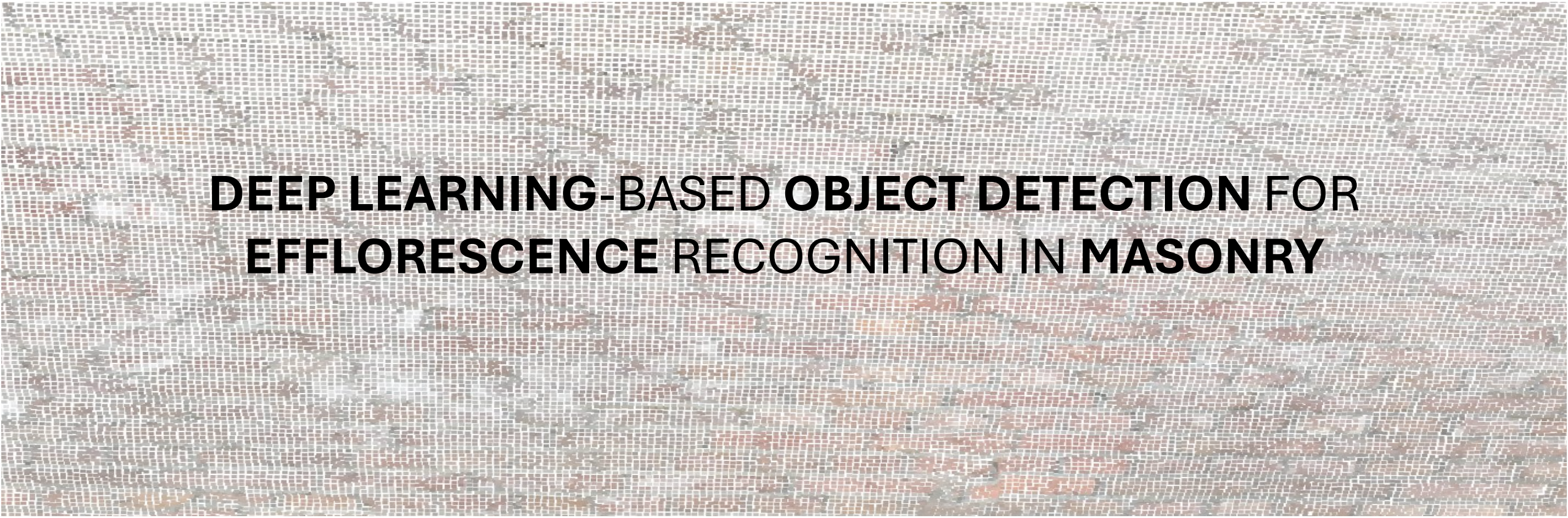

DEEP LEARNING-BASED OBJECT DETECTION FOR EFFLORESCENCE RECOGNITION IN MASONRY

TU Delft

Valentijn Camiel Cloo
5436958

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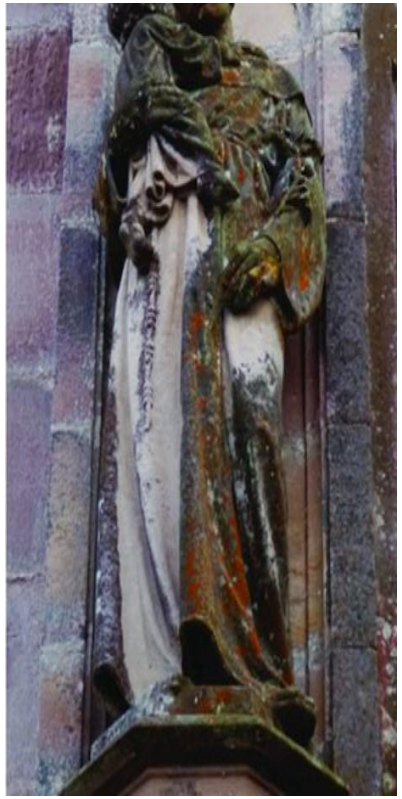
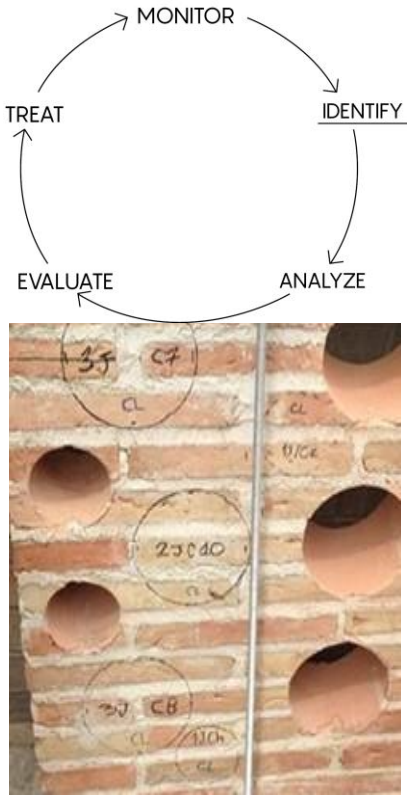
ARCHITECTURAL CONSERVATION



ENVIRONMENTAL VULNERABILITY

PRESERVATION CHALLENGES



SUSTAINABLE CONSERVATION

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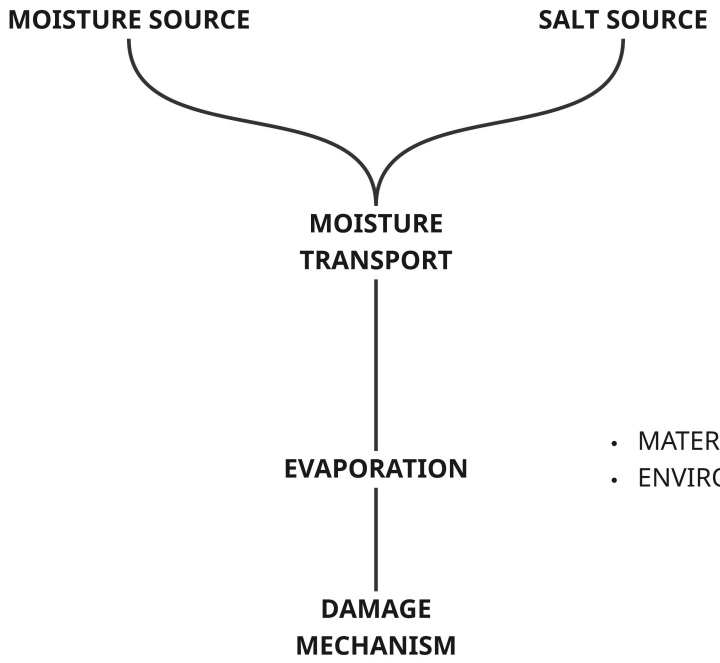
INTRODUCTION & RESEARCH CONTEXT

EFFLORESCENCE: DEFINITION & CONTEXT

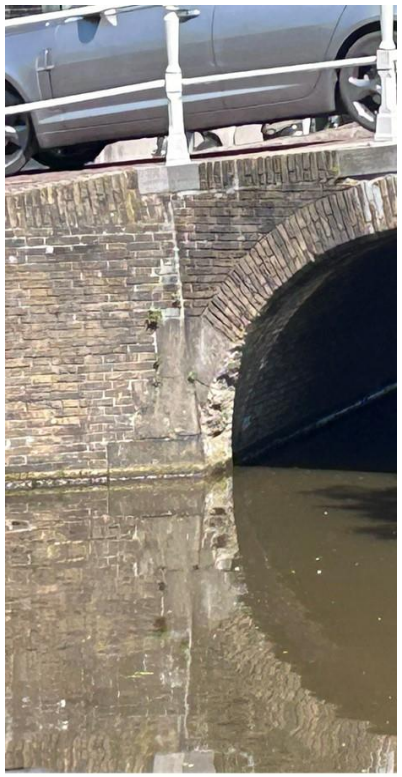
> *“Deposit of (soluble) salt crystals visible on the surface of the (dry) material”*



- MATERIAL PROPERTIES
- ENVIRONMENTAL CONDITIONS

MOISTURE SOURCE

GROUNDWATER



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PRECIPITATION

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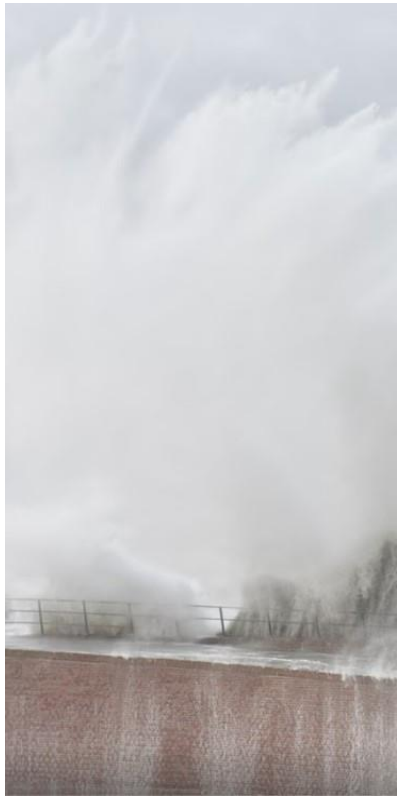
INFILTRATION & LEAKAGE

FLOODINGS

SALT SOURCE

MATERIAL



AEROSOL

EXCREMENTS

GROUNDWATER / SURFACE WATER

DE-ICING SALTS

MOISTURE TRANSPORT

- SOLUBILITY OF DIFFERENT SALTS
- CAPPILARY ACTION (RISING DAMP)
  - PORE SIZE (DISTRIBUTION’
  - DRYING SPEED
  - INTERFACE BRICK VS MORTAR

- SEEPAGE (LEAKAGE)

EVAPORATION

- EVAPORATION FRONT
- CRYSTALISATION PRESSURE

DAMAGE MECHANISM

DAMAGE MECHANISM

POWDERING

SPALLING

CRUMBLING

BLISTERING

ALVEOLIZATION

EROSION

EXFOLIATION

DELAMINATION

INTRODUCTION & RESEARCH CONTEXT

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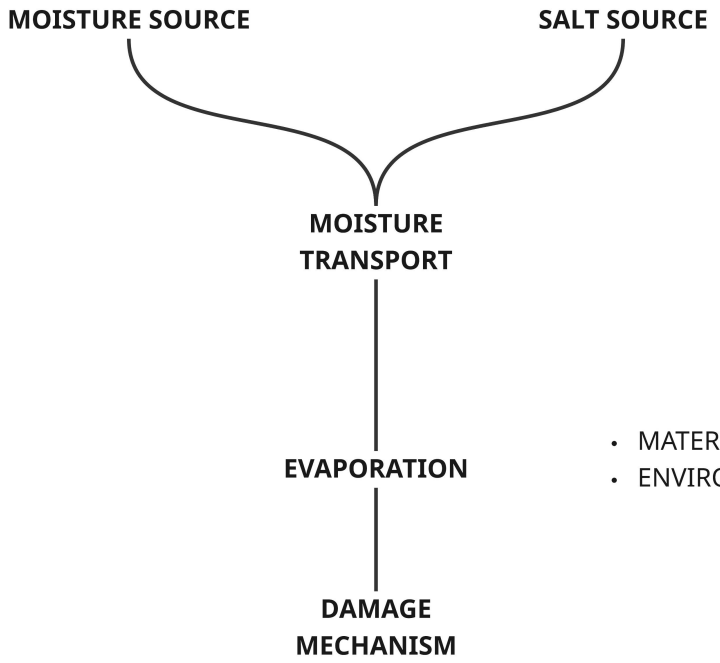


