

Federated Learning for Biometrics Applications

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ON BIOMETRICS 2022**

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Agenda

Part 1

- Motivation
- Federated learning
 - FedAvg
 - SplitNN
- Privacy-enhancing methods for federated learning

Part 2

- Applications
 - Face anti-spoofing
 - Active authentication
 - Thermal to visible face synthesis
- Open problems

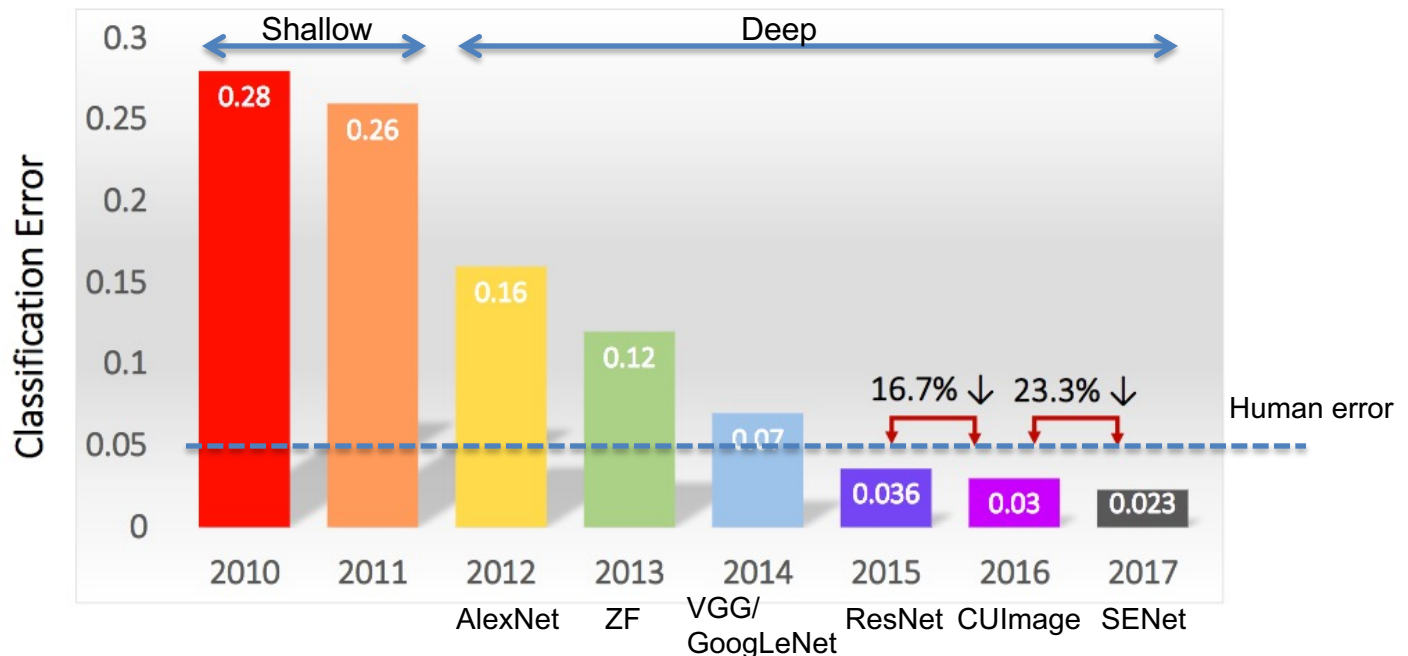
ImageNet Challenge

- Large Scale Visual Recognition Challenge (ILSVRC) 2017

- 1000 object categories
- 1.2M training images



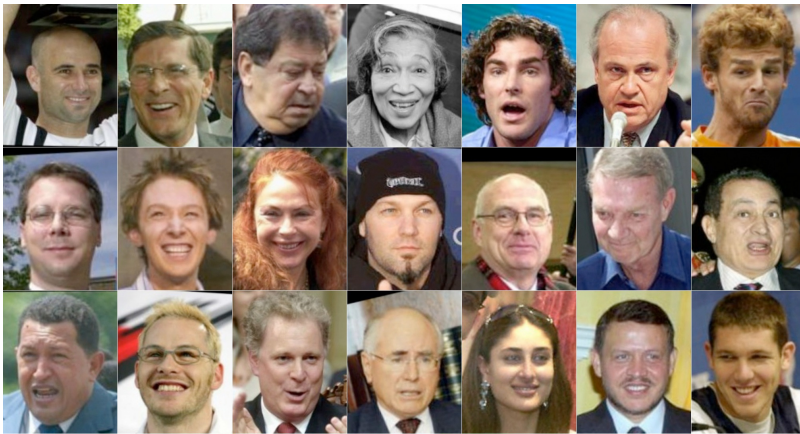
Classification Results (CLS)



Face Recognition

- Labeled Faces in the Wild (LFW)

- 5,749 subjects
- 13,233 faces

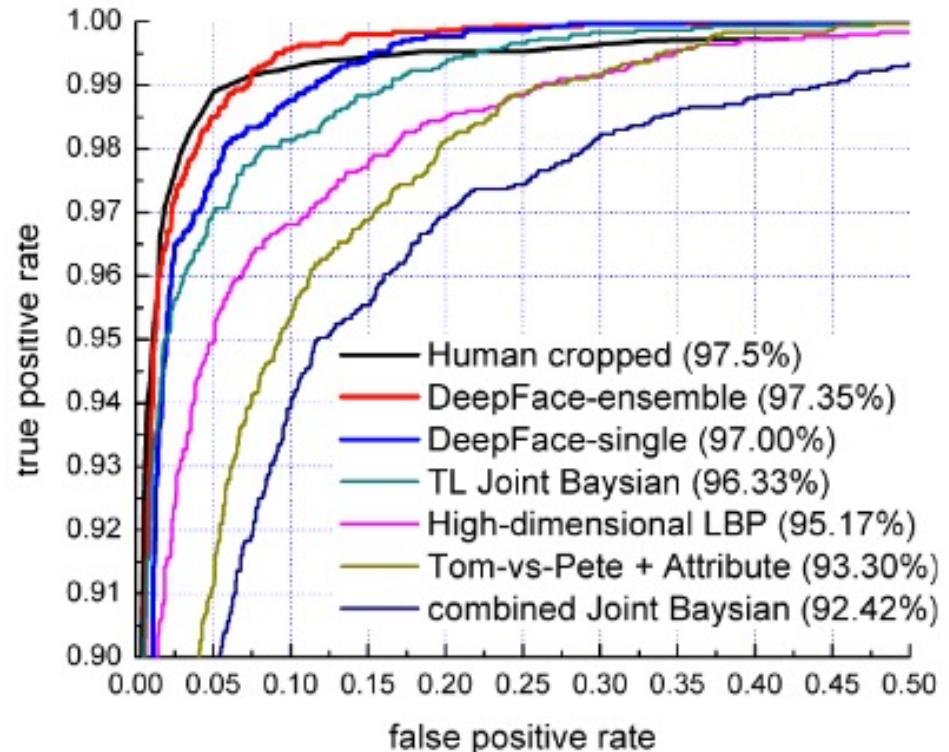


- Mean classification accuracies:

YI+AI (0.9983 ± 0.0024)

FRDC (0.9972 ± 0.0029)

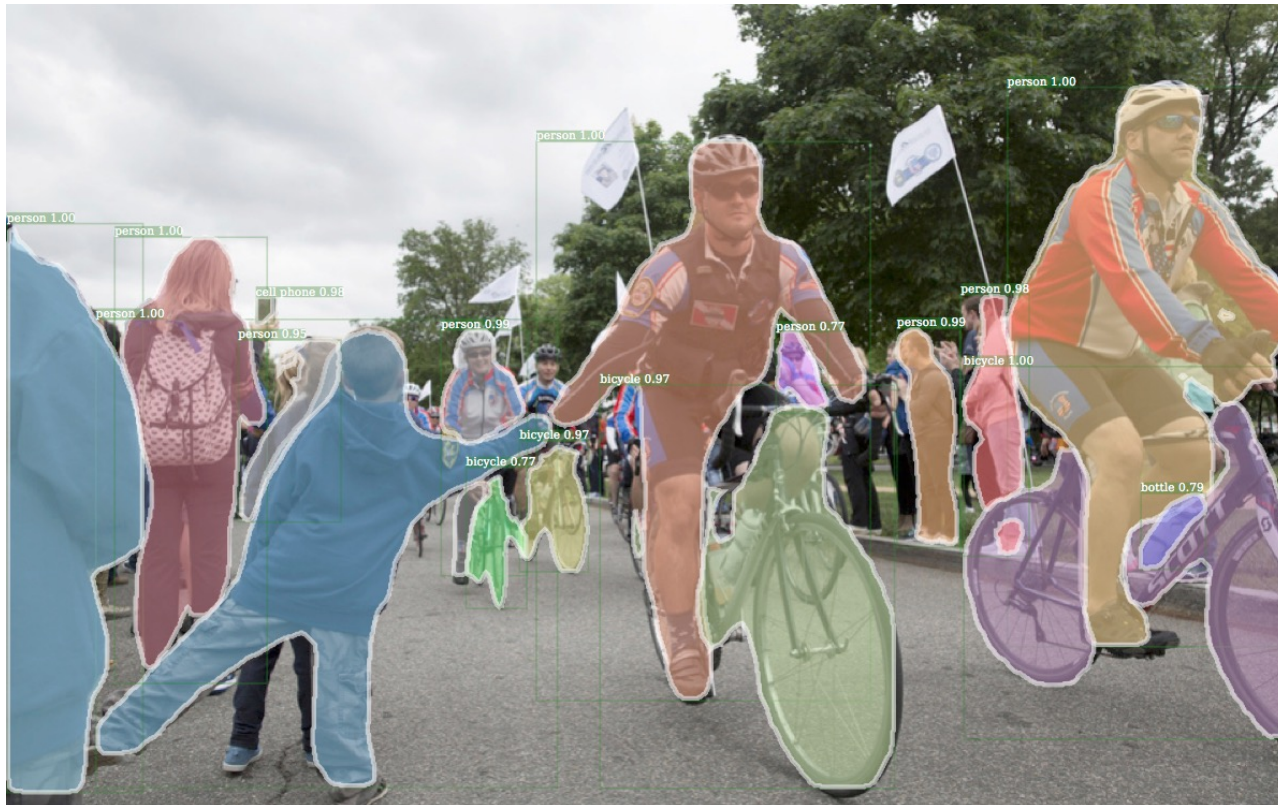
CHTFace (0.9960 ± 0.0025)



