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Diabetic Retinopathy Evaluation using Neural Networks

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ABSTRACT: Diabetic Retinopathy (DR) is a major complication of diabetes which may lead to blindness if not diagnosed in time. Classical screening is dependent on the presence of ophthalmologists, causing a bottleneck in healthcare especially in rural areas. This article presents an automatic deep learning-based diagnosis system, which has been developed to identify and classify the progressivity of DR based on retinal fundus images. The VGG-16 CNN is used to process the images in a pipeline, which includes CLAHE and normalization. They trained the model on datasets with annotations. This lets it pick out certain lesions, things like microaneurysms and exudates. Checking how it performs through confusion matrices shows strong accuracy and sensitivity. All that points to this automated method working as a solid tool. It scales up well and runs efficiently for screening large groups. Plus it helps with early steps to intervene.

KEYWORDS: Diabetic Retinopathy, Deep Learning, VGG-16, Convolutional Neural Networks (CNN), Medical Image Processing, CLAHE, Automated Screening.

I. INTRODUCTION

Diabetic Retinopathy is this ongoing problem where the blood vessels in the retina get damaged. It comes from having diabetes for a long time. The thing is, it does not show symptoms right at the start. So it often gets worse and leads to permanent sight loss before people even go to a doctor. Right now, doctors check it by looking at the fundus by hand or studying color photos of it. Still, doing it that way has big practical issues. There just are not enough eye experts for all the people with diabetes around the world. Plus, the places to get checked are mostly in cities. Rural folks end up without much help. And grading those images takes a lot of time and effort by hand. To fix some of this, our study brings in a system that analyzes images automatically with Artificial Intelligence. It uses Deep Learning, and in particular Convolutional Neural Networks, to make eye care available to more people. We pick the VGG-16 setup and adjust it through transfer learning. That way, it pulls out key details from retina pictures and sorts them by how severe the condition is. In the end, this method cuts down on mistakes from people, gives steady results, and helps start treatment sooner.

II. LITERATURE REVIEW

In recent times, there has been a lot of work on making Diabetic Retinopathy detection automatic. Different teams have tried various network designs and ways to prep the images for better results. For transfer learning, Patel and Chaware looked into MobileNetV2 back in 2020. They kept the early parts fixed and tuned the later ones. It worked okay, but the small number of samples and possible biases in the data held it back. On hybrid models, Bansode and others came up with a mix of CNN and LSTM. They added contrast boosts and ways to outline blood vessels. Feature pulling got better, yet it did not transfer well to other sets of data. Then there are hierarchical setups from Sengar and Dutta. Their method processed images in layers, zeroing in on leaks and red spots. It sped up the computing, but the steps were pretty complicated. Some folks combined CNNs with things like HGACO to tweak the weights better. Accuracy went up, though setting all the parameters right made it hard to use widely. Even with these steps forward, most models are still just in testing phases. Our effort tries to close that space by putting a solid VGG-16 into a web tool that people can actually use in practice.

III. PROBLEM STATEMENT

The main trouble with handling Diabetic Retinopathy is how quiet it stays at first. Signs only show up after the retina has taken real damage. Standard screening needs a lot of resources, like costly gear and rare skills from doctors. In places that are still developing, there are way too few eye specialists for the number of patients. This leaves a huge gap in getting diagnoses. On top of that, people do not always stick to checkups because the centers are hard to reach and not convenient. We really need a setup that works like this. It should be automatic to cut out the hand-grading part. It has to be easy to use in far-off or basic setups. And it needs to catch early signs accurately, such as those small aneurysms. This work tackles those points by building a Deep Neural Network system. It handles the checking process on its own and gives quick feedback from fundus images.

IV. PROPOSED METHODOLOGY

The whole system builds in modules that cover getting the data, prepping it, pulling features, and sorting classes.

A. Data Collection. We train the model on clear, high-detail fundus images from the retina. They come from open sources like the Kaggle set for Diabetic Retinopathy Detection. Those collections have labels that mark images into five levels. No DR, Mild, Moderate, Severe, and Proliferative.

B. Image Preprocessing. To make the model steady no matter the light or camera, we do these prep steps. First, resizing gets all images to 224 by 224 pixels. That fits what VGG-16 expects. Then, we turn them to grayscale. It cuts down on the work for computing but keeps the important shapes. For CLAHE, we use Contrast Limited Adaptive Histogram Equalization. It boosts contrast in local areas. This brings out tiny issues like bleeds without making noise worse in even spots.

