Writer Identification Using Deep Neural Networks: Impact of Patch Size and Number of Patches

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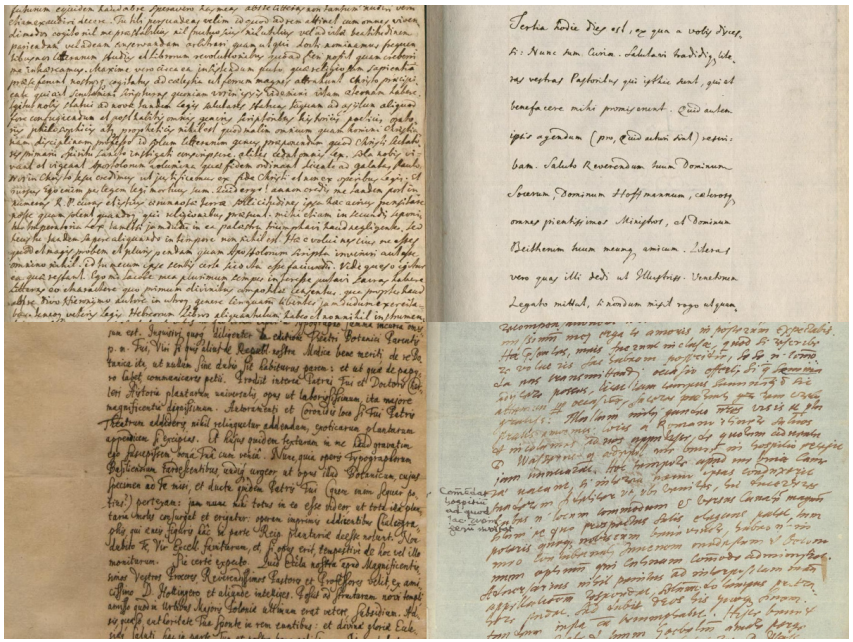
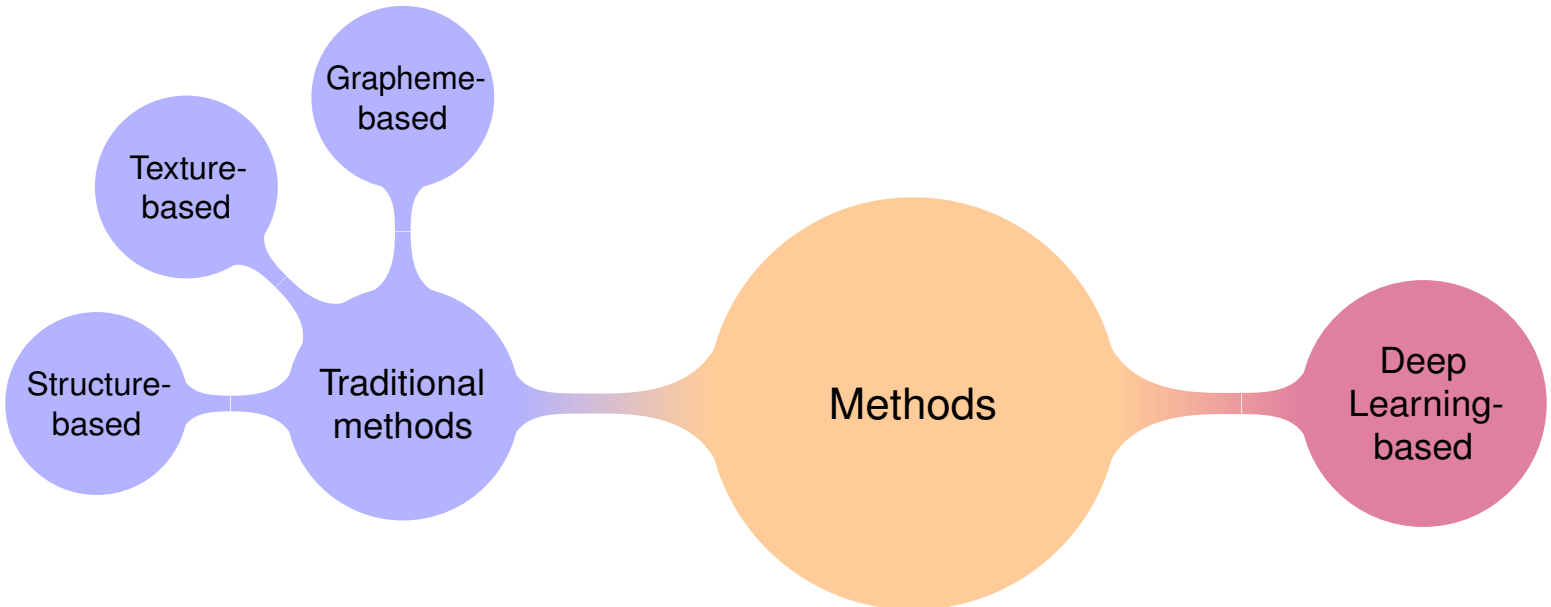
Outline

