picture undergoes a sequence of Convolutional layers. The layers in question engage in the feature extraction process by using filters on the input picture, enabling the detection of patterns and features across various scales. One of the key innovations in the EfficientNet family is using a compound scaling factor to determine the number of layers, the width (number of channels), and the resolution of the network. The scaling factor is a user-defined parameter that influences the overall architecture. EfficientNetB3 has a specific scaling factor that determines its size and capacity.

Depth-wise separable convolution is used extensively in EfficientNetB3. It consists of two main steps:1. Depth-wise Convolution: In this step, each input channel is convolved independently with its own set of filters. 2. Pointwise Convolution: In this step, a 1x1 convolution is applied to combine the output channels from the previous step. EfficientNetB3 uses a modified version of MobileNetV2's inverted residual block. This block is used for feature extraction and helps reduce the number of parameters while maintaining model performance. These inverted residual blocks are stacked multiple times to form the network's backbone. The number of blocks depends on the scaling factor and the desired network depth.

In this paper progresses through the network, the feature maps become smaller spatially but deeper regarding channels. These feature maps contain increasingly abstract representations of the input image. Global average pooling is used in the terminal stage of the network. The procedure above computes the mean values inside each feature map, generating a vector with a constant size. This vector serves as a concise representation of the features retrieved from the input image. A fully connected or linear layer is added to the

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global average pooling layer to perform the final classification or regression tasks. The number of neurons in this layer typically corresponds to the number of output classes in a classification task.

3.2.2 MBConvolutional Layer

In the context of classification tasks, the outcome of the fully connected layer is subjected to a softmax activation function. This function transforms the network's raw scores into probabilities corresponding to each class. EfficientNetB3 is trained using a large dataset with labeled samples, typically through supervised learning. During training, the model's parameters are adjusted to minimize a specified loss function, often categorical cross-entropy for classification tasks. EfficientNetB3 may undergo fine-tuning on a smaller dataset tailored to the particular target job after pretraining on a large dataset to enhance its performance. The EfficientNetB3 architecture is a CNN that attains notable efficiency via depth-wise separable convolutions, inverted residual blocks, and a compound scaling factor. The model's architecture aims to achieve an optimal trade-off between its size and performance, making it highly suitable for various computer vision applications.

The MobileNet Convolutional Layer, also known as a "MBConvolutional Layer," is a specific variant of the Convolutional layer that is often used in DL applications on mobile devices and in scenarios where computational resources are limited. MobileNets, a collection of efficient CNN specifically developed for mobile devices, includes this element as a fundamental component. Its primary purpose is to facilitate tasks such as picture categorization and object recognition. MBConvolutional Layers use depthwise separable convolutions, which include two distinct stages: depthwise convolution, where a single filter is applied to each input channel, and pointwise convolution, where 1x1 filters merge channel information. This design significantly reduces the computational cost while maintaining good performance, making MobileNets suitable for real-time and low-power applications. MBConvolutional Layers often include hyperparameters like expansion ratio, kernel size, and output channels, allowing for flexibility in network architecture design to balance model size and accuracy.

4. EXPERIMENTAL RESULTS

This section describes the results obtained from the simulations conducted using the proposed methodology. The Dataset used in this study was sourced from Kaggle. The Dataset underwent processing using the specified technique. The pictures include retina scan images that have undergone Gaussian filtering to identify cases of DR. The official Dataset may be accessed from the APTOS 2019 Blindness Detection repository. The photos are downsized to dimensions of 224x224 pixels to facilitate their compatibility with various pre-trained DL learning models. The train.csv file given has been used to organize the photos into proper folders based on the severity/stage of diabetic retinopathy. Figure-3 shows the sample images from Dataset. There are five folders (in Figure-3: a-e) containing the corresponding pictures.

