OFFLINE SIGNATURE VERIFICATION USING MACHINE LEARNING

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What is signature verification ?

What is offline signature verification ?

- Online verification

  Speed, pen pressure, directions, pen stroke length etc. dynamic features.

  Not very common.

  Solved with high accuracy.

- Offline verification

  Only image.

  Widely used and accepted.

  Not fully solved yet.

  Generalization problems due to scanning quality, scan noise, lighting etc.

MOTIVATION

Provide a technique to detect handwritten signature forgeries without expert analysis and in a much shorter timespan.

Useful against forgeries in official and financial documents.

EARLIER WORKS

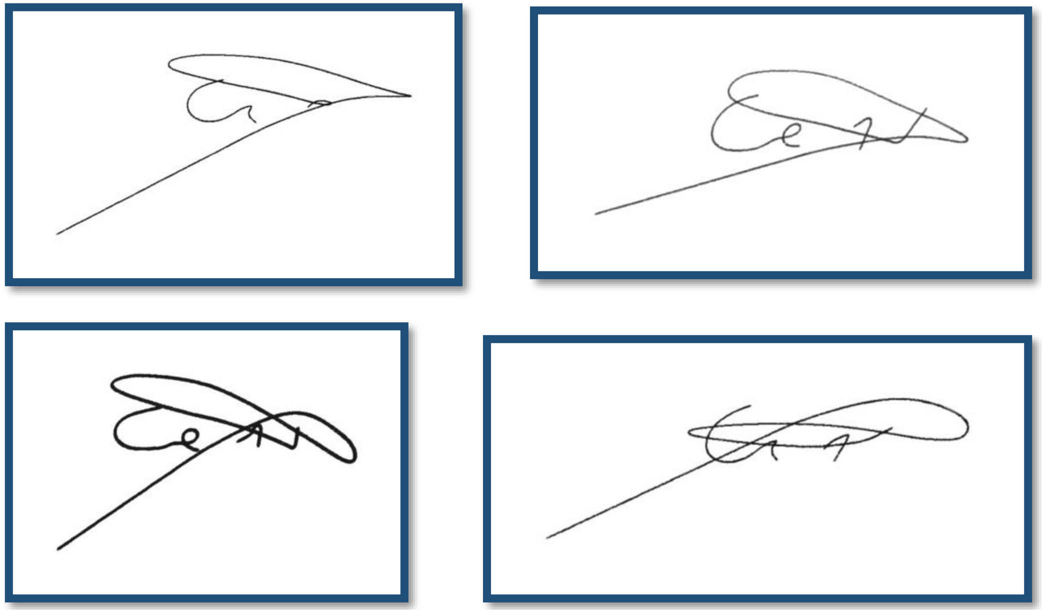
- Hand-engineered features
- Using forgeries during training
- CNNs
- Siamese Networks
- Metric Learning

FINAL GOAL

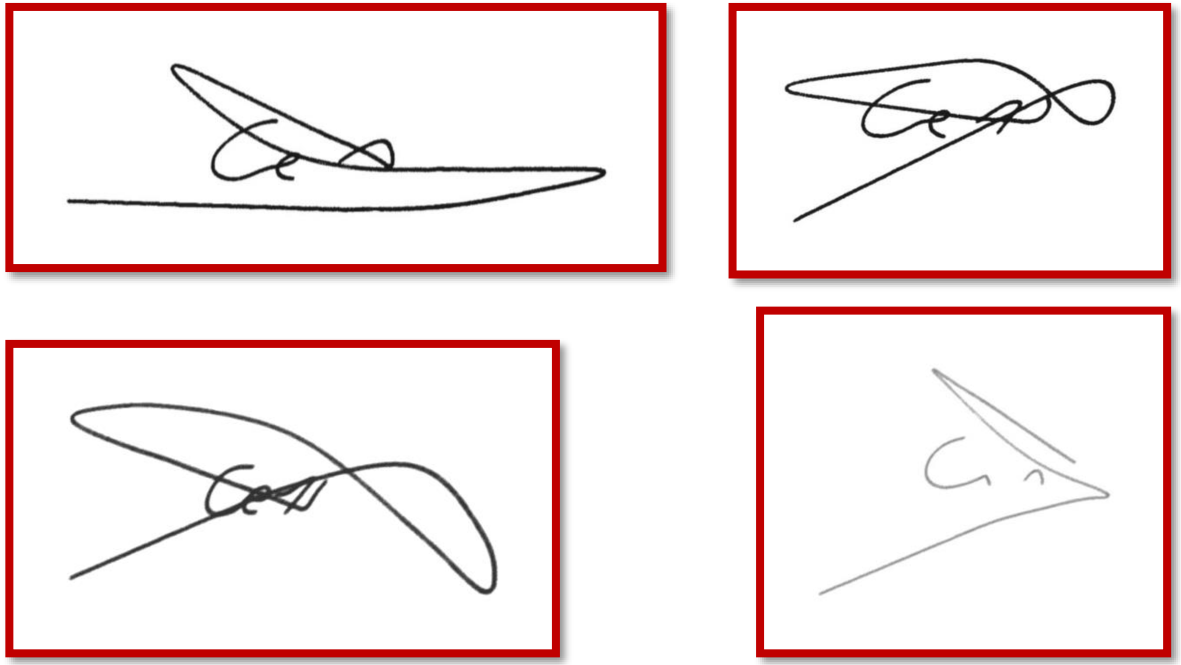
- Do not use forged signatures during training.
- Only learn discriminatory features from genuine signatures.
- Use as little genuine samples as possible.
- Accept new users with little training and adjustment overhead.

