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Medical Image Classification Using CNN

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Abstract

Deep learning is one of the most unexpected machine learning techniques which is being used in many applications like image classification, image analysis, clinical archives and object recognition. With an extensive utilization of digital images as information in the hospitals, the archives of medical images are growing exponentially. Digital images play a vigorous role in predicting the patient disease intensity and there are vast applications of medical images in diagnosis and investigation. Due to recent developments in imaging technology, classifying medical images in an automatic way is an open research problem for researchers of computer vision. For classifying the medical images according to their relevant classes, a most suitable classifier is most important. Where we are proposing our model where the algorithm is trained for classifying medical images by deep learning technique. A pre-trained deep convolution neural network (GoogleNet) is used that which can classifies the various medical images for various body organs. This method of image classification is beneficial to predict the appropriate class or category of unknown images. The results of the experiment exhibit that our method is best suited to classify various medical images.

Keywords: Medical image classification, pre-trained DCNN, convolution neural network, deep learning

1. INTRODUCTION

1.1 Introduction

Image classification is the primary domain, in which deep neural networks play the most important role of medical image analysis. The image classification accepts the given input images and produces output classification for identifying whether the disease is present or not. In our model we mainly classify the different types of organs and predict the accuracy.

One of the most imperative problems faced in the domain area of image recognition is the classification of medical images. The major intention of medical image classification is to classify medical images into several elements to assist medical practitioners or physicists in diagnosing disease. Hence, medical image classification is split into two steps. The first and foremost step of medical image classification is to extract the essential features from the acquired input image. The second step in medical image classification is utilizing the features to construct models that classify the image data set. In the recent past, medical practitioners customarily utilized their specialized experience to extract features so that classification of medical images could be performed into several classes. However, this manual medical image classification was found to be highly cumbersome and time consuming.

Medical image classification involves the process of segregating medical-related information into a useful form. Classification of medical images is based on placing image pixels with similar values into groups. With the placement of similar values into groups, common pixels are identified and are denoted by these pixels. Hence, a correctly classified image usually denotes the areas on the ground that share specific features as specified in the classification scheme.

Image classification is where a computer can analyse an image and identify the 'class' the image falls under. (Or a probability of the image being part of a 'class'.) A class is essentially a label, for instance, 'car', 'animal', 'building' and so on. For example, you input an image of a sheep. Image classification is the process of the computer analysing the image and telling you it's a sheep. (Or the probability that it's a sheep.) For us, classifying images is no big deal. But it's a perfect example of Moravec's paradox when it comes to machines. (That is, the things we find easy are difficult for AI.)

Early image classification relied on raw pixel data. This meant that computers would break down images into individual pixels. The problem is that two pictures of the same thing can look very different. They can have different backgrounds, angles, poses, and etcetera. This made it quite the challenge for computers to correctly 'see' and categories images.

2. Literature Survey

[1] Q. Zhu, B. Du, and P. Yan: Accurate segmentation of the prostate from magnetic resonance (MR) images provides useful information for prostate cancer diagnosis and treatment. However, automated prostate segmentation from 3D MR images still faces several challenges. The complex background texture and large variation in size, shape and intensity distribution of the prostate itself make segmentation even further complicated. Since large-scale dataset is one of the critical components for the success of deep learning, lack of sufficient training data makes it difficult to fully train complex CNNs. To tackle the above challenges, in this paper boundary-weighted domain adaptive neural network (BOWDA-Net) is proposed. To make the network more sensitive to the boundaries during segmentation, a boundary-weighted segmentation loss (BWL) is proposed.

Summary: In this paper boundary-weighted domain adaptive neural network (BOWDA-Net) is proposed. To make the network more sensitive to the boundaries during segmentation, a boundary-weighted segmentation loss (BWL) is proposed. . Furthermore, an advanced boundary-weighted transfer leaning approach is introduced to address the problem of small medical imaging datasets. We evaluate our proposed model on the publicly available MICCAI 2012 Prostate MR Image Segmentation (PROMISE12) challenge dataset.

[2] Q.Zhu, B.Du, P.Yan, H.Lu, and L.Zhang: Bladder wall segmentation from Magnetic Resonance (MR) images plays an important role in diagnosis. Since the thickness of the bladder wall is a key indication of bladder cancer. There are several methods that have been used for bladder wall segmentation, such as level sets and Active Shape Model (ASM). However, the weak boundaries, the artifacts inside bladder lumen and the complex background outside the bladder wall make the bladder wall segmentation very challenging. To overcome these difficulties and obtain accurate bladder walls, in this paper, a shape prior constrained particle swarm optimization (SPC-PSO) model is proposed to segment the inner and outer boundaries of the bladder wall. The bladder walls are divided into two categories: strong boundaries and weak boundaries by the proposed model.

3. OVERVIEW OF THESYSTEM

3.1 Existing System

This model emphasizes an existing method that which is designed using the machine learning architecture which is used to classify the various medical images. With an extensive utilization of digital images as information in the hospitals, the archives of medical images are growing exponentially. Digital images play a vigorous role in predicting the patient disease intensity and there are vast applications of medical images in diagnosis and investigation. To make this in the easier way Support Vector Machine (SVM) is used that which can classifies the various medical images for various body organs.

