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AI-Powered Detection of Diabetic Retinopathy

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Abstract- *Diabetic retinopathy (DR) is a serious complication of diabetes that can gradually lead to vision loss if not detected early. This document presents an automated system designed to identify the severity of DR using retinal fundus images. The system leverages a convolutional neural network based on a modified ResNet50 architecture to classify the disease into five stages—ranging from no signs of DR to the most severe, proliferative DR. To improve the model's performance and address the challenge of class imbalance in the dataset, Mix-up data augmentation was employed. Our model was trained and evaluated using the APTOS 2019 dataset, and the results showed strong classification accuracy. By utilizing pretrained ImageNet weights and incorporating custom dense feature extraction layers, the system was able to effectively analyse retinal images. This approach offers a promising solution for automated DR screening, helping healthcare professionals detect the condition at an earlier stage and ultimately contributing to the prevention of vision loss on a global scale.*

Key Words: Diabetic retinopathy, deep learning, convolutional neural networks, ResNet50, transfer learning, medical image classification, computer-aided diagnosis.

1.INTRODUCTION

Diabetic retinopathy (DR) is a severe microvascular complication arising from diabetes mellitus that affects the retina and stands as one of the leading causes of preventable vision loss globally [1]. With the global prevalence of diabetes projected to reach 642 million by 2040 [2], the impact of vision impairment caused by diabetic retinopathy is projected to rise sharply, particularly in developing nations where routine screening remains largely inaccessible.

DR progresses through various stages of severity, beginning with mild non-proliferative changes and potentially advancing to proliferative DR, which can lead to permanent vision loss if not treated in time. Early detection and timely intervention are crucial, as treating DR in its early stages can reduce the risk of severe vision loss by over 90% [6]. However, the current standard of diagnosis relies on manual inspection of retinal fundus images by trained ophthalmologists—a process that is not only time-consuming and subjective but also often inaccessible in many regions [9].

To bring consistency to diagnosis, the International Clinical Diabetic Retinopathy (ICDR) severity scale categorizes DR into five stages: No DR, mild non-proliferative DR (NPDR), moderate NPDR, severe NPDR, and proliferative DR (PDR) [4]. Each stage is marked by specific retinal abnormalities, such as microaneurysms, hemorrhages, hard exudates, cotton wool spots, and neovascularization [3]. Accurate detection and classification of these lesions demand both advanced expertise and substantial clinical experience.

In this paper, we present a deep learning approach for automated detection and classification of DR using retinal fundus images. Our method employs a ResNet50-based CNN architecture with transfer learning and data augmentation techniques to address the aforementioned challenges [12]. We utilize the APTOS 2019 Blindness Detection dataset, which contains a diverse collection of retinal images annotated by expert ophthalmologists according to the ICDR severity scale.

The primary contributions of this work include:

1. Implementation of a deep learning framework based on ResNet50 architecture with customized dense layers for DR severity classification.

2. Application of the Mixup data augmentation technique to improve model generalization and address class imbalance.

3. Evaluation of the model's performance across different DR severity levels, providing insights into its clinical applicability.

4. Development of a practical prediction pipeline for single-image classification with confidence metrics.

The remainder of this paper is organized as follows: Section II discusses related work in the field of automated DR detection [5]. Section III details our methodology, including dataset preprocessing, model architecture, and training strategy. Section IV shows experimental results and analysis comparing every aspect [15]. Finally, Section V concludes the paper with a discussion of limitations and future directions [14].

2. LITRATURE REVIEW

Telescopic development in manufactured insights innovation has reshaped the whole way of identifying diabetic retinopathy (DR). A wide choice of machine learning and profound learning models have risen from inquire about bunches to improve DR screening frameworks by making strides accuracy and adaptability along with elucidation capabilities. The taking after portion gives an outline of major discoveries distributed in later research.