Genuines vs Forgeries
Synthetic Examples

Genuine Signatures

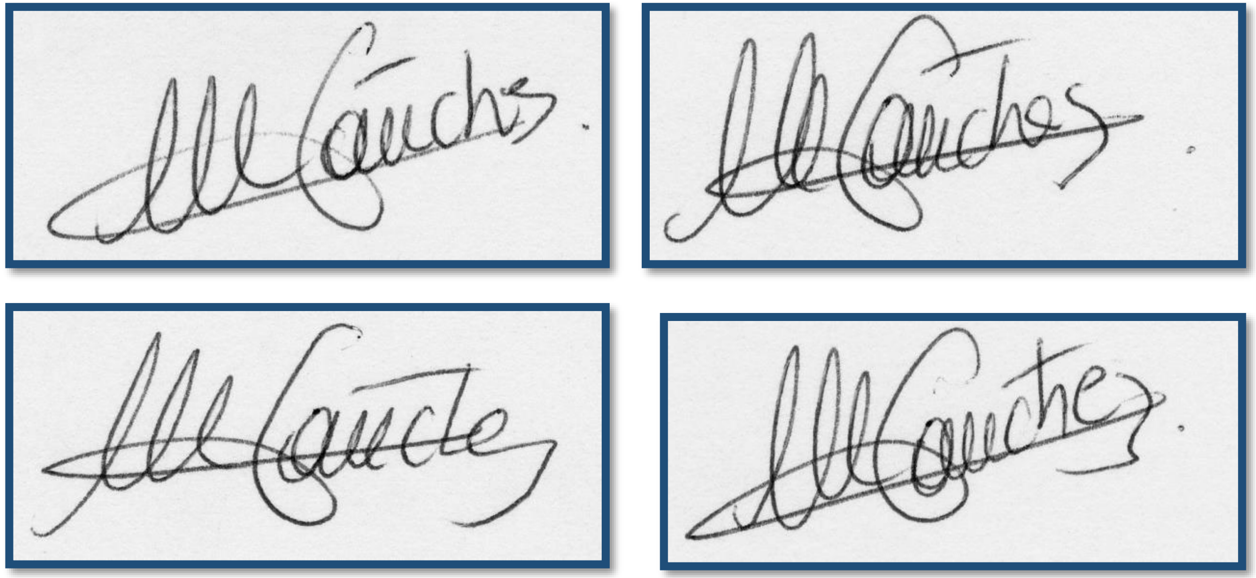


Forgeries



Genuines vs Forgeries
Biometric Examples

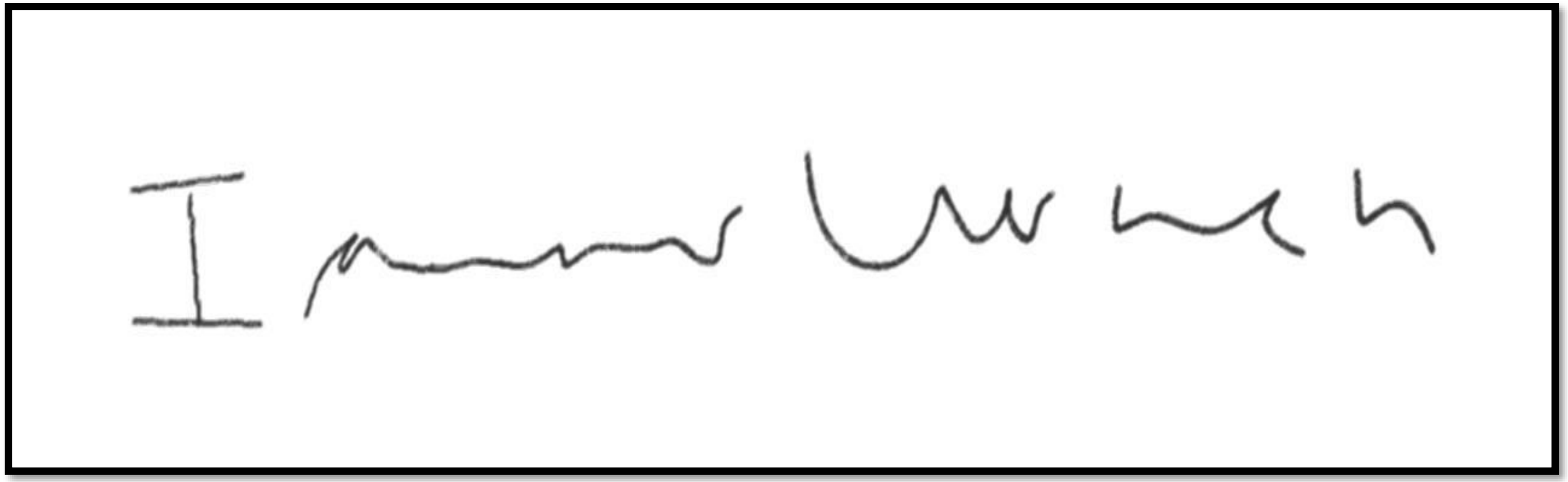
Genuine Signatures



Forgeries

Preprocessing

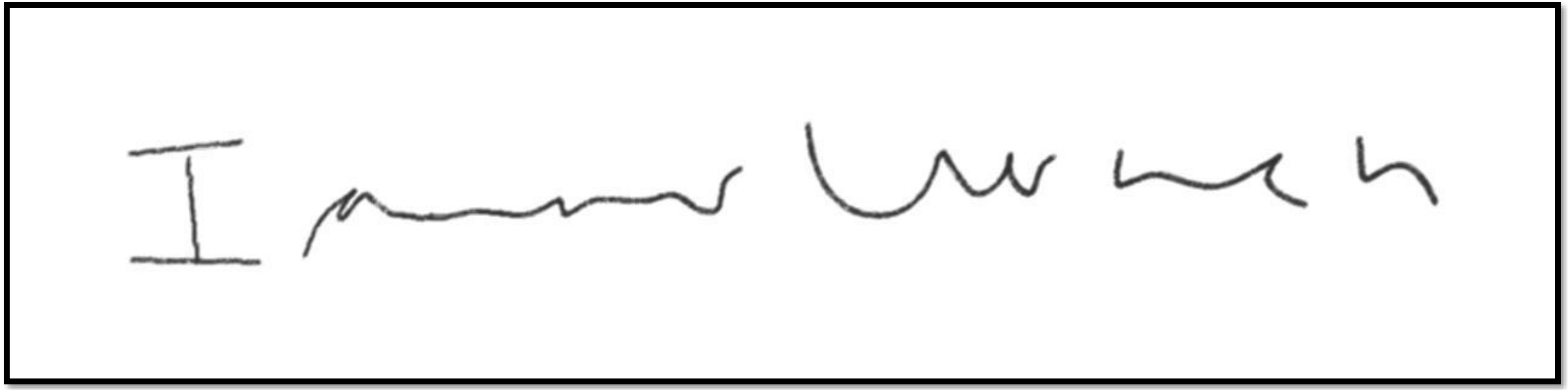
- Normalization, noise filtering, standardized in the literature.