0 - No_DR
1 – Mild
2 – Moderate
3 – Severe
4 - Proliferate_DR

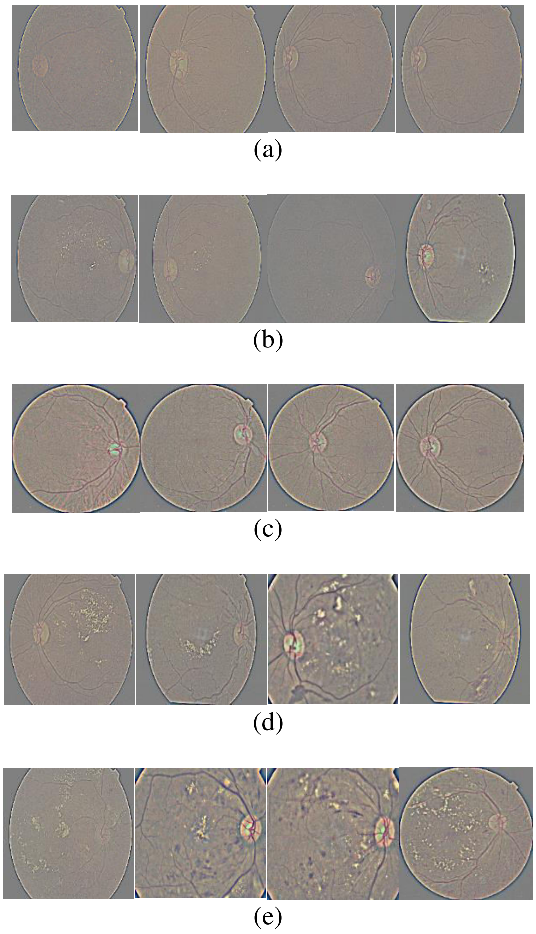

Figure-3. Sample images from Dataset.

The evaluation of training and validation loss is of utmost importance in the context of ML and DL models. The training loss measure assesses the model's capacity to acquire knowledge from the training data. In contrast, the validation loss metric appraises the model's generalization ability by assessing its performance on previously unknown data. This procedure facilitates the identification of problems such as overfitting and underfitting. Achieving a harmonious equilibrium between these two measures is crucial in model building. Minimizing the training loss does not guarantee improved generalization since a significant validation loss implies inadequate model performance. Both durable and accurate developed using ML models, it is necessary to establish a state of equilibrium.

In ML and DL models, assessing training and validation accuracy is paramount. The evaluation of training accuracy pertains to the model's proficiency in acquiring knowledge from the training dataset.

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Conversely, validation accuracy is a metric to gauge the model's capacity to apply acquired knowledge to novel, unseen data, often using a distinct dataset. Ensuring equilibrium between these two measurements is of paramount significance. High training accuracy coupled with poor validation accuracy indicates overfitting, a phenomenon in which the model tends to remember the training data while encountering difficulties in generalizing to new, unseen data. On the other hand, inadequate training and validation accuracy indicate a condition known as underfitting, in which the model cannot accurately capture the inherent patterns within the data. To showcase a competent and flexible model, getting a substantial level of validation accuracy is crucial while concurrently maintaining a commendable level of training accuracy.

4.1 Diabetic Retinopathy Detection

Figure-4 illustrates the training and validation loss data of the DR detection algorithm offered. In the first epoch, the validation loss is recorded as 0.6820, but the training loss is measured as 0.3832. During the fifteenth epoch, the validation loss drops to 0.1288, while the training loss is recorded as 0.1251. At Epoch 30, the validation loss drops to 0.1194, whereas the training loss hits 0. 0711. Figure-5 depicts the training and validation accuracy of the suggested methodology in the context of DR detection.

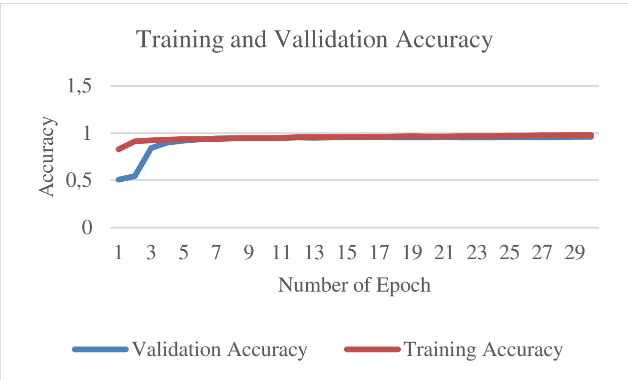

Figure-4. Training loss and validation loss.