Training data: 4 million faces,
4000 identities (facebook)

Detectron – Facebook

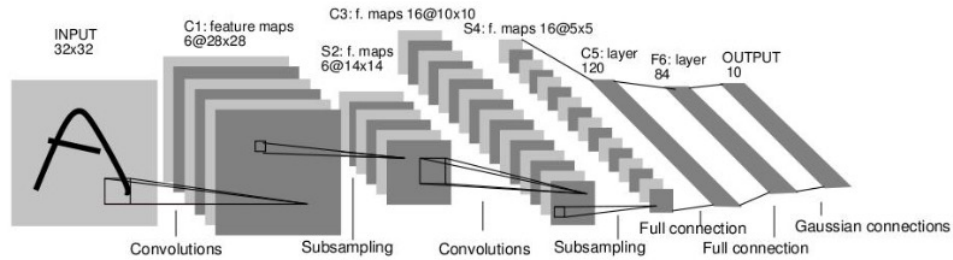
- Detectron model for object detection
 - Trained on 3.5 billion images from Instagram



<https://github.com/facebookresearch/detectron>

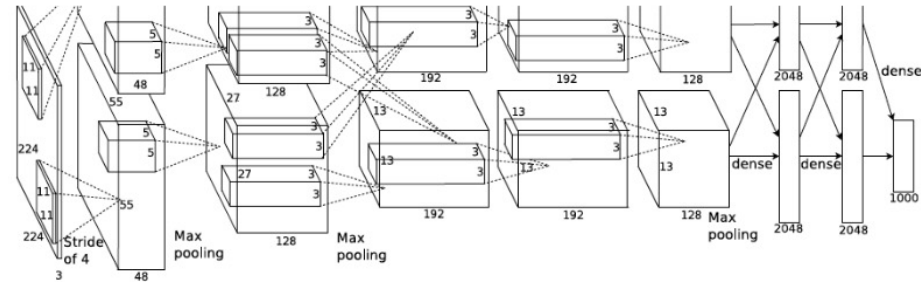
LeNet5 vs AlexNet

LeNet5 LeCun et al. 1998



- Trained on MNIST digit dataset with 60K training examples
- Sigmoid or tanh nonlinearity
- Average pooling
- Fully connected layers at the end

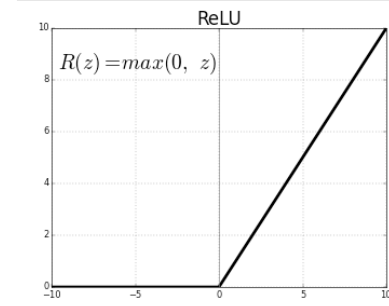
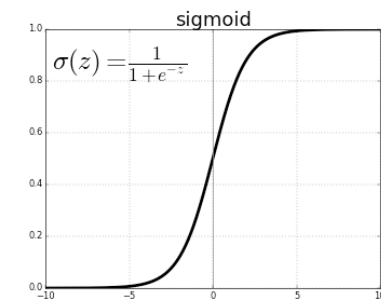
AlexNet Krizhevsky et al. 2012



- Trained on ImageNet dataset with 1.2M training images
- Rectified Linear Unit (ReLU) nonlinearity
- Max pooling
- GPU implementation
 - Trained on two GPUs for a week
- Dropout regularization
- Fully connected layers at the end

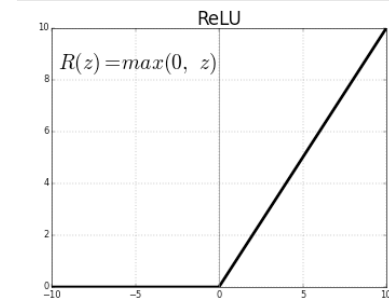
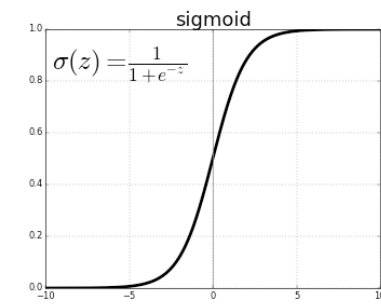
Why?

- Availability of large annotated data
- More layers
 - Capture more invariances
- More computing
 - Availability and affordability of GPUs
- Better regularization
 - Dropout
- New nonlinearities
 - Rectified Linear Unit (ReLU)
 - Parametric Rectified Linear Unit (PReLU)



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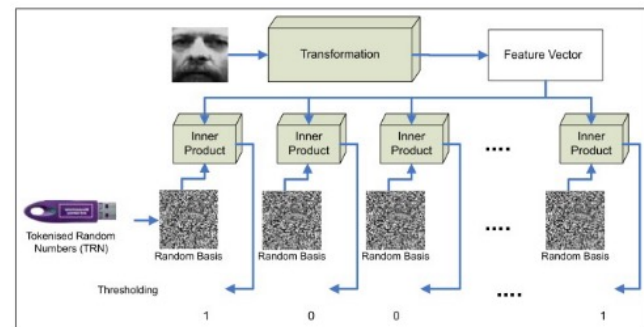
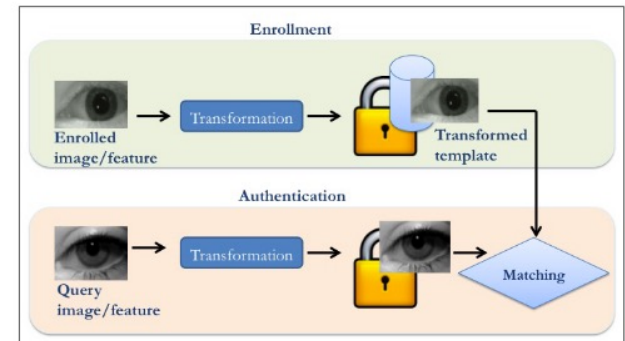


Large Datasets

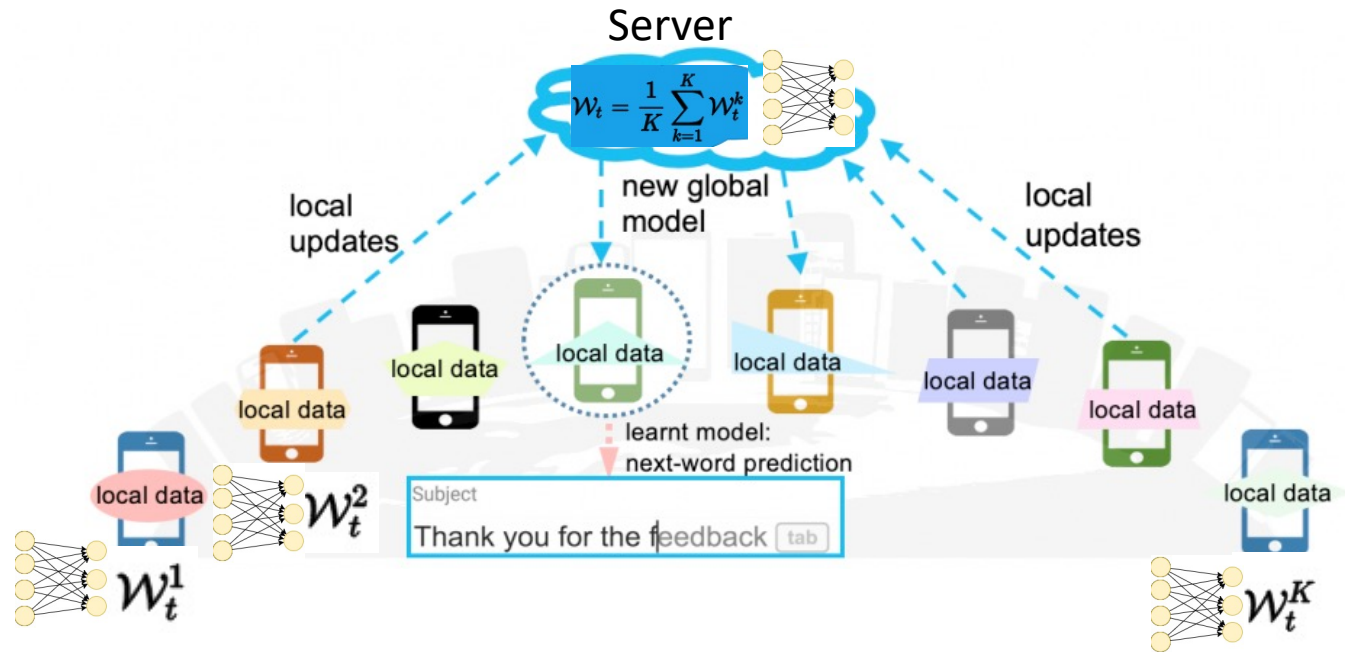
- Collecting and annotating datasets
 - Expensive
 - Labor intensive
 - User privacy issues
 - GDPR: General Data Protection Regulation
 - HIPAA: Health Insurance Portability and Accountability Act, 1996
 - SHIELD: Stop Hacks and Improve Electronic Data Security Act, Jan 1 2019
 - PCI: Payment Card Industry Data Security Standard, 2004
 - IRB: Institutional Review Board

