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AUTOMATED TRANSCRIPTION OF HISTORICAL ENCRYPTED MANUSCRIPTS

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ABSTRACT. This paper deals with historical encrypted manuscripts and introduces an automated method for the detection and transcription of ciphertext symbols for subsequent cryptanalysis. Our database contains documents used in the past by aristocratic families living in the territory of Slovakia. They are encrypted using a nomenclator which is a specific type of substitution cipher. In our case, the nomenclator uses digits as ciphertext symbols. We have proposed a method for the detection, classification, and transcription of handwritten digits from the original documents. Our method is based on Mask R-CNN which is a deep convolutional neural network for instance segmentation. Mask R-CNN was trained on a manually collected database of digit annotations. We employ a specific strategy where the input image is first divided into small blocks. The image blocks are then passed to Mask R-CNN to obtain detections. This way we avoid problems related to the detection of a large number of small dense objects in a high-resolution image. Experiments have shown promising detection performance for all digit types with minimum false detections.

1. Introduction

An automated transcription of historical manuscripts is an open research question in general. Manuscripts may vary based on the time period, used language, writing style, etc. Moreover, transcribing a historical ciphertext (or a cipher key) can be an even more challenging task, because these systems may consist of a large number of various symbols (glyphs), numbers, and letters.

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In this work, we are focusing on the digitization and processing of historical ciphers used in the past by aristocratic families living in the territory of today's Slovakia. The archival documents which are the subject of our research are deposited in several preserved fonds of these aristocratic families in the Slovak National Archive in Bratislava. The encryption system used in these documents is called *nomenclator* [7, 15], which is a complex encryption system consisting of several simpler encryption subsystems linked together during the encryption. These subsystems are mostly based on different types of substitution. The main characteristics of a nomenclator are:

"A nomenclator mostly contains a substitution of letters (monoalphabetic or homophonic substitution) in a combination with substitution of n - grams (bigram and/or trigram substitution), codes, and nulls. It is not widespread, but some nomenclators contain a polyalphabetic substitution, too. The sub-encryption systems (encryption rules) are described by a cipher key, which is very characteristic: the cipher key is mostly drawn on a large paper sheet; the individual sub-encryption systems are mostly graphically separated; the cipher text alphabet is often represented by (combinations of) letters, numbers, and special symbols/glyphs." [3]

A typical ciphertext from our collection is shown in Figure 1 and cipher key in Figure 2. The used cipher symbol set from our collection consists of digits only (including special number modifications). Luckily, the writing style of the encrypted text is clean and the used digits are separated by relatively large spaces. The symbols are therefore easier to read. The aforementioned text readability may be attributed to an effort to minimize the possibility of error occurrence. Writing such clear and easy-to-read encrypted parts requires a lot of skill and patience.

In order to analyze and solve the manuscripts, we first need to perform a transcription of the cipher text represented by image to editable text. One may do it manually, which is a very time-consuming and error-prone process. Another possibility is to use a modern automated method, such as deep convolutional neural networks. Our method is based on Mask R-CNN which is a popular supervised object detector. Once the detector learns digit representation from a sufficient number of examples, it can be used to detect digits from new unseen documents. All the detected digits are finally read in the correct direction to form an editable text document which can be used for cryptanalysis purposes.

I pon Inaden stomifche star NTF5 arino manien zu Dungarn und Hohein Conigin, Bu Defterreich U. 530 \$1300C 445966502518530191192311 14011172 4002 30071010406908149852 30005201916 309669919666444139713956024 CIO 082.88653 +9689380889791 20 00500000 59330494536061 -13 70917254 13380 200 7866 792300 202370 1 77054 2339 4807190080 031681A 70016 41054932733 3535960301 c163 8379998202 734 500 10006: 202220262 2171 7.05300 2.032.034748110115220 44931 30717 003300 30101023571 15941315330491988370310901296 3973999000

FIGURE 1. Encrypted message from 1756 (Slovak National Archives, fond Esterházi - čeklíska vetva, box n. 634).

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FIGURE 2. Cipher key example (Slovak National Archives, fond Pálffy--Daun, Klasse XXXIII – Wierich Daun, fasc. 22).