- MATERIAL PROPERTIES
- ENVIRONMENTAL CONDITIONS

INTRODUCTION & RESEARCH CONTEXT

EFFLORESCENCE: EFFECT

Development of salt crystallization damage over a period of 5 years (Van Hees et al,, 2020)

Year 1

INTRODUCTION & RESEARCH CONTEXT

EFFLORESCENCE: EFFECT

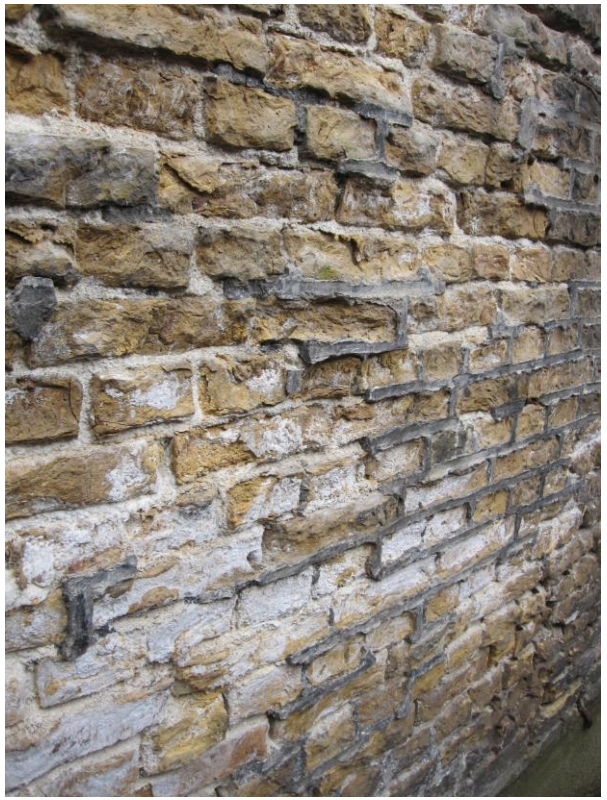
Development of salt crystallization damage over a period of 5 years (Van Hees et al,, 2020)

Year 5

INTRODUCTION & RESEARCH CONTEXT

EFFLORESCENCE: CONTEXT

< 5 years old



> 80 years old

INTRODUCTION & RESEARCH CONTEXT

EFFLORESCENCE: SIMILARITY

ENCRUSTATION

BIOLOGICAL GROWTH

GRAFFITI

PROBLEM STATEMENT & RESEARCH QUESTIONS

PS

The **manual** process of surveying **resource-intensive** lacks **scalability** requires **expert** evaluation, leading to **inefficiencies** and potential **subjective** inaccuracies in **assessing** the conditions while tracking **changes** over time, highlighting the need for reliable, **automated** deep learning-based **detection methods** on **efflorescence** related damage in **heritage** buildings.

RQ

*How can **deep learning** models be applied to **improve** the **detection** of **efflorescence** in **masonry** buildings in the Netherlands?*

PROBLEM STATEMENT & RESEARCH QUESTIONS

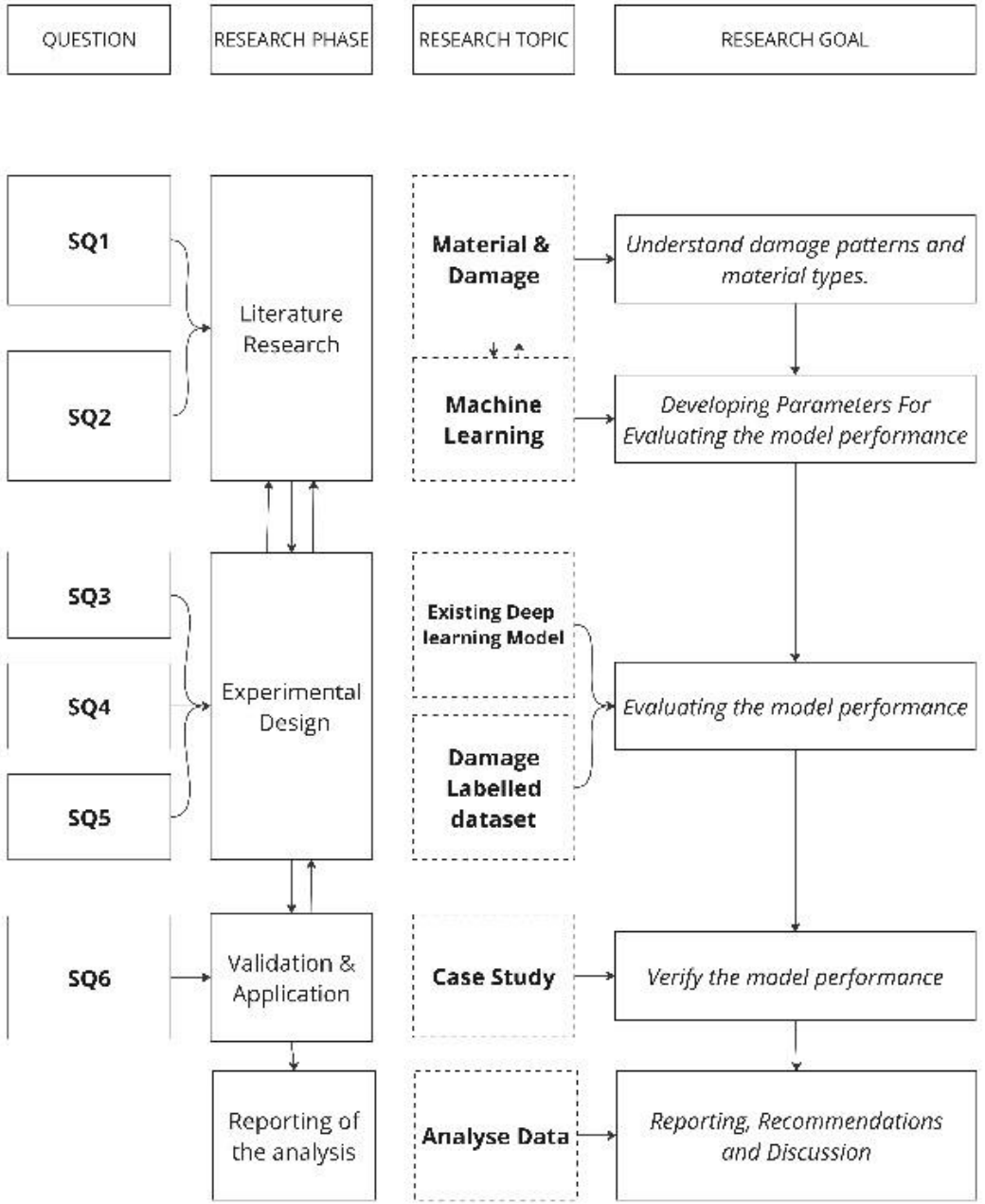
SUB RESEARCH QUESTIONS

SRQ

- What are the **visual characteristics** of **efflorescence** on masonry, and how do these factors present **challenges** for **detection**?
- Which deep **learning models** are most suitable for detecting and **classifying efflorescence** on masonry, based on **performance criteria**?
- What is the effect of **variables** (such as image quality, lighting, and orientation) on the **performance** of the **model**?
- How can we **improve** model **performance** by addressing **misclassification** of similar damage types and **co-occurrence** with **efflorescence**?
- How can the **integration** of **thermal (IR)** imagery **improve** the detection accuracy and reliability of **efflorescence** in masonry?
- How well does the **enhanced model** perform when **evaluated** on unseen data and applied to real-world **case studies** of **efflorescence**?