C. CNN Model Architecture, VGG-16. At the heart is the VGG-16 design. We chose it for how deep it goes and the small 3 by 3 filters it uses. The convolution parts line up with stride one and padding. After that come Max Pooling layers at stride two. The pile of those small filters acts like bigger ones for the field it sees. But it uses fewer settings and adds more bend from several ReLU steps. For the end part, fully connected layers follow the convolution base. Then a Softmax layer sorts the input into DR levels.

D. Training Strategy. We put the model together with Adam for optimizing and cross-entropy for loss on categories. To avoid overfitting and help it work on new stuff, we add twists like rotating and flipping the images

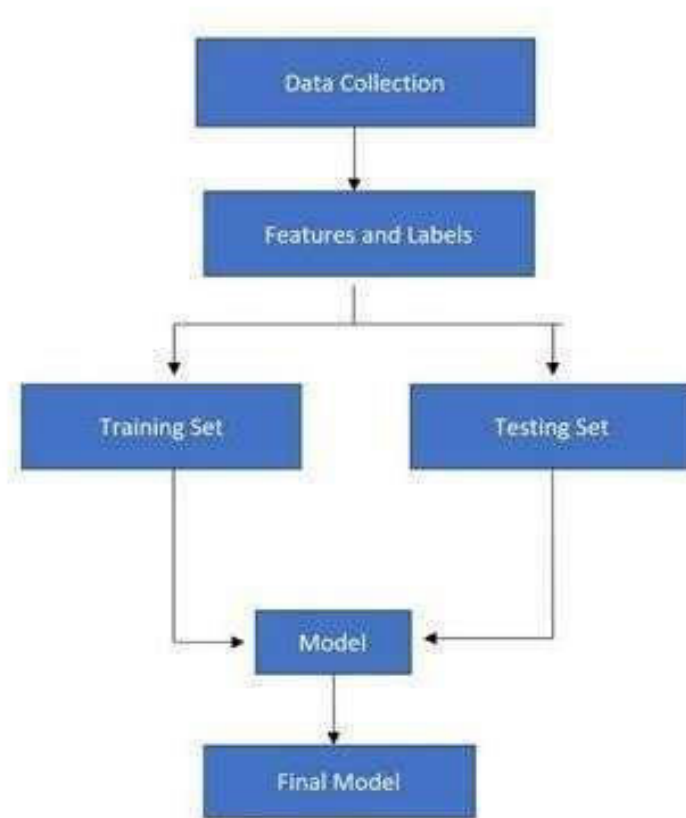


Image 1. Flowchart

V. IMPLEMENTATION

We build this in Python, pulling in tools like NumPy for numbers and Pandas for handling data.

A. Deep Learning Framework. TensorFlow and Keras make up the model. They let us set the layers in sequence for the CNN and manage the training updates. For inputs, it takes png or jpeg files of fundus images. When someone loads one, the back end runs the prep like CLAHE and sizing. Then it feeds the processed array to the ready VGG-16 for results.

B. Web Interface. To let users like doctors or techs get to it easily, we made a web front. The front has safe logins for signing in or up, plus a simple spot to upload. The back handles the image and sends back odds for Diabetic Retinopathy or not. It also shows tips on preventing it and ways to treat, based on what it finds. That helps teach patients.

VI. RESULTS AND ANALYSIS

We tested the trained VGG-16 on a separate set to see if it holds up in actual use. Confusion Matrix Analysis. We showed how it sorts classes with a confusion matrix. That maps real labels to what it predicts. True Positives came to 104. True Negatives hit 61. False Positives were just 3. False Negatives also 3. Overall samples totaled 171. From those numbers, the system did really well. Lots of True Positives mean it catches cases without missing them. That sensitivity matters a ton for screening tools in medicine. Performance Metrics. From the matrix, we got these measures for how good it is. Accuracy sat around 96.5 percent. That is the share of right calls out of all tries.

Precision stays high, so it trusts positive finds. Recall, or sensitivity, keeps false misses low. It spots the disease reliably when it is there. All this shows that adding CLAHE before VGG-16 lifts the accuracy way above old hand methods.