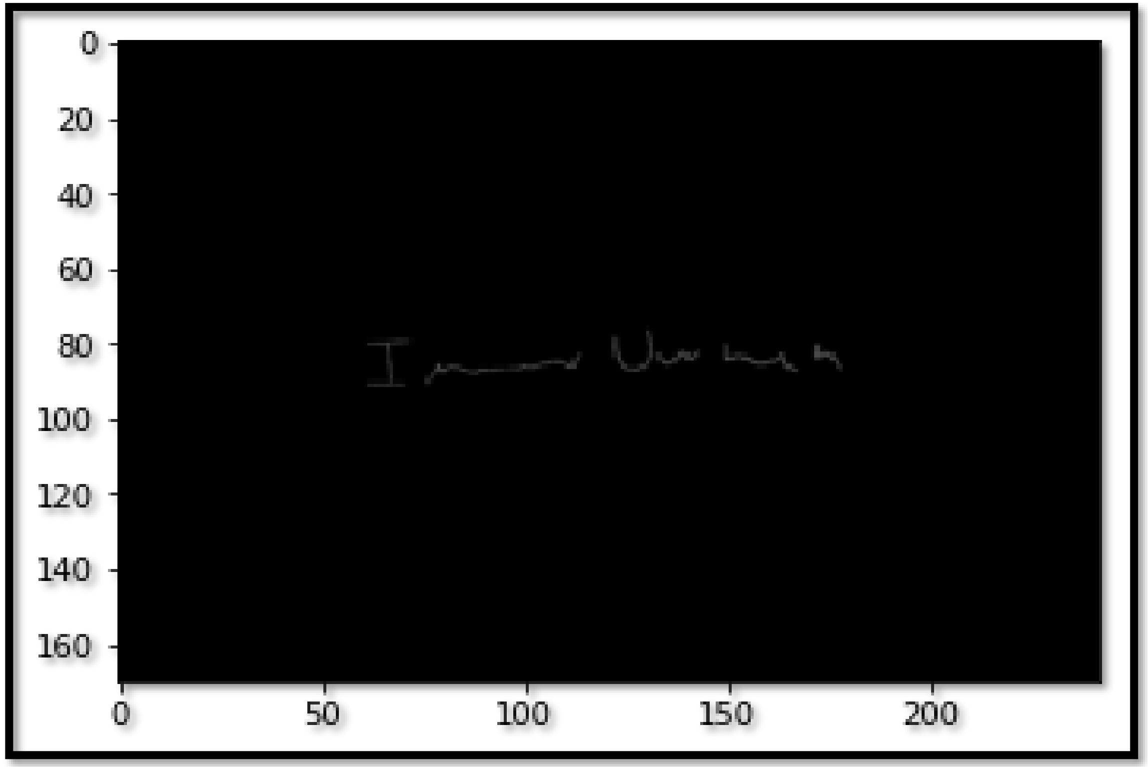


Example genuine signature

Preprocessing Steps

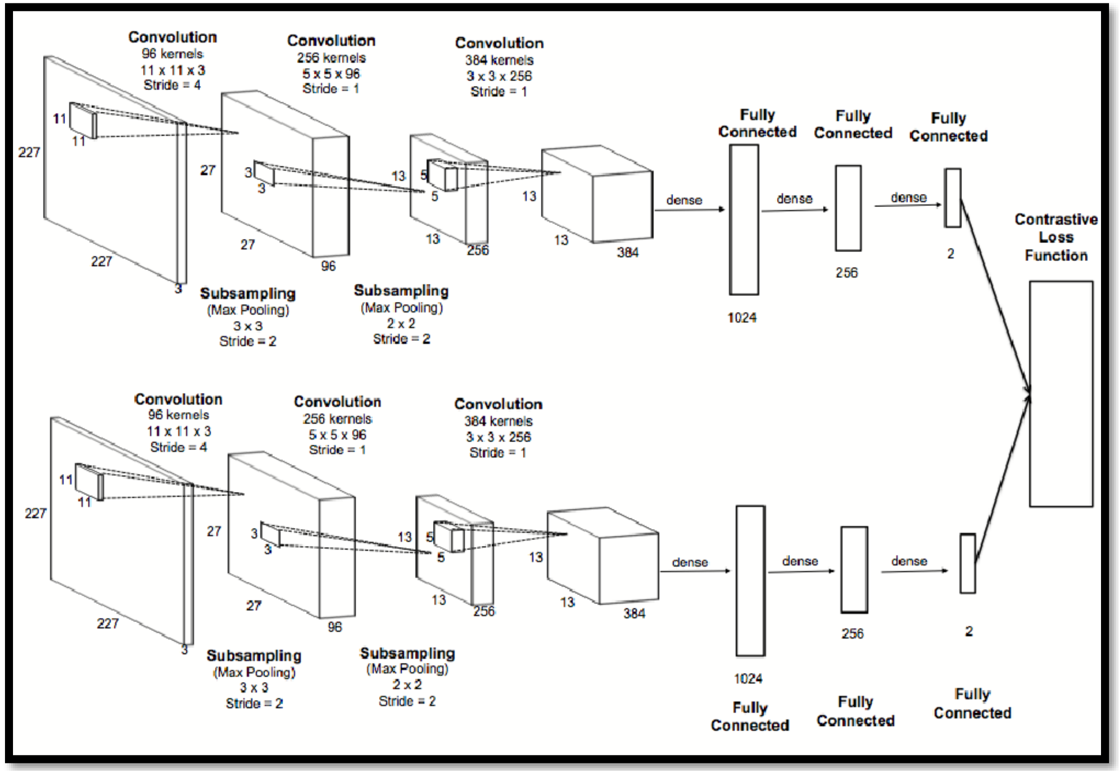
- Size normalization, center to max size and white pad. (1338x2973 for GPDS-S-4000)
- OTSU Thresholding, background set to white(255), foreground is left as-is.
- Inversion
- Resize to 170x242.
- CNN input is 150x220, data augmentation.




