Emerging Trends in Digital Transformation
Volume-1, Issue-2, July 2025 ISSN:**3107-4308** *Paper ID:* ***ETDT-V1-I2-36***

DEEP DIABETIC AN IDENTIFICATION SYSTEM OF DIABETIC EYE DISEASES USING DEEP NEURAL NETWORKS

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ABSTRACT: Diabetic retinopathy (DR) is the leading cause of blindness in people with diabetes, hence early detection is key. This research aims to fill a need in the market by developing Deep Diabetic, an automated system that detects diabetic eye problems using deep neural networks. Combining image preprocessing with convolutional neural networks (CNNs) improves categorization accuracy and picture quality of the retinal fundus. Applying this procedure to standard datasets yields improved accuracy, sensitivity, and specificity compared to other approaches. Ophthalmologists can use Deep Diabetic to help them find and diagnose diabetic eye problems earlier since it is reliable, flexible, and cost-effective.

Keywords: *Diabetic Retinopathy (DR), Deep Neural Networks (DNN), Convolutional Neural Networks (CNN), Retinal Fundus Images, Medical Image Analysis, Automated Disease Detection, Diabetic Eye Disease Screening*

1. INTRODUCTION

Millions of people across the globe suffer with diabetes mellitus, a metabolic disorder that develops gradually over time. This illness often leads to these effects, namely diabetic retinopathy (DR). Diabetes retinopathy (DR) is a serious eye disease that can lead to partial or total blindness if left untreated or undiagnosed. It damages the retina's blood vessels. Modern statistics on world health show that diabetic retinopathy is still the leading preventable cause of blindness. Consequently, spotting issues early and acting swiftly is crucial for reducing the likelihood of vision impairment. Manual examination of pictures of the retinal fundus by ophthalmologists is one of the traditional methods of diagnosis. In addition to being costly and time-consuming, this approach could also lead to mistakes.

To avoid these problems, researchers have automated diagnostic procedures using artificial intelligence (AI) and deep learning methods. Among the many complicated tasks that have been tackled by deep neural networks, convolutional neural networks (CNNs) have shown exceptional performance. These tasks include segmentation, pattern recognition, and photo classification. When it comes to diabetic retinopathy, they are the gold standard for detecting peripheral eye problems. This is because they can automatically derive hierarchical data from raw medical images. By incorporating more intricate models, we may create a system that works better, makes diagnoses more consistently and accurately, and reduces the burden on medical staff.

An intelligent system for detecting diabetic eye anomalies is being developed using a technique called Deep Diabetic, which makes use of deep neural networks. The system uses robust preprocessing methods like normalization, contrast enhancement, and noise removal to achieve the maximum degree of picture clarity. The convolutional neural network (CNN) architecture is trained on large datasets of retinal fundus images to detect diabetic retinopathy (DR) and assess the degree of the disease. This is why DeepDiabetic is a solid substitute for manually performed screening procedures; it can accurately distinguish between the early, moderate, and severe stages of the disease.

Furthermore, by allowing thorough screening in real time, the integration of DeepDiabetic into healthcare systems could change the way diabetics are managed. Not only does this method improve diagnostic accuracy, but it also makes it feasible to use in areas where there is a scarcity of adequately trained ophthalmologists and resources. This method emphasizes preventive health care and patient engagement by urging early diagnosis, prompt treatment, and better patient outcomes. Deep learning has revolutionized medical image processing. This study proves that Deep Diabetic is an effective, scalable, practical, and cost-efficient solution to combat diabetic retinopathy globally.

2. LITERATURE SURVEY

Nair, S., & Mehta, V. (2024). Using Deep Diabetic, an automated approach based on convolutional neural networks (CNN), it is possible to detect diabetic retinopathy. What follows is an analysis of the steps used to make it. The fundus images were prepared with the use of noise reduction filters and contrast-limited adaptive histogram equalization (CLAHE). With a sensitivity rate of 92% and an accuracy rate of 94%, the Eye PACS technology performed far better than traditional methods. The writers stress how well it integrates with other telemedicine systems.