Motivation

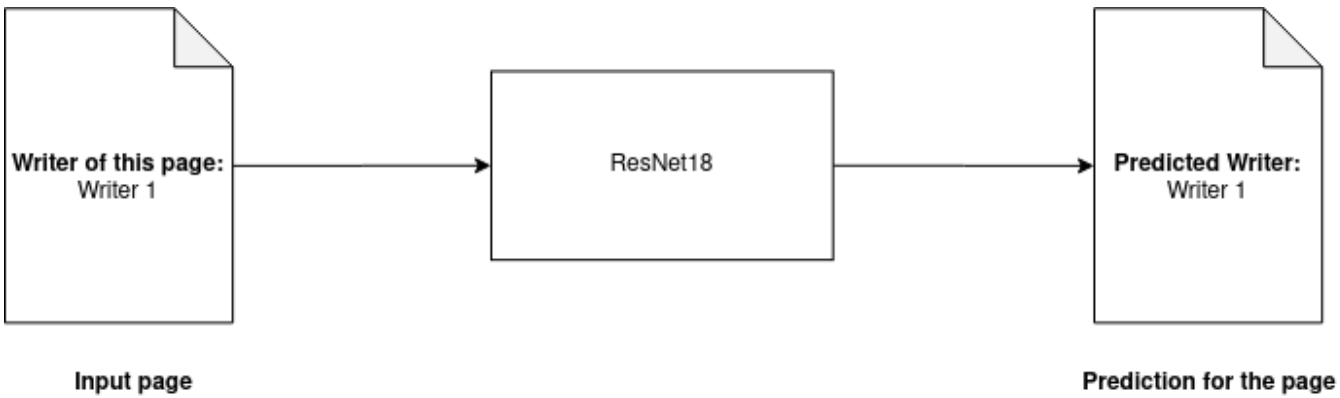
[1]