0
20
40
60
80
100
120
140
160
0
50
100
150
200

Initial Proposal: Siamese Networks

- Low accuracy without forged signatures.
- Difficult to train and combine with low number of samples.
- Around 66% accuracy, confirming the academic literature.



Example Siamese architecture

CNN Architecture

- Very similar to AlexNet.
- 2048 FC units instead 4096.
- Various custom loss functions for different CNN training procedures. (including skilled forgeries during writer-independent feature learning)

Layer	Size	Parameters
Input	1x150x220	
Convolution	96x11x11	stride = 4
Max. Pool	96x3x3	stride = 2
Convolution	256x5x5	stride = 1, pad = 2
Max. Pool	256x3x3	stride = 2
Convolution	384x3x3	stride = 1, pad = 1
Convolution	384x3x3	stride = 1, pad =1
Convolution	256x3x3	stride = 1, pad =1
Max. Pool	256x3x3	stride = 2
Fully Connected	2048	
Fully Connected	2048	

Main Idea

- Train CNNs to differentiate between handwritten user signatures (user-user discriminator)
- Use a less complex classifier (SVM with rbf kernel) to classify using learned features. (genuine-forgery discriminator)
- No need to re-train CNN (for new users)
- Generalized, multi-to-one comparison version of Siamese Networks

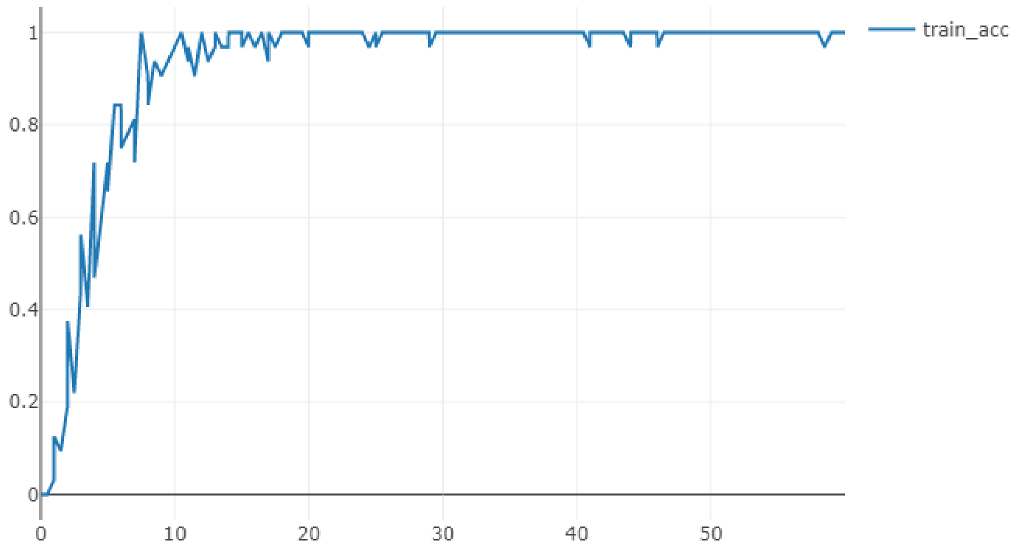
Available Datasets

- GPDS-S 4000
- MCYT-75
- GPDS (extracted features) (881 users)
- MCYT-75 (extracted features)
- CEDAR (extracted features) (55 users)

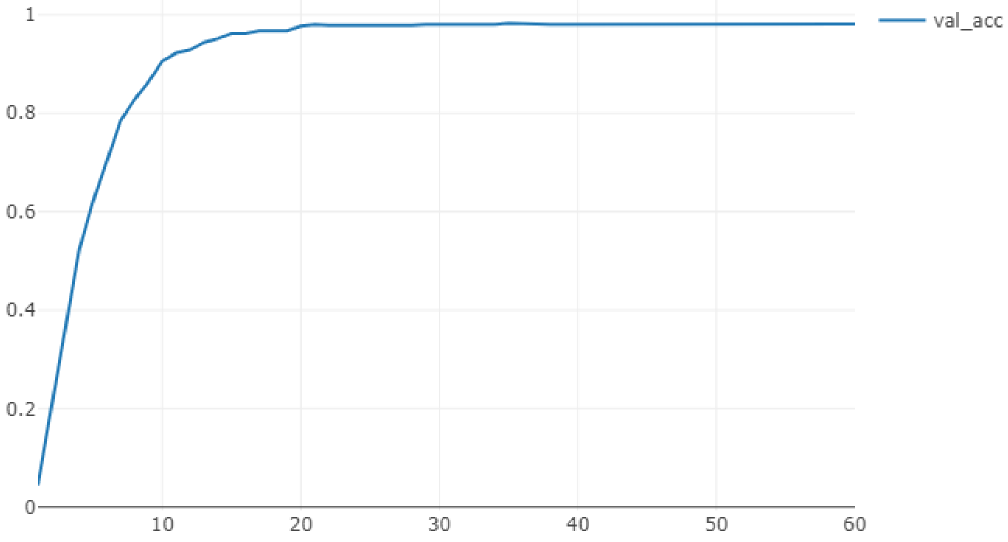
CNN Experimental Protocol

- CNN trained on 1000 users from GPDS-S-4000 (feature learning)
- 10 – 2 training - validation split (split 12 signatures)
- Multiclass user-user classification problem
- %99.8 validation accuracy
- Also forgery based feature learning tested (extra neuron, loss)
- Tested the generalization ability of the learned features from GPDS-S-4000 on MCYT-75