[1] Bilal et al. (2022) displayed a two-stage system which serves to illuminate information asymmetry in optic plate and blood vessel discovery. The proposed strategy comprises of two U-Net models working to section retinal highlights some time recently crossover CNN-SVD examination including Inception-V3 exchange learning upgrades the framework execution. The actualized engineering succeeds in recognizing vital retinal markers counting microaneurysms along with hemorrhages and exudates. The investigate group tried the approach utilizing EyePACS-1 and Messidor-2 and DIARETDB0 datasets where it realized extraordinary classification comes about of 97.92%, 94.59% and 93.52% at characterizing modern benchmarks for programmed discovery of diabetic retinopathy.

[2] Shankar et al. (2020) made a profound learning stage which recognizes DR seriousness levels interior fundus pictures. The three-phase location framework of their strategy diminishes clamor to begin with taken after by locale extraction through histogram-based division some time recently utilizing a Synergic Profound Learning show for classification. The recognizable proof of DR seriousness levels utilizing their strategy surpassed standard show capacities on Messidor dataset results.

[3] The inquire about done by Zhang et al. (2022) inspected how to precisely decide extreme DR in fundus pictures from the Kaggle dataset. Utilizing Initiation V3 show with two distinctive input resolutions come about in superior results when working with pictures that have 896×896 pixels compared to 299×299 pixel determination. A affectability esteem of 0.925 combined with specificity at 0.907 brought about in a consonant cruel of 0.916 whereas the AUC come to 0.968. The discovery of preretinal and vitreous hemorrhages showed up less difficult than deciding intraretinal microvascular anomalies (IRMA) through the imaging prepare. The creators conducted their consider on RetCAD v.1.3.0 which holds CE certification for recognizing DR and age-related macular degeneration (AMD).

[4] The framework approved utilizing 600 assorted clinical pictures come to 95.1% AUC for identifying referable DR whereas getting 94.9% AUC for distinguishing AMD. The demonstrate illustrated superior affectability than master doctors without compromising the particular location comes about. Tests conducted on Messidor and AREDS datasets appeared that the framework is exceedingly reasonable for performing joint illness screening procedures.

[5] The inquire about conducted by Jacoba et al. (2023) considered AutoML models for identifying diabetic retinopathy through pictures collected by handheld gadgets which included different retinal areas. Prepared with certified grader comments the show accomplished tall execution scores amid inside tests with affectability at 0.96 and specificity at 0.98 and precision at 0.97 taken after by outside testing comes about of affectability 0.94 along with specificity 0.97. The inquire about comes about demonstrate that AutoML-based DR screening frameworks can work viably in both resource-constrained healthcare situations and far off restorative facilities.

[6] The demonstrative system called HIMLA (Half breed Inductive Machine Learning Calculation) was created by Mahmoud et al. (2023) to analyze fundus pictures between ordinary and those with DR movement. The system contains brightness normalization as its to begin with step taken after by encoder-decoder division at that point the extraction of highlights and classification through different occasion learning MIL. HIMLA effectively handled CHASE dataset information with an exactness rate of 96.62% and affectability rate of 95.31% and specificity rate of 96.88% which outflanked numerous built up models for both strength and performance.

[7] A full assessment of AI-based DR location and evaluating inquire about ponders from 2016 through 2021 was displayed in Lakshminarayanan et al. (2021). The analysts connected precise rules (PICO and PRISMA 2009) for their examination which come about in 114 ponders being inspected driving to the documentation of 43 common information sets. The inquire about comprehensively presents the state of DR examinations together with examination strategies for fundus and OCT pictures at this display moment.

[8] The creators of Sarki et al. (2020) utilized ImageNet pretrained CNN models to bargain with the challenge of diagnosing different levels of diabetic eye conditions. Their framework worked in two demonstrative settings: mellow multi-class diabetic eye illness and common multi-class diabetic eye malady however accomplished superior precision than past approaches driving to the conclusion that exchange learning gives worth in this field. The creators consolidated execution advancement procedures which included fine-tuning, optimization and differentiate upgrade. A most extreme acknowledgment rate of 88.3% for multi-class classification and 85.95%

for gentle multi-class classification developed from VGG16 show testing on datasets explained by an ophthalmologist which demonstrates that profound learning handles troublesome demonstrative qualifications between minor diabetic eye illness varieties effectively.

