OSVGAN: Generative Adversarial Networks for Data Scarce Online Signature Verification

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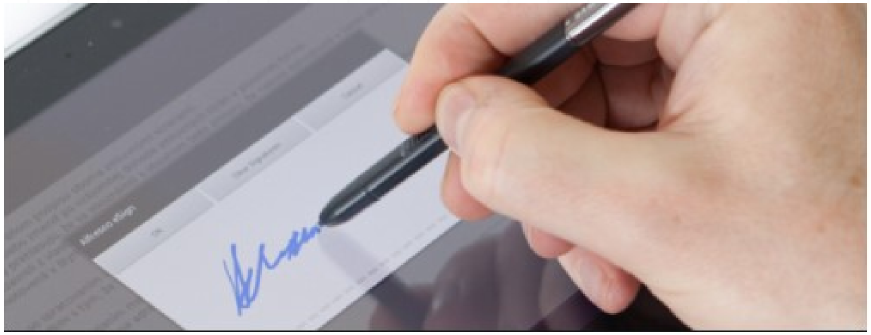
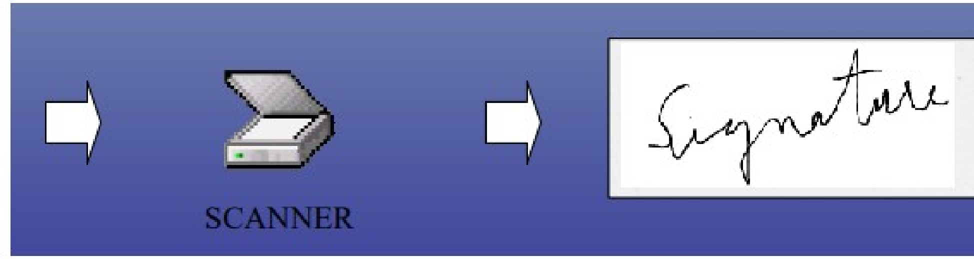
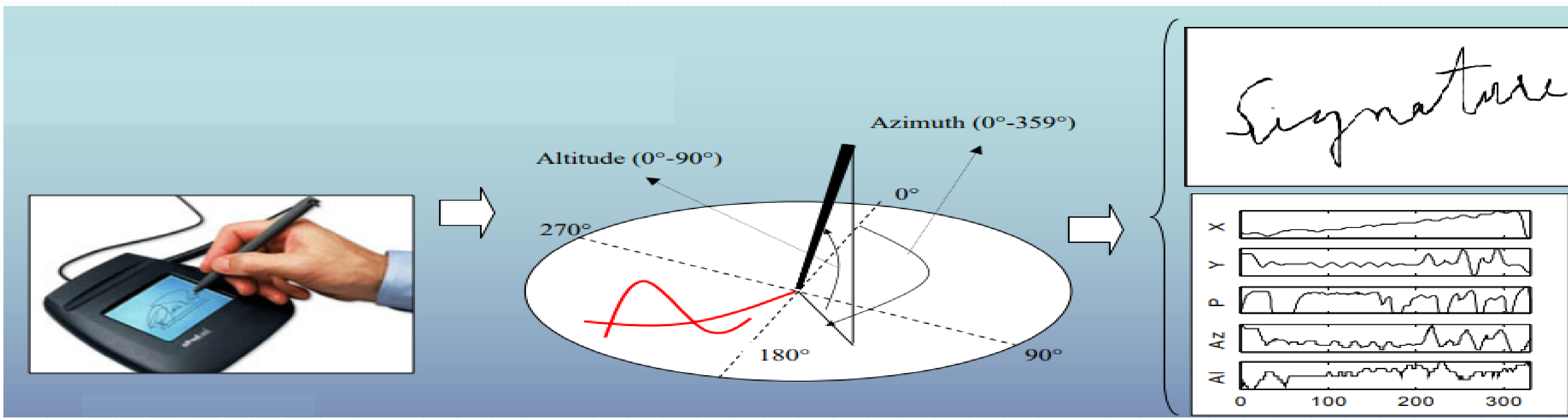
Online and Offline Signature:





Offline Signature : An image consists of Structural information (x, y coordinates).



