A New Computer Vision Prototype for Document Cross Strokes Analysis in a Portable and Non-Destructive Way

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A new computer vision prototype for document cross strokes analysis in a portable and non-destructive way

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Abstract

Documentoscopy is a specialized field in criminalistics that verifies the authenticity of suspect documents during fraud investigations, providing crucial forensic evidence. Traditional documentoscopy relies on costly scanning electron microscopy (SEM), subject to bias, with an accuracy of about 63% in determining stroke sequences. Recent advancements led to cost-effective alternatives. Using Computer Vision (CV) and Convolutional Neural Networks (CNN), a prototype was developed to identify document fraud by analyzing stroke overlap. This electronic eye captures document images inexpensively, automatically, and non-destructively, followed by CNN-based analysis to classify stroke overlap due to different pens and inks. The prototype used with 2052 images of intersecting...
Article Title

lines from various pens and inks, achieved over 94% accuracy for training data and over 65% for testing data, surpassing traditional documentoscopy accuracy. The prototype is simple, affordable, user-friendly without specialized technicians, portable for fieldwork, and non-destructive, preserving samples for forensic counterproof in future investigations.

Keywords: Computer Vision, Documentoscopy, convolutional Neural Network, overlap strokes

1 Introduction

The documentoscopy is an area of criminalistic which is responsible to analyze the documents and generate a scientific technical report on the adulteration or not of the same in the process of criminal fraud of the same [1].

However, one of the main problems found in the documentoscopy is related to the evaluation of overlap of strokes in the falsification of documents in terms of the sequence of it. This type of adulteration can be done with overlap of pens or pen and printer ink. In this scenario, the routine analysis performed by forensic technicians to generate supporting evidence in cases of suspected document forgery use expensive equipment that requires qualified technical training, such as Scanning Electron Microscopy (SEM) and Infrared (IR) spectroscopy. However, these techniques, in addition to being expensive, can often cause destruction of the document, due to the need for cuts and folds to adapt to the instrument used. Another fact that must be considered is their low accuracy due to imprecise and subjective evaluations of the results. Routine cross strokes analyzes in documentoscopy are about 63% accurate [1–5].

In this scenario, which is expensive to analyze, it should be noted that even today, many documentoscopy analyzes are simply carried out by groups of trained people, without any technical instrument to help, which may lead to uncertain conclusions [2, 6, 7]. To overcome the low accuracy associated with the high analysis costs spent in this area of criminalistics, many studies have reported the development of alternative methods of image analysis associated with artificial intelligence algorithms. This is because sensors, electronics and prototyping parts are increasingly cheaper and commercially available, associated with the use of algorithms for processing big data. There are works evaluating the cross strokes between printed text and pen or pen and pen using instruments such as a r stereomicroscope, absorption spectra, laser profilometry, video spectral comparator (VSC) and a hyperspectral camera. As well as evaluation of aging features in documents by spectroscopy associated with multivariate models. However, they are still relatively expensive techniques [3–5, 8–12]. Therefore, in state of art, there is a necessity of develop new technologies
to diagnostic to accurate way overlap of strokes in documents to elucidate suspect of fraud crime. In this, applies computer vision techniques can be promisor. However, images have a big set of no structure data to interpret. In this case, machine learning (ML) tools can be used to interpret patterns, generate prediction and classification models.