3.1.1 Disadvantages of Existing System

- Low efficiency.
- Time consuming.
- High complexities.
- No accurate classification

3.2 Proposed System

The proposed model emphasizes a deep network architecture which is used to classify the various medical images. With an extensive utilization of digital images as information in the hospitals, the archives of medical images are growing exponentially. Digital images play a vigorous role in predicting the patient disease intensity and there are vast applications of medical images in diagnosis and investigation. Hence, we are proposing our model where the algorithm is trained for classifying medical images by deep learning technique. A pre-trained deep convolution neural network (GoogleNet) is used that which can classifies the various medical images for various body organs.

3.3 Methodology

User

1. System:

1.1 Create Dataset:

The dataset containing images of the desired objects to be recognize is split into training and testing dataset with the test size of 20-30%.

1.2 Pre-processing:

Resizing and reshaping the images into appropriate format to train our model. **1.3Training:**

Use the pre-processed training dataset is used to train our model using CNN algorithm.

2. User:

2.1 Register

The user needs to register and the data stored in MySQL database**.**

2.2 Login

A registered user can login using the valid credentials to the website to use a application.

2.1 About-Project

In this application, we have successfully created an application which takes to classify the images.

2.2 Upload Image

The user has to upload an image which needs to be classify the images.

2.3 Prediction

The results of our model is displayed as either Rice Blast, Leaf Blight, Healthy & Brown Spot.

2.6 Logout

Once the prediction is over, the user can logout of the application.

ALGORITHM

1. Convolutional Neural Network

Step1: convolutional operation

The first building block in our plan of attack is convolution operation. In this step, we will touch on feature detectors, which basically serve as the neural network's filters. We will also discuss feature maps, learning the parameters of such maps, how patterns are detected, the layers of detection, and how the findings are mapped out.

Step (1b): ReLU Layer

The second part of this step will involve the Rectified Linear Unit or Relook. We will cover Relook layers and explore how linearity functions in the context of Convolutional Neural Networks.

Not necessary for understanding CNNs, but there's no harm in a quick lesson to improve your skills.

4 Architecture

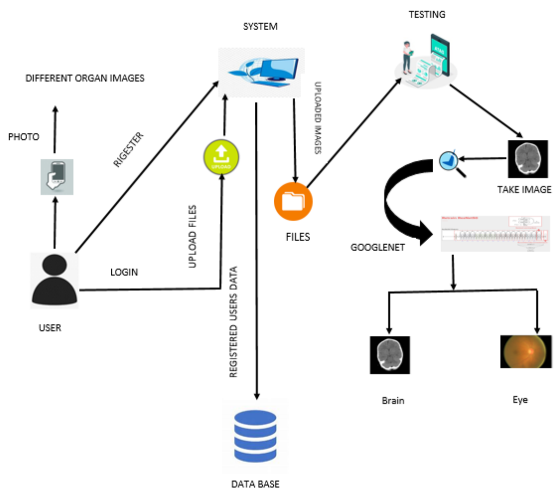
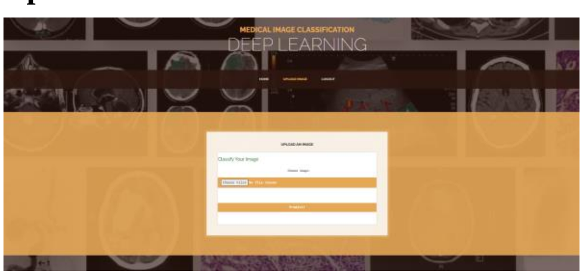


Fig 1: Frame work of proposed method

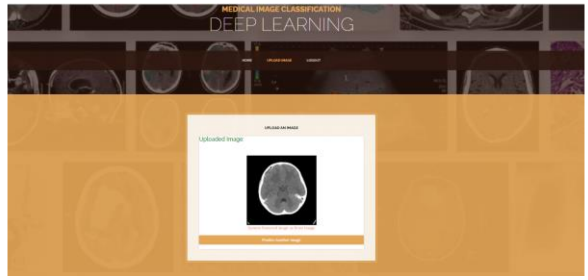
5 RESULTS SCREEN SHOTS

Home Page:

Upload Dataset:



Choose options:



Predict Result:

6. CONCLUSION

For classification purpose, deep learning-based framework for medical image classification by training the images is proposed. In this regard, diagnosis is one of the main requirements of the existing era and investigated or examine to specific diseases. Hence, we have proposed a novel deep convolution network-based approach that is assist of doctors and physicians in making reasonable decisions. The results obtained from the proposed method outperformed state-of the-art methods that is reported for the same dataset.

FUTURE WORK

In future, we aim to explore large-scale image datasets for medical image classification and detection problems. And we can go for another types of pre-trained tea that can perform well and gives high classification. By which, we can classify different types of organs and detect the problems easily.

7. References

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