Contains : 1. Structural information (x, y coordinates).
2. Dynamic properties (such as velocity, pressure, acceleration, azimuth, total signature time etc.,) as numerical data captured through specialized devices.

Online Signature Verification(OSV): Challenges

TABLE I. THE PARTICULARS OF WIDELY USED DATASETS IN OSV

DataSet→	SVC	MobiSig	MCYT
Total number of users	40	83	100
Genuine, Forgery samples per user	20,20	40,25	25,25

Challenge :

1. Very less number of signature samples per user. Maximum Genuine samples = 40 and Forgery samples = 25.

2. Impractical to acquire sufficient number of signature samples from users/writers.

Consequence :

1. OSV frameworks are deployed into production systems by testing with limited samples per users. This results in lack of analysing load handling and robustness analysis of the system.
2. Lack of analyzing the performance metrics in case of more number of samples pers user.

Solution :

1. Generating more number of signature samples using Generative Adversarial Networks and using these synthetic samples to critical evaluation of the frameworks.

Contributions : OSVGAN

1. As represented in Fig 1, a novel variant of Auxiliary Classifier-GAN (AC-GAN) based framework, which generates effective and unlimited writer specific synthetic signature samples.

2. As represented in Fig 2, we propose a Depth Wise Separable Convolution (DWS) based OSV framework, through which we achieve one shot learning with reduced parameters compared to standard convolution based neural networks.

