Bachelor Thesis

Segmentation of three dimensional MRI data

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1 Abstract

Password attacks are at the edge of accessing someones secrets. By learning to judge the strength of a password and by understanding how hackers execute attacks, users can make better estimations on how safe they are.

The entropy is widely used to measure how safe a password is, but many sources draw inaccurate conclusions between the entropy of a random password and the strength of a password that was chosen by a person. It is important to understand how these two differ and why realistic password strength is often hard to determine.

Todays hardware gives hackers incredibly powerful machines to launch different types of password attacks. Common password patterns lower possible permutations by such a magnitude that even seemingly safe passwords can be successfully attacked. In combination with frequently used passwords and personal information, hackers can further increase the effectiveness of their attacks.

By explaining common terminologies and analysing different datasets we will look at password attacks from the perspective of users, system administrators and hackers. All three benefit by understanding how the others operate in practice.

2 Introduction

Recent advances in Artificial Intelligence have led to workflows that not only run fully automated but also often exceed human performance. State of the art neural networks can classify images into thousands of categories more accurate and magnitudes faster than humans. They translate text between hundreds of languages, navigate cars autonomously through cities and detect intruders in computer networks. In most of these cases they have been trained on tens of thousands or even millions of data samples.

Neural networks have also found great success in the medical field, where new types of problems were introduced based on datasets that are much smaller. Medical imaging data includes MRI, Ultrasound and CT of which the latter is an invasive methods because it uses electromagnetic radiation.

3 Literature Review

3.1 Magnetic Resonance Imaging

text

3.2 Epiphyseal Plates

text

3.3 Neural Networks

text

4 Methods

4.1 Dataset

3d, mri, german males, 14-21, different resolutions, different perspectives, segmentation maps for 76, mhd files

4.2 Preprocessing

The number of parameters in a Neural Network usually range from hundreds of thousands to hundreds of millions values which will be adjusted during training. The complexity allows the model to learn on its own which features of an image are important for any given task. This works in conjunction with the fact that high volumes of data are available for the training.

Because of the small dataset that was available for this study, several types of data preprocessing were applied to the images. These techniques reduce the amount of information per sample and the amount of variance between multiple samples. This results in a complexity reduction of the problem the network is supposed to solve. Other preprocessing methods experimented with the difference between 2D and 3D data as well as the influence of seperate segmentation channels on the output.

4.2.1 Cropping

The framing of the raw images included large parts of the thigh and shin to be visible in the picture. Since these weren't relevant for the purpose of the study, they were cropped out. An algorithm was used to detect the center where Tibia and Femur meet and only use a square window around this point. There was no cropping applied on the z-axis.

4.2.2 Resizing

The images were also resized to a resolution that is common for Convolutional Neural Networks. 224x224 Pixels for width and height also allowed the use of Transfer Learning based on pretrained models. Also, this resolution still delivered enough detail for the segmentation maps.

On the z-axis everything was scaled to 36 slices, which meant a 1.5 upscale for the images provided by Jopp et al. and a minor downscale from the 41 slices that were taken specifically for this study.

Every image had now unified dimensions of 36x224x224 voxels.

4.2.3 Normalization

The normalization procedure of this dataset was executed in two steps. First the N4 Bias Correction was applied to the images, which tries to balance irregularities than happen when the MRIs were recorded. In the second step all intensity values were normalized to range from 0 to 1 so that every input is on the same scale.

4.2.4 2D and 3D data

Every three dimensional image was also converted to 36 slices of 224x224 pixels allowing the use of more common two dimensional CNN architectures. This reshaping multiplied the number of available samples by 36, but also reduced the data per image by the same factor. Although the total amount of information stayed the same the comparison between 2D and 3D data showed two major differences.

By using three dimensional convolutions the network can draw conclusions from the order of the slices within one image. This turned out to be helpful for the segmentation process and reduced the number of falsely detected bones. Using 3D data for regression and classification hurt the performance by such a magnitude that training became impossible.

Converting the data from 3D to 2D has no impact on the input information. It does however have a large impact on the output information when working with regression and classification. By using slices instead of volumes we gain 36 times more data points for the backpropagation process.

4.2.5 Seperate Bone Maps

4.3 Architectures

U-Net and alternatives

4.3.1 Channels

growth and initial size

4.3.2 Dropout

4.3.3 Batch Size

4.4 Training

IoU, Adam, early stopping, LR policy

5 Results

best model performance, parameter count, size

6 Discussion

age prediction, size of data, augmentation