A Mobile Net Based Diabetic Retinopathy Detection And Categorization Using Neural Models

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ABSTRACT: Diabetic Retinopathy (DR) is a leading cause of blindness in diabetic patients. Manual screening by ophthalmologists is time-consuming and labor-intensive. Deep Learning-based classification of DR stages from high-resolution fundus images using MobileNet and ResNet models offers a promising solution. The models were trained on the Kaggle dataset to enhance the efficiency and accuracy of DR diagnosis, detection, and prevention of vision loss.

Deep Learning models detect and classify five DR stages (0-4) from fundus eye images with high accuracy. Input images are processed to extract features, which are then used to output the corresponding DR stage using an activation function. Utilizing Artificial Intelligence, the system analyzes large datasets and makes accurate predictions, reducing the workload of ophthalmologists and improving patient outcomes. This technology has the potential to revolutionize DR diagnosis, enabling timely and accurate detection, and preventing vision loss. Deep Learning in medical image analysis demonstrates effectiveness in improving healthcare outcomes, enabling enhanced patient care and treatment.

Keywords: Diabetic Retinopathy (DR), Deep Learning (DL), MobileNet, ResNet, fundus images.

I. INTRODUCTION:

Diabetic Retinopathy (DR) is a progressive microvascular complication of diabetes and one of the leading causes of blindness worldwide. It occurs due to prolonged exposure to high blood sugar levels, which damages the blood vessels in the retina, leading to vision impairment. Early detection and timely intervention are crucial in preventing severe vision loss. Traditional screening methods, which rely on manual grading of fundus images by ophthalmologists, are time-consuming, labor-intensive, and prone to subjectivity. As a result, there is an increasing demand for automated and accurate diagnostic solutions to assist ophthalmologists in DR detection and classification.

Recent advancements in Deep Learning (DL) have revolutionized medical image analysis, offering robust solutions for automated DR detection. Convolutional Neural Networks (CNNs) have shown high accuracy in processing retinal fundus images for early identification of DR. In particular, models like MobileNet and ResNet have been extensively used to classify DR stages with improved efficiency. These networks extract key retinal features and classify DR into five severity levels (0-4), facilitating early diagnosis and treatment. The application of artificial intelligence (AI) in DR detection significantly enhances diagnostic accuracy while reducing the workload of ophthalmologists.
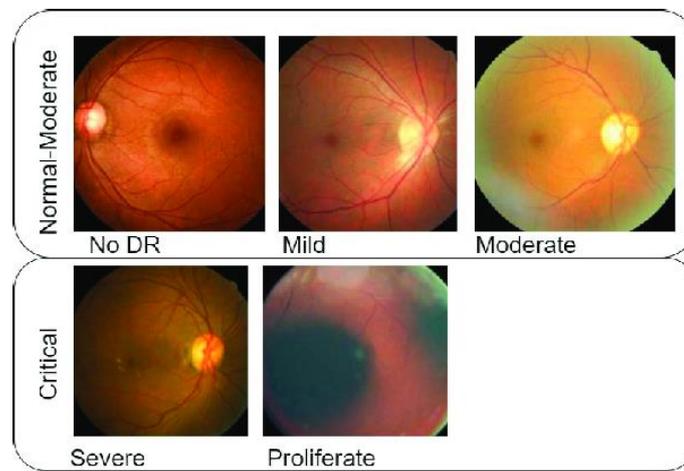
Fig 1: Classification of DR[2]

Several studies have demonstrated the effectiveness of DL-based approaches in DR screening. Varun Gulshan et al. developed a deep learning algorithm for detecting DR using fundus images, achieving diagnostic performance comparable to human ophthalmologists. Kele Xu et al. proposed an automated DR detection system based on CNNs, which showed promising results in early-stage identification. Furthermore, hybrid deep learning architectures, such as Xception and ensemble models, have been explored to enhance classification accuracy. Other research efforts have focused on improving feature extraction techniques and data augmentation strategies to boost model performance. This study aims to develop and evaluate a MobileNet-based DR detection and categorization system. The primary objective is to improve the accuracy and efficiency of DR diagnosis, enabling early intervention and reducing the risk of vision loss. By leveraging AI-driven models trained on large-scale datasets, this research contributes to the advancement of automated DR screening, making it more accessible and reliable for widespread clinical applications.

