

Preventing fraud with vision in the age of Generative AI

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AIAI Boston - October 17, 2024



Online fraud, from individuals to companies & countries

2008



Online fraud, The Economist, Nov'08



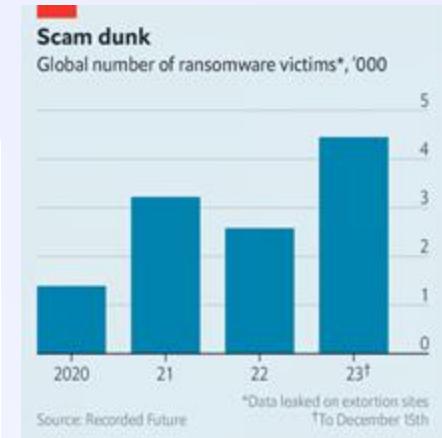
2017



Pilot Study to Measure Financial Fraud, Stanford Center on Longevity & FINRA, Feb'17



2023



How ransomware could cripple countries, not just companies, The Economist, Dec'23



“Consumer fraud” costs Americans more than \$50bn annually

\$1.5M individual ransom payment

Who are we?

Onfido is an online identity verification company.

We let businesses verify the identity of their customers.



Banks

Revolut

 **BARCLAYS**

 **HSBC**

 **Sabadell**

 **bunq**

 **axiata**

Aspiration

 **Millennium
Bank**

Investing

DRIVEWEALTH

TRADING 212

 **Freetrade**

 **PensionBee**

Lending & Mortgage

affirm

 **zilch**

 **moneybox**

 **ZOPA**

Payments

Klarna.

 **MANGOPAY**

 **adyen**

 **LEMONWAY**

mollie

AstroPay

 **SUMUP®**

Gaming

 **DRAFT
KINGS**

 **bet365**

 **William HILL**

 **MegaBet**

Healthcare

 **doctor care
anywhere.**

 **babylon**

 **Teladoc.
HEALTH**

 **ZAVA**

Travel

 **zipcar**

 **Hertz**

 **Europcar**

 **drivy**

Other

 **DocuSign**

 **deliveroo**

 **orange**



Onfido's 3 layers of identity verification

Do you have a
genuine ID?

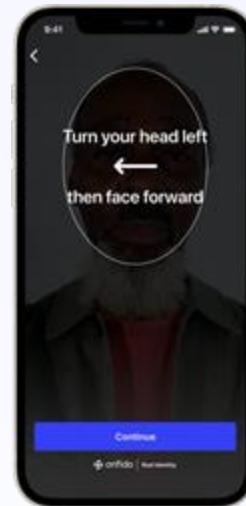
Are you a
real life human?

Does your face
match your ID?

1

2

3





Document Verification

- + Thousands of document types
- + Constantly changing attack vectors
- + Variable image quality (API vs SDK)
- + Very low signal-to-noise ratio





Biometric Verification

- + Low friction and accessibility requirements
- + Bias reduction
- + Deepfakes and injection attacks



