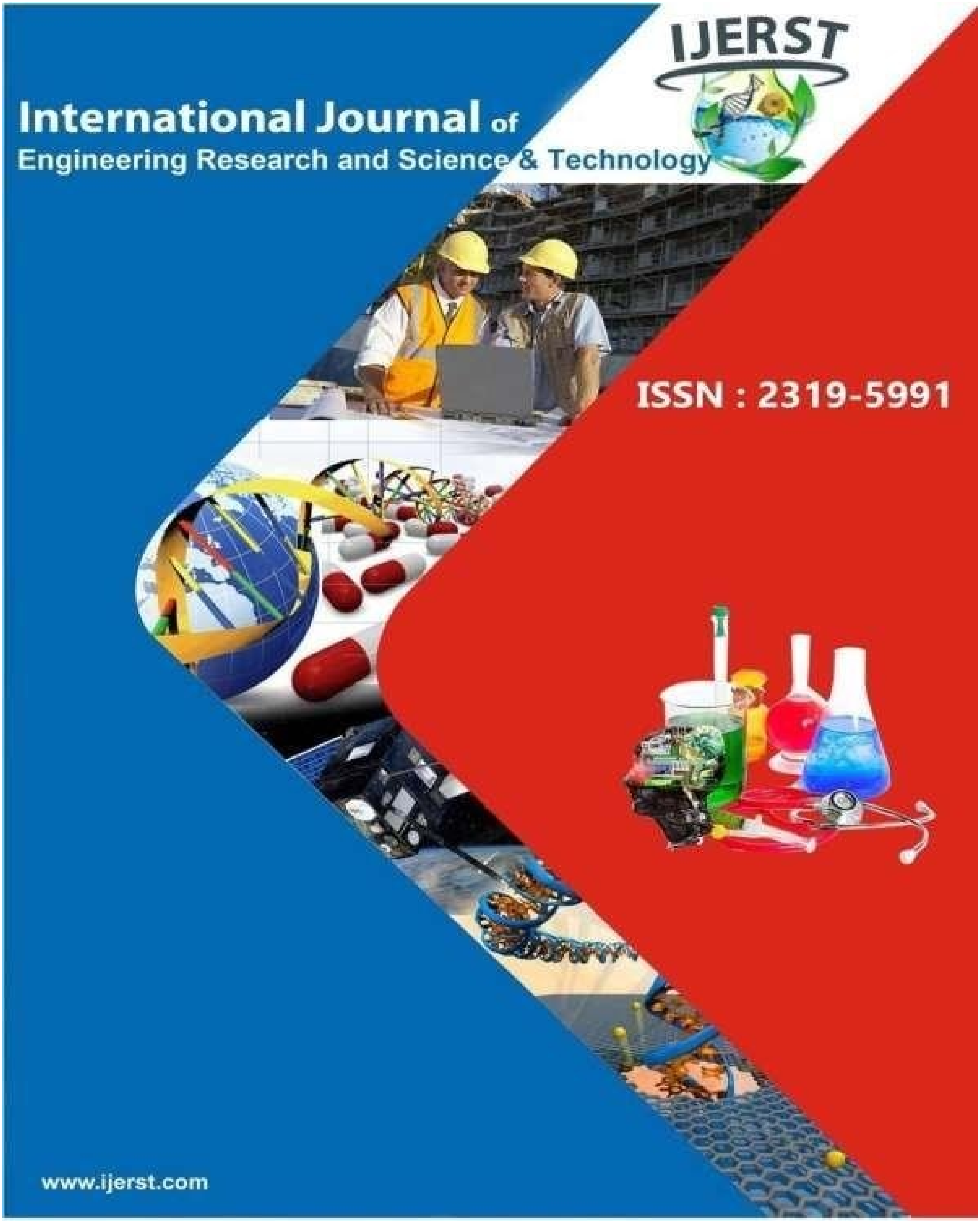

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Diabetic Retinopathy Prediction Using CNN Models

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ABSTRACT

Diabetic Retinopathy (DR) is an eye condition that mainly affects individuals who have diabetes and is one of the important causes of blindness in adults. As the infection progresses, it may lead to permanent loss of vision. Diagnosing diabetic retinopathy manually with the help of an ophthalmologist has been a tedious and a very laborious procedure. This paper not only focuses on diabetic retinopathy detection but also on the analysis of different DR stages, which is performed with the help of Deep Learning (DL) and transfer learning algorithms. ResNet 50, EfficientNet B0, and DenseNet 121 are used on a huge dataset with around 3662 train images to automatically detect which stage DR has progressed. Five DR stages, which are 0 (No DR), 1 (Mild DR), 2 (Moderate), 3 (Severe) and 4 (Proliferative DR) are processed in the proposed work. The patient's eye images are fed as input to the model. The proposed deep learning architectures like ResNet 50, EfficientNet B0, DenseNet 121, are used to extract the features of the eye for effective classification. The models achieved an accuracy of 97.34%, 94.88% and 80.77% respectively. The paper concludes with a comparative study of the ResNet 50, EfficientNet B0, DenseNet 121 architectures that highlights ResNet 50 as the perfect deep learning classification model for automated DR detection. Make the above abstract more professional.

