Offline Handwritten Signature Forgery Detection using Deep Learning Methods

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INTRODUCTION

Biometrics Authentication

Offline Signature

Online Signature

Handwritten Signatures

- They are unique distinctive characteristics in each person.
- They are simple, fast, non-invasive and familiar with people.

Handwritten Signatures

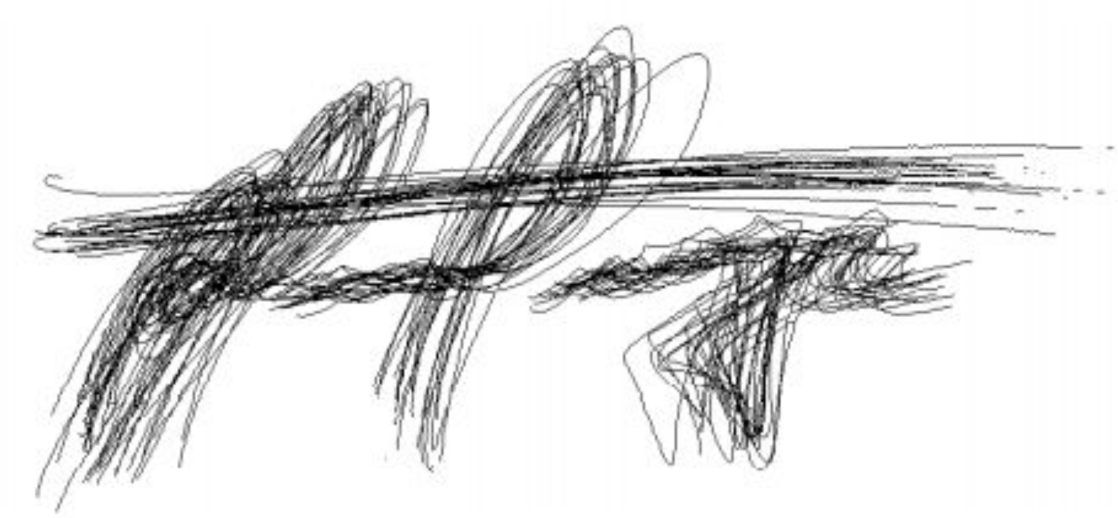
3 types of handwritten forged signatures:

- Random (Blind) forgery
- Simple Forgery
- Skilled Forgey

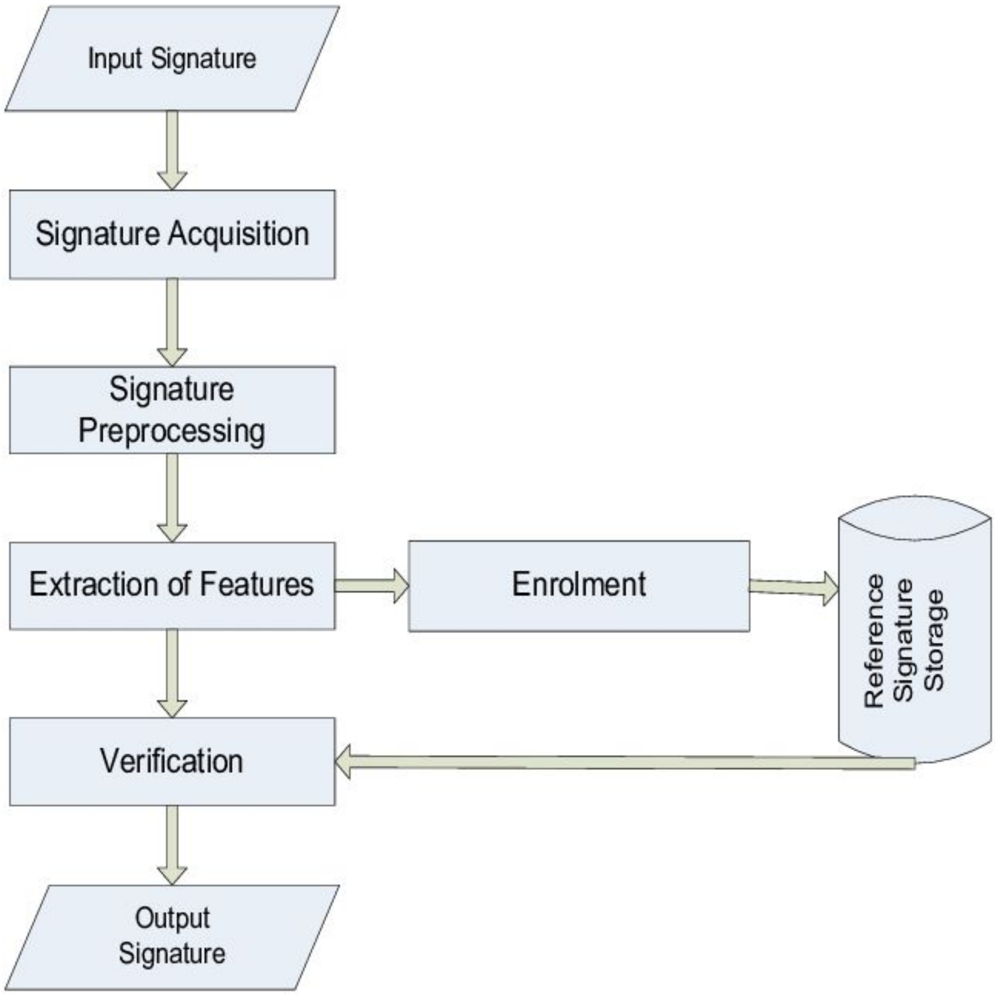
Handwritten Signatures

Challenge:

- They have a large variability between samples, which make it challenging to deal with skilled forgeries.



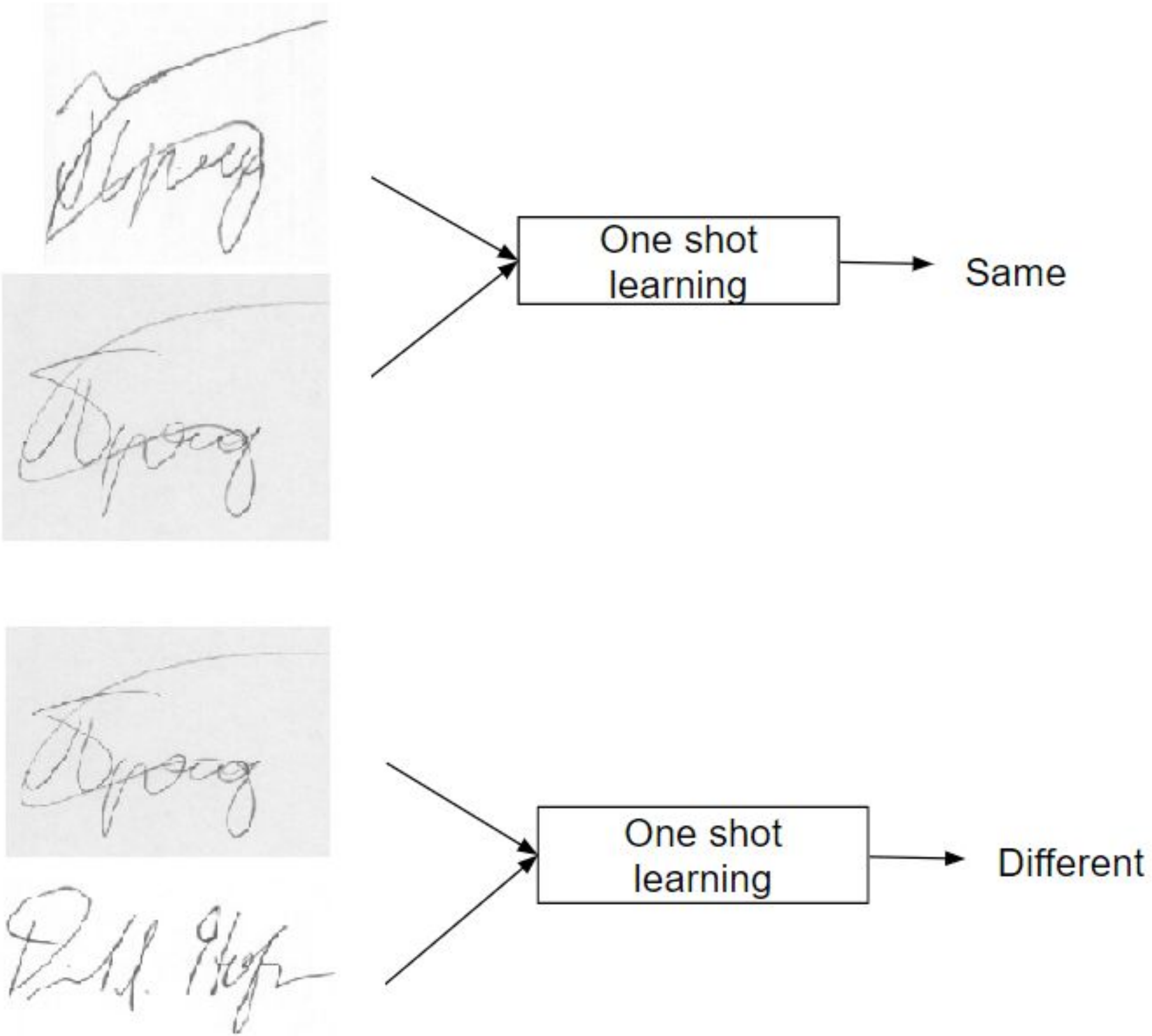
Typical architecture of signature-verification system