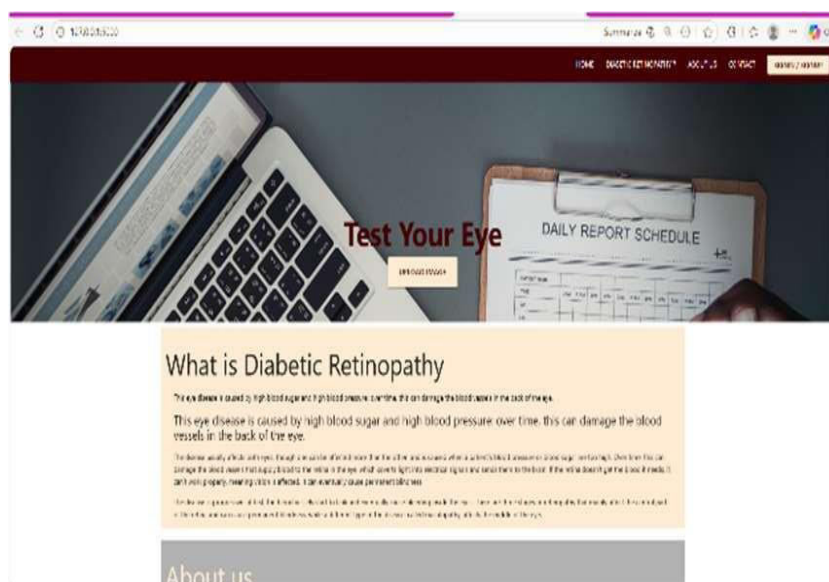


Figure 1. Home page

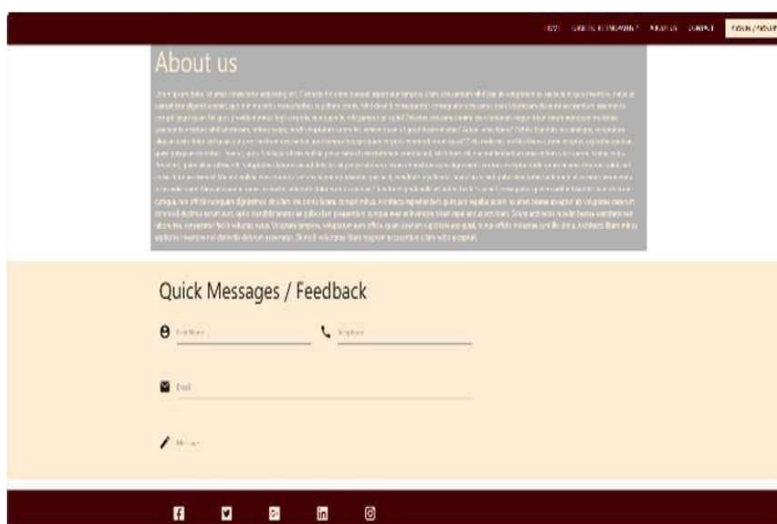


Figure 2. Feedback Page

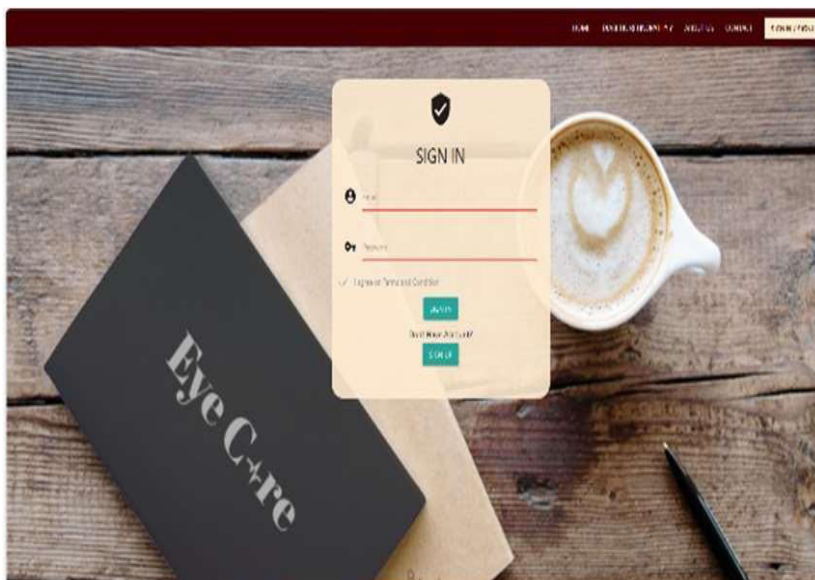


Figure 3. Sign In page

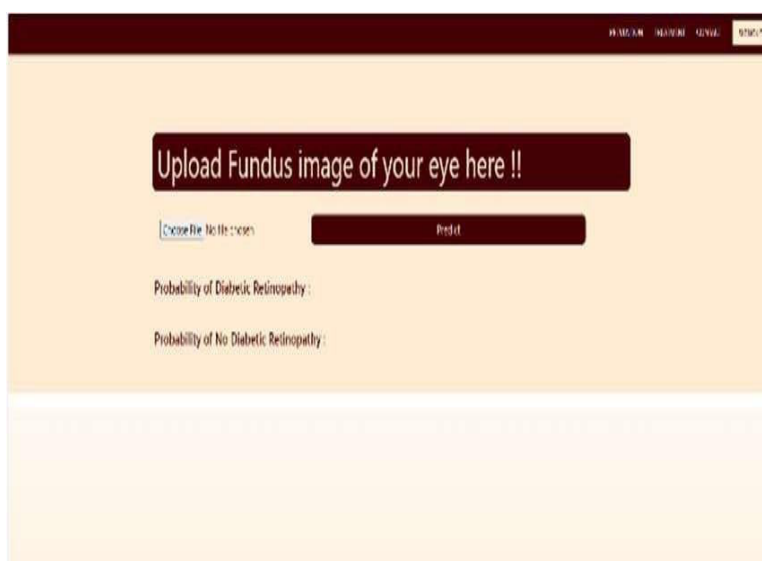


Figure 4. Upload Fundus Image



Figure 5: Preventive Measures and Treatments

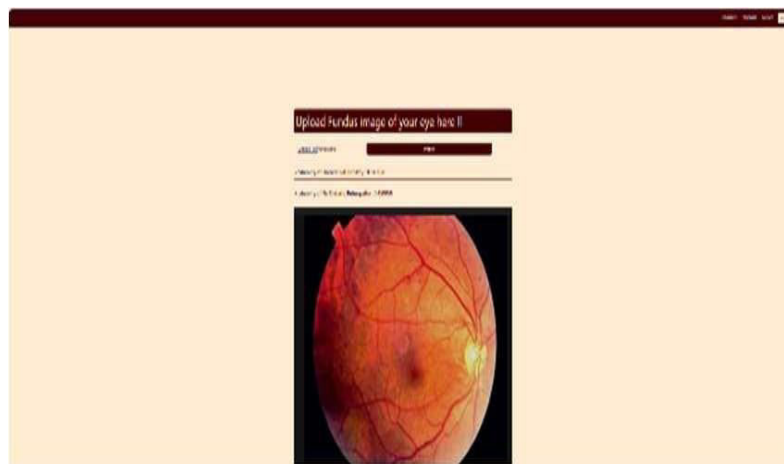


Figure 6: Output After Uploading Fundus Image

VII. CONCLUSION

This effort shows it works to use Deep Convolutional Neural Networks for checking Diabetic Retinopathy automatically. Skipping hand-picked features, the VGG-16 learns to spot tricky retina issues straight from the pixels. Putting in CLAHE helped a lot to make small problems clearer. We hit over 96 percent accuracy in sorting. That meets the goal of a trusty, cheap way to screen. Putting it out in areas short on care could ease the load on eye doctors. It might stop sight loss by finding issues in time. GANs or fancy shape changes could mix up the training data more. It would help it handle various cameras without trouble.

VIII. FUTURE WORK

The system does fine now, but we see ways to build on it later. For multimodal, we could mix in patient info like sugar levels, pressure, or age with the images. That might sharpen risks and fix close calls better. On Explainable AI, tools like GradCAM could show heat maps of what parts drove the call. Doctors would trust it more that way. For edge use,

we could tune it for phones or local devices. That lets screening happen off-grid in spots without steady web. And for better augmentation, GANs or fancy shape changes could mix up the training data more. It would help it handle various cameras without trouble.

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