Deep Learning-Driven Biometric Security: Advancing Liveness Detection and Anti-Spoofing Techniques

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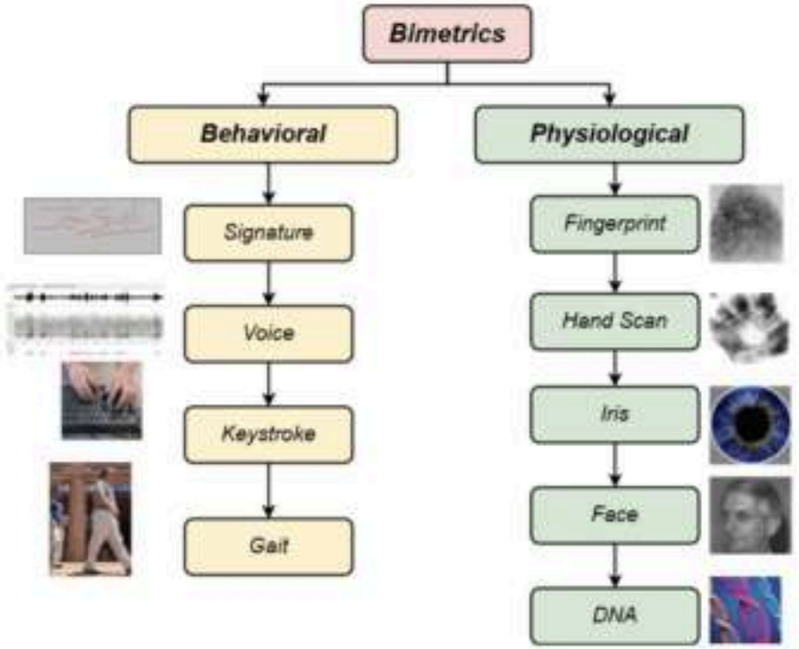
April 2025

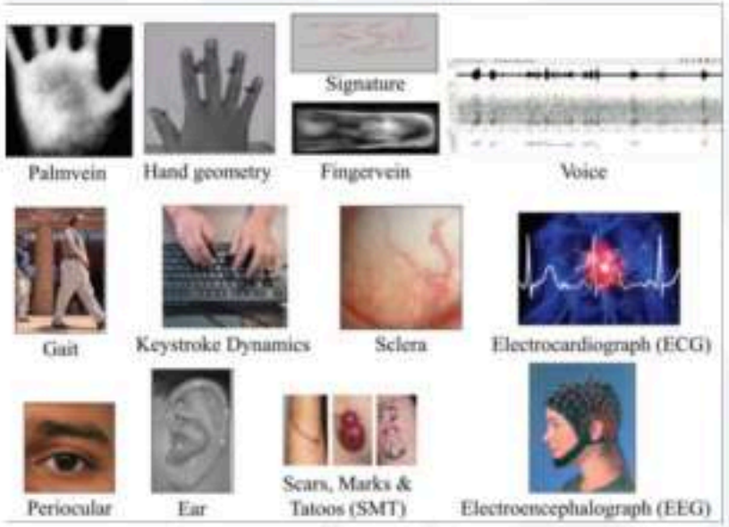


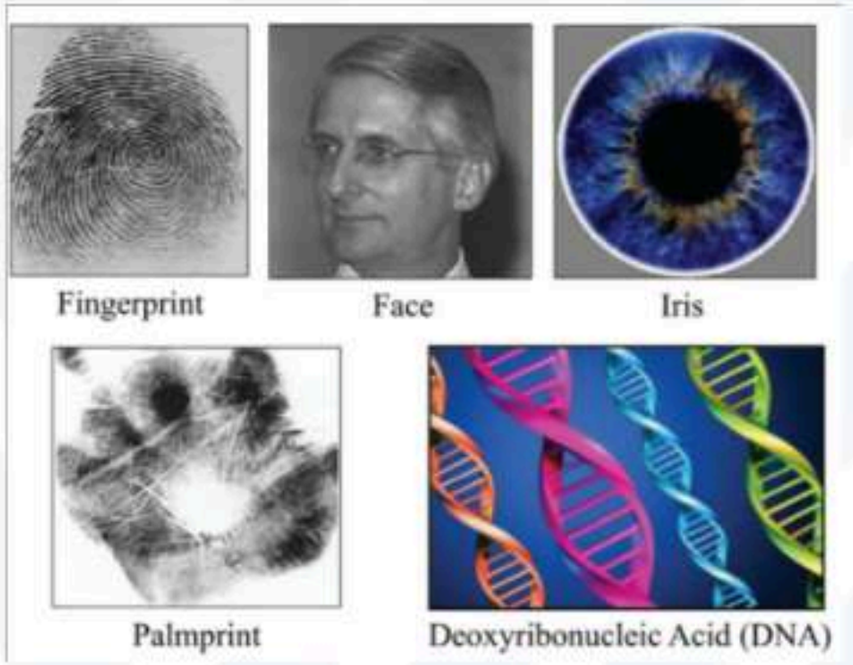
Agenda

- Biometrics Modalities
- Biometric Applications
- Biometric Security & Privacy
- Biometric Spoofing
- Contactless Fingerprint
- Contactless Fingerprint Recognition (Semi-Supervised)
- Contactless Fingerprint Recognition (Unsupervised)
- Face Liveness Detection
- Remote Photoplethysmography (rPPG)
- Proposed GAN-based rPPG Framework

Biometrics Modalities







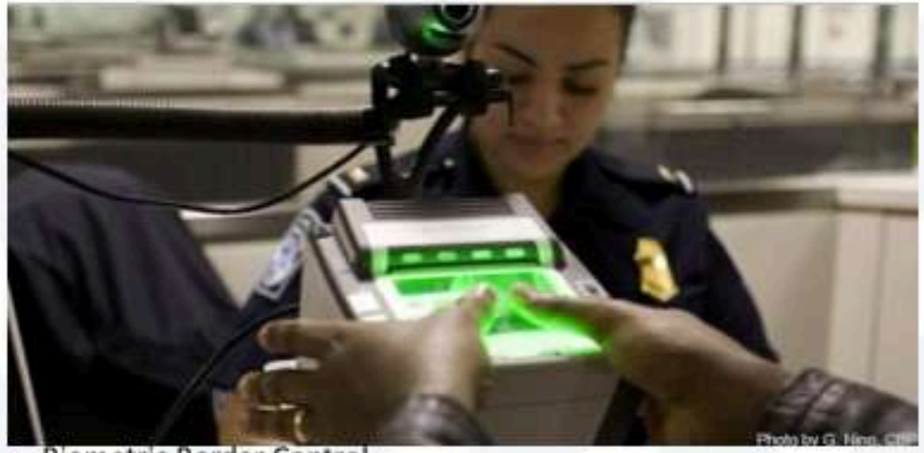
Jain, Anil K., Karthik Nandakumar, and Arun Ross. "50 years of biometric research: Accomplishments, challenges, and opportunities." *Pattern recognition letters* 79 (2016): 80-105.

Biometric Applications

- Border control
- Automotive
- Smartphone
- Transportation & Smart Access



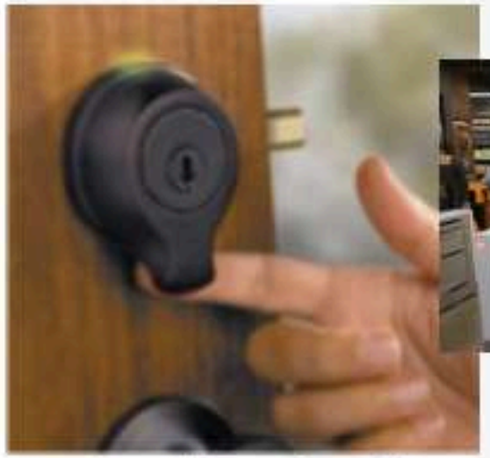
Clear



Biometric Border Control



Biometric Future Car



Personal Access Control



Amazon Go



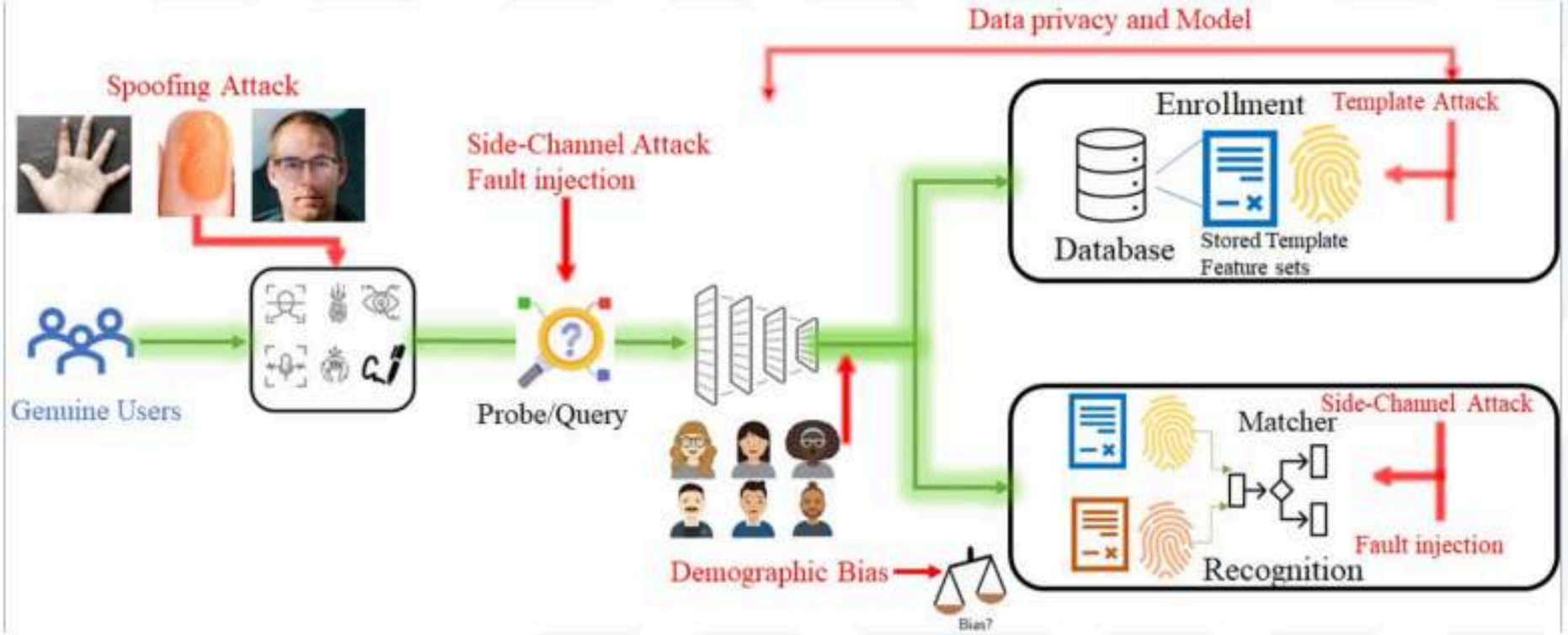
Apple Fingerprint

Biometrics Security and Privacy

- ❑ Template Attack
- ❑ Biometric Spoofing
- ❑ Privacy
- ❑ Fairness and Bias
- ❑ Adversarial Attack &

  Side channel

  attacks



What is Biometric Spoofing?



