

Ain Shams University
Faculty of Engineering
Computer and Systems Department

Image Categorization

A thesis submitted in partial fulfillment for the requirements of Masters of Science degree in Electrical Engineering

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Thesis Summary

This thesis presents an approach of applying image categorization on a medical image data-set. Image categorization helps recognize categories of objects, through training a classifier for those classes. One of the methods for achieving this task is image classification using convolutional neural network. Another idea of classifying image can be done through instance segmentation where objects of interest will be segmented and classified at the same time.

We target classifying different cervix types. To do so we compared two different pipelines for achieving this purpose and then decide which of them is better than the other. We compare the pipeline of instance segmentation which gives the class of the image as one of its outputs beside detecting the object with a bounding box and the mask of the object of interest. The second approach to is train a vanilla convolutional neural network with the bounding boxes detected from the previous pipeline, those networks have shown good results on Imagenet and COCO dataset, so we chose them as our second approach.

We used the dataset provided by Intel & MobileODT Cervical Cancer Screening competition on Kaggle. It was a dataset of 3 different types of cervices and it was required to find a method to classify them.

Using instance segmentation gave better accuracy than using the classification pipeline solely.

We achieved and accuracy of about 62% with first approach compared to 55% with the second method.

Key words: Convolutional Neural Network, Cervical Cancer, Instance Segmentation

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AIN SHAMS UNIVERSITY FACULTY OF ENGINEERING COMPUTER AND SYSTEMS DEPARTMENT

Abstract

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by Marwa SAID

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