Decoding Diabetics: Diabetic Retinopathy Detection using Machine Learning

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***Abstract*— Diabetic Retinopathy, a serious complication linked with diabetes, involves the progressive damage of retinal blood vessels and can lead to severe vision loss or blindness if not detected and treated promptly. This research paper explores the application of Machine Learning (ML) techniques for diagnosing and detecting Diabetic Retinopathy. The study examines essential components including data gathering, preprocessing, model training, and evaluation, highlighting the critical role of early detection and timely treatment in preventing severe visual impairments. Unlike traditional screening methods that depend on manual evaluation by ophthalmologists, which can be labor-intensive and limited in remote or underserved regions, ML algorithms offer a scalable and efficient solution for Diabetic Retinopathy screening through retinal image analysis. This research demonstrates the effectiveness of ML models in automating the detection process. By employing advanced preprocessing techniques like data augmentation and using sophisticated Convolutional Neural Network (CNN) architectures, the proposed method achieves high accuracy and reliability in identifying various stages of Diabetic Retinopathy. The integration of these technologies showcases the potential of ML to revolutionize Diabetic Retinopathy screening practices, enhancing accessibility and improving patient care. The findings of this study highlight the capacity of ML to significantly advance Diabetic Retinopathy detection and management, offering a more efficient and automated approach that could greatly benefit individuals at risk of this condition.**

Keywords*— *Diabetic Retinopathy (DR), Convolutional Neural Networks (CNNs), Image Processing

I. INTRODUCTION

Diabetic Retinopathy is a critical diabetes complication where extended periods of high blood sugar levels result in damage to the retinal blood vessels. Without proper treatment, this condition can cause significant vision loss and potentially lead to blindness [1]. Traditional methods for screening Diabetic Retinopathy, such as manual eye examinations conducted by ophthalmologists, are often resource-intensive and may be inaccessible in remote or underserved areas. This lack of accessibility can lead to delayed diagnoses and treatment, contributing to avoidable vision loss. To overcome these challenges, ML algorithms, particularly those focused on analyzing retinal images, present a promising and scalable solution for Diabetic Retinopathy detection [2][3].

Machine learning-based systems have the potential to revolutionize clinical practice by automating the screening process. These systems can analyze retinal images to detect subtle changes indicative of Diabetic Retinopathy, thus enabling early intervention and improving patient outcomes. The use of ML in this context allows healthcare providers to perform more widespread and accessible Diabetic Retinopathy detection, potentially reducing delays in diagnosis and treatment.

Recent progress in machine learning, particularly through deep learning methods like CNNs, has shown remarkable effectiveness in analyzing medical images for the detection and diagnosis of Diabetic Retinopathy. Research has underscored how these ML models can streamline the Diabetic Retinopathy screening process, delivering prompt and precise diagnoses that aid healthcare professionals in their clinical decision-making [1][2].

Despite these advancements, the integration of ML-based systems into clinical practice presents several challenges. Issues such as data imbalance, the need for models to generalize across diverse populations, interpretability of model decisions, and ethical considerations must be addressed to ensure these technologies are effectively and responsibly implemented in healthcare settings. Ongoing research and collaboration between the medical and technology sectors are crucial for overcoming these challenges and fully leveraging the potential of machine learning in the detection and management of Diabetic Retinopathy.

Machine learning algorithms, particularly those that analyze retinal images, provide a scalable and efficient solution for Diabetic Retinopathy detection, with the potential to significantly enhance clinical practice and improve patient care [3].

II. LITERATURE REVIEW

The advent of machine learning, especially deep learning, has revolutionized medical image analysis, with Convolutional Neural Networks (CNNs) at the forefront of Diabetic Retinopathy detection. Notably, Gulshan et al. (2016) advanced the field by developing a deep learning algorithm that analyzes retinal fundus images for Diabetic Retinopathy detection. The sensitivity and specificity for their model, when tested with an external validation data set, were very promising at 90.3% and 98.1%, respectively [2]. This very fact was the one that made its model succeed—mostly because it was trained on a huge dataset of 128,175 retinal images, through which it could both identify and learn complex patterns correlated with different stages of Diabetic Retinopathy.. This study is frequently referenced as a key example of deep learning's effectiveness in automating Diabetic Retinopathy screening.

