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# Optical Character Recognition for Extremely Low Quality Images

Master's Thesis (30 ECTS)

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## Optical Character Recognition for Extremely Low Quality Images


**Abstract:**

Optical character recognition (OCR) from printed and handwritten documents is virtually a solved problem for all practical purposes. Modern OCR systems are able to achieve a 99.9% detection rate which is on par with human capabilities. Where most OCR systems fall short is when the the input is of low quality, such as containing large amounts of noise or motion blur, or being of low resolution.

A real world use-case of this problem is detecting car licence plates from a security camera feed. Security cameras are often of low resolution, use high levels of compression, and have low framerate since the video footage needs to be stored for a long period of time and storage cost is paramount. In addition, cars can move unpredictably causing motion blur during the capture of a video frame.

The goal of this project is to test various methods of improving OCR accuracy with low quality input. Namely,

- Training a neural network (NN) on low quality images. And testing results on low quality images.
- Training a NN on high quality images and testing on digitally enhanced low quality images.
- Training a NN on digitally enhanced low quality images and testing on digitally enhanced images.
- Using multiframe registration of frames from a video feed to improve detection quality.

The tests will be conducted using frames from a blurry, noisy, and low resolution video feed containing text. Third party solutions are used to extract areas containing text from those frames.

Some of the training and test data is gathered specifically for this task by filming, and extracting frames from, an intentionally blurry video. Additional synthetic motion blur is added to some of the images. Some data is gathered from available open source databases, such as images containing vehicle licence plates.



**Keywords:**

OCR, Deblurring, Low Quality, Low Resolution

**CERCS:**

# Contents

## Unsolved issues

# 1 Introduction

Optical character recognition (OCR) is the conversion of text in analog form, such as images or printed documents, into digital text. OCR is not a new concept by any means, a patent for a system which can be called the predecessor of modern OCR was already granted in 1931. Modern OCR systems are of course far more powerful.

## 1.1 Motivation

For all intents and purposes OCR is basically a solved problem for detecting text from clear and high resolution images containing printed or handwritten text. Modern systems perform on par with human capabilities in this regard, boasting a 99.9% detection rate. A problem still being researched, however, is OCR from low quality images. Low quality can mean low resolution, high levels of compression, containing artefacts generated by scanning for example, containing motion blur caused by movement of the object of the camera during image capture, or any combination thereof.

Accurate OCR from low quality images and video could solve several problems for automating processes where the system needs to detect some text. For example an autonomous parking garage, where a camera is filming approaching cars, a system analyses the video feed and opens the gate or barrier for cars with licence plate numbers matching authorized users.

## 1.2 Contributions

The goal of this thesis was test different approaches for such a system. Namely,

- Training a neural network (NN) on low quality images. And testing results on low quality images.
- Training a NN on high quality images and testing on digitally enhanced low quality images.
- Training a NN on digitally enhanced low quality images and testing on digitally enhanced images.
- Using multiframe registration of frames from a video feed to improve detection quality.

TODOWhat was my actual contribution?

## 1.3 Outline

**Chapter 2** describes the state of the art in OCR and low quality image enhancement and discusses the advantages and drwabacks of each of the approaches.
**Chapter 3** describes the research problem and the necessity of finding a solution to the problem.
**Chapter 4** describes in detail the approach taken to solve the problem.
**Chapter 5** describes the evaluation process of the results as well as comparison to related works.
**Chapter 5** concludes the thesis with a summary and research directions for the future

# 2 State of the Art

This section gives an overview of current commertial OCR and image enhancement solutions as well as research related to the topic.