METHODOLOGY

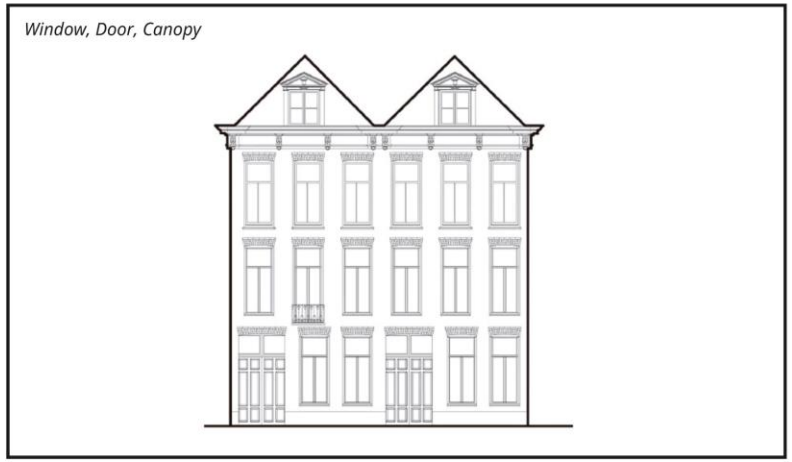
RESEARCH PHASING



RESULTS

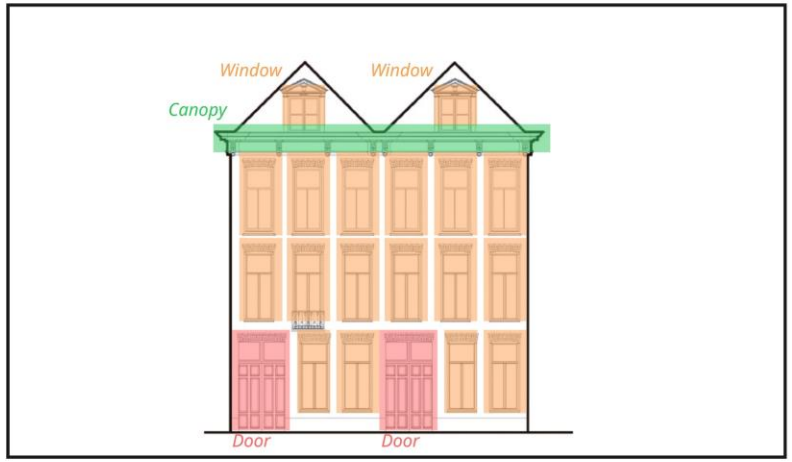
MACHINE LEARNING

Classification



Object Detection

Semantic Segmentation



Instance Segmentation

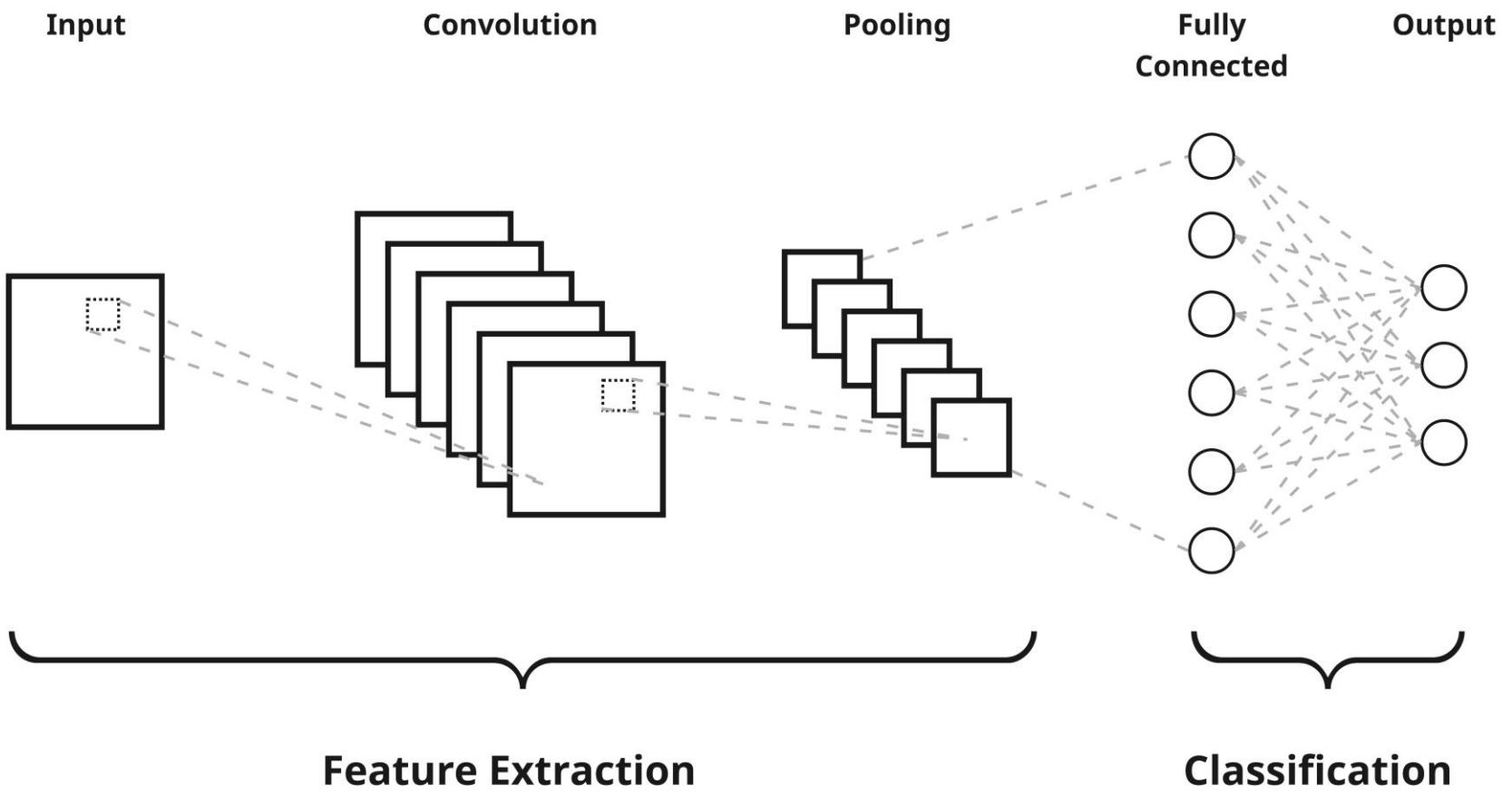
RESULTS

MACHINE LEARNING

Early layers
- Edge detection
- intersection of edges
- textures / lines
- colour gradients

Middle layers
- shapes
- patterns
- objects

Deeper layers
- object parts
- complex objects



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MACHINE LEARNING

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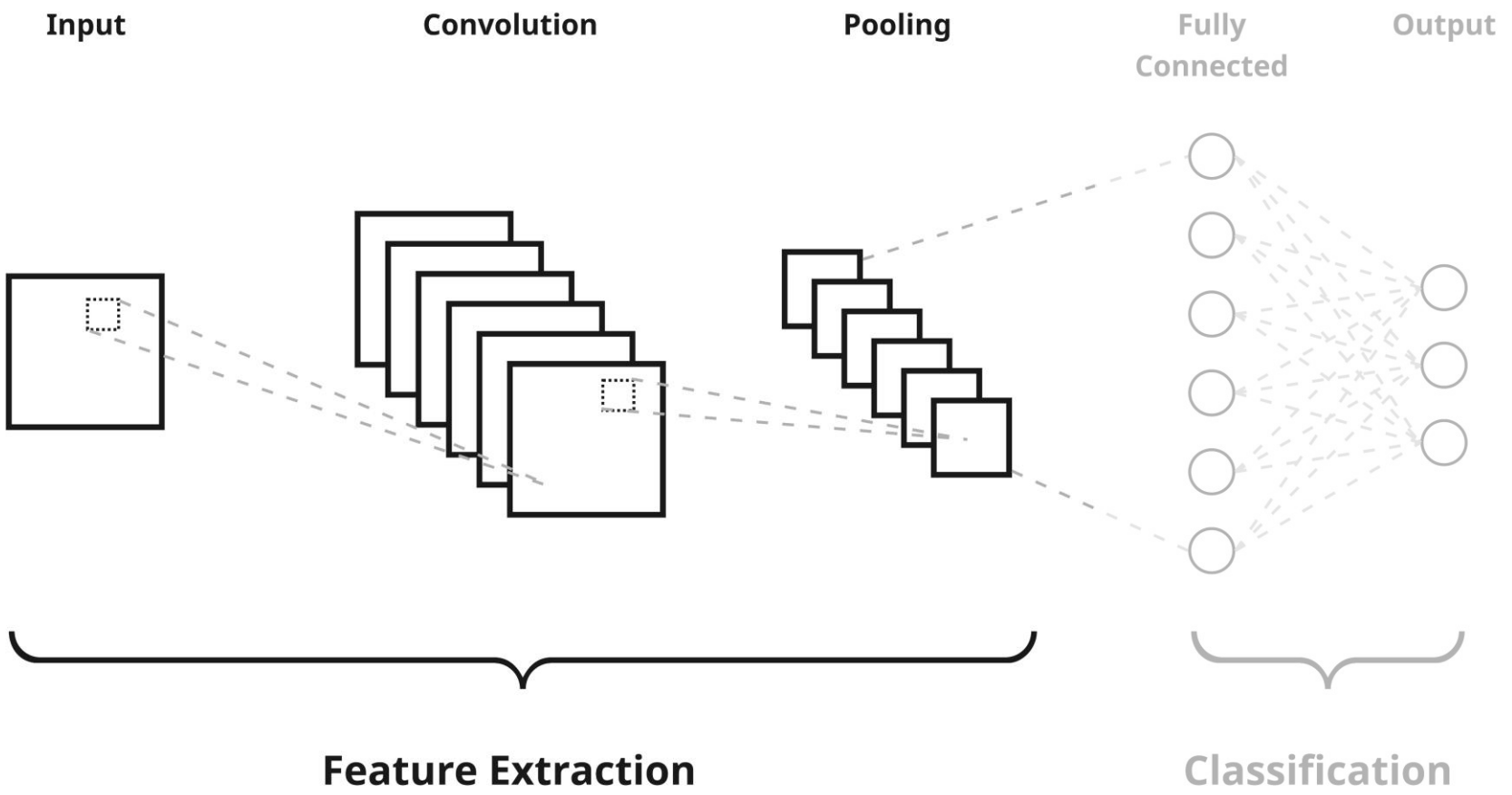

RESULTS

MACHINE LEARNING

RESULTS

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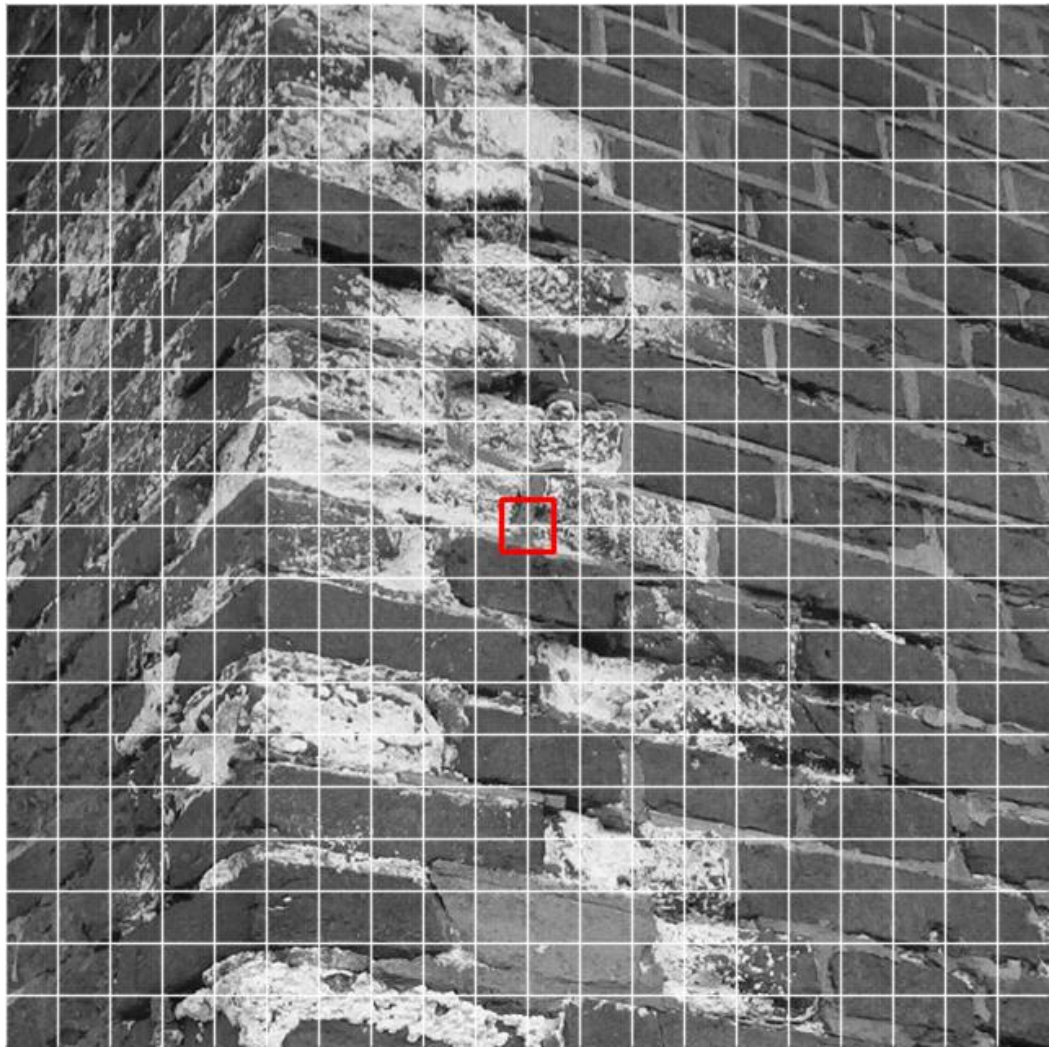
MACHINE LEARNING