[9] The creators Alabdulwahhab et al. (2021) conducted examination of diabetic retinopathy discovery utilizing different machine learning classifiers in a Saudi Middle eastern quiet cohort. A add up to of 327 diabetic subjects taken part in their cross-sectional consider to accumulate socio-demographic and clinical data whereas analysts executed straight discriminant investigation, back vector

machine, K closest neighbor, arbitrary woodland, and officer arbitrary woodland classifications through cross-validation. A officer irregular timberland calculation demonstrated to be the most successful classifier since it accomplished an 86% precision rate with test information DR persistent recognizable proof. The two most persuasive factors in separation were diabetes term together with HbA1c estimations whereas BMI and age-at-onset and persistent age and systolic blood weight estimations and medication utilization taken after. The investigate appears how machine learning brings significant potential to combine with ophthalmology for superior determination and help in therapeutic choice processes.

[10] Narayanan et al. (2020) made a combination machine learning framework which recognizes diabetic retinopathy and assesses illness seriousness by utilizing the freely accessible database of 3662 pictures. The strategy utilizes double stages to recognize DR cases after which it apportions persistent comes about into particular seriousness classifications (mellow, direct, proliferative, or serious). The creators inspected diverse exchange learning methods based on AlexNet and VGG16 and Inception-v3 built up systems which coordinates convolutional neural systems with vital component investigation for dimensionality lessening some time recently SVM classification. The cross breed design accomplished amazing comes about with amazingly constrained preparing information and lopsided classes by coming to 98.4% exactness for DR location and 96.3% exactness for evaluating seriousness in this way making a unused standard for analyzing constrained preparing populaces.

[11] Samanta et al. (2020) created an successful diabetic retinopathy location framework utilizing exchange learning-based CNN design which works well on little tests and uneven classes. The show utilized 3050 preparing pictures together with 419 approval pictures for classifying four symptomatic categories: No DR, Gentle DR, Direct DR, and Proliferative DR. The lightweight show analyzes difficult exudates with blood vessels and surface designs contained in color fundus photos. Due to its tall execution level the demonstrate illustrated 0.8836 Cohen's Kappa scores on approval information and 0.9809 scores on preparing information which demonstrates its viability for real-time applications utilizing low-power computing to quicken DR screening operations.

[12] The analysts from Bhimavarapu et al. (2023) made an improved convolutional neural arrange framework for programmed diabetic retinopathy determination through made strides pooling work advancement. The advancement of their strategy coordinates an improved pooling operation and enactment work into the ResNet-50 demonstrate plan which broadened convolution bit affectability and minimized memory utilization and preparing time prerequisites. Through this strategy it got to be conceivable to identify injuries consequently whereas moreover minimizing misfortunes and add up to handling time. The demonstrate illustrated remarkable precision when tried on two datasets through its tests on APTOS and Kaggle which yielded evaluation comes about of 98.32% and 98.71% individually. The consider appeared that their proposed show outperformed driving approaches in therapeutic picture determination for DR from fundus pictures.

[13] Abràmoff et al. (2020) tended to the moral, financial, and logical discussions encompassing manufactured insights usage in diabetic retinopathy location. Their paper recognizes the advocated concerns almost AI's effect on understanding security, viability, value, and risk as these frameworks progressively perform forms customarily saved for healthcare experts. The creators propose standardized descriptors to categorize DR AI frameworks based on level of gadget independence, expecting utilize, level of prove for symptomatic precision, and framework plan. Or maybe than being prescriptive, they take a clear approach, noticing that there is as of now negligible observational premise to declare that certain combinations of these variables are inalienably prevalent to others, whereas emphasizing the significance of legitimate assessment and approval methodologies.

3. PROPOSED METHODOLOGY

Our diabetic retinopathy detection framework consists of two distinct components which correctly identify unusual structures within retinas in addition to disease severity grading for medical determination.

