Logo detection and recognition using CNN

by

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ABSTRACT

LOGO DETECTION AND RECOGNITION USING CNN

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Thesis supervisor: Senior Lecturer MSc. Konstantin Latuta

Keywords: Logo detection, Logo recognition, Computer Vision, Machine Learning, Convolution Neural Network, Classification, Recurrent Neural Network, Pattern Recognition, Object Recognition,Data augmentation

This thesis describes the research work carried out to fulfill the Bachelor in Computer Science at the Suleyman Demirel University. Research was in Technopark at Suleyman Demirel University and was supervised by Konstantin Latuta. Logo detection and recognition continues to be of great interest to the document retrieval community as it enables effective identification of the source of a document. This paper contributes the design of the system able to detect the logo of any product from the documents and images after that recognize it from the archive via the convolutional neural network. For detecting and recognize of logos implemented via convolutional neural network, which creates initial classification to determine the presence of the logo on the document or image.As regards to the former, a collection of logos was designed and implemented to train the classier, to identify and to extract the logo features which were eventually used for logo detection and recognition. The latter regards the detection of logos from an input image. In particular, the experimental study aimed to detect if the input image contains one or more logos and to decide which logos are contained.

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LIST OF SYMBOLS/ABBREVIATIONS

MSE	Mean-square-error
CNN	Convolutional neural network
RNN	Recurrent Neural Network
CV	Computer Vision
ML	Machine Learning
LRT	Learning Rate
Conv	Convolutional layer
Pool	Pooling layer
ReLU	Rectified Linear Unit
Softmax	Normalized Exponential Function
Sigm	Special case of logistic function

CHAPTER 1

INTRODUCTION

1.1. Overview

Object recognition and object detection are ones of the lasting and most important goals in the computer vision.Because of this problem in a wide range of applications. For example, in copyright detection, contextual advertise placement, vehicle logo for an intelligent AI-based traffic-control system and brand detecting in social media. As well as these algorithms have many applications in location recognition, advertisement, and marketing. Presently advertising is a very powerful tool for income and attracting of customers.For this reason, the analysis of the brand and mention on different resources are very important and primary tasks for business analysts.In order to captive, attractive their customers and make better decisions, companies needs for analyzing the presence of their logos in photos, videos and another type of contents. Logos help to evaluation of identity between something.[1604.06083] [1701.02620] [1711.09822]

The logo mainly includes text and graphical symbols. In such cases, when the logo is in different parts of the image, the logo is inverted, the logo is distorted, as well as changed in size - recognition and definition of the logo is a very problematic and difficult task. For example, logos on their clothes, which are often deformed, which complicates its detection and recognition. [1511.02462]

Recent breakthroughs in deep learning improve recognition models with very extremely minimal loss function.Models which was created for recognition based on neural networks have excellent accuracy, speed, as well as these models, have the ability to be really smart. In short, the ultimate goal of the system, which is based on the recognition model, is to create a method that defines logos accurately and continuously learn from new logos.[1711.09822]

1.2. Related Work

In literature, I can find many works on logo detection, logo extraction, logo classification , logo retrieval and logo recognition.

1.2.1. Logo Detection Methods

CHAPTER 2

PROBLEM STATEMENT AND THESIS ORGANIZATION

2.1. Introduction

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2.2. Statement of the Problem

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2.3. Our Contributions

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2.4. Thesis Organization

The structure of the thesis is organized as follows:

- In Chapter 3, a general review of the most important adaptive filters used for echo cancellation application is presented.
- In Chapter 4, the proposed algorithm is presented. A review of the VSSLMS algorithm and a broad concept of the p-norm constraint are provided. The mean square convergence analysis and a stability criterion of the proposed algorithm are also carried out and presented.
- In Chapter 5, an experimental study is provided in order to compare the performance of the proposed filter with other l_1-norm and p-norm based sparse adaptive filters in the context of AEC.
- In Chapter 6, conclusions and a discussion on possibilities for future work are provided.

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REVIEW OF DEEP LEARNING AND PATTERN RECOGNITION ALGORITHMS

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3.3.5. Edge detection

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3.3.6. Dual clustering method

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3.4. Supervised Learning

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3.5. Optimization

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3.8. Summary

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4.2.2. Logo Recognition Training Framework

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CONCLUSIONS AND FUTURE WORK

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