2. Related work

Historical ciphers (especially nomenclator systems) have been intensively researched in recent years. Many important publications on this subject are presented annually at the International Conference on Historical Cryptology (HistoCrypt). The design and structure of historical cipher keys were investigated in [3,11,14]. These publications are related to the two ongoing projects, namely:

DECRYPT (https://de-crypt.org/) [10] and HCPortal (https://hcportal.eu) [4,5].

These projects are mainly focusing on the digitization and processing of encrypted documents and cipher keys, and developing new methods to solve these ciphers. In some cases, large collections of documents from a particular time period or geographic location [6, 9] are studied which can also help to better understand some aspects of historical cryptography.

One of the fundamental stages of historical encrypted manuscript processing is its automated transcription which takes an image containing the original manuscript and produces an editable text corresponding to the manuscript. This is a rather challenging task that requires a robust method to address issues such as the recognition of complex patterns and handling poor image quality. Nowadays, these problems can be solved using the machine learning approach.

During the literature review, we came across several solutions intended for historical text recognition. There is a well-known web-based and offline solution called Transkribus capable of text recognition and transcription of documents written in any language [13]. Similarly, authors in [8] introduced a novel deep learning architecture named DIGITNET, and a large-scale handwritten digit dataset named DIDA, to detect and recognize handwritten digits in historical document images written in the 19th century. Their solution was based on a well--known YOLO detector. Another attempt was made by researchers in [12] who proposed a handwritten cipher text recognition based on few-shot object detection.

Our proposed solution is based on the modern and robust convolutional neural network Mask R-CNN [16], which belongs to the family of state-of-the-art supervised semantic segmentation methods. Mask R-CNN takes an image of a predefined size as input and performs detection producing a bounding box and polygonal mask for each detected object. Moreover, detected objects are assigned a class label.

Authors of this paper conduct their research at the Institute of Computer Science and Mathematics (Slovak University of Technology). There are several

final theses dealing with the problem of historical encrypted document processing which were supervised at the institute. In [17], the comprehensive analysis and comparison of existing handwritten digit datasets are presented. In addition, two well-known object detectors, Mask R-CNN and YOLOv5, are examined and their detection accuracy is evaluated. Another research was conducted in [18], where image preprocessing and recognition of handwritten digits and their special modifications are presented. The recognition is performed using state-of--the-art convolutional neural networks (VGG, ResNet, ResNeXt, Inception) which form robust ensembles to boost classification performance. Moreover, the entire solution is developed as an interactive web application for highly customized handwritten document analysis. Finally, in [19] and [20], authors created a large collection of handwritten digit annotations and a method for digit detection and web-based document transcription.

3. Automated transcription

Over the course of our research, we have collected a large number of encrypted texts and nomenclator keys. In order to solve the ciphers, one needs to convert the image representation of the document to editable text or symbols for further cryptanalysis. Automated transcription of handwritten documents is the major contribution of this paper, however, it is just a single step in our research workflow which can be summarized as the sequence of the following steps:

- (1) Research in archives which involves collection and digitization of cipher keys and encrypted documents.
- (2) Automated transcription of the obtained documents based on machine learning:
 - (a) Creating digit annotations.
 - (b) Object detector training using the annotations.
 - (c) Digit detection, classification, and transcription to obtain editable text for subsequent analysis.
- (3) Analysis and solving the ciphers from the transcribed documents.

In Figure 3, we see the most important steps of the transcription procedure. For our needs, we manually created a new dataset of handwritten digit annotations using a Python graphical image annotation tool called LabelMe. We created 12 433 polygonal annotations of digits from several handwritten documents. Currently, we are not aware of any similar public dataset of such extent and precision so we consider this to be a substantial contribution in the field. The correctness of digit annotations was further verified by the experts from the Institute of History of the Slovak Academy of Sciences. Finally, the dataset was split into three subsets for training, validation, and testing. The next step

was training our digit detector based on Mask R-CNN. The detector is responsible for locating digits within the document. The trained detector was evaluated on the test dataset. Digit bounding boxes and labels serve for line detection and final transcription.



FIGURE 3. Automated handwritten document transcription workflow.

