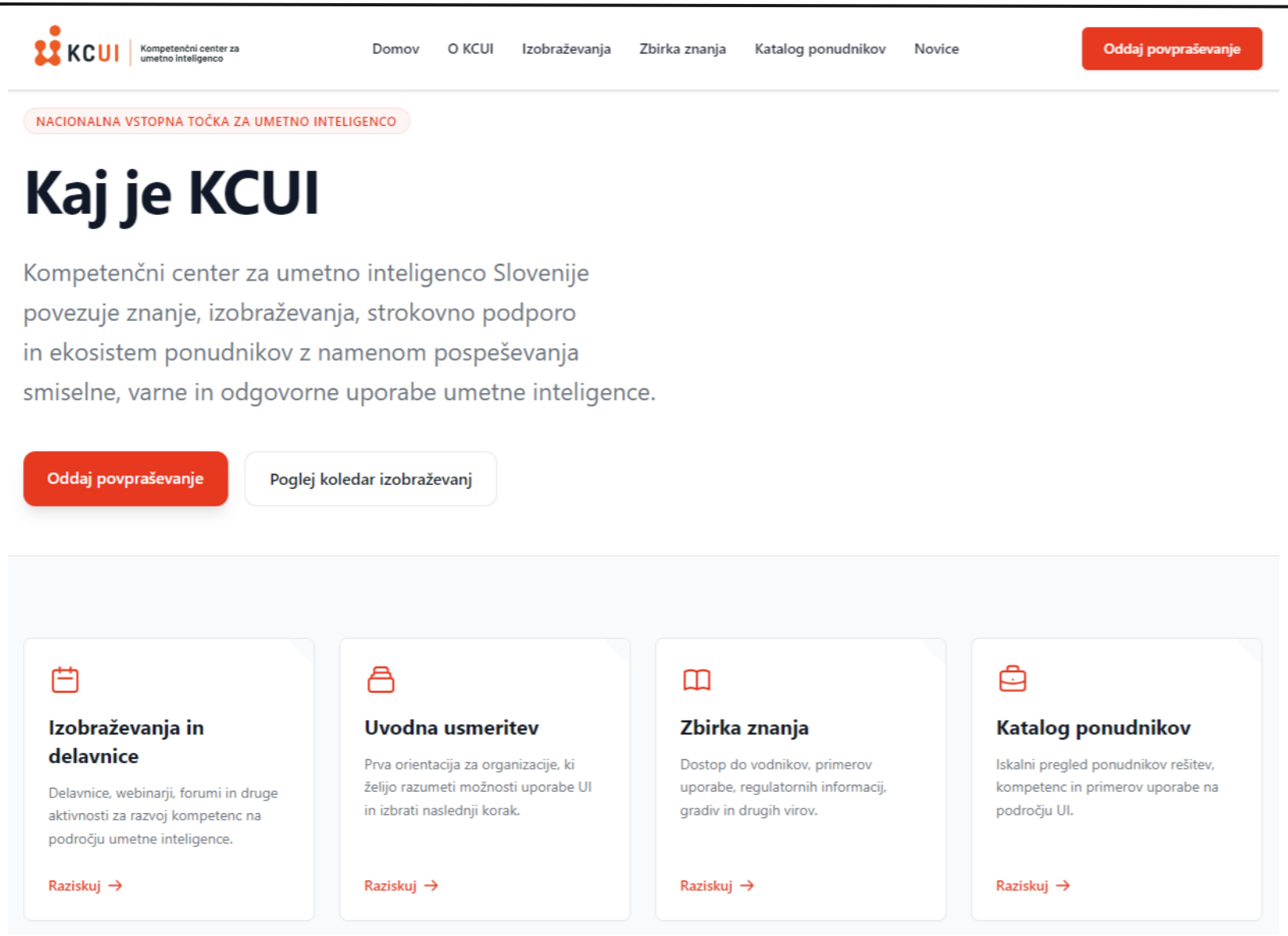
Globoko učenje za vizualni nadzor kakovosti v proizvodnji

dr. Domen Tabernik

Laboratorij za umetne vizualne spoznavne sisteme
Fakulteta za računalništvo in informatiko
Univerza v Ljubljani

GZDBK, Kakovost 2035, 12. 11. 2026

Kompetenčni center za umetno inteligenco



Gospodarska zbornica Slovenije

UNIVERZA V LJUBLJANI FRI Fakulteta za računalništvo in informatiko

FERI Fakulteta za elektrotehniko, računalništvo in informatiko

Institut "Jožef Stefan" Ljubljana, Slovenija

Že od leta 1969 OBRTNO-PODJETNIŠKA ZBORNICA SLOVENIJE

UNIVERZA V LJUBLJANI FE Fakulteta za elektrotehniko

UNIVERZA V NOVI GORICI SCIENTIA 1995 VINCES

UNIVERZA NA PRIMORSKEM Univerza na Primorskem

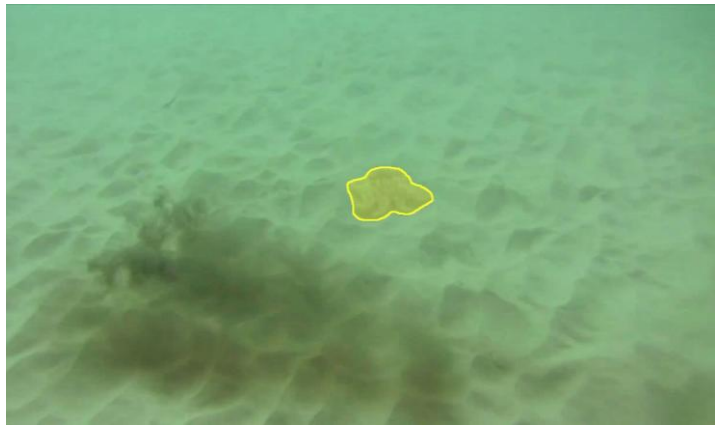
PF UNIVERZA V LJUBLJANI Pravna fakulteta