Although deep learning models, particularly CNNs, have received significant attention, traditional machine learning techniques also offer valuable contributions to Diabetic Retinopathy detection. Pratt et al. (2016) conducted a comparison of various traditional classifiers, including Support Vector Machines (SVMs), Random Forests, and

Artificial Neural Networks (ANNs). Their results indicated that both SVMs and Random Forests achieved high accuracy levels, with AUC scores of 0.93 and 0.92, respectively [3]. This highlights that traditional machine learning methods can be effective, especially in contexts with limited computational resources or where model simplicity and interpretability are preferred over the complexity of deep learning models.

Research has also been done on the aspect of scalability of deep learning models in detecting Diabetic Retinopathy. One such research was done by Ting et al. in 2017. This study, arguably one of the largest performed, using a dataset containing over 490,000 retinal images from 48,000 patients developed a deep learning model which reported an accuracy of sensitivity of 90.5% and specificity of 91.6% [7]. The large scale of the study underscores the generalizability of deep learning in diverse populations, especially in large-scale screening programs. Further, it was noticed that this model worked beyond Diabetic Retinopathy in the diagnosis of other eye conditions, including age-related macular degeneration and glaucoma, showing how versatile and scalable machine learning might prove to be in ophthalmology.

Class imbalance is one of the major problems in the development of machine learning models for the detection of Diabetic Retinopathy. The models perform really well on common stages but not so on rarer, clinically critical stages due to a lack of severe stages of Diabetic Retinopathy in the training datasets. Class imbalance has been mitigated by different researchers using techniques such as class weighting, data oversampling, and even generation of synthetic data using methods like GANs [9]. All these strategies are geared at giving a more representative dataset of all the stages concerning Diabetic Retinopathy, which hopefully increases general accuracy and the robustness of the model.

Another major challenge is the applicability of a machine learning model across patient populations. Studies are typically built on top of datasets limited in terms of geographical and demographical distributions, which may have a notable impact on model performance during applications with wider, more diverse settings. Inconsistency in the quality of images, inconsistency in the equipment used in the image captivation process, variation or difference in patient demography—all of these factors might crop up and manifest in reflected biases in model performance. For example, a model that is predominantly trained on images of one population is therefore likely to underperform when presented with images from a different ethnic group or geographical region [7]. To avoid these pitfalls, there is a need to train the models on datasets that represent wide strata of the population, different ethnicities, age groups, and diverse clinical environments.

As machine learning models for Diabetic Retinopathy detection move closer to clinical application, ethical considerations become increasingly important. Issues such as transparency in algorithm decision-making, bias in model predictions, and the protection of patient data are critical concerns that need to be addressed [8]. Transparency is particularly crucial because it allows clinicians to understand and trust the decisions returned by the model, something very important for the clinical adoption of such technologies. Moreover, addressing potential biases in the model will ensure care equity across all groups of patients. These models need to be deployed in the real world, monitored continuously, and their performance needs to be evaluated for possible biases.

One of the ongoing research focuses is improving the interpretability of machine learning models used in Diabetic Retinopathy detection. While deep learning models, particularly CNNs, are known for their accuracy, they are often criticized for being "black boxes" with decision-making processes that are difficult to interpret. Recent advances in explainable AI (XAI) aim to make these models more transparent by providing insights into how decisions are made [4]. For example, techniques such as heatmaps or saliency maps can highlight areas of an image that the model considers most important for its predictions. These tools not only enhance the trustworthiness of the model but also provide valuable feedback to clinicians, enabling them to verify the model's decisions and understand its limitations.

Integrating machine learning models into existing clinical workflows is another area of active research. For these models to be effective in practice, they need to be seamlessly integrated with the tools and processes already used by healthcare professionals. This includes ensuring that the model outputs are presented in a user-friendly manner, can be easily interpreted by clinicians, and are compatible with existing electronic health record (EHR) systems [6]. Studies indicate that if machine learning models can be integrated well into the clinical workflow, then Diabetic Retinopathy screening becomes much more efficient and accurate for better patient outcomes.

