DeepSign: Efficient Siamese Convolutional Neural Networks for Real-time Signature Verification

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Prediction Task

- Signatures are a common form of verification and a target for fraud
- We apply efficient and high performing siamese convolutional neural networks for the task of real-time signature verification.
- Input: a pair of signatures s1 and s2.
- Output: whether these signatures are from the same person

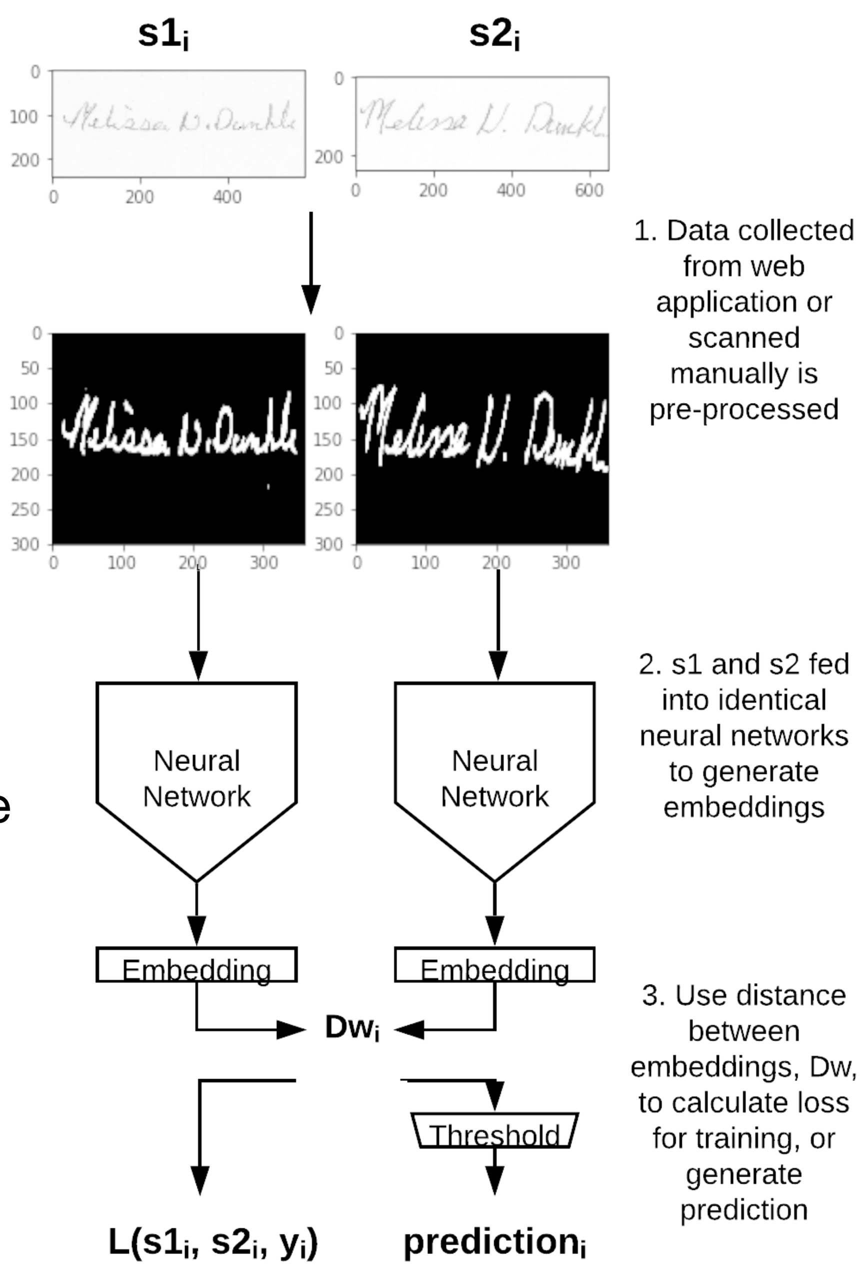


Figure 1. Flow diagram of prediction task.

Data

1. CEDAR (American): n=55, 24 genuine signatures per person, 24 forged signatures per person [1].
2. BHSig260 (Bengali): n=260, 24 genuine signatures per person, 30 forged signatures per person [2].

- We generate our train/val/test sets by performing a 60/20/20 random split by person (Table 1).
- We use all unique signature pairings from the datasets (e.g. in CEDAR there would be 25^2 forged-original pairs and $\sum_{i=1}^{24} i = 300$ original-original pairs per person).

Table 1. Dataset Splits

Dataset	Train	Validation	Test
CEDAR	28,116	9,372	9,372
BHSig260	180,180	60,060	60,060
Combined	208,296	69,432	69,432

Architectures

We use three architectures for our study:

1. SigNet, the state of the art in signature verification on our dataset [3].
2. An adapted and pre-trained MobileNetv2 network, state of the art performing mobile network on ImageNet [4].
3. DeepSign, which is made up of Fire blocks from the SqueezeNet architecture (Table 3) [5].