ASEF AMERICAN SLOVENIAN EDUCATION FOUNDATION

Lab. za umetne vizualne spoznavne sisteme

UNIVERZA V LJUBLJANI | FRI Fakulteta za računalništvo in informatiko

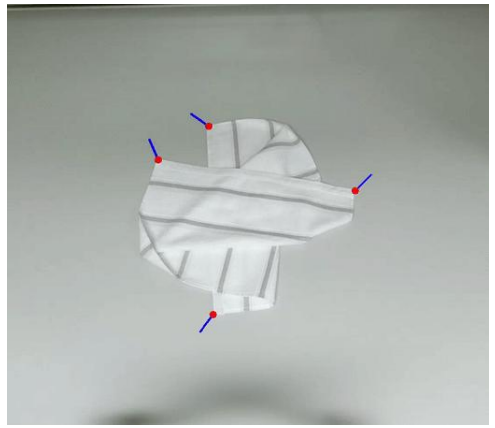
Vizualno sledenje



Detekcija & štetje

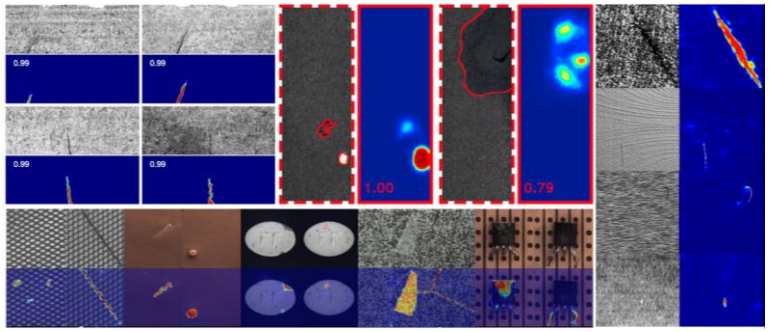


Računalniški vid za robotiko





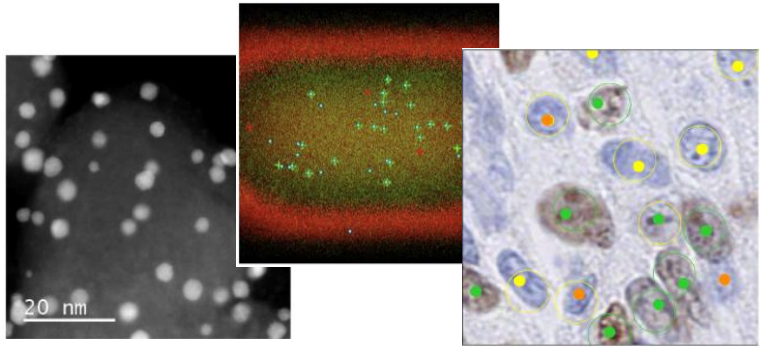
Detekcija viz. anomalij



Opazovanje Zemlje

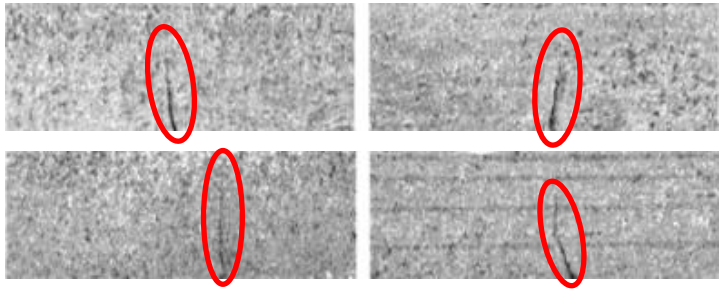


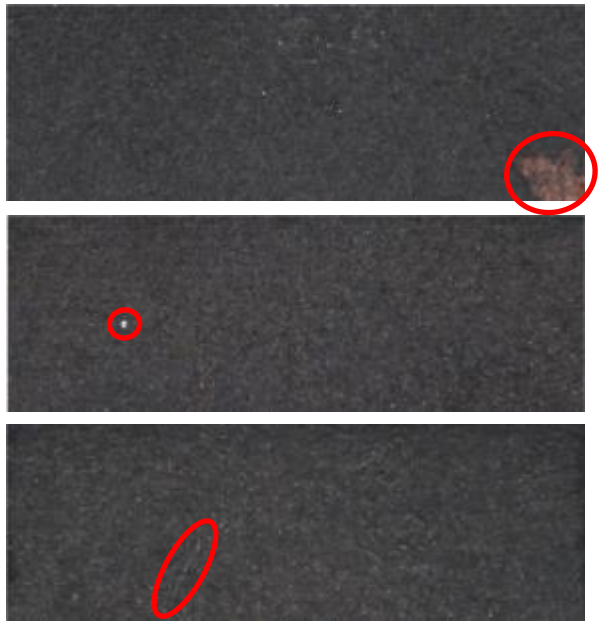
Interdisciplinarne raziskave



NVIDIA. OpenCV MathWorks® intel

Detekcija površinskih napak

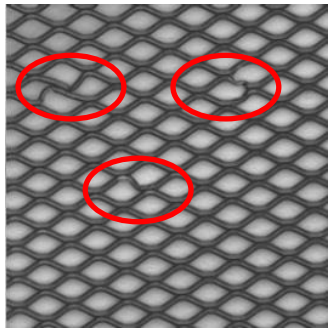




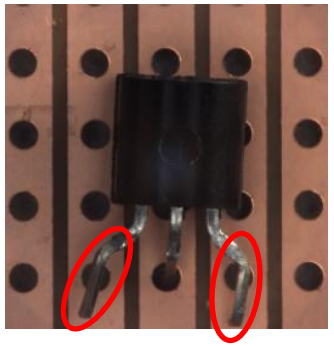


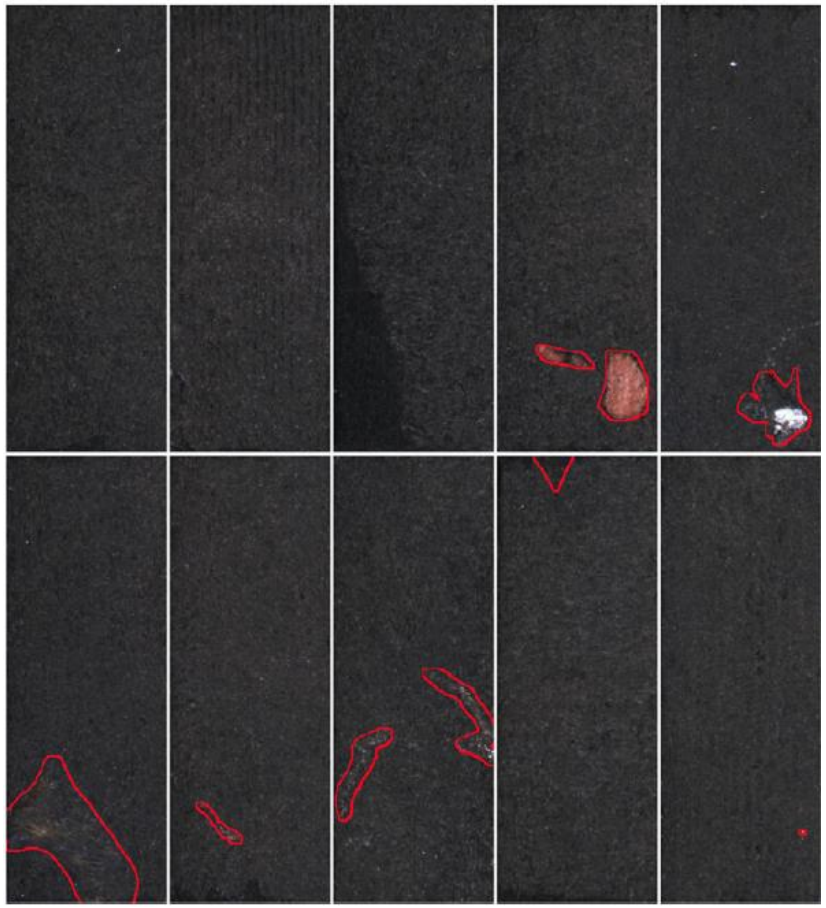




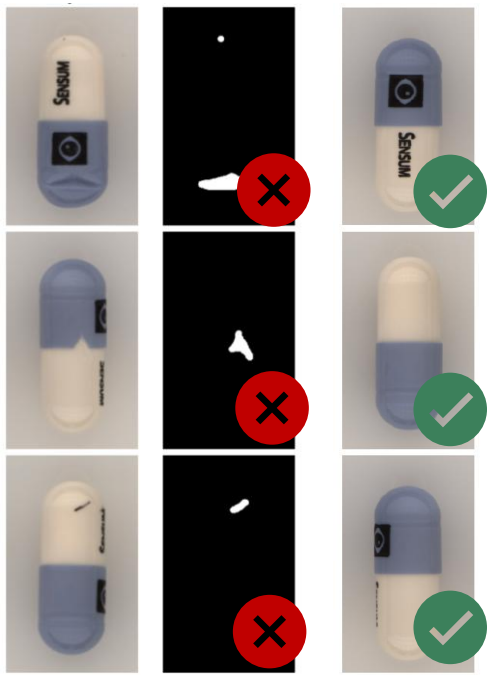






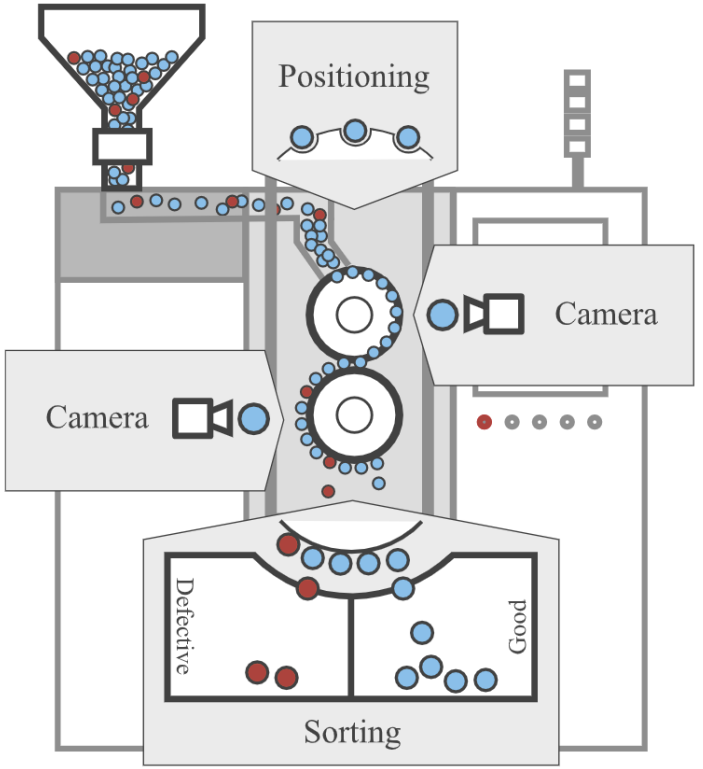


Primer: Vizualni nadzor farmacevtskih proizvodov





sensum.eu

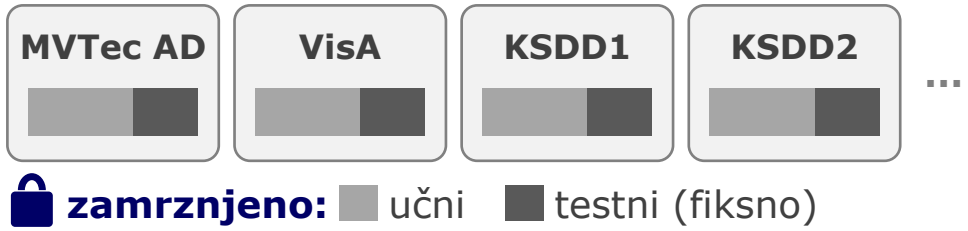


NCAA 2021

Raziskovalni in industrijski vidik

Znanstveni razvoj metod

- Podatkovne zbirke



Več domen, realni ali umetni problemi

Več svobode pri opredelitvi napak

- Razvoj metod glavni cilj



Nove arhitekture in pristopi

Natančna primerjava na istih zbirkah

Uporaba metod v praksi

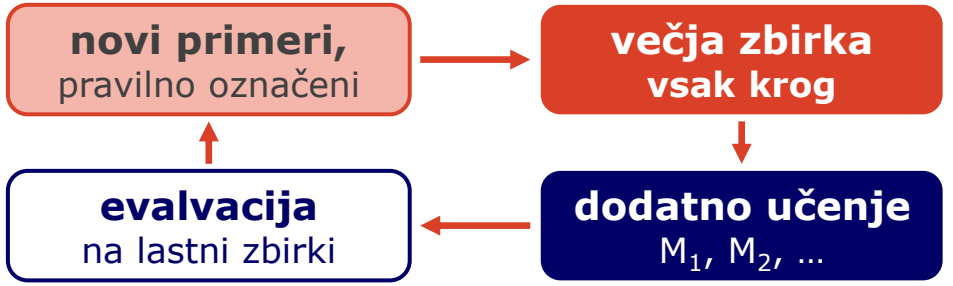
- Podatkovne zbirke ključne



Ena domena, malo vrst napak

Zajem skupaj z integratorji

- Uporaba obstoječih metod

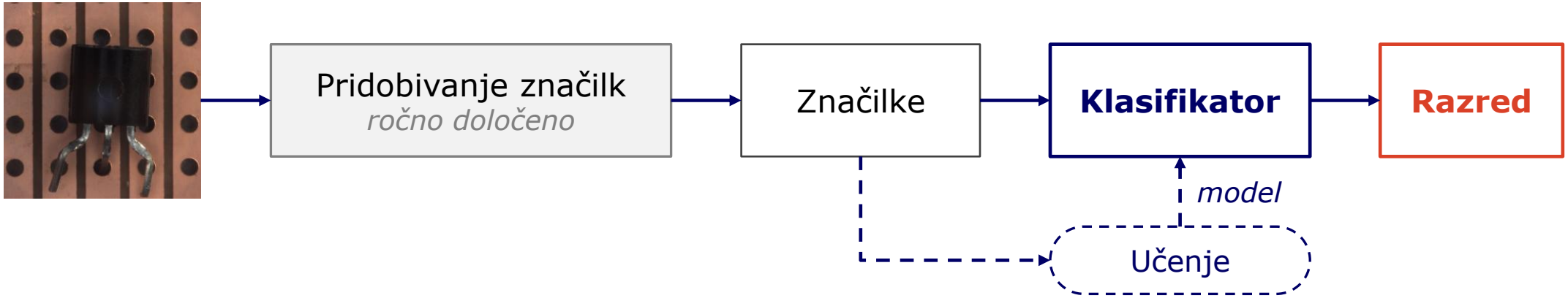


Metode redko razvijamo na novo

Manjše prilagoditve metode

Globoko učenje za računalniški vid

- **Klasični dvostopenjski pristop računalniškega vida s strojnim učenjem**

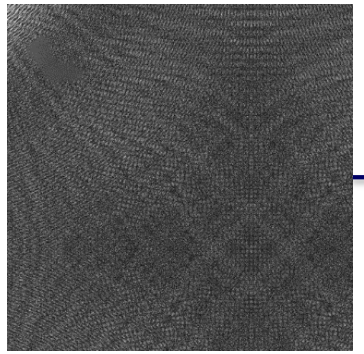


- **Globoko učenje**

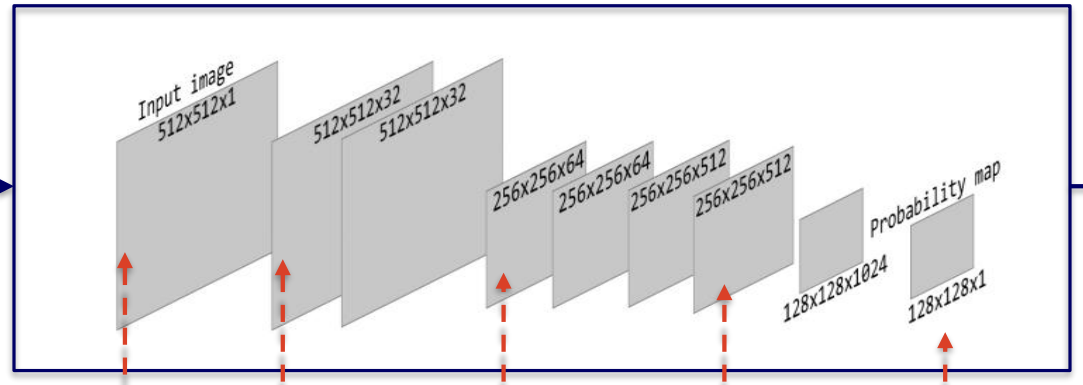


Globoko učenje za računalniški vid

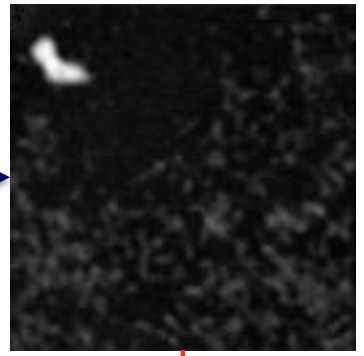
Vhodna slika



Globoka nevronska mreža



Izhodna segmentacija

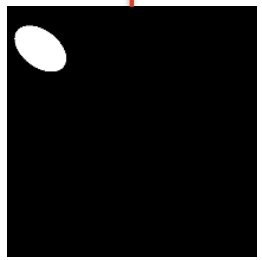


Izguba

Učenje s vzvratnim razširjenjem napake

Posodabljanje uteži po plasteh

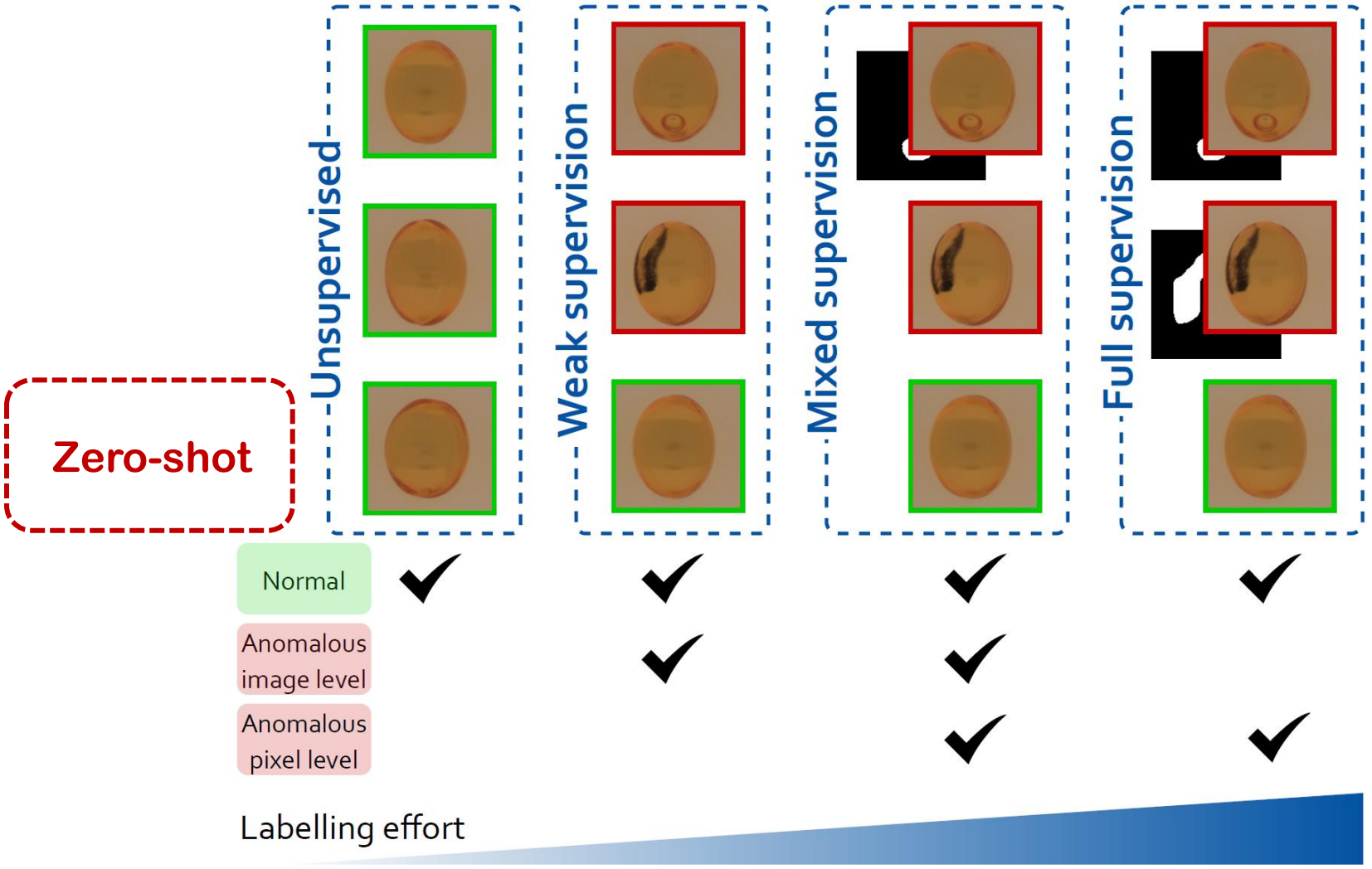
Učni podatki



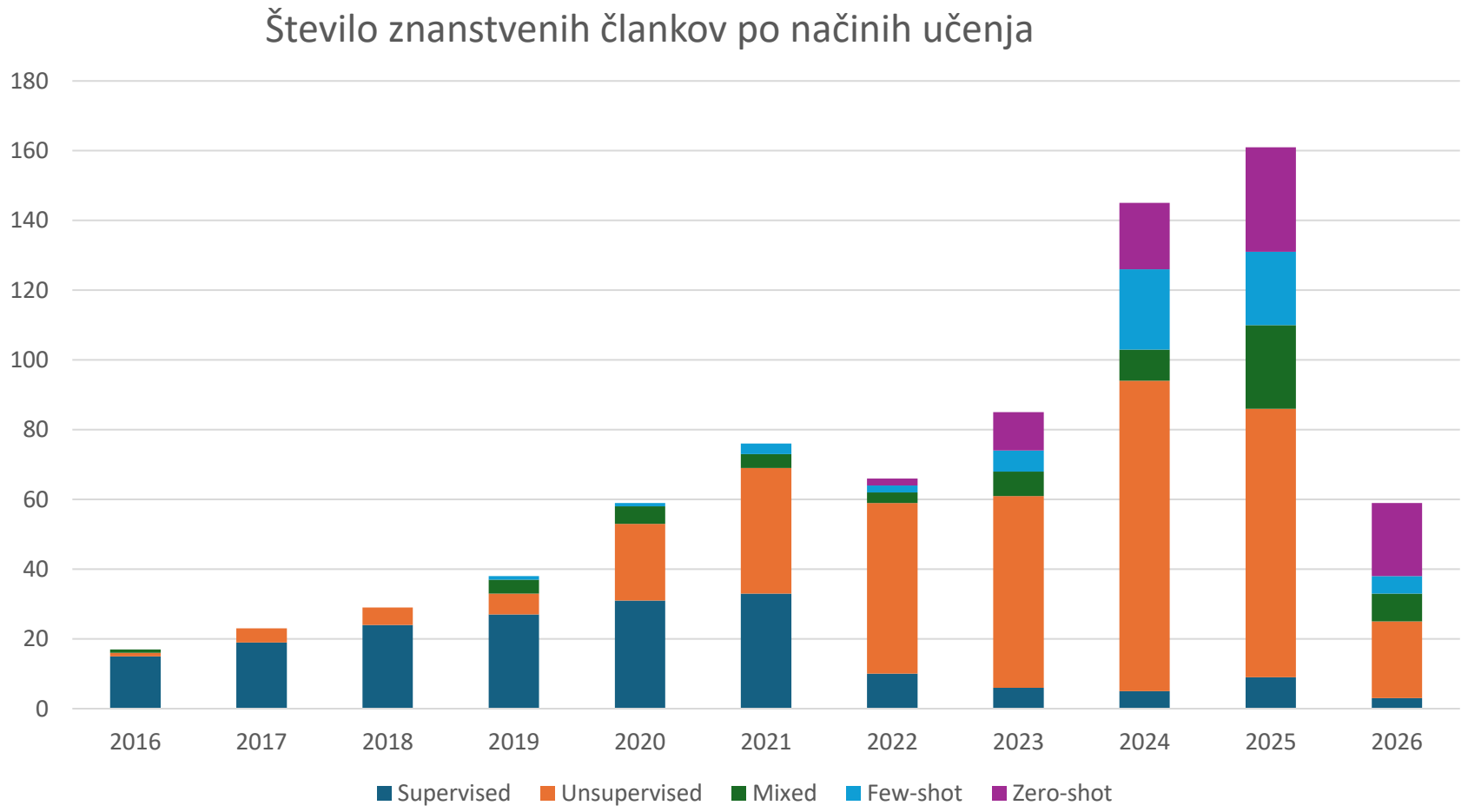
Referenčna maska (GT)

Pridobivanje označb za učenje je drago!

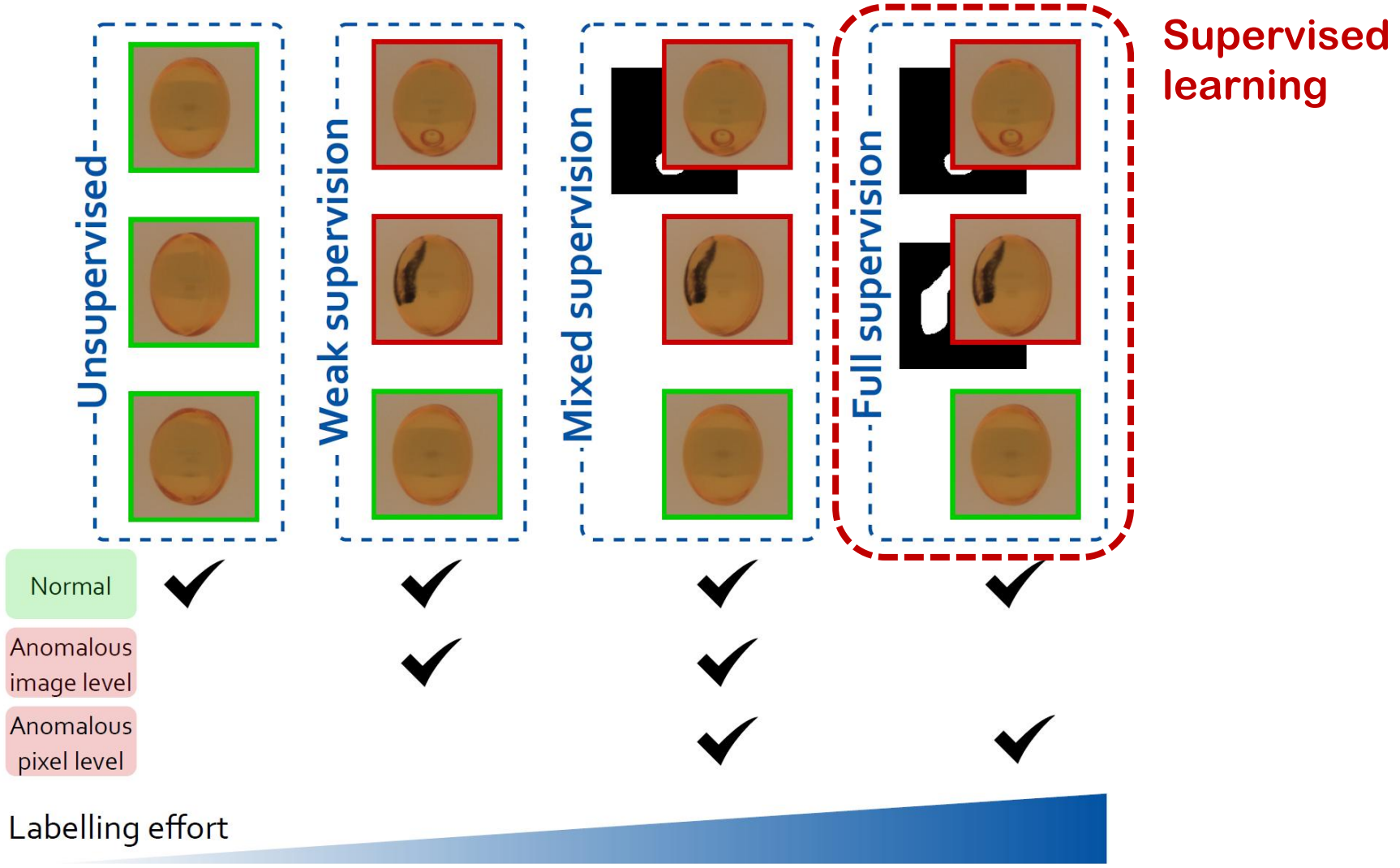
Načini učenja modelov



Zgodovina načinov učenja v literaturi

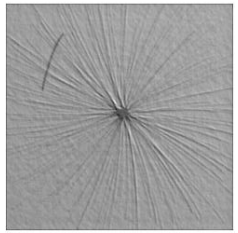


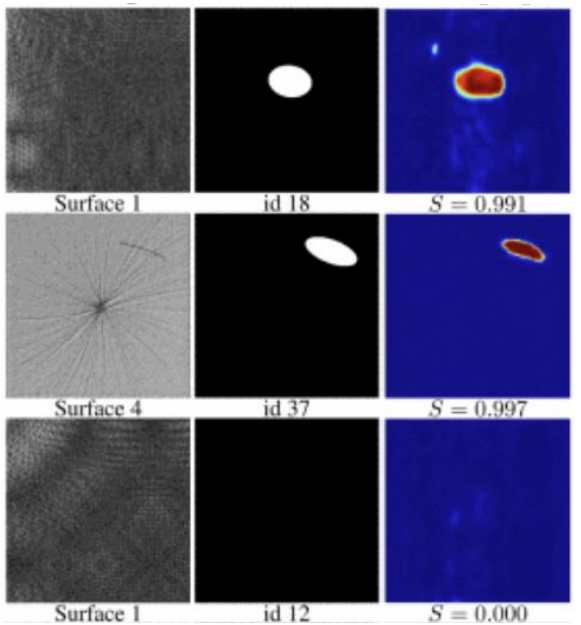
Načini učenja modelov – popoln. nadzorovani



