University of Regina

Diabetic Retinopathy Blindness Detection

Machine Learning

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Table of Content

Introduction : Diabetic retinopathy is a major cause of blindness among working-age adults, affecting millions of people worldwide. Current screening methods rely on highly trained doctors to review images of the retina, which is time-consuming and expensive, especially in rural areas where medical resources are limited. The lack of access to quality healthcare services in these areas can lead to late diagnosis and ultimately blindness. Thus, there is a need to develop a cost-effective and efficient screening system that can detect diabetic retinopathy early and prevent lifelong blindness.

The Blindness DetectionProject focuses on developing a computer-aided diagnosis system that utilises convolutional neural network (CNN) algorithms for the early diagnosis of diabetic retinopathy (DR), one of the main causes of blindness in diabetic patients. In order to improve the performance of the CNN models, the project calls for the usage of a sizable dataset of eye photos obtained from Kaggle and preprocessed to a standard size. Additionally, the project calls for the creation of several CNN models using the TensorFlow and Keras libraries, which will then be applied to the preprocessed data. These models' performance will be assessed using various metrics, including accuracy, sensitivity, and specificity. The ultimate objective of this project is to create an accurate and scientific computer-aided diagnosis system that would enable healthcare professionals in the early detection of diabetic retinopathy, thereby lowering the risk of blindness in diabetic patients.

In this project, we aim to develop a machine learning model to detect diabetic retinopathy in retinal images captured in rural areas. The model will be trained on a dataset of retinal images collected by different hospitals in India (available on Kaggle) and will be optimized for low-resource settings to enable its widespread use.

Background : Diabetic retinopathy is a serious complication of diabetes and one of the leading causes of blindness worldwide [1]. It is estimated that around 93 million people with diabetes are at risk of developing diabetic retinopathy, and this number is expected to increase to 160 million by 2040 [2]. In India, the prevalence of diabetic retinopathy is estimated to be 21% among individuals with diabetes [3]. While effective treatments are available for diabetic retinopathy, early detection is crucial for preventing vision loss and blindness.

The current standard for diabetic retinopathy screening is a dilated eye exam, which involves a trained healthcare professional examining the retina for signs of disease. However, this method is time-consuming and expensive, especially in low-resource settings where there may be a shortage of trained healthcare professionals and equipment. In rural areas, where many people with diabetes live, access to healthcare services is limited, and there is a high risk of late diagnosis and poor treatment outcomes.

In recent years, there has been growing interest in using machine learning to improve the efficiency and accuracy of diabetic retinopathy screening. Several studies have demonstrated the potential of machine learning algorithms to analyze retinal images and detect diabetic retinopathy with high accuracy [4,5]. However, these studies have mostly been conducted on datasets collected in high-resource settings and may not be generalizable to low-resource settings.

Thus, there is a need to develop a machine learning-based screening system that is optimized for low-resource settings and can accurately detect diabetic retinopathy in retinal images captured in rural areas. Such a system could improve access to healthcare services and prevent blindness among people with diabetes living in underserved areas.

Objective : The objective of this project is to develop a machine learning model to automatically detect diabetic retinopathy in retinal images captured in rural areas. The development of an accurate and efficient screening system for diabetic retinopathy in low-resource settings has the potential to improve access to healthcare services and prevent blindness among people with diabetes living in underserved areas. Additionally, the project aims to spread the solution to other Ophthalmologists through the 4th Asia Pacific Tele-Ophthalmology Society (APTOS) Symposium. The ultimate goal is to help prevent lifelong blindness and provide a model that can be used to detect other diseases such as glaucoma and macular degeneration in the future.

Initial Approaches : Here is the list of some initial approaches that we used :

1. **Random Forest** (suggested by Ihab Mohamad) : Random forest is an ensemble learning algorithm that combines multiple decision trees to improve the accuracy of predictions. Each decision tree in the forest is trained on a random subset of the input features and a random subset of the input samples, and the final prediction is made by aggregating the predictions of all the trees. Random forests can be used for both classification and regression tasks.

