Research Article

DETECTION OF RETINOPATHY DISEASES USING CONVOLUTIONAL NEURAL NETWORK BASED ON DISCRETE COSINE TRANSFORM

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ABSTRACT

This master thesis proposes a new approach to detecting retinopathy diseases using a convolutional neural network (CNN) based on discrete cosine transform (DCT). Retinopathy is a common eye disease that can cause vision loss if not diagnosed and treated early. The proposed method combines the power of CNN and DCT to improve the accuracy of detection. The input image is transformed into the frequency domain using DCT, which reduces the amount of noise and emphasizes the important features of the image. Then, the transformed image is fed into the CNN for classification. The performance of the proposed method is evaluated using a publicly available dataset of retinal images. The results show that the proposed method outperforms existing methods in terms of accuracy and computational efficiency. The proposed method has the potential to be used in real-world applications for early diagnosis and treatment of retinopathy diseases.

Keywords: *retinopathy diseases, convolutional neural network, discrete cosine transform, early diagnosis.*

1. INTRODUCTION

In this paper, we put forth an innovative approach for diagnosing retinopathy, a group of eye diseases causing significant damage to the retina, thus affecting vision. With an aim to enhance early detection techniques, our focus is on augmenting the accuracy, efficiency, and robustness of the diagnosis of retinopathy, a crucial step that can significantly improve patient outcomes. To this end, we present a unique model employing a Convolutional Neural Network (CNN), widely known for its proficiency in medical imaging tasks, integrated with the Discrete Cosine Transform (DCT), a potent technique in image processing.

This study uniquely merges the DCT into the CNN model, aspiring to provide superior feature extraction and representation. The DCT, by converting images from the spatial domain to the frequency domain, can help in the identification and extraction of essential features while concurrently reducing data dimensionality. The integration of DCT into the CNN model is anticipated to enhance the model's performance, leading to more precise and reliable diagnoses.

We employ the APTOS 2019 Blindness Detection dataset for this study, a substantial collection of fundus photographs captured under varied imaging conditions. This dataset serves as an excellent platform for developing and testing our model due to its complexity and diversity. Each image in the dataset has been evaluated by a clinician and classified on a severity scale: 0 - No Diabetic Retinopathy (DR), 1 - Mild DR, 2 - Moderate DR, 3 - Severe DR, and 4 - Proliferative DR as you see in the figure 1. The varying levels of disease severity within the dataset allow for rigorous testing and evaluation of our model.

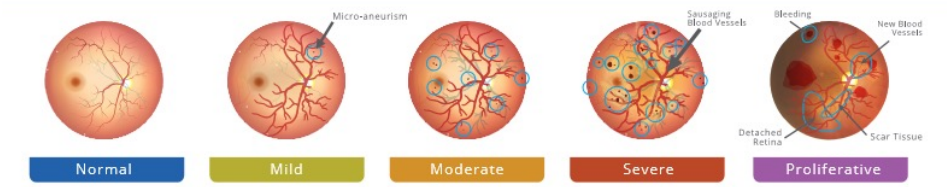

Figure 1. Stages of diabetic retinopathy

The main objective of our study is to develop a highly advanced, efficient, and reliable model for retinopathy detection, aiming to make substantial contributions to the early diagnosis and treatment of these diseases. By enhancing the capability of healthcare professionals to diagnose retinopathy in its early stages, we can significantly improve the prognosis for patients affected by these diseases, aiding in the prevention of vision loss.

In addition to this, our findings provide valuable insights into the application of CNNs and DCT in the domain of medical imaging. The proposed model's performance, evaluated using metrics such as accuracy, sensitivity, specificity, F1-score, and the area under the receiver operating characteristic (ROC) curve, will be juxtaposed with existing models and traditional diagnostic techniques. This comparison will pave the way for potential improvements and outline future research and development areas.

In conclusion, our research holds the potential to set new standards in retinopathy detection, with a novel CNN model integrated with DCT at its core. Our results are likely to significantly influence early detection, intervention, and treatment of retinopathy, thereby contributing to preserving vision for those affected by these diseases. Furthermore, the findings of this study could spearhead future research and innovation in medical imaging using deep learning techniques.