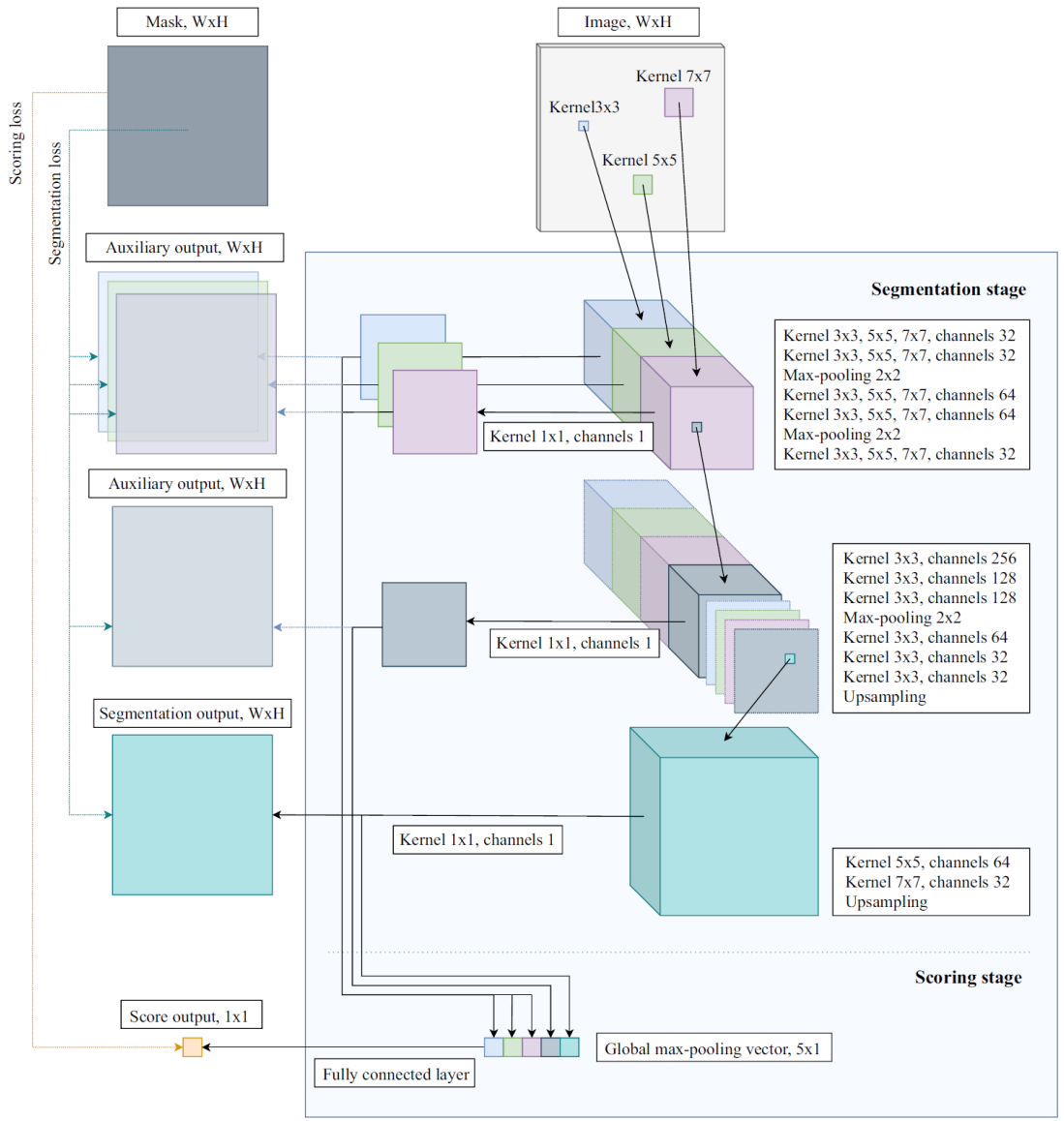
Popolnoma nadzorovani način učenja

WACV 2018



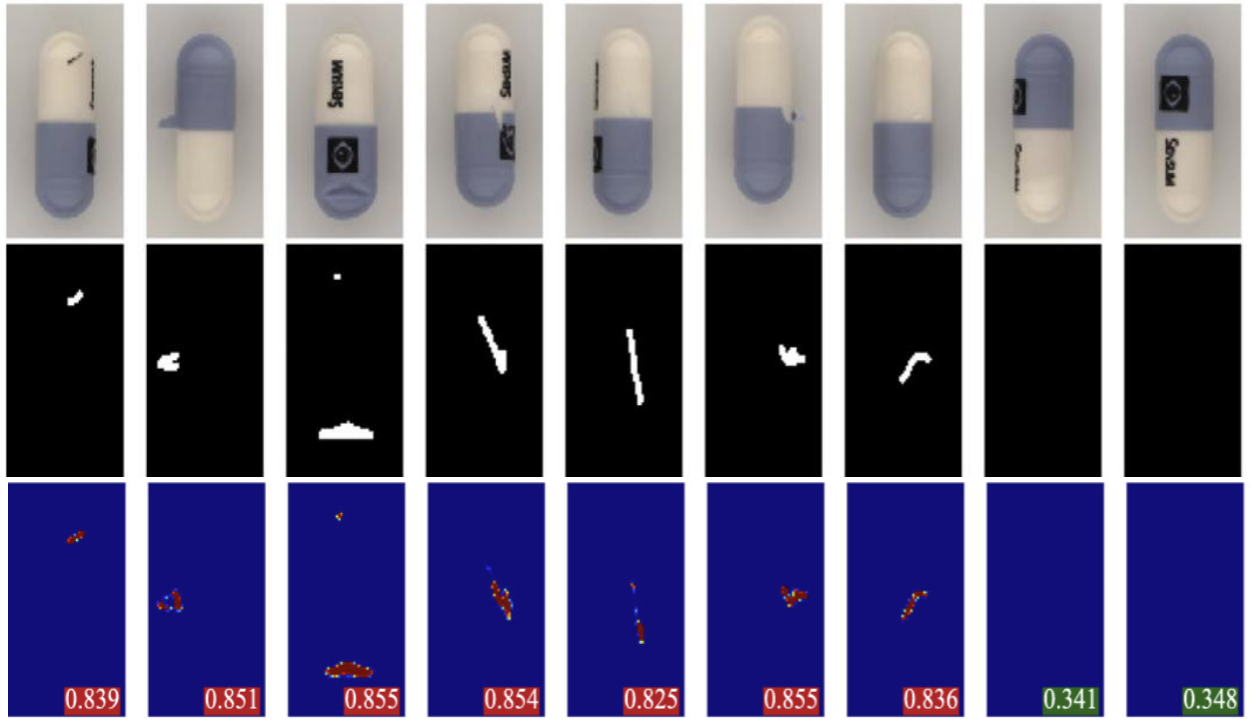


Popolnoma nadzorovani način - TriNet

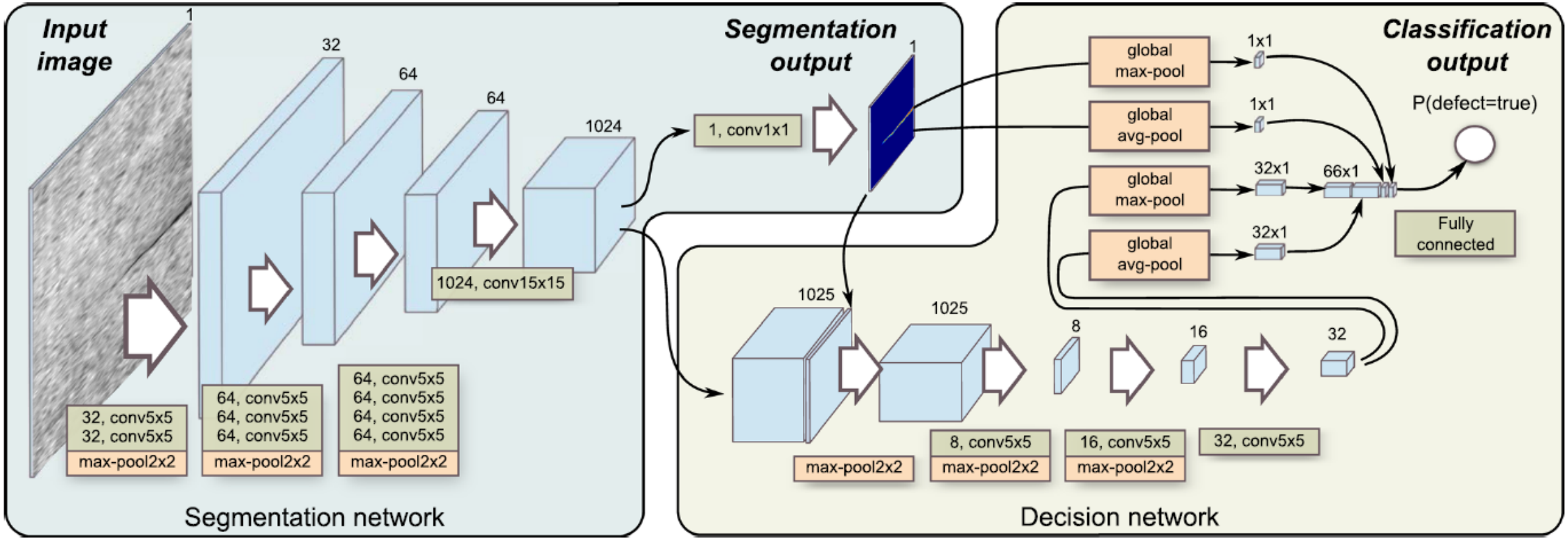




NCAA 2021

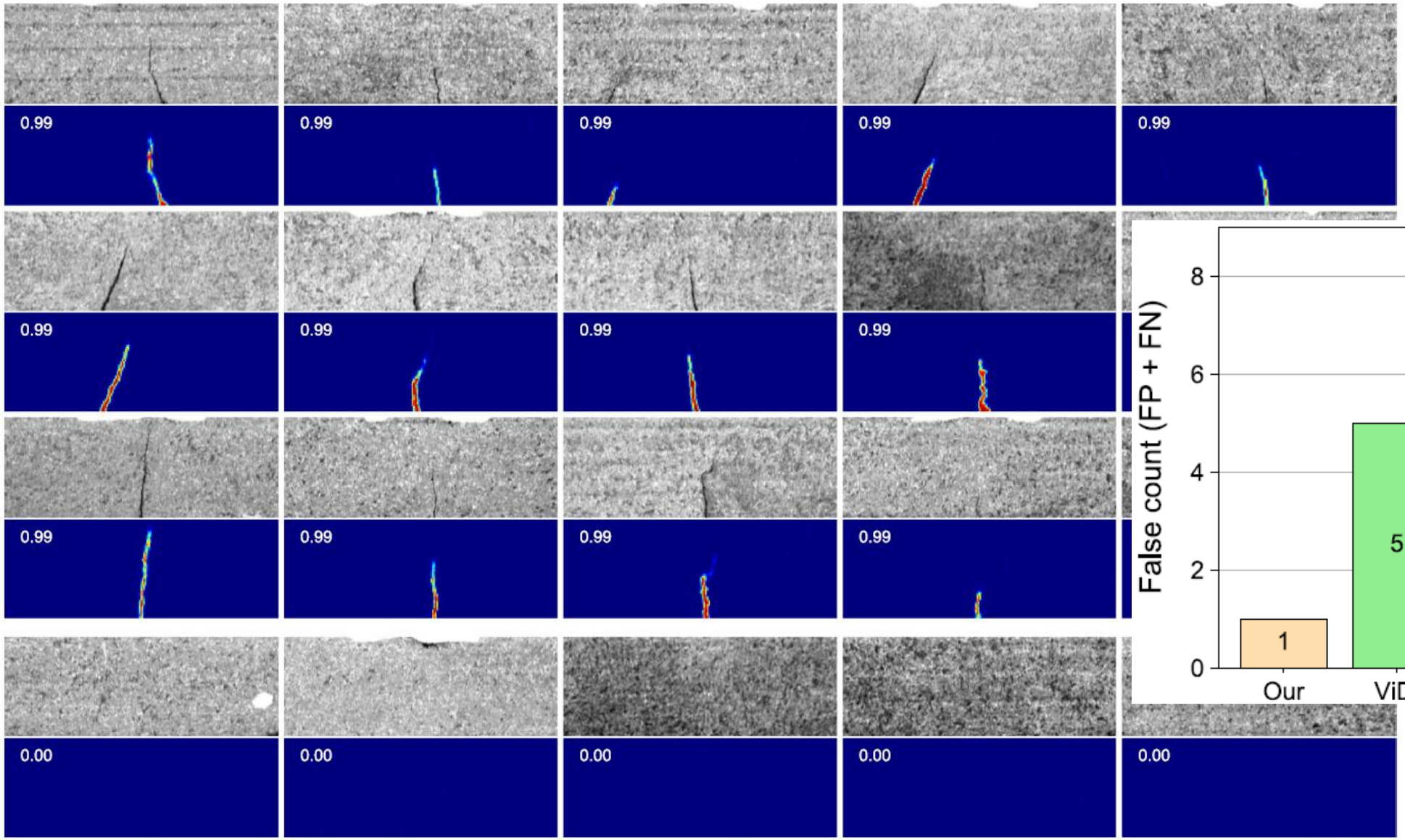


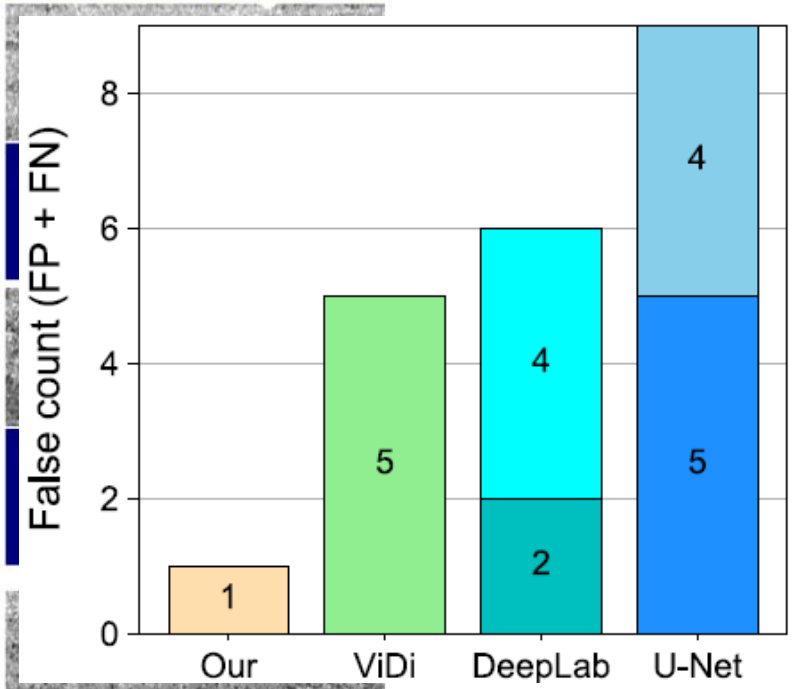
Popolnoma nadzorovani način - SegDecNet



ICVS 2019 | JIM 2020

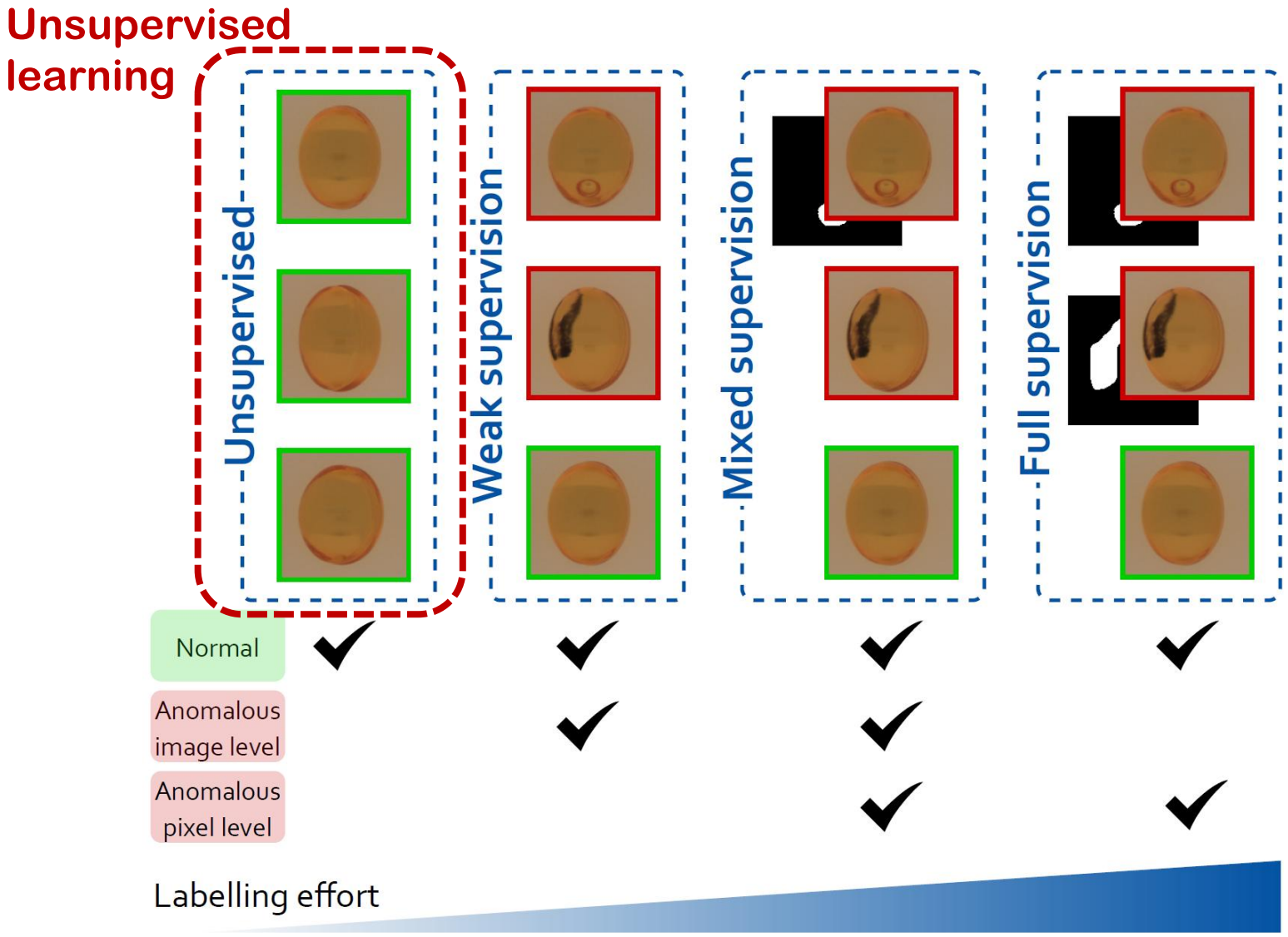
Popolnoma nadzorovani način - SegDecNet





JIM 2020

Načini učenja modelov – nenadzorovano učenje

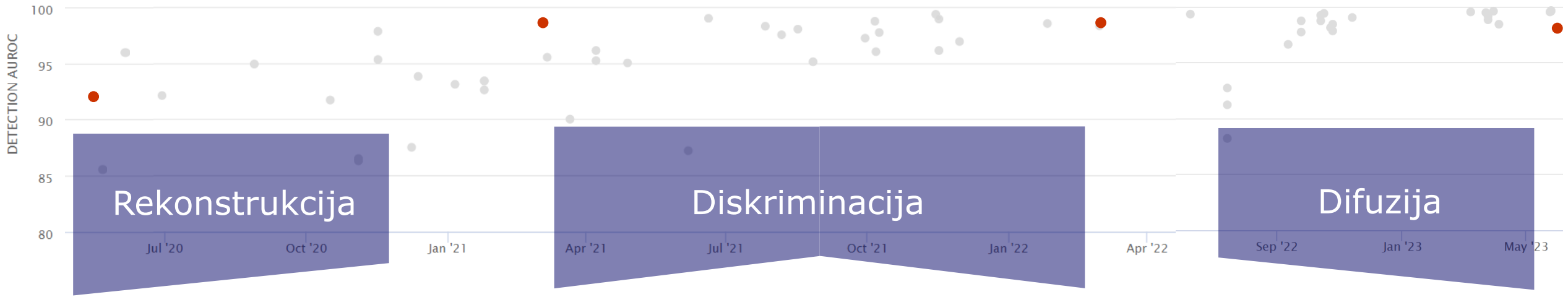


Nenadzorovano učenje

- Zadostujejo samo slike brez napak
- Učenje samo negativnega razreda

- Detekcija AUROC na MVTec AD:

[paperswithcode.com]



RIAD — PR 2021

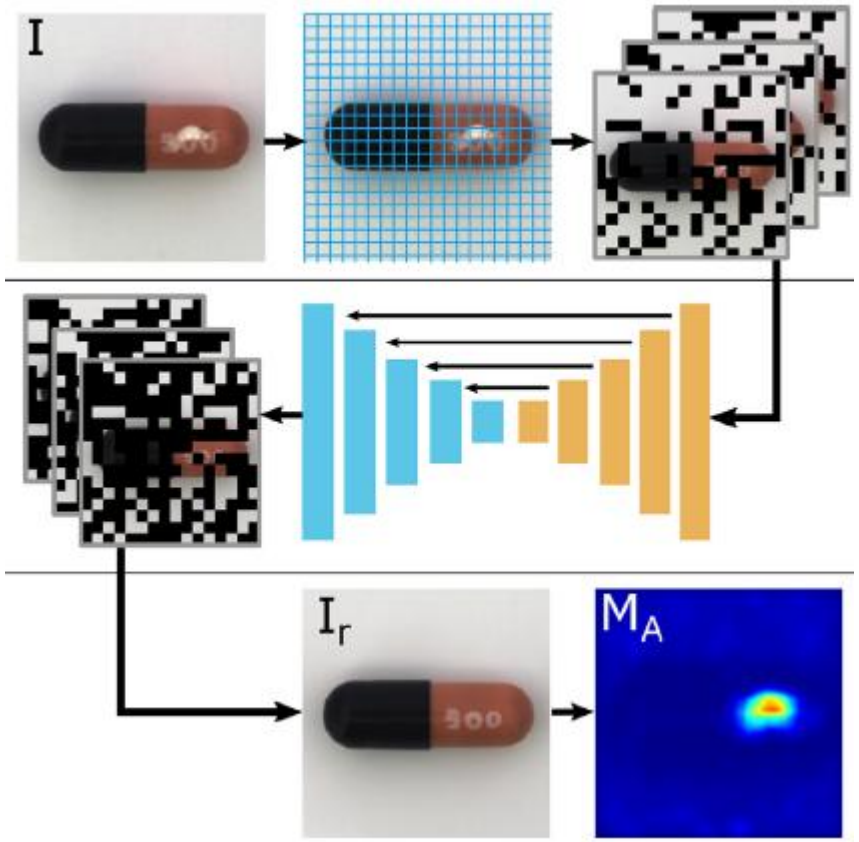
DRAEM — ICCV 2021

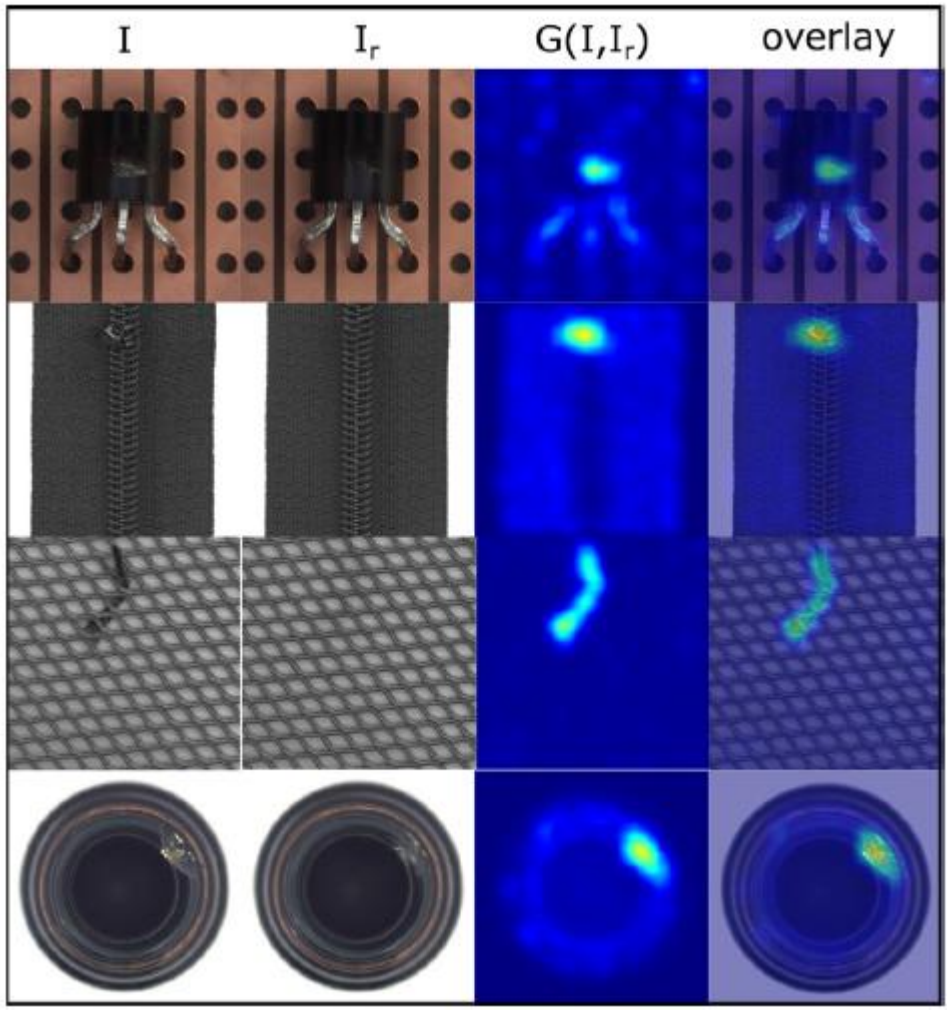
DSR — ECCV 2022

Transfusion — 2023