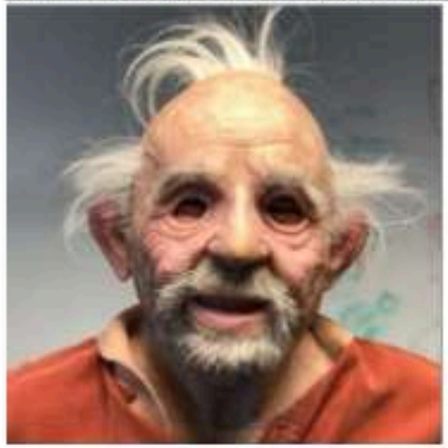
https://www.idrnd.ai/what-is-passive-facial-liveness-and-why-you-shouldnt-use-face-biometrics-without-it/



Aron Ross from MSU demonstrates fake Iris

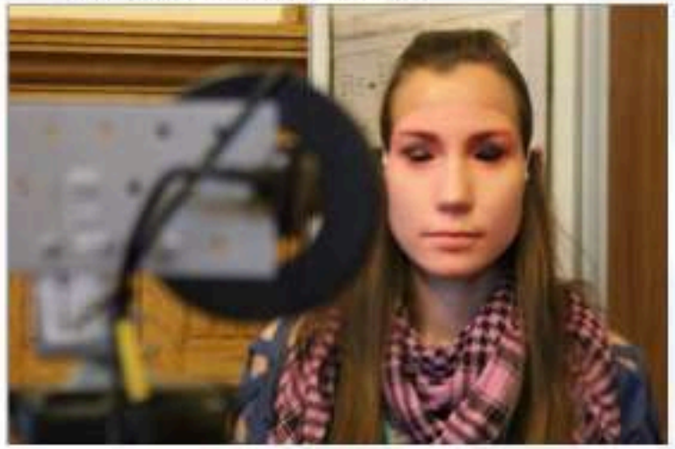


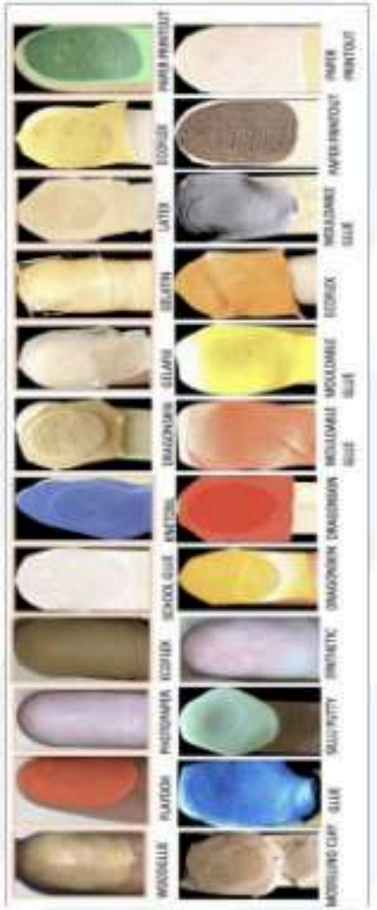
https://www.theverge.com/2017/9/21/16345500/biometrics-fingerprint-identification-technology





https://ec.europa.eu/research-and-innovation/en/horizon-magazine/make-and-fake-fingers-staying-ahead-online-spoofers





Contactless Fingerprint

Why Contactless Biometrics?

- ❑ Hygiene and Safety
- ❑ User Convenience
- ❑ Security Demand
- ❑ Exceptional Speed









IDLOOP Image

Challenges:

- ❑ Susceptibility to Spoofing (Printed photos, Silicone, play materials)



- ❑ Lack of Physical Contact reduces



Limitations of Current Models:

- ❑ Heavy reliance on labeled spoof data.
- ❑ Limited generalization to unseen attack types.
- ❑ Difficulty scaling due to evolving spoofing techniques.

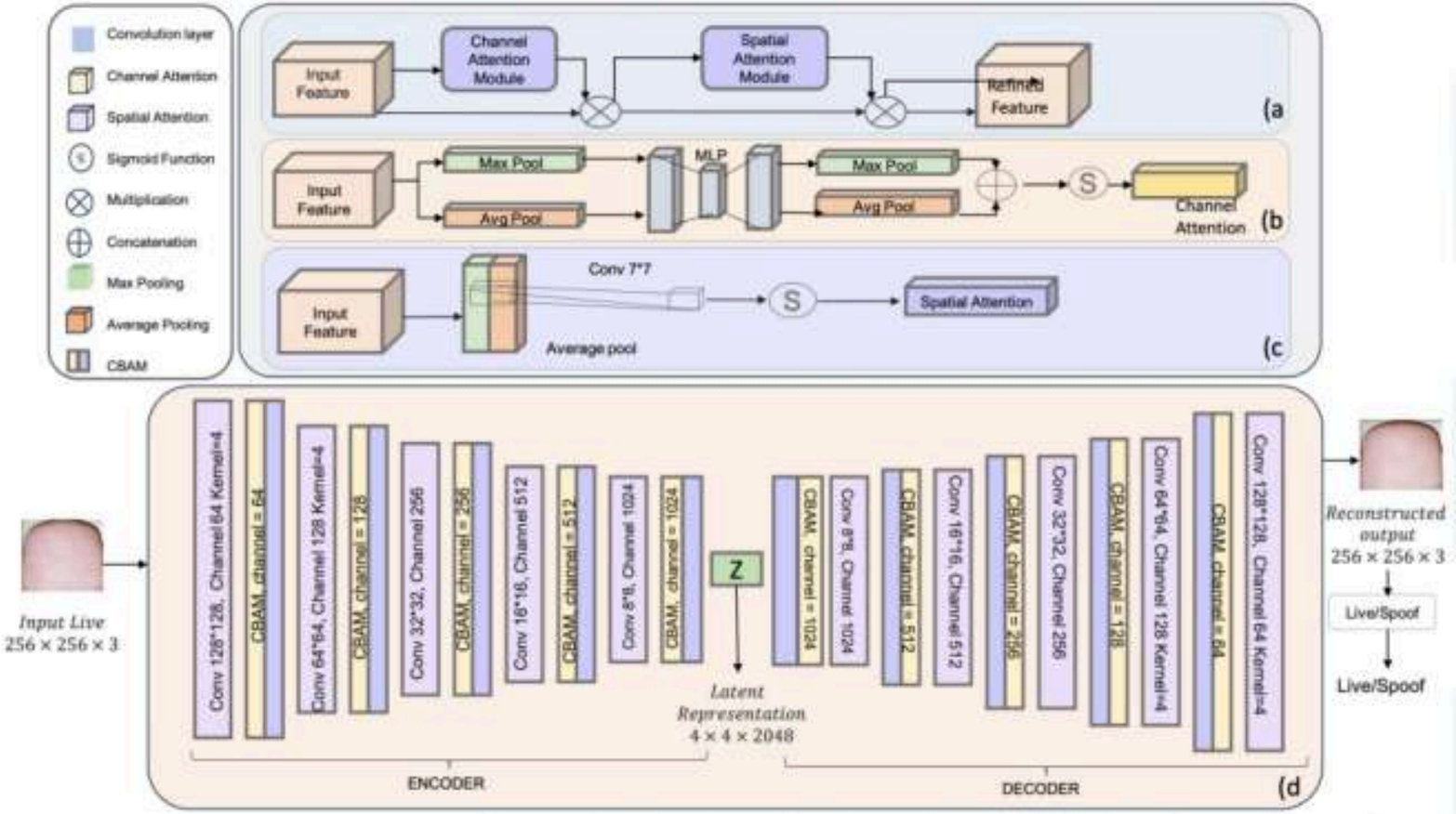


Author	Method	Database	Spoof type	Results
Tanej et al. [2016]	Hand crafted	IITD	Print Attack, Photo Attack	EER = 3.71%
Wasnik et al. [2018]	Hand crafted (LBP, BSIF, HOG, SVM)	50 subjects, 250 images, 150 videos	Print artefact, Electronic replay, Electronic display	BPCER = 1.8, 0, 0.66; APCER = 10
Fujito et al. [2018]	AlexNet	Live: 4096, spoof: 8192	Print Attack, Photo Attack	HTER = 0.04%
Marasco et al. [2022]	AlexNet, DenseNet201, ResNet18/34, DenseNet121, MobileNet-V2	IITD	Print Attack, Photo Attack	D-EER AlexNet = 2.14%, ResNet = 0.96%
Kolberg et al. [2023]	Not Reported	COLFISPOOF	Knotosil, glue, dragon skin, paper printout, ecoflex, playdoh	Not Reported
Purnapatra et al. [2023]	DenseNet121, NASNet	CLARKSON	Ecoflex, playdoh, wood glue, synthetic, fingerphoto, latex	APCER = 0.14%, BPCER = 0.18%
Hailin Li et al. [2023]	AlexNet, DenseNet201, MobileNet-V2, NASNet, ResNet50, GoogleNet, EfficientNet-B0, ViT	CLARKSON	Ecoflex, playdoh, wood glue, synthetic, fingerphoto, latex	EER = 8.26%
Puranpatra et al. [2023]	Two CNN combination	CLARKSON	Ecoflex, playdoh, wood glue, synthetic, fingerphoto, latex	BPCER = 0.62, APCER = 11.35, ACER = 6%
B. Adami et al. [2023]	**ResNet-18/LeakyReLU, Combined Loss**	**CLARKSON COLFISPOOF IITD**	**Ecoflex, playdoh, wood glue, synthetic, fingerphoto, latex**	**APCER = 0.12, BPCER = 0.63, ACER = 0.8**
B. Adami et al. [2024]	**CBAM-Autoencoder, Swin-Transformer**	**CLARKSON COLFISPOOF IITD**	**Ecoflex, playdoh, wood glue, synthetic, fingerphoto, latex**	**APCER = 1.6%, BPCER = 0.96%**