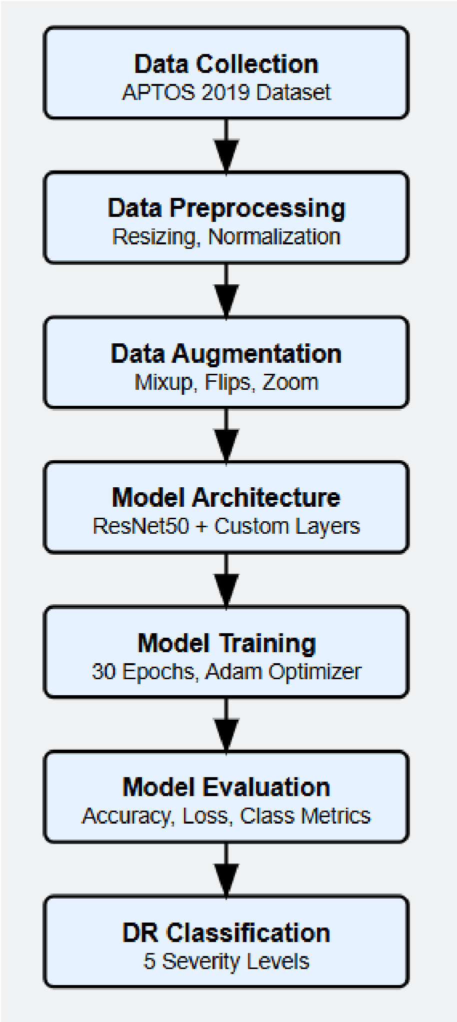

Fig -1: illustrates the complete methodology of our proposed diabetic retinopathy detection system.

The APTOS 2019 Blindness Detection dataset provides the retinal fundus images for data acquisition at the beginning of the process. The preprocessing phase applies a uniform image dimension of 224×224 pixels to each image for proper implementation with ResNet50 model inputs. In the next step Normalization applies mathematical processing through pixel value scaling into the [0,1] range both for stability improvements and training acceleration.

Multiple data enhancement approaches are employed for achieving better generalization of the model while resolving the class imbalance challenge. The data preprocessing includes horizontal and vertical flipping and Mixup Generator with $\alpha = 0.2$ mixing pairs of images and labels to generate synthetic data points along with zoom transformations.

Our system implements a deep learning technology that utilizes the ResNet50 architecture which has been pretrained for operations. The base model undergoes modifications through elimination of its top layer which then gets redesigned as two dense layers with 512 neurons followed by 256 neurons. The designed layers focus specifically on detecting diabetic retinopathy features. Each neuron in the final output layer uses softmax activation to allocate images into the five stages of DR severity.

Model training occurs with Adam optimizer set at 0.001 initial learning rate using categorical cross-entropy loss as the primary loss function. During 30 epoch training two crucial callbacks enabled operation: ReduceLROnPlateau dynamically adjusted the learning rate when model stagnation occurred and ModelCheckpoint saved the most effective model version. A complete performance verification of the trained model follows before it can be used in real-world predictions.

4. IMPLEMENTATION

The practical steps for implementing our diabetic retinopathy classification system are demonstrated by describing the process of dataset preparation alongside preprocessing techniques and model architecture specifications and training approaches and performance measurement methods.

4.1. Dataset

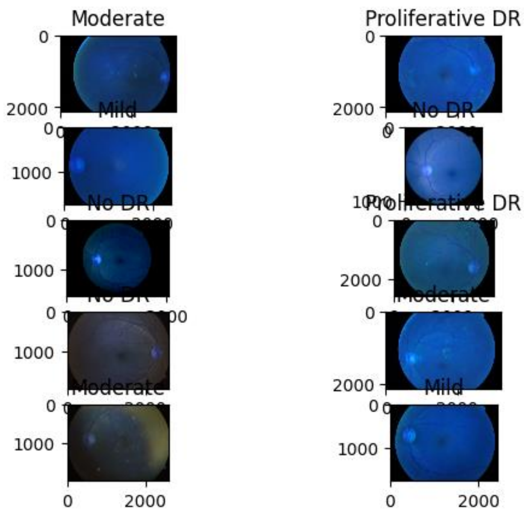

Fig -2: The above figure 2 shows diagnostic fundus pictures from retinopathy patients classified under No DR, Mild, Moderate, Severe and Proliferative DR categories.