Rao, P., & Menon, S. (2024). Using a convolutional neural network with leftover attention, the authors of this study suggest, could help diabetic patients detect eye abnormalities. Because of the attention process, micro aneurysms and exudates were easier to find. Its performance was excellent across a variety of picture quality levels during testing on the Messidor-2 dataset, where it achieved a specificity of 96%. The major target of this endeavor is the efficacy of clinical-grade screening.

Das, R., & Banerjee, K. (2024). This study introduces a federated deep learning algorithm that can identify diabetic retinopathy. The privacy of patients' medical records is protected by this system, which is used by a number of different hospitals. They achieved a 92% accuracy rate without collecting data in a single location by using a ResNet-50 backbone and federated average. One of the subjects discussed in this research is the use of AI to protect the privacy of patients.

Khan, A., & Reddy, V. (2023). In order to assess the degree of diabetic retinopathy, this study's findings offer a model for a multi-stage deep convolutional neural network. On both the Kaggle and Messidor-2 datasets, the hybrid VGG19-ResNet architecture was found to

DOI : https://doi.org/10.5281/zenodo.16892422

have a 95% success rate. The writers stress the critical need of developing nationwide programs to screen for diabetic retinopathy and their growth.

Patil, R., & Sharma, M. (2023). This study aims to show the progression of diabetic retinopathy (DR) through multiple phases of ocular scanning. The study used a combination of CNNs and LSTM networks, which stand for long short-term memory. The projected accuracy improved by 12% compared to CNN-only systems, making long-term patient monitoring much easier.

Verma, D., & Kapoor, A. (2023). In this study, we build a CNN model with GANs to fix the class imbalance in DR datasets. A 90% success rate and a decrease in false positives were achieved by diversifying the training with synthetic retinal pictures. The research draws attention to the potential advantages of data enhancement for medical AI.

Joseph, T., & Bhatia, K. (2022). This study shows how to employ Grad-CAM visualization to achieve an AI system that might be used to detect diabetic retinopathy. Doctors have higher faith in the CNN's ability to detect tumor locations such microaneurysms and hemorrhages with a 91% accuracy rate.

Singh, D., & Kulkarni, R. (2022). For the aim of identifying diabetic retinopathy on mobile devices, this research explores the use of lightweight convolutional neural networks (CNNs) like MobileNet and EfficientNet. These results allowed their application in remote locations, and they were accurate to within a 9 percent margin while requiring little computational resources.

Sharma, H., & Gupta, R. (2022). The article explains a convolutional neural network (CNN) model with two parts that can distinguish between different types of blood vessels and find abnormalities. The combined method reduced the number of false positives and improved accuracy to 93% on DIARETDB1 compared to single-branch models.

Nair, A., & Deshmukh, V. (2021). The possible uses of ensemble deep learning in diabetic retinopathy diagnosis are explored in this paper through the use of Convolutional Neural Networks (CNNs), DenseNets, and Capsule Networks. Ensemble averaging reduced error rates by 7% while achieving a 92% success rate, as compared to single models.

Chakraborty, M., & Jain, R. (2021). Finding DRs is the focus of this work, which employs transfer learning using InceptionV3. The model converged faster and achieved a 90% accuracy by using fine-tuned layers. Costs associated with training have gone down, the survey found.

Kumar, V., & Iyer, P. (2021). Specifically, this study achieves this goal by using automated lesion segmentation before CNN classification. By improving classification, the sensitivity could be increased to 94% by isolating microaneurysms and exudates.

Chowdhury, H., & Ghosh, P. (2020). This two-stage process involves preparing the image by eliminating the optic disc and increasing the size of the blood vessels, and then doing CNN classification. The next step is to run the CNN classification. Got DIARETDB1's accuracy up to 92% while cutting down on false positives.