Nenadzorovano učenje - RIAD

- Pristopi z rekonstrukcijo



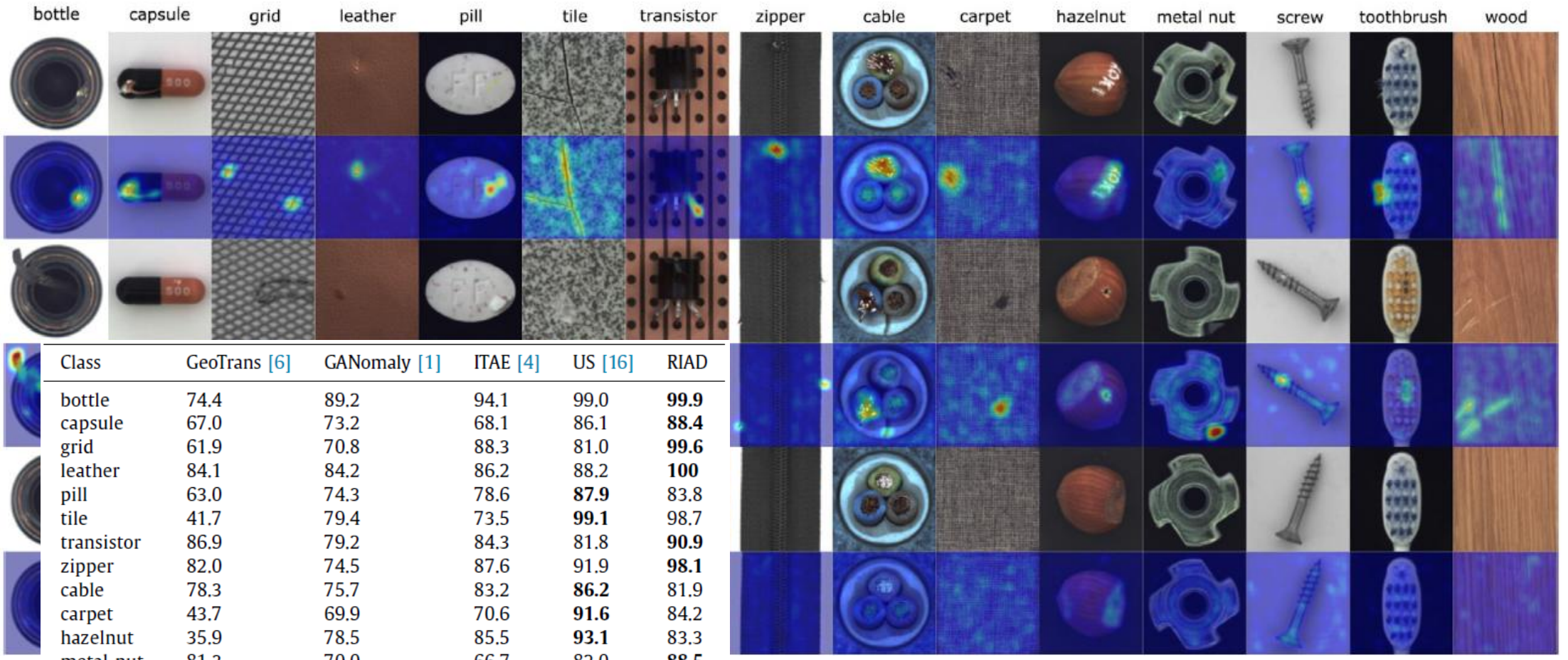


DIVID
2018-2021

CompVis
2019-2024

PR 2021

Nenadzorovano učenje - RIAD



Class	GeoTrans [6]	GANomaly [1]	ITAE [4]	US [16]	RIAD
bottle	74.4	89.2	94.1	99.0	**99.9**
capsule	67.0	73.2	68.1	86.1	**88.4**
grid	61.9	70.8	88.3	81.0	**99.6**
leather	84.1	84.2	86.2	88.2	**100**
pill	63.0	74.3	78.6	**87.9**	83.8
tile	41.7	79.4	73.5	**99.1**	98.7
transistor	86.9	79.2	84.3	81.8	**90.9**
zipper	82.0	74.5	87.6	91.9	**98.1**
cable	78.3	75.7	83.2	**86.2**	81.9
carpet	43.7	69.9	70.6	**91.6**	84.2
hazelnut	35.9	78.5	85.5	**93.1**	83.3
metal nut	81.3	70.0	66.7	82.0	**88.5**
screw	50.0	74.6	**100**	54.9	84.5
toothbrush	97.2	65.3	**100**	95.3	**100**
wood	61.1	83.4	92.3	**97.7**	93.0
avg_{tex}	58.5	76.5	82.2	91.5	**95.1**
avg_{obj}	71.6	75.4	84.8	85.8	**89.9**
avg	67.2	76.2	83.9	87.7	**91.7**