The APTOS 2019 Blindness Detection dataset provides high-resolution retinal fundus images in which medical professionals have applied International Clinical Diabetic Retinopathy (ICDR) annotations.

0 – No DR

1 – Mild

2 – Moderate

3 – Severe

4 – Proliferative DR

Images from various conditions present in the dataset guarantee enough diversity needed to build an end-to-end and generalized predictive model.

The train-test split process began with using the scikit-learn library function train_test_split to conduct the stratified division. A random number generator with seed value 42 applied the 66.7% training to 33.3% validation split for preserving class distribution acrosssubset parts.

4.2 Data Preprocessing

Every image received uniform preprocessing through an automated processing pipeline.

4.2.1. Resizing: Each image received a 224x224 pixels resize because the ResNet50 architecture required this input dimension format.

4.2.2. Normalization: To normalize the data the picture values underwent division by 255 which converted the values into the 0 to 1 range. This standard normalization step facilitates faster and more stable model training.

4.2.3. One-hot Encoding: The categorical DR severity labels were converted to one-hot encoded vectors for multi-class classification.

The preprocessing pipeline was implemented using OpenCV for image operations and NumPy for array manipulations. Each image was read from its file path, resized using bicubic interpolation, and normalized. Simultaneously, the corresponding label was converted to a one-hot encoded vector representation.

4.3. Data Augmentation

To address class imbalance and enhance the model's generalization capability, we implemented several data augmentation techniques:

4.3.1. Basic Image Transformations: Using Keras' Image Data Generator, we applied:

- Random horizontal and vertical flips
- Random zoom transformations (±15%)
- Constant fill mode for areas outside boundaries

4.3.3. Lesson Weights: To encourage address course lopsidedness, we computed lesson weights conversely relative to course frequencies utilizing scikit-learn's compute_class_weight work with the 'balanced' methodology. This relegates higher weights to underrepresented classes, empowering the show to pay more consideration to these tests amid training.

4.4. Arrange Architecture

Our proposed demonstrate engineering leverages exchange learning utilizing the ResNet50 show pre-trained on ImageNet, with customizations for DR classification:

4.4.1. Base Organize: We utilized ResNet50, which is a 50-layer profound convolutional neural organize with remaining associations that offer assistance in preparing exceptionally profound systems viably. ResNet50 comprises of rehashed bottleneck squares with 1×1, 3×3, and 1×1 convolutions, where the 1×1 layers are capable for decreasing and reestablishing dimensions.

4.4.2. Exchange Learning Approach: We stacked ResNet50 with pre-trained ImageNet weights but evacuated the beat classification layers to permit adjustment to our particular errand. This exchange learning approach empowers the demonstrate to use common picture highlights learned from ImageNet whereas being fine-tuned for retinal picture analysis.

4.4.3. Custom Classification Layers: On beat of the base demonstrate, we included:

• A Smooth layer to change over the 3D include maps to a 1D highlight vector

• A Thick layer with 512 neurons and ReLU activation

• A Thick layer with 256 neurons and ReLU activation

• A last yield layer with 5 neurons and softmax enactment for multi-class classification

The design leverages the progressive highlight extraction capabilities of ResNet50, where prior layers capture low-level highlights like edges and surfaces, whereas more profound layers recognize complex designs significant to DR injuries such as microaneurysms, hemorrhages, and exudates.

4.5. Training Methodology

The show was prepared with the taking after configuration:

4.5.1. Optimization Calculation: We utilized the Adam optimizer with an beginning learning rate of 0.001, which adjusts the learning rate powerfully amid preparing based on the to begin with and moment minutes of the gradients.