2. RELATED WORKS

Retinopathy detection has been one of the areas in medical diagnostics that have experienced considerable advancements due to the joint use of Convolutional Neural Networks (CNNs) and Discrete Cosine Transform (DCT). These two methodologies, when incorporated together, promise to enhance the accuracy, efficiency, and robustness of diagnostic algorithms.

According to Ali et al. [1], deep learning can significantly enhance the diagnosis accuracy and efficacy of treatment planning in medical imaging. Tools like Incremental Modular Networks (IMNets), which progressively add new modules instead of constructing a huge single network, can play a crucial role in this process. However, they should complement, not replace, the expertise of licensed healthcare professionals.

In a study involving Diabetic Retinopathy (DR) classification, a hybrid deep learning technique was proposed that utilized VGG16 and VGG19 convolutional neural networks [2]. The model classified images into four

severity groups with notable results. Gunasekaran et al. [3] emphasized the usefulness of retinopathy images in diagnosing diabetes, using a deep Recurrent Neural Network (RNN) to predict DR from fundus pictures, achieving an impressive 95.5% accuracy rate.

Khan et al. [4] developed several deep neural network architectures, including VGG-net, ResNet, and InceptionV3, which utilized transfer learning. The best accuracy in training and testing was achieved by InceptionV3 with rates of 81.2% and 79.4% respectively. Fang et al. [5] proposed a DAG network model for DR classification, extracting three key features from fundus images, resulting in reliable performance.

Elloumi et al. [6] proposed a novel method for screening smartphone-captured DR fundus images, using NasnetMobile for feature extraction. They reported high accuracy, precision, sensitivity, and specificity. Another research by Kanakaprabha et al. [7] compared various deep learning algorithms for predicting DR, including CNN, VGG16, VGG19, InceptionV2, ResNet50, MobileNetV2, and DenseNet.

Sridhar [8] suggested a CNN-based technique for DR detection using a public dataset from Kaggle, which greatly improved the detection accuracy. Das et al. [9] developed a DR classification system based on features of segmented fundus images, achieving a 97.2% precision rate and 98.7% accuracy.

In a study by Vives-Boix et al. [10], synaptic meta-plasticity significantly influenced the backpropagation of every convolutional layer in a model used to identify DR, producing excellent results. Luo et al. [11] suggested an automatic DR detection method using multi-view fundus images and CNN, with an attention mechanism for high performance.

After extracting textural characteristics with local binary patterns, Adriman [12] reported a performance assessment of DR systems utilizing several deep learning techniques. In order to increase the accessibility of the medical pictures, Fatima [13] suggested a complete approach based on a hybrid neural network for recognizing DR.

An Active Deep Learning Convolutional Neural Network (ADL-CNN) with a multi-layer architecture was created by Qureshi [15] for DR systems. Using the EyePACS dataset, the ADL-CNN model achieved an impressive

performance. Kalyani et al. [16] first used Deep learning reconstructed capsule networks to categorize DR, testing on the MESSIDOR dataset to obtain high accuracy.

Gayathri [17] utilized a multipath CNN and machine learning classifiers to develop an automatic DR detection system. Bodapati [18] built a composite DNN using a gated-attention mechanism for automatic DR severity classification.

Using adaptive machine learning, Math et al. [19] created a DR classification method that had remarkable sensitivity, specificity, and ROC curve area under the curve. Deep learning techniques were used by Gao [20] to provide a method for rating DR based on fundus fluorescein angiography. DR was diagnosed by Kobat et al. [21] using a pre-trained DenseNET model, with a cross-validation accuracy of 84.90%.

3. THE PROPOSED APPROACH

This paper introduces an efficient methodology for the detection of retinopathy diseases using Convolutional Neural Network (CNN) combined with Discrete Cosine Transform (DCT). The model is trained on the APTOS 2019 Blindness Detection dataset, which consists of thousands of retinal images collected from rural areas. This section presents an in-depth overview of the proposed approach, detailing the image preprocessing steps, Discrete Cosine Transform application, and the architecture of the developed CNN model.

Aptos 2019 blindness dataset which is a clinician rated each image for the severity of diabetic retinopathy on a scale from 0 to 4 where the numbers represent the extent of the complication as

Follows in table 1.