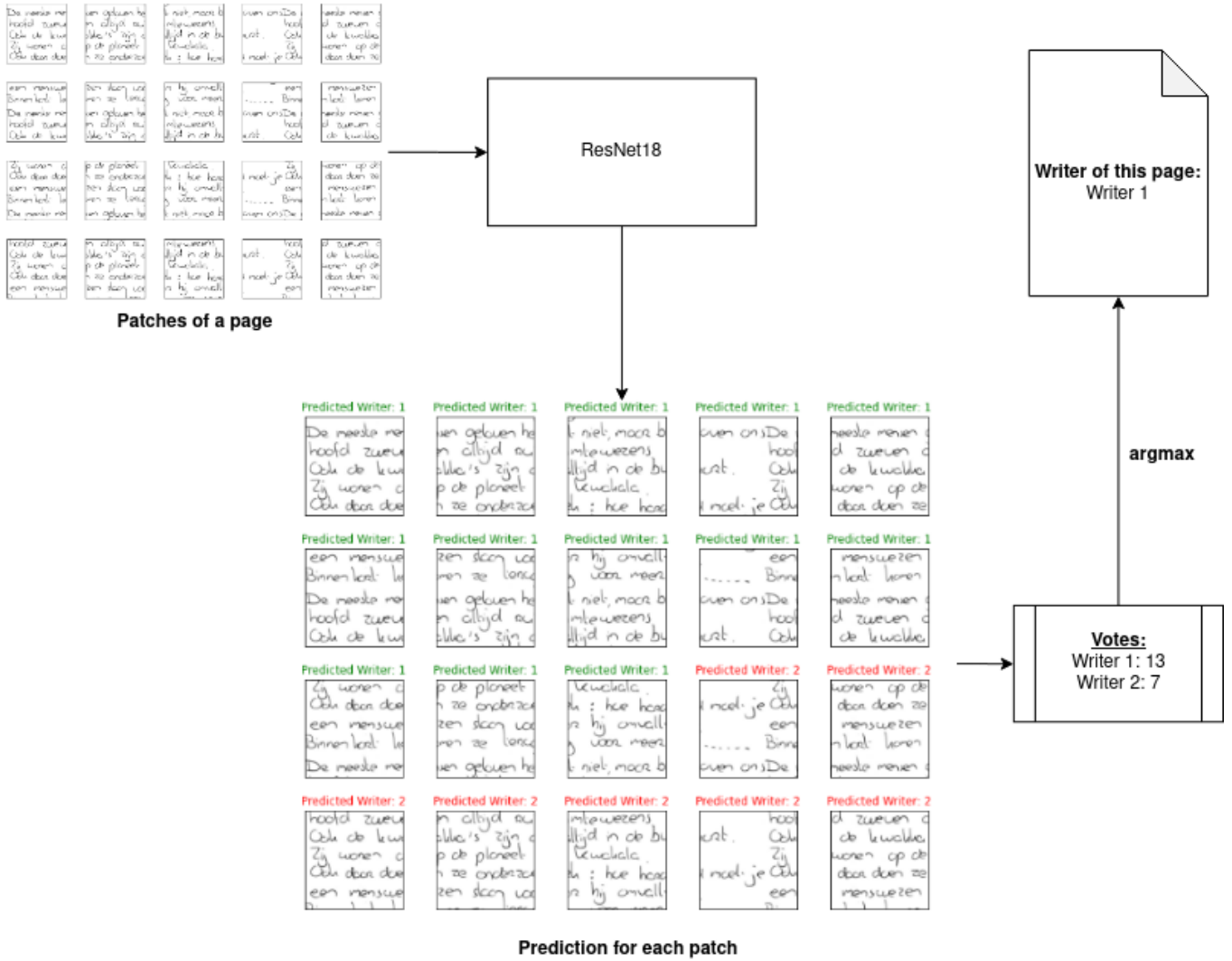
Methods


Grapheme-based
Texture-based
Structure-based
Traditional methods
Methods
Deep Learning-based