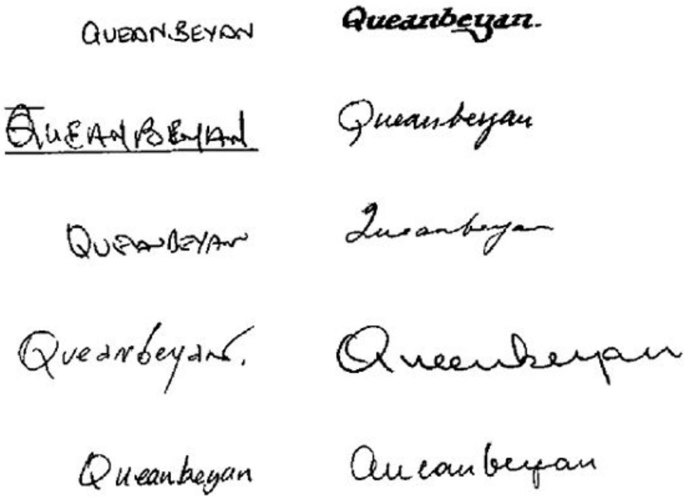
OBJECTIVE

One-shot learning

- Using only 1 signatures as base.
- Comparing each new signature with the base and be able to see the similarity or dissimilarity.



Why do we focus on Forgery Detection?



Related work

FaceNet

Figure 2. **Model structure.** Our network consists of a batch input layer and a deep CNN followed by L_2 normalization, which results in the face embedding. This is followed by the triplet loss during training.

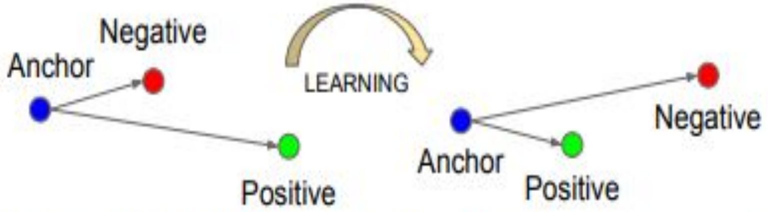
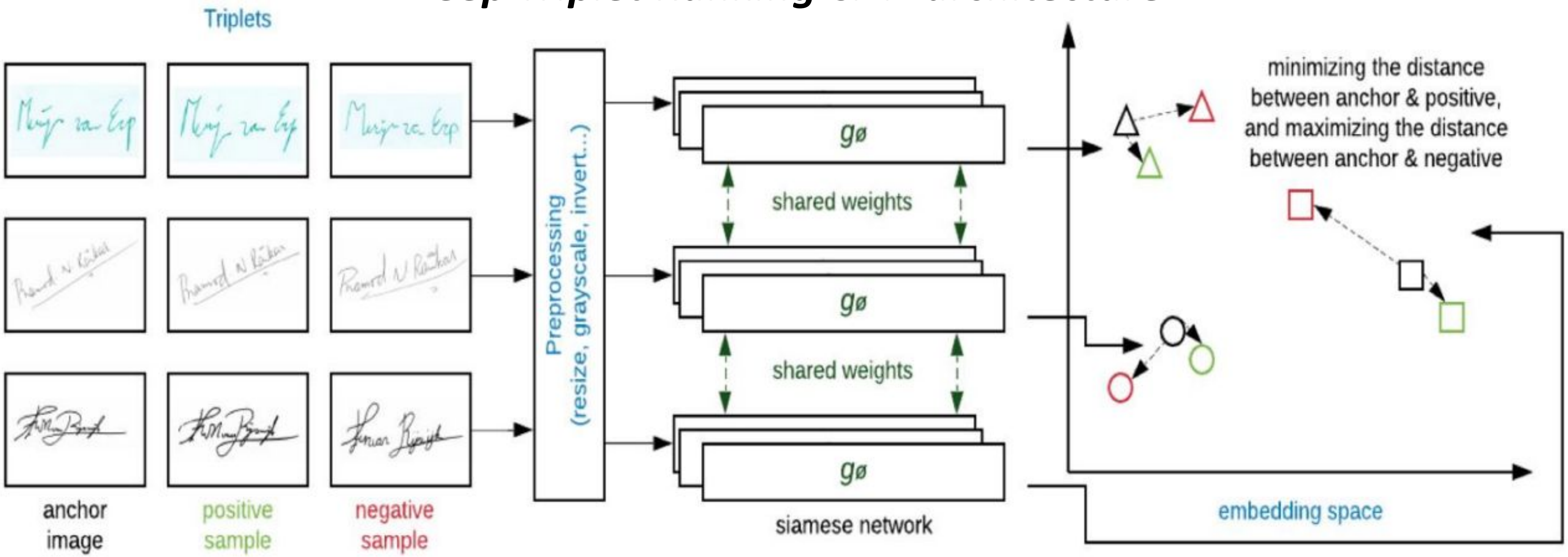


Figure 3. The **Triplet Loss** minimizes the distance between an *anchor* and a *positive*, both of which have the same identity, and maximizes the distance between the *anchor* and a *negative* of a different identity.

Related work

Deep Triplet Ranking CNN architecture



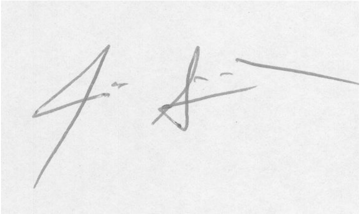
Contribution

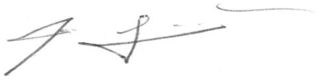
- Applying deep triplet ranking CNN architecture and modifying it.
- Evaluating on various dataset.
- One-shot learning.

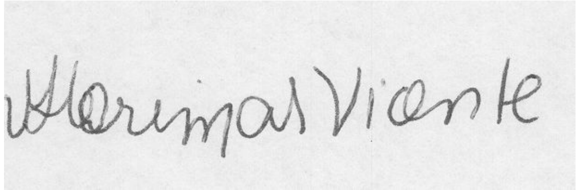
DATASETS & PREPROCESSING

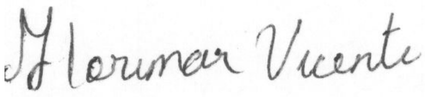
Cedar

- 55 individuals, each has:
  - 24 genuines and 24 forgerie
- Total:
  - 1,320 genuine signatures
  - 1,320 forgeries
- RGB and gray-scale mode.
- Contain Salt/Pepper noise and slant.



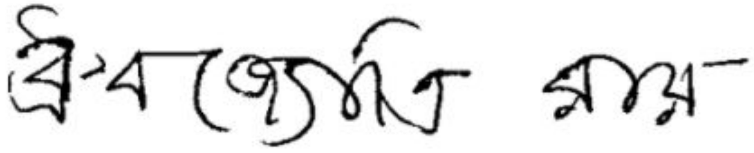






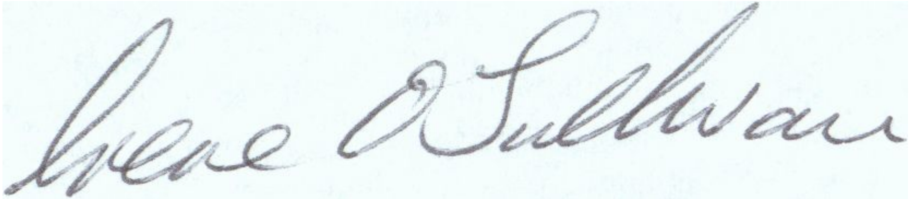
BHSig260 - bengali

- Bengali
- 100 persons
- 24 genuine and 30 forged signature/ 1 person
- Binary mode (only black and white color)

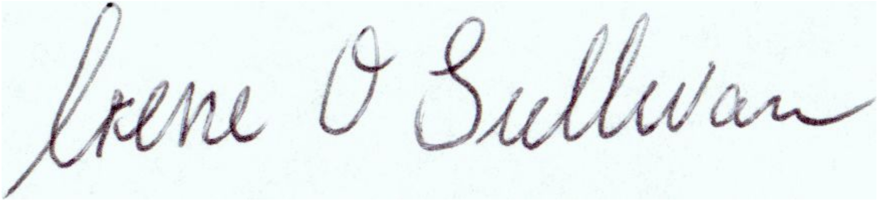


Sigcomp 2011-Dutch(Offline)

- Combination of 2011 and 2009
- RGB



Dataset Name	Number of Users	Genuine Signature for each user	Forgeries for each user
SigComp2009	12	5	150
SigComp2011	54	12	24