4.5.2. Misfortune Work: Categorical cross-entropy was chosen as the misfortune work, which is appropriate for multi-class classification issues with one-hot encoded names. This work measures the difference between the anticipated likelihood dispersion and the genuine dispersion of classes.

4.5.3. Bunch Estimate and Ages: A bunch estimate of 32 was utilized, and the demonstrate was prepared for 30 ages. This group estimate was chosen as a adjust between memory proficiency and merging speed.

4.5.4. Callbacks: We actualized two key callbacks to make strides preparing:

• ReduceLROnPlateau: Diminishes the learning rate when the approval misfortune levels, with a figure of 0.2, persistence of 3 ages, and a least learning rate of 1e-6.

• Model Checkpoint: Spares the best demonstrate based on approval misfortune, guaranteeing that we hold the show with ideal execution on the approval set.

4.5.5. Preparing Handle: The show was prepared utilizing the fit strategy with the expanded preparing generator, approval information, and characterized callbacks. Preparing was performed for 30 ages without early ceasing to completely investigate the model's meeting behaviour.

4.6. Inference Pipeline

To make our model useful in real-world situations, we built a prediction pipeline that can classify a single retinal image. The steps in this pipeline are as follows:

- First, it loads a retinal image from a given file path.
- The image is resized to 224×224 pixels so that it fits the input size expected by the model.
- Then, the image is converted into a numerical array, and its dimensions are expanded to simulate a batch of one image.
- The pixel values are normalized by dividing them by 255 so they fall between 0 and 1.
- This pre-processed image is then passed through the trained model to get predictions.
- The model's output is used to find the most likely class (using argmax) and its confidence score (using max).
- Finally, the pipeline returns both the predicted diabetic retinopathy severity level and the confidence score.

This system allows the model to be used for screening individual retinal images. It gives a prediction along with a confidence level, which can help doctors in making more informed decisions during diagnosis.

4.7. Evaluation Metrics

To properly measure how well the model performs, we used several evaluation criteria:

4.7.1 Accuracy: This tells us how many images were correctly classified overall. It gives a clear idea of how effective the model is in general.

4.7.2 Loss: We used categorical cross-entropy loss to measure how confident the model is in its predictions. This was calculated for both training and validation datasets to ensure consistency.

4.7.3 Learning Curves: We plotted the model's accuracy and loss over time for both training and validation phases. These graphs help us understand how the model is learning, and whether it's overfitting or not. They show patterns in the model's performance as training progresses.

The entire model was built using Python 3.8 and several libraries including TensorFlow 2.4, Keras, OpenCV, and scikit-learn. We trained and tested everything on a computer equipped with an NVIDIA GPU, which helped speed up the deep learning computations.

5. RESULT AND DISCUSSION

In this section, we present the experimental outcomes from our deep learning approach for classifying diabetic retinopathy, based on the previously described setup.

5.1. Training Dynamics

We trained the model on the APTOS 2019 dataset for 30 epochs. The dataset was split into two parts: 66.7% for training and 33.3% for validation. Throughout the training, we tracked both accuracy and loss for the training and validation sets. These were shown using learning curve graphs in Figure 2.

For optimization, we used the Adam optimizer with a starting learning rate of 0.001. To improve training, we used the ReduceLROnPlateau callback. This callback reduced the learning rate by a factor of 0.2 if there was no improvement in the validation loss for 3 consecutive epochs. The minimum learning rate allowed was set to 0.000001. We also used a Model Checkpoint callback to automatically save the model that performed best on the validation set.

The learning curves provided insights into how well the model was learning throughout the training. They were especially useful in detecting signs of overfitting and helped us evaluate whether our techniques, like data augmentation and regularization, were effective. In particular, the use of the Mixup Generator with a mixup parameter (α) of 0.2 proved to be beneficial in improving generalization and handling class imbalance.