Why online identity verification is hard



Low false alarm



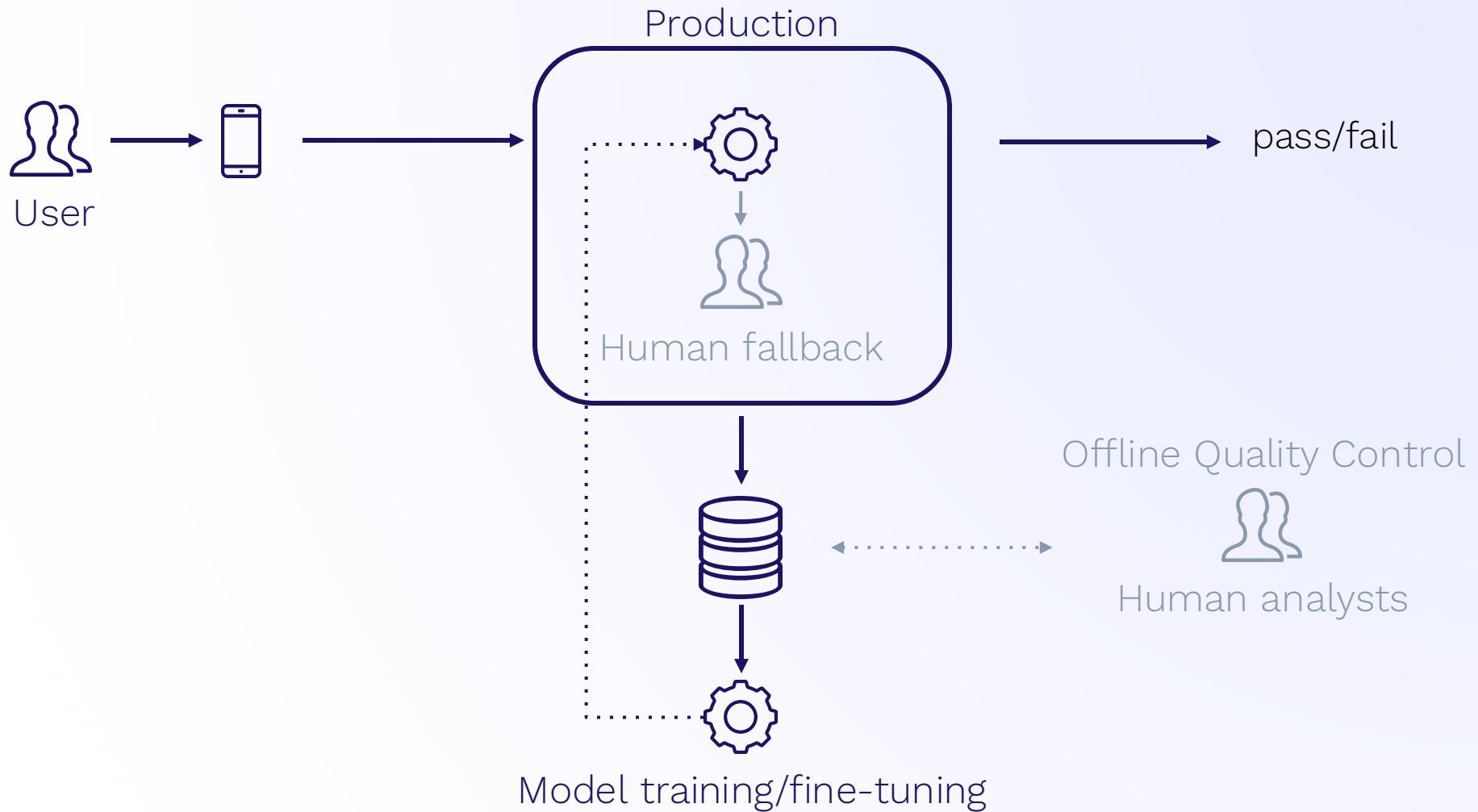
High fraud detection



Global coverage



Constantly evolving attacks



Automation is key for online identity



Fast



Cheap



Robust



Privacy-friendly

The computer vision pillars of IDV



Face Matching



Extraction



Anomaly Detection

Extraction on thousands of government IDs



Official sample - no PII

Classical extraction methods require human fallback



Template-based

Convnet + LSTM

33.4%



Hybrid

96.4%

Extraction accuracy on 10 fields

VLMs unlocks much higher extraction accuracy



Template-based

Convnet + LSTM ↴

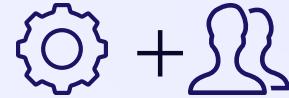


VLM-based

(out of the box)



VLM-based optimized



Hybrid

(template-based +
manual fallback)