60 epochs training & validation accuracy plots 32 batch size

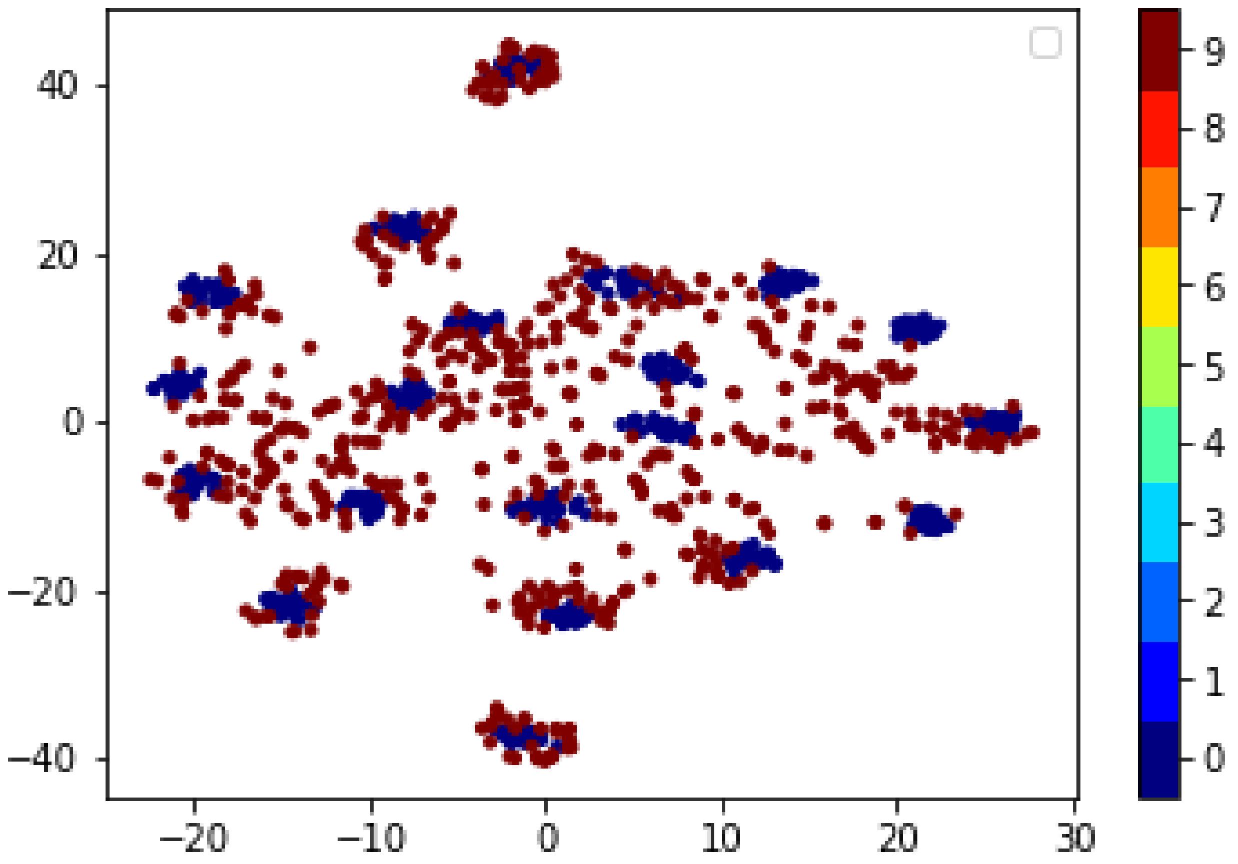


Training accuracy.



Validation accuracy.

CNN Dimensionality Reduction (t-SNE)



Randomly sampled 20 user signatures, blues are genuine, reds are forged signatures.

SVM Experimental Protocol (Feature Verification)

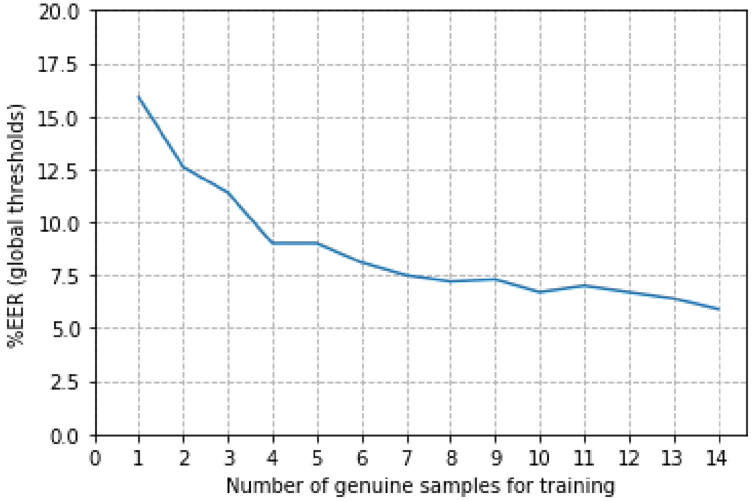
- Binary SVM classifiers for each user.
- From GPDS-S-4000, 200 users are used for feature validation and SVM hyperparameter tuning. (also decision threshold for GPDS-S 4000)
- Tuned models are tested on the rest.

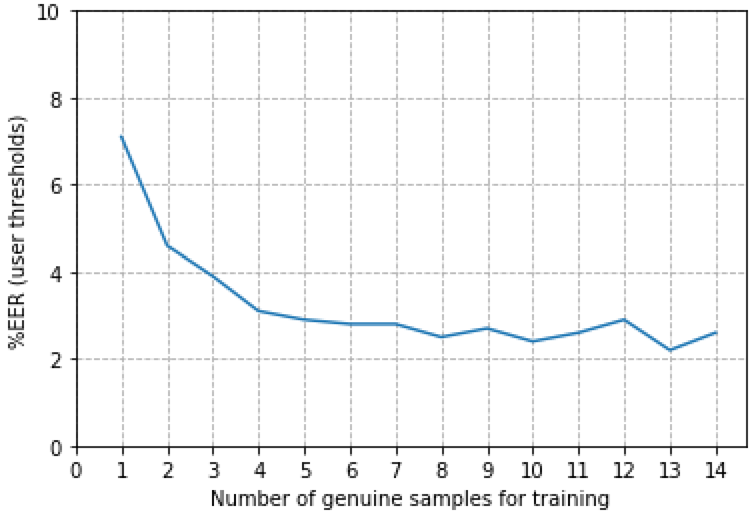
Dataset	Training Split		Testing Split
	Genuine	Random Forg.	
GPDS-Synthetic 4000	n ∈ {1,…,12}	1200 x 14	(10 genuine, 10 forgery)
MCYT- 75	n ∈ {1,…,10}	74 x 15	(5 genuine, 15 forgery)
GPDS	n ∈ {1,…,12}	581 x 14	(10 genuine, 10 forgery)
CEDAR	n ∈ {1,…,12}	54 x 12	(10 genuine, 10 forgery)