Protecting User Privacy

- Data privacy (protect the data)
 - Cancelable biometrics
 - Modify data through revocable and non-invertible transformations
 - BioHashing
 - Random projections are used to generate templates
 - Differential privacy
 - An algorithm is differentially private if its behavior hardly changes when a single individual joins or leaves the dataset
 - Hide unique samples (add noise to data)
 - Homomorphic encryption
 - Perform calculations on encrypted data
- Federated learning (build protection into the models)
 - Machine learning on decentralized data
 - *Communication-efficient learning of deep networks from decentralized data*, AISTATS 2017, McMahan et al. (Google)



Federated Learning - FedAvg



- Different users (clients) collaboratively learn a machine learning model with the help of a server
- Local training
 - Users locally compute training parameters and send them to the server
- Model aggregating
 - The server performs secure aggregation over the uploaded parameters from different users without learning local information
- Parameters broadcasting
 - The server broadcasts the aggregated parameters to the users
- Model updating
 - All users update their respective models with aggregated parameters and test the performance of the updated models

Federated Learning - Applications

- Learning over smart phones
 - Mobile-based biometrics applications
 - Active authentication
- Learning across organizations
 - Multi-institutional collaboration
- Internet of things
 - Wearable devices, autonomous vehicles, smart homes, ...

Federated Learning - Applications

- Next word prediction (Google)
 - Federated Learning for Mobile Keyboard Prediction, Hard et al., 2018
- Speaker recognition (Apple Siri)
 - QuickType (Apple's personalized keyboard)

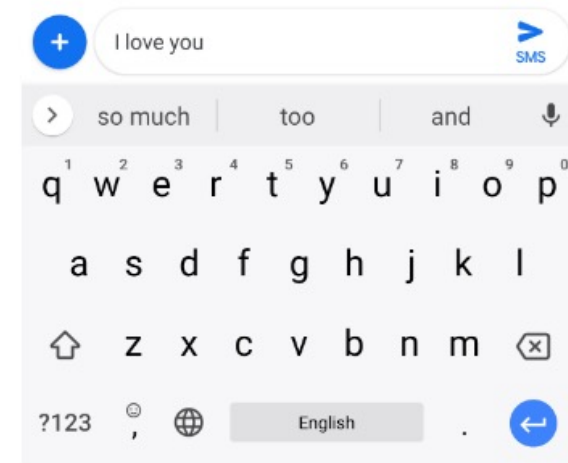


Fig. 1. Next word predictions in Gboard. Based on the context “I love you”, the keyboard predicts “and”, “too”, and “so much”.

Artificial intelligence / Machine learning

MIT
Technology
Review

How Apple personalizes Siri without hoovering up your data

The tech giant is using privacy-preserving machine learning to improve its voice assistant while keeping your data on your phone.

by **Karen Hao**

December 11, 2019

Federated Learning - Challenges

- Communication
 - Federated networks are comprised of a massive number of devices which causes communication in the network to be slower than local computations (i.e. expensive communication)
 - Need communication-efficient methods that iteratively send model updates as part of the training process
- Systems heterogeneity
 - Storage, computational, and communication capabilities of each device in federated networks may differ due to variability in hardware (CPU, memory), network connectivity (3G, 4G, 5G, wifi), and power (battery level)
 - Stragglers and fault tolerance significantly more prevalent
- Non-IID data
 - Devices frequently generate and collect data in a non-identically distributed manner across the network.
 - Unbalanced data
 - Increases the likelihood of stragglers, and may add complexity in terms of modeling, analysis, and evaluation
- Privacy issues

Federated Learning – Privacy Issues

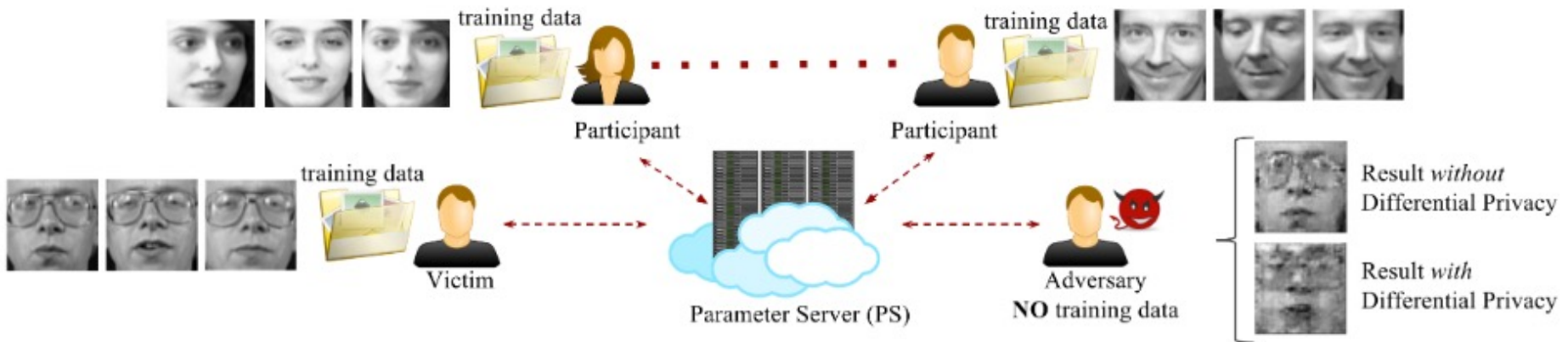
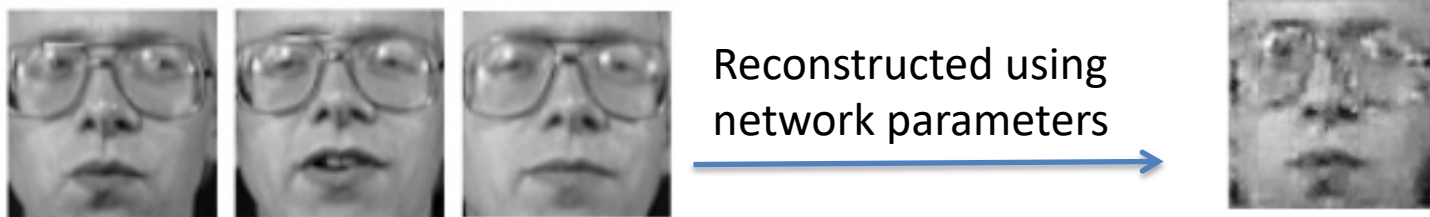


Figure 7: Collaborative deep learning with 41 participants. All 40 honest users train their respective models on distinct faces. The adversary has no local data. The GAN on the adversary's device is able to reconstruct the face stored on the victim's device (even when DP is enabled).



Federated Learning with Differential Privacy

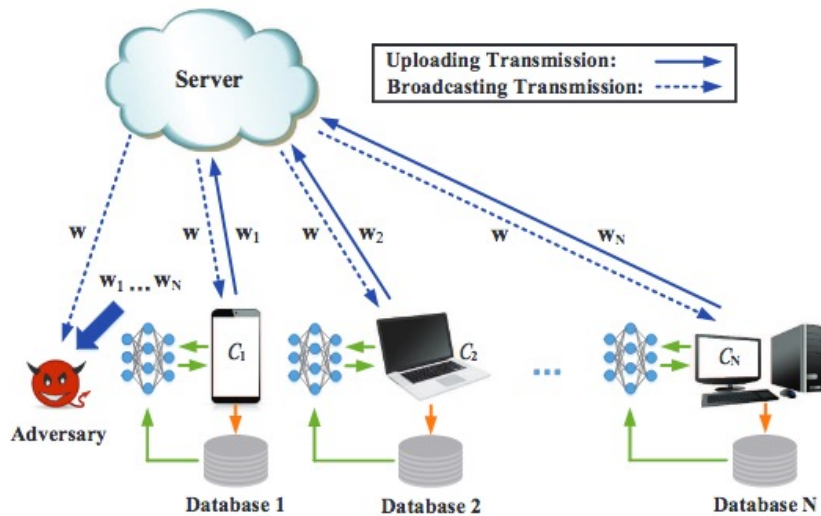


Figure 1: A FL training model with hidden adversaries who can eavesdrop trained parameters from both the clients and the server.