1. INTRODUCTION

Diabetic retinopathy (DR) stands as the most prevalent microvascular complication of diabetes, emerging as a leading cause of blindness globally, with projections estimating its impact on over 200 million individuals by 2040. Characterized by the destruction of tiny blood vessels within the retina due to prolonged exposure to elevated blood sugar levels, DR manifests in two distinct forms: Non-Proliferative Diabetic Retinopathy (NPDR) and Proliferative Diabetic Retinopathy (PDR). NPDR involves vessel swelling and fluid leakage, often leading to macular edema and mild vision impairment, while PDR represents an advanced stage marked by abnormal blood vessel growth on the retinal surface, potentially resulting in severe vision loss. The onset of DR is insidious, often asymptomatic in its early stages, yet its progression can culminate in irreversible vision impairment.

Critical risk factors include diabetes (both type 1 and type 2), ethnicity, hypertension, hyperlipidemia, pregnancy, and familial predisposition. Early diagnosis is paramount for effective management and preservation of vision, as symptoms may not manifest until the disease has advanced significantly, encompassing blurred vision, floaters, night vision impairment, and ultimately, vision loss.

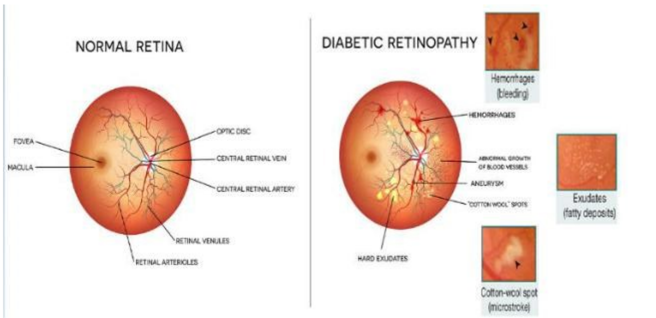

Fig: Difference Between Normal retina and Diabetic Retina

Notably, DR stands as the primary cause of blindness among individuals aged 25 to 74 in industrialized nations, affecting a substantial proportion of diabetic

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patients after 15 years of disease duration. While the importance of glycemic control in mitigating DR risk is well-established, the intricate biochemical and molecular pathways underpinning its development, alongside genetic susceptibilities, continue to be subjects of intensive research and scrutiny. This introduction sets the stage for exploring the advancements and challenges in the detection of diabetic retinopathy, highlighting the imperative of early intervention and the ongoing quest for deeper insights into its pathogenesis.

OVERVIEW

The project addresses diabetic retinopathy (DR), a major cause of global vision loss, by leveraging deep learning technology. It employs three CNN models—ResNet50, EfficientNetB0, and DenseNet121—to classify retinal images into mild, moderate, or severe DR stages. Additionally, it categorizes DR into four stages, including proliferative DR, aiding in comprehensive diagnosis. A user-friendly frontend interface allows healthcare professionals to upload images and receive predictions for DR severity and stage, streamlining clinical integration. This approach enhances accessibility, empowers timely interventions, and improves patient care. Overall, the project represents a significant advancement in DR diagnosis and management, promising accurate screening, efficient workflow integration, and ultimately better patient outcomes, while reducing the strain on healthcare systems.

2. LITERATURE SURVEY

Wilfred Franklin and Edward Rajan [1] developed an automated tool for the precise detection of blood vessels, achieving high accuracy in their methodology. Their work focused on implementing an automatic segmentation algorithm applied to images from the DRIVE database, a widely used dataset in medical imaging. Their algorithm demonstrated an impressive accuracy rate of 95.03% in accurately identifying blood vessels within retinal images, showcasing its potential for aiding in the diagnosis and monitoring of various vascular-related pathologies, including diabetic retinopathy.