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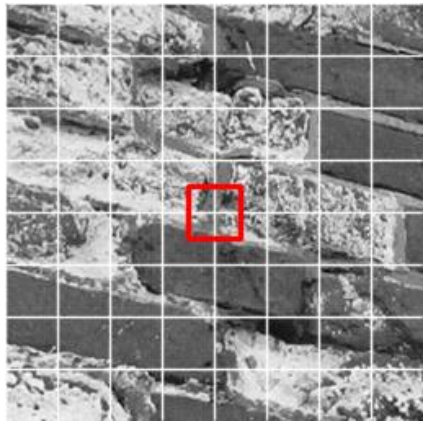
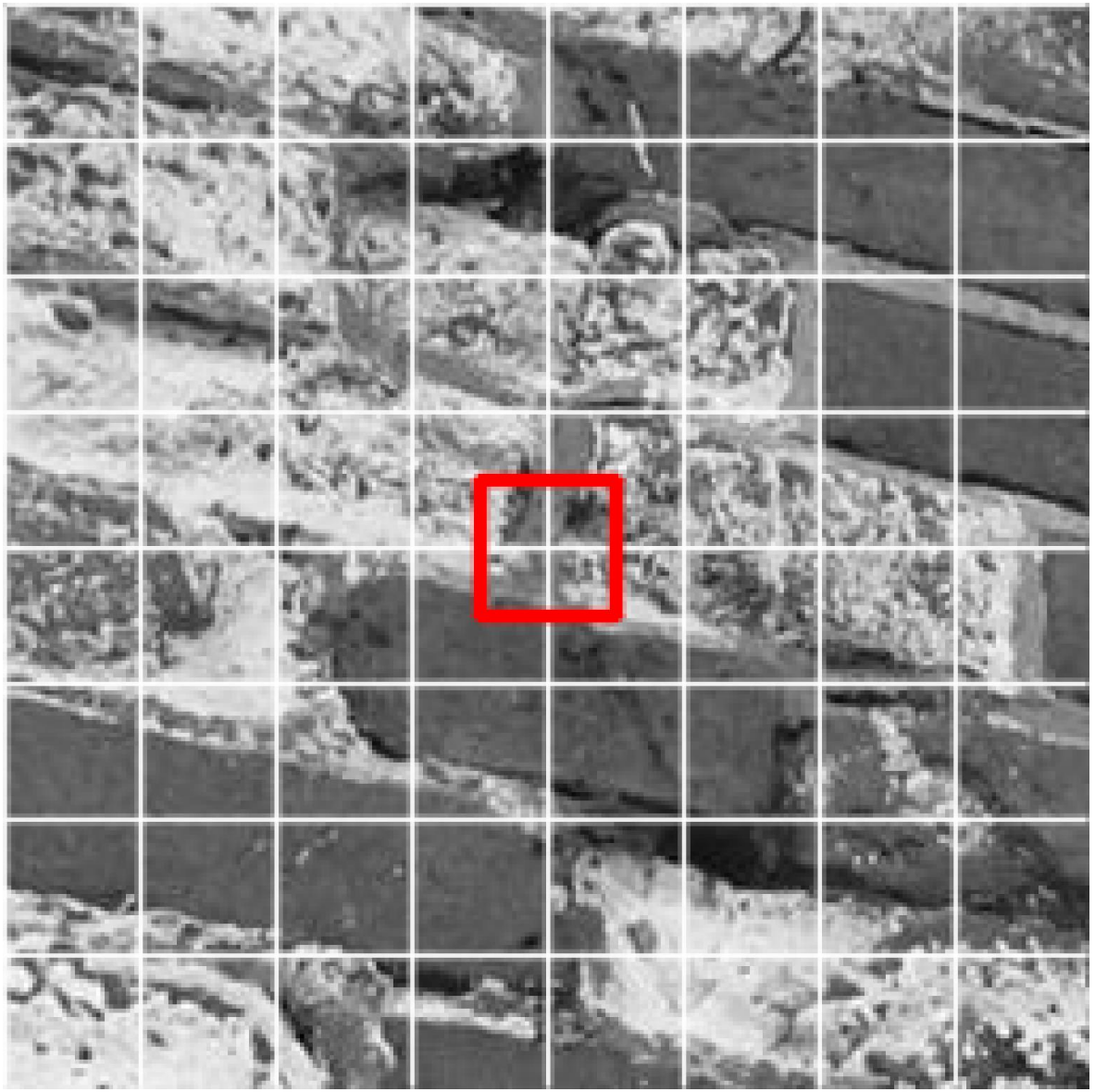


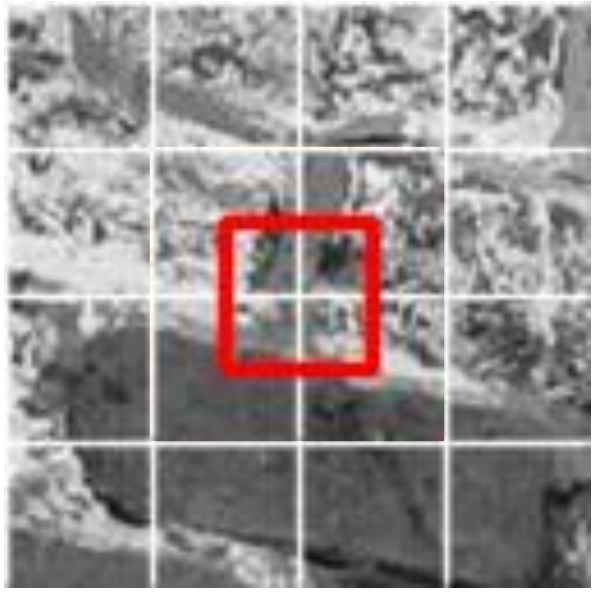
RESULTS

MACHINE LEARNING



RESULTS

MACHINE LEARNING



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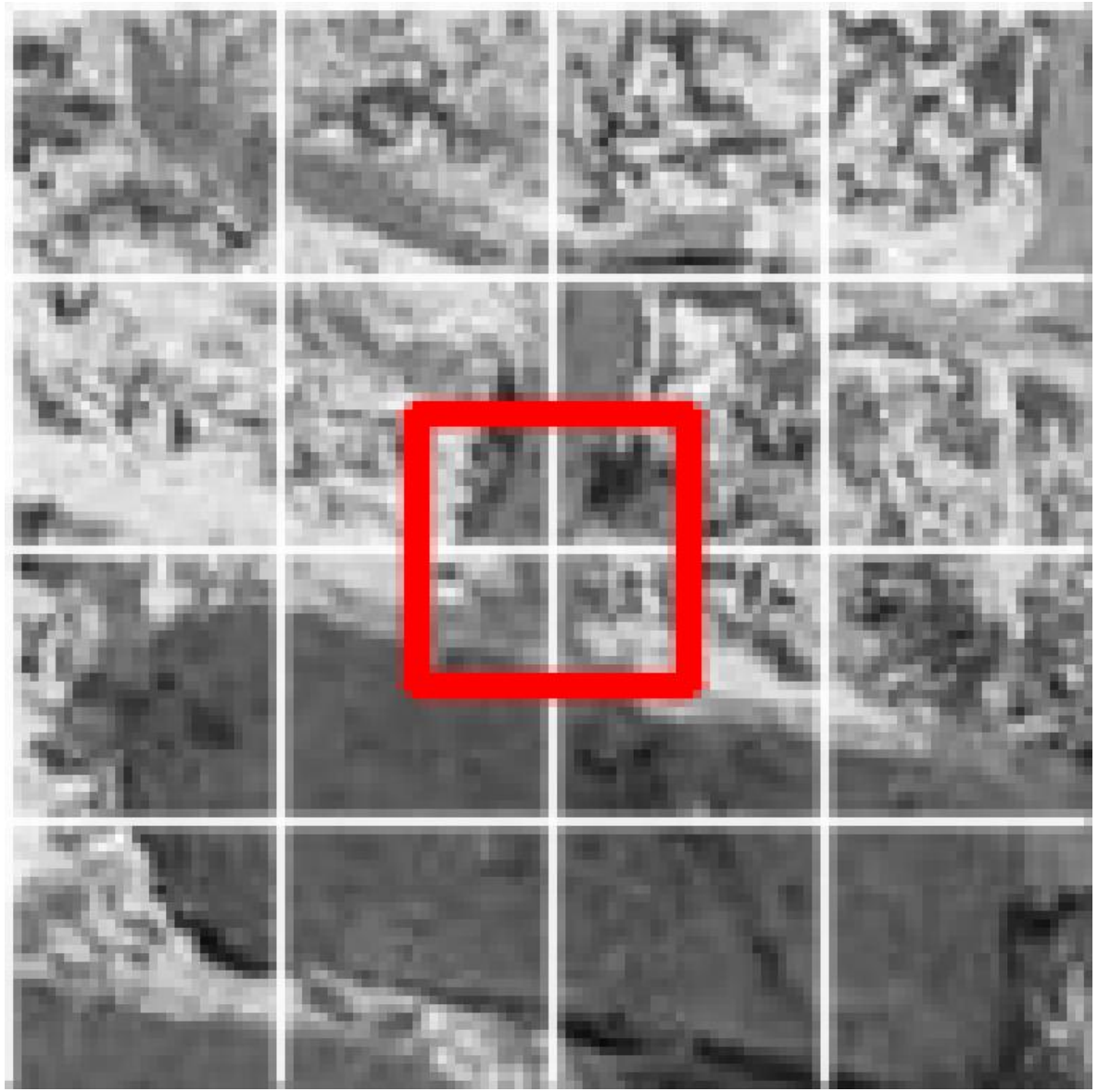
MACHINE LEARNING



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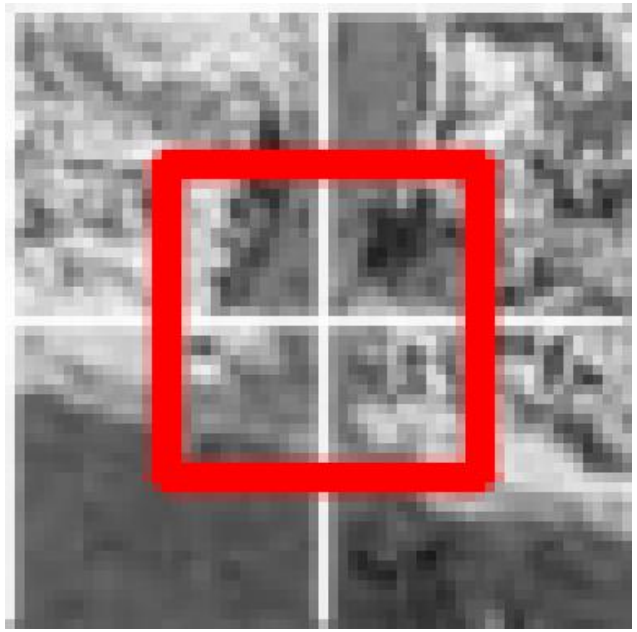