3.1. Database of manuscripts

Our collection of encrypted manuscripts and cipher keys consists of several hundred pages. These documents are deposited in the Slovak National Archive in three different fonds of aristocratic families:

- Esterházi,
- Pálffy-Daun,
- Amade-Üchtritz.

We made digital copies (photographs) of these documents in a high resolution $(4160 \times 6240 \text{ pixels})$. The used camera was mounted on a stand and we used additional light sources. The handwriting is clean and the cipher symbols are clearly separated and easy-to-read on most documents (see Figure 4). However, there are examples of lower quality (see Figures 5, 6, and 7).

The collected manuscripts can be separated into different types of encrypted documents:

- fully or partially encrypted messages (Figure 1),
- encrypted message where the plaintext is written above/below the lines of the ciphertext (Figure 8),
- encrypted parts in a diary (Figure 9),
- draft message containing encrypted passages,
- draft message containing encrypted passages where the plaintext is written above/below the lines of the ciphertext (Figure 6).

019. 104.90.11. 303. 111. 99. 105. 46.201. 98. 28.66. 87. 331.22.03. 17.633.100. 67. 93. 148. 631. 04. 131. 1493. 18. 431. 3723. 116. 83. 111. 49. 121. 44. 93. 121. 18. 17. 801. 44. 101. 312 9. 126. 001. 22. 80. 136. 20. 10. 99. 03. 17. 360. 1. 44. 23. 148. 288. 66.001. TT. 205. 2012. 8451.00. 301. 393. 0. 111. 187. 888.99. 83. 11. 693.105.

FIGURE 4. Clean and easy-to-read ciphertext example (Slovak National Archives, fond Esterházi - čeklíska vetva, box n. 634).

87.5 61A66 A000 A0 880036864 \$1603830165585909630899 2.3678345696666260162660283044639854166668636771 6850A65319311850509,47051167684540271A88980158603062 6713960 33379 107030981892370114131244120208176994 8368910208A9319359219599999999382893289239237825444

FIGURE 5. Lower ciphertext quality - weak background noise and smudged parts (Slovak National Archives, fond Esterházi - čeklíska vetva, box n. 634).



FIGURE 6. Lower ciphertext quality - strong background noise (Slovak National Archives, fond Esterházi - čeklíska vetva, box n. 635).

648.394. 7.343. 495.316. 166. 341. 0321470. 227. 768. 868. 685.697. 632. 758-419.33.308.8.634.219. 766. 810. 308.3.596. 368.284. 854 359.504. 633. 795. 358. 962. 441. 4. 183. 256. 3. 428. 453. 23. 689. 359. 481. 288. 848. \$94. 966. 689. 646. 782 341.390.216. 633.248. 419.9. 308.8.631.214.639. 369. 221 469 481.649 891. 866. 768. 224. 822. 2. 358.981.631 642.438. 827 996. 562. 489. 916. 183. 43835: 666. 297. 2. 962. 885. 183. 428. 646. 218.175 316. 200 518 942. 854 40440.4443. 240.883. 893. 483.694. 236.6. 694.741. 704. 444, 623. 940: 855-183. 648. 866. 288. 854 689 \$17.685. \$13.854.689.9735 8. 900. 104. 444. 4. 622. 502.481.442.113. 891.864.893.672-397.854.766.262.998.304.622.341.593.216.354. 316. 205 \$66.389.689 722 906 Q. 497.354 129.614. 976.361 358.9808. 39. 427. 513. 743.689. 380 11:334.4 .3

FIGURE 7. Lower ciphertext quality - underlined text and strong background noise (Slovak National Archives, fond Esterházi - čeklíska vetva, box n. 631).

107640216252050270381633639771377688703631251965287723 Binab gany mierer letyten 165822536608870.55825505475921 5622008072530623816382321 vin sie benten ; goe ier nber neverein 975582559193705555836016875602896510705522771386051062887023 Die notna fit en mid faechfifther an gelegen 52158370629699377 15201835702657130765025155832 noch nicht zu Itanie ge Komm ware 70172523330788582583558258093273562209530671638620 acurente sich die allgemeine /trimmung yn mileren Vir theil

FIGURE 8. Plaintext written below the ciphertext (Slovak National Archives, fond Amade-Üchtritz, box n. 136).