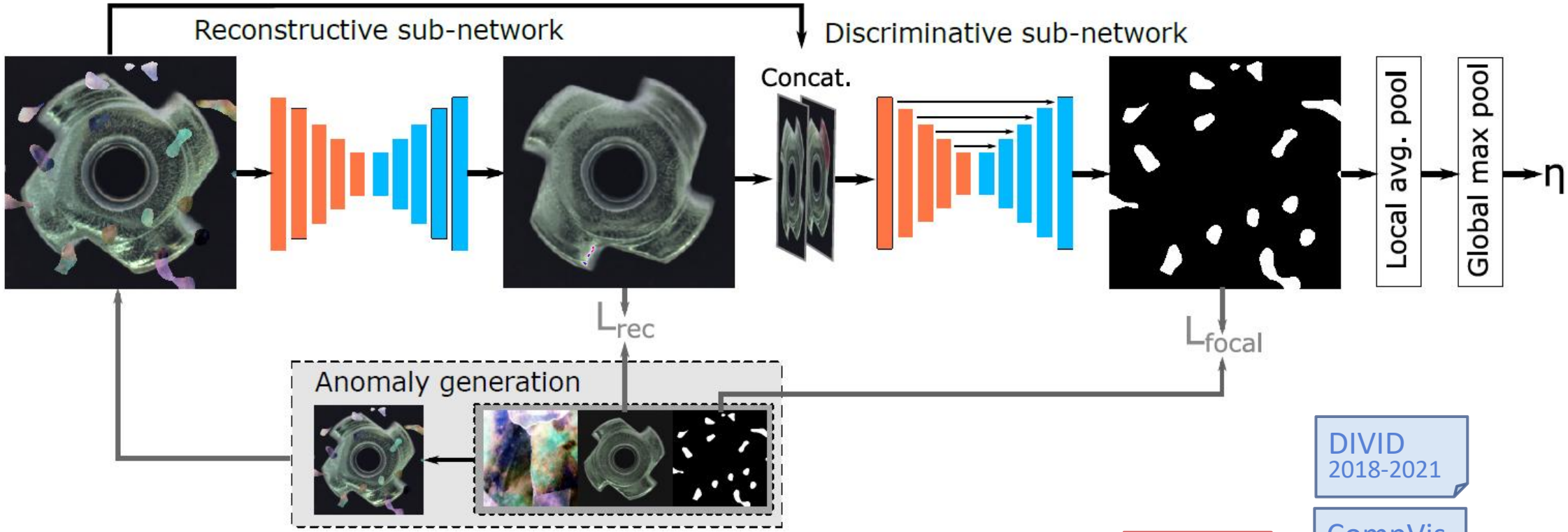
DIVID 2018-2021

CompVis 2019-2024

PR 2021

Nenadzorovano učenje - DRAEM

- Pristopi z rekonstrukcijo in diskriminacijo
- Generiranje sintetičnih anomalij

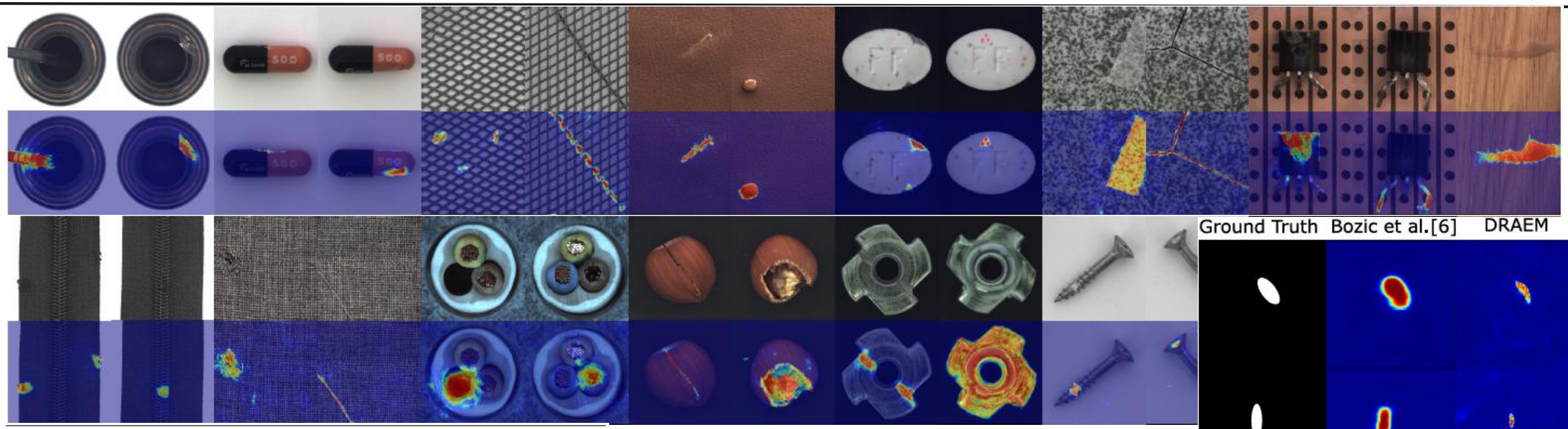


DIVID
2018-2021

ICCV 2021

CompVis
2019-2024

Nenadzorovano učenje - DRAEM



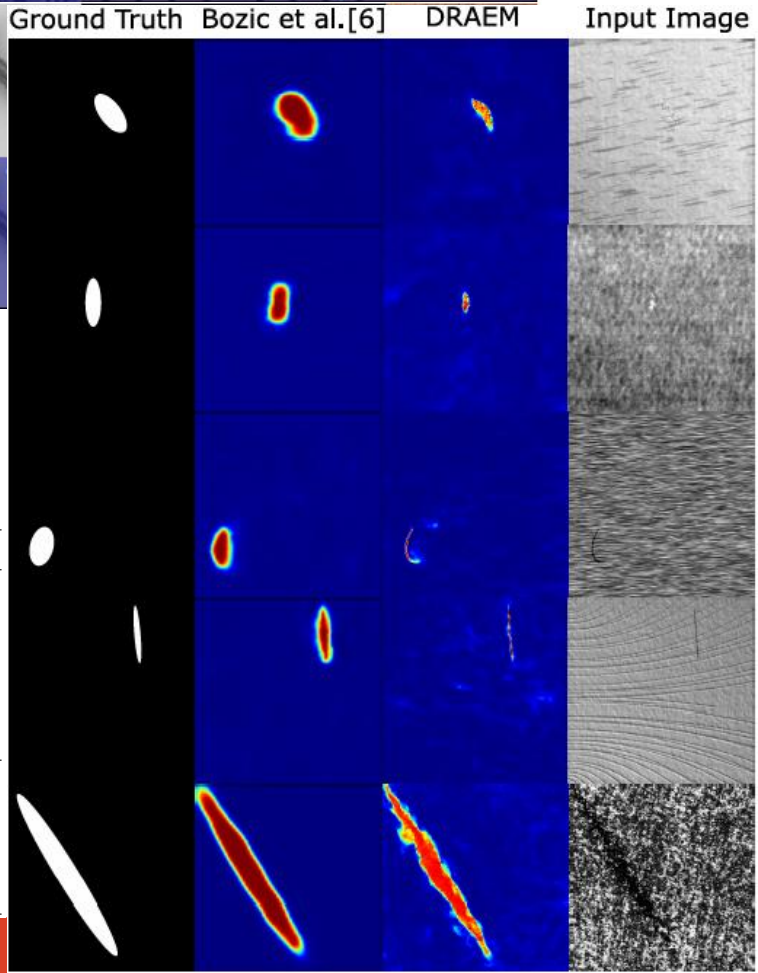
Class	[1]	[26]	[4]	[31]	[20]	[11]	DRÆM
bottle	79.4	98.3	99.0	99.9	**100**	99.9	99.2
capsule	72.1	68.7	86.1	88.4	92.3	91.3	**98.5**
grid	74.3	86.7	81.0	99.6	92.9	96.7	**99.9**
leather	80.8	94.4	88.2	**100**	**100**	**100**	**100**
pill	67.1	76.8	87.9	83.8	83.4	93.3	**98.9**
tile	72.0	96.1	99.1	98.7	97.4	98.1	**99.6**
transistor	80.8	79.4	81.8	90.9	95.9	**97.4**	93.1
zipper	74.4	78.1	91.9	98.1	97.9	90.3	**100**
cable	71.1	66.5	86.2	81.9	**94.0**	92.7	91.8
carpet	82.1	90.3	91.6	84.2	95.5	**99.8**	97.0
hazelnut	87.4	100	93.1	83.3	98.7	92.0	**100.0**
metal nut	69.4	81.5	82.0	88.5	93.1	**98.7**	**98.7**
screw	**100**	**100**	54.9	84.5	81.2	85.8	93.9
toothbrush	70.0	95.0	95.3	**100**	95.8	96.1	**100**
wood	92.0	97.9	97.7	93.0	97.6	**99.2**	99.1
avg	78.2	87.3	87.7	91.7	94.4	95.5	**98.0**

DIVID 2018-2021

CompVis 2019-2024

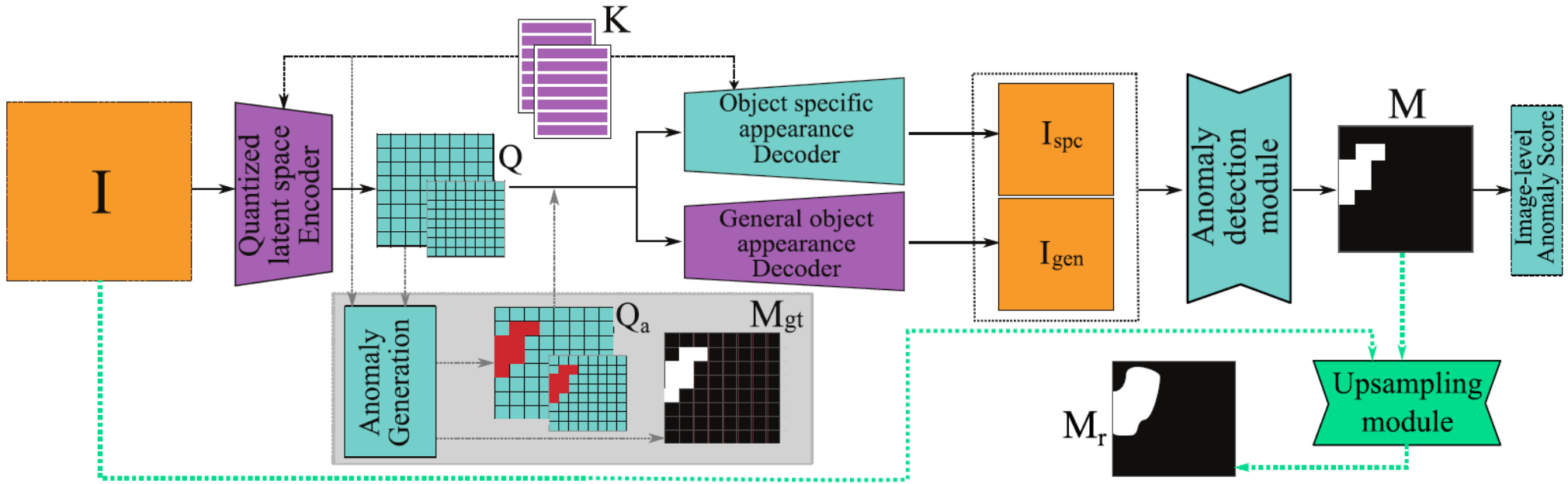
ICCV 2021

	Methods	AUROC	TPR	TNR	CA
Unsup.	RIAD [31]	78.6	79.2	69.1	70.4
	US [4]	72.5	72.6	65.3	66.2
	MAD [20]	82.4	78.7	85.7	66.2
	PaDim [11]	95.0	83.3	97.5	95.7
	DRÆM	**99.0**	**96.5**	**99.4**	**98.5**
Sup.	CADN [32]	-	-	-	89.1
	Rački *et al.* [19]	99.6	99.9	99.5	-
	Lin *et al.* [15]	99.0	99.4	99.9	-
	Božič *et al.* [6]	**100**	**100**	**100**	**100**



Nenadzorovano učenje - DSR

- Generiranje sintetičnih anomalij v prostoru kvantiziranih značilk

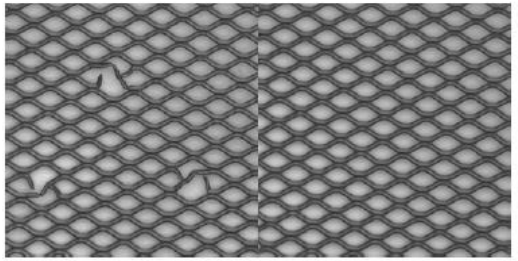


ECCV 2022

MV4.0
2021-2024

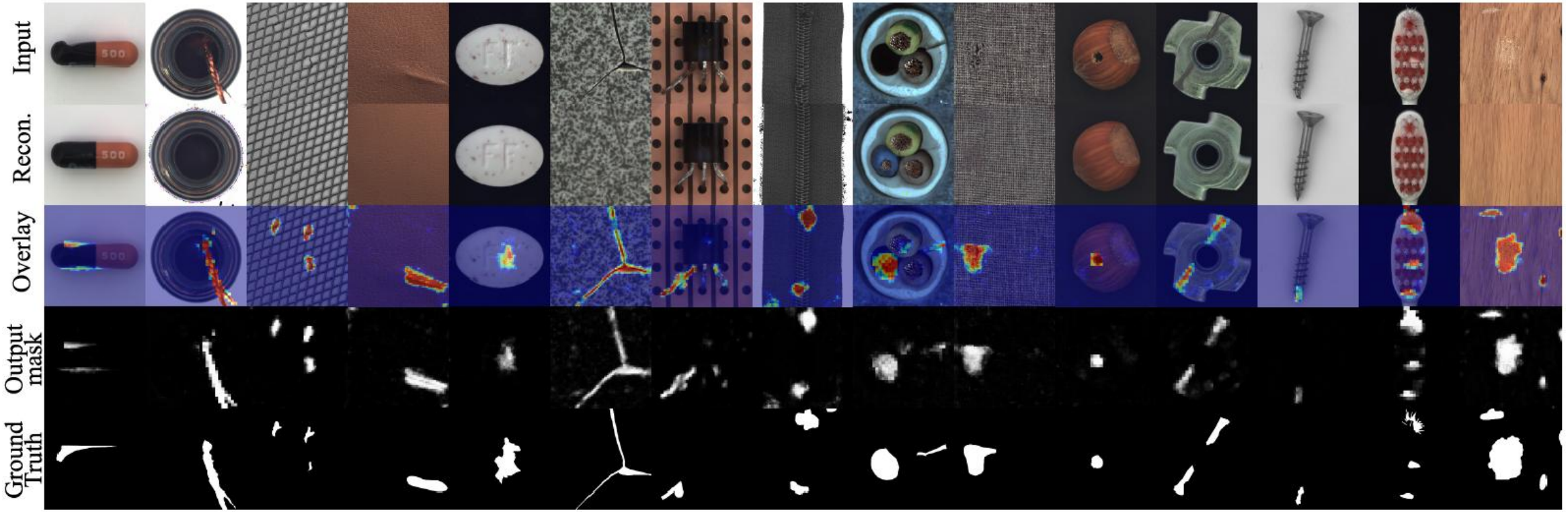








Nenadzorovano učenje - DSR



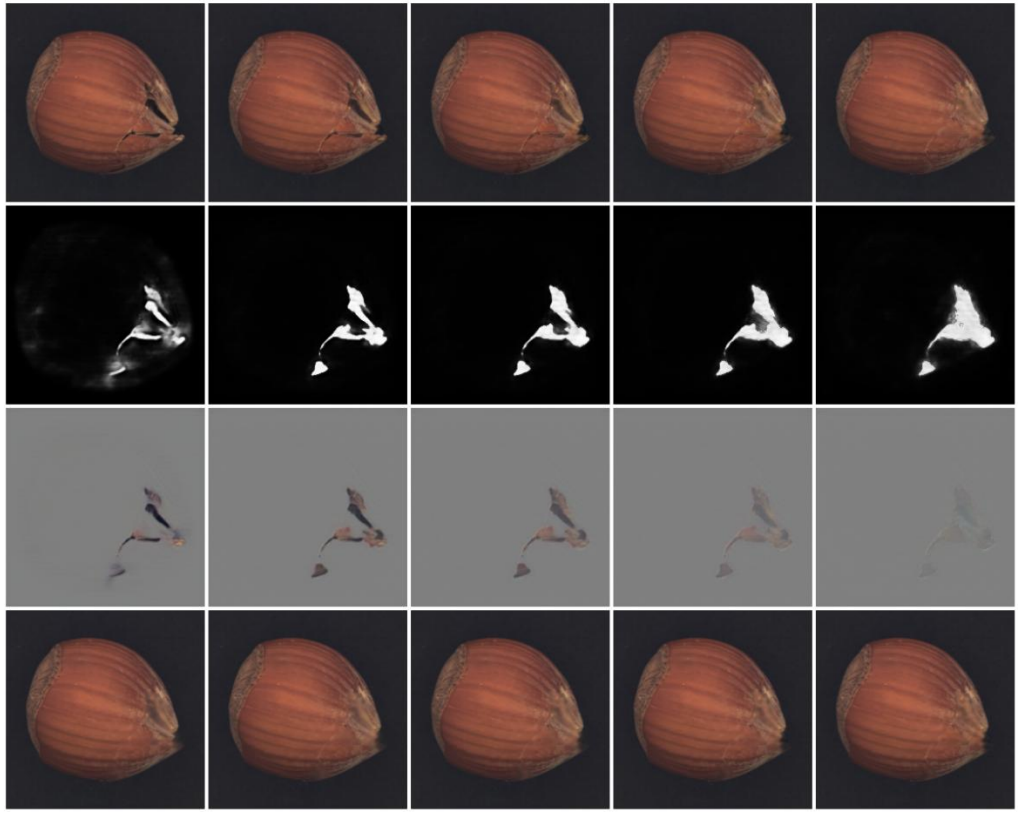
Method	bottle	capsule	grid	leather	pill	tile	trans.	zipper	cable	carpet	hazelnut	m. nut	screw	toothbrush	wood	average
[4]	99.0	86.1	81.0	88.2	87.9	99.1	81.8	91.9	86.2	91.6	93.1	82.0	54.9	95.3	97.7	87.7
[22]	99.9	88.4	99.6	**100**	83.8	98.7	90.9	98.1	81.9	84.2	83.3	88.5	84.5	**100**	93.0	91.7
[17]	**100**	92.3	92.9	**100**	83.3	97.4	95.9	97.9	**94.0**	95.5	98.7	93.1	81.2	95.8	97.6	94.4
[7]	99.8	91.5	95.7	**100**	94.4	97.4	**97.8**	90.9	92.2	99.9	93.3	99.2	84.4	97.2	98.8	95.5
[11]	98.2	98.2	**100**	**100**	94.9	94.6	96.1	99.9	81.2	93.9	98.3	**99.9**	88.7	99.4	**99.1**	96.1
[21]	99.2	**98.5**	99.9	**100**	**98.9**	99.6	93.1	**100**	91.8	97.0	**100**	98.7	93.9	**100**	**99.1**	98.0
DSR	**100**	98.1	**100**	**100**	97.5	**100**	**97.8**	**100**	93.8	**100**	95.6	98.5	**96.2**	99.7	96.3	**98.2**