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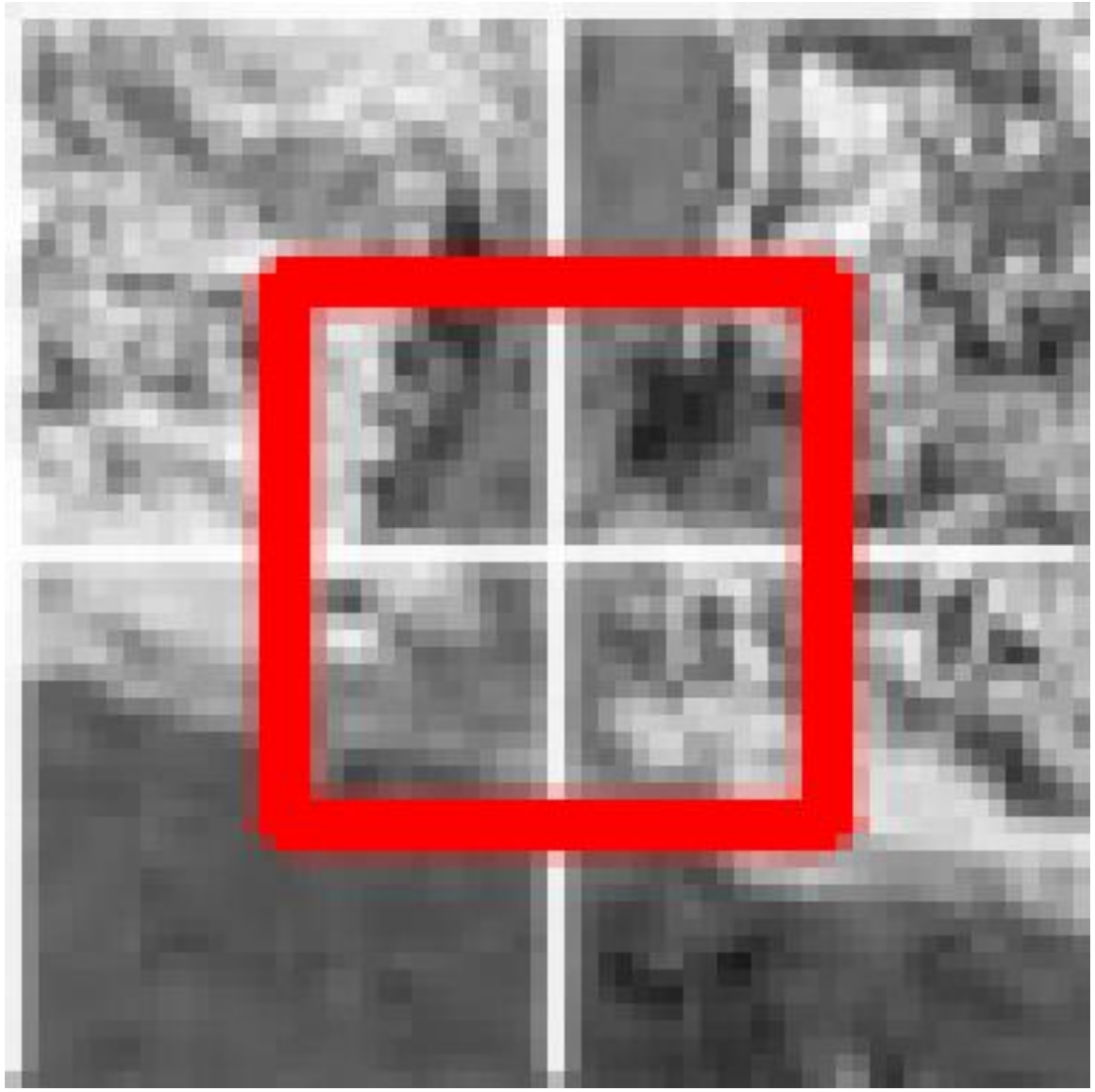

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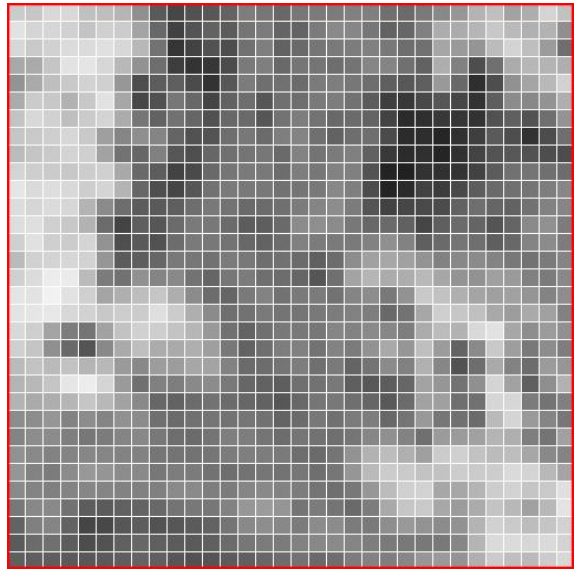

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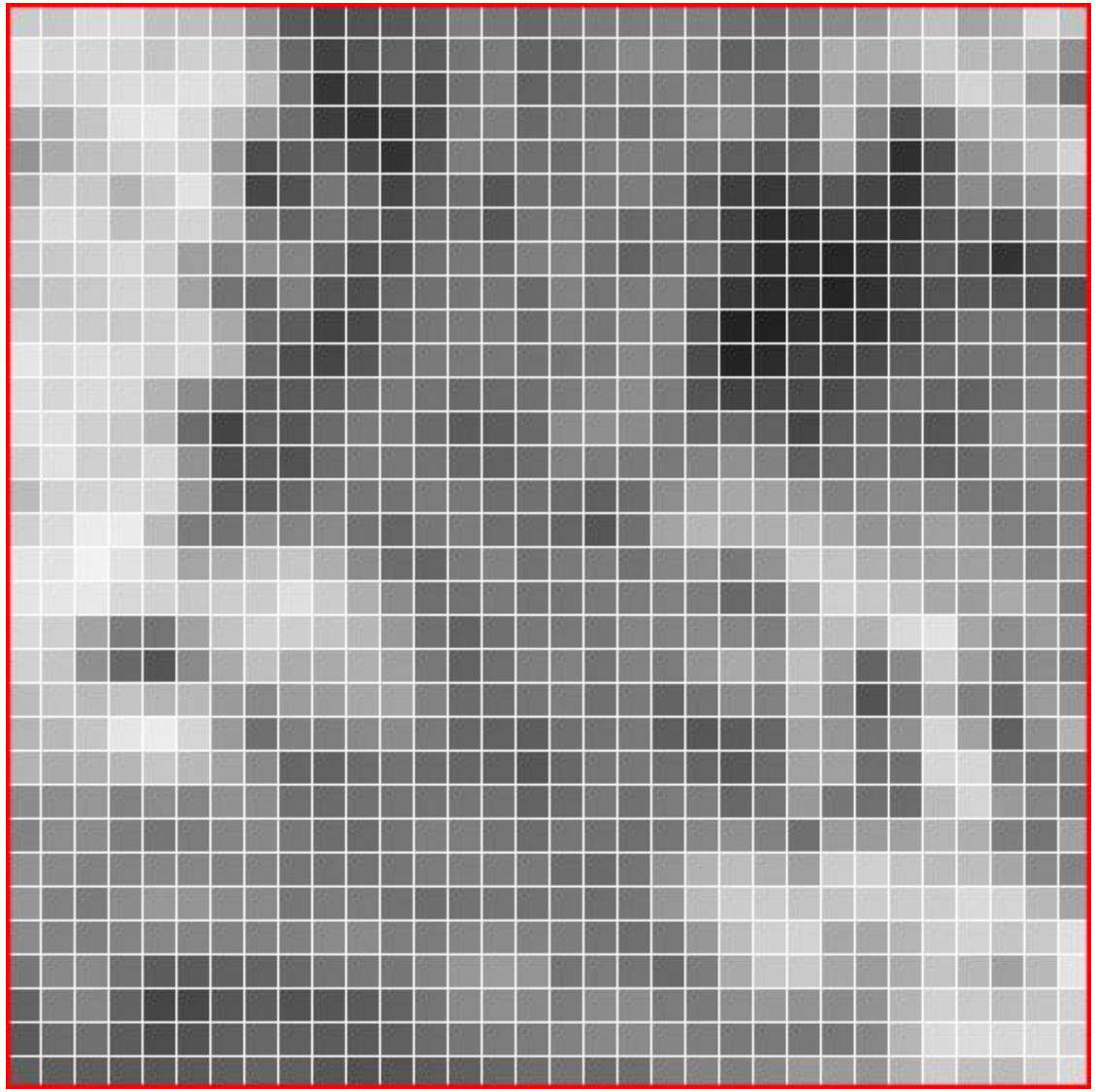

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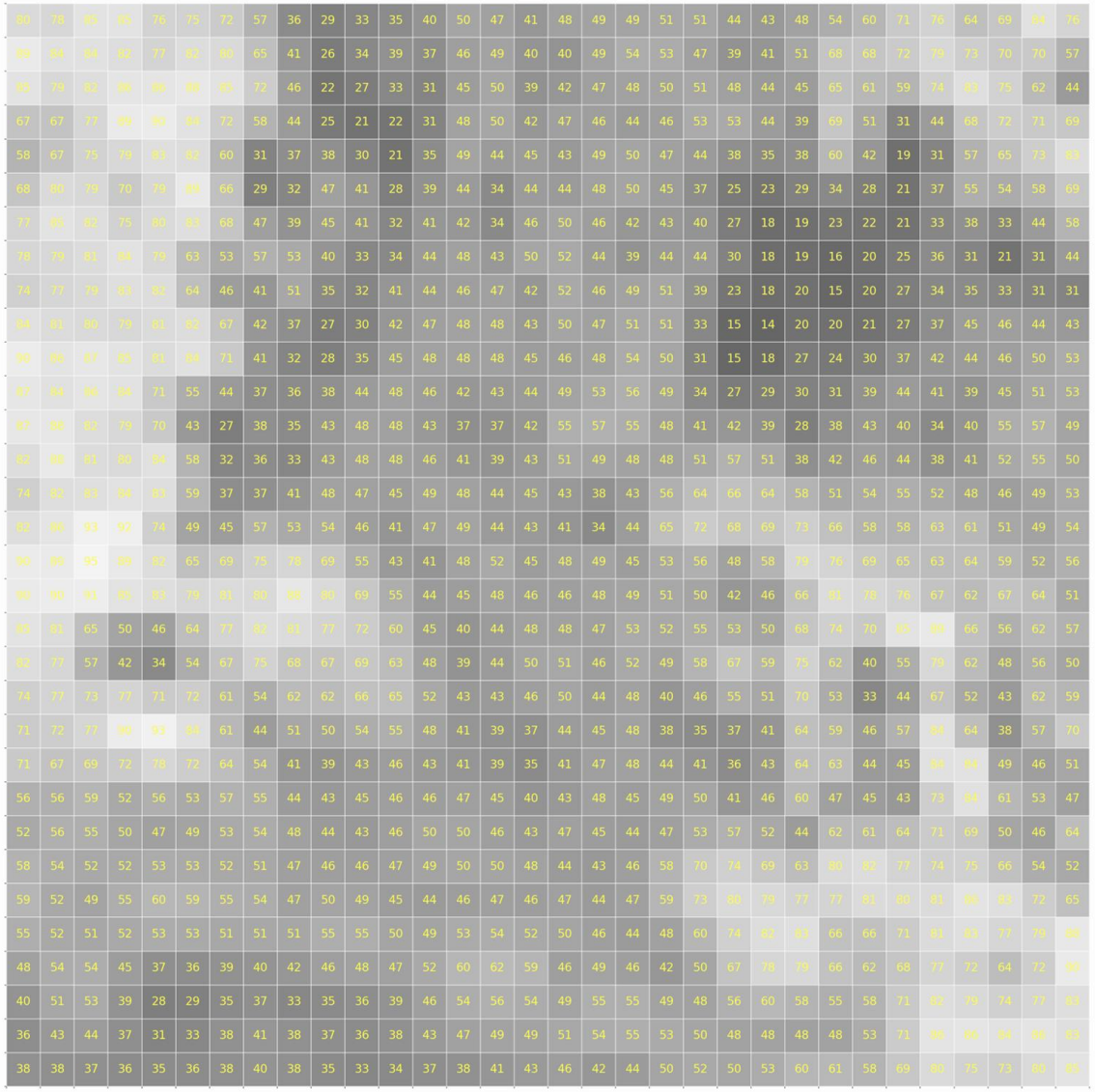