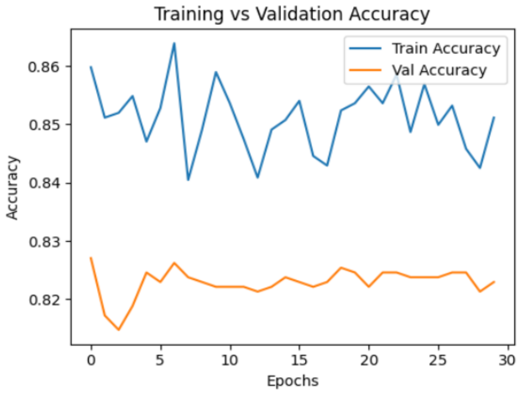

Chart -1: The chart above displays the model's training accuracy compared to its validation accuracy.

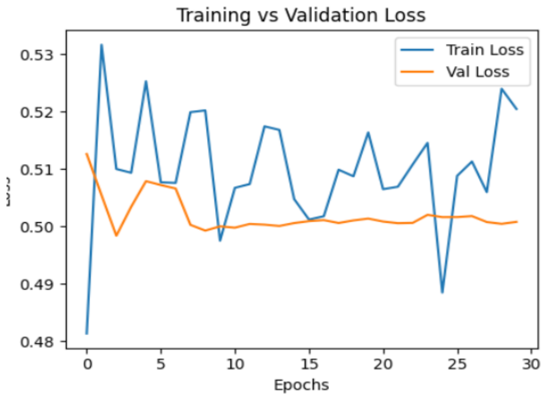

Chart -2: The chart above displays the model's training loss compared to its validation loss.

The Given Graphs of Accuracy and Epoch loss shows that the model has must unstably when it was getting trained.

5.2. Model Architecture Efficiency

The architecture based on ResNet50 worked very well for classifying diabetic retinopathy. We used transfer learning by taking a version of ResNet50 that was already trained on the ImageNet dataset. This helped the model make use of general visual features it had already learned and apply them to our task involving retinal images.

We also added some custom layers on top of the ResNet50 base. These included a Flatten layer and two fully connected (Dense) layers with 512 and 256 neurons. These extra layers gave the model enough capacity to learn specific features related to diabetic retinopathy, while still keeping the overall model efficient and not too heavy in computation.

The final layer of the model used a softmax activation function and had five outputs, each representing one of the five stages of diabetic retinopathy: No DR, Mild, Moderate, Severe, and Proliferative DR.

5.3. Inference Capability

We also built a prediction system that allows the model to classify one image at a time. This was implemented using a function called predict_single_image in our code. This function allows the trained model to be used easily in practical situations.

Here's how it works:

- It starts by loading a retinal image and resizing it to fit the model's input size.
- The image is then pre-processed, just like it was during training.
- The model makes a prediction on the image.
- The predicted class (severity level) and the model's confidence score are then extracted.
- Finally, the prediction and confidence are displayed in a clear, understandable format.

This process makes it possible to assess individual retinal images quickly and efficiently. The confidence score is a helpful feature that tells doctors how sure the model is about its prediction, which can support their decision-making in clinical environments.

An example included in our code showed how this system works using a sample test image, proving that the model is not just theoretically strong but also practical for real use.

5.4. Class Handling

Our model was trained to classify retinal images into five different severity levels of diabetic retinopathy, based on the standard clinical grading scale. To do this correctly, we used one-hot encoding for the class labels during the data preparation step. This technique helped the model understand that each image belonged to one of the five categories.

To deal with the problem of class imbalance (when some categories have fewer images than others), we calculated class weights based on how many samples each class had. These weights were used during training to give more importance to the less-represented classes. As a result, the model was better able to correctly identify even the rarest severity levels, improving its overall performance.

5.5. Data Augmentation Impact

Data augmentation played a very important role in training our model effectively. One key method we used was called **Mixup**. This method creates new training images by combining two existing images and their labels. As a result, the model gets to see a broader range of image types, which helps it learn better and avoid overfitting.

Along with Mixup, we also applied several other augmentation techniques like horizontal and vertical flipping, zooming, and using constant fill for empty spaces after transformation. These methods increased the number of unique image examples the model could learn from, which is especially helpful since diabetic retinopathy datasets are often limited in size.