Vi anore in Ci Jm 28 mm May. 1 14158 2 8 MAY way im altin Ing ; if bin jugt 20. allat 775035571943474319353531271582519434413471931312747 Sund Fraz 2219351943133131194 332715256813313114352725431435 fur finn min. Jun he fabru wir nim mynor nul Brays Juny Benzel ift big allow frimme Une foreide new Ranchary The I

FIGURE 9. Encrypted diary parts (Slovak National Archives, fond Amade--Üchtritz, box n. 150).

The ciphertext symbol set examined so far consists of numbers only, including some markups (see Figure 10). Moreover, some of the ciphertexts consist of numbers separated with a dot (see Figures 4 and 7), other ciphertexts consist of numbers without separators (see Figures 1 and 5).

251.04.151.04.889.15.121 63.11.485.12.99.0131.282.3127.031. 99.136.52.64.19.42.0910.753.117.83.101.60140.83.111.989.30. c 03.631. age. 85. 05.147.63.121. 151. 24. 831.22.351.03.851.24.03. 143. 80.111.96.2.3.148.5312.960.101.3140.119.631.34.2310.893 088 7.01.44.39.199.2.510.610.1. 370.83.11. 373.13.66.403.141.3. 11. 351.34. 988.24. 951.22.131.04.13.11.44.513. 944.70. 031.2. 563

FIGURE 10. Special digit markups (Slovak National Archives, fond Esterházi - čeklíska vetva, box n. 634).

3.2. Object detector

We used a machine learning approach to detect and classify digits in the handwritten encrypted documents. Specifically, we employ Mask R-CNN supervised instance segmentation algorithm. Mask R-CNN is a region-based deep convolutional neural network generating high-quality segmentation masks. Internally, Mask R-CNN takes an input image and extracts salient features using a predefined deep convolutional neural network, e.g., ResNet. Features are then passed to the subsequent layers responsible for a region proposal (RPN network) and prediction of a class and rectangular bounding box. Moreover, additional convolutional layers produce a high-resolution polygonal mask. Mask R-CNN scheme is depicted in Figure 11.



FIGURE 11. Mask R-CNN architecture [21] (this example shows an X-ray image object detection).

In our case, Mask R-CNN produces digit detections where each potential digit is represented by a bounding box, class label, pixel-level mask, and classification confidence as seen in Figure 12.



FIGURE 12. Sample digit detection performed by Mask R-CNN on our dataset (value 3 denotes a class label whereas value 0.992 represents a classification confidence from interval (0, 1)).

3.3. Annotations

The training process of Mask R-CNN requires ground-truth annotations of objects of interest. An accurate digit detector must be trained on a rich training dataset covering intra-class and inter-class variability. Objects of interest, digits from 0 up to 9, were annotated using the LabelMe software tool (see Figure 13). LabelMe allows drawing geometric shapes to spatially delimit the object. We used polygonal annotations to create accurate masks and to avoid digit overlapping.



FIGURE 13. Polygonal digit annotations created by a touch pen using LabelMe software.

3.4. Training and testing

We have created 12433 digit annotations from 18 document images using the LabelMe software (these images were manually analyzed and transcribed by experts so we could later verify the results of detection). This dataset was split into three subsets, namely training, validation, and testing subset.

The split ratio was 70 : 15 : 15, respectively. The digit distribution in the dataset is shown in the table in figure Figure 14. Digits 1 and 3 were more frequent than other digits which can be attributed to the characteristics of the encryption system.



FIGURE 14. Distribution of digit annotations.

Detecting large number of digits in a high-resolution image is a difficult task since Mask R-CNN performance decreases when detecting small dense objects. To solve this issue, we divided the entire document image into smaller 128×128 pixel blocks (see Figure 15) and subsequently performed detection in the blocks.



FIGURE 15. Division of the document image into smaller 128×128 blocks.

Figure 16 shows the original document divided into the blocks and the result of digit detections (green rectangles) inside each of the blocks.



FIGURE 16. Block-level digit detections in the document.