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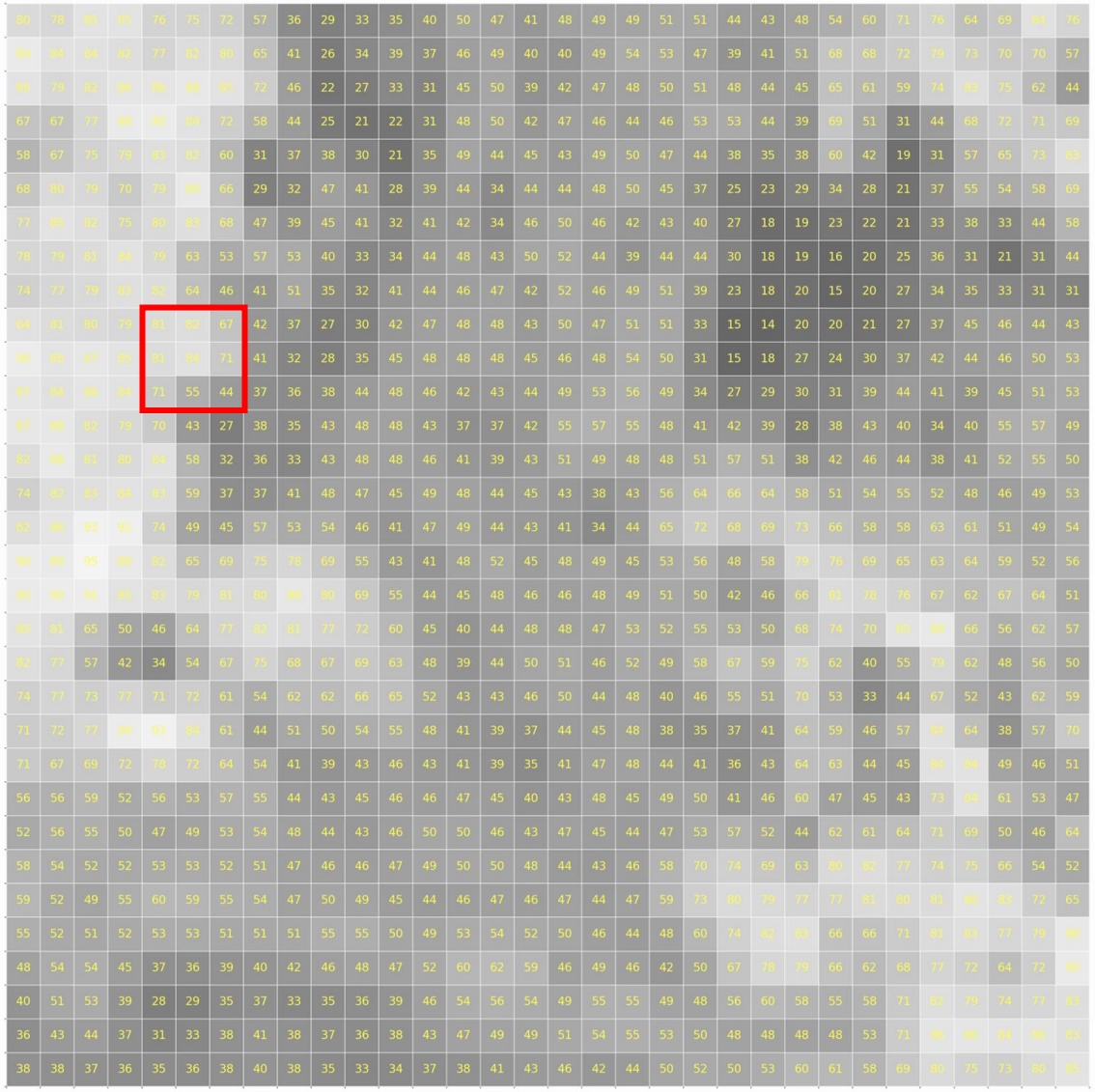

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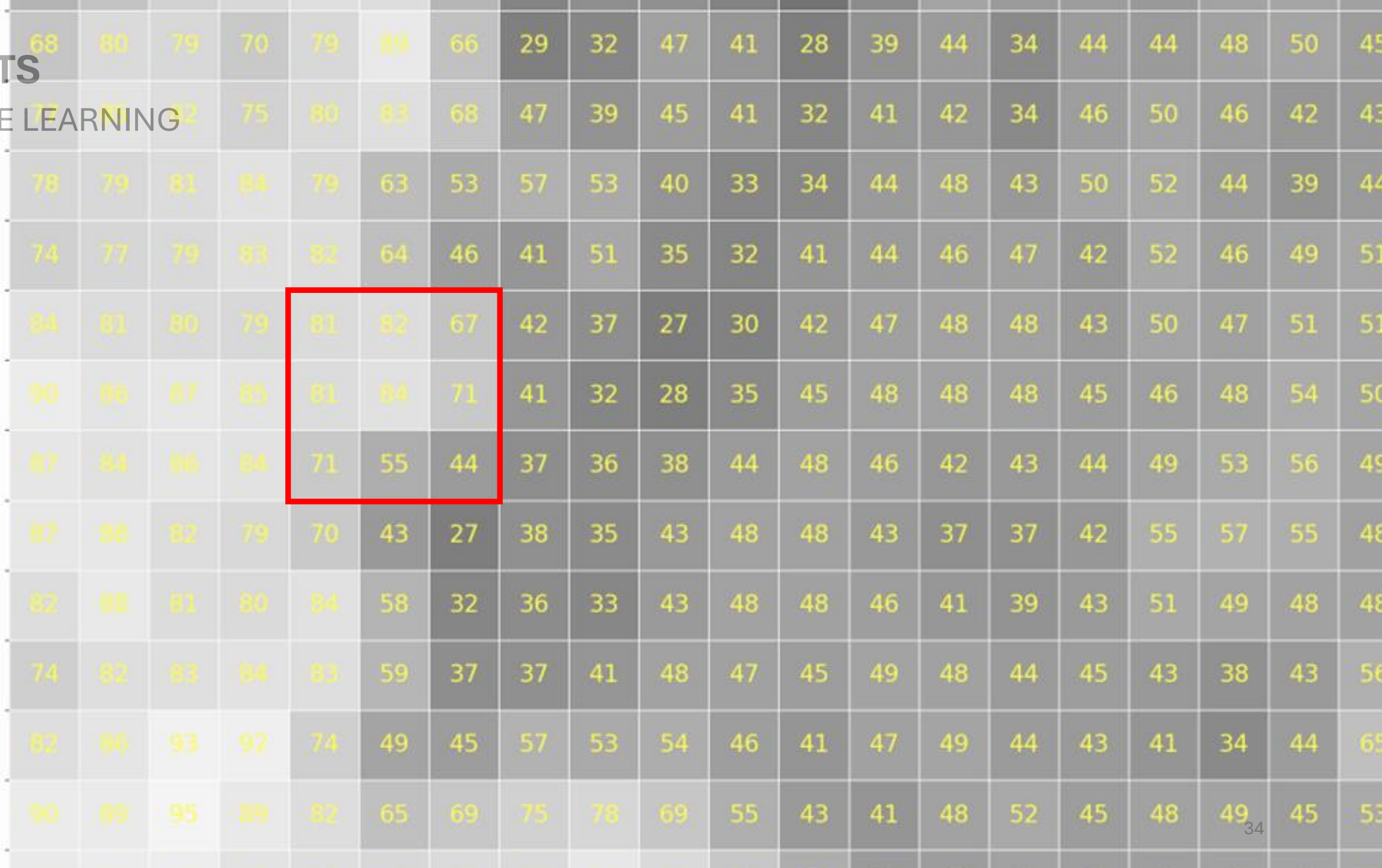

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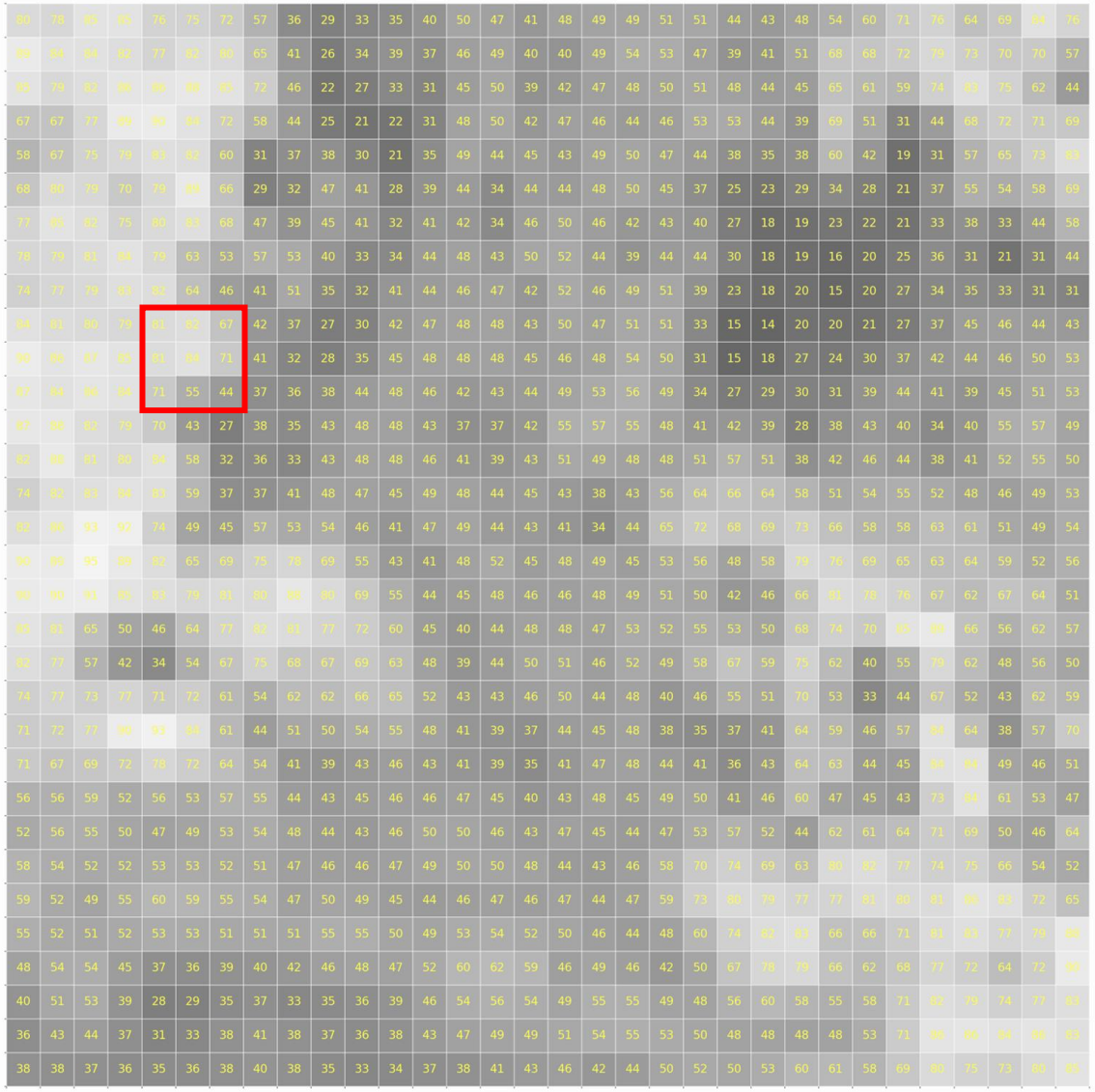