The term machine learning (ML) refers to the area of data science responsible for interpreting patterns and classifying them. The ML has a subdivision named supervised whose has a set of predictors variables and target to training the model in order to generate an accurate prediction model [13, 14]. The target variables can be quantitative or categorical. The most famous non-linear model to predict is Artificial Neural Network (ANN). One type of ANN is deep-learning (DL) which have two or more layers of neurons in hidden layer. However, the number of neurons and layers increase machine consumption, making processing difficult or costly [14–16]. The use of DL introduces the possibility of working relatively easily with unstructured data such as image data. Digital images have 3 dimensions forming a set of arrays with i×j×k, the dimensions in pixels (smallest unit of the image) in the plane (i×j) and the third dimension (k) formed by data from the RGB color space (Red, Green and Blue). Therefore, an image is a set of arrays with RGB values of each pixel. For analysis of it, also called tensors. In this type of data Convolutional Neural Networks (CNN) can be used, which are a type of deep learning. There are several CNN architectures like Inceptionv3 and VGG16 freely available for use to classify images [17]. Therefore, this work aimed to develop an alternative method with a prototype for document image acquisition in a non-destructive way and subsequent classification of images using a CNN and later an Artificial Neural Network (ANN), with its own architecture, to accurately identify overlapping or not of strokes in documents for forensic purposes. In this way, an accurate, simple, low-cost, non-destructive and portable instrument was developed, which allows analysis of documents to serve as evidence for criminal reports involving the investigation of document fraud.

2 Theoretical fundamentals

2.1 Computer Vision

The processing of an image in computer vision is performed in four stages, acquisition, pre-processing, segmentation, feature extraction and interpretation. Each of these steps can be performed in different ways according to the purpose of the analysis and will impact the final classification results [18].

The acquisition can be performed by setting different parameters such as focus adjustment, focal length, brightness, white balance, image resolution, among others. In addition, for reproducibility of the analyzes, it is important to have a fixed and homogeneous illumination throughout the sample, which
can be done using light diffusers. After the acquisition, an important stage is the pre-processing stage, in which algorithms for noise reduction, contrast variation, variation in data dimensionality, centralization, normalization and the like can be used. The immediately subsequent step is the segmentation, which can be performed by applying contour filters to limit pixel variations. Among the filters most commonly used in the literature are Canny and Sobel. Subsequently, the last classification step is performed using ML algorithms. It is worth mentioning that many times it is possible to generate ML models that already have image segmentation steps, as in the case of Deep Learning (DL), not requiring a previous step as described above [16].

2.2 Artificial Neural Network (ANN)

Convolutional Neural Networks are a type of Artificial Neural Network (ANN) that contain several layers, that is, they can also fit into a specific type of Deep Learning (DL). CNN were used for the first time in 1998 by Yan Lecun, since then they have been greatly improved and today there are several CNN architectures defined for free use, such as AlexNet, GoogleNet, VGG16 and InceptionV3. Therefore, to understand the structure of a CNN, it is first necessary to understand the classic structure of an ANN. The first basic structure of an ANN was described by McCulloch and Pitts, describing the model of a network with a single neuron in 1943 [19]. The ANN contains data inputs, in which weights are applied, later these values are summed (aggregated) and a threshold is applied to this value. An activation function is applied to the generated value, which generates a final response, output. The model can be better understood in the illustration of ANN steps in figure 1.

![Fig. 1 Explanation of the McCulloch and Pitts model. Adapted from [20]](image)

In CNN there are several layers containing several neurons, in which each layer is called convolution, and in these several filters can be applied simultaneously, removing the need for previous segmentation of the image. Initially, the image is divided into segments and weights and the activation function are applied to this set, passing the result to the next layer. The set of applied filters is called the kernel. Each weight matrix is separated according to its similarity, thus generating the so-called filter map [21]. Furthermore, a CNN architecture defines the set of pixels that will be jumped from one map to
another, generating the size of the next layer and so on.

Different from the classic computational vision, in the application of CNN it is not necessary to dimension the filters. Only the number of steps and the size. In addition to this described convolution step, there is also pooling, which are data grouping steps, responsible for dimensionality reduction. The first block of the CNN generates vectors called features, to which the classical ANN structure is subsequently applied to generate the data classification. Therefore, to simplify, it can be said that the structure of a CNN can be divided into two, feature generation and classification. The model can be better understood in the illustration of CNN stages and subdivisions in figure 2 [19, 21].

![Fig. 2 Scheme of a CNN (adapted from [21]).](image1)

However, when talking about image analysis by CNN, it is not enough to understand the complex architecture of a CNN, but also, how are the input data, as these will be responsible for the final classification information. The image has width and height, and each pixel of a color image has color channels, usually RGB, used in digital images. The structure of the set of arrays of unstructured data generated by a digital color image and how convolution step is applied can be visualized in figure 3.

