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# Diabetic Retinopathy Detection using Convolutional Neural Network

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## ABSTRACT

In order to automate the identification of diabetic retinopathy (DR) using colour fundus retinal pictures, we suggest a convolutional neural network (CNN) technique. To recognise retinal characteristics like micro-aneurysms and hemorrhages, our network employs CNN and denoising. Our models were created using Theano, an open-source numerical computation tool built on Python. Using a potent GPU and a free Kaggle dataset, we trained this network. On more than 3,000 validation images from a data set of more than 30,000 photos, our model achieves over 95% accuracy for two class classification and over 85% accuracy for five class classification.

## 1 INTRODUCTION

1.1 DiabeticRetinopathy

Diabetes patients may develop the disease known as diabetic retinopathy.The retina, the light-sensitive lining in the back of the eye, suffers gradual damage as a result. Diabetic retinopathy is a serious sight-threateningcomplicationof diabetes.Diabetes impairs the body's capacity to utilise and store sugar. (glucose).

The condition is characterised by an excess of sugar in the blood, which can harm many body parts, including the eyes. Diabetes over time harms tiny blood vessels all across the body, including the retina. When these tiny blood vessels leak blood and other fluids, diabetic retinopathy develops. As a result, the retinal tissue swells, causing vision to become hazy or blurry. Usually, both eyes are affected by the illness.The likelihood of developing diabetic retinopathy increases with the duration of diabetes.Diabetes cretinopathy can result in blindness if neglected.

Having a dark, empty space in the centre of your vision, seeing spots or floaters, blurred vision, and difficulty seeing well at night are all signs of diabetic retinopathy.

What is the treatment for diabetic retinopathy?
Blood and fluid leaking into the retina can be stopped using laser therapy (photocoagulation). In order to try to plug the leaks, tiny burns can be made in parts of the retina with aberrant blood vessels using a laser beam.
The stage of the disease determines the course of treatment for diabetic retinopathy.Any form of treatment aims to delay or halt the disease's course.

Regular monitoring could be the only remedy for non-proliferative diabetic retinopathy in its early stages. Following your doctor's recommendations for food, exercise, and blood sugar management can help slow the progression of the illness.
Drugs are injected into the eyes to prevent the growth of aberrant blood vessels and may lessen the harmful effects of diabetic retinopathy. Macular edoema can develop if the disease progresses and the aberrant blood vessels leak blood and

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fluid into the retina.

This leaking can be stopped using laser therapy (photocoagulation). In order to attempt to stop the leaks, a laser beam of light causes minor burns in regions of the retina with aberrant blood vessels. Proliferative diabetic retinopathy causes widespread blood vessel growth in the retina, which can be addressed by scattering laser burns throughout the retina in a pattern. As a result, aberrant blood vessels diminish and eventually vanish. In order to protect central vision during this treatment, some side vision may be lost.

