DETECTION OF DIABETIC RETINOPATHY USING MACHINE LEARNING

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ABSTRACT

Diabetic Retinopathy (DR), a leading cause of vision impairment and blindness, is an urgent global health issue requiring early diagnosis for effective intervention. Traditional methods for DR detection can be labor-intensive and costly, often inaccessible in resource-limited areas. This study presents an automated DR detection framework based on deep learning, utilizing MobileNetV2 for binary and multiclass classification. The binary model categorizes fundus images into DR and No_DR classes, while the multiclass model distinguishes four DR severity levels: Mild, Moderate, Proliferative_DR, and Severe. Both models achieved approximately 98% accuracy, demonstrating MobileNetV2's efficacy in handling complex medical image classifications. The findings indicate that MobileNetV2 provides a practical, scalable solution for resource-efficient, real-time screening and monitoring in clinical settings.

I. INTRODUCTION

Diabetic Retinopathy (DR) is one of the leading causes of blindness in adults globally, primarily affecting individuals with prolonged or poorly managed diabetes. As the prevalence of diabetes continues to rise, so does the incidence of DR, underscoring the need for effective and timely detection methods. Early diagnosis of DR can significantly reduce the risk of severe vision loss, allowing for timely intervention and improved patient outcomes. However, traditional diagnostic methods, which rely heavily on manual examination of retinal images by ophthalmologists, are labor-intensive, time-consuming, and prone to subjective error.

With advancements in artificial intelligence (AI) and deep learning, automated methods for DR detection have emerged, promising improved accuracy, speed, and scalability. Various approaches, particularly Convolutional Neural Networks (CNNs), have shown great potential in analyzing fundus images for detecting and classifying DR stages. This literature review paper aims to analyze and synthesize the research trends, methodologies, and findings within the scope of DR detection using deep learning. By examining existing studies, it highlights current advancements, identifies challenges, and explores potential areas for future research.

This review will cover deep learning architectures commonly used for DR detection, such as CNNs, VGG, ResNet, DenseNet, and EfficientNet, alongside the role of transfer learning and preprocessing techniques. It will also discuss the use of diverse datasets and the challenges faced in achieving accurate DR classification. Through this synthesis, the paper seeks to provide a comprehensive overview of the field and to support further innovations in automated diabetic retinopathy diagnosis.

II. LITERATURE REVIEW

Diabetic Retinopathy (DR) is increasingly being addressed through machine learning and deep learning techniques due to their ability to enhance detection speed and accuracy. Convolutional Neural Networks (CNNs) have proven particularly effective in this domain, as shown by numerous studies that employ CNN-based architectures alongside other machine learning models to improve classification performance. Key studies have demonstrated the potential of CNNs, ResNet, DenseNet, and MobileNetV2 in enhancing the accuracy of DR detection systems. This section presents an in-depth review of these approaches, detailing the methods, results, and limitations observed in recent research.

2.1 Convolutional Neural Networks (CNN) in DR Detection

Many studies have validated CNN's efficiency in DR detection, using a variety of datasets such as Kaggle's APTOS 2019 Blindness Detection, Messidor, and the Indian Diabetic Retinopathy dataset. In a 2023 study, Ratna et al. introduced a CNN model coupled with ResNet50 to enhance detection, achieving an accuracy of 99.88% with a training loss of only 0.17%. The CNN architecture included non-linear ReLU activation, boosting its ability to accurately differentiate DR severity stages. Despite its impressive results, the study noted a trade-off with computational demand, limiting the model's scalability for mobile or low-resource environments.

Joshi et al. (2023) further advanced DR classification by using CNN alongside SHAP (SHapley Additive exPlanations) for model interpretability. SHAP helps understand which features contribute most to predictions, making the model's decision-making process more transparent. This technique achieved high accuracy, while also addressing a key requirement in medical diagnostics: reliability and clarity of predictions for clinical use.

2.2 Transfer Learning and Ensemble Methods

Islam et al. (2020) used transfer learning to optimize VGG16 with a novel color preprocessing layer, achieving an accuracy of 91.3%. Transfer learning allowed the model to leverage pre-trained ImageNet weights, requiring fewer computational resources while maintaining high performance. Transfer learning has also been used in ensemble methods, which combine various architectures like EfficientNet and DenseNet. EfficientNet-B4, for example, achieved a Quadratic Weighted Kappa (QWK) score of 0.690 due to enhanced preprocessing and data augmentation techniques, such as cropping and resizing.