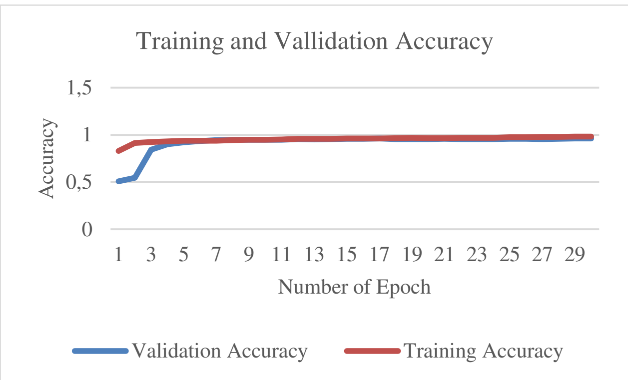

Figure-5. Training accuracy and validation.

During the first epoch, the validation accuracy is recorded as 0.5073, but the training accuracy is seen to be 0.8290. By the fifteenth epoch, there has been a notable enhancement in the validation accuracy, reaching a value of 0.9564. Simultaneously, the training accuracy has also shown improvement, rising to 0.9610. At the 30th epoch, the validation accuracy attains a value of 0.9600. However, the training accuracy surpasses this with a higher value of 0.9813.

The final output of Diabetic is shown in Figure-6.

- DR= Diabetic Retinopathy
- No DR= No Diabetic Retinopathy

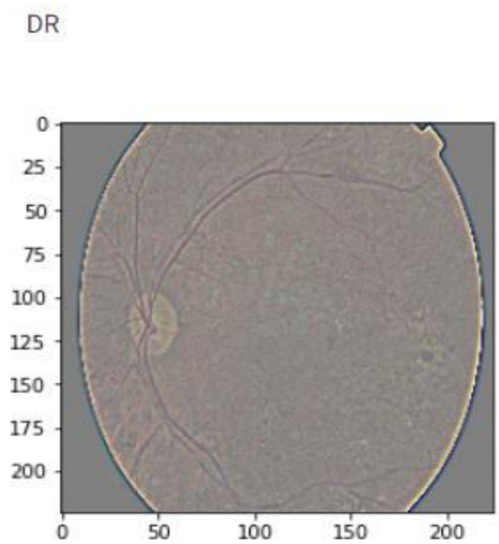

Figure-6. Output of proposed method of DR detection.

The proposed model is compared with state-of-art DL models and a comparative analysis is reported in Table-1.

Table-1. Comparative analysis.

Model	Training Accuracy (%)	Validation Accuracy (%)
CNN	89	69
VGG	96	76
EfficientNetB0	98	78
MobileNet	86	85
Proposed Model	98	95

Table-1 compares several DL models' training and validation accuracy rates. This study examined the CNN, VGG, EfficientNetB0, MobileNet, and Proposed Model. Each model has unique accuracy metrics. CNN had 89% training accuracy and 69% validation accuracy. This difference shows it may require tweaks to generalize to new data. VGG, another popular model, has 96% training accuracy but 76% validation accuracy. This discrepancy suggests fine-tuning or adjustments to improve performance on unknown data. With 98%

training accuracy, EfficientNetB0 learned well. Its validation accuracy was 78%. Therefore, generalization to new datasets might be improved. MobileNet has 86% training accuracy and 85% validation accuracy. Despite modest training accuracy, the model handles unseen data efficiently. Improved measurements may close the gap. Training accuracy of 98% made the Proposed Model a high performer. Its 95% validation accuracy outperformed all other models, demonstrating its remarkable generalization for new data. This study's findings help academics and practitioners choose models for specific tasks by revealing their relative performance.

4.2 DR Classification

The loss values for training and validation of the newly proposed approach for DDR are shown in Figure-7. During the first period, the validation and training losses were recorded as 6.60111 and 7.769, respectively. By the fifteenth epoch, the losses seen in the validation and training sets had notably dropped to 0.91470 and 0.348, respectively. Moreover, at the 20th epoch, the validation and training losses showed a further decrease to 0.79554 and 0.231, respectively.

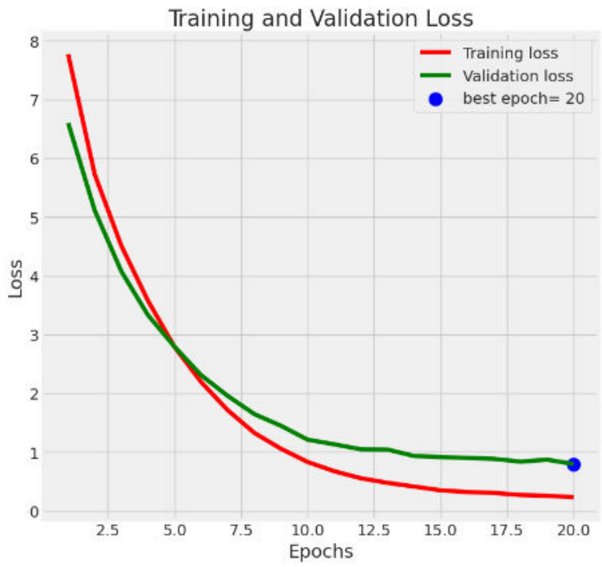

Figure-7. Training loss and validation loss.