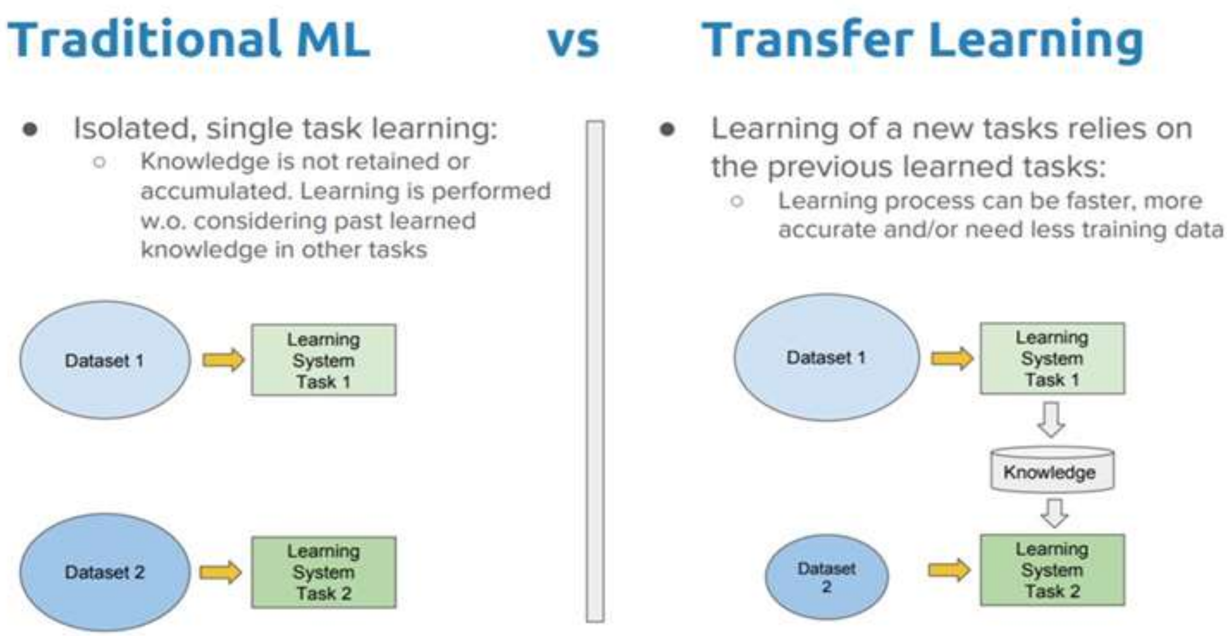


Fig-1: Differences between traditional Machine Learning and Transfer Learning

## 2. LITERATURE SURVEY AND RELATED WORK

In order to discover the necessary features, feature extraction-based classification algorithms require specialist knowledge. They also include a time-consuming process of feature selection, identification, and extraction. Additionally, it has been observed that DL-based systems, such CNNs, outperform feature extraction-based techniques[26].Learning from scratch and transfer learning are the two main types of DLtraining for DR categorization.

To categorise DR, feature extraction-based classification and DL were employed. In Acharya et al.'s study [18], a support vector machine classifier was utilised to extract features from 300 fundus images, and it then classified the images into 5 classes with sensitivity of 82% and specificity of 88%.To extract DR lesions such blood vessels, exudates, and microaneurysms, various algorithms were designed [19]. Exudates have been removed in order to grade DR [20–24].

In order to divide a dataset of 128 175 fundus photos into two classes—the first class containing images with severity levels 0 and 1 and the second class containing levels 2, 3, and 4—a convolutional neural network (CNN) was trained [27].According to an operating cut point chosen for high sensitivity, [27] had a sensitivity of 97.5% and specificity of 93.4% on the 9963-image EyePACS-1 dataset; it scored a sensitivity of 96.1% and specificity of 93.9% on the Messidor-2 dataset; and in an evaluation cut point chosen for high specificity, the sensitivity and specificity were 90.3% and 98.1% on the EyePACS-1 while 87% and 98.

A DL model was trained from scratch on the MESSIDOR-2 dataset for the automatic detection of DR in [29], and a96.8%sensitivity and 87%specificitywere scored. Pratt et al. [28] trained aCNN using stochastic gradient descent algorithm to classify DR into 5 classes, and it achieved 95% specificity, 75% accuracy, and 30% sensitivity.

A CNN was trained from scratch to separate referable and non-referable classes from fundus images from the Kaggle dataset, and it achieved sensitivity and specificity scores of 96.2% and 66.6%, respectively [30]. A dataset of 71896 fundus pictures was utilised to train a CNN DR classifier, which produced sensitivity and specificity values of 90.5% and 91.6%, respectively[31]. A DL model with sensitivity and specificity scores of 94% and 98% was created and trained using a dataset of 75137 fundus images[32].

Mohammadian et al. [33] improved the Inception-V3 and Exception pre-trained models to categorise the Kaggle data set into two classes in order to avoid the time and resources used during DL.After balancing the dataset with data augmentation, [33] arrived at accuracy scores of 87.12% on the Inception-V3 model and 74.49% on the Exception model.

When developing a computer-aided diagnosis for DR, Mansour [38] used the Kaggle dataset to train a deep convolutional neural network utilising transfer learning for feature extraction. 2000 fundus images from the Kaggle data set were used by Dutta et al. [39] to train the deep neural network, VggNet16 model, and allowfeedforward neural network. The accuracy of shallow neural networks was 41%, deep neural networks were 86.3% accurate, and VggNet-16 was 78.3% accurate on a test dataset of 300 images[39].

