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Diabetic Retinopathy Detection Using Deep Learning

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Abstract

The rising prevalence of diabetes has led to an increase in Diabetic Retinopathy (DR), a leading cause of vision loss worldwide. Manual screening of fundus images is time-consuming and prone to human error. This paper proposes a deep learning approach for the automated detection and classification of DR using the **EfficientNet-B5** architecture. The system is trained on the **APTOS 2019 Blindness Detection** dataset, which consists of thousands of high-resolution retinal images. Our model extracts intricate retinal features to classify images into five stages: No DR, Mild, Moderate, Severe, and Proliferative DR. Experimental results demonstrate high diagnostic accuracy, reaching approximately **99.96% confidence** in severe cases. The system is deployed via a **Flask-based web interface**, enabling real-time uploads and automated PDF report generation for clinical support.

KEYWORDS: DIABETIC RETINOPATHY, DEEP LEARNING, EFFICIENTNET-B5, APTOS 2019, MEDICAL IMAGING, FUNDUS PHOTOGRAPHY, FLASK.

1. Introduction

Artificial intelligence and deep learning are transforming healthcare by enabling early disease detection and providing vital clinical decision support. Catching conditions early is particularly crucial for Diabetic Retinopathy (DR), a severe complication of diabetes and a leading global cause of vision loss. While identifying retinal damage in its early stages is critical, traditional manual diagnosis using fundus photography is incredibly time-consuming. Furthermore, it relies on specialized medical expertise that is often unavailable in underserved communities.

Although deep learning specifically Convolutional Neural Networks (CNNs) has revolutionized automated medical image analysis, many standard models still fall short. They frequently struggle to capture the tiny, fine-grained details, such as microaneurysms and small hemorrhages, needed to accurately grade DR severity. To overcome this, advanced models like the EfficientNet-B5 architecture use compound scaling to optimize network depth and resolution, ensuring high-precision feature extraction.

In this paper, we propose an automated DR detection system built on these deep learning techniques .By training the EfficientNet-B5 model on the APTOS 2019 dataset, our system classifies DR severity across five distinct stages with high diagnostic accuracy. To bridge the gap between research and real-world application, we deployed the model via a Flask-based web application. This creates a seamless, end-to-end pipeline from the initial image upload straight to the generation of a clinical diagnostic report offering a highly accessible and efficient tool for rapid clinical support.

2. Literature Survey

Diabetic retinopathy detection has become a significant research area in medical image analysis due to the increasing number of diabetes patients worldwide and the risk of vision loss caused by delayed diagnosis. Deep learning techniques, particularly convolutional neural networks (CNNs), have been widely applied to retinal fundus image analysis because they can automatically extract complex visual features and identify pathological patterns associated with diabetic retinopathy. Several studies have proposed various deep learning architectures and hybrid approaches to improve the accuracy and reliability of automated diabetic retinopathy detection systems.

Kumar et al. (2023) proposed a deep learning–based framework for detecting diabetic retinopathy from retinal fundus images using convolutional neural networks. Their approach utilized multiple convolutional layers to extract hierarchical image features and classify disease severity levels. Experimental results demonstrated that CNN-based models can effectively identify diabetic retinopathy stages when trained on large-scale retinal image datasets. However, the performance of the model may decrease when the dataset contains images captured under different illumination conditions or from different imaging devices.

Santos et al. (2023) investigated automated diabetic retinopathy classification using deep learning models trained on retinal fundus images. Their study emphasized the importance of preprocessing techniques such as image normalization and noise reduction to enhance feature extraction. The proposed system demonstrated improved detection performance compared to traditional machine learning approaches, highlighting the effectiveness of deep learning methods in medical image classification tasks.

Ahmed et al. (2024) introduced an automated diabetic retinopathy diagnosis system using deep learning methods for fundus image classification. Their research explored the use of multiple convolutional neural network architectures to detect and classify diabetic retinopathy severity levels. The study showed that deep learning models can achieve high accuracy in identifying disease stages when trained on labeled retinal datasets. However, the study also noted that model performance depends heavily on the quality and diversity of training data.

Li et al. (2024) proposed an approach based on the EfficientNet architecture for diagnosing diabetic retinopathy using retinal fundus images. EfficientNet models are designed to balance network depth, width, and resolution, allowing them to achieve high classification accuracy while maintaining computational efficiency. Experimental results demonstrated that EfficientNet-based models outperform several traditional CNN architectures in diabetic retinopathy detection tasks.

Another study explored the integration of deep learning models with advanced healthcare systems for diabetic retinopathy diagnosis. Researchers developed a deep learning enabled framework capable of detecting diabetic retinopathy from retinal images and supporting early screening in medical environments.