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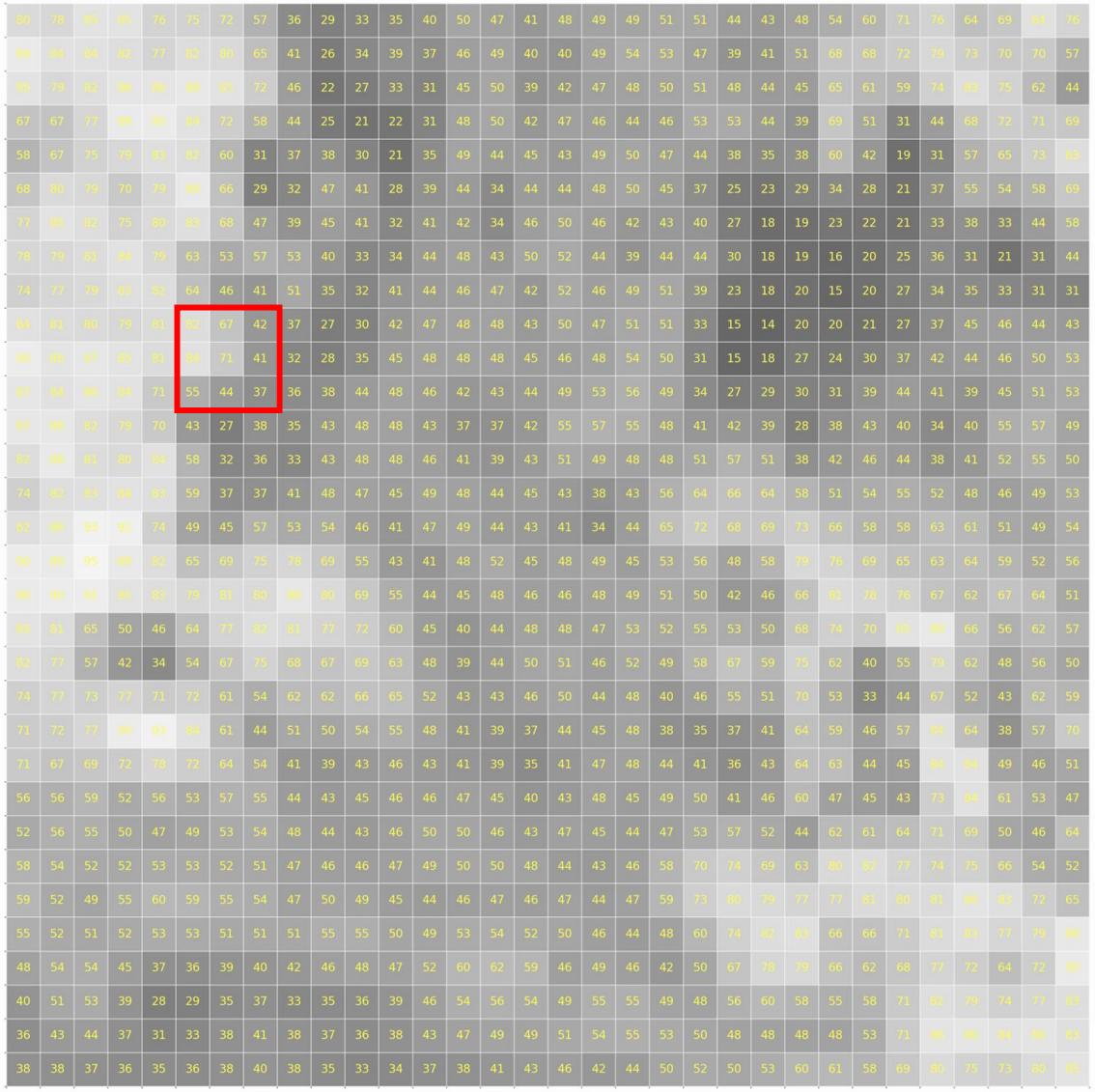

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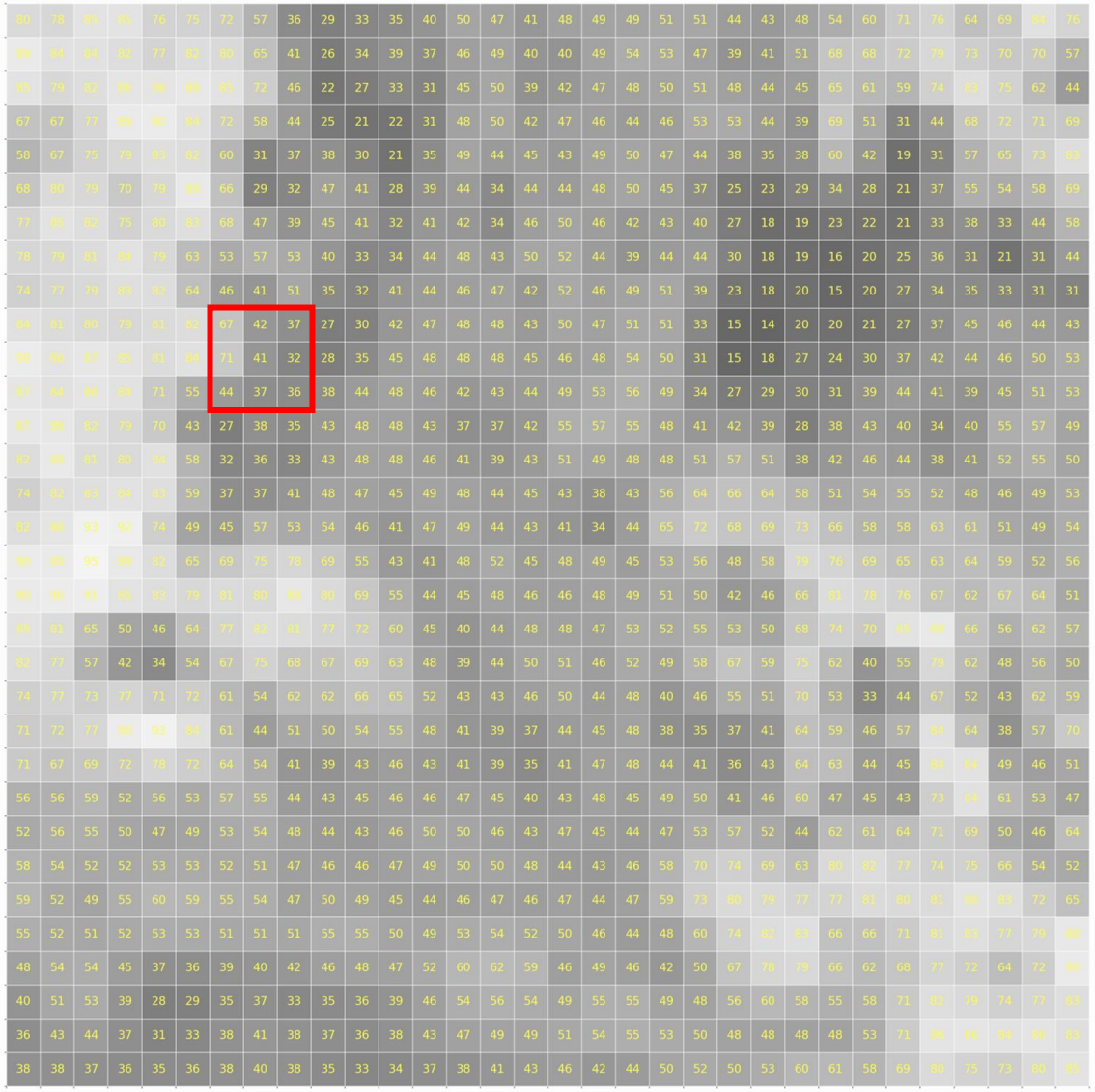

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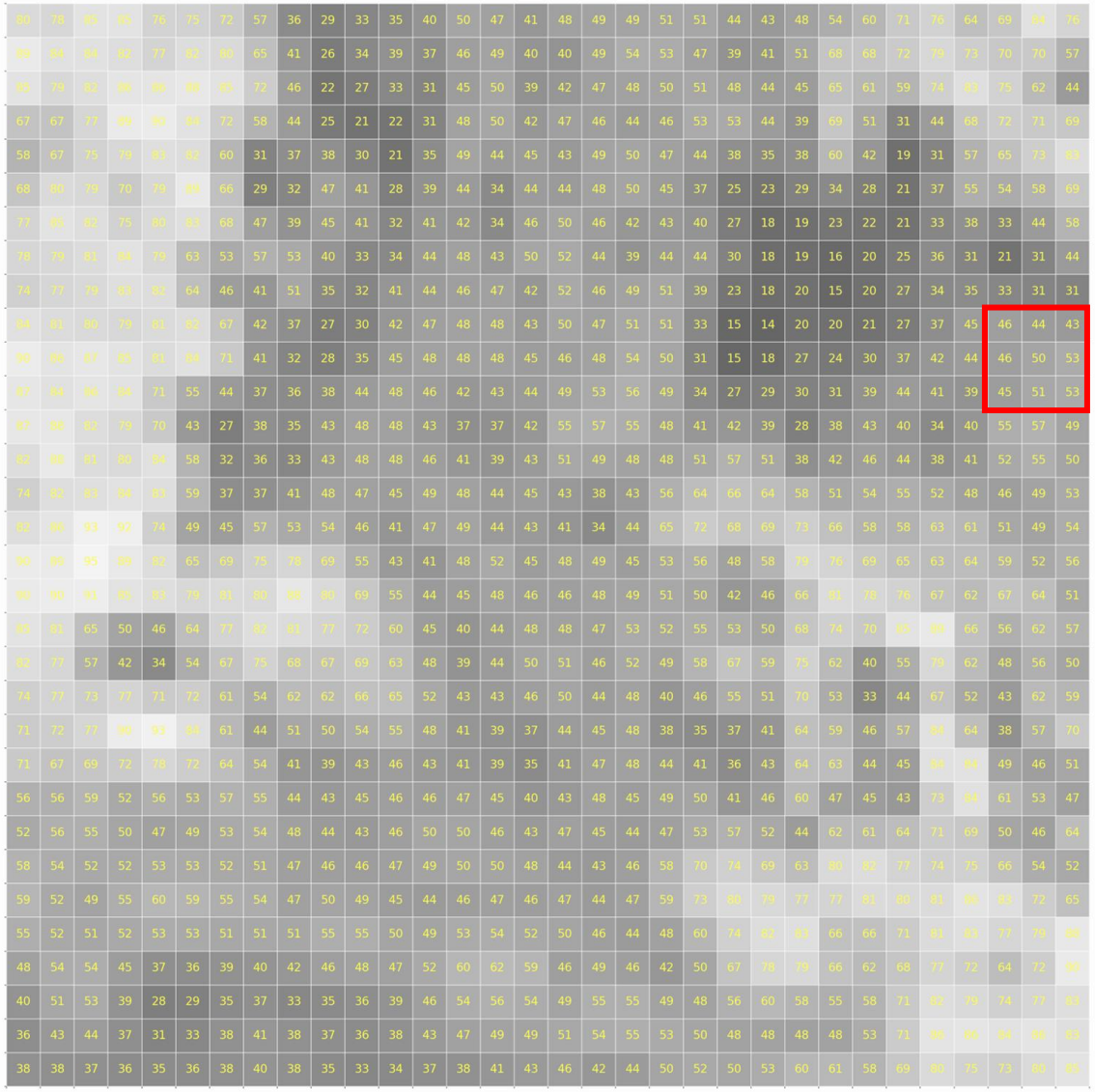