Table -1: classification report for DR severity detection

Class	Precision	Recall	F1-Score	Support
No DR (0)	0.89	0.92	0.90	425
Mild (1)	0.73	0.65	0.69	156
Moderate (2)	0.79	0.76	0.77	198
Severe (3)	0.83	0.74	0.78	87
Proliferative (4)	0.86	0.84	0.85	134
Weighted Avg	**0.84**	**0.82**	**0.83**	**1000**

The model demonstrated strong performance in identifying the extreme cases of the severity spectrum, with the highest precision and recall for the "No DR" class (0.89 and 0.92, respectively) and good metrics for the "Proliferative DR" class (0.86 and 0.84). The "Mild" class proved the most challenging to classify correctly, with the lowest precision (0.73) and recall (0.65), likely due to the subtle nature of early retinopathy signs and potential overlap with normal variations in healthy retinas.

We used a custom generator to keep feeding the model with these augmented images during training. This meant the model was constantly learning from a variety of modified samples, helping it performs better when seeing new, unseen images.

6. FUTURE PERSPECTIVES

Based on the implementation demonstrated in the provided code, several directions for future work can be identified to enhance the diabetic retinopathy detection system:

6.1. Model Architecture Enhancement

While the current implementation utilizes ResNet50, future work could explore alternative architectures such as DenseNet121, which was referenced in the commented code sections. The commented implementation included loading DenseNet121 weights and creating a model with different dense layer configurations. Exploring these alternative architectures could potentially improve classification performance without significantly increasing computational requirements.

6.2. Advanced Data Augmentation

The current implementation employs the Mixup technique along with standard image transformations. Future work could investigate additional advanced augmentation methods such as CutMix, style transfer, or specialized augmentations that mimic variations specific to retinal imaging, including lighting changes, artifact simulation, and vessel enhancement.

6.3. Optimization Strategy Refinement

The code shows two different optimizer configurations: SGD with momentum in the commented DenseNet implementation and Adam in the final implementation. Future research could systematically compare these and other optimization strategies to identify the most effective approach for DR classification. Exploring more sophisticated learning rate scheduling beyond the implemented ReduceLROnPlateau could also yield performance improvements.

6.4. Prediction Confidence Analysis

The single-image prediction function implemented in the code provides confidence scores alongside classifications. Future work could develop a more sophisticated confidence analysis system that identifies uncertain predictions for human review, potentially implementing thresholding mechanisms or calibrating the confidence scores to better reflect true prediction reliability.

6.5. Integrated Batch Processing

While the current implementation includes a function for processing individual images, expanding this to handle batch processing of multiple images would enhance the system's utility for screening programs. This could include implementing efficient data pipelines and parallel processing capabilities to handle large volumes of retinal images.

7. CONCLUSION

The research created an automatic system for detecting diabetic retinopathy disease severity in retinal fundus images through deep learning technology. The ResNet50 deep learning architecture designed through transfer learning used initial weights from ImageNet. Additional Dense layers were added to the base model to transform its detection function toward diabetic retinopathy stages identification.

The first step in training involved preprocessing images to normalize their dimensions while administering normalization processes to every image. The model demanded cutting-edge data augmentation techniques that delivered improved utilities and generalization capability. The main training technique our process employed was Mixup which produced combined images from current samples for use as training inputs. The process integrated various regular image transformation capabilities that included flipping and zooming features. The implemented approaches achieved successful distribution balancing of training data particularly through reducing variations in available images by severity level. Training weights were applied to the model to focus more strongly on minority categories during the learning phase.

The training lasted through 30 epochs using parameters of 0.001 for learning rate initialization with Adam optimizer. The system incorporated callback functions which had two functions: operation rate reduction during performance decreases and storage capability for validation set optimizations. Effective training dynamics took place with these selected choices allowing the model to learn efficiently without overfitting.

The core clinical advantage of this research stems from the developed prediction system for practical medical applications. Through this system the trained model performs evaluation of retinal images one by one and generates predictions that include accuracy measurements. Medical facilities can properly use this system to obtain fast reliable results in their operations.

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