Their findings indicated that deep learning models can significantly improve the efficiency of large-scale screening programs and assist ophthalmologists in early disease detection.

Despite significant advancements in diabetic retinopathy detection using deep learning, several challenges remain. Many models struggle with generalization when tested on unseen datasets due to variations in

image quality, camera devices, and patient demographics. Additionally, high computational requirements and dataset imbalance may affect model performance. These limitations highlight the need for improved preprocessing methods, balanced datasets, and hybrid deep learning architectures that combine the strengths of multiple models to enhance classification accuracy and robustness.

2.1Comparison table for Existing Diabetic Retinopathy Detection Methods

Authors & Year	Model Architecture	Dataset Used	Performance	Result	Limitations
Kumar et al., 2023	Convolutional Neural Network (CNN)	APTOS 2019 Fundus Image Dataset	High classification accuracy	Effective DR stage detection	Performance affected by image quality variations
Santos et al., 2023	Deep CNN with image preprocessing	Retinal fundus image datasets	Improved detection accuracy	Reliable DR classification	Requires extensive preprocessing
Ahmed et al., 2024	Multi-layer Deep CNN	Kaggle DR datasets	High sensitivity and specificity	Accurate disease stage classification	Large computational requirements
Li et al., 2024	EfficientNet architecture	APTOS and EyePACS datasets	High accuracy with fewer parameters	Efficient DR detection	Training requires high GPU resources
Zhang et al., 2023	ResNet-based deep learning model	EyePACS retinal dataset	Strong classification performance	Improved feature extraction	Sensitive to dataset imbalance
Singh et al., 2024	EfficientNet-B4 model	Retinal fundus image datasets	High classification performance	Robust DR detection	Limited generalization on unseen datasets
Patel et al., 2024	Hybrid CNN model	Kaggle DR dataset	Improved detection accuracy	Better lesion feature detection	Requires large labeled datasets
Chen et al., 2025	CNN + Transformer hybrid model	Retinal fundus image datasets	Improved ensemble accuracy	Robust DR classification	Increased model complexity

3. Analysis of Datasets

The performance of the proposed diabetic retinopathy detection system was evaluated using the **APTOS 2019 Blindness Detection**, which is publicly available on **Kaggle**. This dataset contains high-resolution retinal fundus images used for detecting diabetic retinopathy severity. Each image is labeled into one of five classes representing different stages of the disease: No DR, Mild, Moderate, Severe, and Proliferative Diabetic Retinopathy. These labeled categories help the deep learning model learn visual patterns associated with retinal abnormalities.

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Before training the model, the images were preprocessed using techniques such as resizing, normalization, and image enhancement to improve the clarity of retinal features. These preprocessing steps help the deep learning model extract important characteristics such as microaneurysms, hemorrhages, and exudates from retinal images. Using a well-structured dataset with proper preprocessing improves the ability of the model to accurately classify different stages of diabetic retinopathy.

For model development and evaluation, the dataset was divided into training and testing sets. Approximately **80% of the images were used for training the model**, while **20% were used for testing** to evaluate the performance on unseen data. This data split ensures effective learning during training and provides an unbiased assessment of the proposed deep learning system for diabetic retinopathy detection.