Model based on full-pages

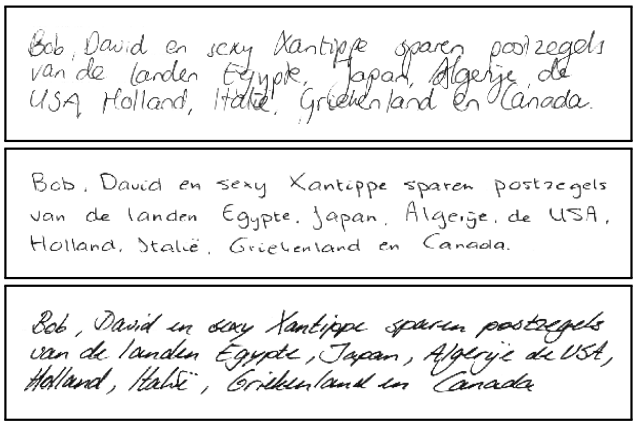


Model based on patches



Datasets

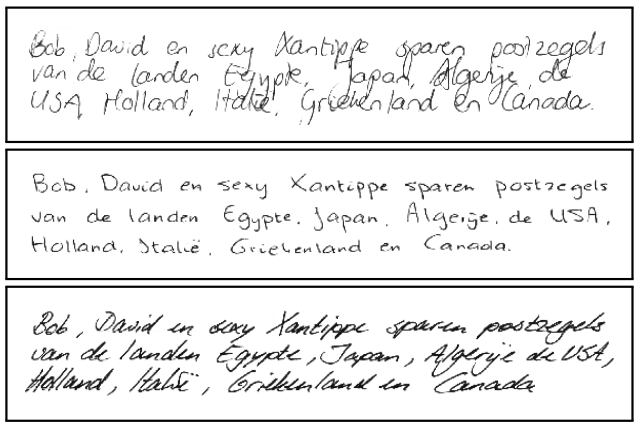
Firemaker



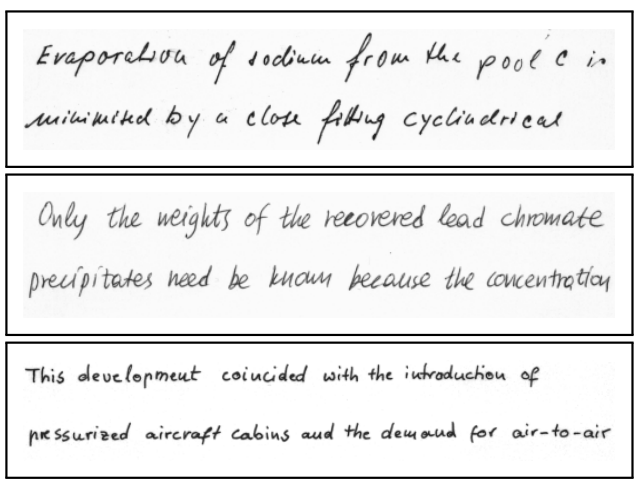
Dataset	Writers	Training	Validation	Testing	Total pages
Firemaker	250	1 page		1 page	500
IAM	657	1 page/ half page		1 page/ half page	1314
ICDAR17	720	3 pages	1 page	1 page	3600

Datasets

Firemaker



IAM



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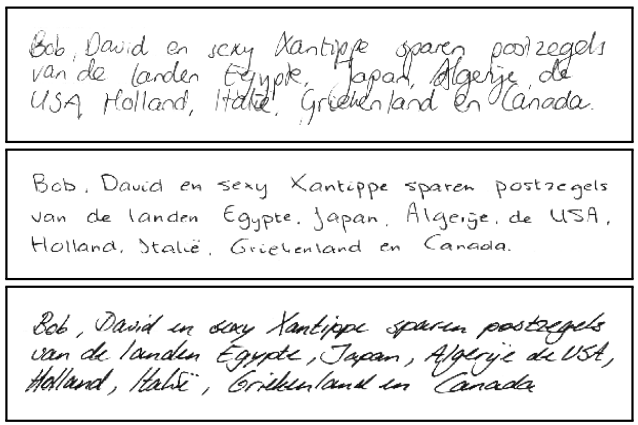

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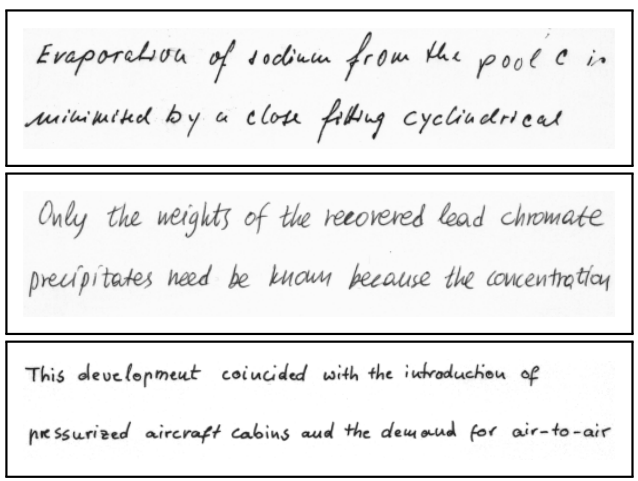

