Data Driven Feature Extraction for Gender Classification using Multi-script Handwritten Texts

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INTRODUCTION

- Handwriting is indicative of rich information about the writer and can be employed as an effective biometric modality.
- A widely established correlation is between handwriting and writer demographics especially the gender of writer.
- Popular computerized methods for gender prediction include extraction and classification of hand crafted global or local features from given set of handwriting samples (Figure 1).



Fig 1: Sample images of (a): Male and (b): Female writings in the QUWI database

Objectives:

- To assess effectiveness of machine learned visual attributes from handwriting samples of males and females for gender prediction.
- To study the impact of scale of observation (e.g. word, patch & page level) on the classification outcome.

CONCLUSION & FUTURE DIRECTIONS

An experimental study is presented to evaluate the performance of state-of-theconvolutional neural network based feature extraction to classify gender from offline har Features were extracted from writing samples by changing the scale of observa comprehensive series of experiments were carried out. Work can be extended in following di

A comprehensive series of experiments can be carried out using other pre-trained models.

Fine tuning of pre-trained models can be done by continued back propagation on the images

Training a network from scratch at word, patch or image levels to allow deeper insights into v writing features contribute to characterize gender can be considered.

Handwriting Sample Im (Word, Patch and Page L

• METHODOLOGY

Feature Extraction

(using Pre-Trained Convol Neural Networks)

Classification

Prediction Decision



important detail Authority (QMA) ha nd the community entry is via the avol the path les

🗏 Asmall, yet very important detail about 141A is that the to the Museum and the community. Alless to the Museum's Main extrance. The entry is via the city's promenade, visitors the museum's urban context; the city and the bay. The planning.



(c) Fig 2: Samples and Activations at (a): (b): Patch Level (c): Page Leve

			1.1		State of the second			1	
3	• EX	PERI	Μ	ENTA	L PROT	OCOL			
			20						
	Dataset			Q	QUWI-English				
				Q	QUWI-Arabic				
	Dro Troined Complet				700 Writers : 300 Writers				
	Pre-Irain	Classifiers							
-	Classifiers Connerie 1			<u> </u>	Text Develoption Text Level 1				
E	Evaluation Scenario 1			01 [6	lext Dependent vs. lext Independent				
	Evaluation Scenario 2				Script Dependent vs. Script Independent				
	ПГС	· · · · · · · · ·			VIVCIC				
	• KES	OLI	20		ALYSIS				
	Image Scale		Classifiers						
stall (a)): ality	Level		LDA		NB	S۱	/M	DT	
	Word		6	7.75%	65.41%	63.	66%	64.33%	
	Patch		70.08%		67.16% 65.		03%	65.58%	
	Page		6	8.50%	<u>66.75%</u> 64.		66%	64.33%	
		Text Dep		t Deper	dent	Text	Text Independent		
	Dataset	Woi	rd	Patch	Page	Word	Patch	Page	
	English	68.33	3%	73.33%	6 70.33%	67.33%	72.00%	69.33%	
	Arabic	64.66	6%	71.66%	69.66%	65.33%	70.66%	66.33%	
			Tra	aining Set	Testing Set	Word	Patch	Page	
	Script Dependent		Er	nglish	English	68.50%	71.50%	6 70.83%	
			Arabic		Arabic	63.66%	69.83%	68.83%	
	Script Independent		English		Arabic	67.50%	65.16%	64.50%	
l			Arabic		English	60.83%	64.83%	63.83%	
	 Highes level 	st accu	racy	/ achiev	ed with CN	N-LDA co	mbinatio	on at patch	