33.4%

76.4%

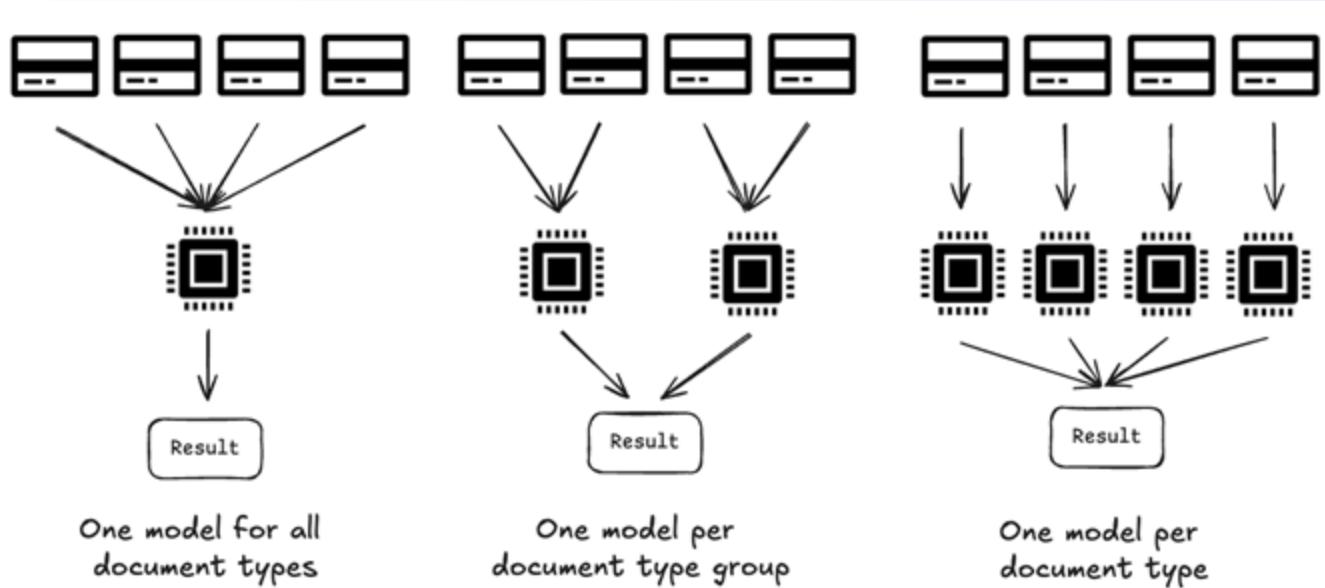
94.6%

96.4%

Extraction accuracy on 10 fields

Leveraging LoRA for cost-efficient extraction

Leveraging large open-source pre-trained models



One model for all
document types

One model per
document type group

One model per
document type

The cost effectiveness of in-housing VLMs



In-house

10 g5 GPUs on the cloud -> \$75K

3rd-party providers

\$0.01 / task -> \$1M

for 100M tasks

More control

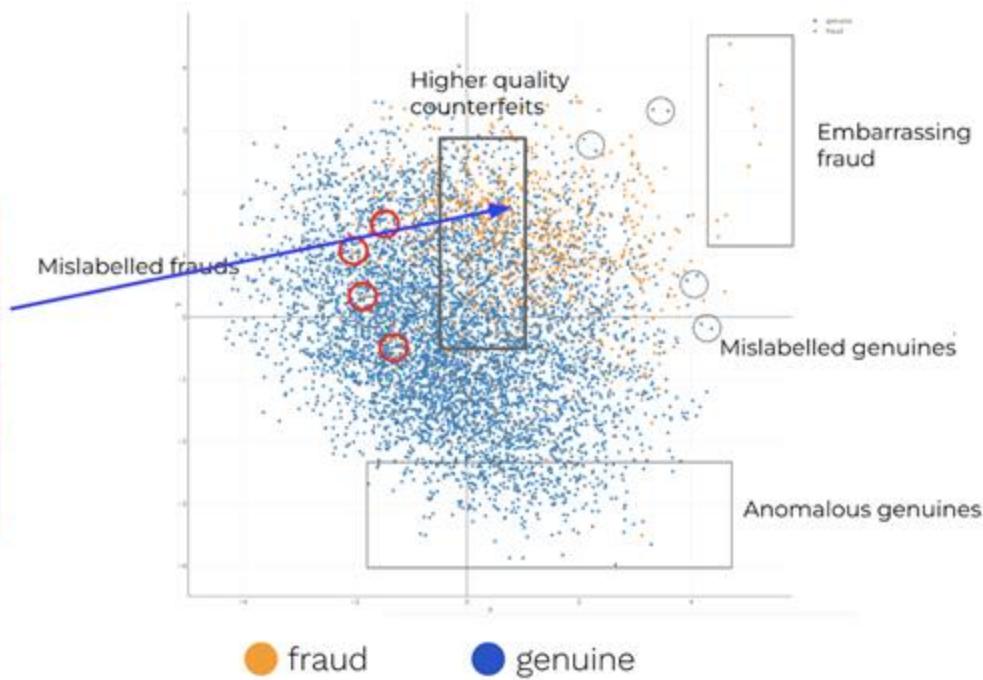
Fine-tune to your need

Increasing regulatory heat

Fraud detection as an anomaly detection problem

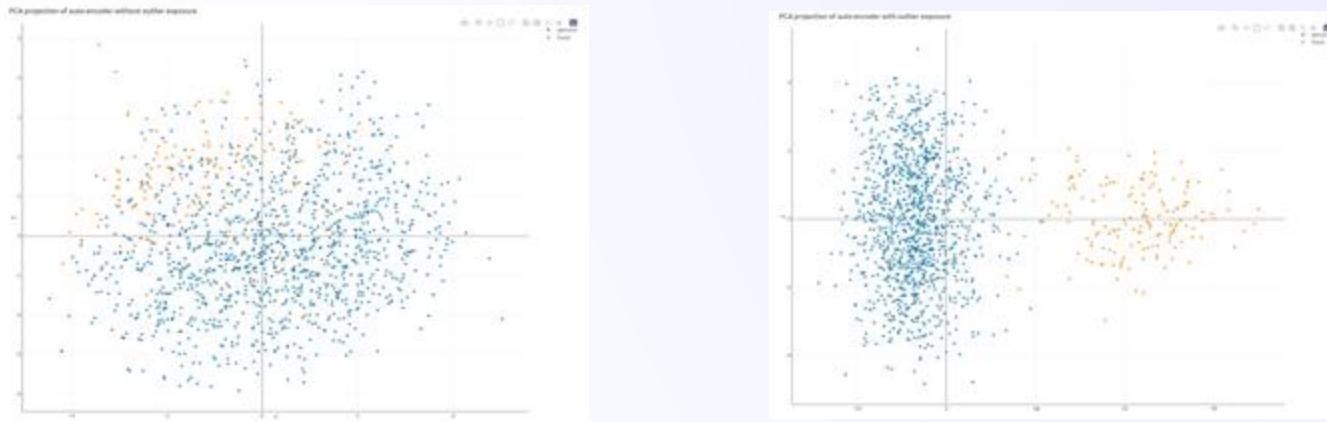
- Determine whether a document is fraudulent or not
- Given a large dataset of genuine samples and a *smaller* dataset of frauds
- Across thousands of document types
- And a very large set of anomalies

Vision Transformers for anomaly detection



Vision Transformers for anomaly detection

Leveraging Transformers for visual fraud detection



Left regular auto-encoder. Right a hybrid auto-encoder with a dedicated loss

$$\min_{\theta, \phi} \frac{1}{N_G} \sum_{i=1}^{N_G} \|g_\phi(f_\theta(\mathbf{x}_i)) - \mathbf{x}_i\|^2 - \frac{1}{N_F} \sum_{j=1}^{N_F} \|g_\phi(f_\theta(\mathbf{x}_j)) - \mathbf{x}_j\|^2$$

Few-shot learning for anomaly detection

Models require hundreds/thousands of samples for training.

Could we make it a few dozens?