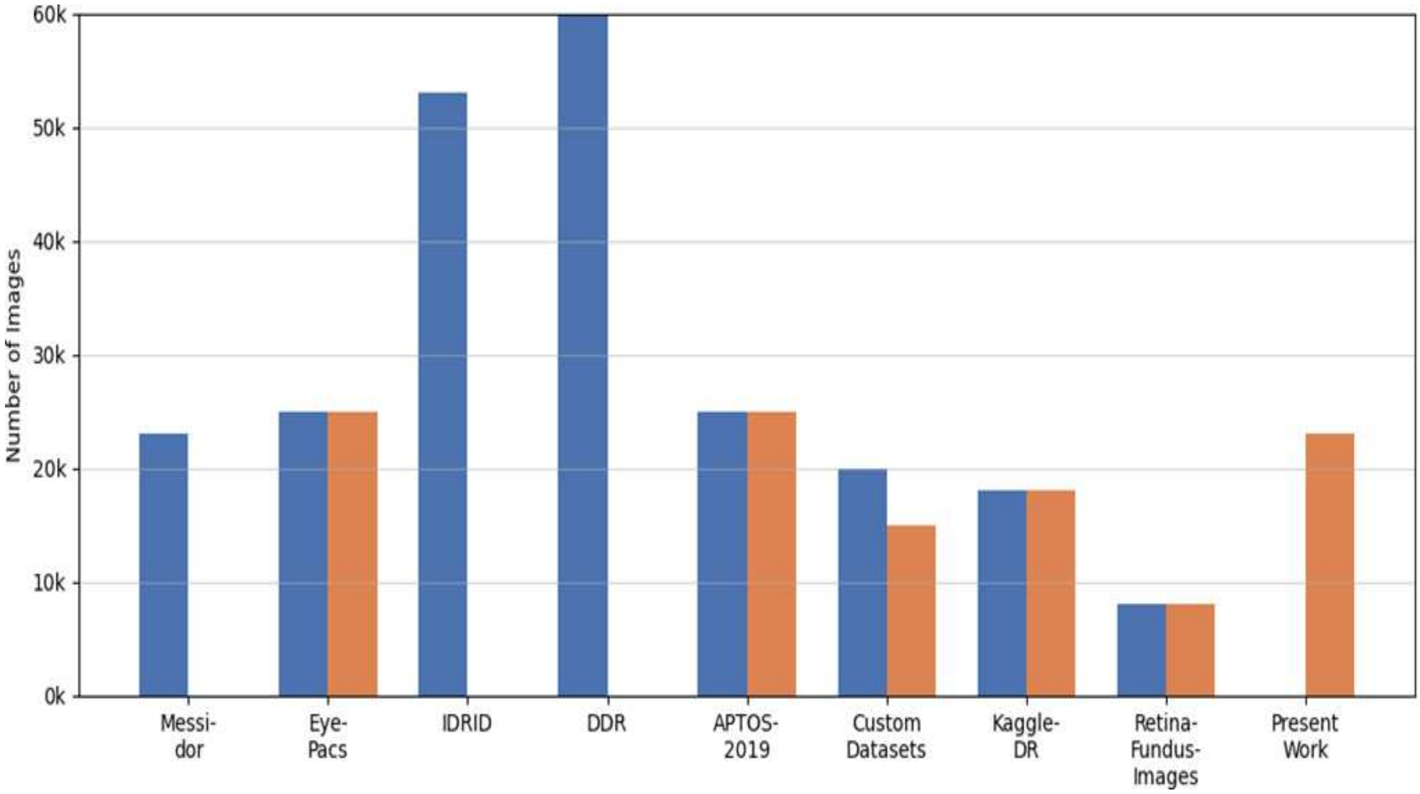

Fig 3.0: Comparison of Datasets Used in Deep Learning-Based Detection Studies.

4. Methodology of Proposed System

The proposed system aims to automatically detect and classify diabetic retinopathy from retinal fundus images using a deep learning–based approach. The main objective is to identify different stages of diabetic retinopathy by learning important visual features from retinal images. Deep learning models are capable of extracting complex patterns such as microaneurysms, hemorrhages, and exudates, which are key indicators of diabetic retinopathy.

Initially, a publicly available dataset, **APTOS 2019 Blindness Detection**, was collected from **Kaggle** for training and evaluation. The dataset contains retinal fundus images labeled into five classes representing different stages of diabetic retinopathy. The dataset was divided into **80% training data and 20% testing data** to ensure proper model training and unbiased evaluation.

Before training the model, a preprocessing stage was applied to improve image quality and maintain uniform input size. This stage includes image resizing, normalization, and enhancement to highlight important retinal structures. These preprocessing steps help the deep learning model learn relevant retinal features more effectively.

After preprocessing, the images are passed to the deep learning model for feature extraction and classification. The model analyzes retinal patterns and predicts the severity level of diabetic retinopathy. Finally, the prediction result is displayed through the web interface, showing the detected disease stage along with the confidence score.