Model	Parameters	Storage Size (MB)
SigNet	6,460,974	25
MobileNetv2	721,589	12
DeepSign	**256,992**	**1.1**

Table 2. DeepSign and MobileNetv2 efficiency over SigNet

Layer	Parameters	Output Shape
Conv2D	$k=3, s=2$	(149, 179, 64)
MaxPool2D	$k=3, s=2$	(74, 89, 64)
Fire	$sqz=16, exp=64$	(74, 89, 128)
Fire	$sqz=16, exp=64$	(74, 89, 128)
MaxPool2D	$k=3, s=2$	(36, 44, 128)
Dropout	$p=0.2$	(36, 44, 128)
Fire	$sqz=32, exp=72$	(36, 44, 144)
Fire	$sqz=32, exp=96$	(36, 44, 192)
Fire	$sqz=32, exp=128$	(36, 44, 256)
MaxPool2D	$k=3, s=2$	(17, 21, 256)
Dropout	$p=0.2$	(17, 21, 256)
Conv2D	$k=1, s=1$	(17, 21, 256)
GlobalAvgPool2D	-	(256,)
Dense	-	(128,)
L2 Norm	-	(128,)

Table 3. DeepSign Architecture

Results

Test Database	Model	Accuracy	Precision	Recall	AUROC
CEDAR Signature Database	SigNet	0.73	0.59	**0.65**	**0.79**
	MobileNetv2	0.72	**0.65**	0.28	0.72
	DeepSign	**0.74**	0.51	0.57	0.72
BHSig260 Signature Database	SigNet	0.81	0.69	0.75	0.85
	MobileNetv2	0.75	0.63	0.65	0.78
	DeepSign	**0.92**	**0.83**	**0.85**	**0.95**
Combined Database	SigNet	0.79	0.66	0.75	0.84
	MobileNetv2	0.76	0.65	0.70	0.82
	DeepSign	**0.85**	**0.76**	**0.84**	**0.93**

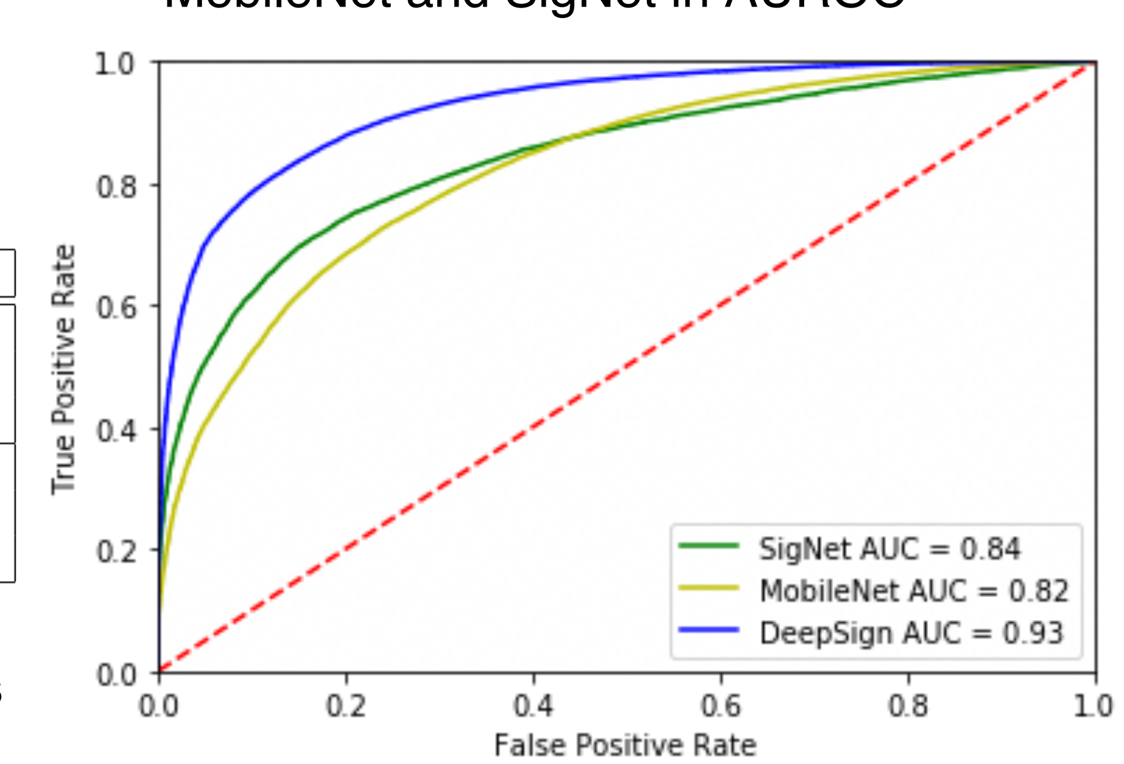
Table 4. Evaluation of models trained on combine dataset

- DeepSign outperforms in every evaluation metric on the combined test set
- DeepSign shows greatest ability to generalize to new datasets and languages