3.5. Transcription

Digit detection and classification are followed by an automated transcription. The overall procedure is as follows:

- (1) Calculation of bounding box (B-box) centers.
- (2) Calculation of histogram for vertical coordinates of B-boxes.
- (3) Local extrema detection in the histogram which leads to line detection.
- (4) Reading digits in the right direction.
- (5) Exporting digits to the text file.

First, we need to compute a histogram of digit bounding box centers. The histogram reveals the distribution of centers on the vertical axis. We used 4-pixel wide bins when plotting the histogram as seen in Figure 17. Histogram peaks denote line positions. We used Python Scipy package to detect the peaks.



FIGURE 17. Histogram of bounding box centers revealing line positions.

Following histogram peak detection, we proceed to obtain line positions. Line positions correspond to the histogram peaks with slight vertical tolerance of +/-12 pixels. Line detections along with line height tolerance and detected digits assigned to the line are visualized in Figure 18.



FIGURE 18. Line detection (green lines) and extraction of digits in the line (white boxes).

Detected digits are assigned to the line based on the distance of their B-box centers to the line's vertical position, taking the aforementioned tolerance into account. Reading digits assigned to the individual lines from left to right results in the transcription of the entire document. Digits are exported in the editable form to the text file (see Figure 19).

47. 561A66 A000 A0 88000 88000 8800 160 8800 165 88 90 9600899 205780468086662001626602830446398541666885687717 B850460019311850009,47051169684540271488980158603062 6713 960 23070 10 70200991892 270114131244120208176994 8068910208490190592105999999909082898219207825444 8109586005118520870688710796910180A186A4145A10086 \$6485ig 40 4982 28i6 2052 50671351666289 872956035ig ibioginesisessingsATAisnon ASAAisAgssigisbioizmios 48797104009088058586081488894859008778178159752 ingrage08087138854581357048410877778003509845 83589683042946i665052103728020107881i80i6igs \$615A0 46505 842883839AHA604010150102478520470 200108025100400601814631040889910021905171515700 8978162 4968117676866876239664518859800314488 11817912000 004817A02051190970059007402905294 80 9000 70 198 Boio 4 8040010 0 00 0888 10 6 12 11 90 94741 502.870 Siyijos 8880 5 74748540 transcription_I Open -..... 825614660340883684816088301585909639 236834696616262880446395416656711 6854651804701664540271488980186036 67139633310703098182370141512417808174 63689048319392159993889329123782544 8133580635852063688179961318164414541086 86451982281620520671316389695603591 1610917318337793474170448441345519186127712 48797140688058586143889485968778178159732 129249333613885438157048410777005945 6558368542946366522103728321378818313 86544658428838344464131310247852070 21083210040061814104388902195115700 897816863876168637633966451885952331488 18179533487174823511909730337402052 090038601004804311063568815621903448 8281038110538885774640

FIGURE 19. Encrypted document transcription (the original image is at the top, the transcribed digits are at the bottom).

4. Results and discussion

In this paper, we present our automated method for the detection, classification, and transcription of digits that are found in historical encrypted manuscripts. Our system based on Mask R-CNN achieves notable accuracy results on the test dataset (1554 samples of digits) reaching overall digit classification accuracy as high as 99.5%. These results were achieved after a relatively short period of training on GPU (100 epochs, using ResNet50 as the backbone feature extraction network). Accuracy results are summarized in Table 1.

Digit	Number of incorrect classifications	Number of missed digits	Number of test samples	Classification accuracy (%)
0	0	2	186	98.92
1	1	0	223	99.55
2	1	0	111	99.09
3	0	0	159	100
4	1	0	146	99.31
5	1	0	129	99.22
6	0	0	157	100
7	0	0	124	100
8	1	0	182	99.45
9	0	0	137	100

TABLE 1. Digit classification accuracy achieved on the test set.

Our system performs well on all digit classes and deals with image quality variations relatively well. Figure 20 shows digit detections across the entire encrypted document.