They divided each image into four 300x300 images and resized the input images to 600x600, then fed these images into separate pre-trained Inception-V3 models, which they called the Inception@4. A training dataset of size 4476 was collected and labelled into four classes depending on abnormalities and required treatment [40]. After it became clear that Inception@4's accuracy results were superior to those of VggNet and ResNet models, it was implemented on a web-based DR classification system.

Higher convolution layer s are thought to enable the network to learn more detailed information.The last convolutional layer, which is the deepest layer of the network, should teach the first layer how to classify DR characteristics like hard exudate. The network starts with convolution layers that include activation, followed by batch normalisation. All max pooling is carried out using strides of size 2x2 and kernelsize 3x3. The network is flattened to one dimension after the last convolutional block. It employs weighted class weights relative to the amount of photos in each class to prevent overfitting. When we reach the dense five node classification layer, which employs a SoftMax activation function to predict our classification, we dropout on dense layers in a similar manner to reduce overfitting. To prevent over reliance on certain network nodes, the leaky rectified linear unit 13 activation function was utilized, applied with a value of 0.01.Similarly,intheconvolutionlayers,L2regularization wasusedforweightandbiases.The often used categorical cross-entropy function was the loss function that was optimised.

## 3 Implementation Study

An artificial neural network termed a convoluted neural network (CNN) processes pixel input using the convolution mathematical function. It is frequently employed for image processing and recognition applications. An input layer, hidden layers, and an output layer make up a CNN. Convolutional, pooling, and completely linked layers are some of the hidden layers.

A convolutional neural network typically includes three layers. And with the use of a classifier example, we can better comprehend each layer individually. It allows you to categorise an image of an X and O. We will therefore comprehend all four layers through the scenario.

**Convolutional Neural Networks have the following layers:**

- Convolutional
- ReLU Layer
- Pooling
- Fully Connected Layer

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## 4 PROPOSED WORK

Using the transfer learning technique, a model developed for one task is applied to another similar task. Transfer learning is an optimisation that enables quick development or better results when modelling the second task.

CNNs can be viewed as image feature extractors that operate automatically. A CNN efficiently leverages nearby pixel information to down sample the image first by convolution and then uses a prediction layer at the end, however if we use an algorithm with pixel vector we lose a lot of spatial interaction between pixels.

Yann Le Cun introduced this idea for the first time in 1998 for the categorization of digits using a single convolution layer. Later, in 2012, Alex Net, using many convolutional layers to attain the state-of-the-art in image net, popularised it. Consequently, they are now the preferred algorithm for picture classification problems.