Preprocessing

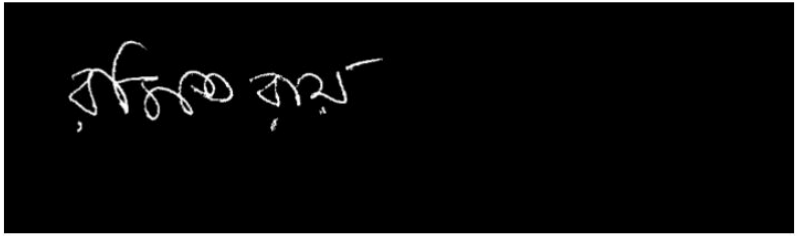


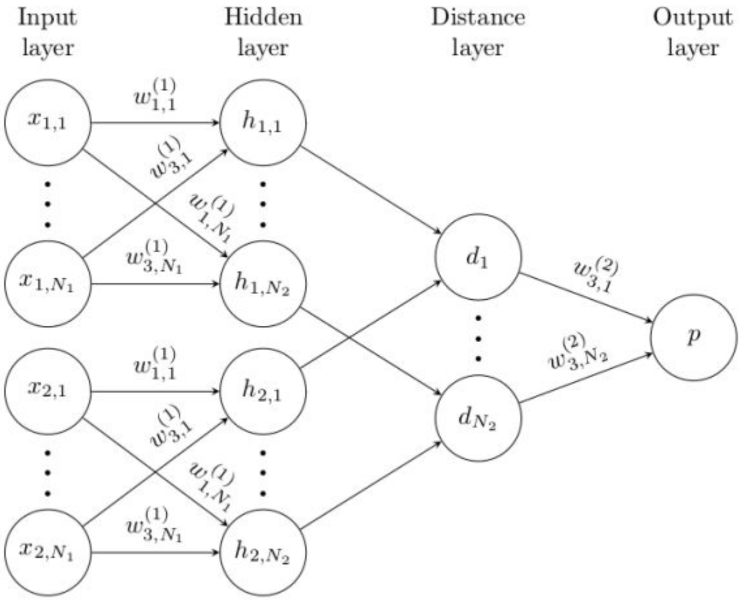
Figure 9. *An example of BHSig260 that has a long width.*

(a) (b)

Figure 10. *Resizing image with* **(a)** *and without padding* **(b)**.