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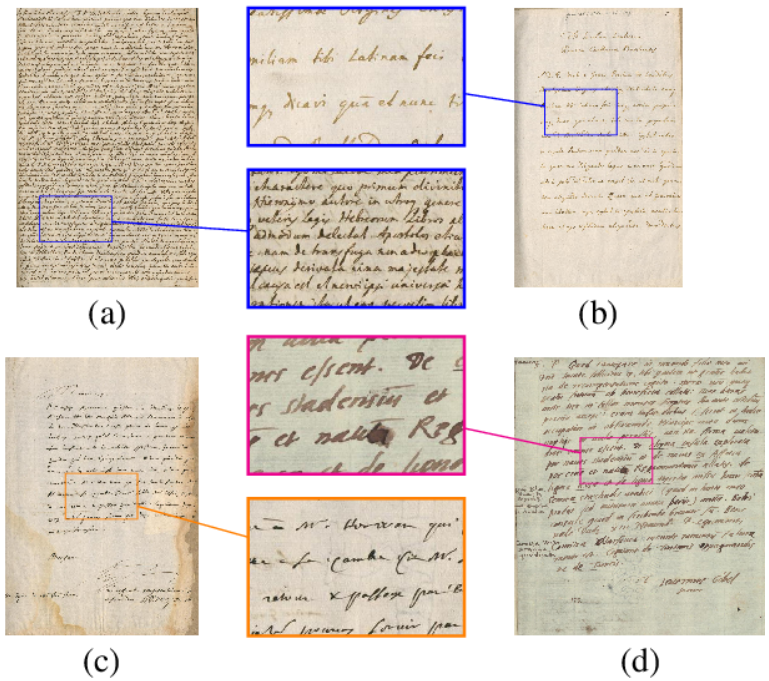
ICDAR 2017

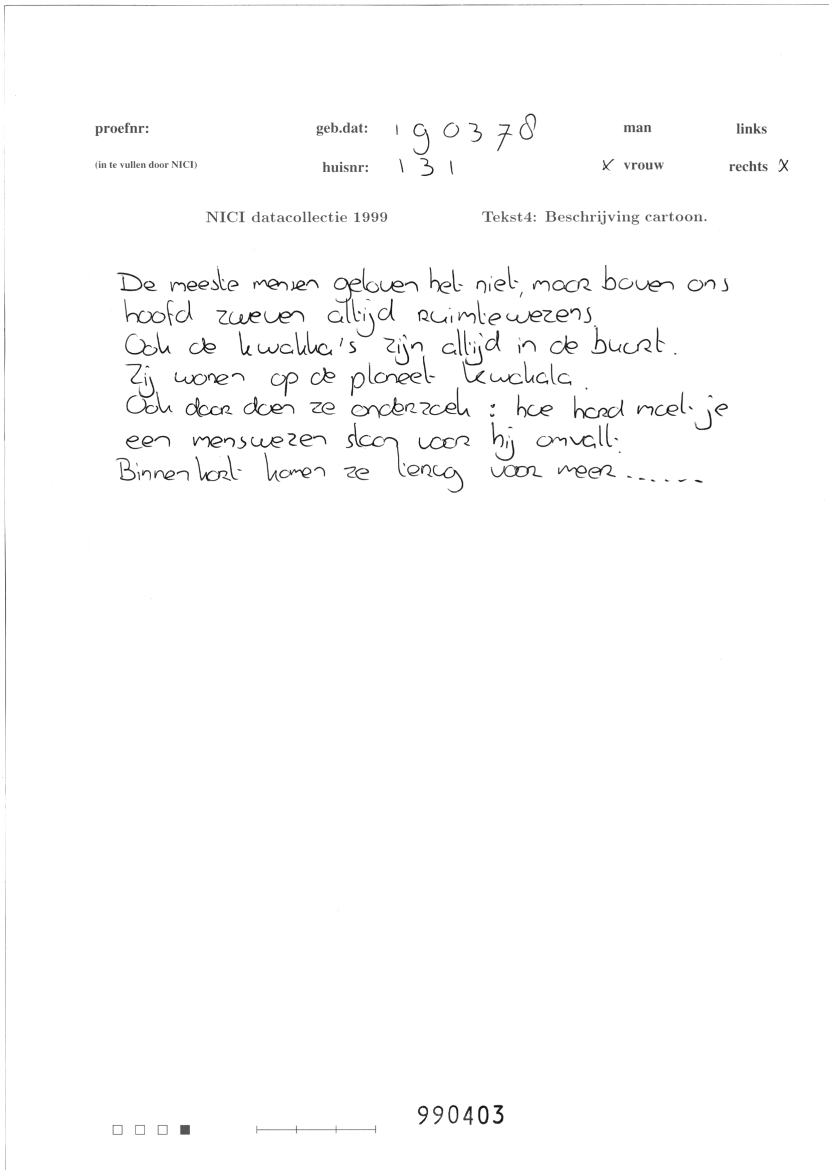


[22]