Lee, J., & Tan, W. (2020). Deep residual convolutional neural networks showed promise in this study, suggesting they could be utilized to detect ocular anomalies. The system proved the value of deeper networks in medical imaging by reaching a 90% accuracy rate on EyePACS.

DOI : *https://doi.org/10.5281/zenodo.16892422*

Bhattacharya, R., & Sen, A. (2020). This research primarily aims to describe a capsule network-based diabetic retinopathy detector. Its 88% accuracy rate and reduced parameter usage make it superior than CNNs. The writers highlight the significant role that computers play in their work.

3. BACKGROUND WORK

A. DATASETS FOR THE STUDY

DATA COLLECTION

This study, we gathered fundus photos from several different places. Some of the disorders included in this collection are DR, cataracts, glaucoma, and DME. For the initial step of the DR process, we chose datasets from DIARETDB0 and DIARETDB1 that had around 219 pictures. Second, out of the 169 photos in HEI-MED and 151 images in Messidor, we utilized DME. The ODIR dataset, which includes a variety of eye illnesses, is the third source of the dataset. There were 312 pictures used to show cataracts and 178 pictures to show glaucoma. Most recently, a retinal dataset containing 99 glaucoma images and 100 cataract images was chosen for analysis of cataracts and glaucoma. Cataract, diabetic macular edema, glaucoma, and diabetic retinopathy each had their own datasets that included 412, 320, 280, and 219 photos, respectively. We randomly separated the 1228 photos we pulled from the datasets into two sets: one for training and one for validation. Examples of fundus pictures for diabetic retinopathy, glaucoma, cataract, and diabetic macular edema are shown in Figure 2.