Few-shot learning for anomaly detection

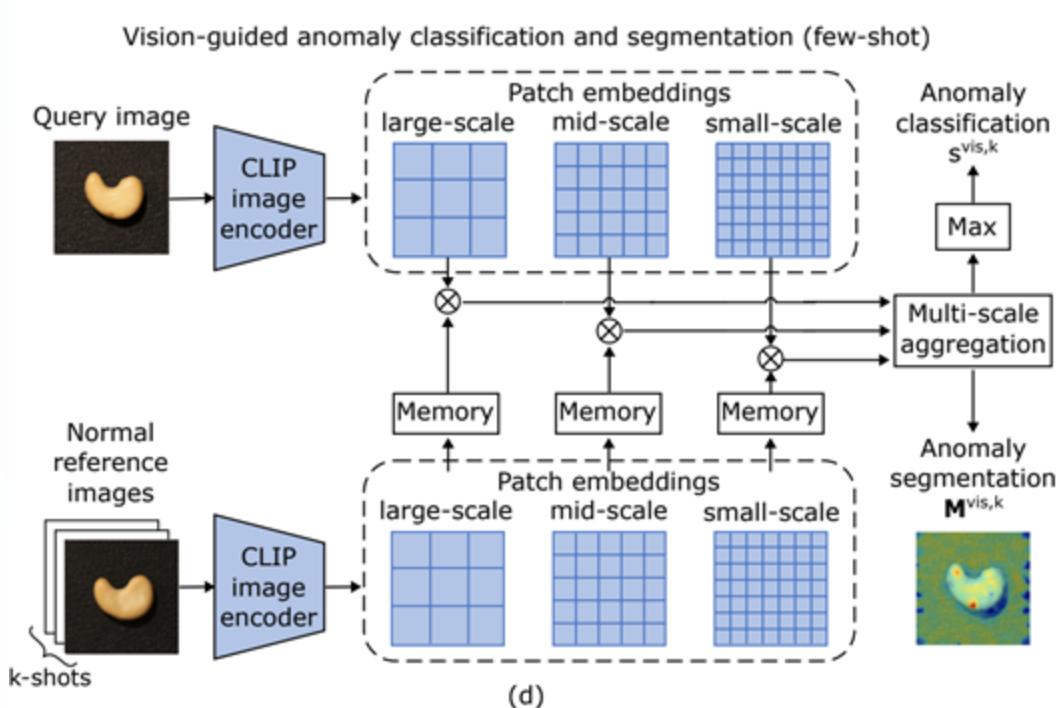
Our approach:

1. Multi-scale GEM embeddings
2. LLM-based prompt ensemble to capture anomaly
3. Zero-shot vision guidance using query image