Preprocessing

- Crop
- Text padding
- Normalize

Text padding



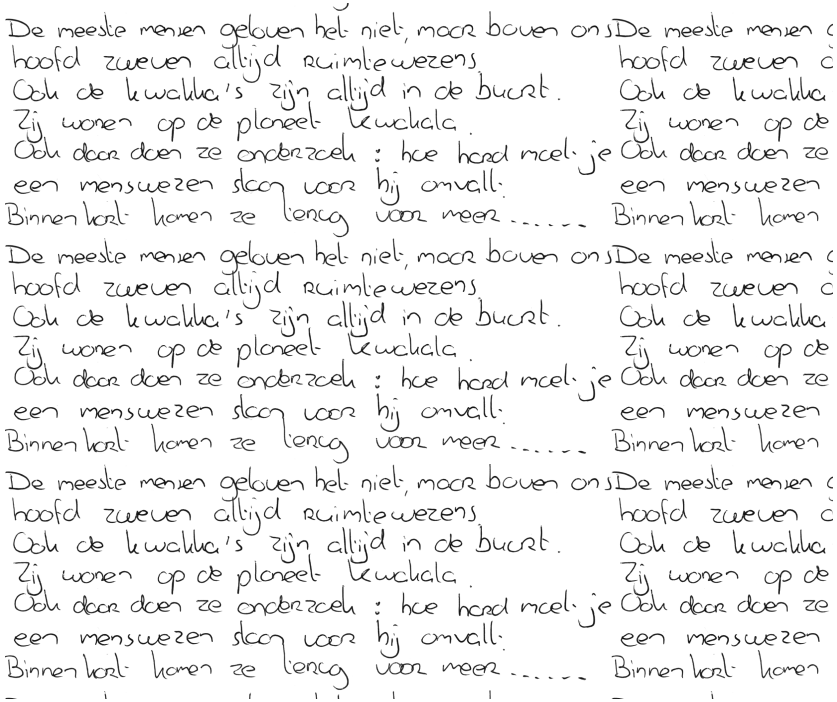
proefnr: geb.dat: 190378 man links

(in te vullen door NICI) huisnr: 131 ✗ vrouw rechts ✗

NICI datacollectie 1999 Tekst4: Beschrijving cartoon.

De meeste mensen geloven het niet, maar boven ons
hoofd zweven altijd ruimtewezens.
Ook de kwallka's zijn altijd in de buurt.
Zij wonen op de planeet kwallala.
Ook daar doen ze onderzoek: hoe hard moet je
een mensweze slaan voor hij omvalt.
Binnenkort komen ze terug voor meer.....

990403



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Experiments: Patches

Patch size	IAM	Firemaker	ICDAR17
100	84.8	78.0	22.6
256	95.7	98.0	63.8
500	**96.8**	98.0	78.3
600	**96.8**	98.4	81.0
800	94.6	98.4	**83.6**
1000	95.0	**99.2**	-
1200	95.4	-	82.5

Table: Accuracy (in %) for increasing patch sizes. The number of patches was 300 for IAM and Firemaker and 64 for ICDAR17

Experiments: Full-pages

Dataset	Batch size	Learning rate	Top1 (%)
IAM	9	0.002	91.34
Firemaker	6	0.003	98.32