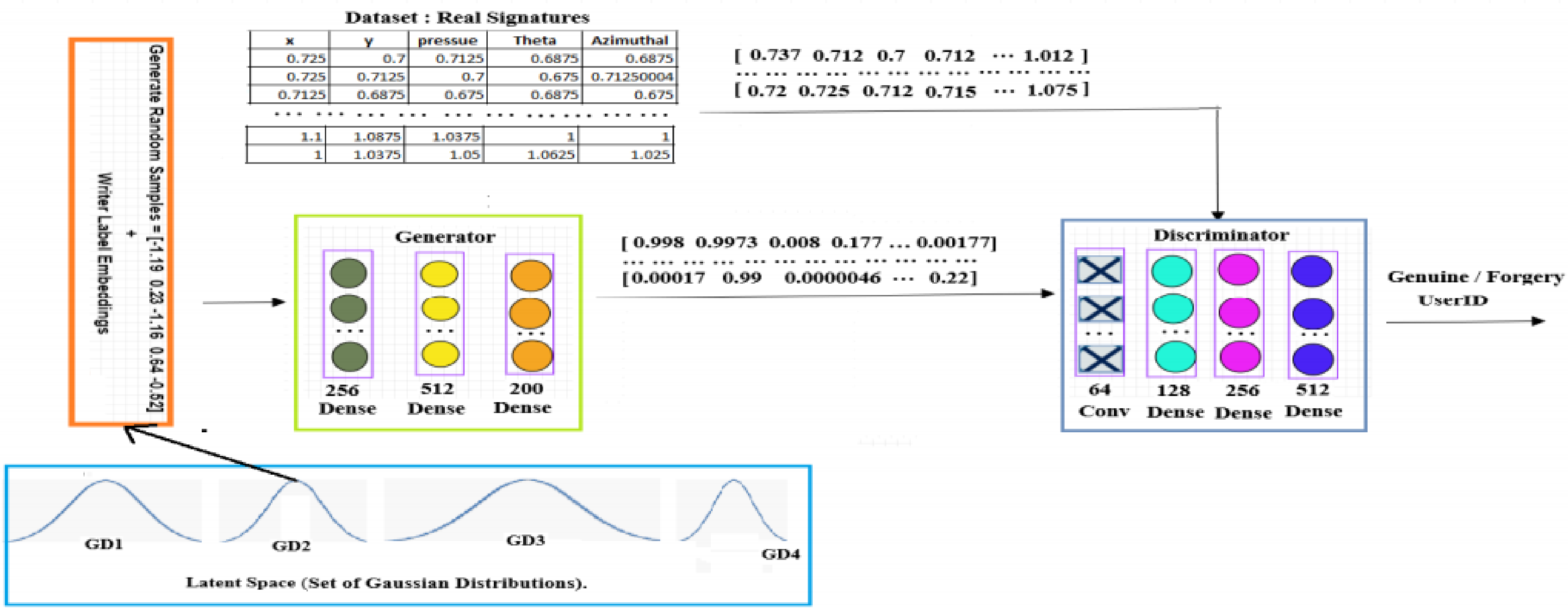


Figure 1. The Proposed OSVGAN architecture, which is a variant of Auxiliary Classifier GAN.

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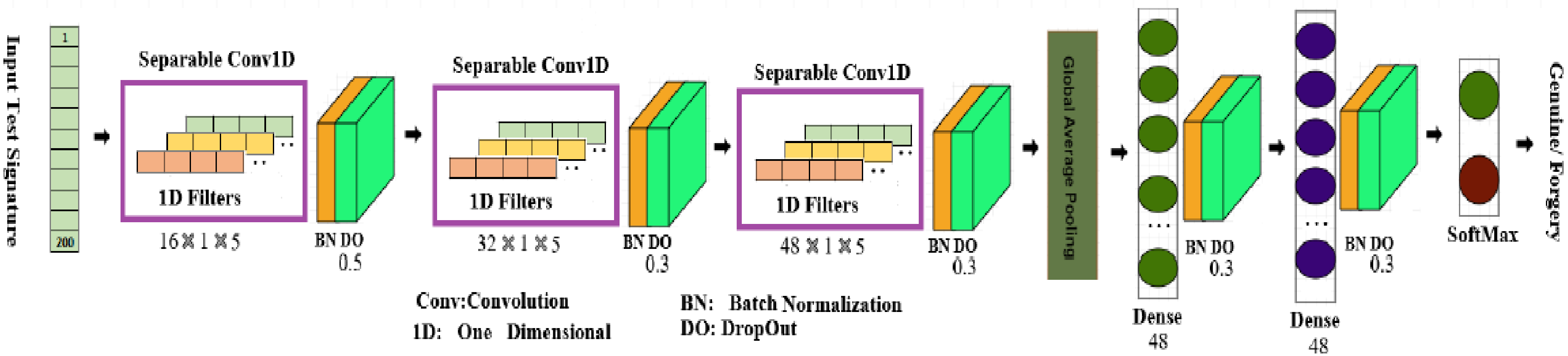


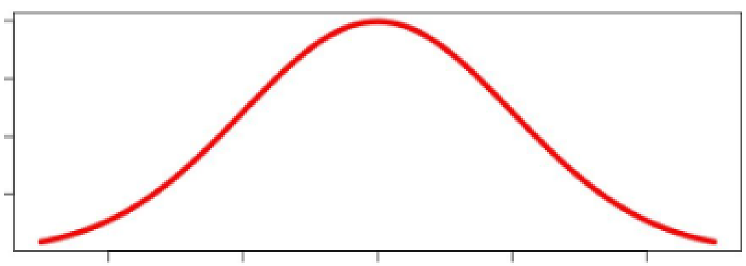
Figure 2. The Proposed Depth Wise Separable Convolution based Neural Network Architecture to classify a test signature.

OSVGAN: Synthetic Signature Generation.

As depicted in Fig 1, 3 to generate high-quality writer specific synthetic signatures, we have proposed OSVGAN, which is a modified version of AC(Auxiliary Classifier)-GAN [5,28].

AC-GAN is widely used variant of vanilla GAN, in which, addition to the noise vector 'n', a corresponding label, $l \sim P_l$ is given as an input to the generator G to generate writer specific synthetic signatures $S_{syn} = G(l,n)$.