H. Jiang [2] employed three deep learning models, Inception V3, ResNet151, and Inception-ResNet-V2, achieving individual accuracies of 87.91%, 87.20%, and 86.18%, respectively, in diabetic retinopathy prediction. However, by integrating these models using the AdaBoost algorithm, the combined system exhibited enhanced accuracy, reaching 88.21%. This demonstrates the effectiveness of ensemble learning techniques in improving predictive performance beyond that of individual models.

Sangwan [3] described a system that identifies different stages of diabetic retinopathy based on blood vessels, haemorrhage and exudates. The features are extracted using image pre-processing and they are fed into the neural network.
Revathy et al. [4], used an SVM-based training approach to data and classified them into three classes as mild, moderate non-proliferative Diabetic Retinopathy and proliferative Diabetic Retinopathy. Approach used various classification algorithms and noted good accuracy with 82%.
Antal and Hajdu et al. [5], used image level, lesion-specific and anatomical components. Author worked on classifiers and tested on the publicly available dataset Messidor, where resultant AUC is observed 0.94.

3. EXISTING SYSTEM

The existing approach to diagnosing diabetic retinopathy (DR) involves manual examination by skilled ophthalmologists or optometrists. Initially, patients with diabetes undergo routine eye screenings to evaluate their risk of DR, with screening frequency tailored to individual factors.

Trained specialists then meticulously examine fundus images to identify abnormalities like microaneurysms and hemorrhages, assessing DR severity based on these findings. DR classified into categories such as mild, moderate, severe, non-proliferative DR (NPDR), and proliferative DR (PDR). However, delays in diagnosis remain a concern, potentially leading to vision loss if DR progresses without timely intervention.

4. PROPOSED SYSTEM

The proposed system for diabetic retinopathy stands as a groundbreaking advancement in medical diagnostics, tailored precisely to tackle the challenges posed by this widespread complication of diabetes mellitus. Through the utilization of convolutional neural network (CNN) models trained on annotated datasets of retinal images, it introduces an automated solution for the early detection and precise classification of diabetic retinopathy severity levels.

An automated screening solution for diabetic retinopathy, leveraging deep learning techniques. By analyzing retinal images with CNN models, it efficiently assess the severity of DR, eliminating the need for manual examination by specialists. Employing CNN architectures, renowned for their prowess in image classification tasks, the system ensures accurate classification. Trained on annotated datasets representing various stages of DR severity, these models deliver precise results. The CNN models are

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meticulously trained to categorize retinal images into distinct categories like mild, moderate, or severe stages of diabetic retinopathy with unparalleled accuracy.

5. SYSTEM ARCHITECTURE

System architecture refers to the conceptual framework that outlines the structure and behaviour of a system, along with various other aspects. An architecture description provides a structured formal depiction and representation of a system, facilitating analysis of its structures and behaviours. The architecture typically includes both the main components and any subsystems designed, all of which are intended to function together to execute the overall system. There have also been initiatives to create standardized languages specifically for describing system architectures, known collectively as architecture description languages (ADLs).

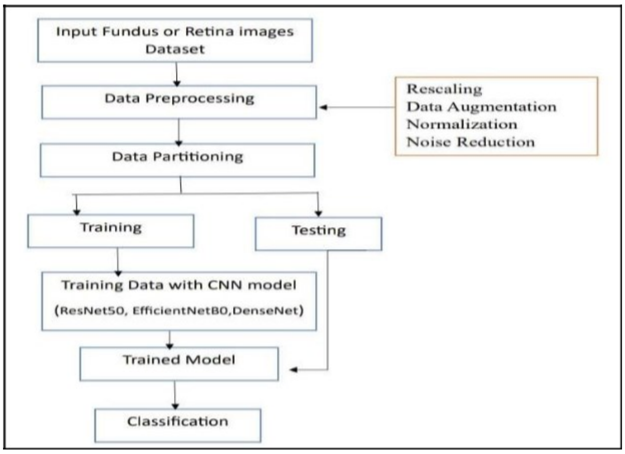

Fig: System Architecture

Retinal images are analyzed to detect diabetic retinopathy stages, aiding in diagnosis and treatment decisions. Continuous evaluation ensures accuracy and relevance in clinical settings.

6. METHODOLOGY

The proposed approach for identifying and managing diabetic retinopathy in retinal images prioritizes speed, accuracy, and real-time processing. It leverages the ResNet50 model, renowned for its exceptional accuracy and efficient memory usage. This choice proves

especially advantageous in scenarios where computational resources are limited, such as embedded systems and mobile devices, as it fulfils the need for rapid and resource-effective medical image analysis.