![Fig. 3 Convolution explains.](image2)
2.3 Architecture of InceptionV3

The InceptionV3 is a CNN with pre-defined architecture from the company Google LLC for free use, trained with 1,281,167 images and tested with 50,000 from the ImageNet database, obtaining an accuracy of 78% [22]. InceptionV3 uses less than 25 million parameters, different from ALexNet which uses 60 million parameters and VGGNet which uses three times more, requiring higher computational cost. As all CNN cited have defined architecture, the input arguments also have pre-established dimensions, as in the case of inceptionV3 where the dimensions are 299×299×3. The inceptionV3 architecture uses convolution steps and pooling steps. In inceptionV3, the convolution layer cuts the input at 299×299×3 and applies a filter using a neuron, thus reducing the data dimension of this new data set that goes to the next convolution layer thus generating the image filter map. It also applies pooling, which are data aggregation steps. The architecture scheme of inceptionV3 can contain the convolution layers with their defined number and step sizes and pooling is shown in figure 4. The output of InceptionV3 is a vector per image with a dimension of 1×2048. Therefore, for n images a matrix of dimensions n×2048 will be generated. It is important to point out that it was previously explained that CNN has a feature generation and subsequent classification stage. In the InceptionV3 application using the Orange Data Mining GUI, there is only the features step (architecture of figure 4 with convolutions and pooling step) generating the matrix of dimensions nx2048. In this matrix it is necessary later to apply an ANN to generate the classification step.

Fig. 4 InceptionV3 architecture schema (adapted from [22, 23])
2.4 Predictive model evaluation metrics

The evaluation of a predictive model is performed through several parameters, which depend on the types of variables involved, whether the target variables are quantitative or categorical. In this work, the model was generated from continuous quantitative predictive variables and categorical target variables. In this case, traditionally in the literature, the parameters area under the ROC curve (Receiver Operator Characteristic), accuracy, precision, recall and F1 are used.

Accuracy is a parameter that measures the model’s ability to predict correct answers, therefore, the measure is given by the number of true positives and true negatives, divided by the total of answers obtained.

\[ CA = \frac{TP + TN}{TP + TN + FP + FN} \]  

true positives (TP); true negatives (TN); false positives (FP); false negative (FN).

Precision is a parameter that measures the relationship between correct positive results and the sum of total positive results.

\[ \text{precision} = \frac{TP}{TP + FP} \]  

Recall is the same as selectivity. This lists the true events by the total number of real events, those found by the model and false negatives.

\[ \text{selectivity} = \text{recall} = \frac{TP}{TP + FN} \]  

Specificity is the opposite of selectivity. This is the ratio of true non-events to total non-events.

\[ \text{specificity} = \frac{TN}{FP + TN} \]  

The area under the ROC (Receiver Operator Characteristic) curve is the area of the curve where the abscissa axis is specificity and the ordinate axis is selectivity. F1 is a metric that relates the terms precision and selectivity.

\[ F1 = 2 \times \frac{1}{\frac{1}{\text{precision}}} + \frac{1}{\text{recall}} \]  

3 Methods

3.1 Samples

The samples were made imitating possible crossings of lines between ball-point, gel and hydrographic pens, each in blue and black colors of different brands and crossing with line made by two black printer inks, in order to mimic possible crossings of lines. 2 cm orthogonal lines were crossed for each material. The pens were used, each in blue and black colors from three different brands and two different printer inks (Table 1). Trace crossing samples totaled 684 samples in which their images were obtained in triplicate, totaling 2052 images. Trace crossing samples were performed on paper of 3 different weights, 75 g/m$^2$, 90g/m$^2$ and 120 g/m$^2$. Of these images, 84% were used for algorithm training and 16% for model validation.