Unsupervised Fingerprint Anti-Spoofing Approach

This method **trains only on genuine fingerprints**, learning normal patterns to detect anomalies as spoof attempts. The approach consists of:

- **Autoencoder** (Feature learning)
- **Convolutional Block Attention Module (CBAM)** (Enhanced representation)
- **Loss Function:** Mean Squared Error (MSE)

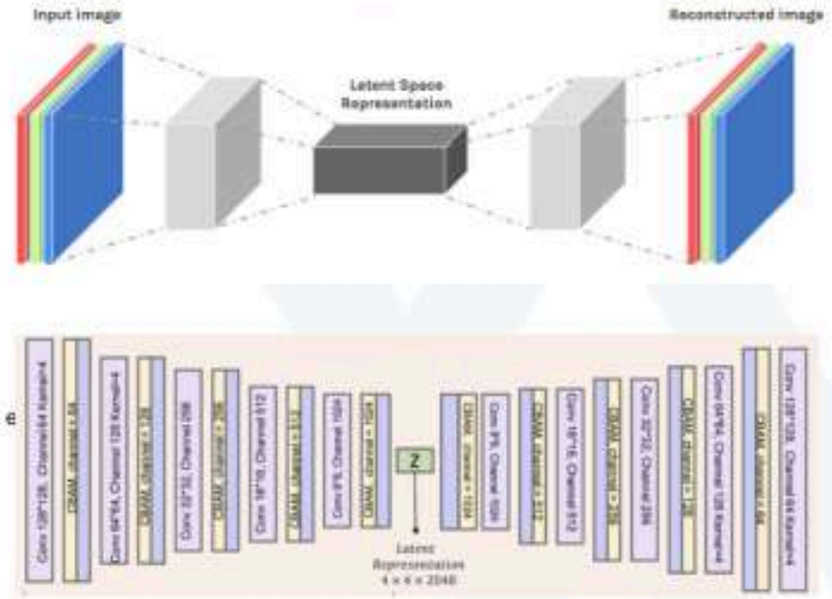


Ablation Study

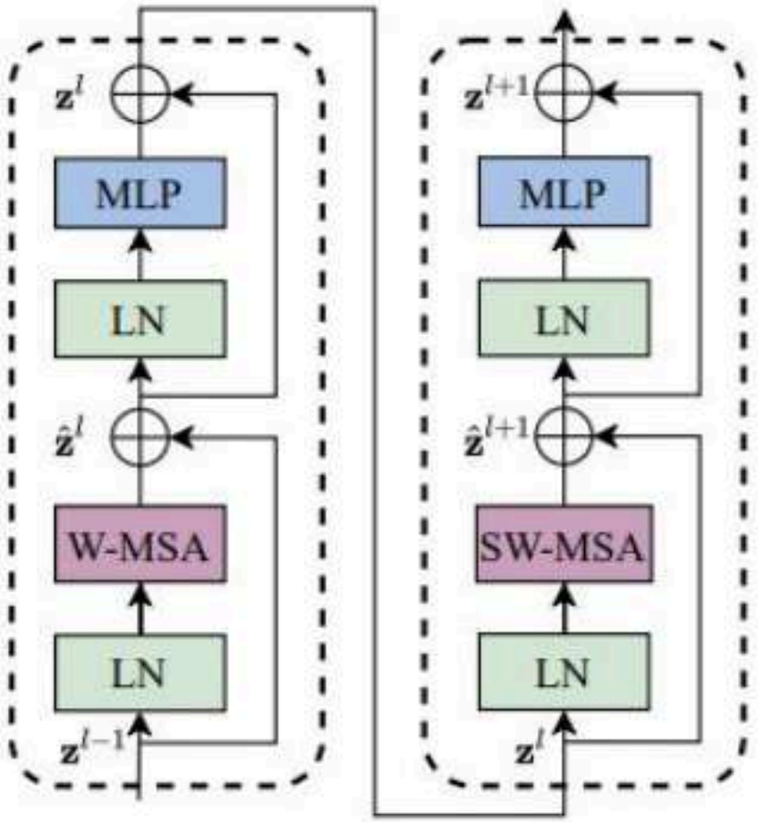
Model Comparison for Contactless Fingerprint Anti-Spoofing

- **1. Baseline Autoencoder (CAE)**
  - Simple CNN-based encoder-decoder
  - No attention or feature refinement
  - ❌ Misses fine texture
  - ❌ Poor generalization to spoof types like photopaper
- **2. CBAM-Autoencoder (Ours)**
  - Adds **Channel + Spatial Attention (CBAM)**
  - ✔️ Focuses on critical fingerprint regions (e.g., ridge flow, e
  - ✔️ Outperforms others on APCER, BPCER, and ACER
  - Best overall generalization to unseen spoof materials
- **3. Swin Transformer Autoencoder**
  - ❌ High model complexity → needs more training data
  - ❌ Sensitive to patch partitioning in small datasets
  - ❌ Usually better to capture long range dependencies

Autoencoder



Swin Transformer



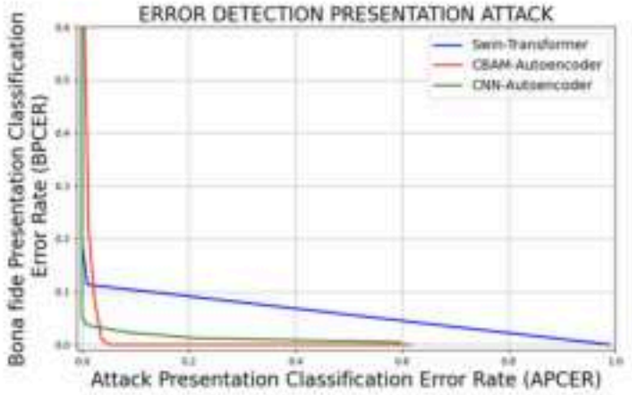
Loss Functions and Results

Loss Function

- **Mean Squared Error (MSE)** used as unsupervised reconstruction loss:

$$\mathcal{L}_{\text{MSE}} = \frac{1}{N}\sum_{i=1}^{N}\left\|X_i - \hat{X}_i\right\|^2$$

- The network learns only from **bonafide (live)** images.
- **Reconstruction error** is used to **classify** spoof vs. live.



CLARKSON													
Method		DL	TRAINING SAMPLES		TESTING SAMPLES		APCER%				BPCER %	HTER %
			LIVE	SPOOF	LIVE	SPOOF	ECO	PH	PL	WO		
DENSENET-121 [19]		S	55,624		5,590		0	88.03	0.14	0	0.18	NA
DENSENET-121(KERAS) [19]		S	55,624		5,590		0	79.01	1.55	0.94	3.64	NA
NASNETMOBILE [19]		S	55,624		5,590		0	82.15	0.71	5.96	9.04	NA
DENSENET-121(GRAYSCALE) [19]		S	55,624		5,590		0.16	98.9	1.98	11	0.18	NA
CASE-1	RESNET50 [20]	S	NA	2099	NA	1248	13.32	-	-	-	3.33	6.9
	DENSNET201 [20]	S	NA	2099	NA	1248	15.33	-	-	-	3.33	7.61
	EFFICIENTNET-B0 [20]	S	NA	2099	NA	1248	16.72	-	-	-	3.33	8.07
CASE-2	RESNET50 [20]	S	NA	3143	NA	1104	-	45.33	-	-	3.33	17.61
	DENSNET201 [20]	S	NA	3143	NA	1104	-	94.72	-	-	3.33	34.07
	EFFICIENTNET-B0 [20]	S	NA	3143	NA	1104	-	100	-	-	3.33	38.89
CASE-3	RESNET50 [20]	S	NA	2624	NA	1623	-	-	17.34	-	3.33	8.28
	DENSNET201 [20]	S	NA	2624	NA	1623	-	-	100	-	3.33	50
	EFFICIENTNET-B0 [20]	S	NA	2624	NA	1623	-	-	100	-	3.33	38.89
CASE-4	RESNET50 [20]	S	NA	3975	NA	272	-	-	-	0.39	3.33	2.63
	DENSNET201 [20]	S	NA	2975	NA	272	-	-	-	5.97	3.33	4.49
	EFFICIENTNET-B0 [20]	S	NA	2975	NA	272	-	-	-	1.74	3.33	3.08
AUTOENCODER+CBAM (OURS)		**U**	**4208**	**0**	**1678**	**4324**	**0**	**29.35**	**0**	**0**	**0.96**	**3.43**
AUTOENCODER(OURS)		U	4208	0	1678	4324	0	67.3	0	0.73	1.92	4.79
SWIN TRANSFORMER(OURS)		U	4208	0	1678	4324	37.1	73.28	0	1.11	0.96	5.9

COLFISPOOOF																			
METHOD	DL	TRAINING SAMPLES		TESTING SAMPLES		APCER%												BPCER %	HTER %
		LIVE	SPOOF	LIVE	SPOOF	ECO	GEL1	GEL2	GLUE1	KNE	LA	CLAY	GLUE2	PA	PL	SL	DR		
AUTOENCODER(OURS)	U	4208	0	1678	7200	0	0	0	0	0	0	0	0	0	0	0	0	1.92	0.96
AUTOENCODER+CBAM (OURS)	**U**	**4208**	**0**	**1678**	**7200**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0.96**	**0.48**
SWIN TRANSFORMER(OURS)	U	4208	0	1678	7200	0	0	0	0	0	0	0	0	0	0	0	0	0.96	0.48

IIITD DATASET									
METHOD	DL	TRAINING SAMPLES		TESTING SAMPLES		APCER %		BPCER %	HTER %
		LIVE	SPOOF	LIVE	SPOOF	PA	PH		
ALEXNET [16]	S	NA	NA	NA	NA	NA	NA	NA	0.04
RESNET18 [17]	S	NA	NA	NA	NA	NA	NA	NA	NA
DENSENET121 [18]	S	NA	NA	NA	NA	NA	NA	NA	1.274
AUTOENCODER+CBAM(OURS)	**U**	**4208**	**0**	**1678**	**8192**	**0**	**0**	**0.96**	**0.48**
AUTOENCODER(OURS)	U	4208	0	1678	8192	0	0.91	1.92	1.13
SWIN TRANSFORMER(OURS)	U	4208	0	1678	8192	0	43.11	0.96	16.48

Building a Semi-Supervised Anti-Spoofing

Architecture Choice

- ResNet-18: Chosen for balance of accuracy & computational efficiency in image classification.