During our experiments, we also investigated situations where the manuscript contains mixed encrypted/unencrypted parts. This is where we wanted our algorithm to detect numbers in the encrypted parts only. There is a related ongoing research focused on the detection of encrypted regions which may decrease false digit detections. As depicted in Figure 21, we see that the detector produces only a very limited number of false detections outside the encrypted regions. We also address the issue of missing digit detections which may occur when digits are located on the interface of the two consecutive image blocks. In [19] and [20], authors contribute to our research by introducing an algorithm that divides the input image into blocks using a differently shifted grid. This way we perform detection in the blocks with various offsets and combine the detection results so that the duplicate detections are removed and the results do not suffer from missing digit detections on the block interfaces.

328 Sin 62 A0004038 20036364 31 50 8 800 16 65 4 2909 530899 120 1834 55 18 366 200 1 2 5602 8 8 8 4 4 C3 9 8 34 155 68 60 B 7 11 64.504 6501 931 8.500 09 4 70.517 646 8 43 402 THE 8 4015 8 10 3002 10 960 13079 10 7000011392 3101141512441 2020 8176994 63 911910 20 8.4 q 21 q 2.5 9 2 1 5 5 9 9 Q 9 10 9 38 2 8 9 3 2 10 2 37 8 2 5 4 4 4 81339862381185 20 Bro 6837107, 15915180A18644143410088 8 54 115 19 40 4 982 2 8 16 2012 2 50 6 rd 20. 5 10 63 2. 819 6 12 9.5 63 354 19 16 10 9 14 30 1 14 231 7 9 0 47.418 30 2 48441 3 493 0 1 1 18 Protections 437911013696183385186081433894159068778178139,32 12391493383 Brissas 408135754841087777800539845 Busto 68.304 - 94613 00 05 2 1037 2 00 201 37 8 211431 Bigs 2515AC4 8005 842883836444864015153132478220470 250108025100400601810601040289900021905111515700 8173162 116331776368658762 5966451113.57323314488

FIGURE 20. Example of digit detection in the entire encrypted document.

MENT 6 1197 73131 2 2 33 42 2 63 720 412 641 8 8 305'05'00 3178100 60 251486051012 74 5.0 2891 2.51 95 8197 117-97504 riseg bais gig bintis gint 2, entis gis iges. 53775. 5 837.00 63 431 436 4941124098 484415 1010909 030065 07 7311735 399500 1083117798359324237948155059440 1.10 3178102. 107164 207345264 1997 62. 7406479 1955 92 77626488109009887369322161961: 162524200006 1000720460947763.0479021099893546400034775727816 institutes strafe high Of The aband if the mart my be . into from goyle both Monsieur de Hopsital glinthis fi -9 if mutfult you 3 Hung withing forthing an Winfing Vor for Fair glithi ansyntig Ellz Sibiliant sat moform and out ing un hu

FIGURE 21. Example of digit detection in the document with mixed encrypted (top region) and unencrypted (bottom region) content.

5. Conclusion

This paper presents an ongoing research focusing on historical manuscripts encrypted using the nomenclator cipher system and their automated transcription. This cipher system uses digits for the representation of a ciphertext. We have a large collection of unsolved digitized encrypted documents and keys of varying structure and quality. We have developed an automated method for the detection, classification, and transcription of handwritten digits. Our system is based on the popular Mask R-CNN object detector. We created a large database of digit annotations and trained the detector. Testing and experiments indicate promising results when it comes to classification accuracy and capability to deal with images of varying quality. Furthermore, the adopted transcription technique turned out to be relatively accurate in detecting lines and reading symbols to form a final editable text document.

In addition to ciphertexts, we are also addressing the processing of cipher keys (nomenclators), which is a challenging task. These keys are mostly drawn on a paper sheet and the individual sub-encryption systems are visually separated. We are working on a (semi)automated computer vision method to identify, separate, and process the individual sub-encryption parts.

We plan to publish our developed transcription tools and our dataset (polygonal annotations) of historical handwritten digits and cipher symbols as open-source projects (available for other researchers). All projects will be documented and integrated into the *Portal of Historical Ciphers*¹ [4, 5] which is a special online project focusing on historical cryptology. We believe that our results can help other researchers avoid the need for time-consuming manual transcription of handwritten documents, not only in the field of historical cryptology.

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¹https://hcportal.eu

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