In vanilla GAN [3,4], Generator G, transforms a random noise 'n' into a 1D vector (signature profiles) or 2D image i.e. $x_G = G(n)$. The noise 'n' typically chosen from an easy-to-sample uniform distribution, typically 'n' $\sim U(-1,1)$. The generator aims to maximize the generated data (synthetic signature profiles) as similar as possible to the target data distribution (signature dataset).



$$P_{data}(S_G) = \int_n P_{data}(S_G, n) = \int_n P_{data}(S_G|n).P_n(n)dn \quad (1)$$

principally GAN attempt to learn a mapping from a basic latent distribution $P_n(n)$ to the complicated data distribution $P_{data}(S_G|n)$. Therefore, the joint optimization problem for the GAN can be represented as given below:

$$Min_G\, Max_D(V(G,D)) = Min_G\, Max_D(E_{x\sim Pdata}[logD(x)]) + E_{z\sim Pz}[\log(1 - D(G(z)))] \quad (2)$$

Online Signature Verification: AC-GAN

An Auxiliary Classifier GAN [5], as depicted in Fig1, 'G' takes as input both the class label 'c' (in the signature context, genuine/forgery) and the noise 'n' i.e. $S_{fake} = G(c, n)$. Similarly, the discriminator outputs the probability distributions over signature labels L_S (genuine/forgery) and the class (writer) labels L_w (writer id) i.e. $P(S \mid X), P(L \mid X) = D(X)$. The discriminator's objective function is represented as below:

$$L_S = E[\log P(S = real \mid X_{real})] + E[\log P(S = fake \mid X_{fake})] \quad (3)$$
$$L_w = E[log\ P(L = w \mid X_{real})] + E[log\ P(L = w \mid X_{fake})] \quad (4)$$

The generator and the discriminator compete to maximize L_S

Online Signature Verification: AC-GAN

Swaminathan et al [4] proposed a novel attempt in which, to increase the modelling power of the prior distribution, they have reparametrized [6] the latent generative space of vanilla GAN into a set of Gaussian mixture models and learn the best mixture model specific to each writer. Motivated by Swaminathan et al [4] work, we have reparametrized the latent generative space of Auxiliary Classifier GAN into a set of mixture models and learn the best mixture model specific to each writer.

Applying "reparameterization trick" [6] on equation (6), which divides the single Gaussian distribution into '*G*' Gaussian distributions. The noise from the i[th] Gaussian distribution is calculated using $z = \mu_i + \sigma_i . \epsilon$, where $'\epsilon'$ represents an auxiliary noise variable such that, $\epsilon \sim N(0, 1)$. μ_i is a sample from a uniform distribution $U(-1, 1)$ and σ_i is set to 0.4. User is advised to read [4] for further analysis.

Proposed OSV Framework:

As depicted in Fig 2, a Gaussian random noise of size 5 is derived from the selected Gaussian distribution and the label embeddings are given as an input the Generator G. The generator generates the corresponding profile of an online signature of size 1*200.

The signature profile is fed as an input to the discriminator 'D', consists of a one-dimensional convolution layer, followed by three dense layers to classify the synthetic signature profile as real or generated.

The generator is trained to generate the synthetic profiles close to the samples from the target space (signature dataset) through backpropagation of discriminator error in classifying the real and generated signature profiles.