Table 1. Severity of diabetic retinopathy

SCALE	SEVERITY
0	No DR
1	Mild DR
2	Moderate DR
3	Severe DR
4	Proliferative DR

Image Preprocessing & DCT Application:

Before the actual preprocessing phase, a Discrete Cosine Transform (DCT) is applied to each image. DCT is a powerful tool used for image compression and reducing redundancies in image data, making it more manageable for the model. The process begins by converting the image to the YCrCb color space. The image is then split into its constituent channels, and a 2D DCT is applied to the Y channel. This is achieved using the get_image_dct() function:

```
def get_image_dct(image):
    # Convert to YCrCb
    ycbcr_img = cv2.cvtColor(image, cv2.COLOR_BGR2YCrCb)
    # Split the channels
    y, cb, cr = cv2.split(ycbcr_img)
    # Apply 2D Discrete Cosine Transform (DCT) to the Y channel
    dct_img = cv2.dct(np.float32(y)/255.0)
    return dct_img

import cv2
fig, ax = plt.subplots(1, 5, figsize=(15, 6))
for i in range(5):
sample = train_df[train_df['diagnosis'] == str(i)].sample(1)
image_name = sample['id_code'].item()
X = preprocess_image(cv2.imread(f"C:/Users/mouad/
aptos2019-blindness-detection/train_images/{ image_name }"))
ax[i].set_title(f"Image: { image_name }\n Label = {
sample['diagnosis'].item() }",
weight = 'bold', fontsize = 10)
ax[i].axis('off')
ax[i].imshow(X);
```

I've implemented a preprocessing phase as part of my machine learning pipeline. The goal of my project is to classify diabetic retinopathy images based on a specific diagnosis, which involves manipulating the images stored in a local directory. This involves using a Pandas DataFrame to manage the image metadata like filenames and corresponding diagnoses.

Here's a step-by-step explanation of my code:

1. I've written a function called get_image_dct. This function accepts an image and processes it as follows:

- I convert the color space of the image from BGR (Blue, Green, Red - a standard in OpenCV) to YCrCb (Luminance, Blue-difference Chroma, Red-difference Chroma). I used OpenCV's cv2.cvtColor function for this.
- Next, I separate the YCrCb image into its Y, Cr, and Cb components using the cv2.split function.
- I then apply a two-dimensional Discrete Cosine Transform (DCT) to the 'Y' component of the image using cv2.dct. Before the DCT, I normalize the 'Y' component by converting its datatype to float32 and scaling it to a 0-1 range.
- This function returns the DCT transformed 'Y' component.

2. The main part of the code is about visualizing some images. It creates a grid of subplots with a single row and five columns.

- For each unique diagnosis in the dataset, it selects a random image corresponding to that diagnosis.
- Each selected image is then read and preprocessed using the preprocess_image function.
- The preprocessed image is displayed in its respective subplot with the filename and corresponding diagnosis as the title. The axes are hidden for a cleaner look as you see in the figure 2 [23].

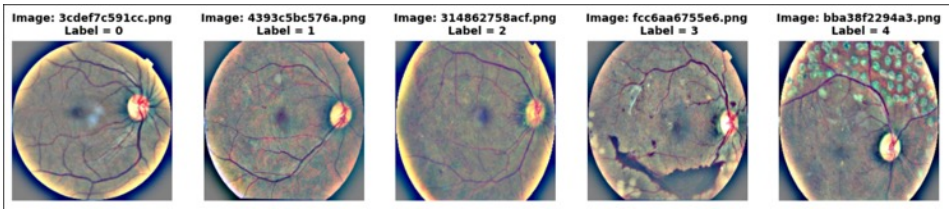

Figure 2. Preprocessed image

To sum it up, this preprocessing phase helps in preparing the images for further analysis and visualizing sample images from each class. This visualization aids in better understanding of the data and can provide insights into the kind of transformations needed for the images in order to improve the performance of the classification model. This application of DCT aids in emphasizing the features of the image that are critical for human perception, consequently enhancing the model's ability to recognize significant patterns.