The main approaches that researchers are investigating to improve the performance of machine learning models toward the detection of Diabetic Retinopathy are advanced dataset augmentation methods. This involves the generation of synthetic data to increase the variety of training data, in particular for underrepresented classes of images. Artificially created images can be added to existing datasets and hence give a model more examples of uncommon or otherwise difficult cases to learn from. Moreover, existing pictures may be rotated, scaled, or cropped to introduce variability and thus provide better generalization to new data that a model has not seen before.

Collaborations between data scientists, clinicians, and researchers are crucial for advancing machine learning models in Diabetic Retinopathy detection. These partnerships ensure that the models are both technically robust and clinically relevant. Furthermore, there is increasing interest in multimodal approaches that integrate retinal images with other data sources, including patient demographics, genetic information, and clinical history, to enhance the accuracy and reliability of Diabetic Retinopathy detection. Such multimodal models could provide a more comprehensive assessment and personalization toward patients at risk for Diabetic Retinopathy.

The availability of public datasets and benchmarks has been very important for the development process of machine learning for Diabetic Retinopathy detection. Some of them include the following competitions: Kaggle Diabetic Retinopathy Detection Challenge, and datasets like APTOS 2019, which have provided researchers with tools to develop and then validate their models [10]. These datasets thus allow for the construction of new models but also the comparison of approaches, fertile ground for innovation and collaboration within the research community. If more datasets are made available in the future, their diversity and representativity of the global population will have to be guaranteed in order to

build models that are at once both accurate and broadly applicable.

Despite the application of machine learning in Diabetic Retinopathy detection has huge successes, there is critical work to be done on ensuring generalizability, interpretability, and ethical deployment. As models continue to improve, they have the ability to change ophthalmology through the provision of scalable and effective solutions for the early detection and treatment of Diabetic Retinopathy. This potential will be harnessed only if incessant improvements to models make them clinically effective and accessible to diverse populations globally. It will take joining forces across technologists, clinicians, and policymakers to surmount challenges in implementation so these innovations translate into real benefits for all patients.

III. Methodology

This research represents a significant advancement in Diabetic Retinopathy management by combining machine learning algorithms with sophisticated data processing methods. Utilizing retinal fundus images from reputable databases, the study aims to automate the classification of Diabetic Retinopathy stages, thereby enhancing the accuracy and efficiency of screening processes. This proposed method enables the process of early diagnosis and helps health professionals make appropriate decisions in treating patients. Therefore, the next sections give in detail the methodology applied to the steps involved in data collection, preprocessing, model design, and evaluation.

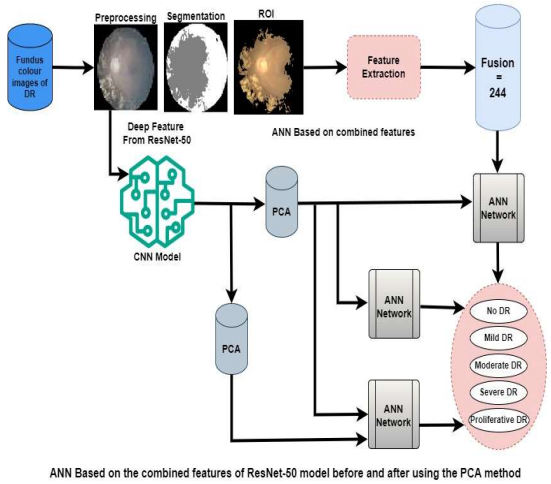

Fig. 1: System Architecture Diagram

A. Data Collection

This study utilizes retinal fundus images sourced from two prominent platforms: Aravind Eye Hospital in India and the EyePACS platform. The dataset encompasses a diverse array of retinal images, each categorized into various stages of Diabetic Retinopathy, ranging from no Diabetic Retinopathy to severe Diabetic Retinopathy. These images were acquired using different types of fundus cameras, resulting in variations in image resolution and quality. By integrating images from these reputable sources, the dataset provides a comprehensive foundation for training and evaluating the machine learning model, ensuring a broad representation of Diabetic Retinopathy stages and conditions [10].