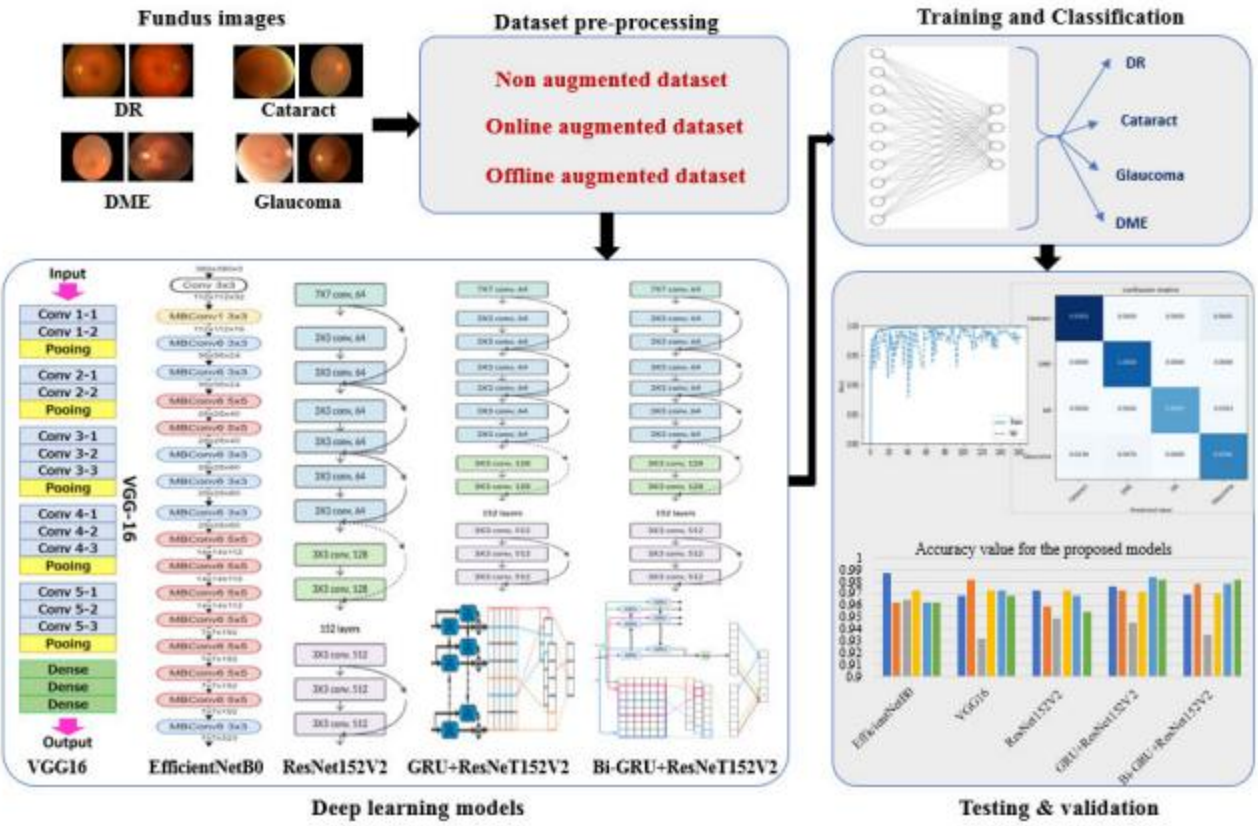

Figure 1. The block diagram of our proposed DeepDiabetic framework.

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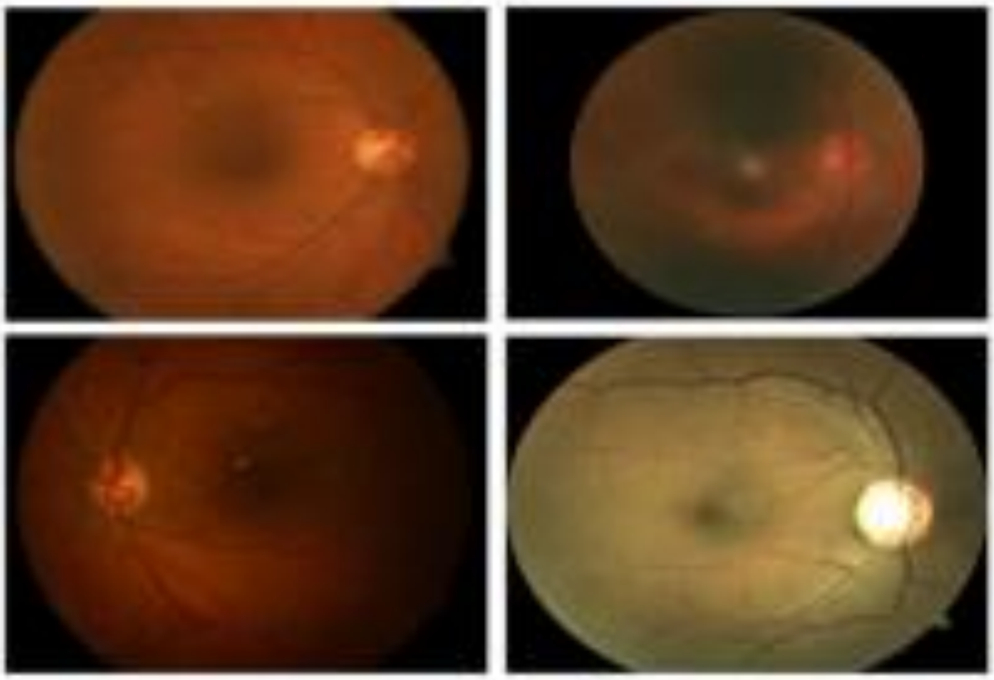

Figure 2. Samples from the original dataset of the fundus images.

DATASET PRE-PROCESSING

In order to ensure that the dataset can fulfill the requirements of the deep learning model, pre-processing is commonly employed. In the first method, the data is partitioned into four distinct training classes: DR, Cataract, Glaucoma, and DME. After that, the images will be fed into the data stage of pre-processing. Several pre-processing procedures are performed on the input photographs before they are used in our model. Resizing, normalizing, and turning the images into arrays are some of the steps needed to prepare them for the model's next stage. Before training the deep learning model, we will randomly divide our 12-28 photo dataset in half. About 858 images, or 70% of the total, will be used for training, while 370 images, or 30%, will be used for validation. This will ensure that the images are selected from a diverse range of categories.