Training Strategy

- Semi-Supervised Learning: Trained on real + synthetic fingerprint images for better generalization.

Objective

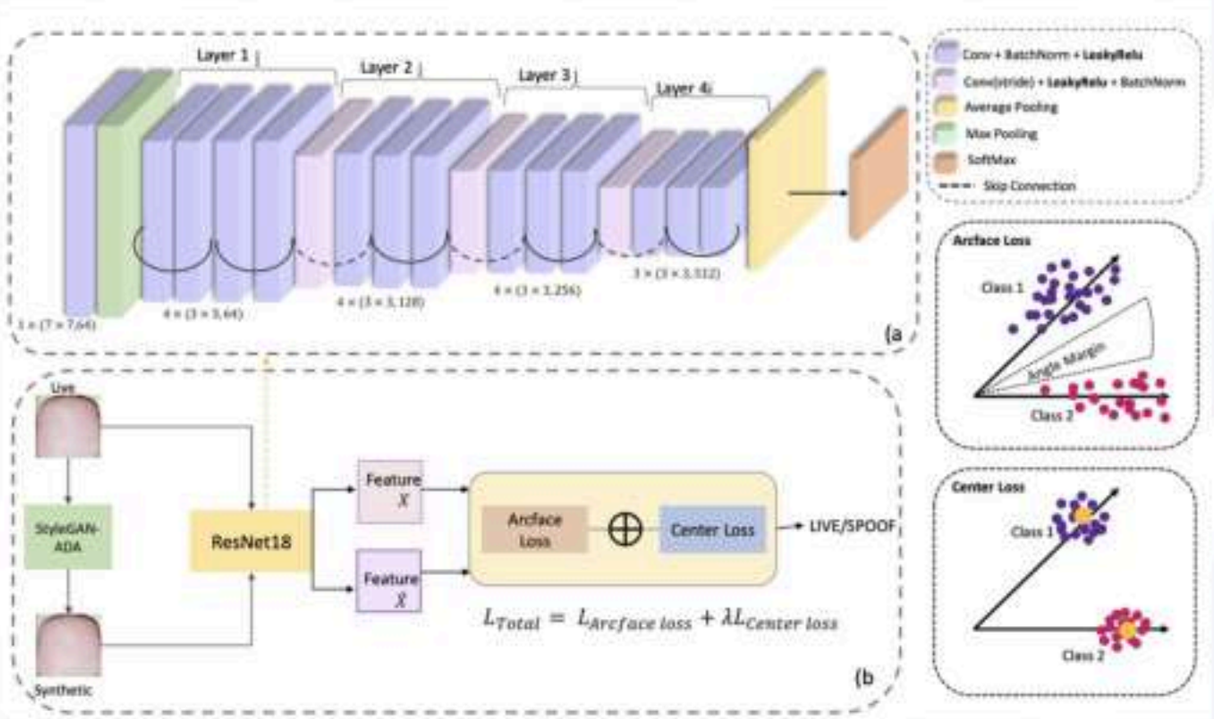
- Robust Loss Function: Improve feature discrimination between genuine & spoofed fingerprints.

Loss Components

- **ArcFace Loss:** Maximizes inter-class variance via angular margin.
- **Center Loss:** Minimizes intra-class variance, encourages feature compactness.

Activation Function:

- Relue
- Leaky Relue



$$L_{\text{joint}} = -\log \frac{e^{s\cos(\theta_{y_i}+m)}}{e^{s\cos(\theta_{y_i}+m)}+\sum_{j=1,j\neq y_i}^{N} e^{s\cos\theta_j}} + \lambda\frac{1}{2}\sum_{i=1}^{m}\|x_i - c_{y_i}\|_2^2$$

$$L_{\text{joint}} = L_a + \lambda L_c$$

Experimental Results

APCER%		
API/METHOD	**ResNet-LRelu**	ResNet-Relu
DRAGONSKIN	**0**	0
ECOFLEX	**0**	0
GELAFIX	**0**	0
GELATIN	**0**	0
GLUE	**0**	0
KNETOSIL	**0**	0
LATEX	**0**	0
MODELLING-CLAY	**0**	0
MODULABLE-GLUE	**0**	0
PAPER-PRINTOUT	**0**	0
PLAYDOH	**0**	0
SILLY-PUTTY	**0**	0

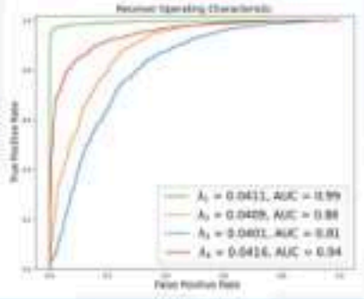
APCER%		
API/METHOD	**ResNet-Leaky-Relu**	ResNet-Relu
ECOFLEX	**0**	0
PHOTOPAPER	**9.43**	18.60
PLAYDOH	**0**	0
WOODGLUE	**0**	0
SYNTHETIC	**0.15**	0.25
BPCER%		
LIVE	**0.12**	0.12

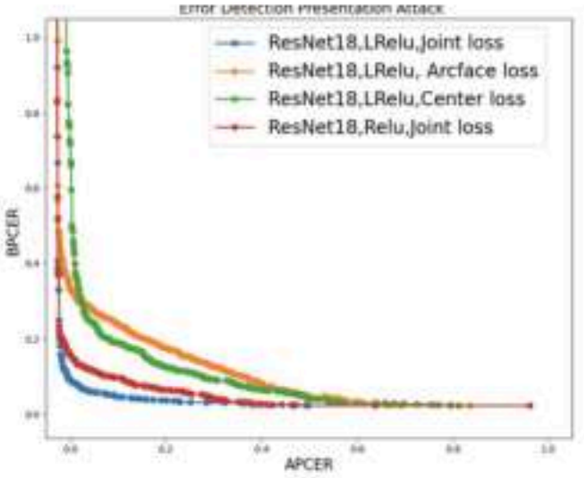
Method	(%)APCER					(%)BPCER
	ECOFLEX	PHOTOPAPER	PLAYDOH	WOODGLUE	SYNTHETIC	LIVE
DenseNet-121 [13]	0	88.03	0.14	0	0.13	0.18
DenseNet-121 (keras) [13]	0	79.01	1.55	0.94	0.79	3.64
NasNetMobile [13]	0	82.15	0.71	5.96	4.12	9.04
DenseNet-121 (grayscale) [13]	0.16	98.9	1.98	11	11.58	0.18
ResNet-18/Relu (Combined Loss)	0	18.6	0	0	0.25	0.12
Resnet-18/Leaky Relu (Combined Loss)	**0**	**9.43**	**0**	**0**	**0.15**	**0.12**
ResNet-18/Relu (Arcface Loss)	0	45.12	0	0	0.32	0.37
ResNet-18/Relu (Center Loss)	0	20.14	0	0	0.26	0.26

Table 7. Performance of different deep learning architectures across spoofed and non-spoofed samples, measured in terms of BPCER and APCER.

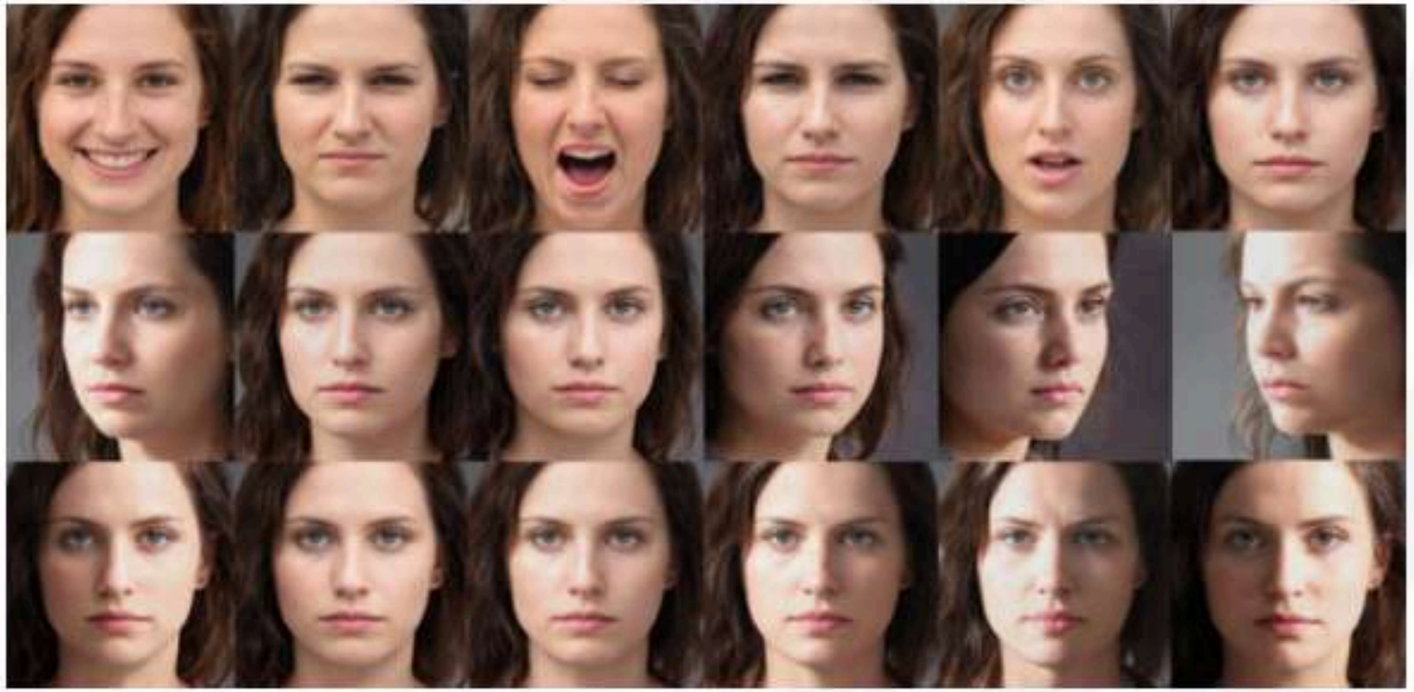
APCER%		
Metrics/METHOD	**ResNet-Leaky-Relu**	ResNet-Relu
APCER%	**0.63**	1.25
BPCER%	**0.12**	0.12
ACER%	**0.37**	0.68