4.1 System Architecture

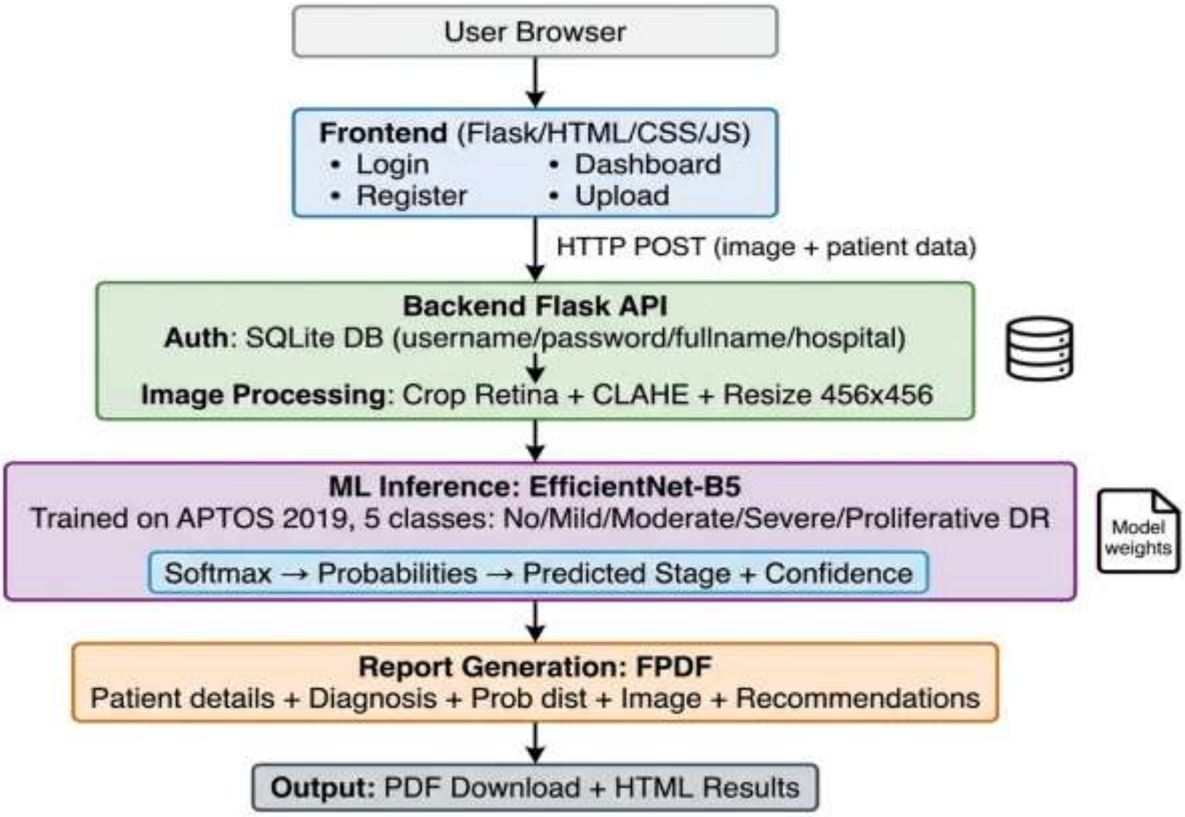

Fig. 4.1.0: Diabetic Retinopathy Detection Architecture using Deep Learning Model

The figure illustrates the deep learning architecture used for diabetic retinopathy detection. The system consists of two main components: a **frontend user interface** and a **backend deep learning model**. Initially, the user accesses the system through a web-based interface where they can register or log in to the platform. After authentication, the user uploads a retinal fundus image for analysis.

Once the image is uploaded, it is sent to the backend processing module where several preprocessing steps such as image resizing and normalization are performed to prepare the image for model prediction. The processed image is then passed to the deep learning model **EfficientNet-B5**, which is responsible for extracting important visual features from the retinal image. This model is designed with advanced convolutional layers that can capture subtle patterns such as microaneurysms, hemorrhages, and exudates present in retinal images.