Table 1 Material used in the samples:

<table>
<thead>
<tr>
<th>Pen type</th>
<th>Color</th>
<th>Brands</th>
<th>Model</th>
<th>Nib</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ballpoint</td>
<td>blue</td>
<td>Bic</td>
<td>Cristal</td>
<td>1.0 mm</td>
</tr>
<tr>
<td>Ballpoint</td>
<td>black</td>
<td>Bic</td>
<td>Cristal</td>
<td>1.0 mm</td>
</tr>
<tr>
<td>Ballpoint</td>
<td>blue</td>
<td>Faber-Castell</td>
<td>Trilux</td>
<td>1.0 mm</td>
</tr>
<tr>
<td>Ballpoint</td>
<td>black</td>
<td>Faber-Castell</td>
<td>Trilux</td>
<td>1.0 mm</td>
</tr>
<tr>
<td>Ballpoint</td>
<td>blue</td>
<td>TRIS</td>
<td>Slide</td>
<td>0.7 mm</td>
</tr>
<tr>
<td>Ballpoint</td>
<td>black</td>
<td>TRIS</td>
<td>Slide</td>
<td>0.7 mm</td>
</tr>
<tr>
<td>Gel</td>
<td>blue</td>
<td>Pentel</td>
<td>EnergGel Makkuro</td>
<td>0.7 mm</td>
</tr>
<tr>
<td>Gel</td>
<td>black</td>
<td>Pentel</td>
<td>EnergGel Makkuro</td>
<td>0.7 mm</td>
</tr>
<tr>
<td>Gel</td>
<td>blue</td>
<td>Pentel</td>
<td>EnergGel-X</td>
<td>0.7 mm</td>
</tr>
<tr>
<td>Gel</td>
<td>black</td>
<td>Pentel</td>
<td>EnergGel-X</td>
<td>0.7 mm</td>
</tr>
<tr>
<td>Gel</td>
<td>blue</td>
<td>Cis</td>
<td>Gelix</td>
<td>1.0 mm</td>
</tr>
<tr>
<td>Gel</td>
<td>black</td>
<td>Cis</td>
<td>Gelix</td>
<td>1.0 mm</td>
</tr>
<tr>
<td>Hydrographic</td>
<td>black</td>
<td>Maped</td>
<td>-</td>
<td>0.4 mm</td>
</tr>
<tr>
<td>Hydrographic</td>
<td>blue</td>
<td>Maped</td>
<td>-</td>
<td>0.4 mm</td>
</tr>
<tr>
<td>Hydrographic</td>
<td>black</td>
<td>Faber-Castell</td>
<td>-</td>
<td>0.4 mm</td>
</tr>
<tr>
<td>Hydrographic</td>
<td>blue</td>
<td>Faber-Castell</td>
<td>-</td>
<td>0.4 mm</td>
</tr>
<tr>
<td>Hydrographic</td>
<td>black</td>
<td>Bic</td>
<td>-</td>
<td>Medium</td>
</tr>
<tr>
<td>Hydrographic</td>
<td>blue</td>
<td>Bic</td>
<td>-</td>
<td>Fine</td>
</tr>
<tr>
<td>printer cartridge</td>
<td>black</td>
<td>HP</td>
<td>667 recharged</td>
<td>-</td>
</tr>
<tr>
<td>printer cartridge</td>
<td>black</td>
<td>HP</td>
<td>667</td>
<td>-</td>
</tr>
</tbody>
</table>

3.2 Electronic eye (Hardware)

The prototype was built using a 5 megapixel Raspberry PI SNS3D camera with sample (document to be analyzed) distance of 20 cm. A light disperser positioned between the light source and the sample holder with 1.8 cm of distance, a Raspberry PI model 4 from Newmark Corporation, a circuit, a led panel of 5 W and 450 lumens from the Inspire brand, positioned 7.5 cm from the sample. The physical structure of the portable analyzer instrument was designed in Blender version 2.93.6, the 3D object was sliced in Ultimaker Cura.
version 4.12.1 and built using black 1.75mm PLA filament, brand 3DFila for printing on a 3D printer CTMax3D model Core A3V2. All software used in this work are free.