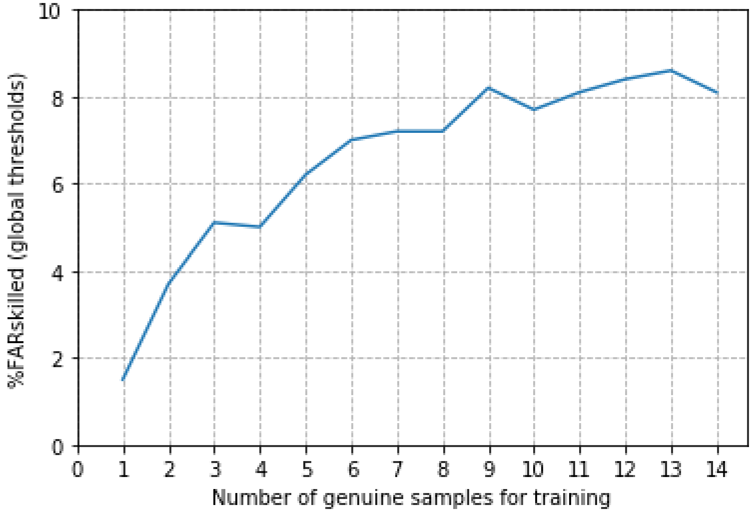
Evaluation Metrics

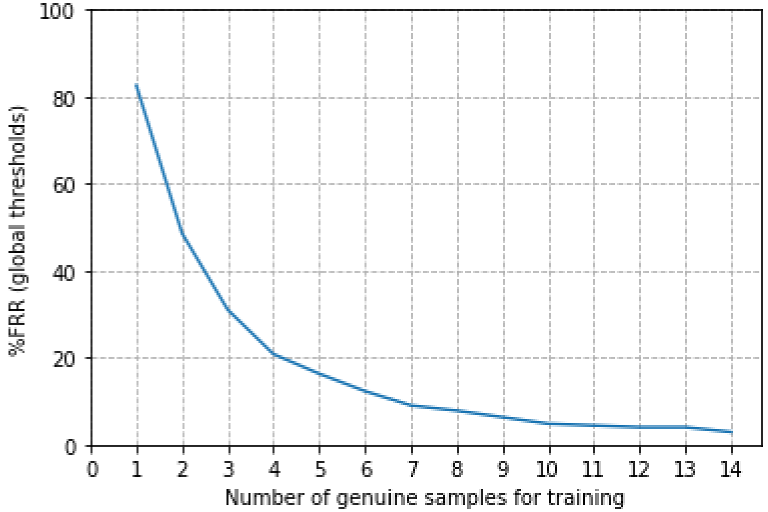
EER_{global} ,EER_{user} , FRR, $FAR_{skilled}$

Effect of Training Sample Count (GPDS-S 4000)









Performance on Datasets

Reference	EER_{global}(%)
Dutta et al. [30]	26.33
Dey et al.[25]	22.24
Soleimani et al. [31]	13.30
Ferrer et al.,[32]	16.44
Serdouk et al.,[33]	16.68
Zhang et al.[34]	14.79
Proposed	**6.96**

Performance on GPDS-S 4000, using 10 genuine 10 skilled forgeries. FRR = 7.17%, FARskilled = 6.83%.

Reference	EER_{user} (%)
Gilperez et al.[37]	6.44
Vargas et al.[36]	7.08
Ooi et al. [35]	9.87
Soleimani et al.,[31]	9.86
Hafemann et al.[14]	**2.87**
Proposed	4.00

Performance on MCYT-75, using 10 genuine 10 skilled forgery samples.

Performance using pre-extracted Features

Reference	# genuine samples	EER_{user} (%)
Hu and Chen[38]	10	7.66
Guerbai et al.[39]	12	15.07
Serdouk et al.[40]	16	12.52
Soleimani et al.[31]	10	20.94
Yilmaz.[41]	12	6.97
Hafemann et al.[14]	10	1.69
Proposed	**10**	**1.33**

Performance on GPDS using pre-extracted features for the proposal.

