

Deep Learning For Fraud Detection

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ICPR Fraud Detection Contest

- Identify which receipt is frauded.
- Small dataset of **600 Images** (470 genuine, 130 frauded).

Idea

- **Dividing** the image into smaller frames to increase the dataset.
- ► We used **linear methods for data augmentation** (rotation,flip).
- Detecting important information using Image Manipulation.
- Feed those important information to a **Deep Learning Network**.
- **Train** the network to detect if the image is **tampered** or **genuine**.

Finetune Deep Learning Models



Local Binary Patterns

$$\begin{pmatrix} 15 & 200 & 115 \\ 27 & 70 & 24 \\ 213 & 5 & 60 \end{pmatrix} \longrightarrow \begin{pmatrix} 1 & 0 & 0 \\ 1 & x & 1 \\ 0 & 1 & 1 \end{pmatrix} \mathcal{P} \begin{pmatrix} 2^0 & 2^1 & 2^2 \\ 2^3 & x & 2^4 \\ 2^5 & 2^6 & 2^7 \end{pmatrix} \longrightarrow \begin{pmatrix} 15 & 200 & 115 \\ 27 & 217 & 24 \\ 213 & 5 & 60 \end{pmatrix}$$

We first compare the reference pixel (here the pixel with the value 70) to each of his neighboor, if the neighboor is greater we replace it by a 0 and if it is lower or equal we replace it by a 1. We use \mathcal{P} for the ponderation operator, to transform the matrix into a binary number, $(11011001)_2 = 217$.

Discrete Wavelet Transform

$$x_{n,i} = \{70\ 56\ 61\ 49\} \rightarrow \{x_{n-1,i}, d-1_{n,i}\} = \{63\ 55\ 7\ 6\}$$

The transformation replaces the sequence with its pairwise average $x_{n-1,i}$ and difference $d_{n-1,i}$ defined as:

$$x_{n-1,i} = \frac{x_{n,2i} + x_{n,2i+1}}{2}, d_{n-1,i} = \frac{x_{n,2i} - x_{n,2i+1}}{2}$$

Results

All learning were done with a graphic card **Titan X Pascal** on the framework **Tensorflow**, 24 hours were needed to fully train our best network.

Network	Combined Methods	Accuracy
AlexNet	RGB	62 %
AlexNet	ELA+PCA+LBP	65 %
AlexNet	ELA+Wavelet+LBP	74 %
AlexNet	ELA+Wavelet+GrayScale	76 %
AlexNet	ELA+Wavelet+GrayScale+Fraud Creation	85 %
ResNet152	RGB	63 %
ResNet152	ELA+PCA+LBP	65 %
ResNet152	ELA+Wavelet+LBP	75 %
ResNet152	ELA+Wavelet+GrayScale	80 %
ResNet152	ELA+Wavelet+GrayScale+Fraud Creation	91 %

We extend the one-dimensional Wavelet transform in two dimensions.

$$\begin{bmatrix} 70 \ 56 \ 61 \ 49 \\ 52 \ 46 \ 39 \ 43 \\ 63 \ 45 \ 46 \ 54 \\ 53 \ 39 \ 40 \ 44 \end{bmatrix} \rightarrow \begin{bmatrix} 63 \ 55 \ 7 \ \ 6 \\ 49 \ 41 \ 3 \ -2 \\ 54 \ 50 \ 9 \ -4 \\ 46 \ 42 \ 7 \ -2 \end{bmatrix} \rightarrow \begin{bmatrix} 56 \ 48 \ 5 \ \ 2 \\ 50 \ 46 \ 8 \ -3 \\ 7 \ \ 7 \ \ 2 \ \ 4 \\ 4 \ \ 4 \ 1 \ -1 \end{bmatrix}$$

We first apply one dimensional Haar-wavelet in each row and then on each column.

Error Level Analysis

To find the tampered parts, we first apply **JPEG compression** with the quality loss of **90%**, then we calculate the difference between the first image and the compressed one.



Conclusion

- Achieved more than 90 % accuracy.
- Easily **adaptable** to any types of images (bills, document).
- Creating different types of image manipulation might improve our model's reliability.

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Figure 1:Left: Frauded image. Right: Manipulated areas found with ELA

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This technique is based on the idea that tampered areas can act differently to JPEG compression than the rest of the image.

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