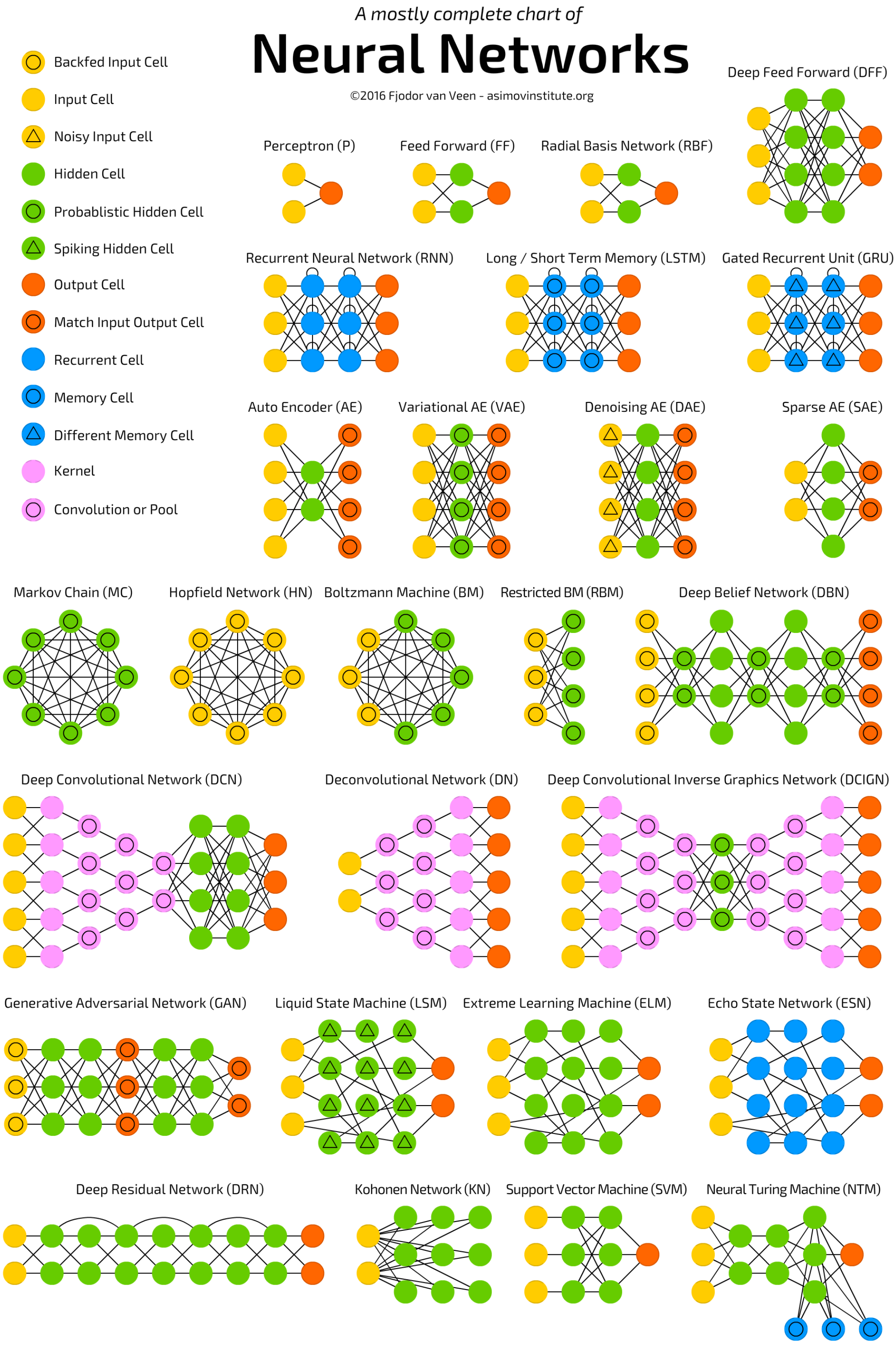
## 2.1 History

The history of OCR can be traced back to the late 1920s when inventor Emanuel Goldberg started developing a system he called a "Statistical Machine" which searched microfilm archives using an optical code recognition system. He was granted a patent for his invention in 1931, which was later acquired by IBM. [1]