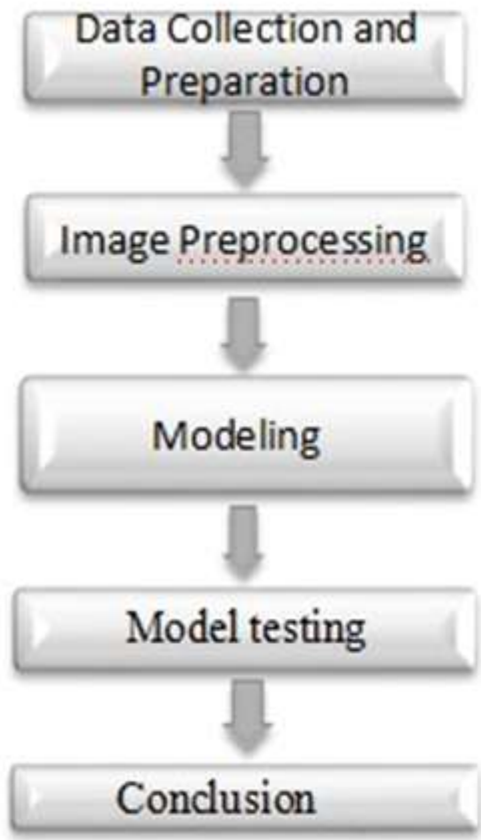


Fig-1: System architecture

## 5 METHODOLOGIES

**Step1: Processing**

Step 2: Pre-trained deep learning model and direct feature extraction

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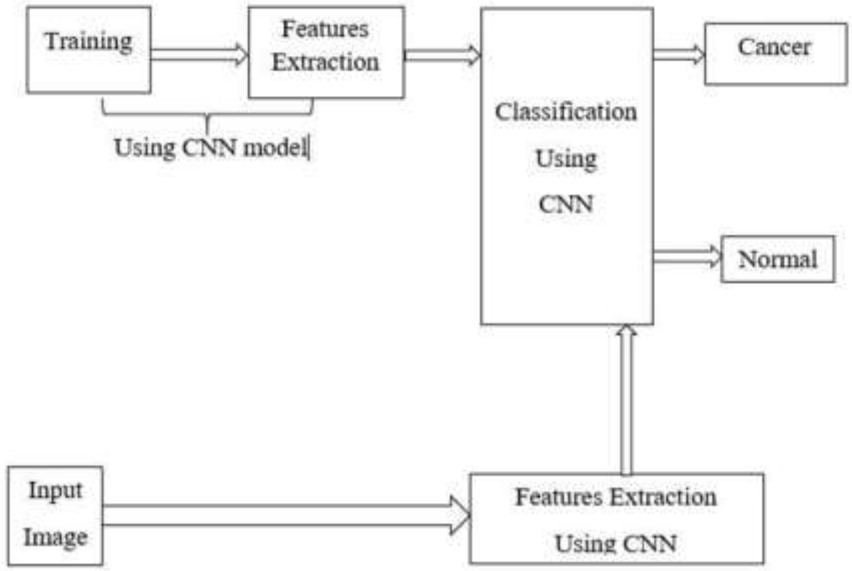


**Fig-1: Usage of CNN model**

The training and validation processes are among the crucial steps in developing an accurate process model using CNNs. The dataset for training and validation processes consists of two parts; the training features set which are used to train the neural network and the validation features set which are used to validate the neural network's performance.

Neural networks are used in the automatic detection of cancer in blood samples because of their well-known technique as a successful classifier for many real applications. The training and validation processes are among the crucial steps in developing an accurate process model using CNNs. In the training part, connection weights were always updated until they reached the defined iteration Number or suitable error.

## 6 RESULTS AND DISCUSSION SCREENSHOTS

```
In [1]: from tensorflow import lite
        import tensorflow as tf
        from tensorflow import keras
        from tensorflow.keras import layers
        import numpy as np
        import pandas as pd
        import random, os
        import shutil
        import matplotlib.pyplot as plt
        from matplotlib.image import imread
        from keras.preprocessing.image import ImageDataGenerator
        from tensorflow.keras.metrics import categorical_accuracy
        from sklearn.model_selection import train_test_split

        Using TensorFlow backend.
```

**Fig-2: Importing modules**

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[2]:

| | id_code | diagnosis | binary_type | type |
|---|---|---|---|---|
| 0 | 000c1434d8d7 | 2 | DR | Moderate |
| 1 | 001639a390f0 | 4 | DR | Proliferate_DR |
| 2 | 0024cdab0c1e | 1 | DR | Mild |
| 3 | 002c21358ce6 | 0 | No_DR | No_DR |
| 4 | 005b95c28852 | 0 | No_DR | No_DR |