$$L_{\text{joint}} = L_a + \lambda L_c$$





Face Liveness detection



IDIAP Research Institute

Introduction to Remote Photoplethysmography

Remote Photoplethysmography (rPPG) is a **non-contact method** for measuring blood volume changes in the body using just a **camera**, typically by analyzing facial videos. Unlike traditional PPG that requires sensors, rPPG offers a **convenient and touch-free alternative** for capturing cardiac signals.

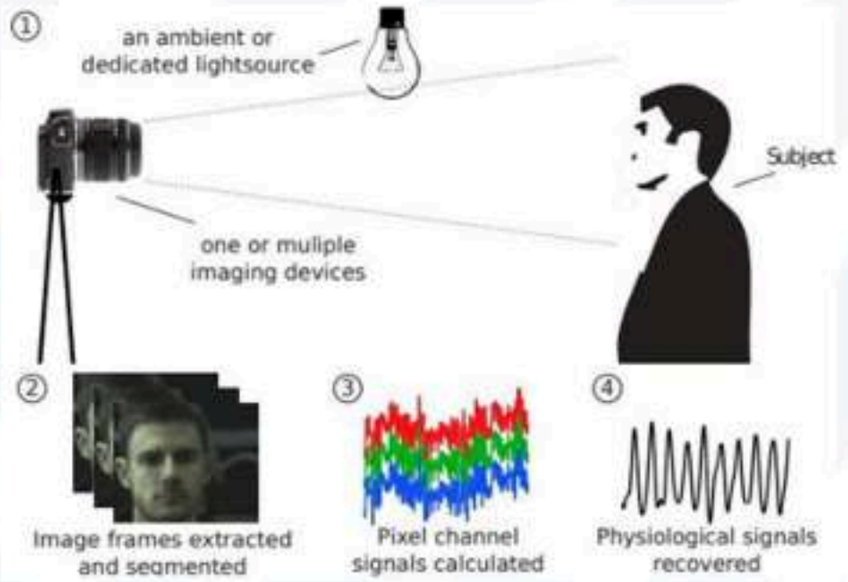
This technique has multiple benefits:

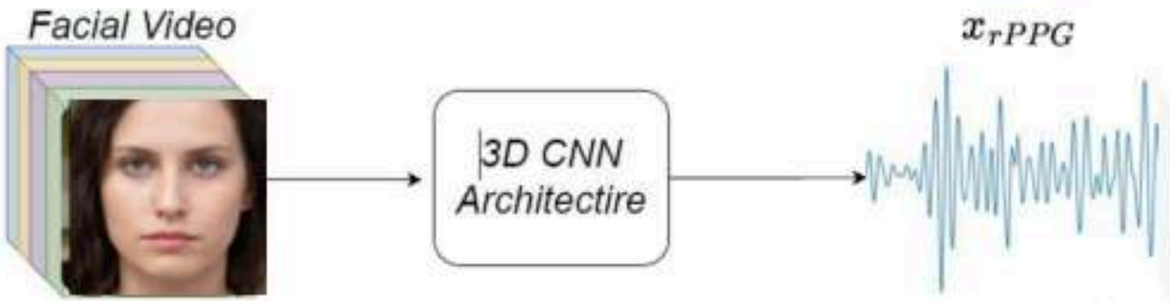
- ✅ **Non-invasive health monitoring** without physical contact
- ✅ **Biometric authentication** to enhance face recognition security
- ✅ **Vital sign tracking**, like heart rate and respiration
- ✅ **Early detection** of cardiovascular or stress-related conditions

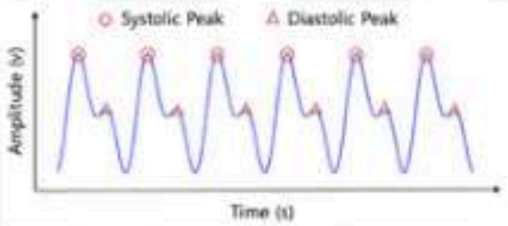
However, rPPG also comes with **challenges**:

- ❌ It can **struggle to capture fine signal details** like systolic and diastolic peaks
- ❌ It's **sensitive to noise and head motion**, especially in real-world settings









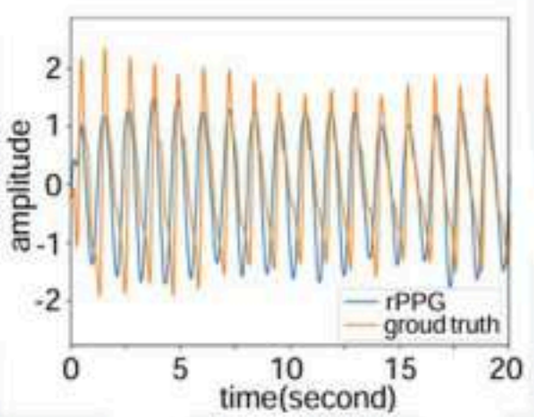
Motivation and Limitations of Existing rPPG Methods

Motivation: Accurate rPPG could provide insights into cardiovascular health without physical contact, crucial for medical and wellness applications.

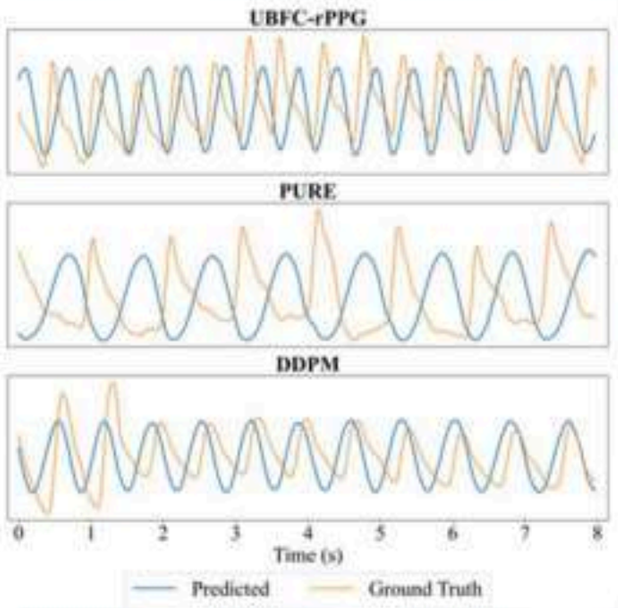
Limitations of Existing Approaches:

- ❑ Focused primarily on heart rate (HR) detection.
- ❑ Struggle with waveform accuracy, particularly in capturing systolic-diastolic characteristics.

Solution: A novel GAN framework that accurately reconstructs rPPG signals, capturing key physiological features.

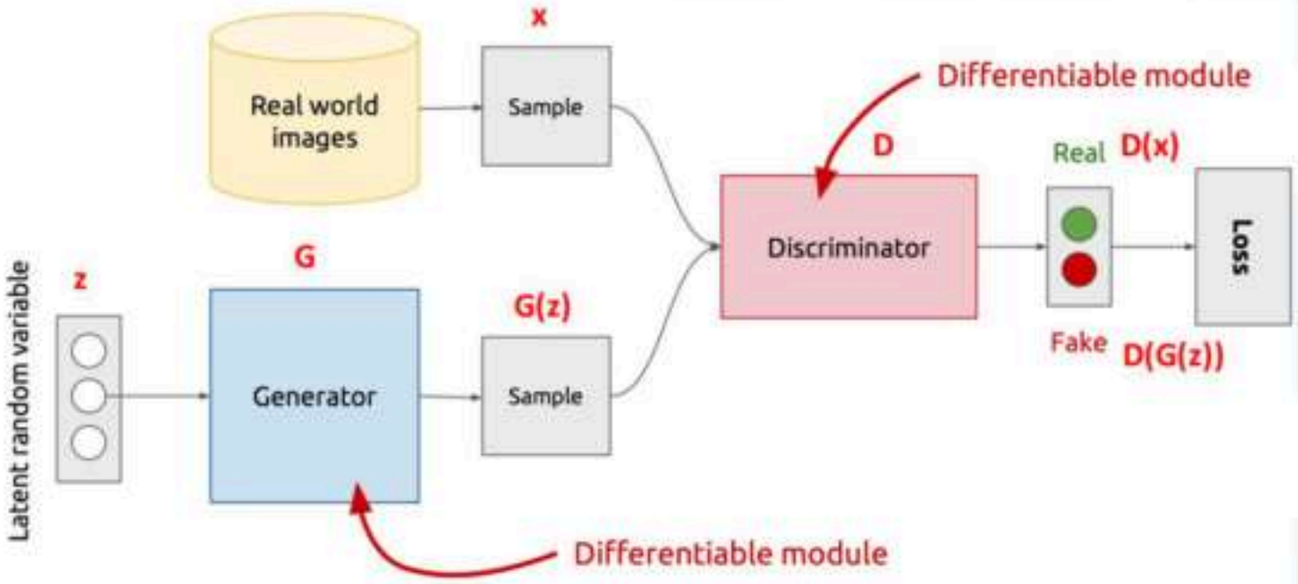


Contrast-Phys (ECCV2022)