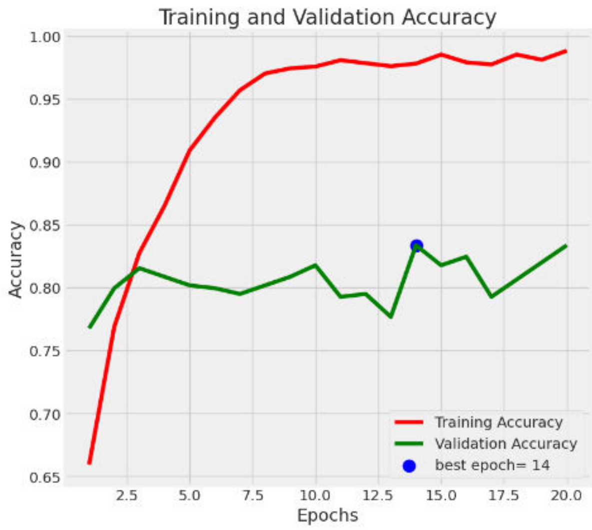

Figure-8. Training accuracy and validation accuracy.

The accuracy of the proposed technique for DDR is shown in Figure-8, showcasing the training and validation results. During the first epoch, the validation accuracy was recorded as 0.7676, whereas the training accuracy was observed as 0.6592. At the 15th epoch, the validation accuracy has risen to 0.8177, while the training accuracy has attained a value of 0.9853. During the 20th epoch, the validation accuracy shows a notable improvement, reaching a value of 0.8337. Additionally, the training accuracy achieves a high level of performance, reaching a value of 0.9883.

The Confusion Matrix is shown in Figure-9. A crucial method for evaluating an ML classifier's performance, particularly in the context of classification issues, is using a confusion matrix. The tabular format makes it easier to understand the model's predicted performance across several classes and pinpoints probable mistake sources. The layout of the confusion matrix, which displays a classification problem with five distinct classes, makes it easier to evaluate the model's effectiveness. With the rows denoting the real or true classes and the columns denoting the expected classes, the matrix in this example illustrates how the two correlate. Each element in the matrix represents the quantity of data points that fall into a particular mix of true and predicted classifications. This statistic makes it easier to see how often the model correctly predicts values for each class while also helping spot possible misclassification instances.

Beginning with the "Mild" category, it is evident that the model accurately classified it as "Mild" on 16 occasions and as "Moderate" on eight occasions, without any instances of misclassification for the "Mild" category. Transitioning to the "Moderate" category, the model accurately classified it as "Moderate" on 65 occasions. Nonetheless, the model tended to classify instances as "Moderate" on six occasions when the actual class was "Mild" and on five occasions when it was "Proliferate_DR." This suggests a certain level of

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ambiguity or misclassification between these particular classes. The classes labeled as "No_DR" were correctly predicted as "No_DR" in 143 instances without any misclassifications to other categories. Similarly, the "Proliferate_DR" category was accurately identified as such in 14 instances, although it was also misclassified as "Moderate" 15 times. This observation underscores a challenge faced by the model in effectively discerning between these two categories.

In the "Severe" category, there were eight accurate severity predictions. Nevertheless, the model made three predictions of "Moderate" and four predictions of "Proliferate_DR," indicating a potential challenge in accurately differentiating between these two classifications.