ResNet50

In the world of convolutional neural network (CNN) architectures, ResNet-50 is considered the best due to its deep learning capabilities and exceptional performance in image recognition tests. ResNet-50, which first emerged by Kaiming He et al. in 2015, transformed convolutional neural network topologies by using residual connections to solve the vanishing gradient issue while also rendering it easier to train its intricate 50-layer network. The fundamental components of ResNet-50 are residual building pieces, which are organized to improve computational efficiency and feature extraction capacity. These components include batch normalization, an ordered set of convolutional layers (1x1, 3x3, and another 1x1), and ReLU activation functions.

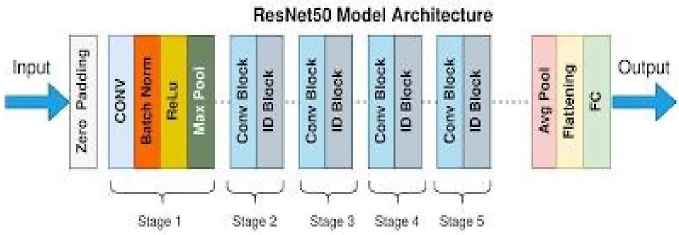

Fig: Resnet Model Architecture

The ResNet50 architecture consists of 50 layers, including residual blocks. It employs skip connections to alleviate the vanishing gradient problem, facilitating the training of very deep networks. ResNet50's architecture enables it to effectively capture intricate features, contributing to its superior accuracy in tasks like diabetic retinopathy detection.

EfficientNetB0

An assortment of convolutional neural network (CNN) architectures called EfficientNet has been developed specially for categorization of images applications. It is a novel family of CNN architectures for image classification that was unveiled by Mingxing Tan and Quoc V. Le in 2019. It is characterized by its cutting-edge performance with fewer parameters and its computational economy. In an effort to attain balanced growth and enhanced performance, the series employs a novel technique called compound scaling, which entails simultaneously scaling the network's depth, width, and resolution. In order to maximize accuracy and reduce processing demands, the baseline model, EfficientNetB0, has a lean structure with 11 million parameters. It also uses the Swish activation function and inverted residual blocks. This makes EfficientNetB0 particularly appropriate for resource-constrained jobs like medical imaging, where its accuracy and efficiency are crucial, such embedded systems or mobile devices.

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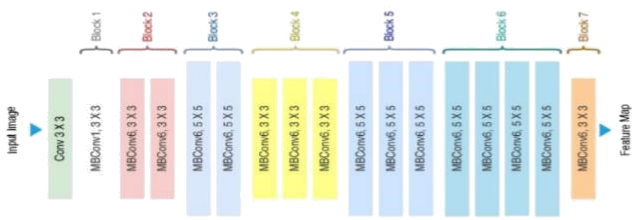


Fig: EfficientB0 Architecture

This architecture balances model depth, width, and resolution using compound scaling. It efficiently optimizes computational resources by scaling network dimensions uniformly, achieving remarkable performance with fewer parameters.

DenseNet121

DenseNet, an acronym for Dense Convolutional Network, modifies conventional CNN designs by providing dense connectivity among layers within a dense block, in which each layer gets input from every layer that had come before it. The network's capacity for identifying intricate patterns is improved by this structure, which makes extensive feature reuse and stable gradient flow possible. Transition layers, which help control computational complexity by down sampling the feature maps via convolutional and pooling procedures, come after each dense block in DenseNet. The classification head with global average pooling and a fully connected layer activated by softmax is the culmination of the architecture. DenseNet performs well in many kinds of applications for computer vision due to its effective parameter usage and capacity to enhance feature propagation.

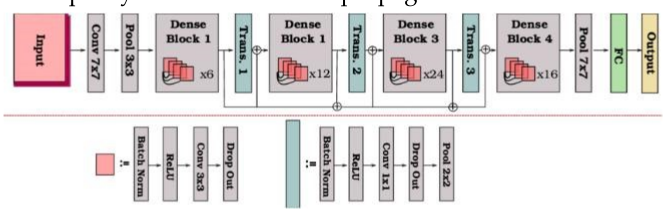


Fig: DenseNet121 Architecture

This architecture promotes feature reuse, facilitating better information flow and enabling the model to capture intricate patterns efficiently.