Most of modern OCR systems are based on artificial neural networks, often called just neural networks (NNs). The theoretical base for NNs dates back to the end of the 1800s and is based on the structure of the human brain in which neurons interact with eachother and the bonds between neurons can strengthen and weaken over time. [2]

An artificial neural network consists of many simple connected processors, called artificial neurons, which produce activations based on an activation fuction producing real numbers in a predefined range. The simplest neural network consists of an input layer and an output layer. The neurons in the input layer produce activations based on the input. The output layer produces an output based on the activations of input layers. [2]

Most NNs are not as simple as that and contain any number of hidden layers between the input and output layers. These hidden layers each consist of any number of neurons which each produce an activation based on the output of another layer. There are various architectures used for NNs, some are combinations of other types of networks. This work mostly focuses on convolutional neural networks (CNNs) and recurrent neural networks (RNNs). [2]


A mostly complete chart of
Neural Networks
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Backfed Input Cell
Input Cell
Noisy Input Cell
Hidden Cell
Probablistic Hidden Cell
Spiking Hidden Cell
Output Cell
Match Input Output Cell
Recurrent Cell
Memory Cell
Different Memory Cell
Kernel
Convolution or Pool
Perceptron (P)
Feed Forward (FF)
Radial Basis Network (RBF)
Deep Feed Forward (DFF)
Recurrent Neural Network (RNN)
Long / Short Term Memory (LSTM)
Gated Recurrent Unit (GRU)
Auto Encoder (AE)
Variational AE (VAE)
Denoising AE (DAE)
Sparse AE (SAE)
Markov Chain (MC)
Hopfield Network (HN)
Boltzmann Machine (BM)
Restricted BM (RBM)
Deep Belief Network (DBN)
Deep Convolutional Network (DCN)
Deconvolutional Network (DN)
Deep Convolutional Inverse Graphics Network (DCIGN)
Generative Adversarial Network (GAN)
Liquid State Machine (LSM)
Extreme Learning Machine (ELM)
Echo State Network (ESN)
Deep Residual Network (DRN)
Kohonen Network (KN)
Support Vector Machine (SVM)
Neural Turing Machine (NTM)

[3]

CNNs are primarily used for image processing. CNNs are feedforward networks (FFNs), which means neurons do no back-propagate any information and only pass it forward to the next layer. A distinct feature of CNNs is that they consist of convolutional layers in which not all neurons are connected to all neaurons in the previous and next layers. [2]

RNNs are primarily used for text and speech processing. RNNs are FFNs like CNNs, however unlike CNNs they are stateful, meaning in addition to receiving data from the previous layer, each neuron retains data from previous passes. RNNs are also able to handle arbitrary input and output lengths unlike CNNs [2]

1979: convolution + weight replication + subsampling (Neocognitron)

## 2.2 State of the Art

CNNs and RNNs are not mutually exclusive, however, and Baoguang Shi et al devised one of the most promising novel OCR concepts in recent history in the form of a convolutional recurrent neural network (CRNN) in their 2015 paper "An End-to-End Trainable Neural Network for Image-based Sequence Recognition and Its Application to Scene Text Recognition".

Their reasoning is that popular models like CNN cannot be applied to sequence prediction, since they operate on fixed size inputs and outputs. CRNN then behaves like an RNN in that it can accept inputs and return outputs of arbitrary size, while still retaining properties of CNNs which make them invaluable in image processing.

### 2.2.1 Commertial OCR systems

Tesseract is probably the most well known OCR engine. It started as proprietary software developed by Hewlett Packard in 1985, but was open sourced in 2005. Since then its development is continued by the community. Development has been sponsored by Google starting from 2006.

citations

Tesseract supports over 100 languages by default and can be trained to work with any language or script.

## 3 Conclusion

what did you do?

What are the results?

future work?

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# Appendix

# I. Glossary

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