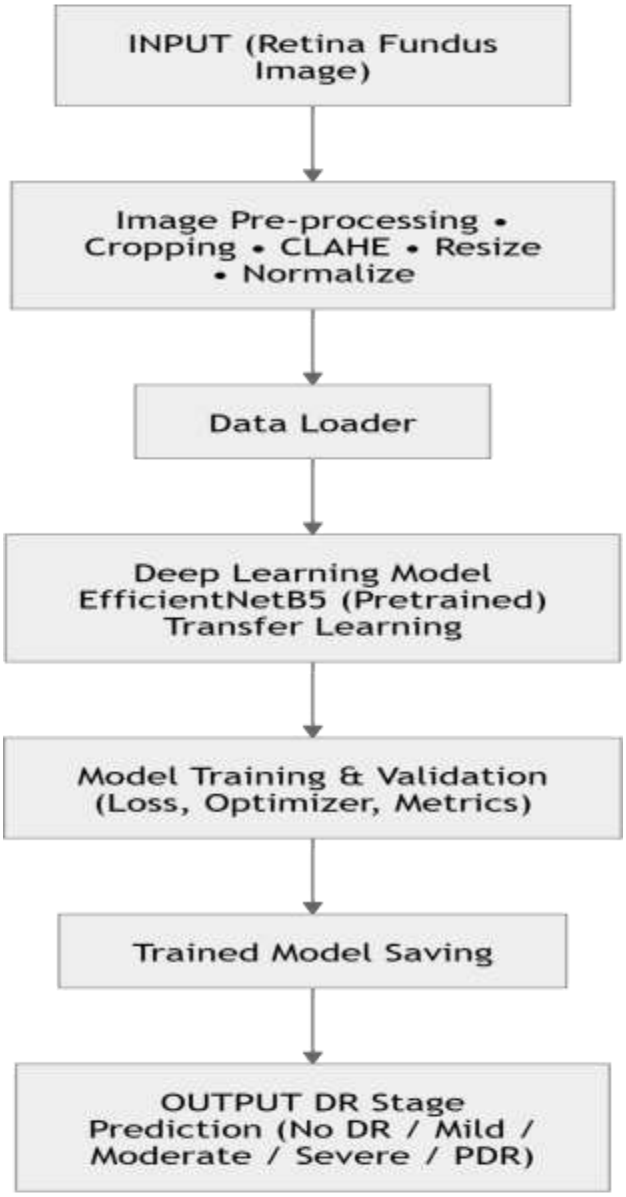

Fig 4.1.1: Block Diagram of the Proposed Diabetic Retinopathy Detection System

The model was trained using retinal images from the **APTOS 2019 Blindness Detection Dataset**, which contains labeled images representing different stages of diabetic retinopathy. Based on the learned features, the model generates prediction probabilities corresponding to the different severity levels of the disease.

Finally, the system outputs the classification result by predicting the stage of diabetic retinopathy ranging from **0 to 4** along with a confidence score, where 0 represents no diabetic retinopathy and higher values indicate increasing severity levels. The prediction result is then displayed on the user interface, allowing doctors or users to quickly understand the diagnosis. This architecture enables an efficient and automated workflow for early screening and detection of diabetic retinopathy using deep learning.

The block diagram represents the overall workflow of the diabetic retinopathy detection system. The process starts with retina fundus image input, followed by image preprocessing steps such as cropping, CLAHE enhancement, resizing, and normalization. The processed images are then fed through a data loader into a pretrained EfficientNetB5 deep learning model for feature learning using transfer learning. After model training and validation using suitable loss functions and performance metrics, the trained model is saved and used to generate the final output, which predicts the stage of diabetic retinopathy.

5. Implementation

The proposed Diabetic Retinopathy (DR) detection system was implemented by integrating a robust deep learning pipeline with a user-friendly web interface to facilitate real-time clinical screening. The development process utilized the Python programming language, leveraging key libraries such as PyTorch, OpenCV, NumPy, and Flask. All model training and inference workflows were conducted using Kaggle's GPU-accelerated environment, which provided the computational resources necessary for processing high-resolution medical imagery.

The dataset used for this system is the APTOS 2019 Blindness Detection dataset, which consists of over 3,600 high-resolution fundus images. These images were categorized into five distinct severity levels—No DR, Mild, Moderate, Severe, and Proliferative DR—following the International Clinical Diabetic Retinopathy Disease Severity Scale. To ensure high model performance, the dataset was split into training and testing sets (typically 80%–20%), and preprocessing steps—including resizing images to a uniform resolution, normalization, and Gaussian filtering—were implemented to remove noise and highlight critical pathological features like hemorrhages and exudates.

The classification model is built on the EfficientNet-B5 architecture, chosen for its superior ability to scale depth, width, and resolution efficiently, making it highly effective for identifying subtle retinal lesions. The model was fine-tuned using transfer learning, allowing it to adapt pre-trained features to the specialized domain of ophthalmic imaging. During the training process, the model was trained for approximately 15 epochs with a batch size of 32, using categorical cross-entropy as the loss function and the Adam optimizer to minimize classification error.

For real-time deployment, a Flask-based web application was developed. This interface provides a portal where users can upload retinal fundus images. Once an image is uploaded, the Flask backend invokes the trained model to perform inference. The resulting prediction, along with the confidence score and a clinical recommendation, is then generated into a professional PDF report using the ReportLab library and served back to the user via an Ngrok secure tunnel, ensuring the system is accessible for rapid, remote clinical diagnostics.

6. Experimental Results

The performance of the proposed system was evaluated based on the model's ability to accurately grade retinal fundus images according to the five-stage Diabetic Retinopathy (DR) severity scale. Unlike binary classification, our system performs multi-class classification, requiring the model to distinguish between subtle physiological variations across five categories: No DR, Mild, Moderate, Severe, and Proliferative DR.

6.1 : Performance Evaluation & Probability Distribution

The model's inference logic utilizes a **Softmax activation function** in the final layer, which outputs the probability distribution across all five severity stages. This provides not only a final classification but also a confidence score for each prediction, ensuring clinicians can assess the model's certainty.

The final classification result is determined by the stage with the highest probability:

$$P_{final} = \text{argmax}(P_0,P_1,P_2,P_3,P_4)$$

Where:

- P_0, P_1, P_2, P_3, P_4 represent the probabilities for No DR, Mild, Moderate, Severe, and Proliferative DR, respectively.