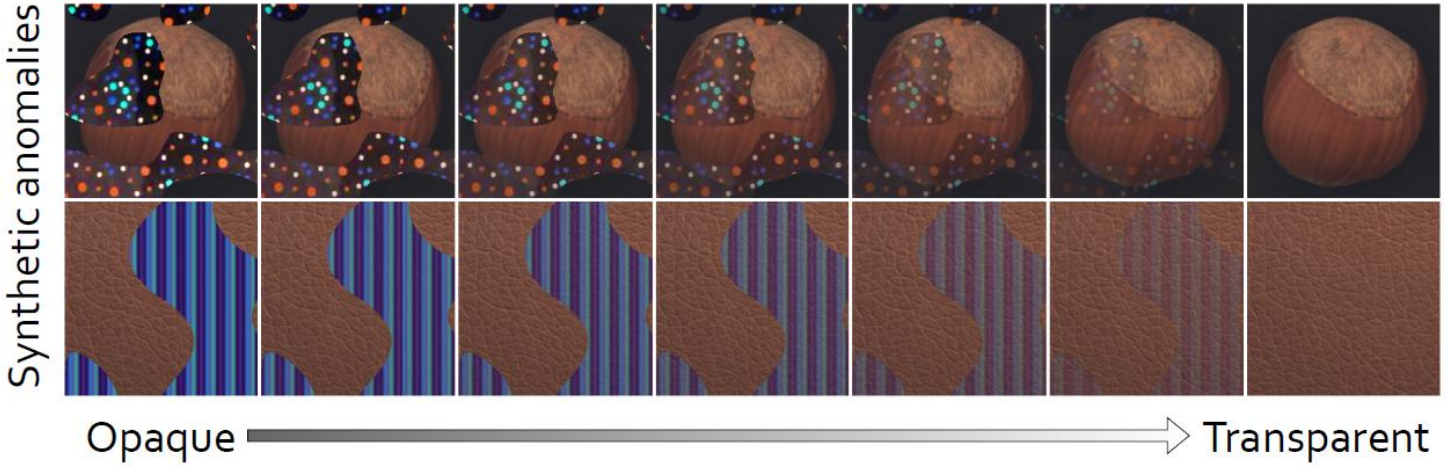
Nenadzorovano učenje - Transfusion

- Transparentna difuzija (TRANSparent difFUSION)
- Namesto rekonstrukcije cele slike z modelom difuzije sočasno ocenimo:
  - Masko anomalije
  - Anomalijo
  - Normalno sliko

MV4.0
2021-2024

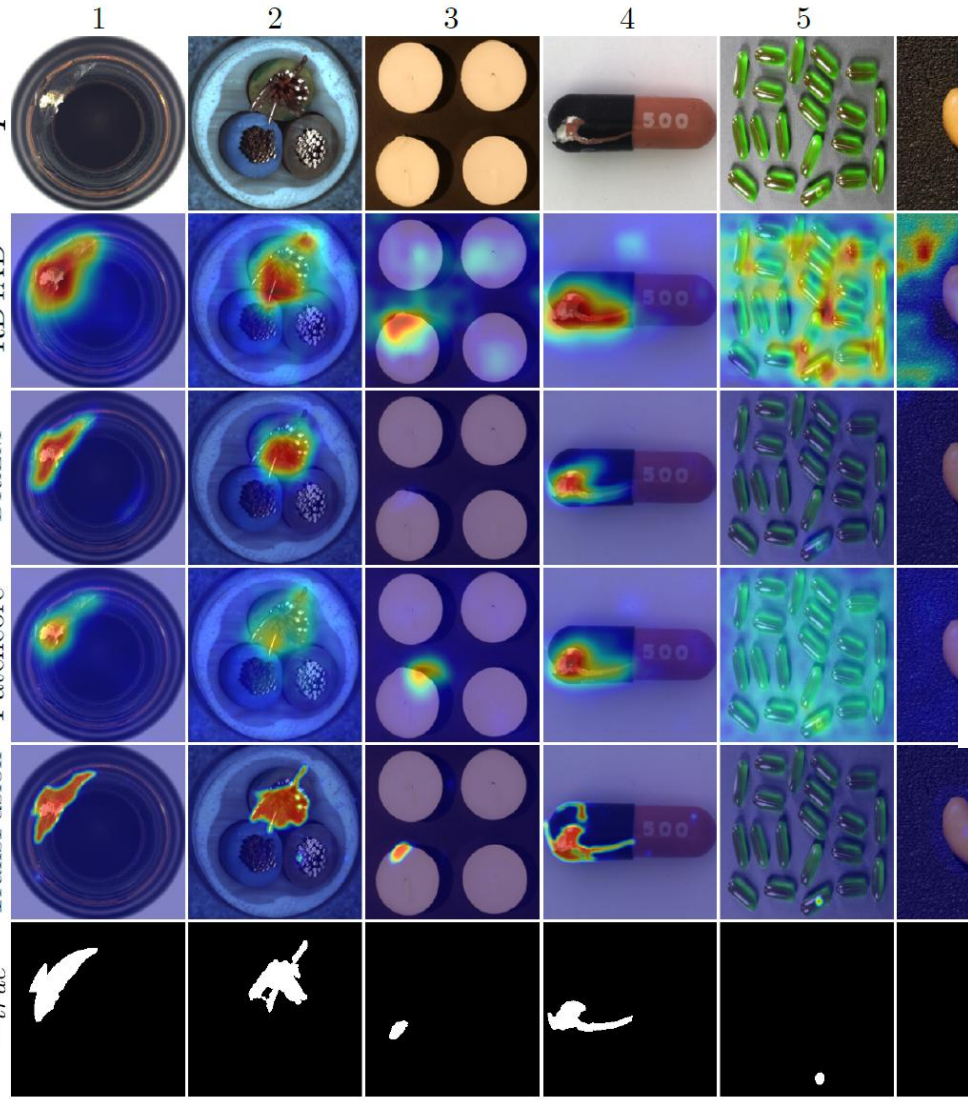
ECCV 2024





$$x_{t-1} = x_t - (\beta_t - \beta_{t-1})(M_t \odot \epsilon_t) + (\beta_t - \beta_{t-1})(M_t \odot \hat{x_0}^{(t)})$$

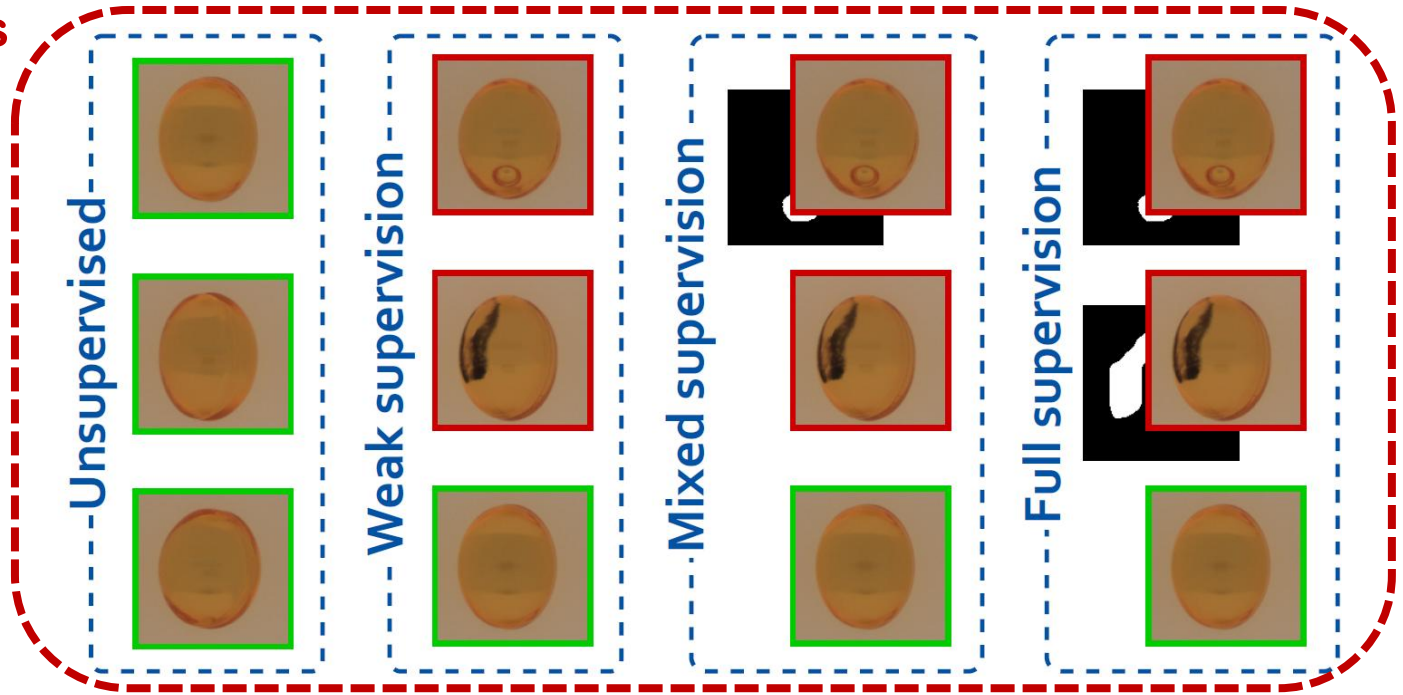
Nenadzorovano učenje - Transfusion



Method	Venue	VisA		MVTec AD		*Average*	
		Det.	Loc.	Det.	Loc.	Det.	Loc.
AnoDDPM	CVPRW'22	78.2	60.5	83.5	50.7	80.9	55.6
DRÆM	ICCV'21	88.7	73.1	98.0	92.8	93.3	83.0
SimpleNet	CVPR'23	87.9	68.9	**99.6**	89.6	93.8	79.3
DiffAD	ICCV'23	89.5	71.2	98.7	84.8	94.1	78.0
DSR	ECCV'22	91.6	68.1	98.2	90.8	94.9	79.5
FastFlow	ArXiv'21	93.9	86.9	99.4	92.5	96.7	89.7
Patchcore	CVPR'22	94.3	79.7	99.1	92.7	97.0	86.2
AST	WACV'23	94.9	81.5	99.2	81.2	97.1	81.4
RD4AD	CVPR'22	96.0	70.9	98.5	93.9	97.3	82.4
TransFusion	ECCV 2024	**98.5**	**88.8**	99.2	**94.3**	**98.9**	**91.6**

Načini učenja modelov

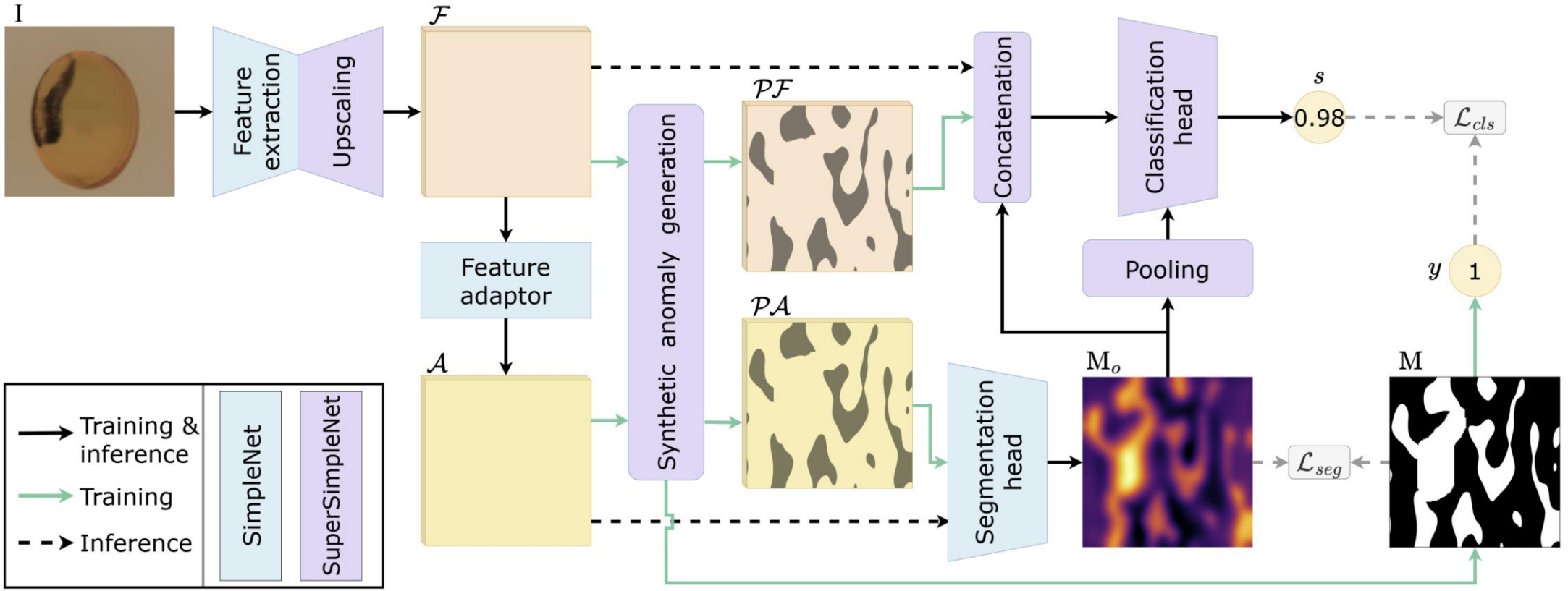
All learning regimes



JIM 2025

	US	WS	MS	FS	**Ours**	SDNet	TNet	MMNet	DRA	EAD	BGAD	DSR	SN	FF	PC	DRÆM	PRN
normal only	✓				✓					✓	✓	✓	✓	✓	✓	✓	
ano. image level		✓	✓		✓	✓	✓	✓	✓								
ano. pixel level			✓	✓	✓	✓	✓	✓			✓	✓					✓
Speed ($< 10ms$)					✓	✓	✓	✓	✓	✓							