Algorithm 1: Noising before Aggregation FL

Data: T , $\mathbf{w}^{(0)}$, μ , ϵ and δ

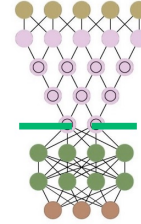
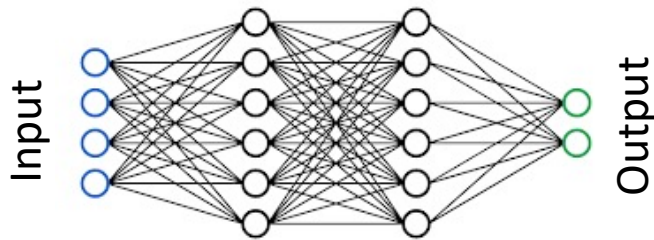
- 1 Initialization: $t = 1$ and $\mathbf{w}_i^{(0)} = \mathbf{w}^{(0)}$, $\forall i$
- 2 **while** $t \leq T$ **do**
- 3 **Local training process:**
- 4 **while** $C_i \in \{C_1, C_2, \dots, C_N\}$ **do**
- 5 Update the local parameters $\mathbf{w}_i^{(t)}$ as
- 6
$$\mathbf{w}_i^{(t)} = \arg \min_{\mathbf{w}_i} (F_i(\mathbf{w}_i) + \frac{\mu}{2} \|\mathbf{w}_i - \mathbf{w}^{(t-1)}\|^2)$$
- 7 Clip the local parameters
- 8
$$\mathbf{w}_i^{(t)} = \mathbf{w}_i^{(t)} / \max\left(1, \frac{\|\mathbf{w}_i^{(t)}\|}{C}\right)$$
- 8 Add noise and upload parameters
- 8
$$\tilde{\mathbf{w}}_i^{(t)} = \mathbf{w}_i^{(t)} + \mathbf{n}_i^{(t)}$$
- 9 **Model aggregating process:**
- 10 Update the global parameters $\mathbf{w}^{(t)}$ as
- 11
$$\mathbf{w}^{(t)} = \sum_{i=1}^N p_i \tilde{\mathbf{w}}_i^{(t)}$$
- 12 The server broadcasts global noised parameters
- 13
$$\tilde{\mathbf{w}}^{(t)} = \mathbf{w}^{(t)} + \mathbf{n}_D^{(t)}$$
- 14 **Local testing process:**
- 15 **while** $C_i \in \{C_1, C_2, \dots, C_N\}$ **do**
- 16 Test the aggregating parameters $\tilde{\mathbf{w}}^{(t)}$ using local dataset
- 17 $t \leftarrow t + 1$

Result: $\tilde{\mathbf{w}}^{(T)}$

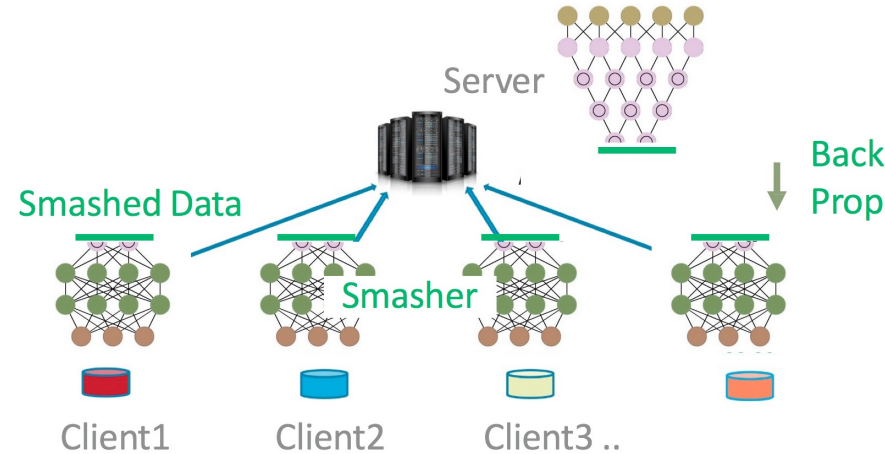
Federated Learning with Differential Privacy

- Three key properties
 - There is a tradeoff between convergence performance and privacy protection levels, i.e., better convergence performance leads to a lower protection level
 - Given a fixed privacy protection level, increasing the number N of overall clients participating in FL can improve the convergence performance
 - There is an optimal number aggregation times (communication rounds) in terms of convergence performance for a given protection level

Split Learning Network (SplitNN)



b2. Split Learning



- Each client trains a partial deep network up to a specific layer (cut layer)
- Outputs at the cut layer are sent to another entity (server) which completes the rest of the training
- The gradients are now back propagated again from its last layer until the cut layer in a similar fashion
- The gradients at the cut layer are sent back to client centers
- This process is continued until the distributed split learning network is trained
- **Computational, communication, and memory efficient**
- **Large number of clients: Split learning shows positive results**

Gupta, Otkrist and Raskar, Ramesh, *Distributed learning of deep neural network over multiple agents*, Journal of Network and Computer Applications, Vol.116, pp.1–8, 2018.

<https://splitlearning.github.io/>

Federated Learning - Tools

- OpenMind (www.openmined.org)
 - An open-source community whose goal is to make the world more privacy-preserving by lowering the barrier-to-entry to private AI technologies.
- PySyft: Python library for secure and private Deep Learning
 - <https://github.com/OpenMined/PySyft>)
- TensorFlow Federated
 - Machine learning on decentralized data
 - <https://www.tensorflow.org/federated>
- Federated-Learning (PyTorch)
 - <https://github.com/AshwinRJ/Federated-Learning-PyTorch>

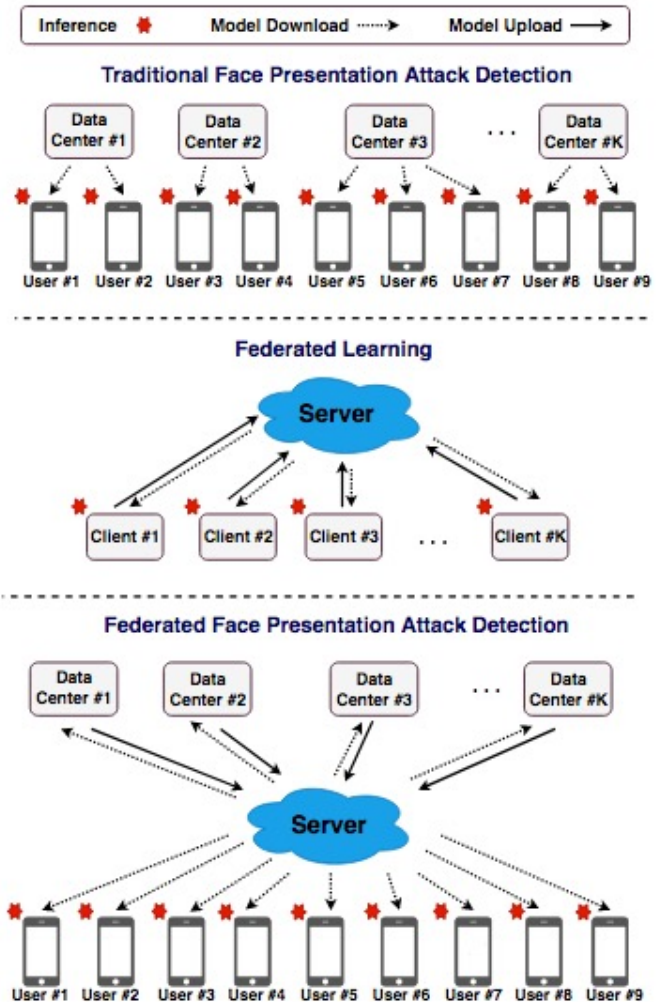
Applications

- Face presentation attack detection
 - Multi-institutional collaboration
- Mobile-based active authentication
 - Learning over smart phones
- Thermal to visible face synthesis

Federated Face Presentation Attack Detection (FedPAD)