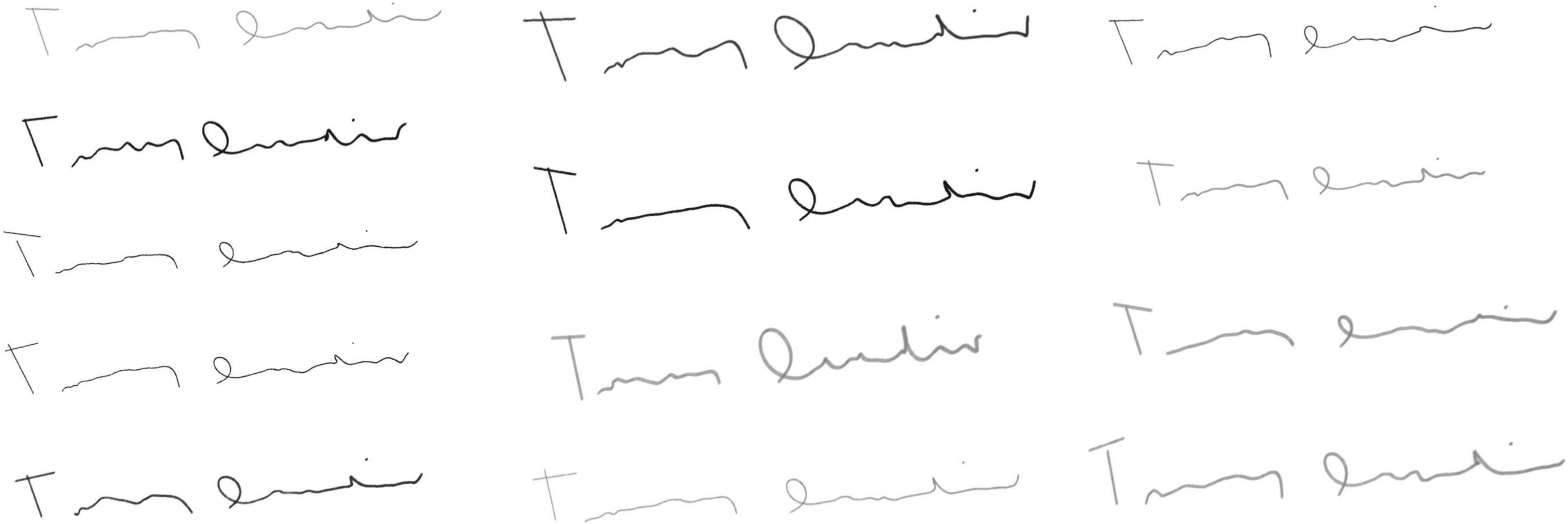
Reference	EER_{user} (%)
Gilperez et al.[37]	6.44
Vargas et al.[36]	7.08
Ooi et al. [35]	9.87
Soleimani et al.,[31]	9.86
Hafemann et al.[14]	**2.87**
Proposed	4.00
Proposed(pre-extracted)	3.14

Performance on MCYT-75, 10 samples each, included using pre-extracted features for the proposal.

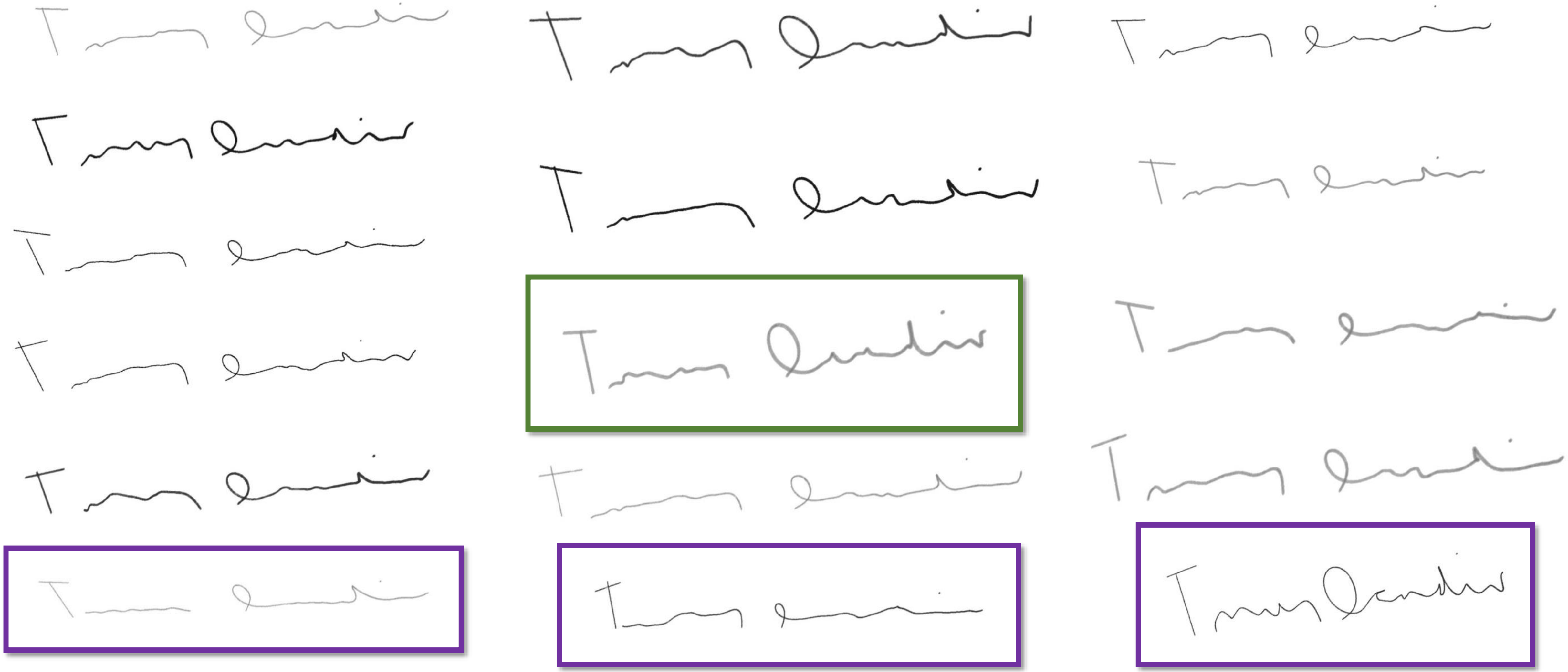
Reference	# genuine samples	EER_{user} (%)
Chen and Srihari	16	7.9
Bharatri and Shekar	12	15.07
Guerbai et al.	12	5.6
Hafemann et al.[14]	12	4.63
Proposed	**12**	**2.87**

Performance on CEDAR using pre-extracted features for the proposal.