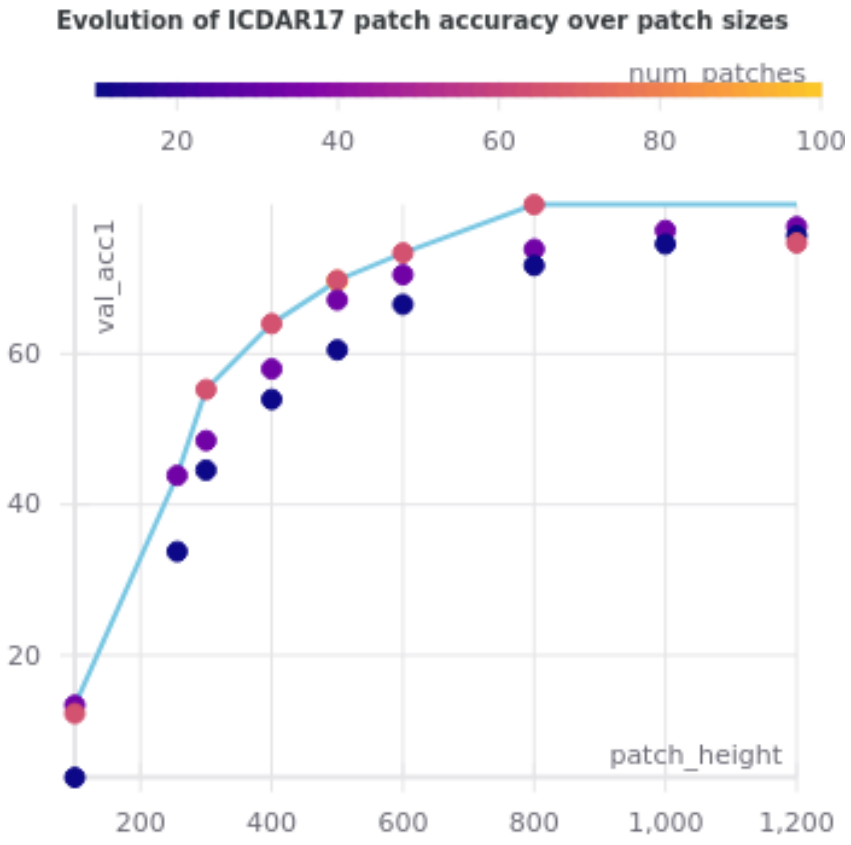
Experiments: Historical manuscripts

Dataset	Batch size	Learning rate	Top1 (%)
ICDAR17	9	0.002	75.42

Table: Best model with full-pages

Dataset	Num patches	Patch size	Top1 (%)	Patch accuracy (%)
ICDAR17	64	800	83.75	80.1

Table: Best model with patches



Results on the IAM dataset

Year	Feature	Classifier	Ref.	Writers	Top1 (%)	Top5 (%)	Top10 (%)
2020	CNN with word fragments (FragNet-64)		[15]	657	96.3	–	–
2019	SIFT + RootSIFT	GMM	[7]	650	97.85	–	–
2018	CNN with tuples of images of size 64x64		[16]	650	93.14	–	–
2016	Multi-stream CNN (DeepWriter)		[17]	657	97.3	–	–
2016	p(Is,Iθ), p(IBOS)		[8]	657	86.9	91.6	94.7
2016	Chain code	KDA	[5]	650	82.7	–	92.2
2015	Graphemes	SR-KDA	[9]	657	92	93	97
2014	MSDH + TDH	KNN	[2]	657	97.1	98.8	99.2
2014	SDS + SOH	Euclidean	[3]	657	**98.5**	99.1	99.5
2013	Texture LPQ	SVM	[6]	650	96.7	–	–
2013	Connected	KNN, x2	[10]	650	94.8	–	–
2012	Quill–Hinge	NN	[4]	657	97	–	98
2012	SIFT	x2	[11]	650	93.1	–	–
2011	KAS	SVM	[12]	650	92.1	94.5	95.8
2010	Codebook and contour	KNN	[14]	650	91	–	97
2007	Contour PDFs and ink trace	PDFs	[1]	650	89	–	97
2020	CNN with patches of size 600		Ours	657	96.3	–	–

Results on the Firemaker dataset

Year	Feature	Classifier	Ref.	Writers	Top1 (%)	Top5 (%)	Top10 (%)
2020	CNN with word fragments (FragNet-64)		[15]	250	97.6	–	–
2019	SIFT + RootSIFT	GMM	[7]	250	97.98	–	–
2019	CNN with tuples of images of size 64x64		[16]	250	93.56	–	–
2014	SDS + SOH	Euclidean	[3]	250	92.4	96.2	98.8
2013	Connected	KNN, x2	[10]	250	95.2	–	99.2
2012	Quill–Hinge	NN	[4]	251	86	–	97
2007	Contour PDFs and ink trace	PDFs	[1]	250	83	–	95
2020	CNN with patches of size 1500		Ours	250	**99.2**	–	–

Conclusions

- Proposed a new preprosessing method called *Text padding*
- Demonstrated the promising performance of using bigger patch sizes
- Provided an open-source [1] deep learning based writer identification system that obtained competitive accuracy

[1] `github.com/akpun/writer-identification`

Thanks for watching!
Contact: akpun@inf.upv.es

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[18] Youbao Tang and Xiangqian Wu.
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