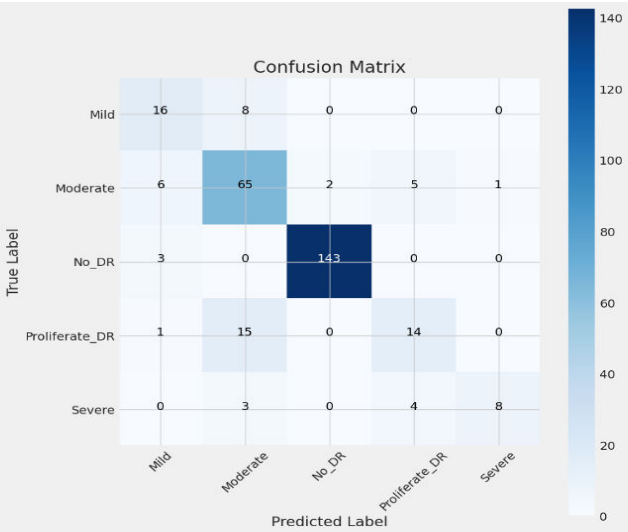

Figure-9. Confusion matrix.

Table-2. Classification report.

	Precision	Recall	F1 Score
Mild	0.62	0.67	0.64
Moderate	0.71	0.82	0.76
No_DR	0.99	0.98	0.98
Proliferate_DR	0.61	0.47	0.53
Severe	0.89	0.53	0.67

Table-3. Comparative analysis.

Model	Training Accuracy (%)	Validation Accuracy (%)
ResNet50	91	56
EfficientNetB0	74	59
AlexNet	96	70
DenseNet	91	73
InceptionV3	91	74
Proposed Model	97	84

The classification report that assesses the performance of a classification model across several groups or categories is shown in Table-2. The study includes three key measures that are often used in the field of ML to evaluate the efficacy of the model: precision, recall, and F1-score. Precision assesses how well positive predictions are made, while Recall evaluates the model's ability to accurately identify every real positive occurrence. However, a fair assessment of a model's overall performance is offered by the F1-score, which is calculated as the harmonic mean of Precision along with Recall.

The performance of the model is evaluated concerning five distinct categories in the provided table, namely "Mild," "Moderate," "No_DR" (indicating the absence of DR), "Proliferate_DR," and "Severe." The table lists the Precision and Recall and F1-score metrics for each class, which gauge how well the model can distinguish between and categorize samples within each class. For example, the results show that the model properly classifies cases as "No_DR" with high Precision, Recall, and F1-score values of 0.99, 0.98, and 0.98, respectively. However, an F1-score of 0.53 and a Recall value of 0.47 indicate it has trouble correctly identifying occurrences as "Proliferate_DR." The provided table presents significant information on the model's performance across different classes, facilitating the evaluation and future enhancement of the classification model. The classification accuracy comparison is reported in Table-3.

The table compares training and validation accuracy for ResNet50, EfficientNetB0, AlexNet, DenseNet, InceptionV3, and the proposed model. These accuracy measures are crucial for evaluating these models and understanding their capabilities in various tasks. ResNet50 is a popular CNN design with 91% training and 56% validation accuracy. The decreased validation accuracy signals overfitting, even when the model performs well on training data. EfficientNetB0 has 74% training accuracy and 59% validation accuracy. This suggests that the model is less likely to overfit than ResNet50 but still lacks validation accuracy. AlexNet is an early DL model with 96% training and 70% validation accuracy. It excels during training, but the accuracy difference between training and validation implies overfitting. DenseNet, like ResNet, has 91% training accuracy but 73% validation accuracy. Since the difference between training and validation accuracy is less, DenseNet has better generalization. InceptionV3 is another popular design, with 91% training accuracy and 74% validation accuracy, like ResNet50. Like DenseNet, InceptionV3 generalizes better. Finally, the proposed model achieves 97% and 84% training and validation accuracy.

5. CONCLUSIONS

In this paper, a reliable approach that uses DL models to diagnose and categorize DR is suggested. The results show that the technique is beneficial in raising the accuracy and efficacy of DR diagnosis. The capacity of the lightweight CNN for detection to accurately recognize instances of retinopathy in fundus images was shown by its accuracy of 95%. This high accuracy rate is essential for early diagnosis and intervention, both of which have the potential to improve the results for patients greatly. In addition, the classification model, built on the EfficientNet architecture, was able to attain an accuracy of 84% in categorizing the severity levels of DR. Because of its effectiveness and Precision, this model is an invaluable resource for ophthalmologists and other healthcare professionals in making well-informed choices on treatment and subsequent care. A complete solution for DDR is provided by a combination of a lightweight CNN for detection and the efficient EfficientNet for classification. This research advances the field of automated medical image analysis. It highlights the potential of DL techniques to enhance the early detection and treatment of DR, thereby enhancing patients' quality of life.

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