IDENTIFICATION OF DEFECTIVE PRODUCTS WITH A CONVOLUTIONAL AUTOENCODER

HIBÁS TERMÉKEK FELISMERÉSE KONVOLÚCIÓS AUTOENKÓDERREL

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1 Abstract

1.1 English

With the utmost importance of successful detection of defective products in mass production, the need for more precise detection technologies have arisen. One of these technologies are deep neural networks, more precisely convolutional autoencoder architectures. These archictectures have the advantage, that their requirement for training data on anomalous object are nonexistent, therefore bypassing the limitations of regular classification networks. In our work, we took on the challenge to develop, optimize and evaluate a convolutional autoencoder network for the successful identification of defective products. We built on the work of Bergmann et al. and used the MVTec dataset.

1.2 Hungarian

A selejtes termékek kiszűrésének problémájának rendkívüli fontossága miatt megnövekedett az igény a precíziós észlelési technológiák iránt. Az egyik ilyen technológia a mély tanulási, ezen belül is a konvolúciós autoencoder architektúrák. Ezen architektúrák előnye, hogy nincs szükség a hibás termékek, és azon belül is a különböző hibák egyenkénti betanítására, ezáltal lényegesen hatékonyabbak tudnak lenni a hagyományos, klasszifikációra használt hálóknál. A projekt során vállaltuk a kihívást, és egy már elkészített autóenkódert fejlesztettünk tovább, és optimalizáltunk az általunk vizsgálni kívánt termékre. Bergmann és társainak a munkáját felhasználva az MVTec adatbázisában összegyűjtött képanyaggal dolgoztunk.

2 Introduction

At our current age almost all of our goods are being mass produced. Mass production however needs to have strict quality assurance. The vast majority of current state-of-the-art production technologies are so advanced that defective products rarely appear on the production lines. Because of this, regular quality assurance methods have a hard time identifying and withholding these products. Therefore factories are interested in more advanced identification technologies, many of which are provided by the IT field. One of the most sought after technology is the usage of computer aided defective product identification, which mostly are built on some type of artificial intelligence, for example neural networks. The problem with regular classification neural networks arises from the fact, that defective products rarely appear and these defects can take on several different forms. Therefore training a regular classification network can be challenging. As a solution to this problem Convolutional Autoencoders (CAE) are being developed. This architecture allows us to identify anomalies on the given image of the product with minimal training data on the anomaly itself. We took on the challenge to develop a CAE architecture, optimize it, then successfully identy the vast majority of anomalous object. In our work we built on the work of Bergmann et al. and used the MVTec Anomaly Detection Dataset [1].

3 Literature review

"For the evaluation of methods that segment anomalies in images, only very few datasets are currently available to the public. Many of them are limited to the inspection of textured surfaces or focus on novelty detection in multi-class semantic segmentation scenarios".

There is a wide range of methods and approaches that have been suggested to solve the challenge of unsupervised anomaly detection, however these solutions are quite diverse.

There have been a lot of different databases available, but they they all lacked something. A dataset was specifically designed by Wieler and Hahn for optical inspection of textured surfaces, but the pictures were artifically generated, that can only be taken as an approximation to the real world, and the dataset was poorly labeled and the variance between the textures and generated was data is insignificant. [2-5]

4 Neural network Architecture, Testing and Performance metrics

Our neural network follows the convolutional autoencoder model which means the network first encodes the image in a layer with smaller dimensions. After that it tries to replicate the image and as the network is only trained on images with no anomalies it has a hard time reproducing them. This way if we send an image with an anomaly through the network and compare it with the original the anomaly should mostly disappear and it will not resamble the original image. This way we can filter out anomalies. Fort he network we added four convolutaional layers and a maxpooling on one side and it went from 128 filters down to 32 and after we decoded it back to 128 with a mirrored kind of neural network. Afte that we used the adam optimizer. We did not have much images so we thought the network for 100 epochs and set 16 s our batch size. To mach these numbers we set the steps per epoch to 250/16 and the validation steps to 2.

After that we extract the encoder network with trained weights in ordet to get the compressed output (latent space) of the input image. The compressed output is then used to calculate the KDE. Then we Calculate the KDE using sklearn. Get the encoded output of input images, Flatten the encoder output because KDE from sklearn takes 1D vectors as input and fit the KDE to the image latent data. After that we created a function that checks if the images are anomalies. We do this by checking the images density and reconstruction error. The numbers we compare these to are selected by trial and error and work most of the time. We have not thested for all of the data together yet only manually for a few examples.

5 Plans for the future

In the future we could improve on the model with adding more images to database even with just rotating the ones available. That would allow us to run more epochs and have better reconstuctive abilities.

References

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