Train/Test Database	Model	Accuracy	Precision	Recall	AUROC
CEDAR/CEDAR	SigNet	0.65	**0.70**	0.15	0.78
	MobileNetv2	0.68	0.67	0.22	0.72
	DeepSign	**0.76**	0.65	**0.59**	**0.80**
CEDAR/BHSig260	SigNet	0.65	0.53	0.26	0.64
	MobileNetv2	0.63	0.52	0.12	0.59
	DeepSign	**0.74**	**0.82**	**0.50**	**0.86**

Table 5. Generalization of models to different languages

Figure 1. DeepSign outperforms both MobileNet and SigNet in AUROC



Visualization

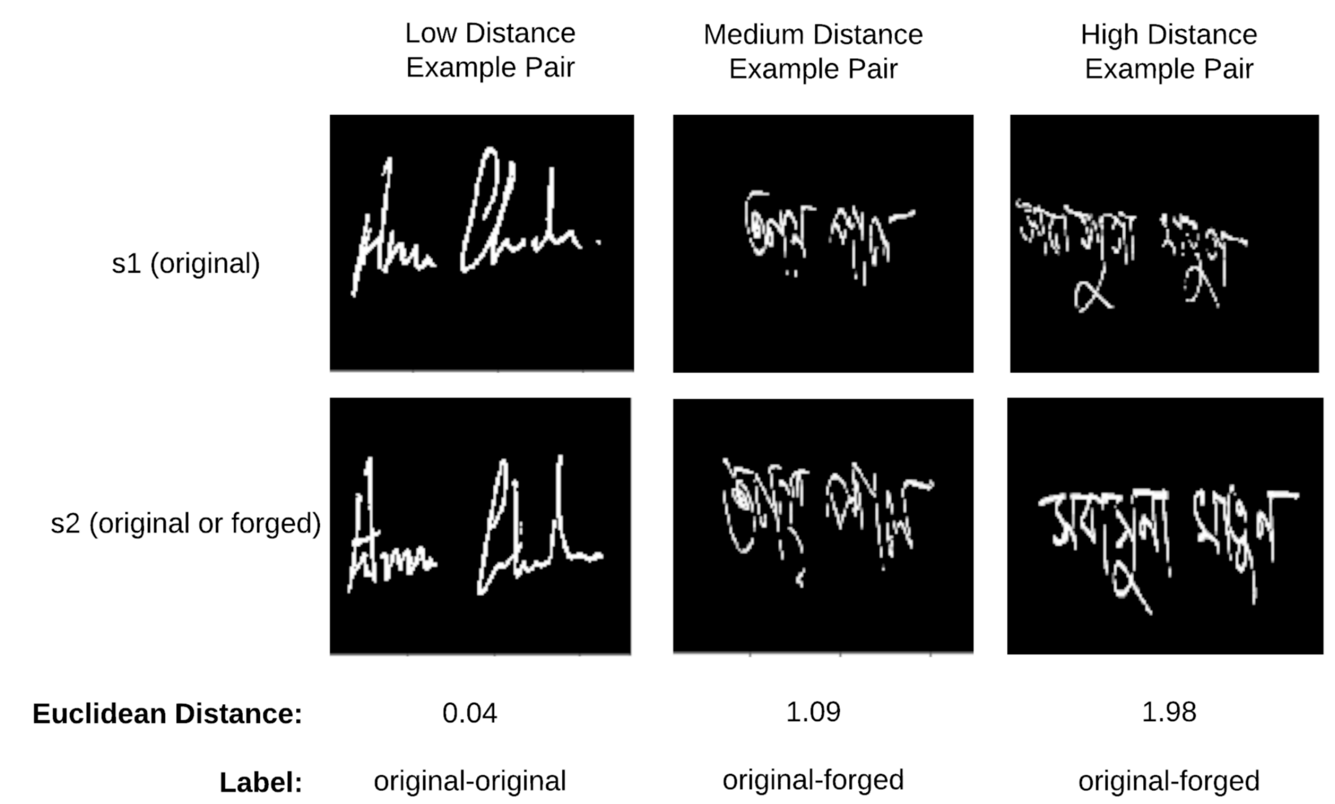


Figure 2. Visualization of outputs from DeepSign

- Our model is able to generate an embedding representations of signatures, where visually similar signatures have lower distances

Conclusion & Next Steps

- DeepSign has 25x fewer parameters and storage size then the state of the art SigNet, and outperforms in all of our evaluation metrics
- We have developed a publicy avilable web application (deepsign.koplex.io) that can perform real-time signature verification.
- Future work includes hyperparameter tuning, ensembling, and further investigation into using the bottleneck blocks in MobileNetv2.

References

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[3] Sounak Dey, Anjan Dutta, J Ignacio Toledo, Suman K Ghosh, Josep Llado ́s, and Umapada Pal. Signet: Convolu- tional siamese network for writer independent offline signa- ture verification. *arXiv preprint arXiv:1707.02131*, 2017

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