The image window captured with the prototype consumable distances was 6.0 cm long by 3.5 cm wide. The window of the captured image starts at 4.2 cm from the base of the paper and the center of the images was placed at 5.7 cm from the base of the paper. Figure 5 shows the 3D design of the prototype and its marked parts.

![3D design of the prototype and its marked parts.](image)

**Fig. 5** 3D design of the prototype and its marked parts.

The prototype was developed being controlled by Raspberry PI and the program for automating the image acquisition was written in Python language. A program was written using the PiCamera library for image acquisition and OS library to save the data with a sample named. The code written and used in this work can be seen in the supplementary material.

### 3.3 CNN and ANN implementation environment (Orange)

Image processing was performed using the Orange software version 3.30.1 and the Image Analytics add-on for image processing, and the ANN function was used for classification. The functions used were Import Images, Image Viewer, Image embedding, Select Columns, Data Table, Save data, file, Neural Network, Test and Score, predictions, confusion matrix and scatter plot. Scheme of how the data processing was done in orange can be seen in figures 6 and 7.
3.4 The CNN function used within Image Embedding was InceptionV3

The Image Embedding generated were saved in .xlsx format and an extra column was added content the categorical targets. The classifiers were the types of pen that was on top at the intersection of the strokes of each sample. The name of classifiers were aesfazul(1), aesfazul(2), aesfazul(3), aespreta(1), aespreta(2), aespreta(3), agelpreta(1), agelpreta(2), agelpreta(3), agelpreta(1), agelpreta(2) and agelpreta(3).

Several ANN architectures were built by varying the activation function, the number of layers and the number of neurons in each layer. The activation
functions used were Identity and Logistic and the number of neurons and layers were 80, 60 and 40 (3 layers), 80 (one layer), 80, 60 (two layers) 90 (one layer) and 75 (one layer). The optimizer used was Adam and the number of epochs was 500. Cross-validation is stratified with a number of folds equal to 5.

4 Results and Discussion

The design of the prototype developed in this work was thought to make sample acquisition reproducible. Therefore, it is completely closed so that there is no influence from external light, with a fixed light source of 5 W and the use of a light diffuser so that the illumination reaches the sample homogeneously. The sample holder for inserting the document was a hole so that any document size and with any weight could be fitted in a non-destructive way, containing a sliding door so that no light enters it, adjusting the weight of the document (Figure 8). It should be noted that the material used in its construction is much cheaper than that used in conventional analysis instrumentation, such as SEM. The high focal distance was used to improve image definition, because a fixed focus camera was used. However, it culminated in images containing part of the inner wall of the prototype.

![Actual prototype image.](image)

The CNN plus ANN application in the 2052 images has a good accuracy and precision for the set of training which has 84% of these samples. The evaluation metrics as AUC, CA, F1, precision and recall are shown in table 2. The model evaluation metrics with the test data (16% of the total samples) obtained lower accuracy and precision, where the ANN architecture that presented the best values was the one with 80 neurons in a single layer, Logistic activation function, 500 epochs and ADAM solver, as shown in Table 3. However, despite the accuracy values close to 65%, this is considered an excellent value close to the 63% reported in the literature for routine analysis in documentoscopy.
### Table 2
Evaluation metrics of models trained with different activation functions and 80 neurons and 500 iterations.

<table>
<thead>
<tr>
<th>activation function</th>
<th>Solver</th>
<th>AUC</th>
<th>CA</th>
<th>F1</th>
<th>Precision</th>
<th>Recall</th>
</tr>
</thead>
<tbody>
<tr>
<td>Identity</td>
<td>ADAM</td>
<td>0.994</td>
<td>0.909</td>
<td>0.909</td>
<td>0.910</td>
<td>0.909</td>
</tr>
<tr>
<td>Logistic</td>
<td>ADAM</td>
<td>0.998</td>
<td>0.949</td>
<td>0.949</td>
<td>0.950</td>
<td>0.949</td>
</tr>
</tbody>
</table>