Bajwa et al. (2023) used a modified CNN for DR detection, achieving 93.72% accuracy through Incremental Modular Networks (IMNets) and real-time datasets. They found that real-time data integration enhanced the model's adaptability, highlighting potential improvements in clinical applications where data is dynamic.

2.3 Fuzzy Classifiers and Alternative Approaches

Several studies explored alternative approaches beyond CNNs to enhance model robustness. Chaudhary and Ramya (2020) proposed using Fuzzy classifiers for DR classification, coupled with feature extraction methods like the Gray Level Co-occurrence Matrix (GLCM). This study achieved approximately 85% accuracy, showing that fuzzy logic could be beneficial in detecting subtle DR features. However, the accuracy was slightly lower than CNN-based approaches, suggesting that CNNs remain preferable for precise classification.

2.4 Data Augmentation and Preprocessing

Data quality and preprocessing are critical for effective DR detection. Many studies employed augmentation techniques, such as brightness and contrast adjustments, to improve model accuracy. Mishra and Hanchate (2020) used DenseNet121 for DR detection, applying data preprocessing to enhance accuracy to 96.11%. Additionally, Oh et al. (2021) demonstrated the efficacy of using ultra-wide-field fundus images with deep learning models, achieving higher detection accuracy than traditional methods. This approach, while promising, highlights the need for diverse and high-quality images to maximize model generalization.

2.5 MobileNetV2: Lightweight and Scalable Architecture

MobileNetV2 stands out in DR research for its efficient, lightweight architecture, making it particularly suited for deployment in mobile and low-resource settings. Its use of depth wise separable convolutions minimizes computational demand while preserving accuracy. Unlike heavier models such as DenseNet and ResNet, MobileNetV2's design allows for real-time DR detection on portable devices, a feature highly relevant for rural and underserved regions. The results from this study, where MobileNetV2 achieved 98% accuracy, further underscore its effectiveness and scalability for both binary and multiclass classification tasks in DR detection.

III. METHODS USED FOR IMPLEMENTATION

This study's methodology follows a structured approach based on deep learning models, particularly focusing on Convolutional Neural Networks