II. LITERATURE SURVEY:

Diabetic Retinopathy (DR) detection has advanced with deep learning, starting with Qummar et al. [1], who introduced an ensemble model combining ResNet50, InceptionV3, Xception, DenseNet121, and DenseNet169 for improved classification. Atwany et al. [2] reviewed Vision Transformers and self-supervised learning, while Zhu et al. [3] explored lightweight models like MobileNet and SqueezeNet. Qiao et al. [4] enhanced early-stage detection using CNN-based microaneurysm segmentation with GPU acceleration, and Zhang et al. [5] improved vessel segmentation using locally adaptive derivative frames. Preprocessing advancements include Haleem et al. [6]'s SLO image artifact removal and Wisaeng [7]'s keypoint elimination for image registration. Imran et al. [8] confirmed deep learning's superiority in segmentation. Bhatia et al. [9] used SVM, AdaBoost, and Random Forest for classification, while Bilal et al. [10] optimized a hybrid SVM-KNN-Binary Tree model, achieving 98.06% accuracy.

Abushawish et al. [11] surveyed 26 CNN models, emphasizing transfer learning and Grad-CAM visualization to enhance interpretability in medical imaging tasks. Their analysis highlighted the strengths and weaknesses of various architectures in diabetic retinopathy (DR) detection. Kaushik et al. [12] introduced a stacked CNN model incorporating gray-world color constancy to address illumination variations, achieving 97.92% binary and 87.45% multi-class accuracy on retinal image datasets. Gayathri et al. [13] utilized Haralick texture features and Adaptive Dual-Tree Complex Wavelet Transform (ADTCWT) for feature extraction, with a Random Forest classifier reaching 99.82% accuracy, showcasing the potential of handcrafted features in DR detection. Al-Antary and Arafa [14] proposed MSA-Net, integrating multi-scale feature pyramids and attention mechanisms, which improved the model's focus on critical retinal regions for accurate DR classification. Bernabé et al. [15] applied CNNs for both DR and glaucoma detection, achieving 99.89% accuracy, demonstrating the model's versatility in multi-disease detection tasks. Soomro et al. [16] developed an Independent Component Analysis (ICA)-based image enhancement technique, which improved the sensitivity

of vessel segmentation from 72% to 75%, achieving 96% accuracy on the DRIVE and STARE datasets, thereby enhancing the reliability of downstream classification tasks.

III. METHODOLOGY OVERVIEW:

STEP 1: DATA COLLECTION

Relevant datasets are gathered from reliable sources, ensuring they contain sufficient features and labels required for model training. This step involves cleaning and preprocessing the data to handle missing values and anomalies.

Step 2: Data preprocessing

The collected data is preprocessed through normalization and standardization techniques to improve model performance. Feature engineering is applied to extract meaningful insights and enhance predictive accuracy.

Step 3: Model Selection

A suitable machine learning model or deep learning architecture is chosen based on the nature of the problem. Considerations include model complexity, interpretability, and computational requirements.

Step 4: Data Splitting

The preprocessed data is split into training and testing sets to ensure the model's ability to generalize well to unseen data. Typically, 70-80% of the data is allocated for training, while the remaining 20-30% is used for testing.

Step 5: Model Training

The model is trained using the training dataset through backpropagation, where it learns patterns and relationships within the data. During training, the model's weights are adjusted iteratively to minimize the error between predicted and actual outputs.

Step 6: Model Validation

Validation is performed using the testing dataset to evaluate the model's performance on new data. The model's accuracy, precision, recall, and other metrics are measured to determine its effectiveness.

Step 7: Hyperparameter Tuning

Based on validation results, hyperparameters such as learning rate, batch size, and the number of epochs are fine-tuned. This optimization step helps enhance model performance and reduce overfitting.

Step 8: Model Deployment

After achieving satisfactory performance, the model is deployed into a production environment. This involves integrating the model into applications or systems where it can generate predictions on real-world data.