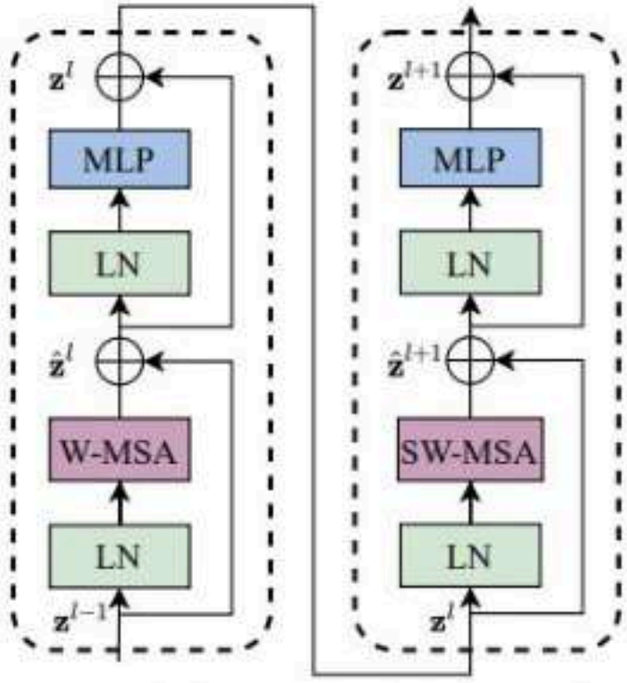
GAN and Transformer

"Generative Adversarial Nets", NIPS 2014

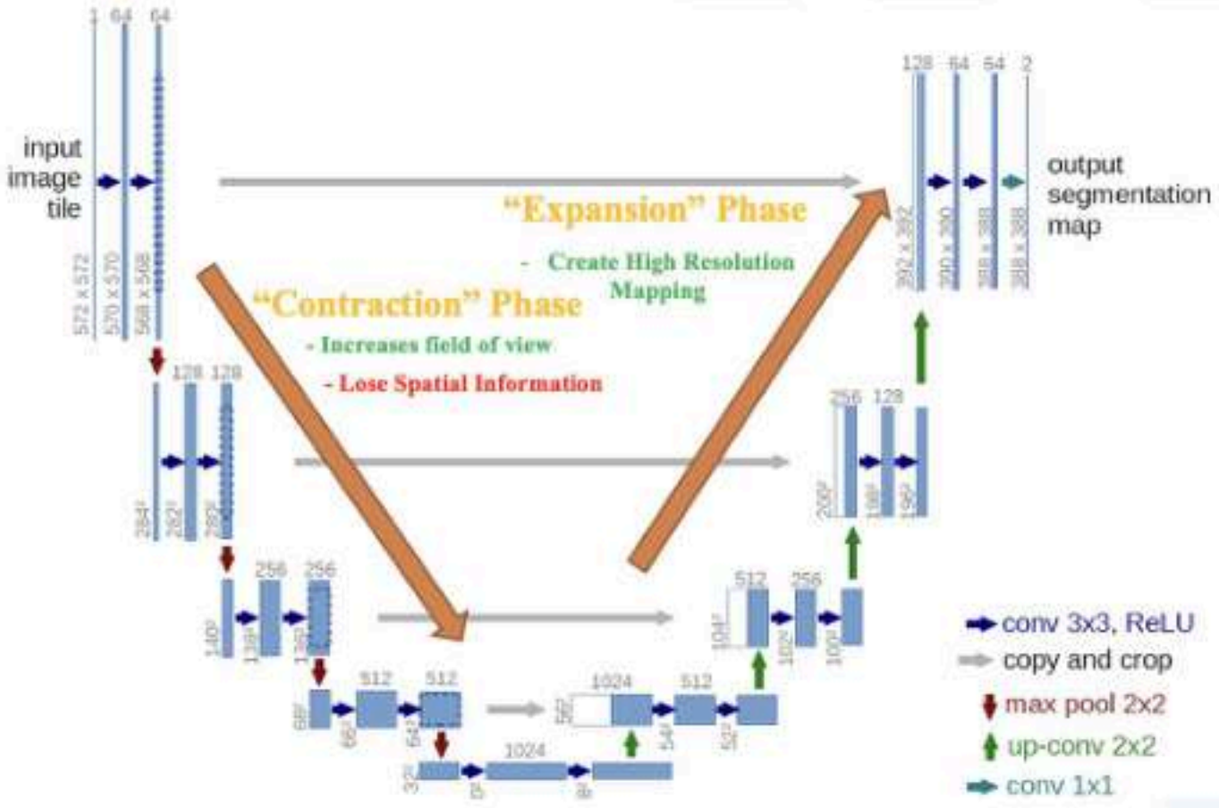


- Z is some random noise (Gaussian/Uniform).
- Z can be thought as the latent representation of the image.

Swin Transformer



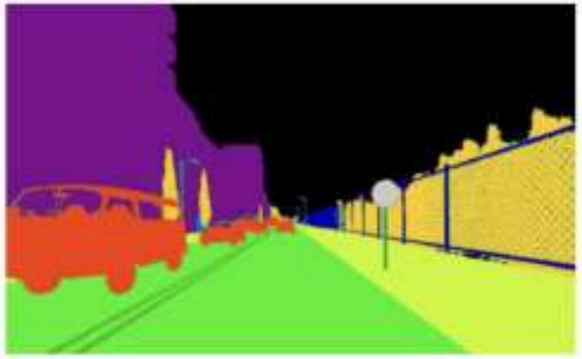
U-Net Architecture



http://deeplearning.net/tutorial/_images/unet.jpg



Input image



Semantic Segmentation

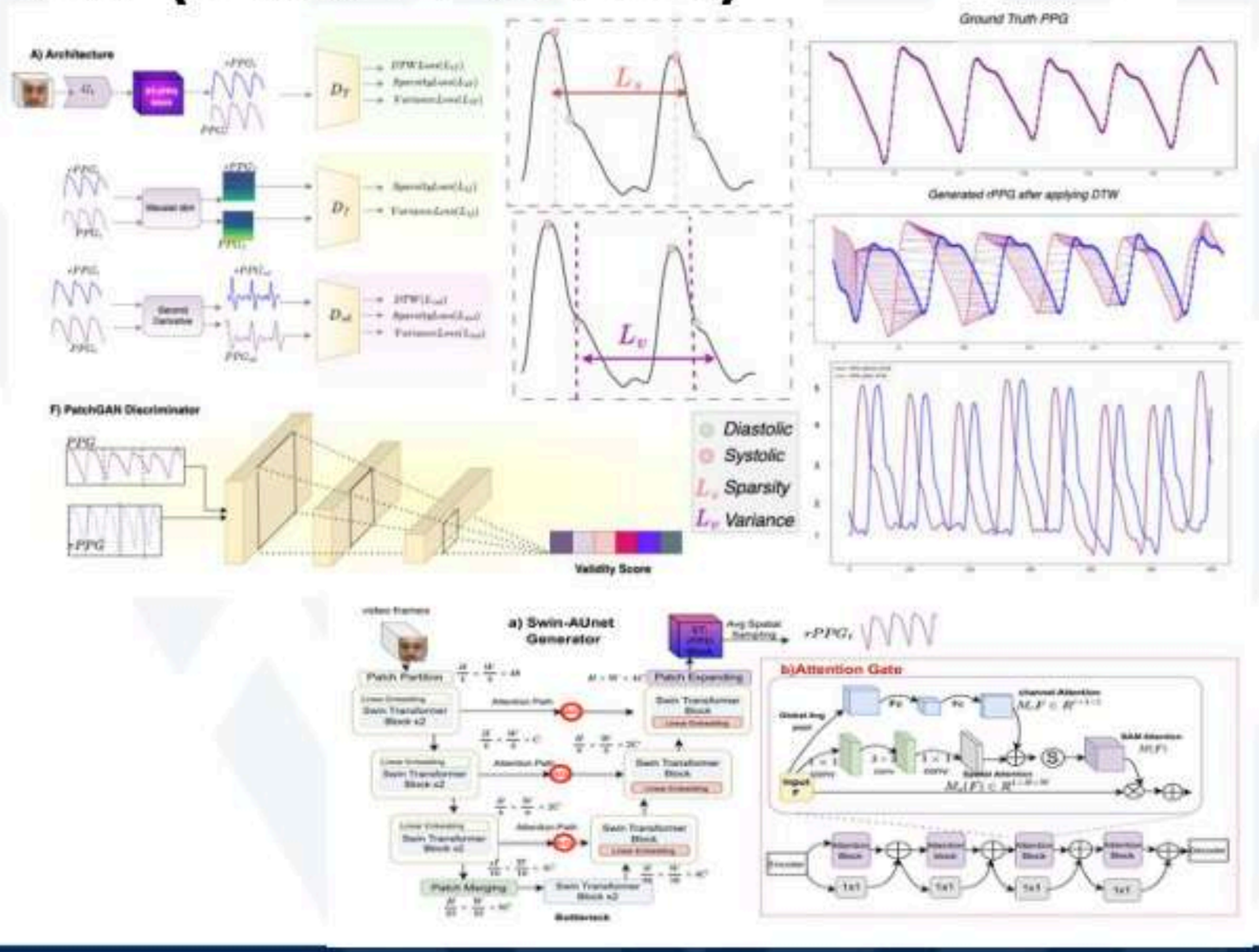
Swin-Attention U-Net (Swin-AUnet)

Generator:

- **Swin Transformer:** Captures hierarchical spatial-temporal features for rPPG.
- **Attention Gates:** Focus on specific facial regions where signal fidelity is highest.
- **U-Net Backbone:** Supports the spatial and temporal connections between features.

Time Domain Discriminator

- **Mechanism:** PatchGAN discriminator processes time-series patches to detect inconsistencies in temporal signal structure.
- **Impact:** Time-domain discrimination strengthens temporal alignment with real PPG signals, helping the GAN learn accurate waveform dynamics.