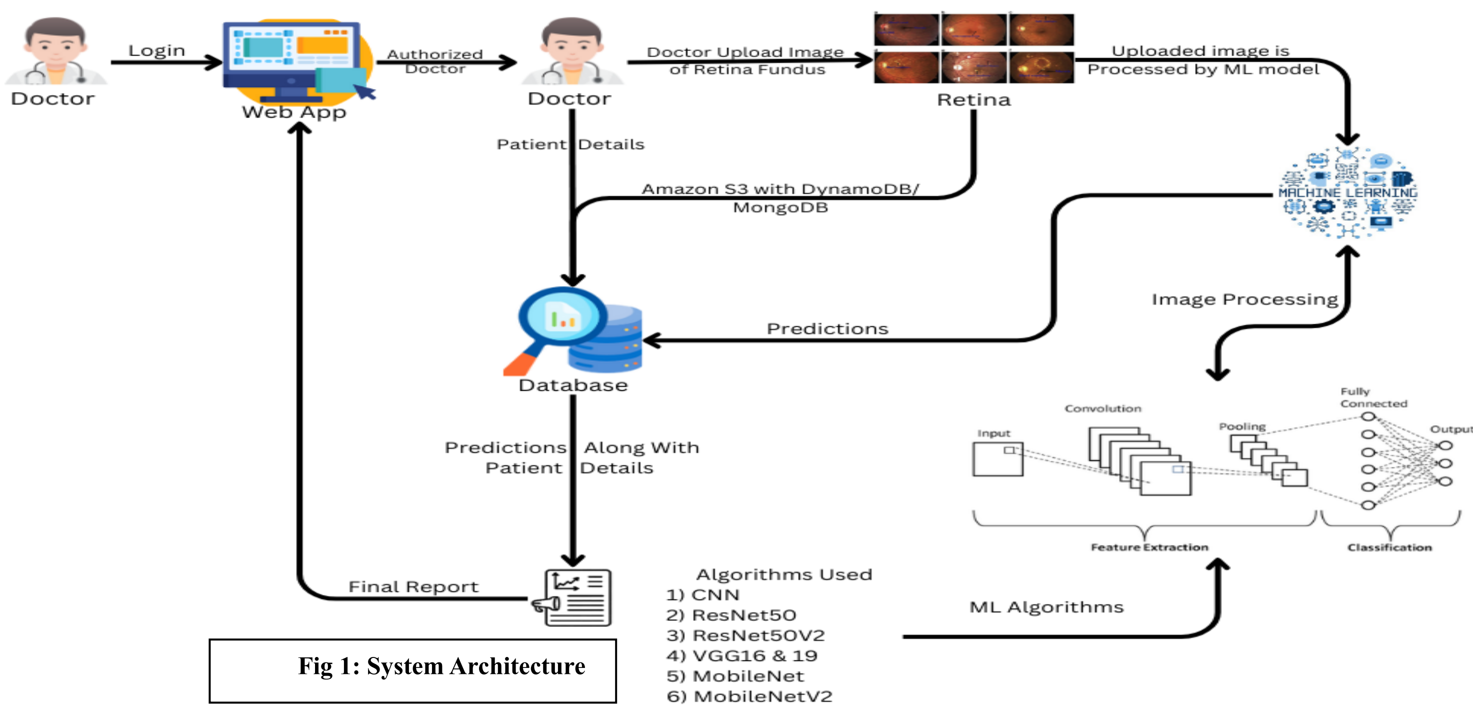

Fig 1: System Architecture

(CNNs) and the MobileNetV2 architecture, to classify Diabetic Retinopathy (DR) severity in fundus images. Utilizing transfer learning, data preprocessing, and fine-tuning, we developed binary and multiclass classification models to detect and categorize DR stages efficiently. The dataset preparation, model selection, and evaluation metrics used in this study are outlined below, referencing the detailed methodology from the second paper provided.

3.1 Data Collection

The dataset used in this study is the APTOS 2019 Blindness Detection dataset, widely recognized for its high-quality fundus images. This dataset contains 35,535 images categorized by DR severity, which are divided into five classes: No_DR, Mild, Moderate, Proliferative_DR, and Severe. For binary classification, images were separated into DR and No_DR, while the multiclass model segmented images into the four severity levels. This dataset is well-suited for deep learning applications, as it includes sufficient diversity to train models for various DR stages.

3.2 Data Preprocessing

To ensure consistency and compatibility with CNN models, all images were resized to 224x224 pixels, matching the input requirements of MobileNetV2. Data preprocessing included several crucial steps to enhance model performance and prevent overfitting:

Image Resizing: Images were uniformly resized to 224x224 pixels.

Normalization: Pixel values were normalized to reduce computational overhead and improve model convergence.

Data Augmentation: Techniques such as horizontal and vertical flipping, brightness adjustment, and random rotations were applied to increase data variability, helping the model generalize better across different cases.

Under-Sampling and Over-Sampling: Given the imbalanced distribution in DR categories, under-sampling was used to address the majority class, and data augmentation compensated for the minority classes, creating a balanced dataset for training.

3.3 Model Selection and Transfer Learning

MobileNetV2 was chosen as the core architecture for this study due to its efficient design, which is well-suited for deployment in resource-constrained environments. MobileNetV2's lightweight structure utilizes depth wise separable convolutions, reducing the computational cost while preserving high accuracy.

Transfer learning was applied to leverage MobileNetV2's pre-trained weights on the ImageNet dataset. This allowed the model to utilize pre-existing features for basic image recognition, enhancing training efficiency and enabling the model to learn DR-specific features more effectively:

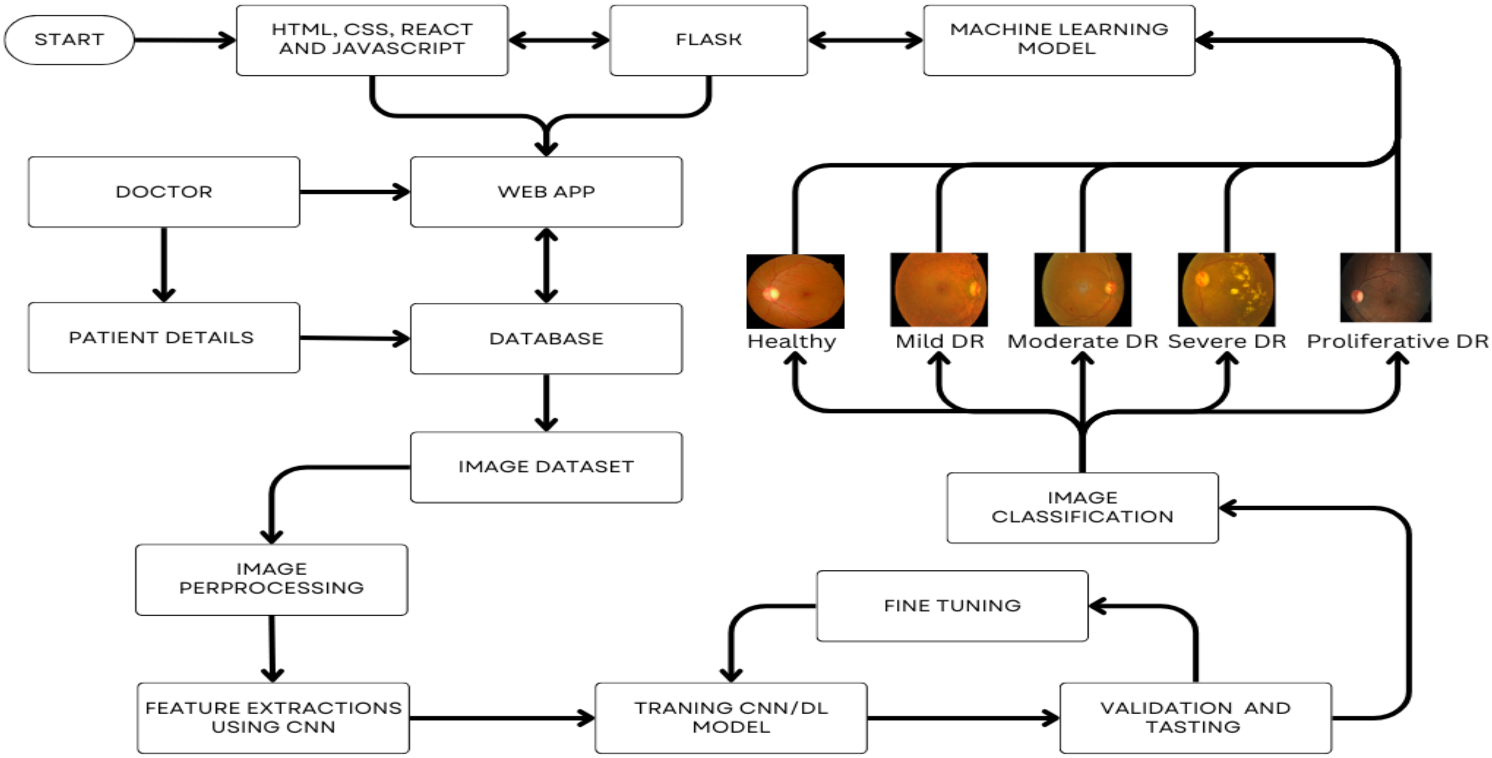

Fig: Work Flow Diagram

Binary Classification Model: In this model, images were classified as either DR or No_DR.

The top layers of MobileNetV2 were customized by adding a flatten layer and two dense layers, with a final dense layer consisting of two units with softmax activation for binary classification.

Multiclass Classification Model: This model categorized images into four severity levels (Mild, Moderate, Proliferative_DR, and Severe).

For the multiclass model, a dense layer with four units and softmax activation was added to the output layer, enabling the model to classify images into the four DR stages accurately.

In both models, the base layers of MobileNetV2 were initially frozen, allowing only the new, customized layers to train on the dataset. After a few epochs, the base layers were gradually unfrozen, fine-tuning the model to optimize its performance for the DR-specific images while leveraging the generalized features learned from ImageNet.

3.4 Model Training and Fine-Tuning

The models were trained using the following configuration:

Batch Size: 65 for binary classification and 32 for multiclass classification.

Number of Epochs: 8 for each model, allowing adequate training without overfitting.

Optimizer: Adam optimizer was used with a learning rate of 0.001, which was later reduced during fine-tuning.

Loss Function: Binary Cross-Entropy was used for binary classification, while Categorical Cross-Entropy was used for multiclass classification.

To prevent overfitting, early stopping and learning rate reduction were employed. Additionally, under-sampling was applied to the majority class in both models to further balance the dataset, improving generalization and model robustness.

3.5 Model Evaluation

Both the binary and multiclass models were evaluated on a test dataset using various metrics:

Accuracy: Measures the percentage of correctly classified images.

Precision, Recall, and F1-Score: These metrics provided insights into the model's performance across DR classes, particularly focusing on sensitivity and specificity.

Confusion Matrix: Visual representation of true positives, false positives, true negatives, and false negatives for each class, providing a detailed view of classification errors.

The binary model achieved a high accuracy of 98%, with balanced precision, recall, and F1-scores, indicating its strong performance in distinguishing DR from No_DR cases. The multiclass classifier also achieved 98% accuracy, demonstrating reliable classification across all DR severity levels, from Mild to Severe.