   To apply the random forest algorithm to the problem of diabetic retinopathy detection, we used following steps:

- Prepare the dataset: Preprocess the retinal images to extract the green channel image from original rgb image which is the feature.
- Split the dataset: Split the dataset into training and testing sets.
- Train the random forest model: Train a random forest model on the training set using the extracted features and the corresponding diabetic retinopathy severity labels.
- Test the model: Test the model on the testing set and evaluate its accuracy using metrics such as accuracy and precision
- Fine-tune the model: Adjust the hyperparameters of the random forest model, such as the number of trees, the depth of each tree, and the number of features used in each tree, to improve its accuracy.

2. **k-Nearest Neighbours** (suggested by Ramanpreet Singh) **:** kNN is a simple yet effective classification algorithm that uses the distance between input samples to predict their corresponding labels. Given a new input sample, the kNN algorithm finds the k nearest training samples to the input in the feature space and assigns the input the label that is most common among those k samples.

   To apply the kNN algorithm to the problem of diabetic retinopathy detection, we used following steps:

- Prepare the dataset: Preprocess the retinal images to extract the green channel image from original rgb image which is the feature.
- Split the dataset: Split the dataset into training and testing sets.
- Train the kNN model: Train a kNN model on the training set using the extracted features and the corresponding diabetic retinopathy severity labels.

- Test the model: Test the model on the testing set and evaluate its accuracy using metrics such as accuracy, precision, recall, and F1-score.
- Fine-tune the model: Adjust the hyperparameter k, which determines the number of nearest neighbors to consider, to improve the model's accuracy.

3. **CNN** (suggested by Amandip Padda) **:** CNNs are deep learning models that are commonly used for image classification tasks. They consist of multiple layers, including convolutional layers, pooling layers, and fully connected layers. In a CNN, the convolutional layers learn to extract features from the input images by convolving a set of learnable filters over the image. The pooling layers downsample the feature maps, reducing their spatial dimensionality. Finally, the fully connected layers classify the extracted features into their respective categories.

   To apply CNNs to the problem of diabetic retinopathy detection, we used following steps :

- Prepare the dataset: Preprocess the retinal images to extract the green channel image from original rgb image which is the feature.
- Split the dataset: Split the dataset into training, validation, and testing sets.
- Build the CNN model:We are using Inception V3 architecture, including the number and size of convolutional and pooling layers, the number and size of fully connected layers, and the activation functions used.
- Train the CNN model: Train the CNN model on the training set using the extracted features and the corresponding diabetic retinopathy severity labels. This involves iteratively adjusting the weights and biases of the model to minimize the loss between the predicted and actual labels.

- Validate the model: Validate the CNN model on the validation set to check for overfitting and adjust the model's hyperparameters, such as the learning rate, batch size, and number of epochs, as needed to improve its accuracy.
- Test the model: Test the CNN model on the testing set and evaluate its accuracy using metrics such as accuracy and precision.

Out of these three approaches we were getting better results with the CNN, so we choose this algorithm to go with.

Implementations of CNN : Here are the steps for the implementation of the data :

Splitting Data : The first step in implementing a CNN for diabetic retinopathy detection is to split the dataset into training and validation sets. In this implementation, the dataset of 3600 images is being split into 5 folders, with each folder corresponding to one of the five severity levels of diabetic retinopathy. This is done to ensure that the model is trained on a balanced dataset that includes images of all severity levels.

Data Augmentation : Data augmentation is a critical step in CNN implementation. It involves generating new training samples by applying random transformations such as rotation, flipping, and scaling to the original images. This helps to increase the size and diversity of the training dataset, which in turn improves the robustness and accuracy of the model. In this implementation, data augmentation is being used to generate additional training samples and improve the performance of the CNN model. We have used rescaling to scale images from 0 - 255 to 0 - 1. This ensures that the data is normalized and ready to go. The next data augmentation was based of a horizontal flip. The reason why we ended up choosing horizontal flip and not vertical flip is because the way the data is positioned. In the dataset both sides of the eyes can either be flipped right or left; not up and down. Our rotation range is about 5 degrees to increase the dataset. The other parameter was the zoom range which was set to either zoom in or zoom out 5 percent. This way we increased the training dataset by 4 folds.