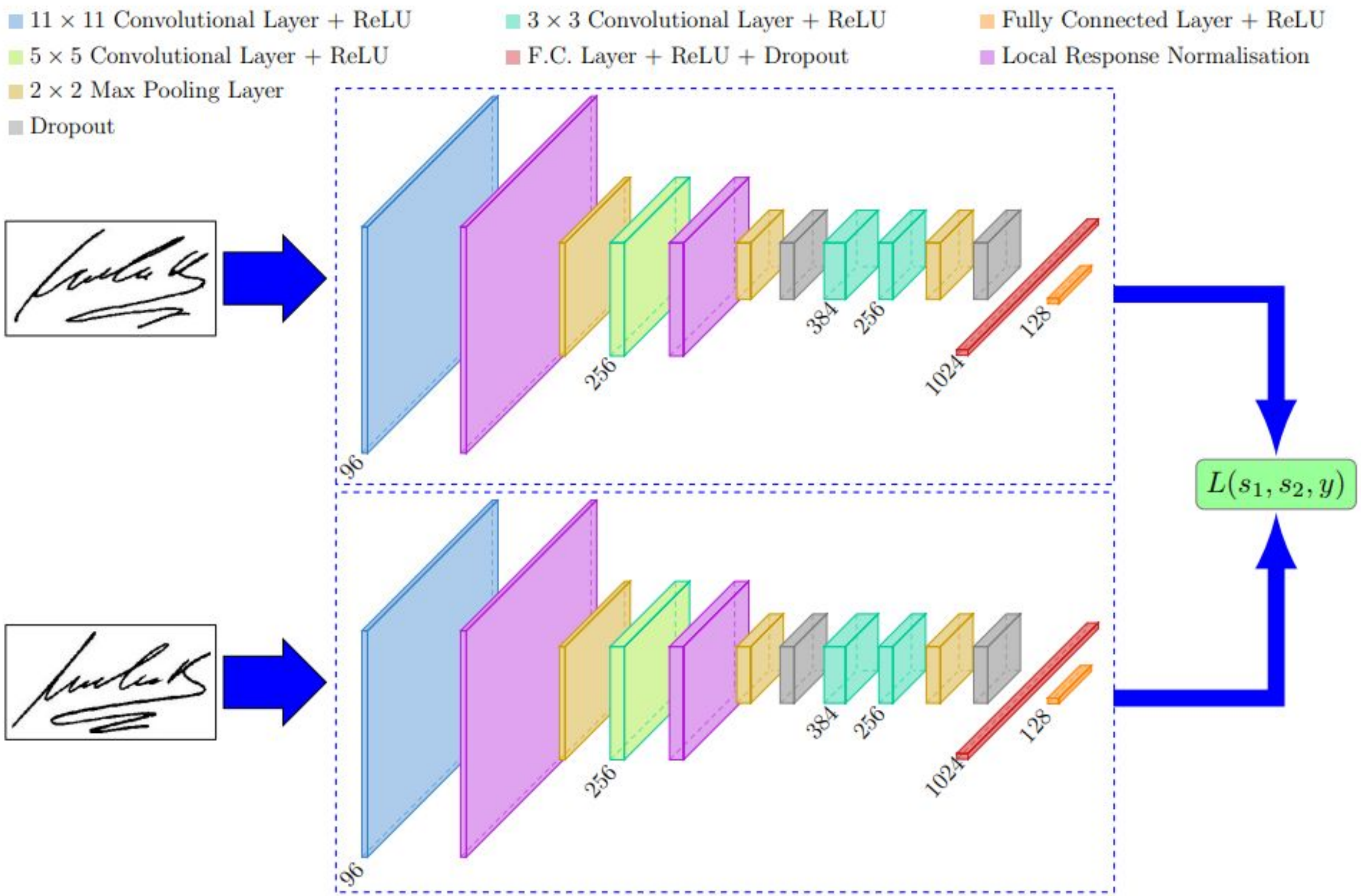
METHODOLOGY

Siamese net

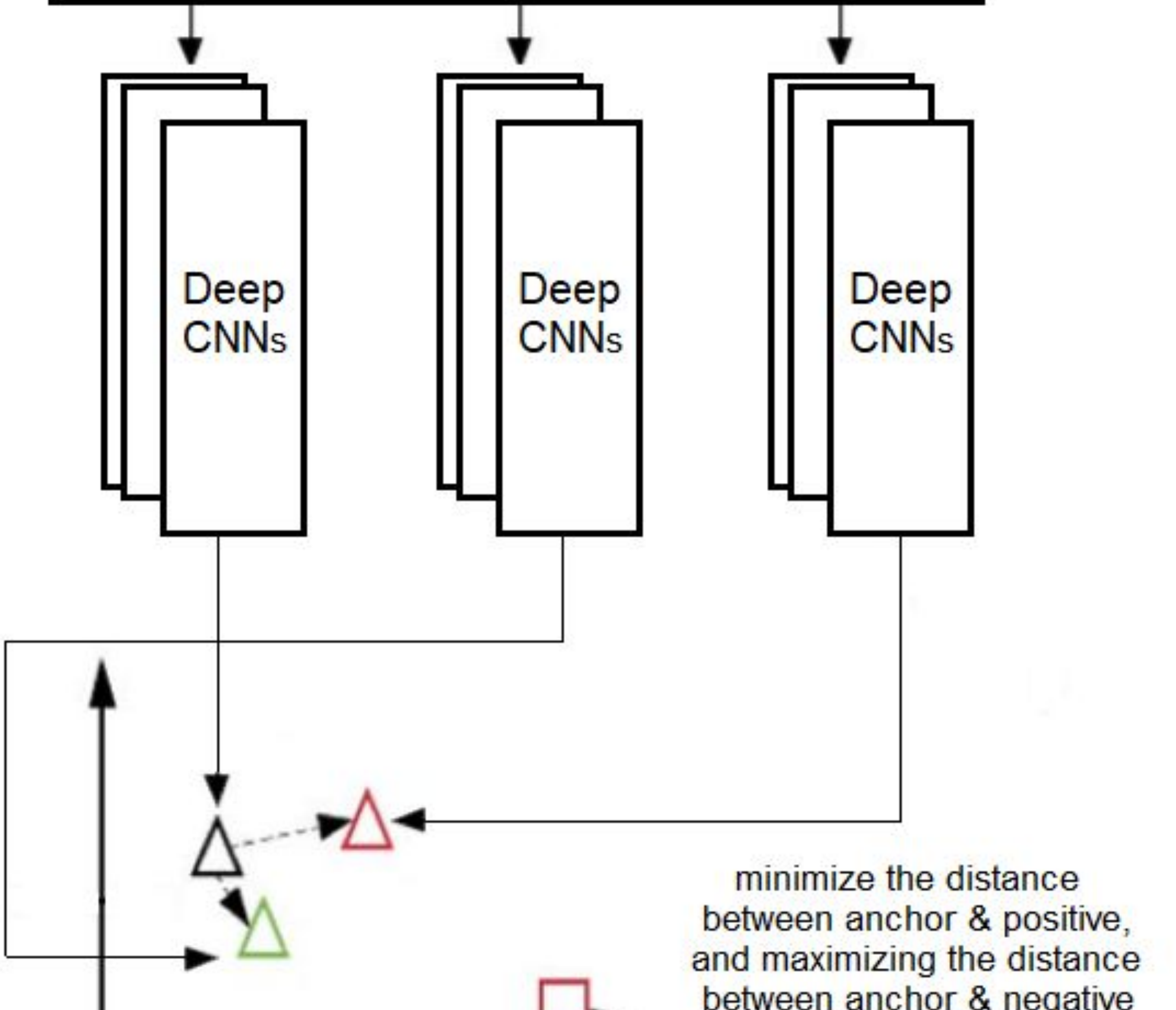


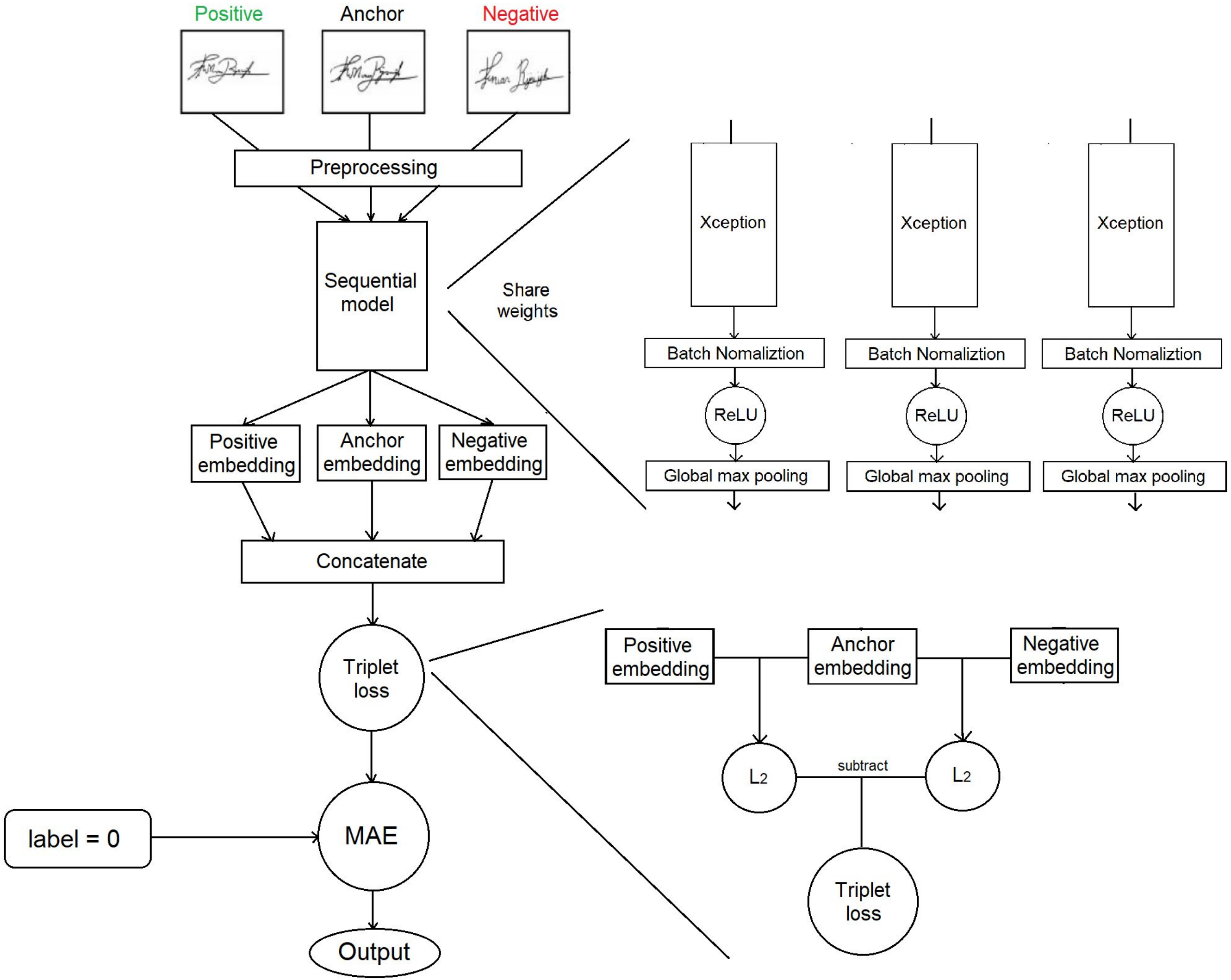
Input layer
Hidden layer
Distance layer
Output layer
$x_{1,1}$
x_{1,N_1}
$x_{2,1}$
x_{2,N_1}
$h_{1,1}$
h_{1,N_2}
$h_{2,1}$
h_{2,N_2}
d_1
d_{N_2}
p
$w_{1,1}^{(1)}$
$w_{3,1}^{(1)}$
$w_{1,N_1}^{(1)}$
$w_{3,N_1}^{(1)}$
$w_{3,1}^{(2)}$
$w_{3,N_2}^{(2)}$

Deep CNN Siamese Network with Contrastive Loss



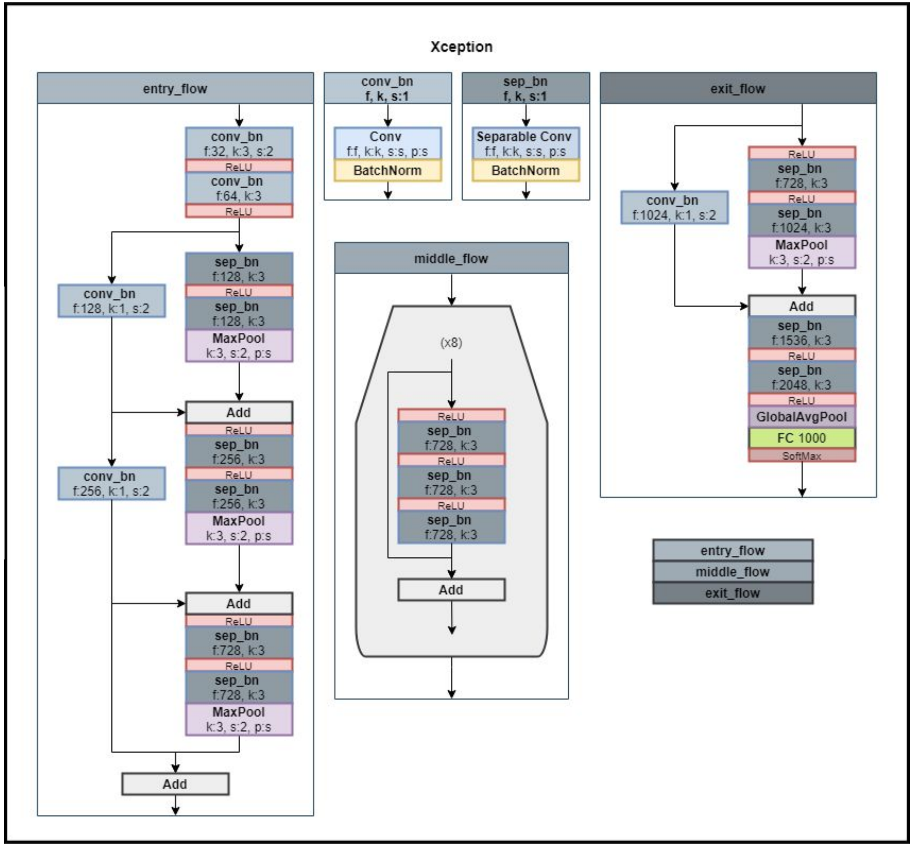
Deep Triplet Ranking CNNs




Positive
Anchor
Negative
Preprocessing
Sequential model
Share weights
Xception
Xception
Xception
Batch Nomaliztion
Batch Nomaliztion
Batch Nomaliztion
ReLU
ReLU
ReLU
Global max pooling
Global max pooling
Global max pooling
Positive embedding
Anchor embedding
Negative embedding
Concatenate
Triplet loss
label = 0
MAE
Output
Positive embedding
Anchor embedding
Negative embedding
L2
subtract
L2
Triplet loss

Xception model

	Top-1 accuracy	Top-5 accuracy
VGG-16	0.715	0.901
ResNet-152	0.770	0.933
Inception V3	0.782	0.941
Xception	**0.790**	**0.945**



Triplet loss function

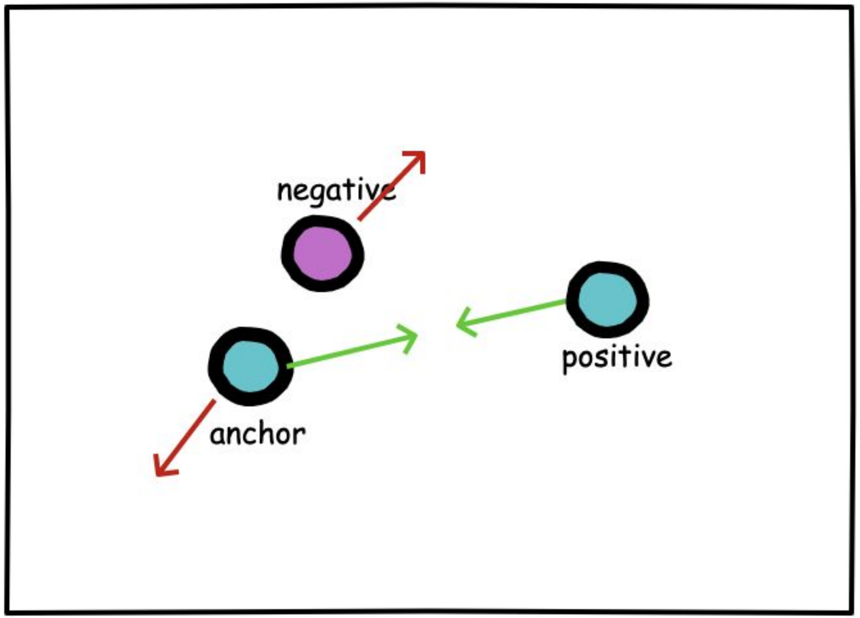
$$L(x^a, x^b, x^n, \alpha) = \frac{1}{N}\sum_{i}^{N} max\left\{D(f(x_i^a), f(x_i^p)) - D(f(x_i^a), f(x_i^n)) + \alpha,\ 0\right\} \quad (1)$$