Step 9: Monitoring and Maintenance

The deployed model is continuously monitored for performance and accuracy. Maintenance tasks, including retraining with new data and updating algorithms, are performed to ensure the model remains effective over time.
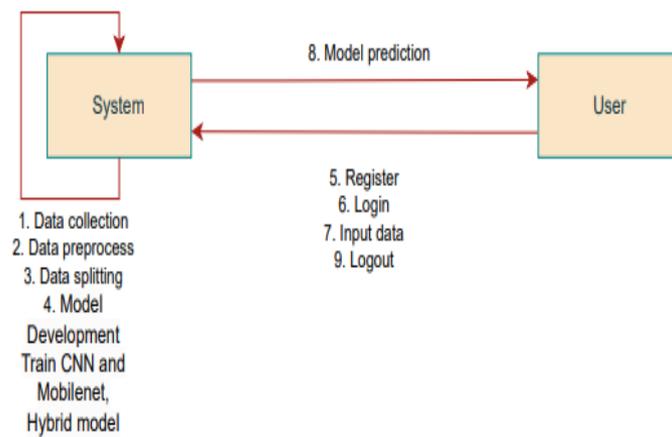
Fig 2. Methodology Used

IV. PROPOSED SYSTEM:

The proposed system for Diabetic Retinopathy (DR) screening integrates the robust feature extraction capabilities of ResNet (Residual Networks) with the efficiency of MobileNet to create a hybrid model that enhances both accuracy and performance. This system is designed to assist healthcare professionals by automating the analysis of retinal fundus images and providing predictive insights into the stages of DR, ultimately contributing to early diagnosis and improved patient care.

System Architecture:
1. **Data Acquisition:** High-resolution retinal fundus images are sourced from the Kaggle dataset.
2. **Preprocessing:** Images undergo resizing, normalization, and augmentation (rotations, flips, brightness adjustments) to improve generalization. Contrast enhancement and noise reduction techniques highlight critical retinal features such as microaneurysms, hemorrhages, and exudates.

Feature Extraction:
- **ResNet Component:** Deep feature learning through a residual learning framework to capture intricate patterns, especially for advanced DR stages.
- **MobileNet Component:** Efficient feature extraction with depthwise separable convolutions, maintaining high performance with a reduced computational footprint.
- **Hybrid Model Advantage:** Balances accuracy and efficiency, ideal for real-world healthcare deployment.

Classification Module:
- Categorizes DR into five clinical stages (0 to 4) using a softmax activation function for probability distribution.
- Incorporates transfer learning and fine-tuning with pre-trained ImageNet weights to boost performance on medical imaging data.

Evaluation and Deployment:
- Performance Metrics: Accuracy, precision, recall, F1-score, and AUC.
- Testing Strategy: Cross-validation and hyperparameter tuning to enhance model robustness.
- Deployment: Cloud-based infrastructure (e.g., AWS) for scalable processing.
- User Interface: Facilitates image upload, automated analysis, and reporting. Includes Grad-CAM heatmaps for interpretability by highlighting key image regions influencing predictions.

V. RESULT:

- The database is loaded with fundus/retinal image of diabetic patients from kaggle dataset then took an input from the database images.
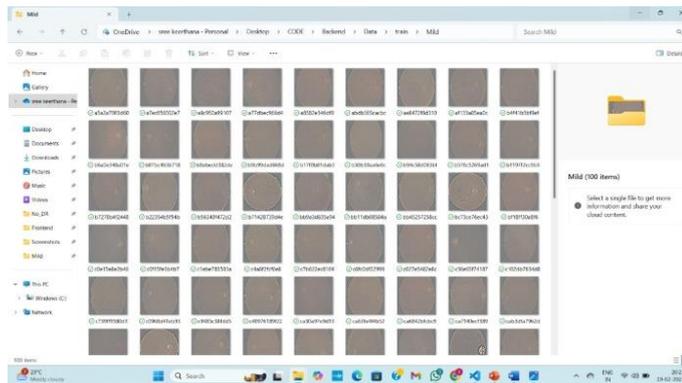