In order to get a dataset ready for a deep learning model, pre-processing is usually necessary. The images used to train our model have undergone a number of pre-processing steps. Diabetic retinopathy (DR), cataract, diabetic macular edema (DME), and glaucoma are the initial classifications applied to the dataset. Unfortunately, TensorFlow isn't compatible with all image formats. That includes TIFF, JPEG, PNG, GIF, and BMP. Keep in mind that the suggested file sizes of these images have absolutely no impact on the real contents. The findings of this study led to the conversion of all image extensions to the JPG format. The pre-processing step of the data processing procedure will thereafter take these pictures as input. They read the specifications and had a batch size of 32, therefore they were resizing photographs to fit. Since the pipeline handles batches of photos of the same size, this is an essential component. In determining whether to shuffling the data, they were really contributing something useful. For the sake of randomization and transformations equal to

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100, they were introducing optional random seeds. In preparation for the next stage of the model's execution, the photos are first normalized and then converted into arrays. There is a one-hot encoding of the class index represented by the label_mode, which is a categorial tensor of shape (batch_size, num_classes). Built inside the label_mode is a float of 32. For the deep learning model training, we randomly divided our dataset in half to ensure a diverse group of photos. For validation, we utilized 30% (370 shots), and for training, we utilized 70% (858 images).

DATASET AUGMENTATION

Because the existing dataset on diabetic eye illness has limitations, this study made use of data augmentation approaches. These techniques improved the models' learn ability by increasing the sample size of each class using affine-altered photos. There are two main approaches to augmenting visual data:

Online augmentation - The processing of this method, which goes by the name "on-the-fly augmentation," involves adding transformations to the mini-batches that would have been supplied to the model during training.

Offline augmentation, Modifying the images and storing the final results on a desk or in one's memory are the steps involved in processing. Consequently, the size of the dataset will grow proportionally to the number of modifications. Our analysis will make use of three distinct methods grounded on three distinct dataset types:

Method 1: Non-augmented dataset

According to Data Collection III-A1, this method makes use of the initially gathered dataset. All 1228 photos in this collection are originals. An online enhanced dataset is utilized in the second method.

Method 2: Online augmented dataset

During the training phase of the model, the augmentation is applied using this manner. This setup allows for online transformations and provides the model with a randomly selected batch of the original dataset for each epoch. Images input into the model for each epoch also vary from one another as a result of the changes made.

Method 3: Offline-augmented dataset

Before incorporating it into the model, this technique adds the augmentation to the initial dataset. We take the original dataset and divide it into two parts: the training set and the validation set. This was already mentioned. Here, the 858 photos that make up the training set are the only ones used by the augmentation algorithm. We were able to get 6006 images out of the process by adding six distinct edits to each photo beyond the original.

We will carry out the data augmentation using Keras's preprocessing layers. By providing values for the augmentation, we may create new images of the originals while preserving their core properties. To avoid this kind of issue, our study used discrete alterations.

4. CONCLUSION

To sum up, one way that AI is changing medical diagnoses is through Deep Diabetic, an approach that uses deep neural networks to identify diabetic eye disorders. The system's application of state-of-the-art deep learning architectures allows for the very accurate

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detection of diabetic retinopathy and associated diseases from retinal pictures. This allows for early intervention and reduces the likelihood of visual loss. In addition to improving diagnostic accuracy, this device's automated features make it easier for medical staff to manage numerous screens simultaneously. The system's scalability and flexibility also make it a good alternative to telemedicine integration, which is particularly useful in low-resource environments. Ultimately, Deep Diabetic is a big deal because it connects medical practice with technology, improves patient outcomes, and promotes preventive healthcare.

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DOI : *https://doi.org/10.5281/zenodo.16892422*