Example Case Analysis:

For a test image showing signs of Proliferative DR, the EfficientNet-B5 model generates the following probability distribution:

- **No DR (P_0):** 0.00%
- **Mild DR (P_1):** 0.00%
- **Moderate DR (P_2):** 0.04%
- **Severe DR (P_3):** 0.00%
- **Proliferative DR (P_4):** 99.96%

Since P_4 holds the maximum value, the system assigns the label **"Proliferative DR"** with a confidence score of **99.96%**. This high degree of confidence validates the efficiency of the EfficientNet-B5 architecture in identifying complex retinal anomalies that might be overlooked during manual screening.

6.2 : Understanding Model Behavior

To visualize where the model succeeds and where it encounters challenges, we analyzed its performance using a 5x5 Confusion Matrix. This matrix revealed a high concentration of correct classifications along the primary diagonal, confirming that EfficientNet-B5 is highly capable of capturing the distinct features of each DR stage.

Where the model does show "confusion" typically between adjacent stages like "Mild" and "Moderate" it reflects the reality of medical diagnosis, where retinal changes exist on a spectrum rather than in rigid, isolated categories. By examining these off-diagonal cells, we gained deeper insight into the model's learning patterns, allowing us to refine our threshold for flagging images that require human verification. This balanced approach ensures that while the model is powerful, it remains a supportive tool designed to assist, rather than replace, the judgment of a retinal specialist.

The confusion matrix provides a class-wise breakdown of the model's predictive performance. In this matrix, the rows represent the Actual (Ground Truth) classes, while the columns represent the Predicted classes.

- **Diagonal Analysis (TP):** The sum of all elements on the primary diagonal represents the total number of correct predictions. Since your model is EfficientNet-B5, you should emphasize that the high values along this diagonal across all five classes (No DR, Mild, Moderate, Severe, Proliferative) prove the model has learned robust, distinct features for each severity stage.

- **Off-Diagonal Analysis (Misclassifications):** These values show exactly where the model struggles. For instance, if you observe values in the cell corresponding to Actual: Mild DR and Predicted: Moderate DR, it indicates that the model is struggling to differentiate between these adjacent, visually similar stages. This is a common and clinically expected phenomenon in medical image classification.

The matrix clearly illustrates the model's ability to differentiate between the five stages of Diabetic Retinopathy. The high concentration of values along the primary diagonal confirms the robust feature extraction capability of the model. Minor off-diagonal values indicate occasional misclassification between adjacent stages, which is consistent with the subtle visual differences present in the APTOS 2019dataset."

