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## Face Severity Analysis By Using Deep Learning

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### Abstract

Facial diagnosis became common due to discussions thousands of years ago of the link between disease and the face. Here we will use deep learning (CNN) techniques for the detection of facial diseases. In this article, we propose the use of computer-assisted facial diagnosis to perform deep transfer learning for facial recognition in several diseases. In our study, we performed computer-assisted facial diagnosis for several diseases (Beta-thalassemia, hyperthyroidism, Down syndrome, and leprosy) using a limited data set. In the test, facial recognition deep transfer learning can achieve an overall accuracy rate of more than 90%, which is better than clinicians and traditional machine learning techniques.

**Keywords:** Facial Diagnosis, Facial recognition, Deep transfer learning, beta-thalassemia, hyperthyroidism, Down syndrome, leprosy

### Introduction

Nowadays, it is still difficult for people to take a medical examination in many rural and underdeveloped areas because of the limited medical resources, which leads to delays in treatment in many cases. Even in metropolises, limitations including the high cost, long queuing time in hospital and the doctor-patient contradiction which leads to medical disputes still exist. Computer-aided facial diagnosis enables us to carry out non-invasive screening and detection of diseases quickly and easily. Deep learning inspired by the structure of human brains is to use a multiple-layer structure to perform nonlinear information processing and abstraction for feature learning. Face recognition refers to the technology of verifying or identifying the identity of subjects from faces in images or videos. A CNN is a set of stacked layers consisting of nonlinear and linear processes. These layers are collectively called convolutional layers, clustering layers, nonlinear directed linear unit (ReLU) layers, and in typical multilayer neural networks, fully connected layers, background loss layers of any CNN model. These layers are learned in a joint manner. The main building blocks of any CNN model are: convolutional layer, pooling layer, nonlinear Rectified Linear Units (ReLU) layer connected to a regular multilayer neural network called fully connected layer, and a loss layer at the backend. CNN has known for its significant performance in applications and used to detect or identifying the image.

### Related Work

#### 1. Material and Methods:

##### 1.1 Dataset:

The Disease-Specific Face (DSF) dataset used includes disease-specific face images which are collected from professional medical publications, medical forums, medical websites and hospitals with definite diagnostic results. In the task, face images (JPG files) in the dataset, and there are images in each type of disease-specific faces should be trained.

##### 1.2 Data Pre-processing:

Pre-processing is used to prepare picture data for model input so this pre-processing is necessary. For instance, convolutional neural networks' fully connected layers demanded that all the images be in arrays of the same size selection. This pre-processing also helps to reshaping and resizing the images into correct pixels.

##### 1.3 Testing & Training:

Testing and Training is a method to measure the accuracy to predict the image. We can split the data set into two sets: a training set and a testing set, 80% for training, and 20% for testing. We can train the model using CNN algorithm.

## 2. Algorithm

### 2.1 CNN Algorithm

Convolutional Neural Network, also known as ConvNet. CNN is an artificial neural network widely used in image recognition and classification. Therefore, CNNs are used to recognize images. CNNs play an important role in various tasks/functions such as image processing problems. ConvNets require much less pre-processing than other classification methods. It has 4 steps, they are given below:

- 1.Convolution layer
- 2.ReLU layer
- 3.Pooling layer
- 4.Fully connected layer

#### Step 1: Convolution Layer

In this process of extracting valuable features from an image. A convolution layer has several filters that perform the convolution operation. Every image is considered as a matrix of pixel values.

#### Step 2: ReLU Layer

ReLU stands for the rectified linear unit. Once the feature maps are extracted, the next step is to move them to a ReLU layer. ReLU performs an element-wise operation and sets all the negative pixels to 0. It introduces non-linearity to the network, and the generated output.

#### Step 3: Pooling Layer

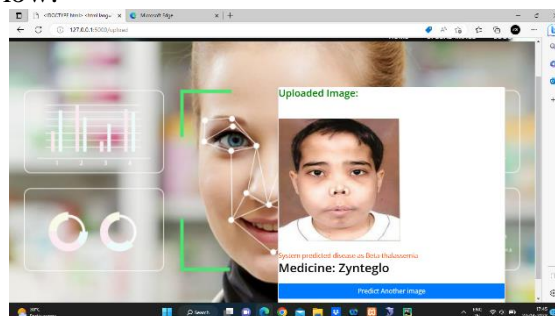
Pooling is a down-sampling operation that reduces the dimensionality of the feature map.

#### Step 4: Fully connected Layer

Fully connected layer refers to a neural network in which each neuron applies a linear transformation to the input vector through a weight's matrix. As a result, all possible connections layer-to-layer are present, meaning every input of the input vector influences every output of the output vector.

## 3. Result:

By using deep learning technique, we can detect facial diseases (Beta-thalassemia, hyperthyroidism, Down syndrome, and leprosy) and predict it easily by using CNN algorithm. Example the image is displayed as below.



**Fig:** Prediction of Beta-thalassemia

Like this the system can predict and detect all the facial diseases easily.

## 4. Conclusion:

In this more and more studies have shown that computer-aided facial diagnosis is a promising way for disease screening and detection. In this paper, we propose deep transfer learning from face recognition methods to realize computer-aided facial diagnosis definitely and validate them on single

disease and various diseases with the healthy control. The experimental results of above 90% accuracy have proven that CNN as a feature extractor is the most appropriate deep transfer learning method in the case of the small dataset of facial diagnosis. It can solve the general problem of insufficient data in the facial diagnosis area to a certain extent. In future, we will continue to discover deep learning models to perform facial diagnosis effectively with the help of data augmentation methods.

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