SuperSimpleNet



JIM 2025

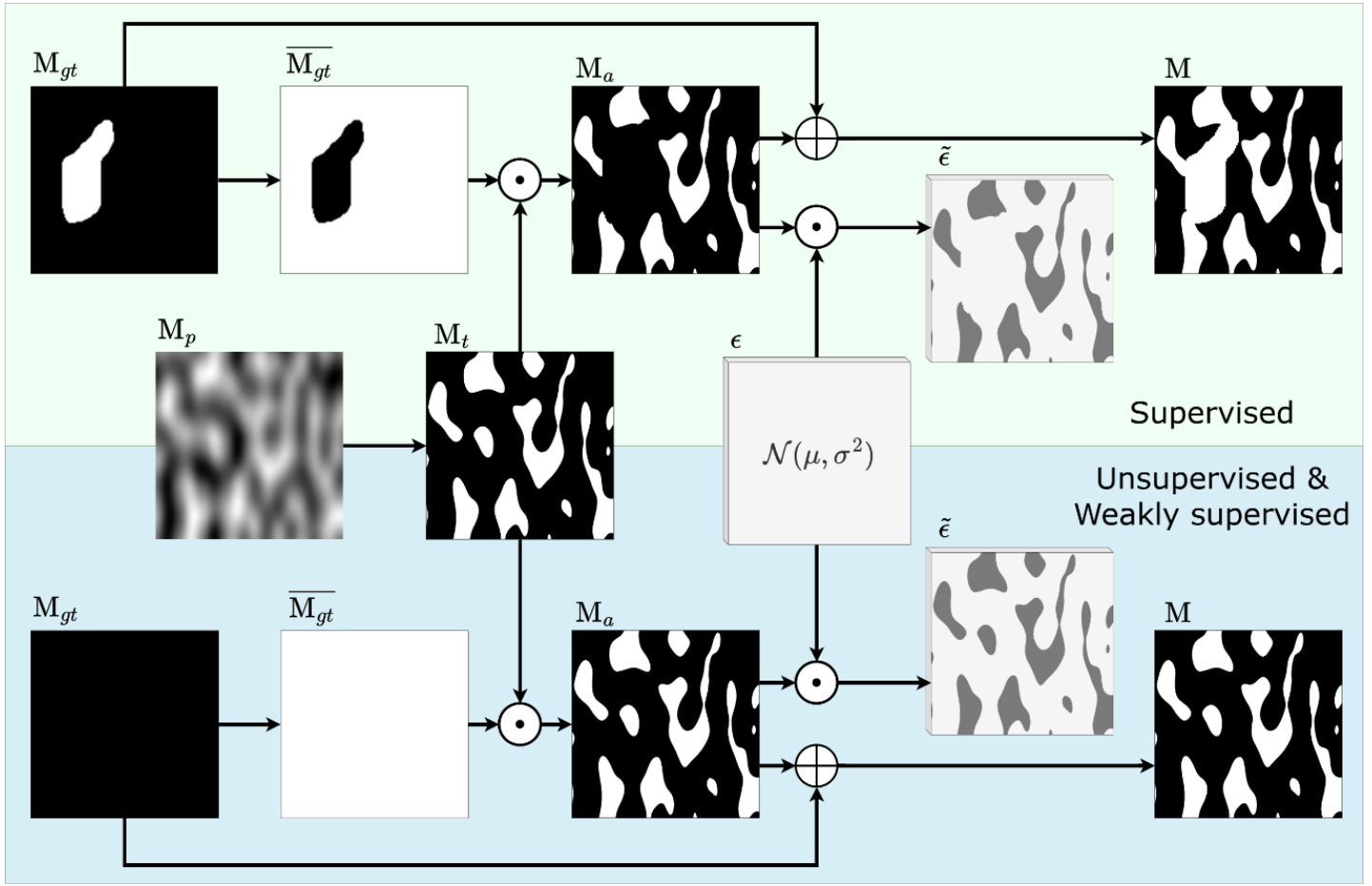
$$\mathcal{L} = \gamma \cdot \mathcal{L}_{seg} + \mathcal{L}_{cls}$$

$$\gamma = \begin{cases} 1; \text{ if image is normal;} \\ 1; \text{ if image is anomalous and fully labelled;} \\ 0; \text{ if image is anomalous and weakly labelled;} \end{cases}$$

[3] Z. Liu, Y. Zhou, Y. Xu, Z. Wang, SimpleNet: A Simple Network for Image Anomaly Detection and Localization, CVPR 2023.
[4] B. Rolih, M. Fučka, D. Skočaj, No Label Left Behind: A Unified Surface Defect Detection Model for all Supervision Regimes, JIM, 2025.

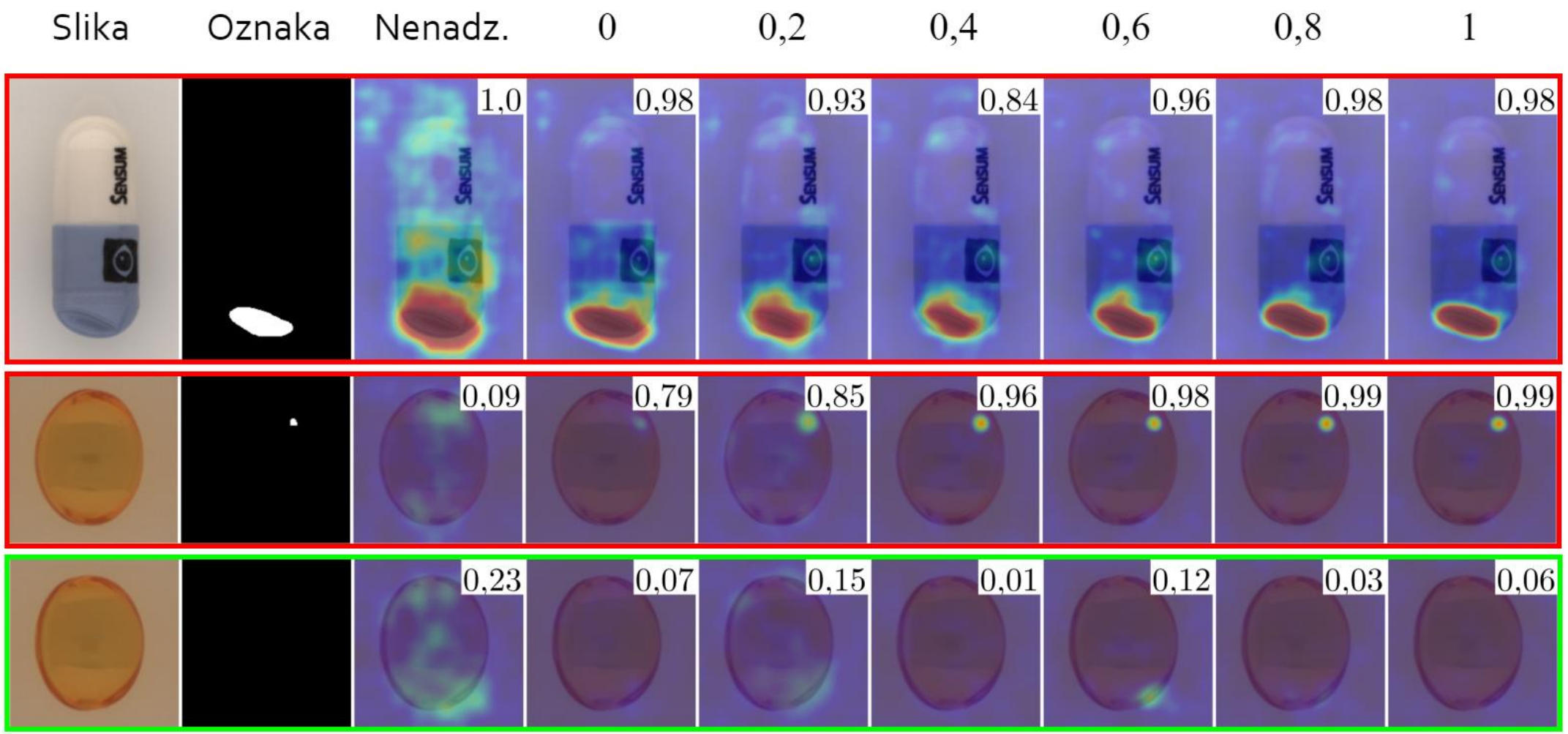
Generiranje anomalij

- Kombiniramo resnične in sintetične anomalije
- Perlinov šum
- Gaussov šum
- Oznake
  - Na nivoju slike
  - Na nivoju pikslov
- Omogočimo:
  - Delno nadzorovani način
  - Nenadzorovani način

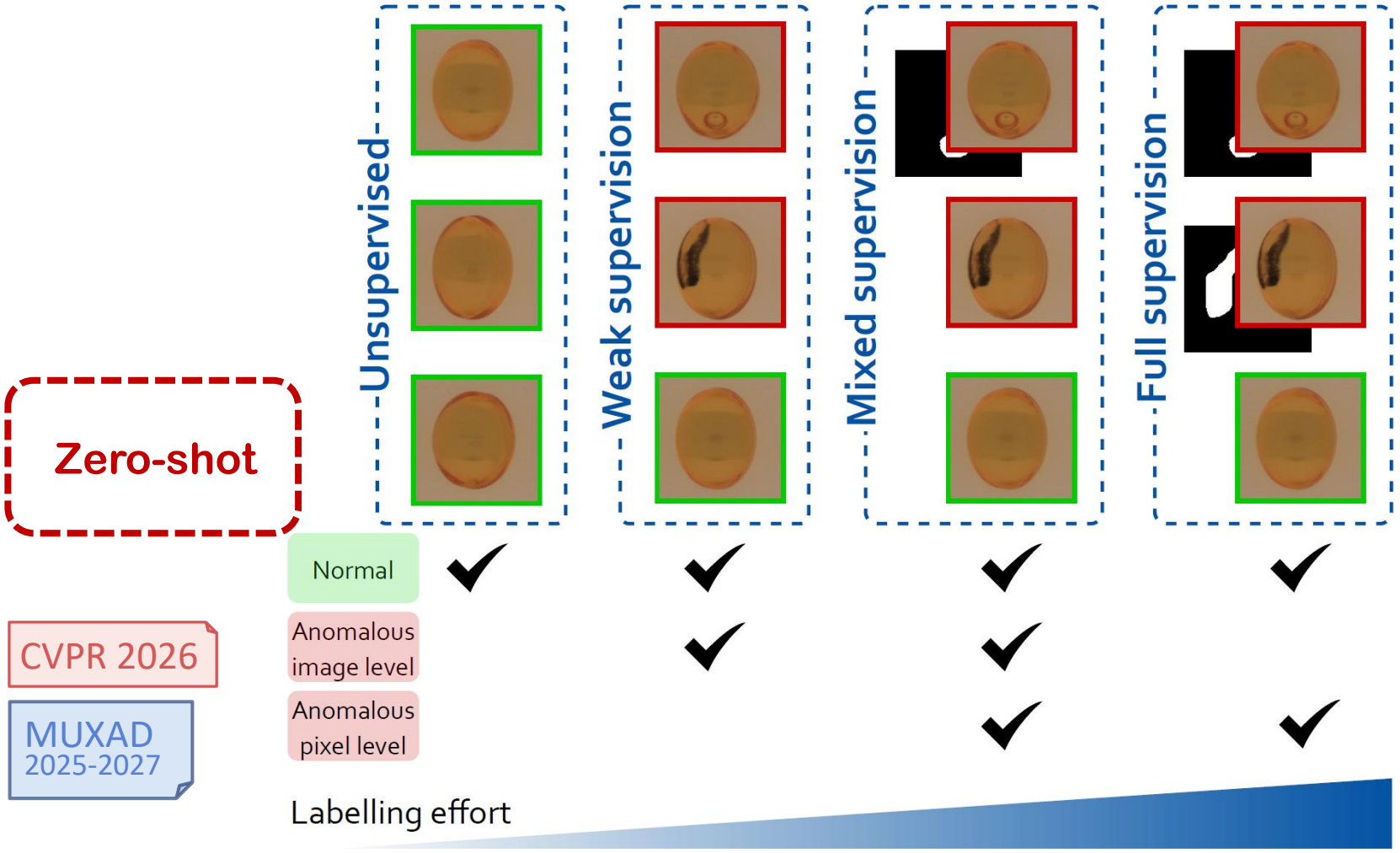


Kvalitativni rezultati

- Delno nadzorovano učenje -> Mešani nadzor -> Popolnoma nadzorovano učenje

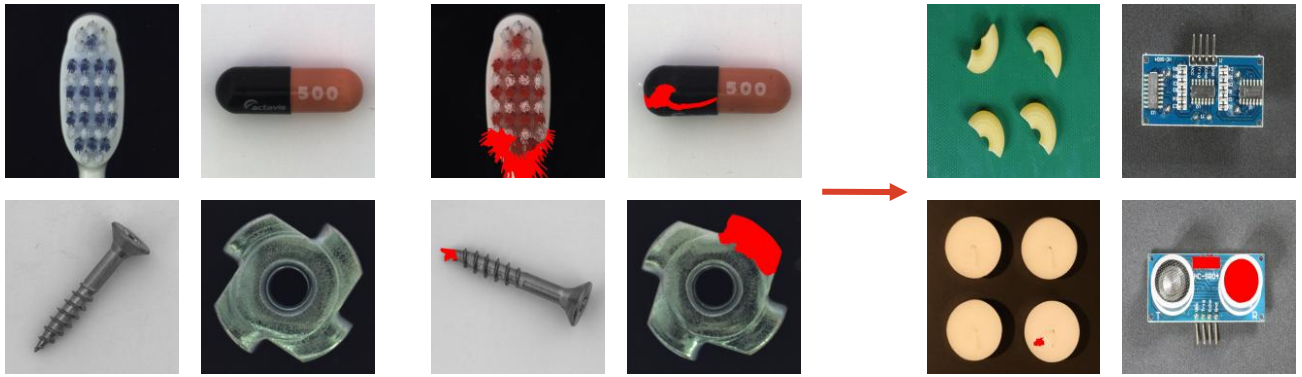


Načini učenja modelov



Detekcija anomalij brez učnih primerov slik

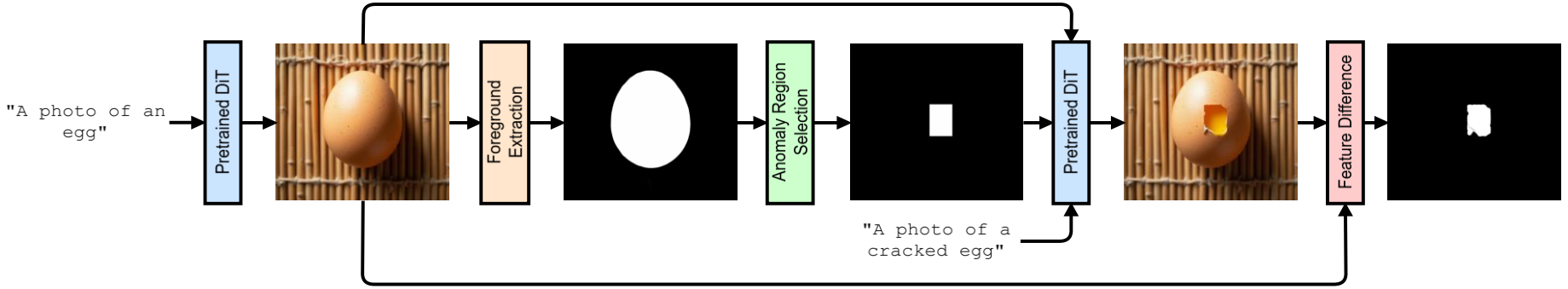
- Dejansko predstavlja **splošno detekcijo / segmentacijo napak**
- Učimo na učni bazi A → Testiramo na nepovezani bazi B
- Uporabljamo znanje, zakodirano v velikih slikovno-jezikovnih in vizualnih temeljnih modelih (VLM & VFMs, MLLMs)



Učenje Testiranje

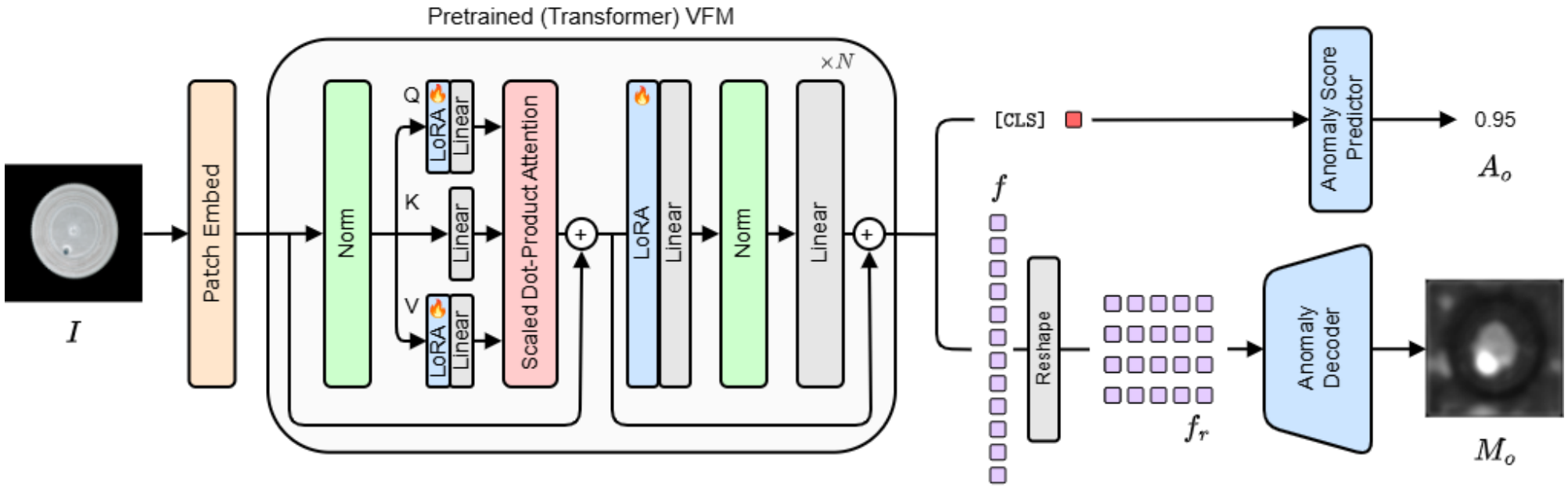
- Predlagani pristopi:
  - **Shema za sintetično generiranje napak** → večja raznolikost podatkov
  - **AnomalyVFM** → značilke v VFM, prilagojene za detekcijo napak