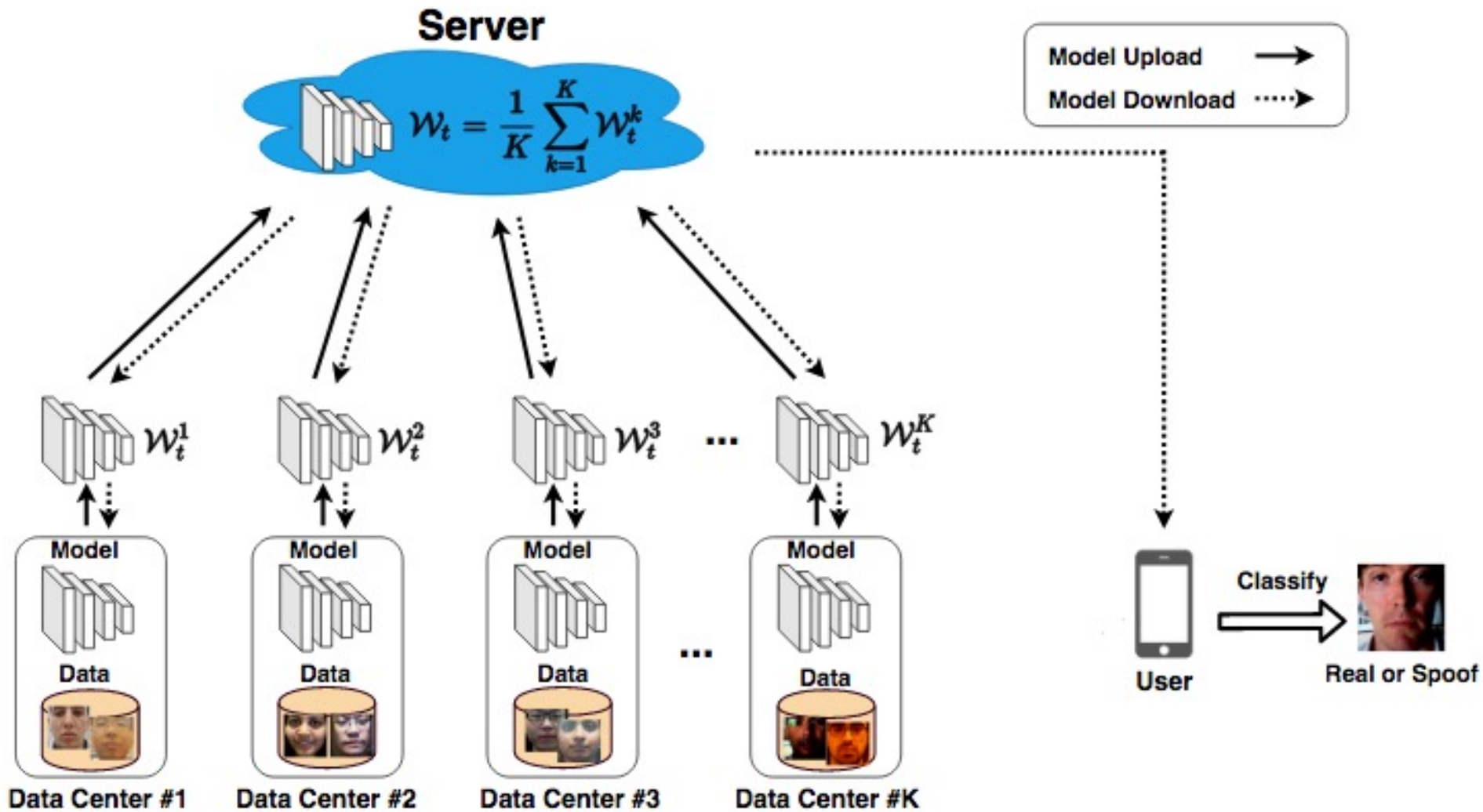
Marcel et al.



Shao et al, FG 2021
<https://arxiv.org/pdf/2005.14638.pdf>

Figure 1. Comparison between fPAD (top), traditional federated learning (middle) and the proposed FedPAD (bottom). FedPAD can be regarded as a special case of traditional federated learning.

FedPAD Framework



Shao et al, 2020

<https://arxiv.org/pdf/2005.14638.pdf>

FedPAD Data



Table 1. Comparison of seven experimental datasets.

Dataset	Extra light	Complex background	Attack type	Display devices
C	No	Yes	Printed photo Cut photo Replayed video	iPad
I	Yes	Yes	Printed photo Display photo Replayed video	iPhone 3GS iPad
M	No	Yes	Printed photo Replayed video	iPad Air iPhone 5S
O	Yes	No	Printed photo Display photo Replayed video	Dell 1905FP Macbook Retina
S	Yes	Yes	Printed photo Display photo Replayed video	Dell 1905FP iPad Pro iPhone 7 Galaxy S8 Asus MB168B
3	No	No	Thatsmyface 3D mask	Kinect
H	Yes	Yes	Thatsmyface 3D mask REAL-f mask	MV-U3B

FedPAD Results

Table 2. Comparison with models trained by data from single data center and various data centers.

Methods	Data Centers	User	HTER (%)	EER (%)	AUC (%)	Avg. HTER	Avg. EER	Avg. AUC
Single	O	M	41.29	37.42	67.93	36.43	34.31	70.36
	C	M	27.09	24.69	82.91			
	I	M	49.05	20.04	85.89			
	O	C	31.33	34.73	73.19			
	M	C	39.80	40.67	66.58			
	I	C	49.25	47.11	55.41			
	O	I	42.21	43.05	54.16			
	C	I	45.99	48.55	51.24			
	M	I	48.50	33.70	66.29			
	M	O	29.80	24.12	84.86			
	C	O	33.97	21.24	84.33			
	I	O	46.95	35.16	71.58			
Fused	O&C&I	M	34.42	23.26	81.67	35.75	31.29	73.89
	O&M&I	C	38.32	38.31	67.93			
	O&C&M	I	42.21	41.36	59.72			
	I&C&M	O	28.04	22.24	86.24			
Ours	O&C&I	M	19.45	17.43	90.24	32.17	28.84	76.51
	O&M&I	C	42.27	36.95	70.49			
	O&C&M	I	32.53	26.54	73.58			
	I&C&M	O	34.44	34.45	71.74			
All (Upper Bound)	O&C&I	M	21.80	17.18	90.96	27.26	25.09	80.42
	O&M&I	C	29.46	31.54	76.29			
	O&C&M	I	30.57	25.71	72.21			
	I&C&M	O	27.22	25.91	82.21			

Single: Obtain a trained model from one data center.

Fused: Obtain multiple trained models from several data centers and fuse their prediction scores during inference

Ours: Performance of a trained model is evaluated against a dataset that has not been observed during training

All: Model is trained with data from all available data centers (not privacy preserving)

FedPAD Results

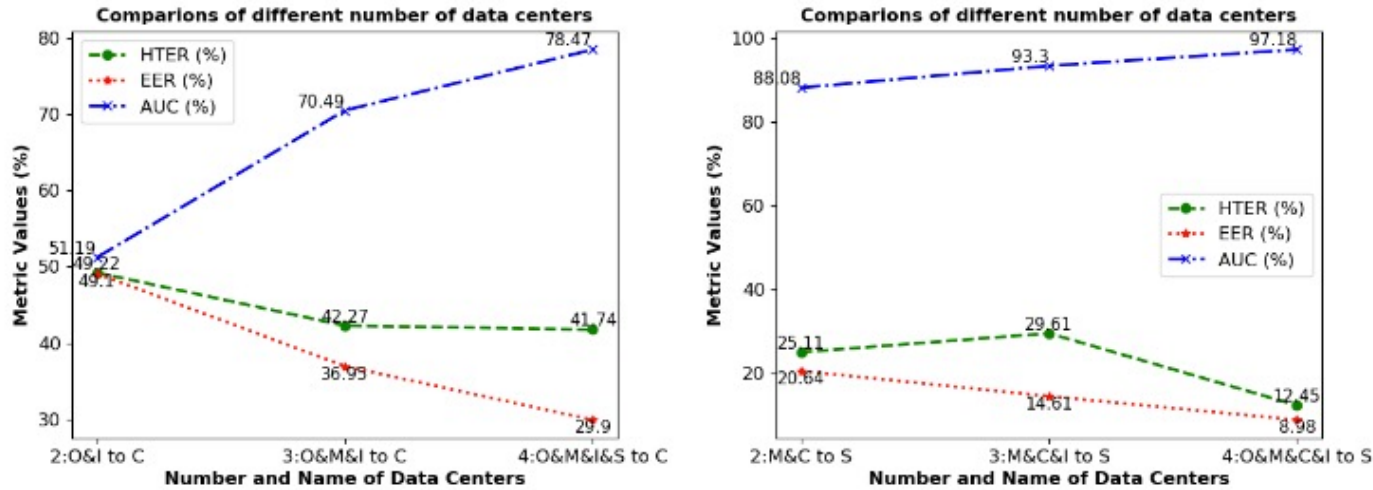


Figure 5. Comparison of different number of data centers.