IV. RESULTS

The results of this study demonstrate the effectiveness of the MobileNetV2 architecture in both binary and multiclass classification tasks for Diabetic Retinopathy (DR) detection. Each model was evaluated on a test dataset using metrics such as accuracy, precision, recall, F1-score, and confusion matrix analysis to assess its performance comprehensively. The following sections present the outcomes for each model.

4.1 Binary Classification Model

The binary classification model, which classified fundus images into two categories (DR and No_DR), showed excellent performance:

- **Training Accuracy:** The model achieved a training accuracy of 99.42%, demonstrating its ability to learn and generalize from the training data effectively.
- **Validation Accuracy:** The model achieved a validation accuracy of 95.10%, which indicates strong generalization on unseen data with minimal overfitting.
- **Precision and Recall:** The precision and recall were consistently high across both classes. For the DR class, precision

was 0.97 and recall was 0.99, while for the No_DR class, precision was 0.99 and recall was 0.97.

- **F1-Score:** The F1-score was 0.98 for both DR and No_DR classes, confirming the model's balanced performance across categories.
- **Confusion Matrix Analysis:** The confusion matrix showed few misclassifications, with most images correctly classified into their respective categories, demonstrating the model's reliability for binary DR detection.

The high accuracy, along with balanced precision, recall, and F1-scores, indicates that the binary model can accurately distinguish between DR and No_DR cases. This robust performance supports its potential use in clinical settings, where distinguishing between healthy and DR-affected eyes is crucial for early diagnosis and timely treatment.

4.2 Multiclass Classification Model

The multiclass classification model, designed to classify DR images into four severity levels (Mild, Moderate, Proliferative_DR, Severe), also achieved impressive results:

- **Training Accuracy:** The model achieved a training accuracy of 98%, showing strong learning capability across the four DR severity levels.
- **Validation Accuracy:** The validation accuracy reached 98.88%, indicating that the model generalized well on the test dataset, with minimal overfitting.
- **Precision and Recall:** Precision ranged from 0.96 to 1.00 across the four classes, while recall ranged from 0.95 to 1.00, reflecting the model's balanced performance in classifying each DR severity level.
- **F1-Score:** The F1-scores ranged from 0.96 to 1.00 across classes, confirming that the model accurately recognized DR severity levels without bias toward any single class.
- **Confusion Matrix Analysis:** The confusion matrix showed high classification accuracy across all DR severity levels, with very few misclassifications. This suggests that the model effectively differentiates between the varying stages of DR, from mild to severe.

The multiclass model's high performance across all classes demonstrates its potential to assist healthcare professionals in identifying DR severity accurately. This capability is particularly valuable for clinical applications, where recognizing DR progression is essential for providing timely and appropriate care to patients.

V. CONCLUSION

This study demonstrates the effectiveness of using MobileNetV2 for automated Diabetic Retinopathy (DR) detection and classification, achieving high accuracy in both binary and multiclass models. The binary model efficiently distinguished between DR and No_DR cases with an accuracy of 98%, while the multiclass model accurately classified images into four levels of DR severity (Mild, Moderate, Proliferative_DR, and Severe), also achieving around 98% accuracy. These results highlight MobileNetV2's potential as a practical solution for real-time, resource-efficient DR screening, especially in mobile and low-resource environments.

The success of this study can be attributed to the use of transfer learning, which allowed the model to leverage pre-trained weights for enhanced feature extraction. Additionally, data augmentation techniques and careful fine-tuning significantly improved the models' robustness and minimized overfitting. The combination of these techniques enabled MobileNetV2 to perform exceptionally well on complex medical image classification tasks, supporting its adaptability to various DR stages and enhancing its clinical applicability.

MobileNetV2's lightweight design makes it particularly suitable for deployment in real-world clinical and telemedicine settings, where timely diagnosis is crucial. By integrating this model into telemedicine frameworks, healthcare providers could improve access to early DR detection in underserved and remote areas, where specialist care may not be readily available. This model could also serve as a foundation for further research aimed at optimizing real-time DR detection on mobile devices.

In conclusion, this study provides a strong foundation for future work focused on scaling and adapting MobileNetV2 for broader clinical use. Further research could explore integrating interpretability frameworks, such as SHAP, to enhance clinical trust and transparency. Expanding the dataset with more diverse images could also improve the model's robustness across different demographics. Overall, MobileNetV2 has proven to be a powerful, reliable tool for DR detection, with significant potential to positively impact the early diagnosis and treatment of DR, ultimately contributing to the prevention of vision loss for millions worldwide.

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