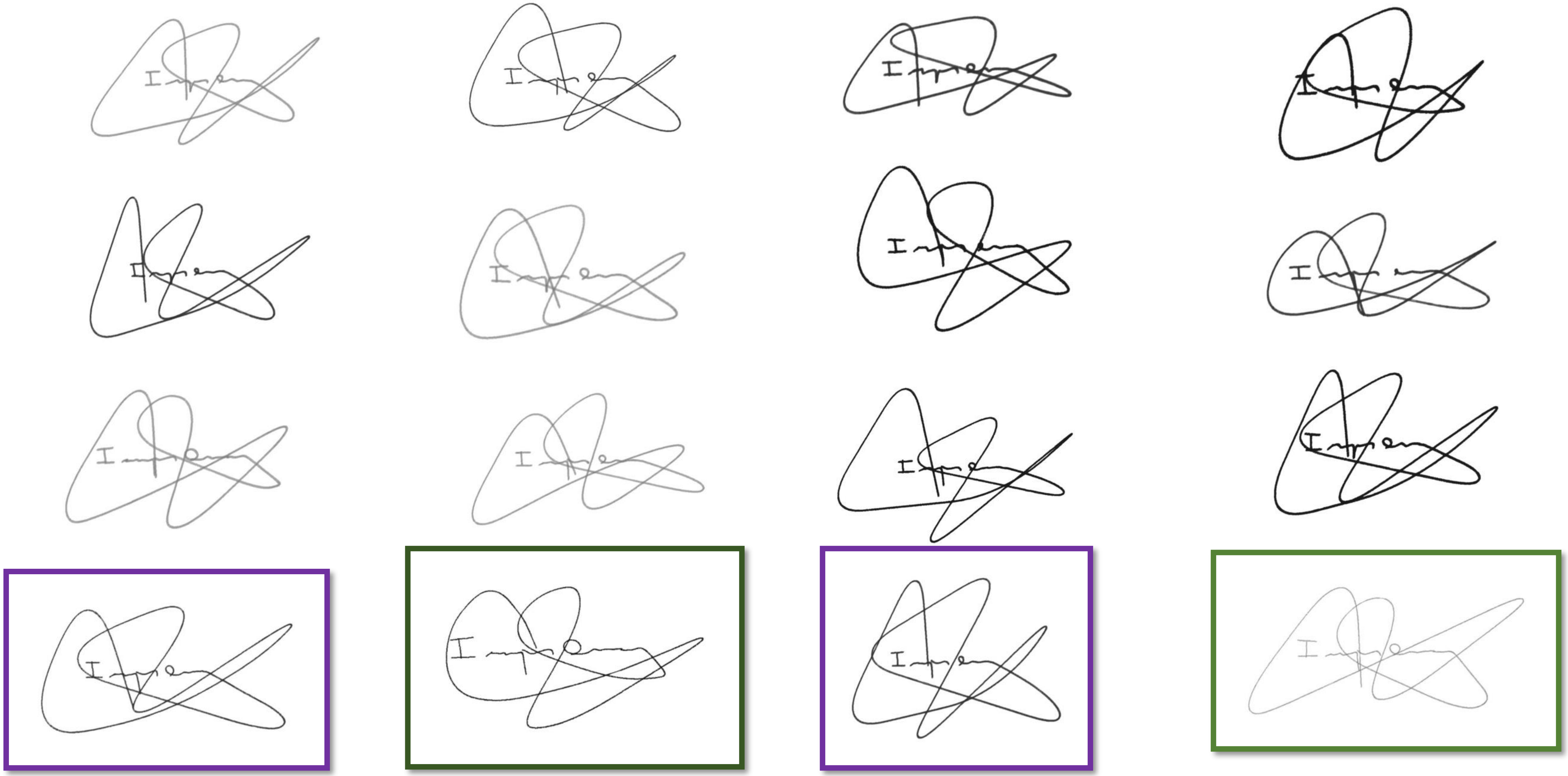
False Acceptance Example



False Acceptance Example

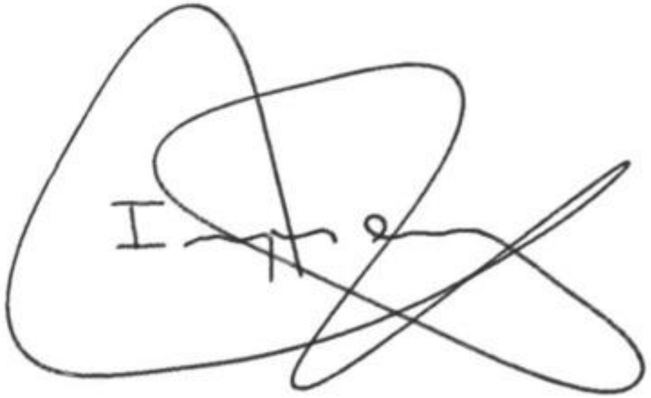


False Rejection Example

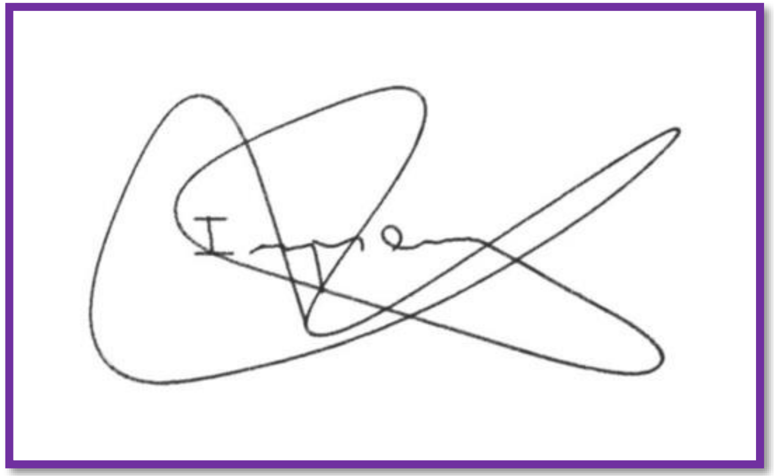


Closer Look

Training Examples



Falsely Rejected



Comparison vs State of the Art

- No superior CNN architecture
- SVM hyperparameters better tuned ca. +%0.5 score
- Loss function was changed for better forgery feature learning (generalized poorly)
- Tested decision tree and MLP based classifiers, SVM was best
- However neural architecture search can possibly find a better architecture since MLP scores were close
- Surpassed the state of the art on the synthetic new dataset. (GPDS-S 4000)

Conclusion & Future Work

- CNNs are strong feature extractors
- But deeper CNNs lose their generalization capability
- Learnable forgery features do not generalize (CNN side)
- Correct architecture is critically important
- Synthetic features generalize to biometric data
- But not as good as biometric-biometric generalization capability yet
- GAN might be very useful in the future for generating forgeries

Q & A

https://github.com/gonultasbu/sigver_v2

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