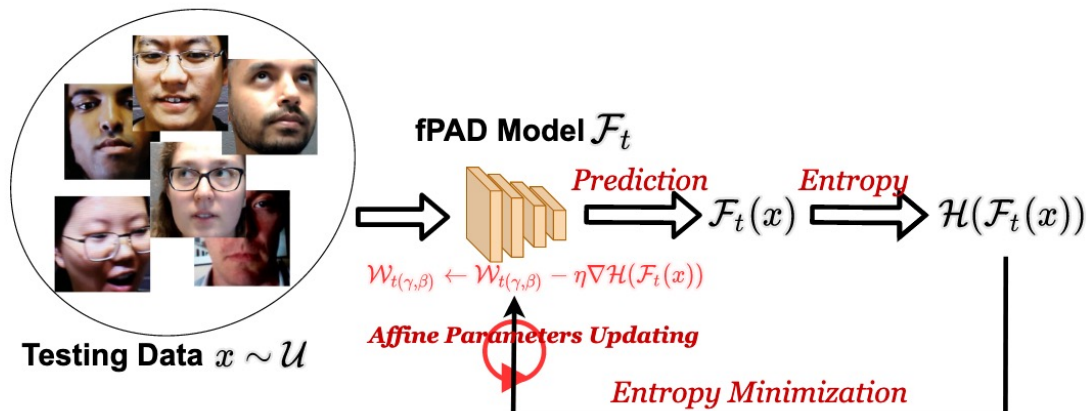
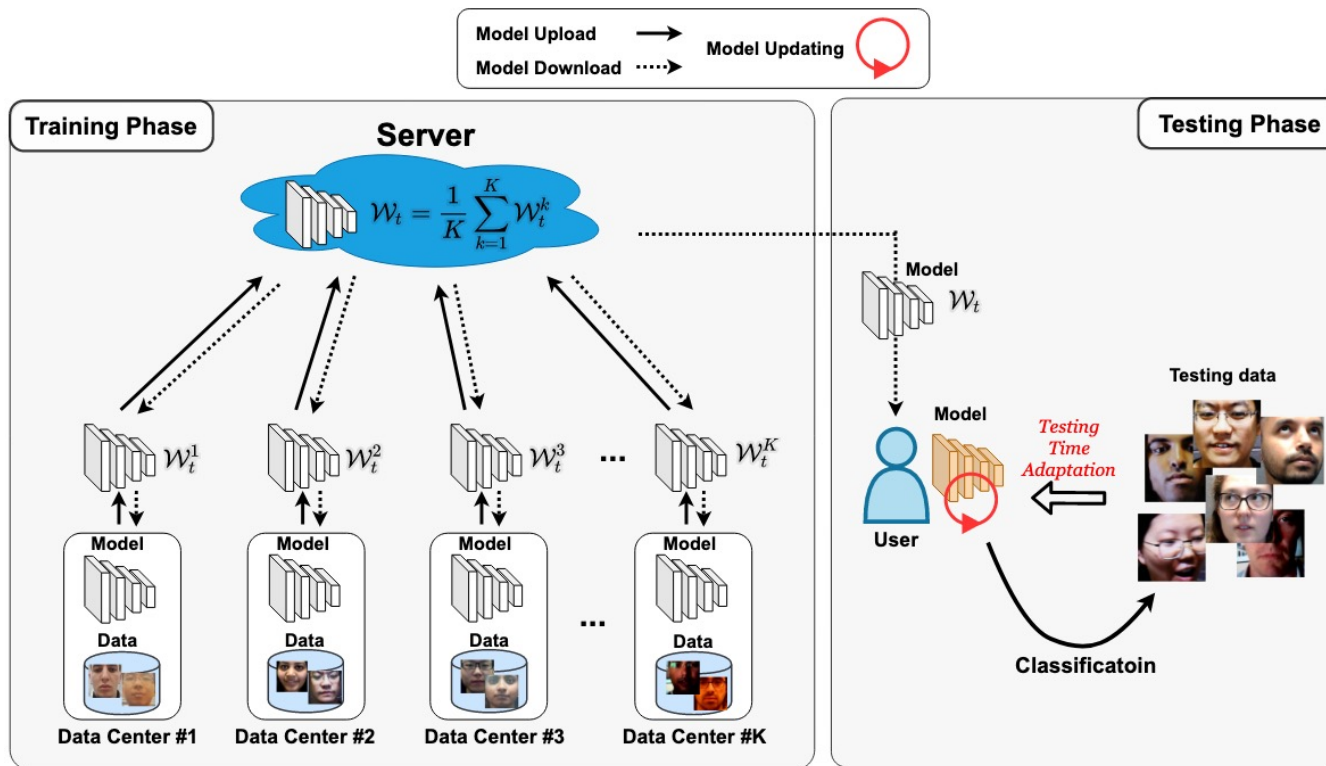
Table 3. Effect of using different types of spoof attacks

Methods	Data Centers	User	HTER (%)	EER (%)	AUC (%)
Single	I (Print)	M (Print, Video)	38.82	33.63	72.46
	O (Video)	M (Print, Video)	35.76	28.55	78.86
Fused	I (Print) & O (video)	M (Print, Video)	35.22	25.56	81.54
Ours	I (Print) & O (video)	M (Print, Video)	30.51	26.10	84.82

Table 4. Impact of adding data centers with diverse attacks

Data Centers	User	HTER (%)	EER (%)	AUC (%)
O&C&I&M (2D)	H (3D)	47.02	18.31	85.06
O&C&I&M (2D)&3 (3D)	H (3D)	34.70	14.20	92.35

Test-Time Adaptive FedPAD

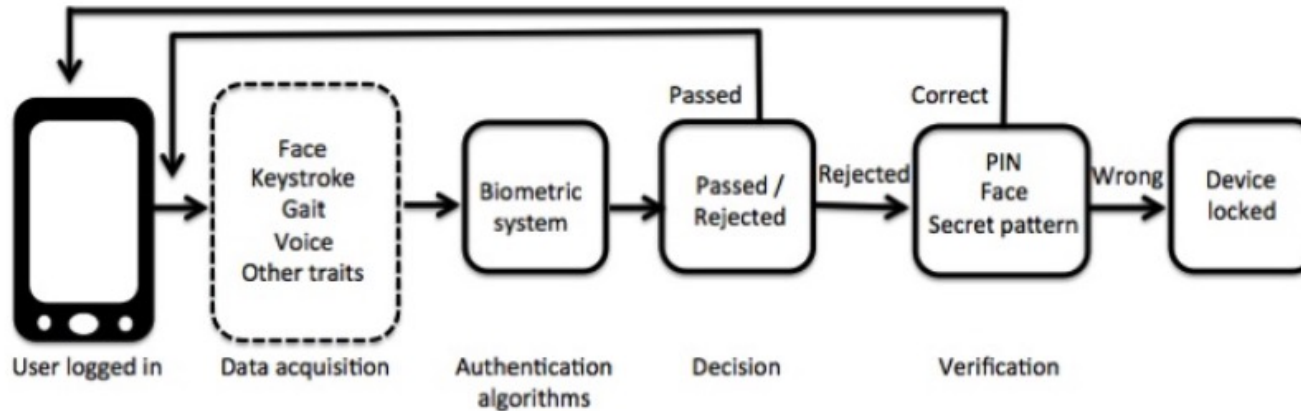
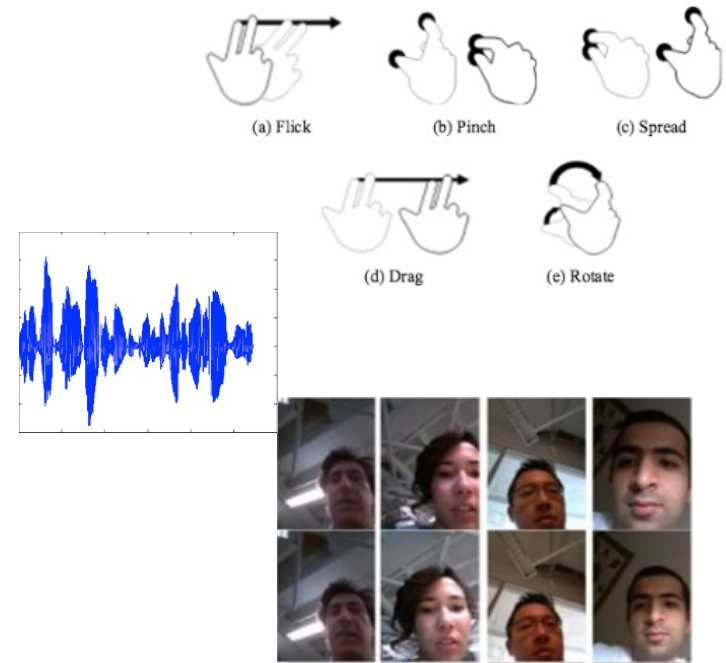


Test-Time Adaptive FedPAD Results

COMPARISON WITH MODELS TRAINED BY DATA FROM SINGLE DATA CENTER AND VARIOUS DATA CENTERS.

Methods	Data Centers	User	HTER (%)	EER (%)	AUC (%)	Avg. HTER	Avg. EER	Avg. AUC
Single	O	M	41.29	37.42	67.93	41.61	36.66	67.07
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	O&M&I	C	26.33	29.75	77.77			
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	I&C&M	O	23.09	23.09	83.21			

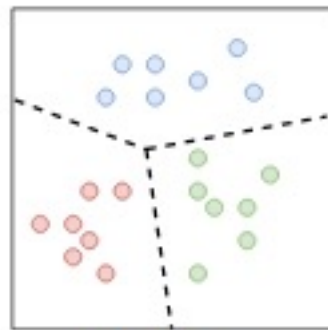
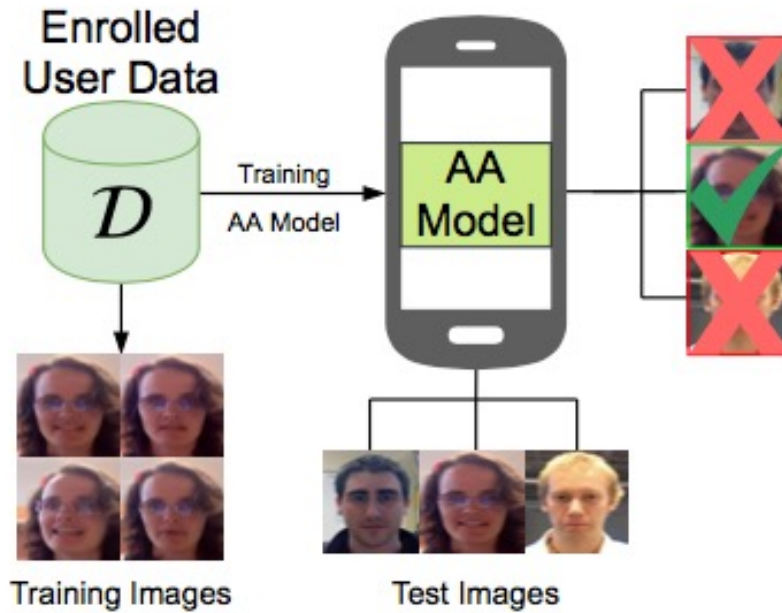
Active Authentication (AA)



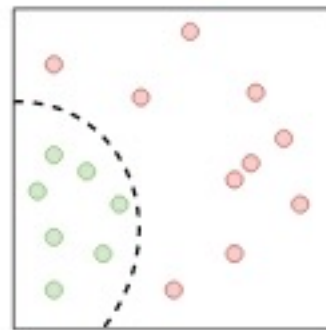
V. M. Patel, R. Chellappa, D. Chandra and B. Barbello, "Continuous User Authentication on Mobile Devices: Recent progress and remaining challenges," in IEEE Signal Processing Magazine, vol. 33, no. 4, pp. 49-61, July 2016.