$f(x)$ refers to an embedding of the image x

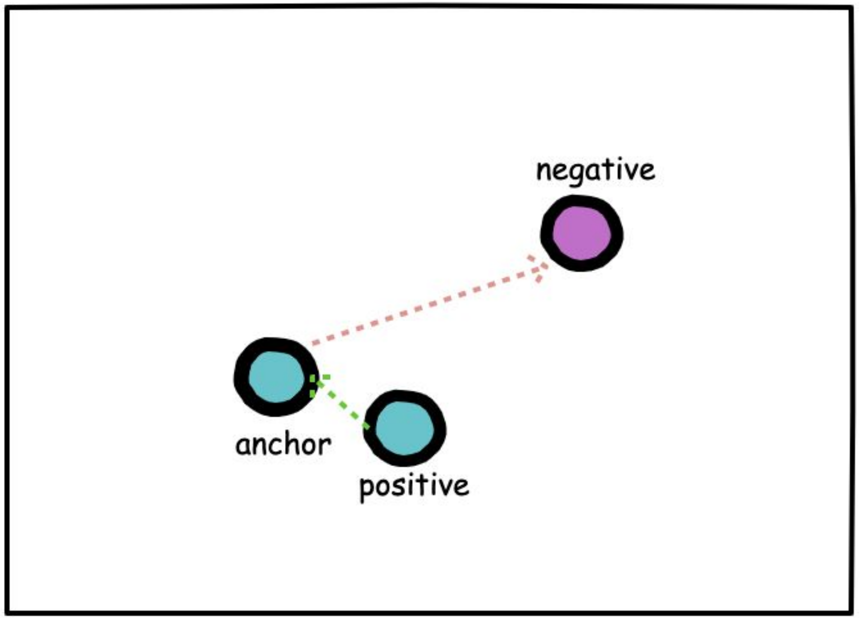
x^a, x^p, x^n are the anchor image, positive image and negative image, respectively

$D(f(x^a), f(x^p))$ is the Euclidean distance between the $f(x^a)$ and $f(x^p)$

α is a constant (or margin) used to make sure that the network does not try to optimize towards the case $D(f(x_i^a), f(x_i^p)) = D(f(x_i^a), f(x_i^n)) = 0$.



Embeddings before triplet loss update



Embeddings after triplet loss update

Train Step

Triplet selection

- **easy triplets:** triplets which have a loss of 0, because:

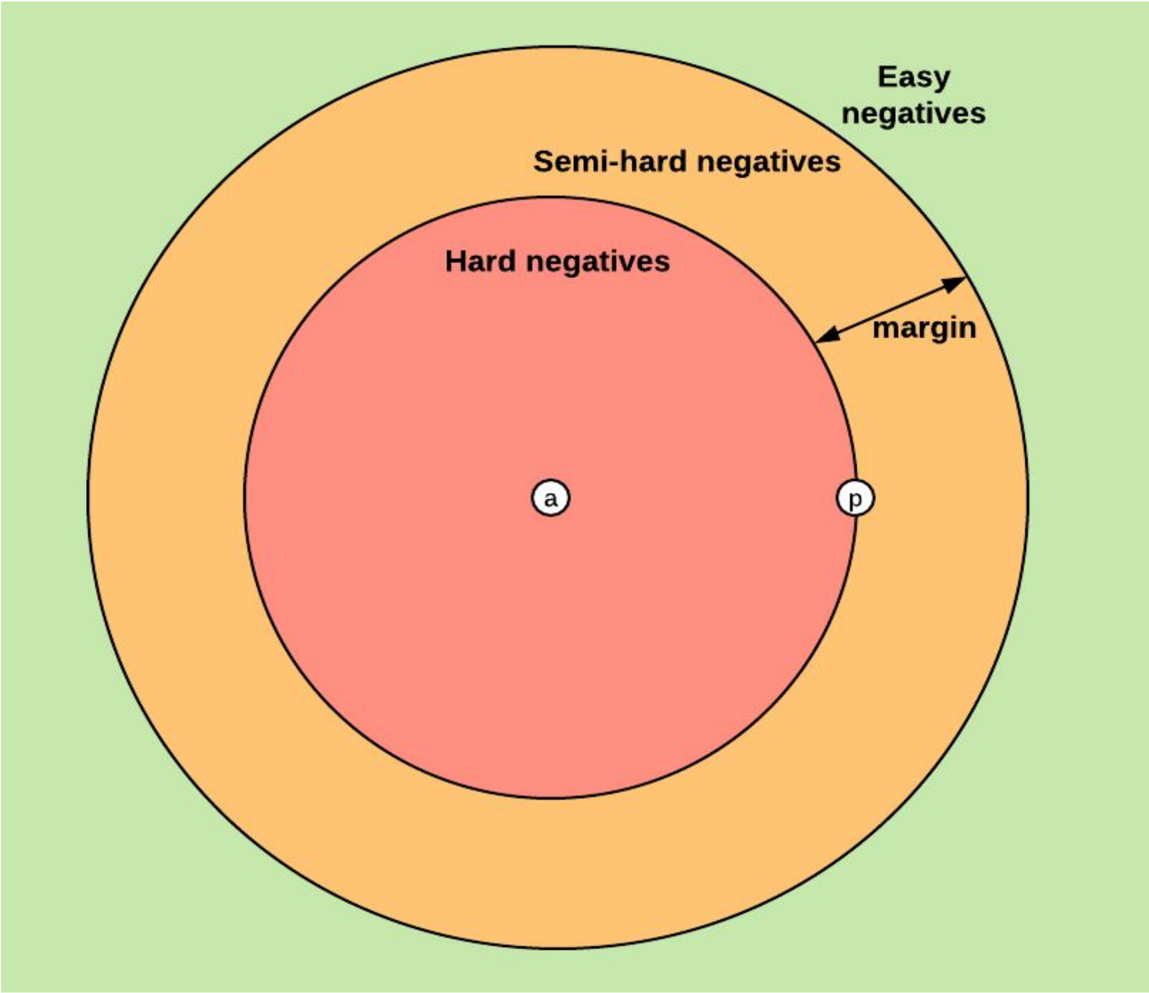
$$d(a,p) + \text{margin} \quad < \quad d(a,n)$$

- **hard triplets:** triplets where the negative is closer to the anchor than the positive:

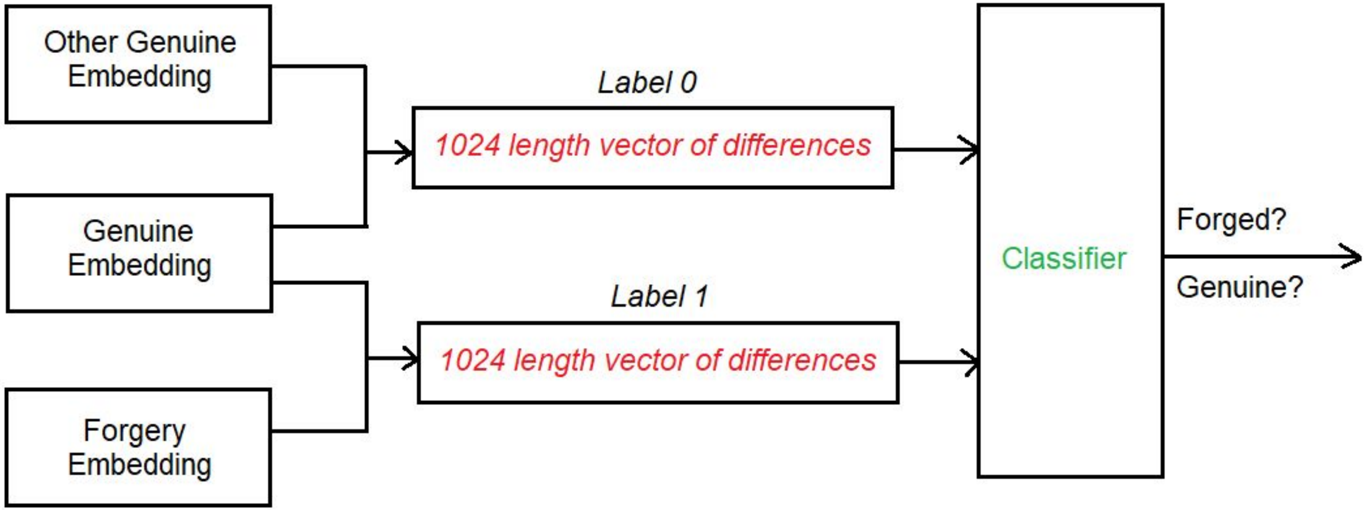
$$d(a,n) \quad < \quad d(a,p)$$

- **semi-hard triplets:** triplets where the negative is not closer to the anchor than the positive, but which still have positive loss:

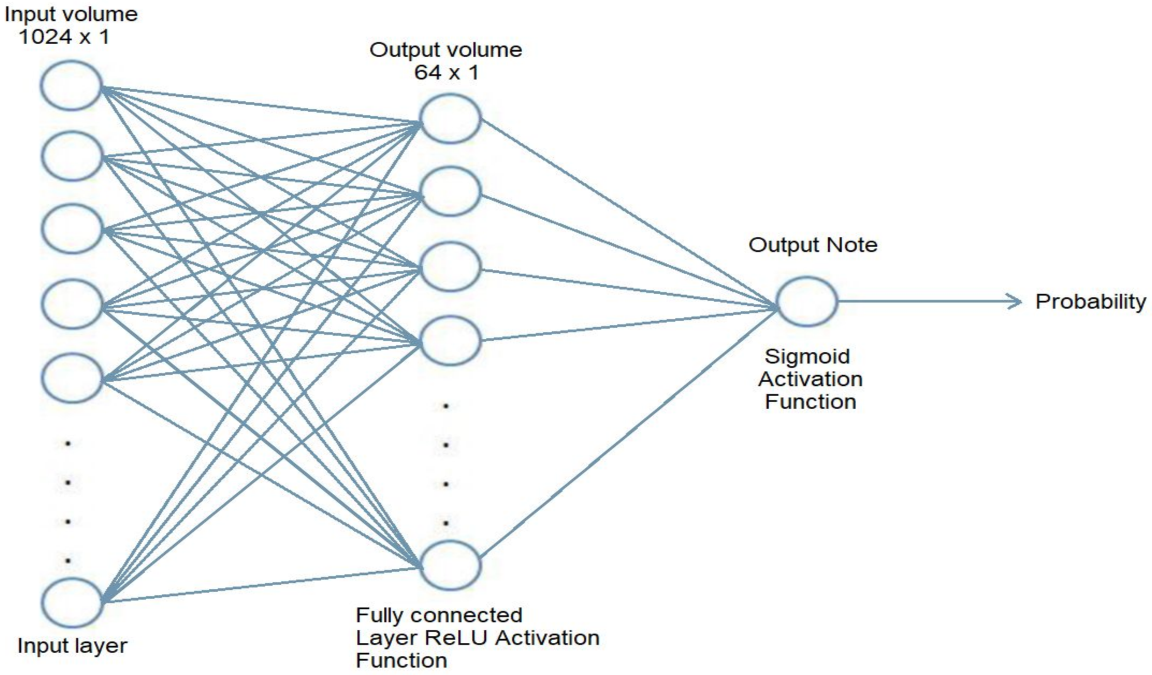
$$d(a,p) \quad < \quad d(a,n) \quad < \quad d(a,p) + \text{margin}$$


Easy negatives
Semi-hard negatives
Hard negatives
margin
a
p

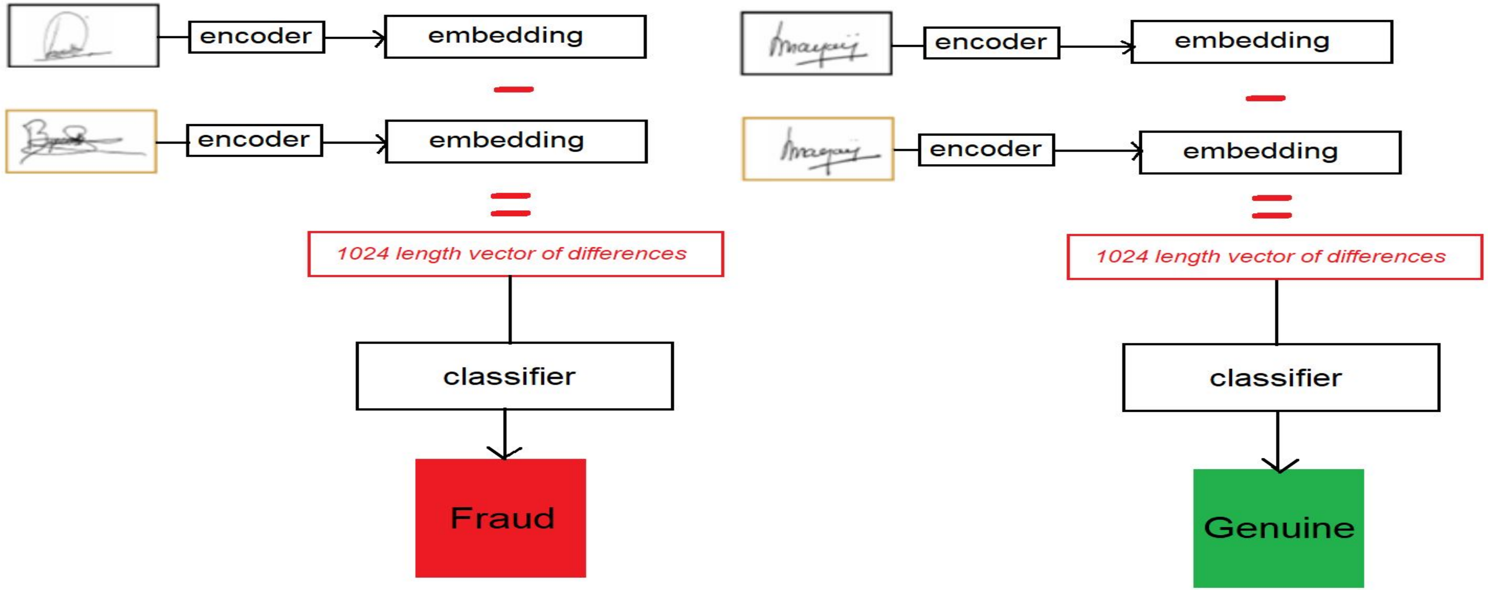
Classification model



Classification model



Final model overview



EXPERIMENTAL RESULTS

Evaluate Triplet model

A valid triplet can occur when: $d(a,p) < d(a,n)$

Accuracy = number of valid triplets / total number of triplets

Evaluation metrics for classification model

$$Precision = \frac{TP}{TP + FP}$$

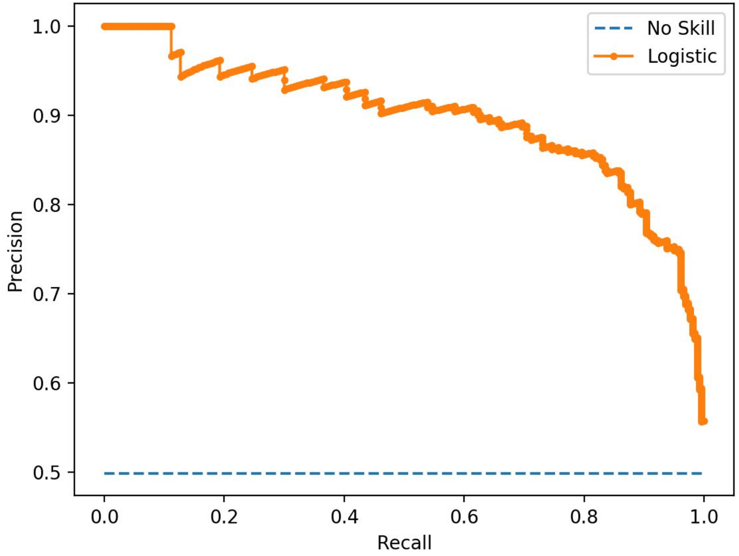
$$Recall = \frac{TP}{TP + FN}$$

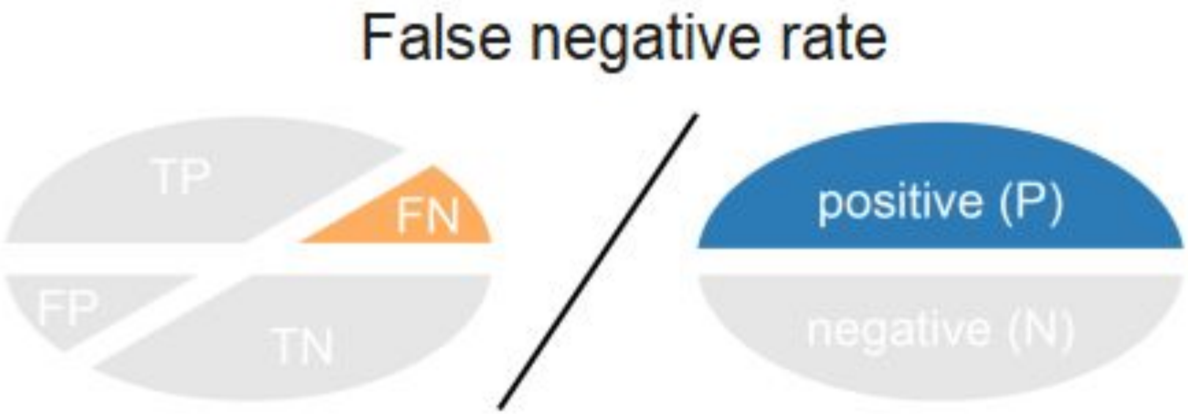
$$F1 = 2 \cdot \frac{precision \cdot recall}{precision + recall}$$

		Predicted	
		Negative	Positive
Actual	Negative	True Negative (TN)	False Positive (FP)
	Positive	False Negative (FN)	True Positive (TP)

Precision recall curve (PRC)

A plot of the tracehold between precision (y-axis) and the recall (x-axis) for different thresholds





- False negative rate is calculated as the number of incorrect negative (FN) divided by the total number of positive (P).
- This can be defined as the False Acceptance Rate (FAR) in our problem.