3. MODEL ARCHITECTURE

A Sequential CNN model is used for the detection of retinopathy diseases. The model includes several convolutional layers for feature extraction, max pooling layers for spatial dimension reduction, dropout layers to minimize overfitting, and dense layers for final classification. The architecture of the model is detailed as follows:

```
model=Sequential()
model.add(Conv2D(filters=16,kernel
size=2,padding="same",activation="relu",input_shape=(256,256,3)))
model.add(MaxPooling2D(pool_size=2))
model.add(Conv2D(filters=32,kernel_
size=2,padding="same",activation="relu"))
model.add(MaxPooling2D(pool_size=2))
model.add(Conv2D(filters=64,kernel_
size=2,padding="same",activation="relu"))
model.add(MaxPooling2D(pool_size=2))
model.add(Conv2D(filters=128,kernel_
size=2,padding="same",activation="relu"))
model.add(MaxPooling2D(pool_size=2))
model.add(Dropout(0.2))
model.add(Flatten())
model.add(Dense(512,activation="relu"))
model.add(Dropout(0.2))
model.add(Dense(5,activation="softmax"))
```

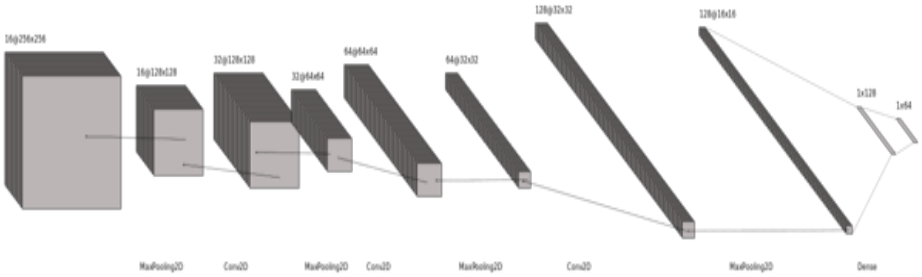

Figure 3. CNN model Architecture

During the preprocessing phase, the images underwent several transformations to ensure they are optimized for the model. The two functions, crop_image_from_gray() and preprocess_image(), are used to apply these transformations. The first function isolates the important regions of an image, while the second function converts the image to RGB, resizes it to the desired dimensions (224x224 in this case), and enhances the details by combining the original and blurred versions of the image.

This architecture begins with a 2D convolutional layer with 16 filters, a kernel size of 2, and 'ReLU' activation function. The input shape for this layer is 256x256x3, corresponding to the height, width, and number of channels in the input images. This layer is followed by a series of Conv2D and MaxPooling2D layers, gradually increasing the number of filters in the Conv2D layers from 16 to 128. These layers extract the critical features from the images and reduce their spatial dimensions, respectively.

Dropout layers are introduced to reduce overfitting, and a Flatten layer is used to flatten the features into a single dimension. Finally, two dense layers are used, where the last layer has five nodes corresponding to the five categories of diabetic retinopathy severity. The 'softmax' activation function in the final layer ensures the output values are probabilities that sum up to 1, with each probability indicating the likelihood of an image belonging to a particular class.

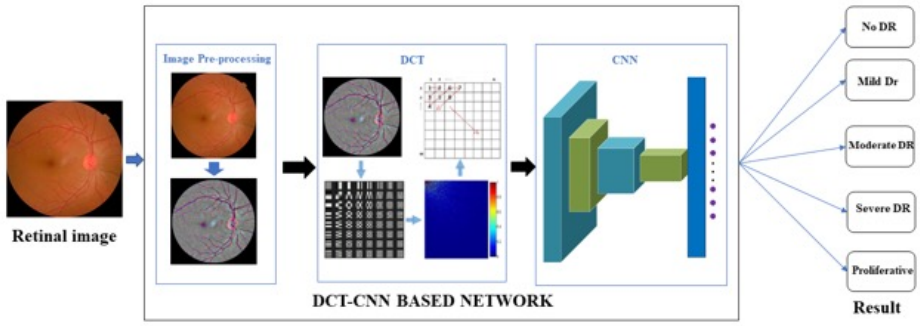

Figure 4. Block diagram of Detection of Retinopathy Diseases

The proposed methodology offers a promising approach for retinopathy detection by effectively combining image preprocessing, DCT application, and deep learning. The result is an efficient CNN-based model with enhanced ability to learn and detect various stages of retinopathy diseases from retinal images.