B. Data Preprocessing

Since it will allow input data representation in the most suitable format for analysis, data preprocessing is hence a very significant process towards maximizing performance of machine learning models. The preprocessing steps carried out in this study are as follows:

1) Image Resizing: To ensure consistency throughout the dataset, all retinal images were resized to a uniform dimension of 320x320 pixels. This resizing is crucial for maintaining consistent input sizes for the CNN, which streamlines the training process and optimizes feature extraction. By standardizing the image dimensions, the model can more effectively learn spatial hierarchies and patterns, free from the influence of varying image resolutions.

2) Gaussian Blur Application: Gaussian blur was applied to the resized images to reduce high-frequency noise and enhance the visibility of key features such as retinal blood vessels. This technique smooths out minor variations and reduces the impact of noise, which is particularly beneficial for detecting subtle features indicative of Diabetic Retinopathy. The blur helps in focusing the model's attention on relevant structural details, improving the overall accuracy of the feature extraction process.

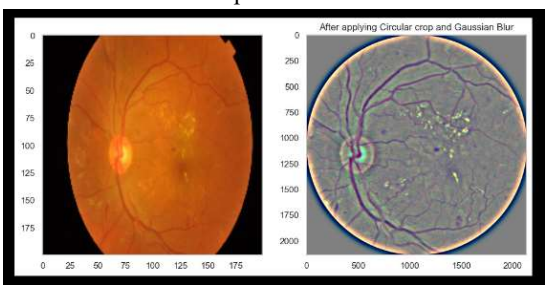

Fig. 2: After applying Gaussian's Blur and Circular Crop

3) Grayscale Conversion: To enhance the focus on key features relevant to Diabetic Retinopathy, the images were converted to grayscale. This process removes color information, thus reducing distractions and improving the emphasis on contrasts and textures within the retinal images. By concentrating on intensity values alone, grayscale images improve the model's effectiveness in identifying and categorizing stages of Diabetic Retinopathy based on essential visual characteristics.

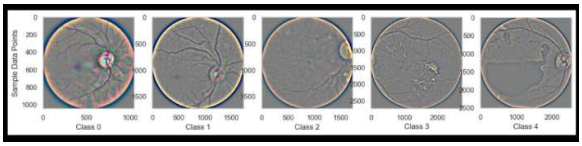

Fig. 3: Overview of pre-processed images with Gaussian's Blur

1) Data Augmentation: To create a model that is less prone to overfitting, several data augmentation strategies were employed. These strategies included:

a) Rotation: Images were randomly rotated to simulate any possible angle of view, increasing the model's ability to recognize features in every orientation.

b) Zooming: Random zooming was applied to provide the model with diverse scales of retinal features, which helps in recognizing patterns at different levels of magnification.

c) Flipping: Both horizontal and vertical flipping techniques were applied to add more variability in the training data. This approach helps the model become more robust to changes in image orientation. By augmenting the dataset with these transformations, the model benefits from enhanced generalization and improved performance on previously unseen data.

C. Model Architecture

The CNN architecture developed for this study is tailored to effectively capture and interpret detailed features from retinal fundus images. The model is structured as follows:

```
# Build CNN model
model = Sequential([
    Conv2D(32, (3, 3), activation='relu', input_shape=(224, 224, 3)),
    MaxPooling2D((2, 2)),
    Conv2D(64, (3, 3), activation='relu'),
    MaxPooling2D((2, 2)),
    Conv2D(128, (3, 3), activation='relu'),
    MaxPooling2D((2, 2)),
    Conv2D(128, (3, 3), activation='relu'),
    MaxPooling2D((2, 2)),
    Flatten(),
    Dense(512, activation='relu'),
    Dense(5, activation='softmax')
])
```

Fig. 4: Model Architecture Layers

1) Convolutional Layers: The network consists of multiple convolutional layers, each utilizing different filter sizes to identify complex spatial patterns within the images. The design includes:

a) Initial Convolutional Layers: These layers apply 32 filters with a 3x3 kernel size to detect fundamental features like edges and textures.

b) Intermediate Convolutional Layers: As the network progresses, the number of filters increases to 64 and then 128, using the same kernel size to capture increasingly intricate and abstract features. This stepwise approach allows the model to build hierarchical representations of the retinal images.