### Table 3
Result of samples with different numbers of layers and neurons in the hidden layer. All with 500 iterations Logistic Activation function and ADAM Solver

<table>
<thead>
<tr>
<th>Nº de neurônios</th>
<th>AUC</th>
<th>CA</th>
<th>F1</th>
<th>Precision</th>
<th>Recall</th>
</tr>
</thead>
<tbody>
<tr>
<td>90</td>
<td>0.930</td>
<td>0.654</td>
<td>0.660</td>
<td>0.689</td>
<td>0.654</td>
</tr>
<tr>
<td>80</td>
<td>0.924</td>
<td>0.657</td>
<td>0.663</td>
<td>0.690</td>
<td>0.657</td>
</tr>
<tr>
<td>80,60</td>
<td>0.922</td>
<td>0.599</td>
<td>0.609</td>
<td>0.644</td>
<td>0.599</td>
</tr>
<tr>
<td>80,60,40</td>
<td>0.897</td>
<td>0.559</td>
<td>0.566</td>
<td>0.600</td>
<td>0.559</td>
</tr>
<tr>
<td>75</td>
<td>0.927</td>
<td>0.651</td>
<td>0.657</td>
<td>0.685</td>
<td>0.651</td>
</tr>
</tbody>
</table>

However, excessive non-linearity, with many neurons and layers, can result in an overfit in the model. Therefore, one of the most used ways to minimize overfit is to perform a dropout. This effect is demonstrated in this work, because, when evaluating the evaluation parameters of the model, verifying its predictive power with test samples (different data from what is used to build the model), the model that presented the best results was that of 80 neurons in a single layer.

The predictability of this model can be seen more clearly through the confusion matrix, where the relationships between true values of the samples and values found by the model are shown. That is, this graph shows the relationship obtained in the model of true positives, false positives, true negatives and false negatives. Figure 9 shows the confusion matrix of the model with 80 neurons in a single layer, Logistic activation function, 500 epochs and ADAM solver for the training sample set.

Therefore, the computer vision prototype generated in this work has results with potential application in the area of forensics, more specifically in cross strokes analysis in documentoscopy, as it presented precision (95%) and accuracy (94.9%) for training samples and reasonable accuracy (65.7 %) and precision (69.0%) for test samples. These results are better than current routine forensic analysis, in which, according to Martins and collaborators, in 2019 the accuracy was around 63%. In addition, the InceptionV3 used in this work, when it was developed with 1,281,167 images, presented an accuracy close to that obtained here, with 78%. Therefore, this analysis proves to be an excellent alternative to routine analyses, being a low-cost, portable prototype that can be taken to field analysis and without the need for technical expertise for use.
Fig. 9 Confusion matrix of the training sample set.

5 Conclusion

The tool for analysis of fraud by cross strokes by computer vision obtained results for the test sample comparable to those of the routine analysis by SEM, having obtained 65% of accuracy against the classic analysis that has 63%. Optimizations can still be performed on the prototype, which may culminate in greater accuracy. Therefore, the use of computer vision in documentoscopy can bring more precise and accurate analyzes in criminal cases with suspected fraud in documents, in addition to being low-cost effective, simpler, portable and non-destructive tool for the use of forensics.

Supplementary information. The code used in the prototype written in python language is show here:
#importing the camera library
from picamera import PiCamera

# asking operator sample name
nome = input('nome da amostra')

# variable name the function
camera = PiCamera()

# resolution
camera.resolution = (1080, 1080)

# to connect camera
camera.start_preview()

# take picture and save as nome
camera.capture('/home/pi/Desktop/DV/nome.jpg')

# turn off camera
camera.stop_preview()

# importing os library
import os

# renaming photo to name given by operator
os.rename('/home/pi/Desktop/DV/nome.jpg', nome)

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Compliance with ethical standards. The authors declare that are according to compliance with ethical standards.

Data Availability statement. Raw data were generated at Federal University of Rio de Janeiro and at D.L.V’s home.

Ethical Approval (applicable for both human and/ or animal studies). Not applicable.

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