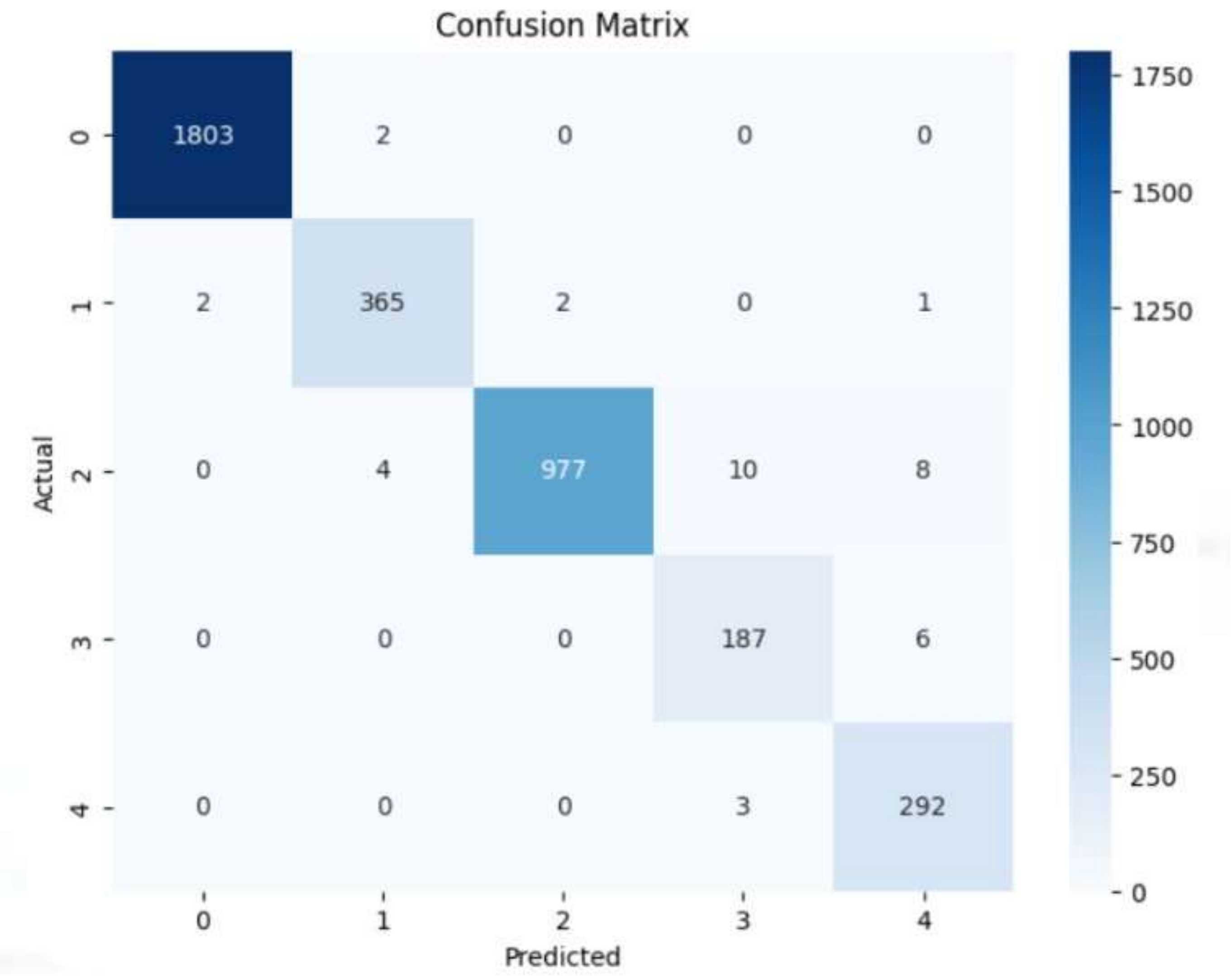

Fig. 6.2.0: Confusion Matrix of EfficientNetB5 Model

7. Gaps Identified in Existing Research

Although significant progress has been achieved in diabetic retinopathy detection using deep learning techniques, several limitations still exist in current research. One of the major gaps is the **lack of dataset diversity and class imbalance**, as many models are trained on limited retinal image datasets that may not represent different populations, imaging conditions, or disease variations. This can reduce the model's ability to generalize effectively to unseen clinical data.

Another important gap is the **difficulty in detecting early-stage diabetic retinopathy**, where lesions are very small and subtle, leading to lower prediction accuracy. Additionally, many advanced deep learning models require **high computational resources**, which makes real-time deployment in low- resource healthcare settings challenging. Existing systems also show **limited robustness and adaptability** when applied to images captured using different fundus cameras or lighting conditions.