Outperforms PatchCore and WinCLIP+

On par with AnomalyCLIP, AnomalyGPT and APRIL-GAN w/o auxiliary datasets

Few-shot learning for anomaly detection

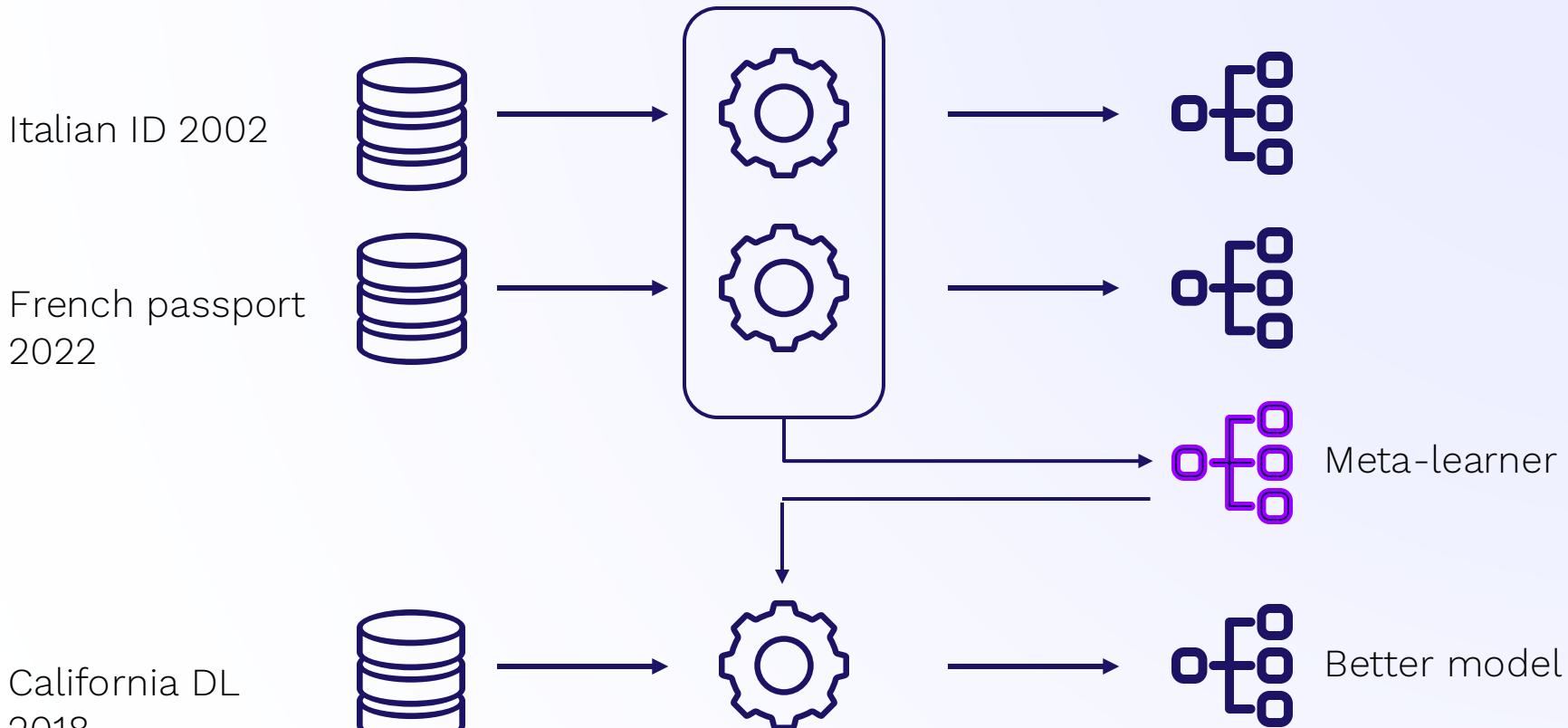


Few-shot learning for anomaly detection

Anomaly Classification		MVTec-AD			VisA		
Setup	Method	AUROC	AUPR	<i>F</i> 1-max	AUROC	AUPR	<i>F</i> 1-max
0-shot	WinCLIP	91.8±0.0	96.5±0.0	92.9±0.0	78.1±0.0	81.2±0.0	79.0±0.0
	FADE (ours)	90.0±0.0	95.6±0.0	92.4±0.0	75.6±0.0	78.5±0.0	78.6±0.0
1-shot	PatchCore	83.4±3.0	92.2±1.5	90.5±1.5	79.9±2.9	82.8±2.3	81.7±1.6
	WinCLIP+	93.1±2.0	96.5±0.9	93.7±1.1	83.8±4.0	85.1±4.0	83.1±1.7
	FADE (ours)	93.9±0.7	96.8±0.3	94.8±0.2	86.7±2.0	87.9±1.5	84.7±0.8
2-shot	PatchCore	86.3±3.3	93.8±1.7	92.0±1.5	81.6±4.0	84.8±3.2	82.5±1.8
	WinCLIP+	94.4±1.3	97.0±0.7	94.4±0.8	84.6±2.4	85.8±2.7	83.0±1.4
	FADE (ours)	95.2±1.0	97.6±0.5	95.0±0.4	89.2±0.4	90.2±0.2	85.9±0.6
4-shot	PatchCore	88.8±2.6	94.5±1.5	92.6±1.6	85.3±2.1	87.5±2.1	84.3±1.3
	WinCLIP+	95.2±1.3	97.3±0.6	94.7±0.8	87.3±1.8	88.8±1.8	84.2±1.6
	FADE (ours)	96.3±0.4	98.1±0.2	95.5±0.4	90.7±0.3	91.9±0.4	87.0±0.2

Table 1: Comparison of AC performance on MVTec-AD and VisA. We report the mean and standard deviation over 5 random seeds. Bold indicates the best performance.

Meta-learning for low-sample training



Meta-learning for low-sample training

Zero-shot: MAML outperforms the best pretraining baseline

Few-shot: MAML outperforms significantly in low-data regime, on par in high-data regime

Data generation enables faster iteration



Deepfakes are a curse... and a blessing



Synthetic documents

Many problems are still open

- Distillation and transfer learning
- On-device / efficient ML
- Self-supervised learning
- Few-shot learning

We share with the community



[FADE: Few-shot/zero-shot Anomaly Detection Engine using Large Vision-Language Model](#), BMVC 2024, Yuanwei Li, Elizaveta Ivanova, Martins Bruveris



tfimm

Star 267

clusterfun

Star 14

[Serving models at scale with LoRA](#),
Martins Bruveris, Oct 2024

[Enhancing Deep Learning with Bayesian Inference](#),
Sept'23, Matt Benatan, Jochem Gietema, Marian
Schneider