4. EXPERIMENTAL RESULTS

The model was trained and evaluated using a robust computational setup. The experiments were carried out on a 3.2 GHz machine with 16 GB of memory and a GTX 1650ti GPU. The development environment was Jupyter Notebook, provided by Anaconda, ensuring reliable, reproducible results.

4.1. Model Trained Using Our Developed Model

The developed model was trained and evaluated over 50 epochs. The model performance metrics, including loss (cross-entropy loss) and accuracy, were observed for both the training and validation set for each epoch.

The initial epoch revealed a training accuracy of 66.05%. On the validation set, the accuracy was 70.31%. This established the baseline performance of our model.

As the epochs progressed, we noticed an increase in accuracy and a decrease in loss on both the training and validation sets, indicating the learning capability of our model. By the end of the second epoch, the model achieved a training accuracy of 72.43%, and the validation accuracy improved to 70.74%.

By the 7th epoch, the validation accuracy had reached 72.44%, and the model's loss had reduced to 0.494. At the 8th epoch, we observed a significant jump in the validation accuracy, reaching 74.72%. This suggested that the model was generalizing well and was capable of classifying unseen data accurately.

However, in the following epochs, there was a slight increase in the validation loss, despite the model's improved accuracy, suggesting a bit of overfitting. After the 10th epoch, the training accuracy reached 83.78%, and the validation accuracy stood at 78.01%.

4.2. Model Trained Using Pretrained Model Xception

In my research project, I leveraged the power of the pre-trained Xception model for an image classification task. After applying my preprocessing pipeline and running the model, the Xception model demonstrated strong performance. Specifically, during the 21st epoch, the Xception model achieved an impressive accuracy of 74.52% on the validation set. This result underscores the efficacy of the Xception model in this particular image classification task, illustrating its robust generalization capabilities.

4.3. Model Trained Using Pretrained Model Resnet152v2

In a parallel analysis during my research, I applied the same image preprocessing procedure to another renowned pre-trained model, ResNet152V2, in the same image classification task. The performance of the ResNet152V2 model was robust and achieved a notable accuracy. Precisely, during the evaluation stage, the ResNet152V2 model reached an accuracy of 73.07% on the validation set. This result highlights the strong performance and the model's capability to effectively generalize in this specific image classification context.

In conclusion, our developed model demonstrated promising performance with accuracy of 78%, achieving a respectable accuracy in classifying the severity of retinopathy in the APTOS 2019 Blindness Detection dataset. Future work may include tuning the model to mitigate overfitting, enhancing its generalizability, and potentially improving the model's performance further.

5. CONCLUSION

One of the illnesses with the fastest recent growth rates is diabetes. A patient with diabetes has a 30% chance of developing diabetic retinopathy,

according to several surveys. There are several phases of DR, from moderate to severe, and PDR (Proliferative Diabetic Retinopathy) is the last stage. If the condition is not discovered in the earlier stages, it progresses to blindness, floaters, and impaired vision in its later stages. There is still a need for simple access to such models despite the fact that several computer vision-based strategies for the automatic identification of DR employing hands-on engineering and end-to-end learning approaches have been offered.

In this regard, the study described in this paper suggests a novel method for early DR detection based on a Convolutional Neural Network (CNN) model based on Discrete Cosine Transform (DCT) that is specially designed for mobile devices.

In developing this model, we utilized one publicly accessible Kaggle dataset for training and validating our CNN-based DCT network. We found that image pre-processing is an essential step in this process.

Our results indicate that the CNN-based DCT model successfully classifies the early stages of DR. This aligns with our central aim of encouraging early detection before the progression to more advanced stages such as PDR. However, it's important to note that the model does encounter some difficulty in classifying the final stages of DR.

Early DR stages are notoriously difficult to classify, as confirmed by related work in the field. However, our proposed CNN-based DCT model exhibits encouraging results for early stage classification. It particularly excels at distinguishing Non_DR from the mild to moderate stages, thanks to the pre-processing technique employed.

Nonetheless, our study did uncover a limitation in the model's performance when it came to classifying the last two stages of the disease. We believe this could be due to the fact that the characteristic features of DR's later stages do not replace the earlier stages' features but rather augment them. This means that features from the earlier stages still exist in the later stages, complicating their differentiation. Future work will aim to improve the model's performance for these advanced stages.

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