Frequency Domain and Second Derivative Discriminator

- **Purpose:** Verifies frequency characteristics of the generated signal, covering high and low-frequency components.

  Technique: Wavelet transform (DB4 wavelet) analyzes rPPG in frequency bands.

  Impact: Guarantees the presence of heart rate, respiratory rate, and other physiological frequency features, refining the frequency fidelity of rPPG.

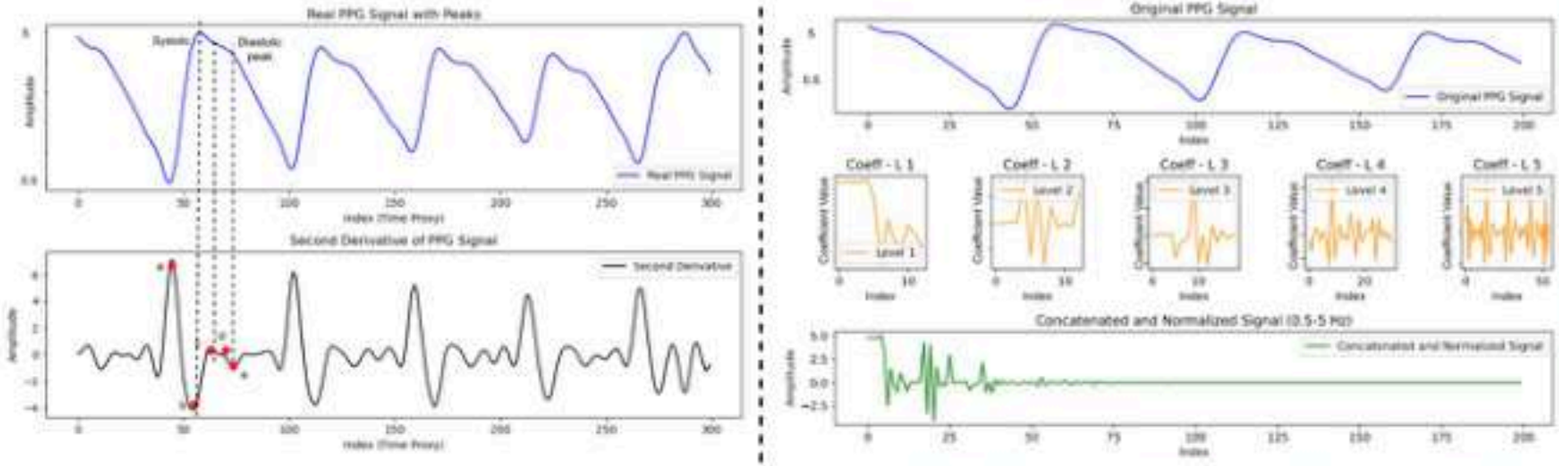
- **Purpose:** Focuses on capturing subtle waveform features such as systolic-diastolic peaks using the second derivative.

  Explanation:

  - ❏ The second derivative (SDPPG) highlights the onset, peak, and decay points in the PPG signal.
  - ❏ This approach provides unique insight into systolic and diastolic phases.

  Visuals: Comparison between PPG and second derivative SDPPG waveform with annotated systolic/diastolic features.

  Benefit: Enabling the GAN to focus on detailed morphology



Dynamic time warping

Overview

- DTW is a powerful technique for measuring similarity between two temporal sequences that may vary in speed or length.
- Commonly used in speech recognition, biosignal alignment (e.g., ECG, PPG), and time series analysis.

Why DTW?

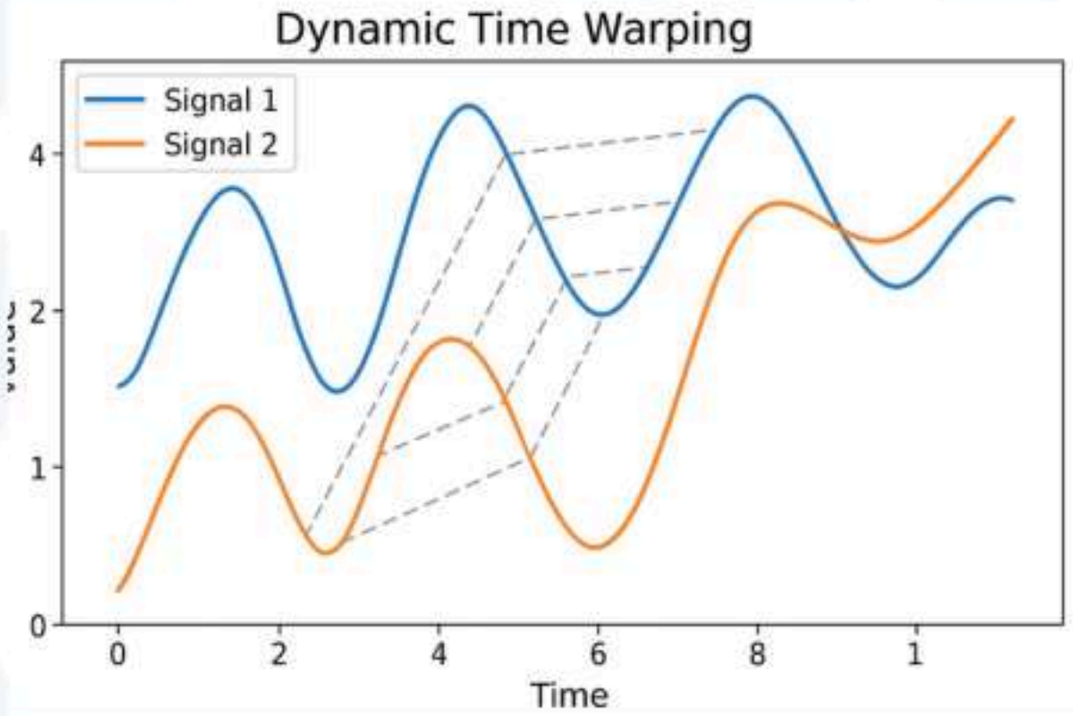
- Time series may be misaligned or have temporal distortions.
- Euclidean distance is sensitive to local shifts—DTW handles non-linear alignments.

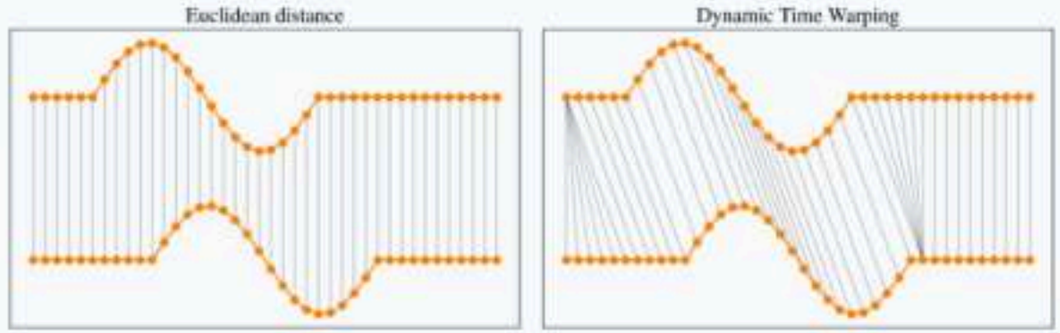
Key Idea

- Warps one signal to match the shape of another by computing an optimal alignment path that minimizes cumulative distance.

$$Let(X = (x_1, x_2, \ldots, x_n) and (Y = (y_1, y_2, \ldots, y_m).$$

$$DTW(X, Y) = \min_{w \in W} \sum_{(i,j) \in w} d(x_i, y_j)$$

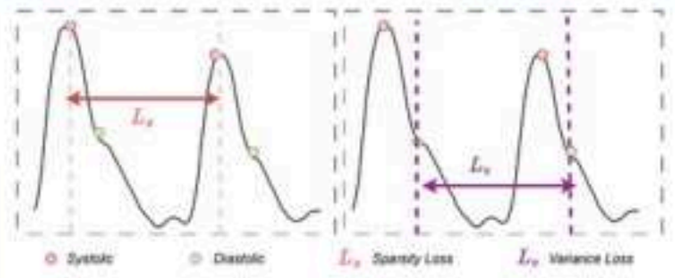


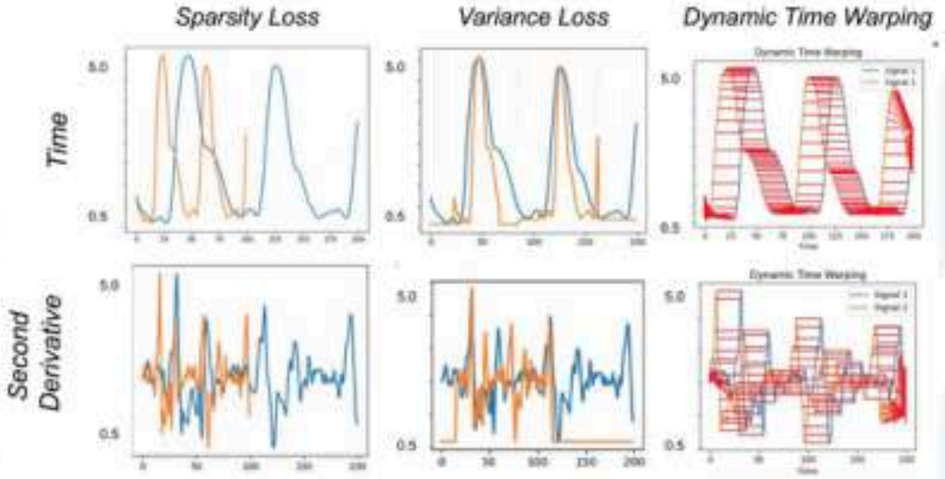


Loss Functions Overview

Loss Components

- **Sparsity Loss**
  - Highlights key peaks (systolic & diastolic).
  - Applied in time, frequency.
  - Helps improve heart rate accuracy.
- **Variance Loss**
  - Ensures consistent signal patterns.
  - Measures distribution differences.
  - Applied in time, frequency.
- **Soft-DTW Loss**
  - Aligns predicted and true signals over time.
  - Handles non-linear timing shifts better than Euclidean distance.
  - Improves temporal structure of generated signals.