Result

Dataset Name	Number of triplet combinations
SigComp2011 Dutch	33 580
CEDAR	284 832
BHSig260 Bengali	654 120

Table 7. *Number of training triplet combinations among various datasets.*

Set(Train/Test)	Pair	Label
Train Users	**Genuine - Genuine**	0
	Genuine - Forgery	1
Test Users	**Base Genuine - Genuine**	0
	Base Genuine - Forgery	1

Table 8. *Pairs labeling method for train and test*

Table 9. *Deep Triplet CNN model performance.*

Dataset	Accuracy on training set (%)	Accuracy on validation set (%)	Accuracy on test set (%)
SigComp2011	*95.3*	*95*	*80*
CEDAR	*67.85*	*67.92*	*72.84*
Bengali	*96.46*	*96.36*	*81.8*

Pairing method

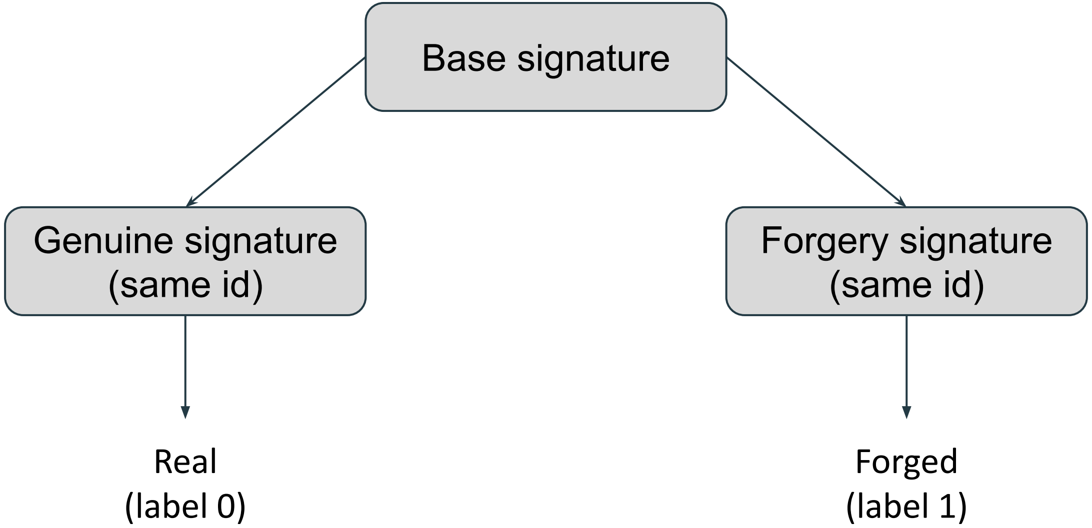


Table 11. *Performance on test set*

Dataset	**AUC (%)**	**ERR**	**FAR**	**FRR**
SigComp2011	65.11	50	70.39	18.82
CEDAR	68.21	34.55	52.09	16.15
Bengali	86.16	22.75	18.57	27.97

Pairing method

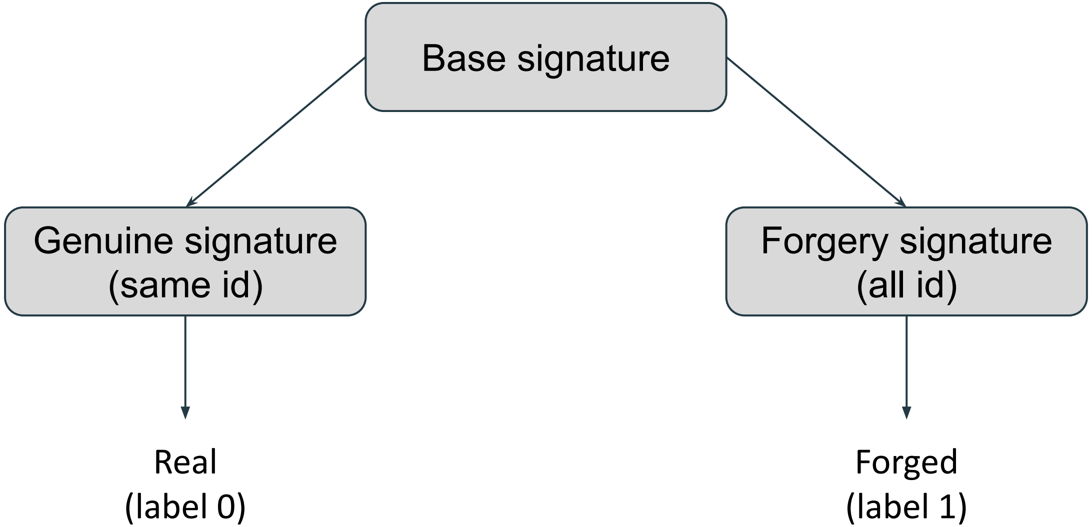


Table 12. Performance on test set with random forgeries by other user forged signatures

Dataset	AUC (%)	ERR	FAR	FRR
SigComp2011	98.41	75	75.75	13.73
CEDAR	96.69	42.84	45	16
Bengali	99.34	14.18	13.66	27.97

Pairing method

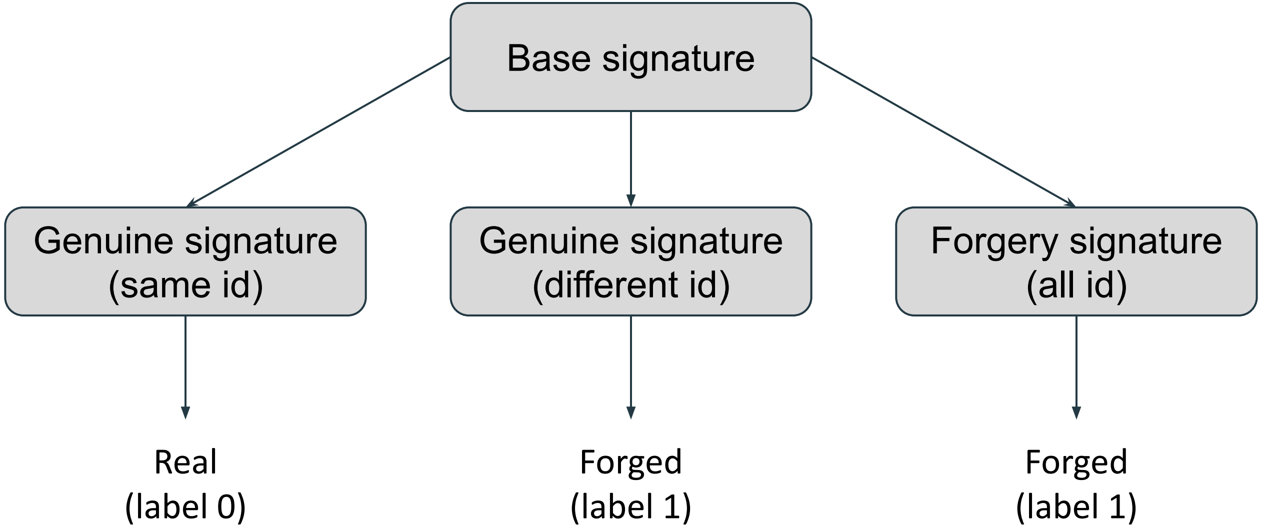


Table 13. *Performance on test set with random forgeries by other user genuine signatures*

Dataset	AUC (%)	ERR	FAR	FRR
SigComp2011	98	79.98	81.14	18.83
CEDAR	97.73	54.09	55.73	16.32
Bengali	99.32	30.9	30..96	27.97