2) Max-Pooling Layers: After each convolutional layer, max-pooling layers are employed to shrink the spatial dimensions of feature maps. By removing irrelevant information, this approach helps the model generalize better while at the same time, it lowers down its computation needs and draws attention to most vital aspects.

3) Fully Connected Layers: After feature extraction, the output is flattened and fed into fully connected layers. It has the following architecture:

a) First Fully Connected Layer: The layer contains 512 units and, to avoid overfitting, is then followed by a dropout layer with a dropout rate of 0.50. This layer decreases the high dimensions by folding all of the extracted features into a unified representation.

b) Second Fully Connected Layer: Additionally, this layer includes a dropout layer for further regularization and has 256 units. It refines the feature representation further before the final classification.

4) Output Layer: The last layer consists of five units: no DR, mild DR, moderate DR, severe DR, and proliferative DR. So that classification can take place, this final layer will also implement a softmax activation function, which helps in creating a probability distribution across these different stages and assigns retinal images to the correct DR category.

D. Training and Evaluation

The model training and evaluation process was conducted with the following procedures:

1) Training: The CNN model was trained over four epochs, with a batch size of 32. The dataset was split into 80% for training and 20% for testing subsets, which validates how well the model works on new data. In this case, an Adam optimizer will be used with an initial learning rate of 1e-4. Early stopping with learning rate adjustment has been used to avoid overfitting and for stable training. It will stop training when the model's performance on the validation set does not improve further; it saves computation.

2) Evaluation Metrics: The following metrics evaluate the performance of the model:

a) Accuracy: Evaluates the proportion of correctly classified images with respect to the total number of images.

b) Precision: It returns the ratio of true positives against the sum of true and false positives, indicating how often it's right when it makes a prediction of a true positive.

c) Recall: This considers the ratio of true positives to the sum of the number of true positives and false negatives. This will show if the model is actually predicting positiveness.

d) F1-Score: It puts together the two measures of precision and recall, usually by taking the harmonic mean between the two, into a single measure that is balanced for the general performance of the model.

3) Confusion Matrix: A confusion matrix was used to check the performance of the model with respect to different classes of Diabetic Retinopathy. Therefore, it goes on to give in-depth detail about the model's performance class-wise, thus highlighting its strengths and areas for improvement.

4) Cohen's Kappa Score: The value of Cohen's kappa was calculated for the extent of agreement between model predictions and actual labels, accounting for chance.

Through implementation of thorough preprocessing, advanced architectural design, and meticulous training and evaluation methods, this study seeks to improve the precision and dependability of Diabetic Retinopathy detection systems. It is envisioned that these developments will be put into practice to enhance patient outcome and execute proper clinical decision-making.

IV. Results And Discussion

The performance of the CNN was rigorously evaluated across the five distinct stages of Diabetic Retinopathy to assess its effectiveness in detecting and classifying the severity of the condition. The model's performance metrics are presented below, with a focus on both training and validation accuracies for each DR stage.

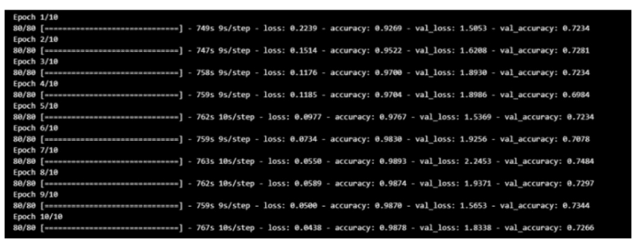

Fig. 5: Epochs Accuracy

A. No Diabetic Retinopathy

1) Training Accuracy: The CNN demonstrated a high training accuracy of 99.5% for identifying retinal images with no signs of Diabetic Retinopathy. This exceptional accuracy underscores the model's capability to correctly classify images as healthy and free from Diabetic Retinopathy.