**Fig-3: Displaying Data**

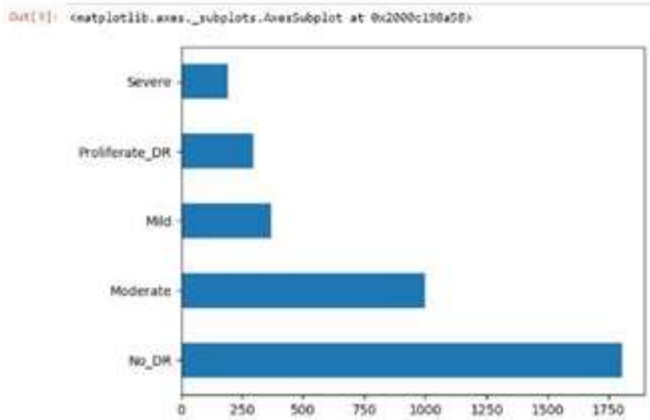


**Fig-4: Displaying Bar graph**

```
No_DR            1263
Moderate          699
Mild              258
Proliferate_DR    207
Severe            135
Name: type, dtype: int64

No_DR            271
Moderate         150
Mild              56
Proliferate_DR    44
Severe            29
Name: type, dtype: int64

No_DR            271
Moderate         150
Mild              56
Proliferate_DR    44
Severe            29
Name: type, dtype: int64
```

```
Found 2562 images belonging to 2 classes.
Found 550 images belonging to 2 classes.
Found 550 images belonging to 2 classes.
```

**Fig-5: displaying individual data in the dataset**

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```
18/18 [==============================] - 23s 1s/step - loss: 0.6789 - acc: 0.5127
Loss:  0.6788606428437762
Accuracy:  0.51272726
```

**Fig-6: Showing loss and accuracy**

```
WARNING:tensorflow:From c:\users\rushitha\appdata\local\programs\python\python37\lib\site-packages\tensorflow_core\python\ops\i
nit_ops.py:97: calling GlorotUniform.__init__ (from tensorflow.python.ops.init_ops) with dtype is deprecated and will be remove
d in a future version.
Instructions for updating:
Call initializer instance with the dtype argument instead of passing it to the constructor
WARNING:tensorflow:From c:\users\rushitha\appdata\local\programs\python\python37\lib\site-packages\tensorflow_core\python\ops\i
nit_ops.py:97: calling Zeros.__init__ (from tensorflow.python.ops.init_ops) with dtype is deprecated and will be removed in a f
uture version.
Instructions for updating:
Call initializer instance with the dtype argument instead of passing it to the constructor
WARNING:tensorflow:From c:\users\rushitha\appdata\local\programs\python\python37\lib\site-packages\tensorflow_core\python\ops\i
nit_ops.py:97: calling Ones.__init__ (from tensorflow.python.ops.init_ops) with dtype is deprecated and will be removed in a fu
ture version.
Instructions for updating:
Call initializer instance with the dtype argument instead of passing it to the constructor
DR
```

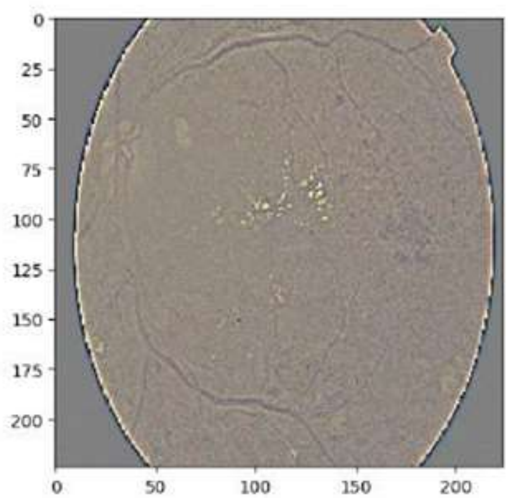


**Fig-7: Displaying Final output**

## 7. CONCLUSION AND FUTURE WORK

Transfer learning is used in this study to categorise DR into 5 classes with substantially less training data than other DR classification algorithms previously applied. This was done in order to develop a method for effectively learning from tiny datasets in order to build a DL model that works well on unseen data because training data is scarce in healthcare.Our model has a greater data accuracy than previous methods that used transfer learning to classify data over the whole Kaggle DR challenge dataset. Due to the chosen training approach, batch gradient descent with increasing learning rate, and the quadratic weighted kappa loss function, our model has achieved a superior performance. Deep learning techniques should be used to classify DR since they can be used to other medical image classification issues that face the challenge of insufficient training data. These algorithms can learn from tiny datasets to categorise medical images. It is important to conduct tests to compare the results of various trained deep convolutional network.

We will apply the feature extraction portion from the pre-trained model and apply to algorithms such as support vector machines and changing the performance measures such as specificity and sensitivity as it gives healthcare more confidence in the use of the model in real time. we will apply the different image pre-processing techniques to the dataset and compare the performances and will compare the different transfer learning techni

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