Training Model: Once the dataset has been split and augmented, the CNN model is trained using the training dataset. The training process involves adjusting the weights and biases of the network to minimize the difference between the predicted and actual outputs. This is typically done using an optimization algorithm such as stochastic gradient descent. Firstly, we decided to go with VGG16 (suggested by Ihab). The reason was that the starting of the neural were 16 and can be implemented effectively with less toll on the system. It didn't go as expected due to the fall of accuracy and the increase of loss function. We ended up with 48.64% as our final accuracy. We ended up discarding the model and look into models with more hyper parameters. Our next model was a choice of EfficientnetV2L (suggested by Ramanpreet). We didn't got any accuracy with this model as the code runs forever. We then switched to EfficientnetV0 architecture and then our accuracy was boasted to 55% which is 7% higher than VGG16. At last, we trained our CNN model with Inception-v3 architecture(suggested by Amandip), which is a popular and effective CNN architecture for image classification tasks. This architecture gave us the accuracy of about 77% which is the best of all four architectures that we used. So, this is out final model.

Precision and Accuracy : After training the CNN model, its precision and accuracy are evaluated using the validation dataset. Precision is a measure of how many of the predicted positive cases are actually positive, while accuracy is a measure of how many of the predicted cases are correct overall. These metrics are important for evaluating the performance of the model and determining whether further adjustments or improvements are necessary. In this implementation, the precision and accuracy of the CNN model are being used to evaluate its performance in detecting diabetic retinopathy. We tested some random images that are different from training data and for most of the images that we passed thru the model we got right answers. We tested like 66 images awith our model and predicted 50 right images which left us with apprize 75 % of accuracy.

Conclusion : In conclusion, the implementation of a CNN for diabetic retinopathy detection is a complex process that involves several important steps, including data splitting, data augmentation, model training, and precision/accuracy evaluation. By using an effective CNN architecture such as Inception-v3 and following best practices for data preparation and model training, it is possible to build a high-performing CNN model for diabetic retinopathy detection.

The use of CNNs for medical image analysis has shown promising results, particularly in the field of ophthalmology. With the ability to accurately detect and diagnose diabetic retinopathy, CNNs have the potential to improve the early detection and treatment of this debilitating condition, and to potentially detect other types of eye diseases in the future.

However, there is still much work to be done to improve the accuracy and reliability of CNN models for medical image analysis. Future research should focus on developing more sophisticated CNN architectures, exploring different data augmentation techniques, and further refining the training process to optimize performance.

Overall, the implementation of a CNN for diabetic retinopathy detection represents an important step forward in the development of advanced technologies for medical diagnosis and treatment, and has the potential to greatly benefit patients in need of early and accurate detection of diabetic retinopathy.

Future Works : There are several areas of future work that could be explored in order to further improve the accuracy and effectiveness of CNN models for diabetic retinopathy detection:

1. Improving CNN architectures: While Inception-v3 has shown promising results, there may be other CNN architectures that could perform even better for diabetic retinopathy detection. Further research could explore different CNN architectures and assess their performance on this task.
2. Exploring different data augmentation techniques: Data augmentation is an important step in training CNN models, as it can help to prevent overfitting and improve generalization. Future work could investigate different data augmentation techniques and assess their effectiveness for diabetic retinopathy detection.
3. Refining the training process: The training process for CNN models can be complex and time-consuming. Further research could explore different training techniques and optimization algorithms to improve the efficiency and effectiveness of the training process.
4. Evaluating CNN models on larger datasets: The dataset used in this study consisted of 3600 images. Future work could evaluate CNN models on larger datasets to assess their scalability and performance on a wider range of images.

5. Applying CNN models to other types of eye diseases: While this study focused on diabetic retinopathy detection, CNN models could potentially be used to detect other types of eye diseases as well. Future work could explore the use of CNN models for other types of eye disease diagnosis and treatment.

By continuing to improve CNN models for medical image analysis, we can potentially improve the early detection and treatment of a wide range of medical conditions, and help to improve patient outcomes and quality of life.

References

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