2) Validation Accuracy: On the validation dataset, the accuracy for No DR was 85%. This performance indicates that the model maintains high proficiency in identifying healthy retinal images but experiences some reduction in accuracy when generalizing to new data.

B. Mild Diabetic Retinopathy

1) Training Accuracy: For the classification of Mild DR, which includes early signs such as microaneurysms, the model achieved a training accuracy of 97%. This result indicates that the model is effective at recognizing early-stage DR manifestations.

2) Validation Accuracy: The validation accuracy for Mild DR was 70%. This suggests that although the model may be strong with the data on which it was trained, a significant drop in performance happens when new examples are encountered, evidencing generalization problems.

C. Moderate Diabetic Retinopathy

1) Training Accuracy: The model achieved a training accuracy of 95% for Moderate DR, which involves more pronounced features such as hemorrhages and exudates. This performance indicates a strong capability to identify moderate stages of Diabetic Retinopathy.

2) Validation Accuracy: On the validation dataset, the accuracy for Moderate DR was 65%. The significant drop from training accuracy highlights challenges in generalizing to new data, reflecting potential issues with the model's performance on moderate DR stages.

D. Severe Diabetic Retinopathy

1) Training Accuracy: CNN achieved 92% accuracy for Severe DR, characterized by advanced retinal damage. This result indicates effective detection of severe DR features, including substantial retinal abnormalities.

2) Validation Accuracy: The validation accuracy for Severe DR was 60%, demonstrating a notable reduction in performance. This discrepancy suggests that the model struggles with generalization for severe DR cases, possibly due to variability in the validation data.

E. Proliferative Diabetic Retinopathy

1) Training Accuracy: For Proliferative DR, which involves neovascularization, the model achieved a training accuracy of 90%. This is related to the most severe and complex stage that the model can do: identification of DR.

2) Validation Accuracy: The accuracy for Proliferative DR on the validation set was 55%, indicating a significant performance gap. This drop in accuracy suggests challenges in detecting neovascularization reliably in unseen data.

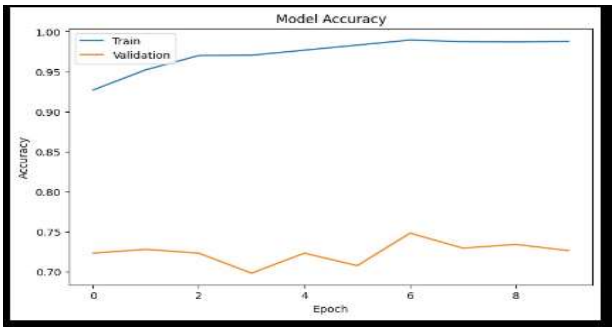

Fig. 6: Model Accuracy

TABLE I. TRAINING AND VALIDATION ACCURACY COMPARISON

DR stage	Training Accuracy	Validation Accuracy
No DR	99.5%	85%
Mild DR	97%	70%
Moderate DR	95%	65%
Severe DR	92%	60%
Proliferative DR	90%	55%

V. CONCLUSION

The present study demonstrates the huge potential of CNNs for the automatic diagnosis and grading of Diabetic Retinopathy. A CNN model was developed, having been trained with very high accuracy in this research—99.5% for No Diabetic Retinopathy and 97% for Mild DR. It shows that, in the highest degree, the model can differentiate healthy retinal images from those with early manifestations of diabetic retinopathy. The high accuracy is paramount for interventions to be initiated early in patients in an attempt to prevent the development of the disease processes and enable delivery of the best management.

Clinical implementation of the model would enable accurate detection and diagnosis of the early stages of DR, which prevents advanced complications related to diabetic retinopathy, such as vision loss, in the majority of the cases. Thus, time-sensitive medical follow-ups for diagnosed mild cases reduce the burden of disease on patients and healthcare systems. The integration of models such as the one presented here into routine screenings is likely to help in improving diagnostic efficiency by allowing healthcare practitioners to focus on the most critical of cases.