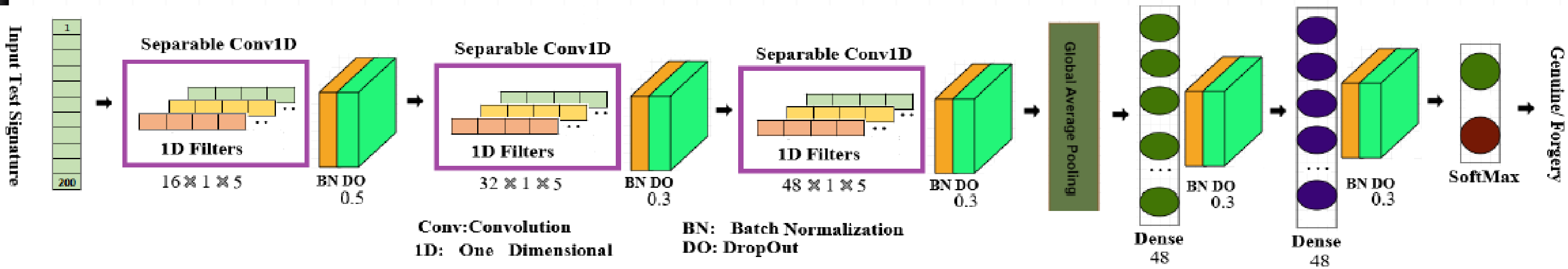


Figure 2. The Proposed Depth Wise Separable Convolution based Neural Network Architecture to classify a test signature.

GANOSV: Results : SVC Dataset

Technique	S_01	S_05	S_10	S_15
Proposed Model : (GAN+ Handcrafted features): X-Axis	5.17	3.99	4.82	2.75
Proposed Model : (GAN+ Handcrafted features): Y-Axis	4.78	4.2	3.27	2.12
Proposed Model : (GAN+ Handcrafted features): Pressure	6.8	4.27	3.32	1.89
Proposed Model : (Only GAN generated features): X-Axis	2.95	3.14	2.83	2.67
Proposed Model : (Only GAN generated features): Y-Axis	**2.86***	5.24	**1.42****	1.76
Proposed Model : (Only GAN generated features): Pressure	4.52	2.62	1.48	1.9
Proposed Model : (Handcrafted features): X-Axis	**2.87****	3.19	2.71	2.71
Proposed Model : (Handcrafted features): Y-Axis	2.97	5.18	1.46	**1.29****
Proposed Model : (Handcrafted features): Pressure	4.6	**2.59****	1.23	**1.07***
SVM +SPW+ mRMR (10-Samples) [18]	-	-	**1.00***	-
LCSS[10]	-	-	5.33	-
Relief-1 [17]	-	-	8.1	-
SPW[18]	-	-	**1.00***	-
PDTW(case 2) [22]	-	-	-	-
Relief-2 [17]	-	-	5.31	-
Stroke-Wise [16]	18.25	-	-	-
PCA [16]	-	-	7.05	-
TW [16]	18.63	-	-	-
PDTW [22]	-	-	-	-
Variance selection [17]	-	-	13.75	-
Curvature +Torsion [21]	-	-	6.61	3.10
DTW+ warping path score [11]	-	-		-
RNN+LNPS [14]	-	**2.37***	-	-
DTW[9]	-	2.73	-	-
SynSig2Vec -Common Threshold [23]	11.96	4.65	-	-
SynSig2Vec – User Specific Threshold [23]	7.34	-	-	-
Template matching + time-series averaging [26]		2.98	1.80	

Proposed OSV framework: Contributions

TABLE III. COMPARISON OF EER PERFORMANCE OF VARIOUS RECENT OSV FRAMEWORKS EVALUATED ON MOBISIG DATASET.

Technique	**S_01**	**S_05**	**S_10**	**S_15**
Proposed Model : (GAN+ Handcrafted features): X-Axis	19.74	15.84	14.88	13.3
Proposed Model : (GAN+ Handcrafted features): Y-Axis	17.65	15.01	14.62	13.56
Proposed Model : (GAN+ Handcrafted features): Pressure	13.84	15.05	12.78	12.26
Proposed Model : (Only GAN generated features): X-Axis	14.91	8.52	6.39	6.97
Proposed Model : (Only GAN generated features): Y-Axis	12.78	6.44	5.87	5.68
Proposed Model : (Only GAN generated features): Pressure	**7.78****	6.5	**2.42****	**2.55****
Proposed Model : (Handcrafted features): X-Axis	10.65	6.32	5.87	4.31
Proposed Model : (Handcrafted features): Y-Axis	10.72	**6.1***	4.91	4.27
Proposed Model : (Handcrafted features): Pressure	**5.17***	**6.21****	**2.18***	**2.14***
Baseline [15]	-	25.45, 19.27	-	-
Stroke-based RNN [24]	16.08, 16.261	-	-	-
Recurrent Adaptation Networks [25]	-	10.87	-	-