- Then extracted the features and trained the models mobilenet and resnet and then opened the home page, where there are sign in and log in icons are presented.
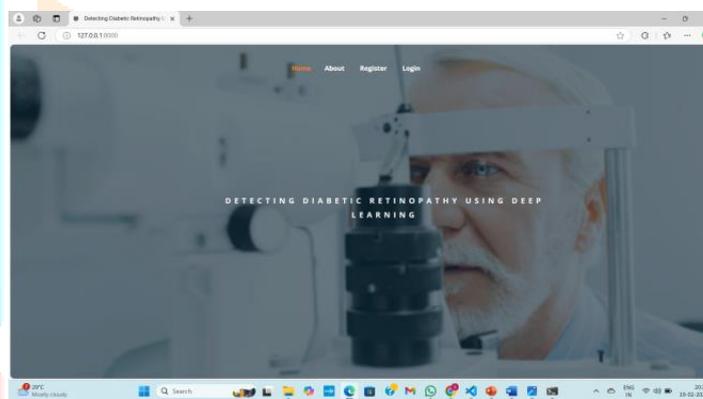
- After signing into the account using login cardinals ophthalmologists can access and upload the DR fundus images.
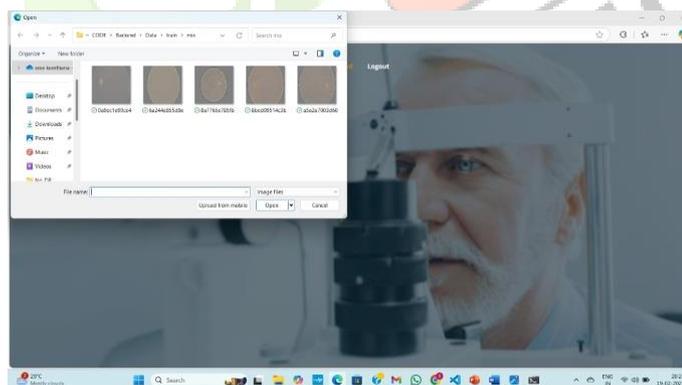
- Based on the models trained, the DR fundus images are classified into various stages based on their severity.
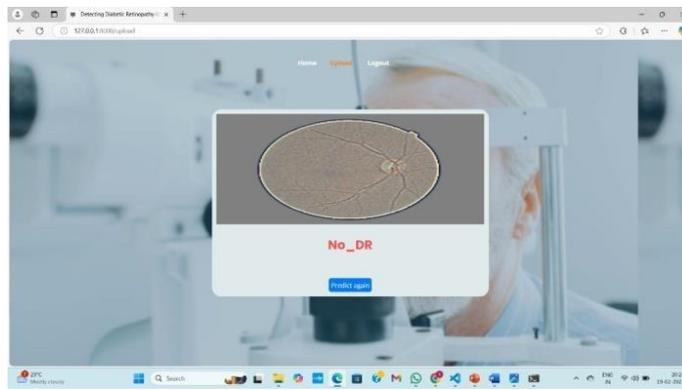
VI. CONCLUSION AND FUTURE SCOPE:

The application of deep learning in detecting Diabetic Retinopathy (DR) has proven to be a significant advancement in the field of medical diagnostics. Traditional DR detection methods, which rely on manual screening by ophthalmologists, are time-consuming, resource-intensive, and often subject to human error. This project leveraged deep learning models, particularly MobileNet and ResNet, to automate the detection and classification of DR stages using retinal fundus images. By training the model on a large dataset, the system achieved high accuracy in diagnosing different severity levels of DR, demonstrating its potential for real-world clinical applications.

Through the implementation of convolutional neural networks (CNNs), the proposed system efficiently extracted relevant features from high-resolution fundus images, significantly improving diagnostic accuracy and reducing the burden on healthcare professionals. The model's ability to classify DR into five distinct stages allows for early intervention, which is crucial in preventing severe vision impairment and blindness. In conclusion, this research highlights the effectiveness of deep learning in medical imaging and demonstrates the potential of AI-powered DR detection systems to revolutionize ophthalmic diagnostics. With continued innovation and integration into clinical practice, such technologies can play a crucial role in early diagnosis, improved patient outcomes, and the global fight against diabetic blindness. Future advancements, such as integrating AI with wearable retinal imaging devices and telemedicine solutions, can further enhance accessibility in remote and underserved areas. Additionally, predictive analytics and real-time monitoring could enable early intervention and personalized treatment plans, ultimately improving patient care and reducing the global burden of diabetic blindness.

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