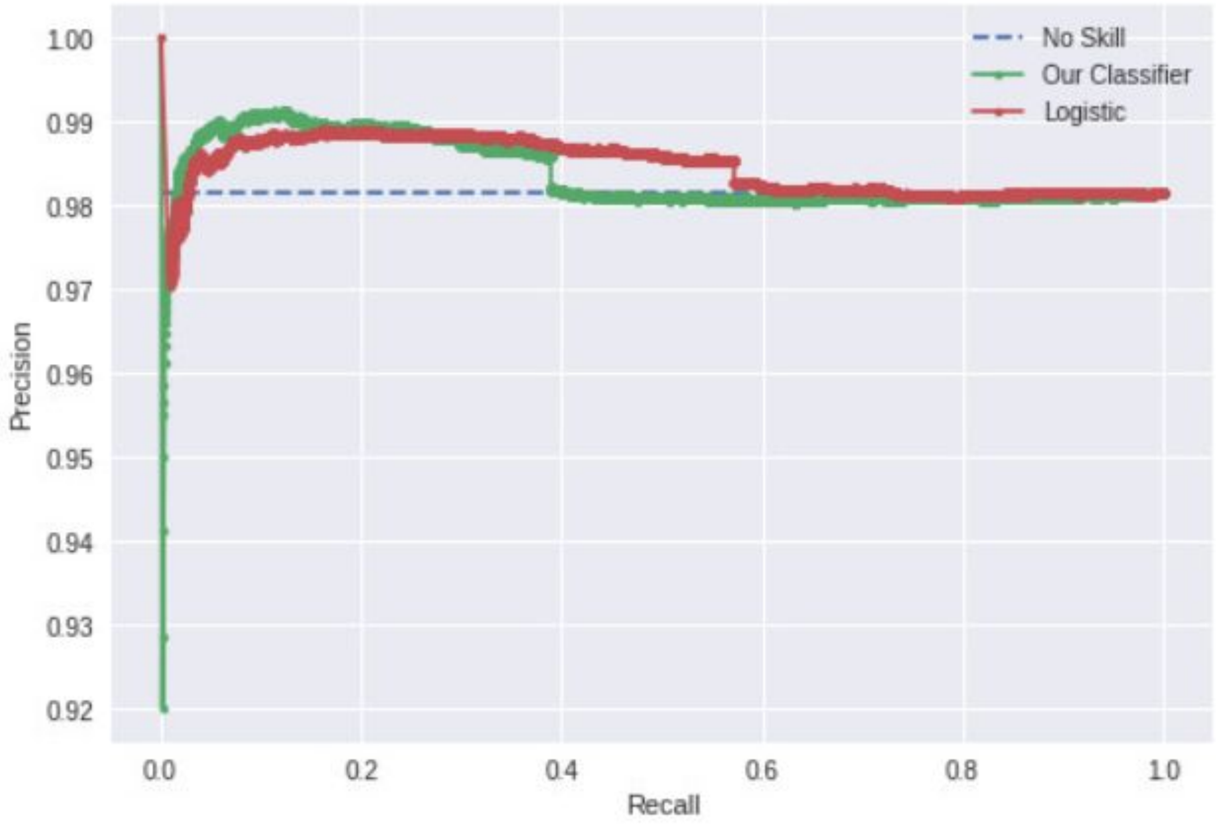


Figure 21. *PR Curve on SigComp2011 test set.*

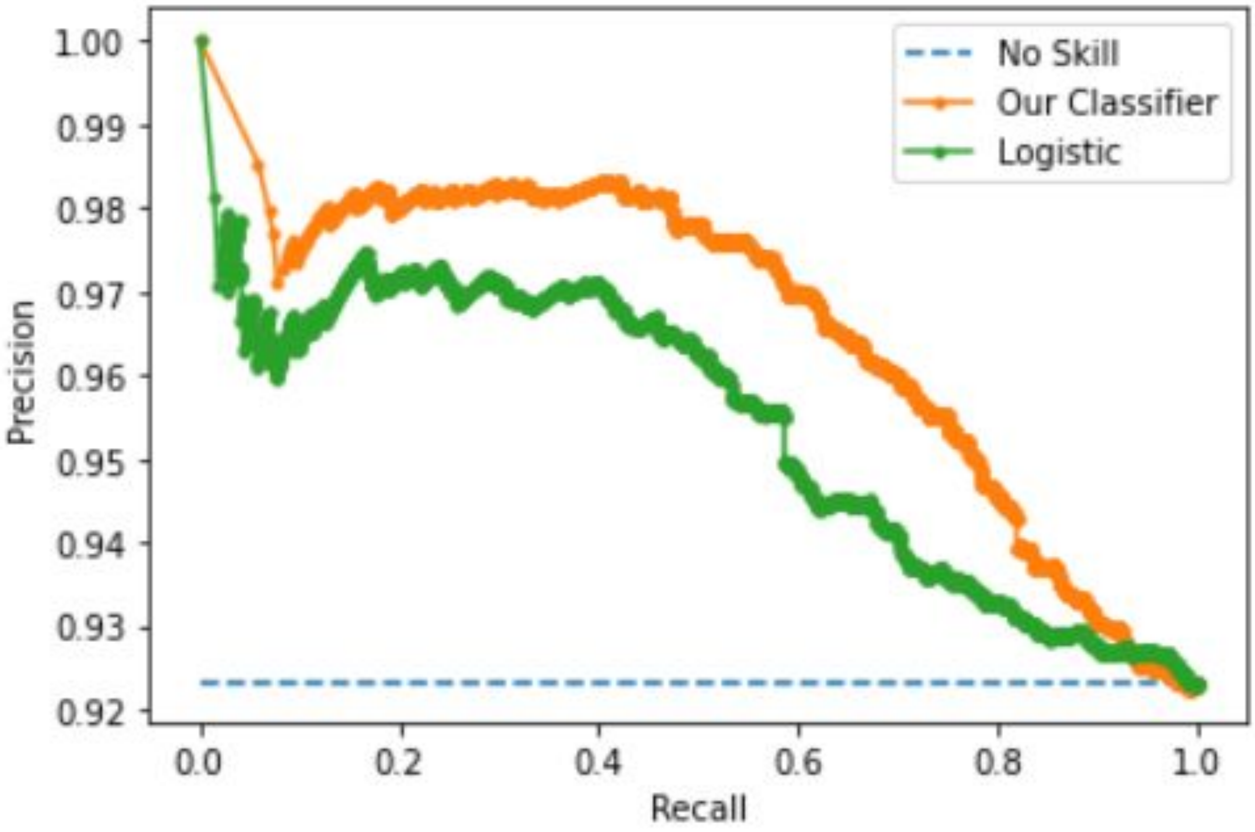


Figure 22. *PR Curve on CEDAR test set.*

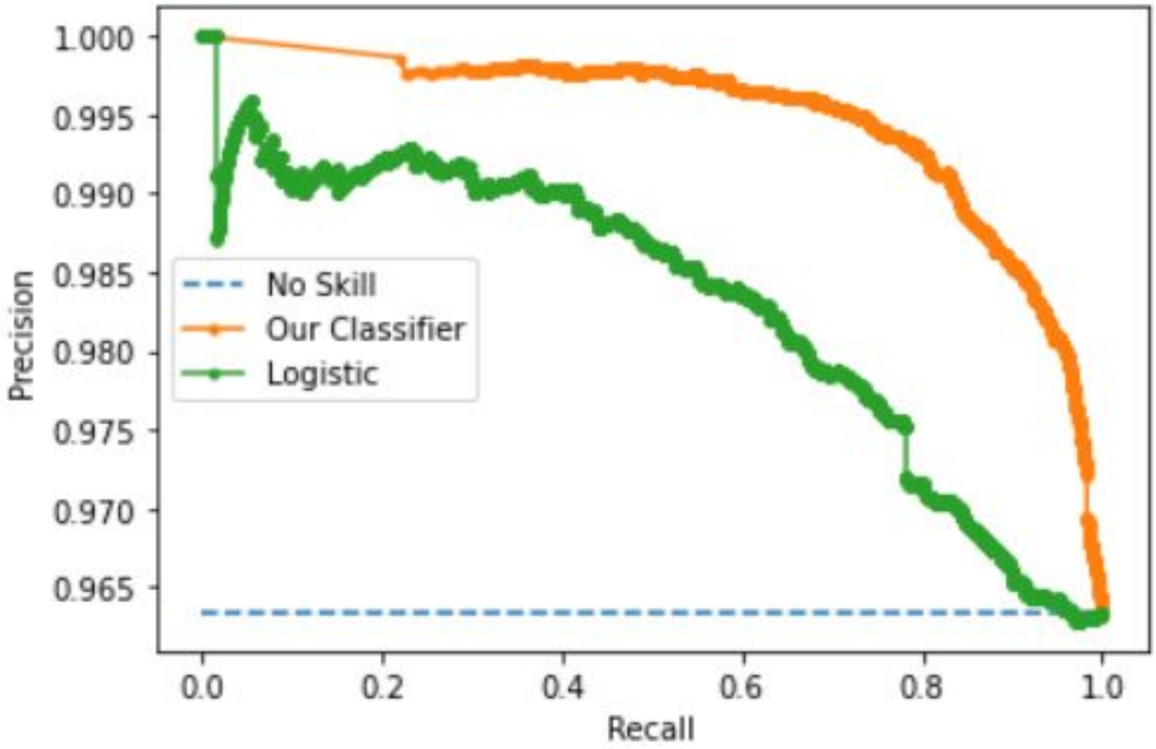


Figure 23. *PR Curve on BHSig260 test set.*

Table 15. *State-of-the-art performance on BHSig260 Dataset (WD = Writer Dependent, WI = Writer Independent).*

Language	Type	Features & algorithm	FRR	FAR
Bengali	WI [24]	SigNet	13.89	13.89
	WI [25]	Dutta et al	14.43	15.78
	WI [26]	Pal et al.	33.82	33.82
	-	**Our model**	27.97	**13.66**

CONCLUSION
&
FUTURE WORK

- New preprocessing strategy
- Triplet selection: new mining method
- Triplet loss: tuning hyperparameters

Thank you
for listening!

Any question?