$$L_{stime} = \sum_{n=a}^{N} |x[n]|$$

$$L_{sd} = \sum_{n=a}^{N} |x''[n]|$$

$$L_{s_{freq}} = \frac{\sum_{i=a}^{\arg\max(F)-\Delta F} F_i + \sum_{i=\arg\max(F)+\Delta F}^{b} F_i}{\sum_{i=a}^{b} F_i}$$

$$L_{domain} = \frac{1}{d} \sum_{i=1}^{d} \left(CDF_i(Q_{domain}) - CDF_i(P_{domain})\right)^2$$

$$DTW(x, y) := \min_{A \in \mathcal{A}} \langle A, \Delta(x, y) \rangle$$

$$\begin{aligned} L_{\text{total}} = \alpha \left(DTW(t) + L_{\text{sparsity}(t)} + L_{\text{variance}(t)}\right) \\ + \beta \left(L_{\text{sparsity(freq)}} + L_{\text{variance(freq)}}\right) \\ + \gamma \left(L_{\text{DTW(sd)}} + L_{\text{sparsity(sd)}} + L_{\text{variance(sd)}}\right) \end{aligned}$$

Experimental Setup

- We evaluated our model's performance by comparing its estimated heart rate (HR) with ground truth data from various datasets. The HR evaluation metrics included mean absolute error (MAE), root mean squared error (RMSE), and Pearson's correlation coefficient (R).
- We also assessed the quality of the reconstructed rPPG signals by comparing them to the ground-truth PPG signal using several quantitative metrics (beyond methods focusing solely on HRV):

$$\rho = \frac{(y_{PPG} - \bar{y}_{PPG})^T (y_{rPPG} - \bar{y}_{rPPG})}{|y_{PPG} - \bar{y}_{PPG}|^2 |y_{rPPG} - \bar{y}_{rPPG}|^2}$$

$$FD = \min\left(\max_{i \in Q}\left(d\left(y_{PPG_i}, y_{rPPG_i}\right)\right)\right), \quad Q = [1, m]$$

Dataset	Subject	Session/Task	Remarks
PURE	10	6 sessions per subject (~1 min each)	Stationary capture
UBFC-rPPG	42	1-minute resting videos	Frontal face, good illumination
OBF	100	Before & after exercise	Captures physiological variation
MR-NIRP	8	NIR videos during static & motion conditions	Uses near-infrared imaging
MMSE-HR	40	Emotion-elicitation experiments	Includes expressions and head motion

Results

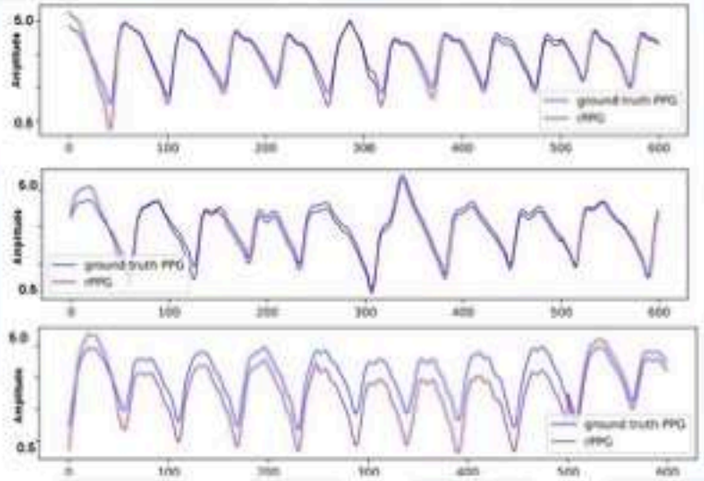
Method	UBFC-rPPG			PURE			OBF			MR-NIRP (NIR)			MMSE-HR		
	MAE (bpm)	RMSE (bpm)	R	MAE (bpm)	RMSE (bpm)	R	MAE (bpm)	RMSE (bpm)	R	MAE (bpm)	RMSE (bpm)	R	MAE (bpm)	RMSE (bpm)	R
GREEN [28]	7.5	14.41	0.62	-	-	-	-	2.462	0.99	-	-	-	-	-	-2
ICA [27]	5.17	11.76	0.65	-	-	-	-	2.73	0.98	-	-	-	-	-	-
CHROM [6]	2.37	4.91	0.89	2.07	9.02	0.99	-	2.733	0.98	-	-	-	-	13.97	0.55
2SR [41]	-	-	-	2.44	3.06	0.98	-	-	-	-	-	-	-	-	-
POS [40]	4.05	8.75	0.78	-	-	-	-	1.066	0.991	-	-	-	-	-	-
Meta-rPPG [10]	5.97	7.42	0.53	-	-	-	-	-	-	-	-	-	-	-	-
Dual-GAN [18]	0.44	0.67	0.99	0.82	1.31	0.99	-	-	-	-	-	-	-	-	-
PhysNet [43]	-	-	-	2.1	2.6	0.99	-	1.812	0.992	4.07	7.55	0.655	1.22	4.49	0.94
rPPGNet [43]	-	-	-	-	-	-	-	1.8	0.992	-	-	-	-	-	-
Contrast-Phys [35]	0.64	1.00	0.99	1.00	1.4	0.99	0.51	1.39	0.994	2.68	4.77	0.85	-	-	-
PulseGAN [31]	1.19	2.10	0.98	-	-	-	-	-	-	-	-	-	7.5	14.41	0.62
Nowara2021 [26]	-	-	-	-	-	-	-	-	-	2.31	4.46	0.85	-	-	-
Gideon2021 [8]	1.85	4.28	0.93	2.3	2.9	0.99	2.83	7.88	0.825	4.75	9.14	0.61	3.98	9.65	0.85
Contrast-phys+ [36]	0.64	1.00	0.99	1.00	1.40	0.99	0.51	1.39	0.994	2.68	4.77	0.85	3.83	0.96	3.72
PhysFormer [44]	-	-	-	-	-	-	-	0.804	0.998	-	-	-	1.48	4.22	0.95
Swin-AUnet(Ours)	**0.36↓**	**0.51↓**	**0.99↑**	**0.23↓**	**0.36↓**	**0.99↑**	**0.49↓**	**0.51↓**	**0.99↑**	**0.89↓**	**0.74↓**	**0.99↑**	**0.89↓**	**0.75↓**	**0.99↑**

Table 1: HR results. The best results are in bold.

Models	RMSE		FD		ρ	
	μ	σ	μ	σ	μ	σ
Swin-AUnet	**0.167**	0.059	**0.248**	0.185	**0.915**	0.057
Contrast-phys [35]	0.469	0.279	0.538	0.225	0.621	0.251
Dual-GAN [18]	0.356	0.346	0.471	0.118	0.703	0.117

Method	Cross-dataset(UBFC → MMSE-HR)			Intra-dataset(MMSE-HR→ MMSE-HR)		
	MAE(bpm)	RMSE(bpm)	R	MAE(bpm)	RMSE(bpm)	R
CHROM [6]	-	13.97	0.55	-	13.97	0.55
PhysNet [43]	2.04	6.85	0.86	1.22	4.49	0.94
PhysFormer [44]	2.68	7.01	0.86	1.48	4.22	0.95
Contrast-Phys [36] (supervised)	1.76	5.34	0.92	1.11	3.83	0.96
Contrast-Phys [36] (semi-spervised)	2.30	6.32	0.89	1.20	3.89	0.96
Contrast-Phys [35] (unsupervised)	2.43	7.34	0.86	1.82	6.69	0.87
Gideon2021 [8]	4.10	11.55	0.70	3.98	9.65	0.85
Swin-AUnet(ours)	**0.98↓**	**1.16↓**	**0.96↑**	**0.23↓**	**0.95↓**	**0.99↑**

Table 2: Cross-dataset and intra-dataset HR. The best results are in bold.



Conclusion

- Developed a series of **contactless fingerprint anti-spoofing models**, including:
  - Unsupervised deep learning approaches
  - Semi-supervised
- Identified a novel direction:
  Extracting physiological signals from contactless fingerprints
- Due to the **lack of fingerprint video datasets**, initial experiments were conducted on **facial videos**
- Proposed a **GAN-based rPPG model** that:
  - Successfully mimicked the **shape and features of PPG signals**
  - Validated the feasibility of physiological signal extraction from visual data
- **Next Step:** Extend the rPPG framework to **contactless fingerprint videos**
  - For enhanced **anti-spoofing**
  - With potential applications in **healthcare and biometric monitoring**

Selected Publication

- **A Universal Anti-Spoofing Approach for Contactless Fingerprint Biometric Systems**
  B. Adami, et al.
  IJCB 2023
- **Liveness detection competition-noncontact-based fingerprint algorithms and systems (livdet-2023 noncontact fingerprint) (Co-Author)**
  (Co-Author)
  IJCB 2023
- **Contactless Fingerprint Biometric Anti-Spoofing: An Unsupervised Deep Learning Approach**
  B. Adami, et al.
  IJCB 2024
- **Face Liveness Detection Competition (LivDet-Face) (Co-Author)**
  (Co-Author)
  IJCB 2024
- **rppg-sysdiagan: Systolic-Diastolic Feature Localization in rPPG Using GAN with Multi-Domain Discriminator**
  B. Adami, et al.
  ECCV Workshop 2024
- **rECG: A Guided Diffusion Framework for Remote Electrocardigraphy Reconstruction from Facial Video**
  B. Adami, J. Dawson, N. Karimian
  Will be submit at IJCB 2025 by May 5

🏆 **Competition Achievement**

- **Face Liveness Detection Competition (LivDet-Face) – 2024-** 🥈 **2nd Place Overall Ranking**
  Hosted at IEEE IJCB 2024
- **Liveness detection competition-noncontact-based fingerprint algorithms and systems (livdet-2023 noncontact fingerprint)** 🥈 **2nd Place Overall Ranking**
  Hosted at IEEE IJCB 2023

Acknowledgement and Thank You

Thank you to my committee and guests for being here today

Dr. Nima Karamian

Dr. Jeremy Dawson

Dr. Matthew Valenti

THANK YOU :)