Generiranje sintetičnih podatkovnih zbirk





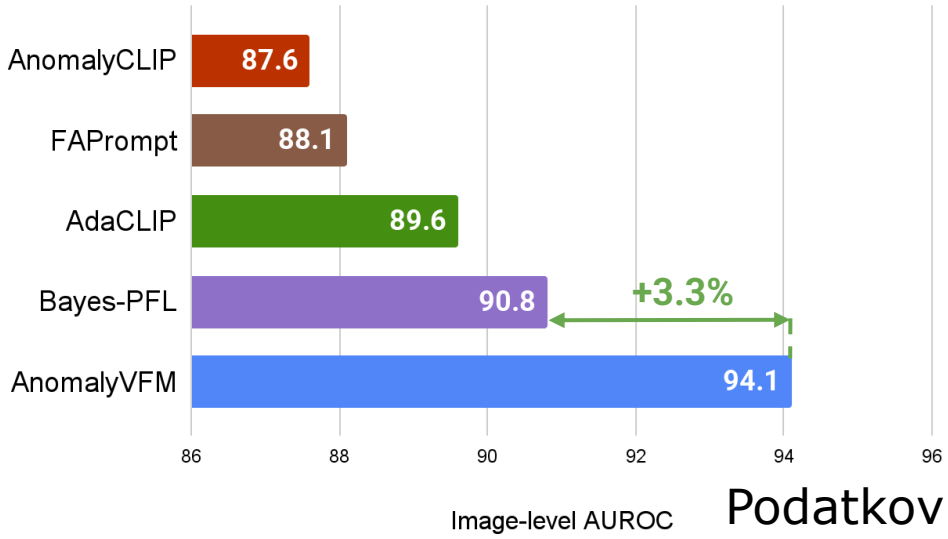
AnomalyVFM

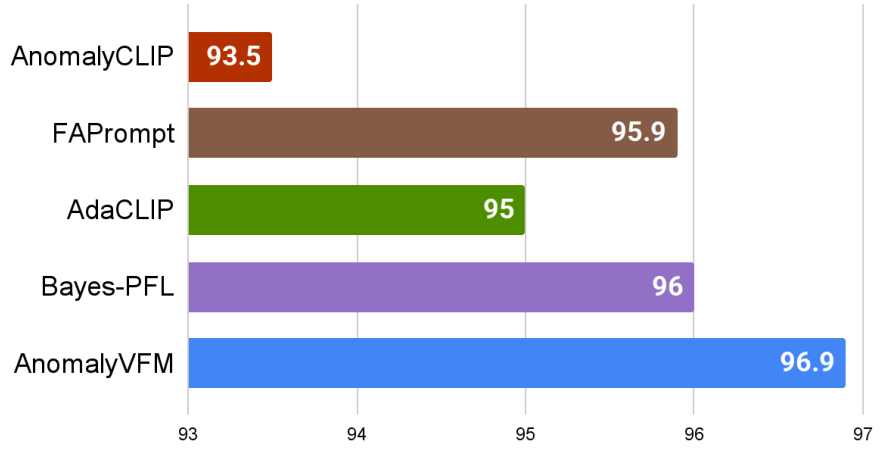


- Dodamo LoRA na vsak nivo VFM
- Dodamo dekoder in prediktor
- **Močen VFM za detekcijo splošnih anomalij**

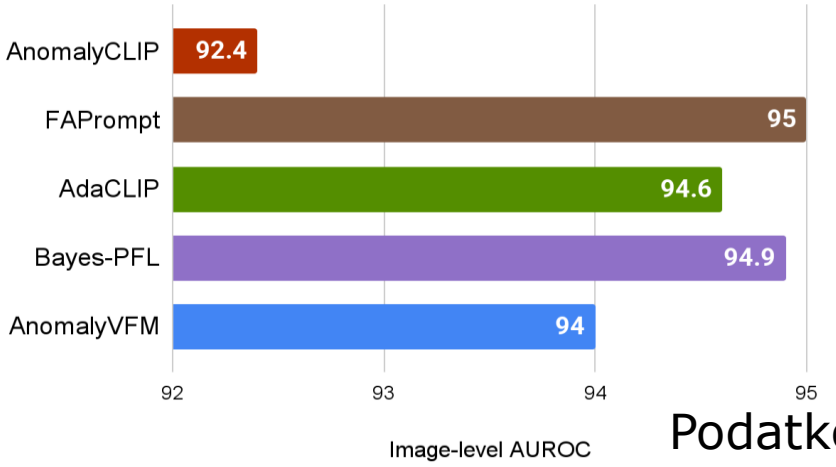
CVPR 2026

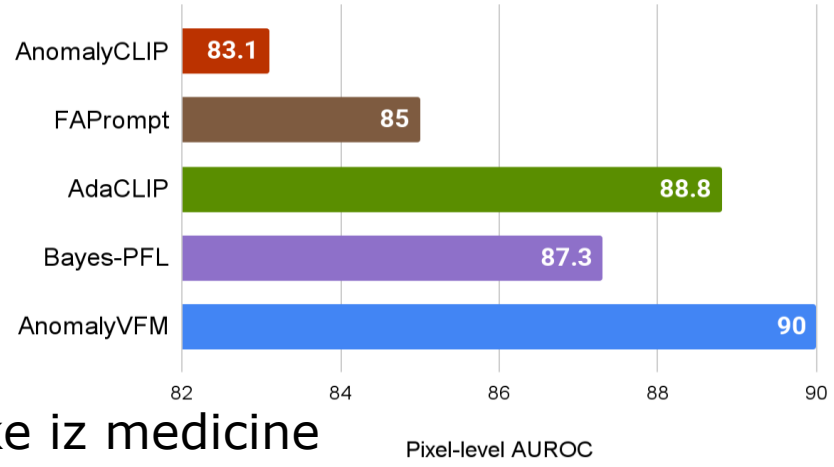
AnomalyVFM - rezultati





Podatkovne zbirke iz industrije

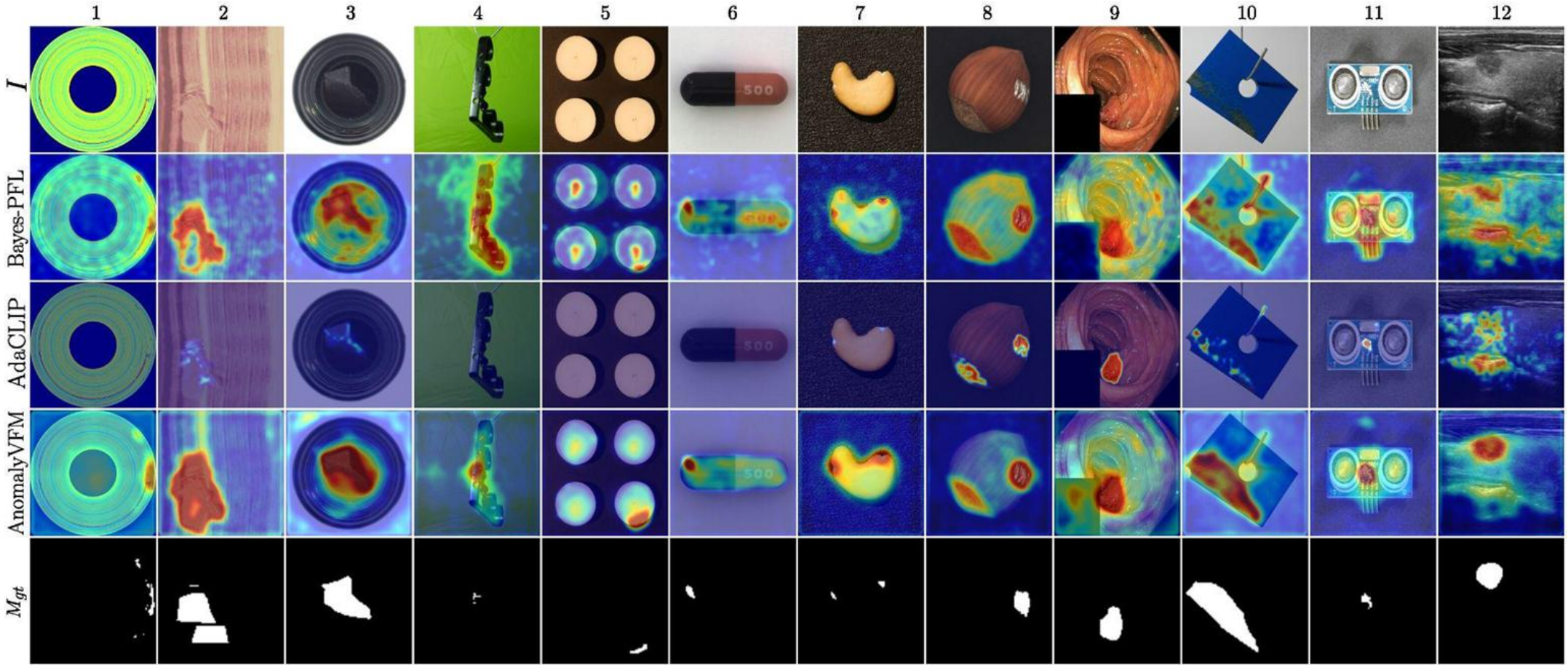




Podatkovne zbirke iz medicine

CVPR 2026

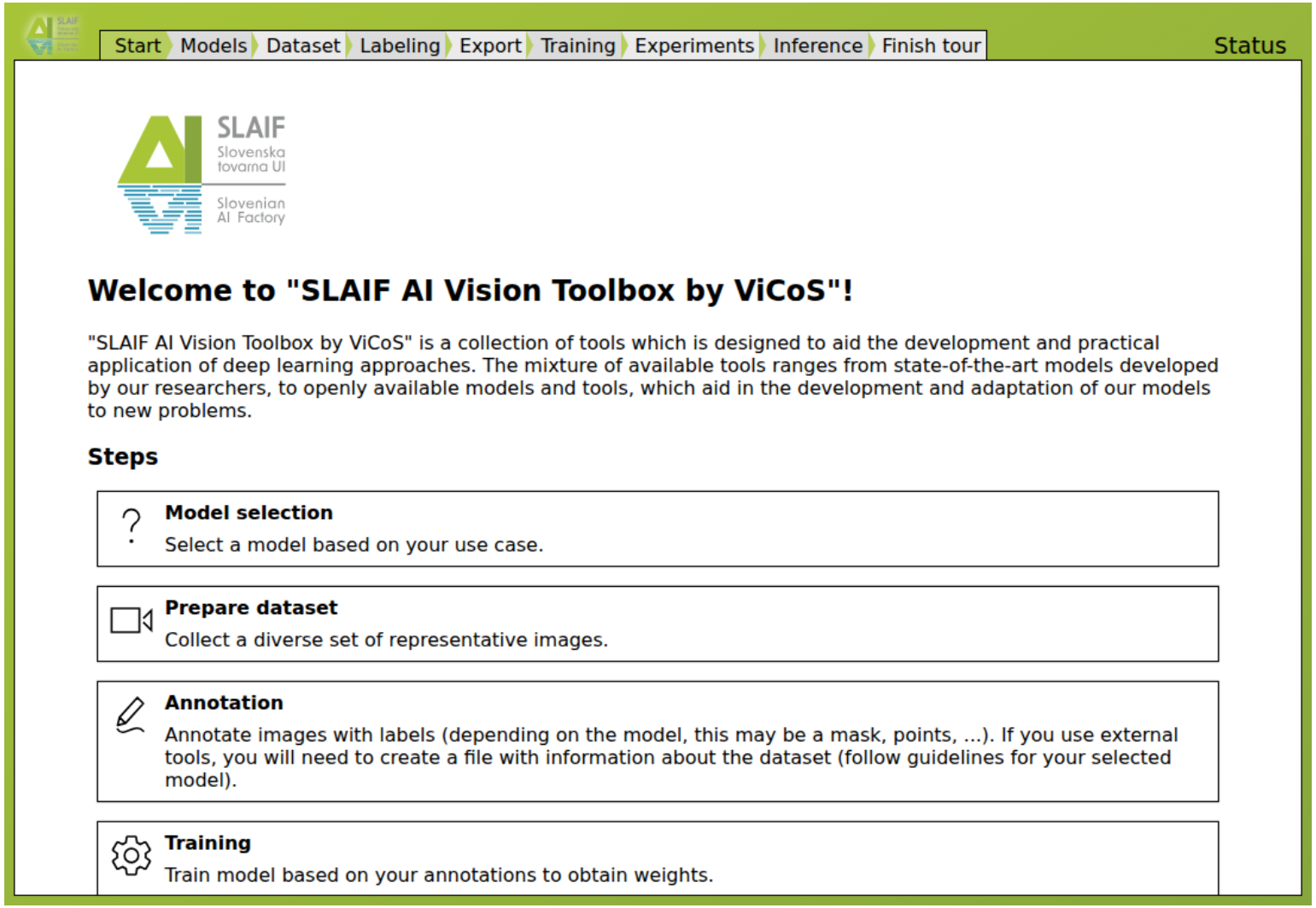
AnomalyVFM – kvalitativni rezultati



Slovenska tovarna umetne inteligence (SLAIF)

Izbrani modeli na voljo industriji za praktično uporabo

- Omogoča uporabnikom:
  - Polavtomatsko označevanje podatkov
  - Učenje modelov na domeni
  - Evalvacija na domeni
  - Inferenca na novih slikah
- Trenutno dostopni:
  - SuperSimpleNet
  - CeDiRNet

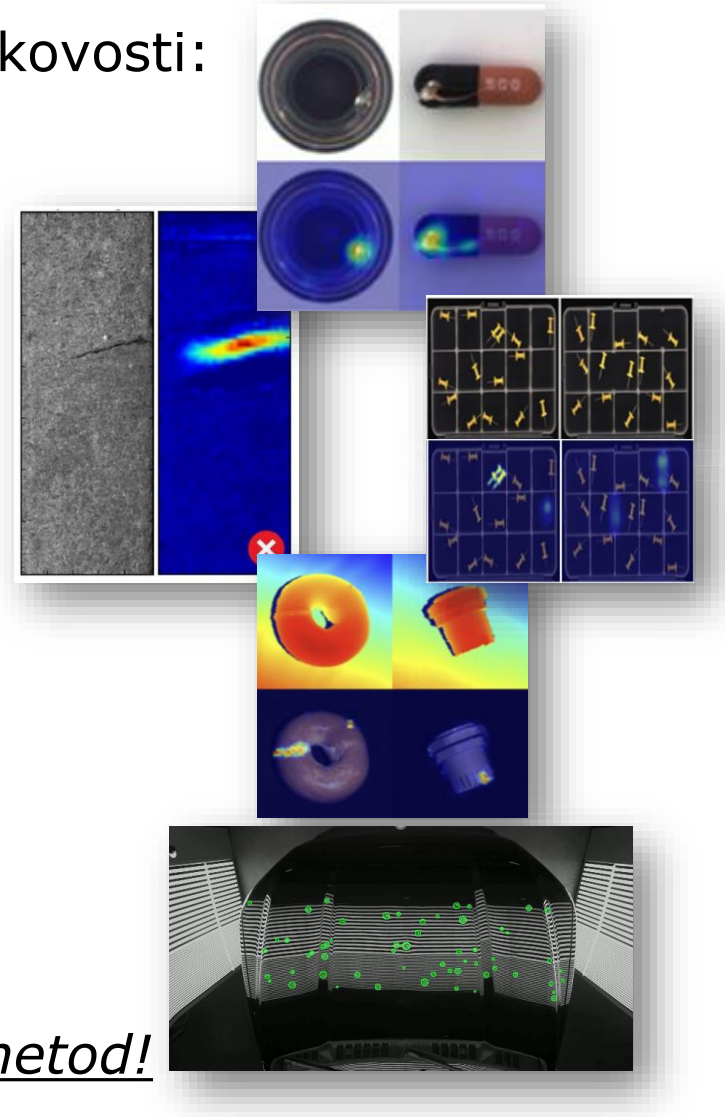


https://www.slaif.si/services (storitev "Image Analysis for Quality Control")

Zaključek

Ključni izzivi za podjetja, ko se lotijo avtomatizacije nadzora kakovosti:

- Definirati, kaj je napaka in kaj ni napaka!
  Veliko slik + besedilni opis.
- Ali je napaka razvidna SAMO iz slike?
  Mogoče slika RGB ni dovolj!
- Kako zajeti slike, da bo napaka dovolj velika na sliki?
  Mogoče je potreben zunanji integrator opreme za strojni vid.
- Ali je dovolj slik izdelkov z napakami in brez napak?
  Če niso na voljo, že evalvacije ni mogoče izvesti!



Ključni izziv za raziskovalne skupine pri razvoju novih metod:

- Ali rešujejo relevantne probleme za industrijo?

Primerni učni podatki so potrebni za znanstveni razvoj metod!