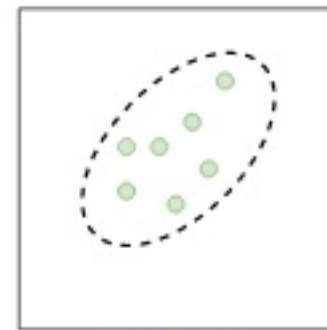
AA - OCC Problem



Multi-class Classification



Multi-class Detection



One Class Classification

Federated AA Framework

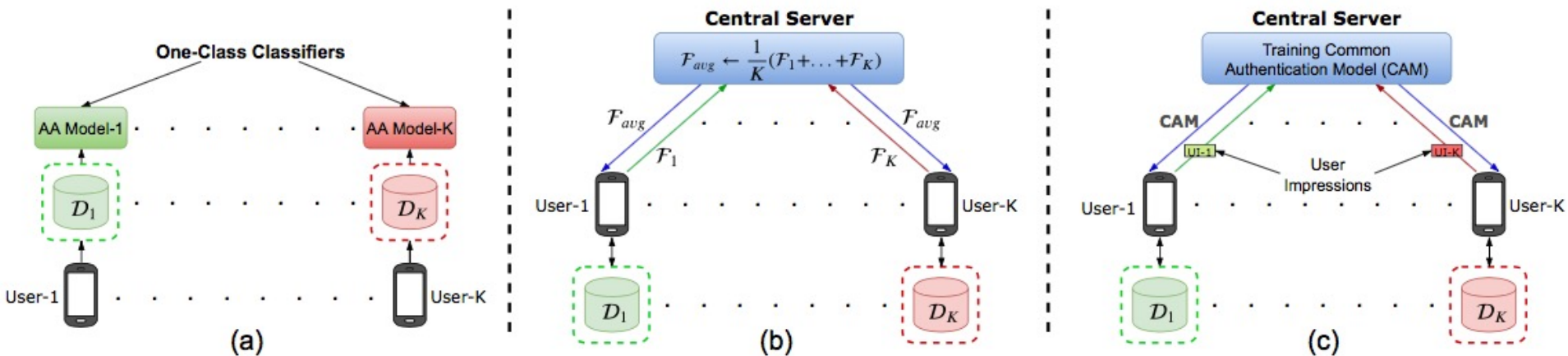
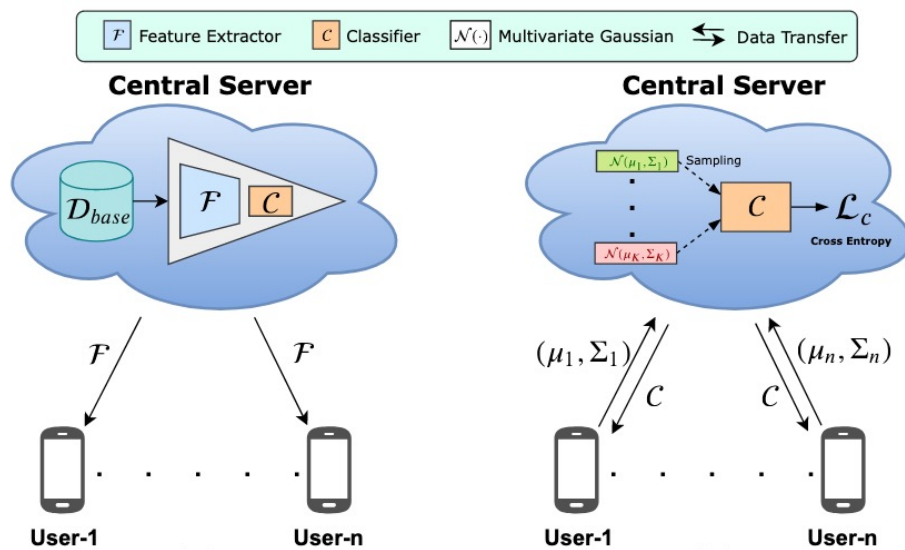


Figure 2. Active authentication based on (a) One class classification, (b) Federated Averaging, and (c) Proposed Method.



Federated AA

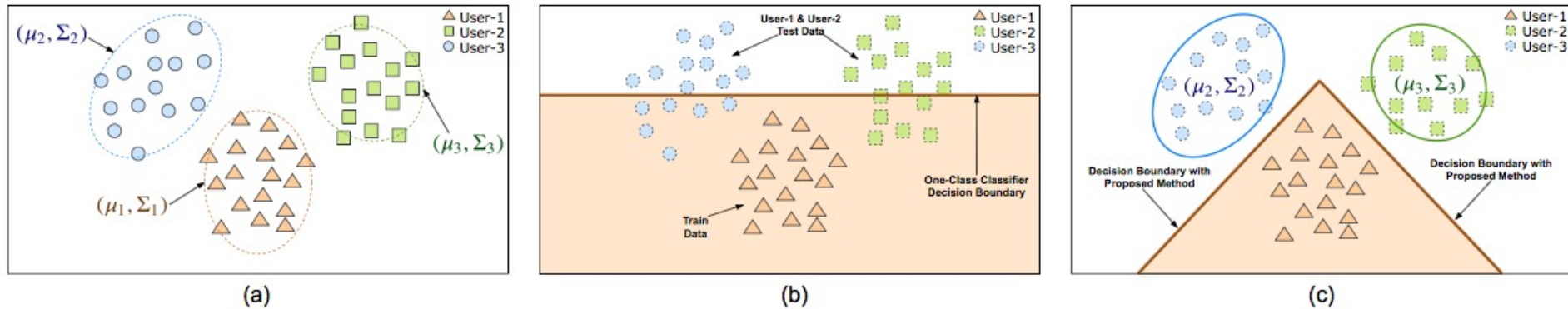
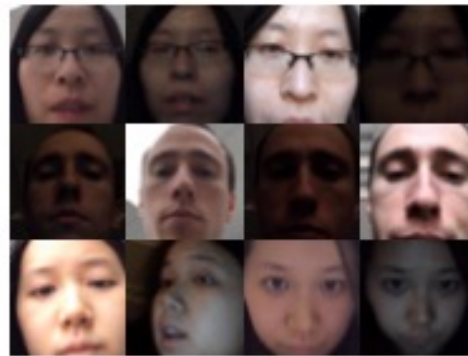


Figure 5. Toy example with three users to show the effectiveness of proposed method compared to one-class modeling based methods. (a) Feature space location (mean μ_i) and shape (variance Σ_i) estimated for each user. (b) Modeling as a one-class classification problem to learn a decision boundary for user-1. When such a model is tested there are many samples from user-2 and user-3 that are mis-classified as user-1. (c) Learning decision boundary using proposed method to train the authentication model for user-1 using user-1, user-2 and user-3's mean and variance. This model does not make the same mistake of mis-classifying user-2 and user-3 data as user-1 similar to one-class based method. As visible from the figure, the learned decision boundary is also better in comparison to one-class method.