OSVGAN: EER for each user

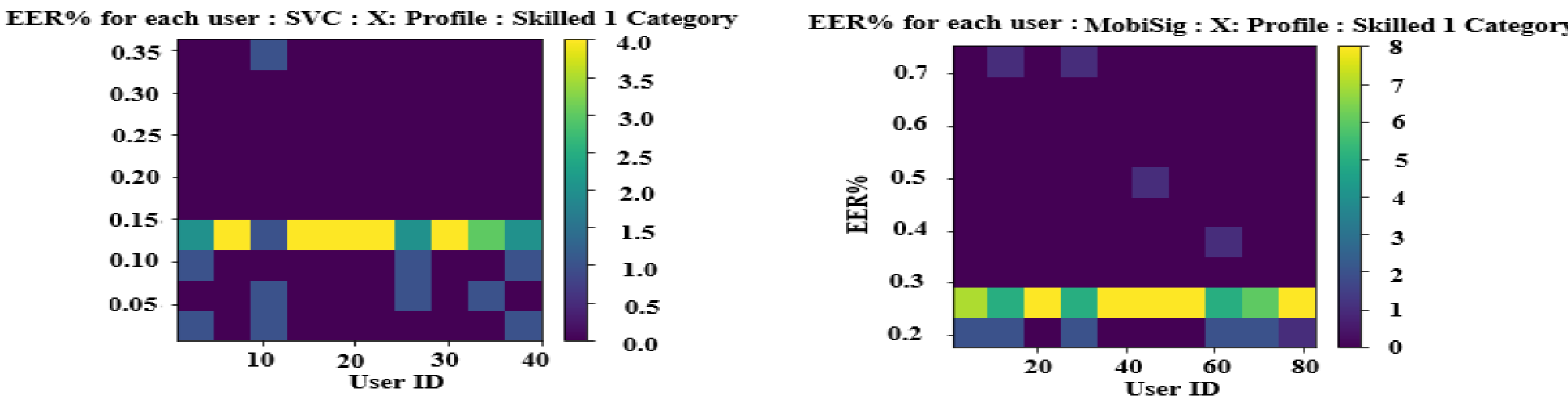


Figure 4. A 2D-histogram representing EER registered for each user in case of SVC and Mobisig datasets under Skilled_1 category.

Conclusion

In this work, two most challenging requirements of OSV are addressed.

1. Data scarcity to thoroughly test the framework for real time deployment in critical applications.

--- To address this, we have proposed a first of its kind of an attempt to generate virtually unlimited synthetic signature samples per user from a maximum of 40 signatures per user based on a modified version of AC-GAN.

2. Achieving few shot learning, especially one-shot learning to classify the genuineness of test signature with as minimum as one training sample per user.

The efficiency of the proposed model is confirmed through state-of-the-art achievement in various categories compared to the frameworks evaluated with reduced number of test samples. In future, to grasp the generative skills of GANs, we will focus on filling the missing and noisy parts of the signatures.

References

4. G.Swaminathan,S.R.Kiran and R.V.Babu, DeLiGAN : Generative Adversarial Networks for Diverse and Limited Data, 30TH IEEE conference on Computer viison and pattern recognition (CVPR 2017),pp. 4941-4949,JUL 21-26, 2017

5. A.Odena, C.Olah and J.B Shlens, Conditional image synthesis with auxiliary classifier GANs, 34th International Conference on Machine Learning (ICML), vol 70, pp:2642–2651, august 2017.

Thank You