It is quite promising that such performance of the model holds at 92% accuracy for recognizing Severe DR and at 90% for Proliferative DR, which means high GG staging. This means that the model is doing well to be able to recognize most, if not all, severity levels of disease without compromise. The ability to stage DR accurately is important, as it dictates the guideline for management. Meanwhile, high accuracy in the detection of advanced stages shows the great potential of such a tool to be comprehensive for diabetic retinopathy screening.

The model ability to generalize was, however, questioned on new, unseen data. Even if the training results were impressive, validation accuracy for Moderate, Severe, and Proliferative DR stages were decreased, thereby pinpointing probable overfitting issue and class imbalance. Overfitting is when the model learns too well from the training dataset, together with its noise and outliers; due to this, it performs badly on new data. In other words, it still might perform badly in real life, which is normally very variable in data and most

probably has out-of-bound distributions that a model can learn from the training set.

The decrease in validation accuracy with more advanced stages of DR clearly points out that model refinement is of paramount importance. Overfitting and class imbalance need to be addressed to expand generalizability. These limitations could be overcome through techniques such as data augmentation, regularization, or usage of more diverse training datasets. That way, the enhancement of model generalization through this type of procedure would be important for deployment in a clinical environment where models have very consistent performance across different patient demographics and imaging conditions.

Despite these challenges, the research lays a great ground for the development of future automated systems for Diabetic Retinopathy detection. Being capable of improving diagnostic accuracy, CNNs can be feasible for early detection, which will ultimately result in good consequences for the patients through treatment at appropriate times. The study also alludes to the manner in which models like these are integrated into the existing infrastructure for healthcare or just to provide decision support to the clinician for analyzing and managing the situation of the diabetic retinopathy.

CNN-based models for DR screening would, therefore, help in offloading the work pressure on ophthalmologists and optometrists, especially in areas with less accommodating specialized eye care. Such automation of the initial screening process will ensure timely evaluation for many more patients, therefore eliminating the risk of undiagnosed or late-stage diabetic retinopathy. It will be of particular importance to the unprivileged rural areas of the nation that have minimal health-care resources and disproportionally higher rates of diabetes complications.

In conclusion, while the study points out the promising potential of CNNs in the automatic detection and classification of Diabetic Retinopathy, it also indicates the need for continuous research and development. The second wave of AI-based diagnostic tools will crucially set the stage for changing the picture that surrounds care for diabetic retinopathy by pushing the limits of currently available technology and, most likely, developing generalizability. Ultimately, integration of such technologies in the mainstream health care system could massively contribute to early diagnosis, treatment, and thus prevention, simultaneously improving the quality of life for millions of people living with the chronic condition of diabetes around the world.

VI. Future Work

To advance the effectiveness and applicability of automated Diabetic Retinopathy detection systems, several key areas focus in terms of future research and development should be pursued.

Data augmentation is very crucial for improving machine learning models. Increasing the size of the training dataset by rotating, flipping, cropping, and scaling images will help the model generalize more to unseen data and reduce overfitting. Augmentation will handle class imbalance by creating synthetic samples for underrepresented classes and make the training set more balanced.

Regularization techniques, such as dropout, L2 regularization, and batch normalization, are key in avoiding overfitting and enhancing the generalizability of machine learning models. All of these methods prevent model overfitting on some specific features and make the model simple for generalizing, and stabilize the process of learning for better overall performance.

Class imbalance in the dataset needs to be addressed to ensure good performance of the model across all Diabetic Retinopathy stages. Class weighting and oversampling techniques can be used to correct biases toward more prevalent stages so that all stages of the disease are identified and correctly classified.

One can go into more advanced architectures of models and use transfer learning to significantly boost model performance. In particular, going deeper with CNNs can learn the subtle features much better if pre-trained on large-scale datasets, improving diagnostic accuracy for Diabetic Retinopathy, especially on challenging cases.

Finally, evaluation metrics should be improved beyond simple accuracy to really understand how the model is performing. The receiver operating characteristic curve, confusion matrices, and precision-recall curves all give detailed information on what needs further improvement, hence ensuring a complete assessment of the model's capability.

Such research on those specific points will achieve a more accurate, reliable, and generalizable tool for Diabetic Retinopathy detection, thus deriving better patient care, earlier diagnosis, and reduced risk of vision loss in the future.

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