Federated AA - Results



(a) MOBIO



(b) UMDAA-01

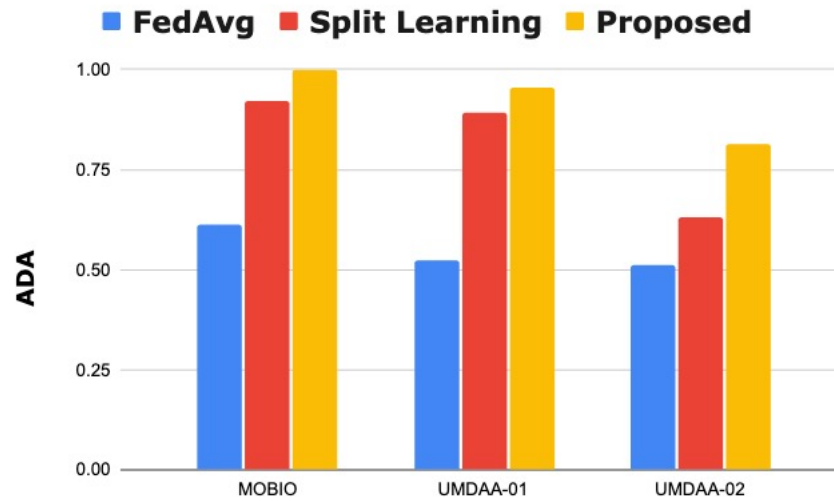


(c) UMDAA-02

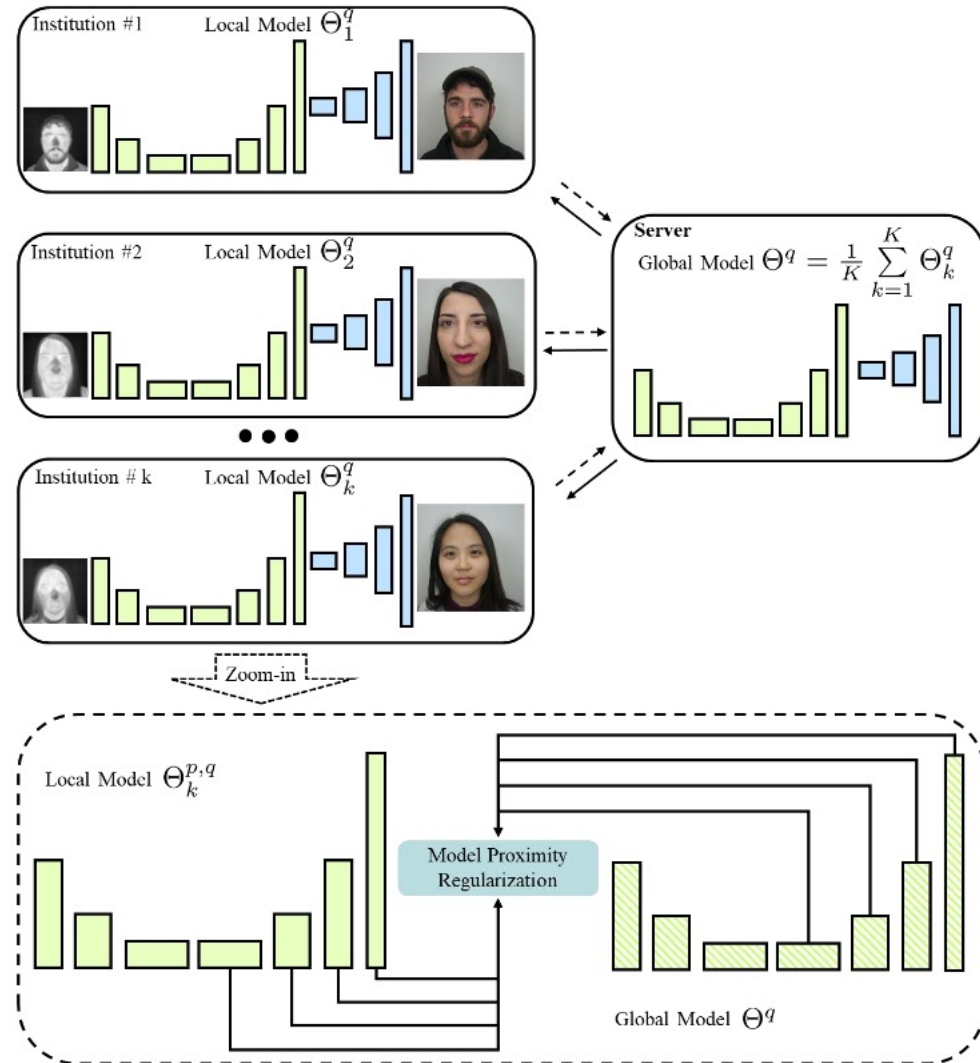
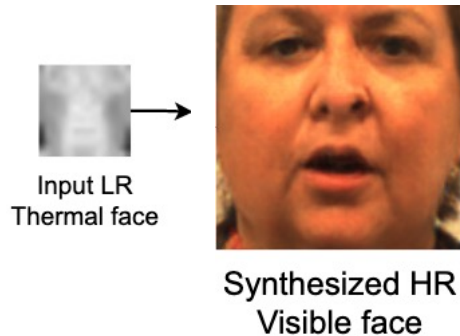
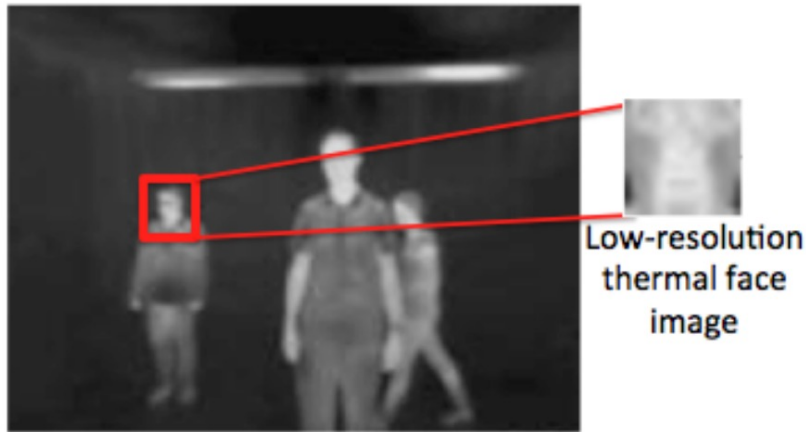
Table 1. Performance comparison with state-of-the-art active authentication methods evaluated in terms of average detection accuracy. The best performing method for each dataset is shown in bold fonts.

	1SVM	k1SVM	SVDD	kSVDD	kNFST	1vSet	1MPM	DMPM	OC-ACNN	Proposed
MOBIO	0.632 (0.004)	0.748 (0.004)	0.582 (0.007)	0.763 (0.013)	0.560 (0.003)	0.670 (0.005)	0.768 (0.003)	0.825 (0.007)	0.938 (0.005)	0.998 (0.003)
UMDAA-01	0.622 (0.002)	0.731 (0.009)	0.615 (0.018)	0.701 (0.009)	0.567 (0.012)	0.593 (0.017)	0.816 (0.003)	0.869 (0.001)	0.891 (0.002)	0.954 (0.005)
UMDAA-02	0.614 (0.008)	0.649 (0.004)	0.515 (0.007)	0.550 (0.007)	0.556 (0.003)	0.538 (0.003)	0.722 (0.006)	0.760 (0.007)	0.735 (0.009)	0.813 (0.006)

Federated AA - Results



Federated Thermal to Visible Synthesis



Federated Thermal to Visible Synthesis Results

VIS-TH



ARL-VTF



GT/TH

Pixel2Pixel

HiFaceGAN

GANVFS

SAGAN

AxialGAN

VPGAN

128 → 512

Federated Thermal to Visible Synthesis Results

Table 2. Verification results on the **VIS-TH** dataset.

Method	Rank-1	VR@FAR=1%	VR@FAR=0.1%
LightCNN [60]	30.48	8.57	2.86
Pixel2Pixel [19]	15.24	2.21	0.07
HiFaceGAN [62]	44.76	10.95	2.86
GANVFS [67]	18.11	7.29	1.90
SAGAN [6]	63.33	23.81	<u>17.62</u>
AxialGAN [18]	<u>66.67</u>	<u>24.76</u>	13.81
VPGAN (ours)	76.67	45.71	20.00

Table 3. Image quality results on the **ARL-VTF** dataset.

Methods	LPIPS↓	NIQE↓	Deg.↑	PSNR↑	SSIM↑
TH	0.6721	10.176	42.34	5.63	0.2940
Pixel2Pixel [19]	0.2038	6.298	70.67	19.46	0.7759
HiFaceGAN [62]	0.2166	7.274	70.11	19.67	0.7954
GANVFS [67]	0.2433	6.679	67.26	19.76	0.7511
SAGAN [6]	<u>0.1925</u>	<u>6.155</u>	<u>71.12</u>	20.11	0.7772
AxialGAN [18]	0.1998	6.223	69.75	<u>20.17</u>	0.7770
VPGAN (ours)	0.1713	6.059	72.00	20.29	<u>0.7883</u>

Table 4. Verification results on the **ARL-VTF** dataset.

Method	Rank-1	VR@FAR=1%	VR@FAR=0.1%
LightCNN [60]	11.07	9.24	4.57
Pixel2Pixel [19]	70.96	56.35	33.60
HiFaceGAN [62]	70.15	56.65	32.18
GANVFS [67]	70.76	45.99	22.03
SAGAN [6]	71.16	54.11	<u>38.07</u>
AxialGAN [18]	<u>71.57</u>	<u>57.16</u>	37.36
VPGAN (ours)	74.16	59.96	41.27

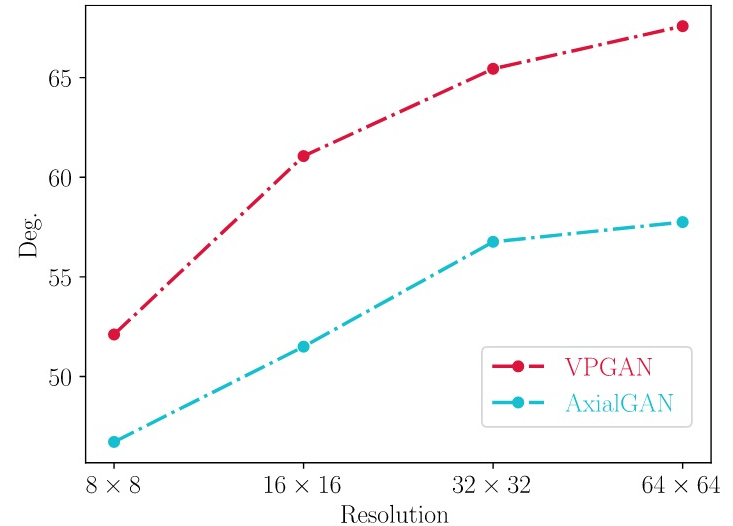


Figure 1. Effect of input resolution

Summary

- Federated learning promises to be an active area of research
- Open problems
 - Domain adaptive FL methods
 - Benchmarks
 - Unsupervised and semi-supervised FL
 - Privacy preserving FL methods
 - Novel FL models for biometrics and surveillance applications

Acknowledgments



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More Information,

VISION & IMAGE
UNDERSTANDING

Vision and Image Understanding (VIU) Lab @JHU

<https://engineering.jhu.edu/vpatel36/>

Thank You!