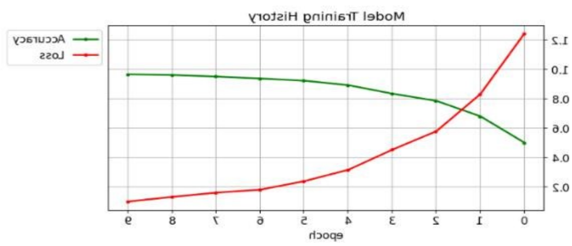
7. DISCUSSION AND RESULTS

The effectiveness of three sophisticated CNN architectures—ResNet50, EfficientNetB0, and DenseNet121—in determining the presence of diabetic retinopathy from retinal images are investigated in the present study. With an incredible accuracy rate of 97%, ResNet50 beat its competitors. This can be due to its deep design, which is effective in capturing subtle illness markers. Though they scored admirably, with accuracy ratings of 94% and 91%, respectively, EfficientNetB0 and DenseNet121 were marginally less successful for this particular job. The results indicate that while ResNet50 is now better, further studies could investigate how to improve EfficientNetB0 and DenseNet121 using ensemble methods or more advanced training approaches. Furthermore, expanding the dataset size may improve the resiliency of the model, especially for stages that are currently classified less effectively.

Model Name	Precision	Recall	F1 Score	Accuracy
ResNet 50 V2	0.97274	0.96937	0.96928	0.97344
DenseNet121	0.84000	0.85333	0.85004	0.84773
EfficientNet B0	0.945450	0.919900	0.915320	0.918870

Table: Result Comparison

The above table shows that ResNet50 demonstrated superior performance in diabetic retinopathy detection, achieving a 97% accuracy rate due to its deep design capturing subtle markers. EfficientNetB0 and DenseNet121 scored slightly lower at 94% and 91% respectively.



The image shows the accuracy increasing and loss decreasing rapidly in the initial epochs, indicating effective learning. However, both curves plateau later, suggesting convergence, local optimum, or potential overfitting. Evaluating performance on a validation set and applying techniques like regularization or architecture changes may help mitigate overfitting and improve generalization.

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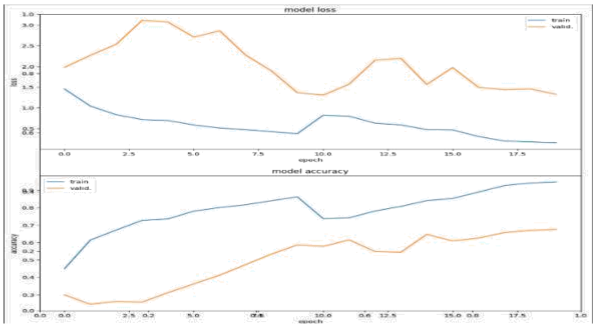

In the model loss graph, training loss steadily decreases from about 1.8 to 0.5, indicating effective learning on the training set. Conversely, validation loss starts high at around 2.5, fluctuates significantly, and stabilizes near 1.5, suggesting the model overfits the training data. In the model accuracy graph, training accuracy increases consistently from approximately 0.4 to 0.85, demonstrating improved performance on training data.

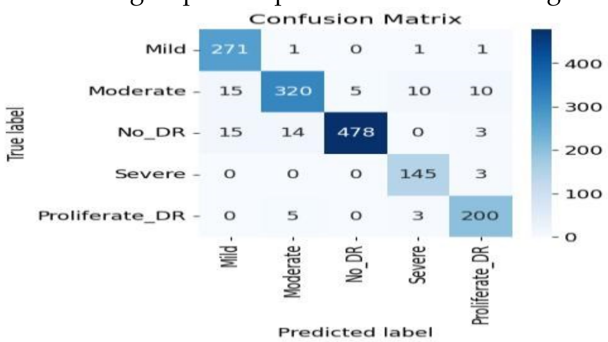

Fig: Confusion Matrix

The confusion matrix indicates that the classification model is generally good at predicting the correct class, especially for No_DR, where the majority of predictions are accurate. However, the model struggles a bit more with Moderate and Proliferate_DR classes, where there are more misclassifications. This detailed breakdown can help in understanding the performance of the classification model and in identifying areas where improvements are needed.

8. CONCLUSION

CNN models like ResNet50 V2, DenseNet121, and EfficientNet B0 have been utilized in the development of an end-to-end deep learning system for automated diabetic retinopathy (DR) diagnosis with the objective to boost the scalability, accuracy, and efficiency of detection processes. ResNet50 V2 performs substantially better than DenseNet121 and EfficientNet B0 in terms of accurately and precisely forecasting the severity of DR. This underscores how essential it is to use the right model architectures for the best possible classification of medical images. The project has an intuitive interface that makes it simple to upload images and run diagnostics, improving system accessibility while encouraging broader acceptance. Future studies should improve the robustness, universality, and comprehension of the models in order to further transform healthcare via automated DR detection systems.

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