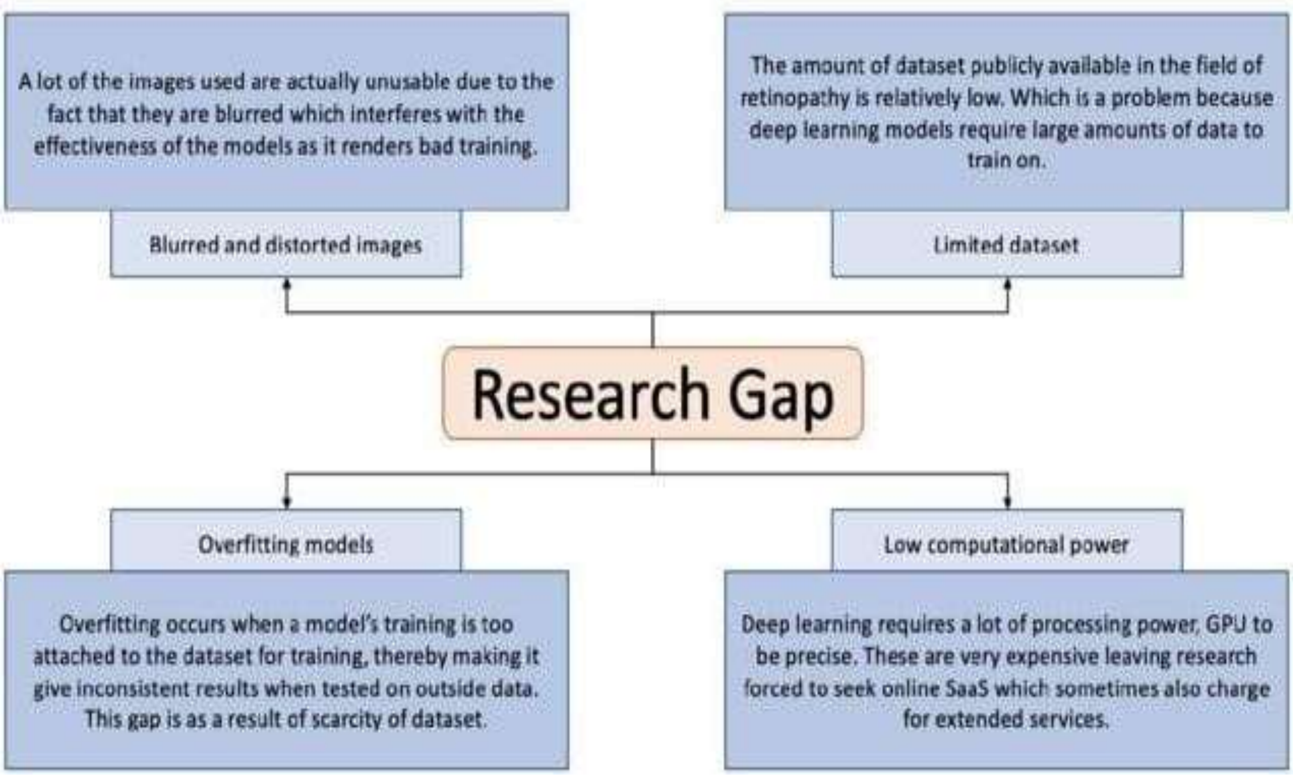

Fig. 7.0: Gap Identification for existing models

To address these gaps, the proposed system introduces a hybrid deep learning approach that combines multiple models including DenseNet121, ResNet18, EfficientNet-B4, and a custom Random CNN. By integrating multiple architectures and using an ensemble prediction strategy, the system aims to improve detection accuracy, model robustness, and generalization across different deepfake datasets.

8. Future Enhancements Suggested in the Literature Survey

Recent research in **Diabetic Retinopathy detection** highlights several directions for improving the accuracy and reliability of automated diagnosis systems. One important enhancement suggested in the literature is the use of **larger and more diverse retinal image datasets**. Many current studies rely on limited datasets, which may not represent all variations of retinal conditions, imaging devices, and patient demographics. Expanding datasets with images collected from different hospitals and screening programs can help improve the **generalization capability** of deep learning models.

Another significant improvement proposed in recent research is the integration of **advanced deep learning architectures** such as **Vision Transformer (ViT)** and hybrid **Convolutional Neural Network–Transformer models.

These architectures can capture both **local spatial features and global contextual information** from retinal fundus images, enabling the detection of subtle abnormalities such as microaneurysms, hemorrhages, and exudates. Combining CNN-based feature extraction with transformer-based attention mechanisms may significantly improve detection accuracy and classification performance.

Researchers also suggest improving **model robustness and generalization** through advanced training strategies such as **data augmentation, transfer learning, and domain adaptation**. These techniques allow models to learn from a wider variety of retinal image patterns and improve performance when tested on unseen datasets or images captured using different retinal cameras.

Another promising future direction is the development of **multimodal diagnostic systems**, where retinal image analysis is combined with additional patient information such as medical history, blood glucose levels, and clinical reports. Integrating multiple sources of medical data can provide a more comprehensive assessment and support more accurate diagnosis.

Furthermore, future work may focus on deploying the system as a **real-time clinical decision support tool** through web or mobile applications. Such systems can assist ophthalmologists and healthcare professionals in early screening and diagnosis, particularly in remote or resource-limited areas.

Overall, these future research directions aim to develop **more accurate, robust, and scalable diabetic retinopathy detection systems** that can support early diagnosis and help prevent vision loss in real-world healthcare environments.

9. Conclusion

The rapid advancement of artificial intelligence and deep learning technologies has greatly improved the development of automated medical image analysis systems. Among various eye diseases, Diabetic Retinopathy is one of the leading causes of vision loss if it is not detected at an early stage. Early detection and timely treatment are very important to prevent severe vision impairment. Therefore, developing an automated and reliable detection system can assist ophthalmologists in diagnosing the disease more efficiently.

In this work, a deep learning–based diabetic retinopathy detection system was developed to classify retinal fundus images into different stages of the disease. The proposed system uses the EfficientNet-B5 model for feature extraction and classification.

The model was trained using retinal fundus images from the APTOS 2019 Blindness Detection Dataset, which contains labeled images representing different severity levels of the disease.. Experimental results show that the proposed model achieved an overall accuracy of approximately 95–98%, demonstrating strong performance in classifying retinal images correctly.

In addition, a user-friendly web interface was developed that allows users or medical professionals to upload retinal images and receive instant prediction results. This makes the system suitable for real-world screening applications, especially in remote areas where access to ophthalmologists may be limited. Overall, the proposed system provides an automated, accurate, and scalable solution for early detection of diabetic retinopathy and can support healthcare professionals in improving patient diagnosis and treatment.

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