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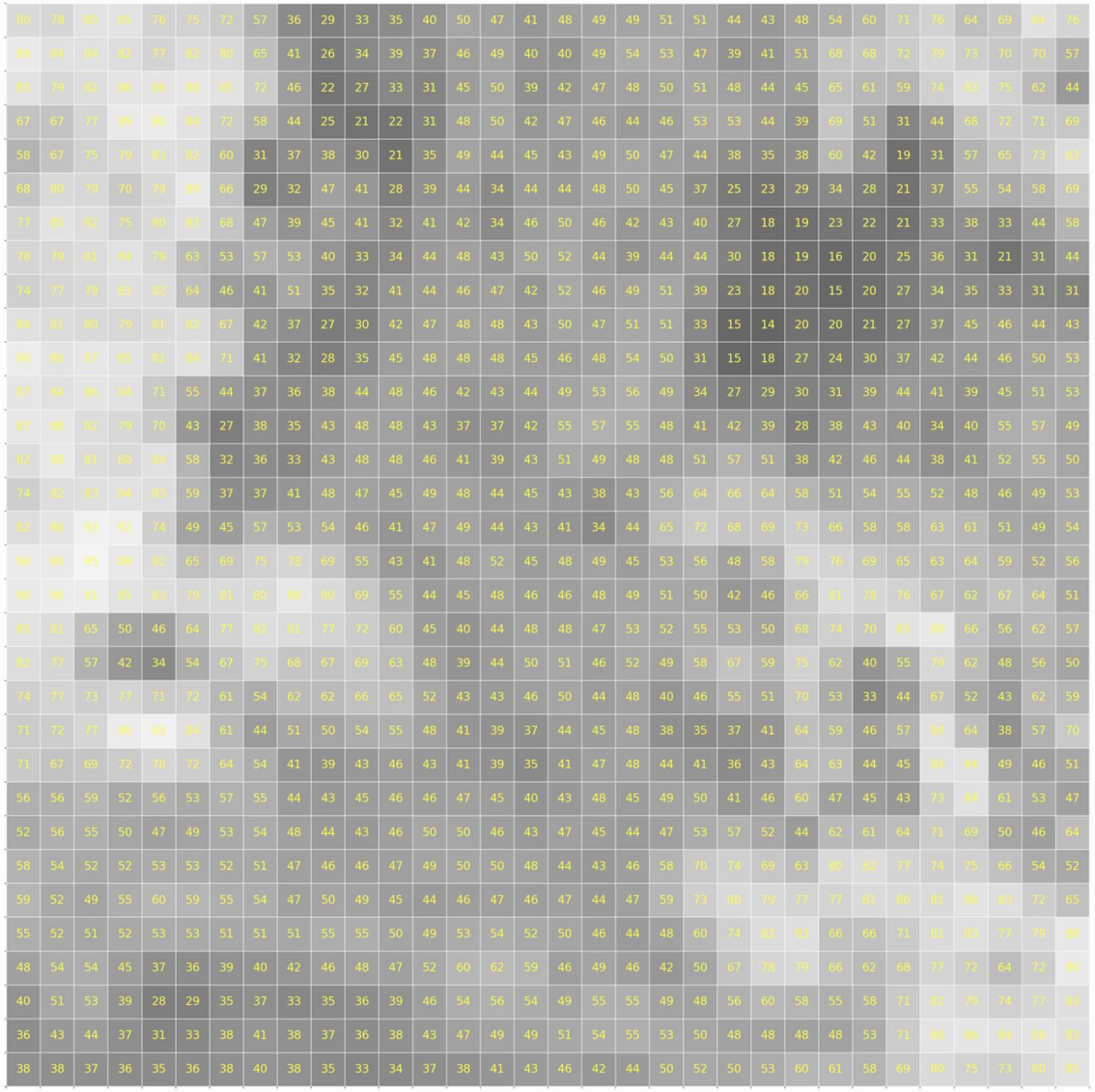

RESULTS

MACHINE LEARNING

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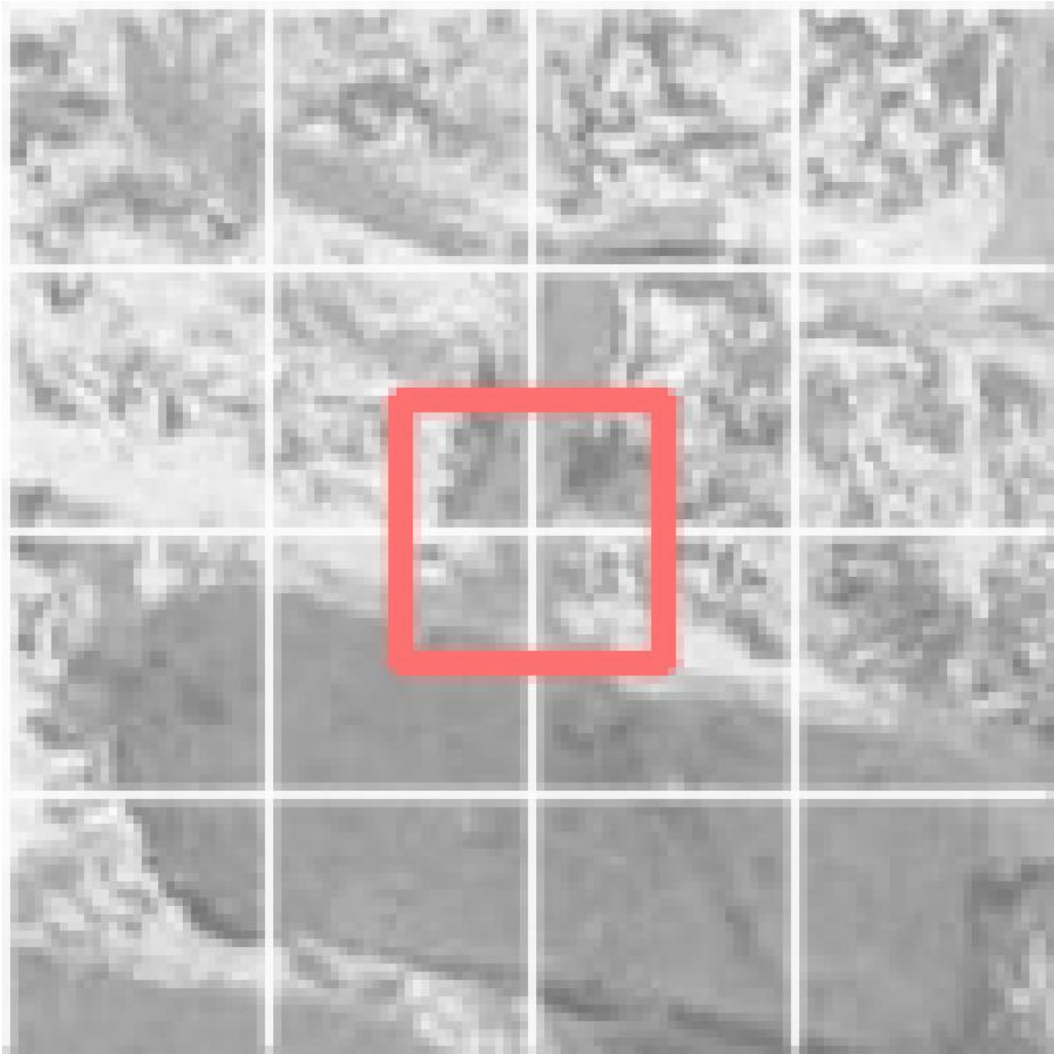

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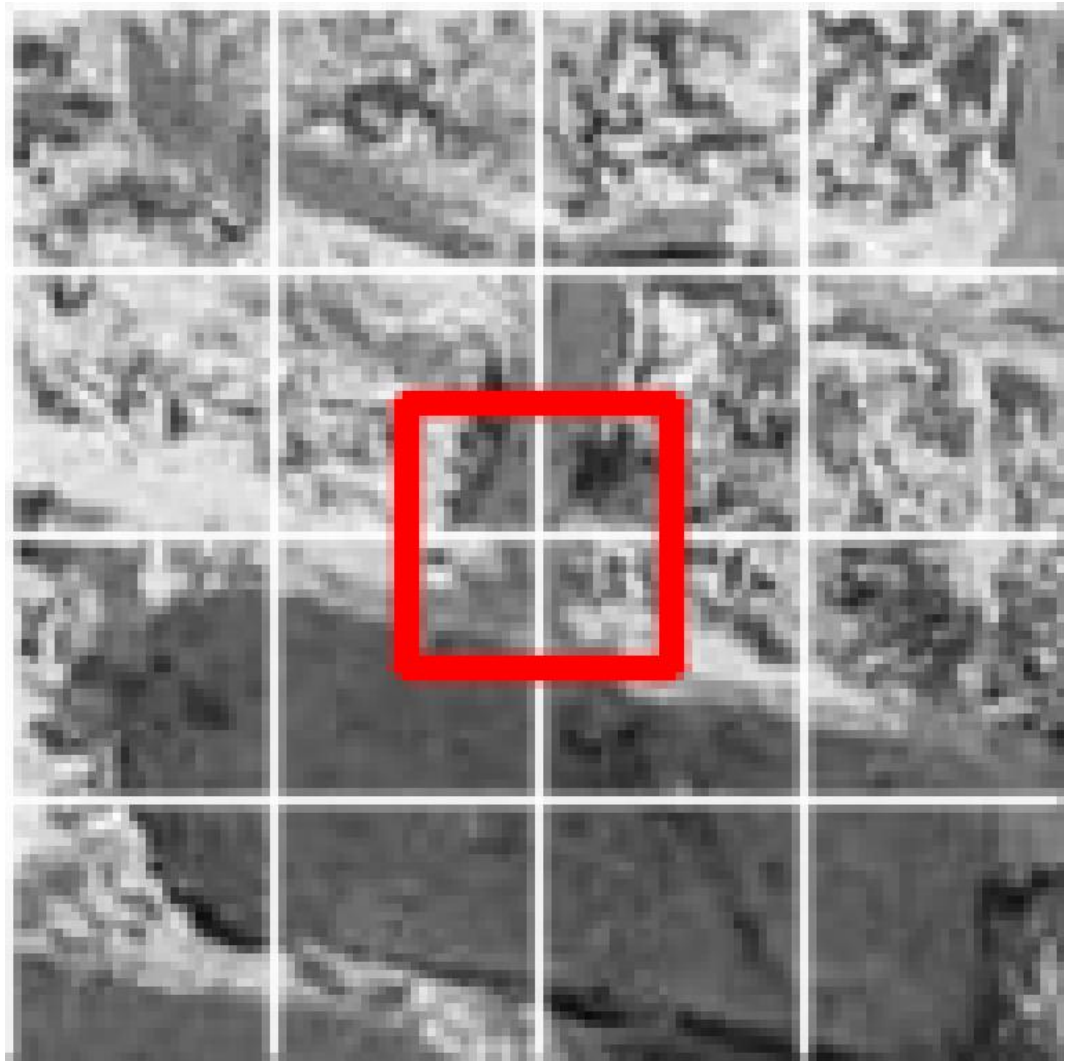

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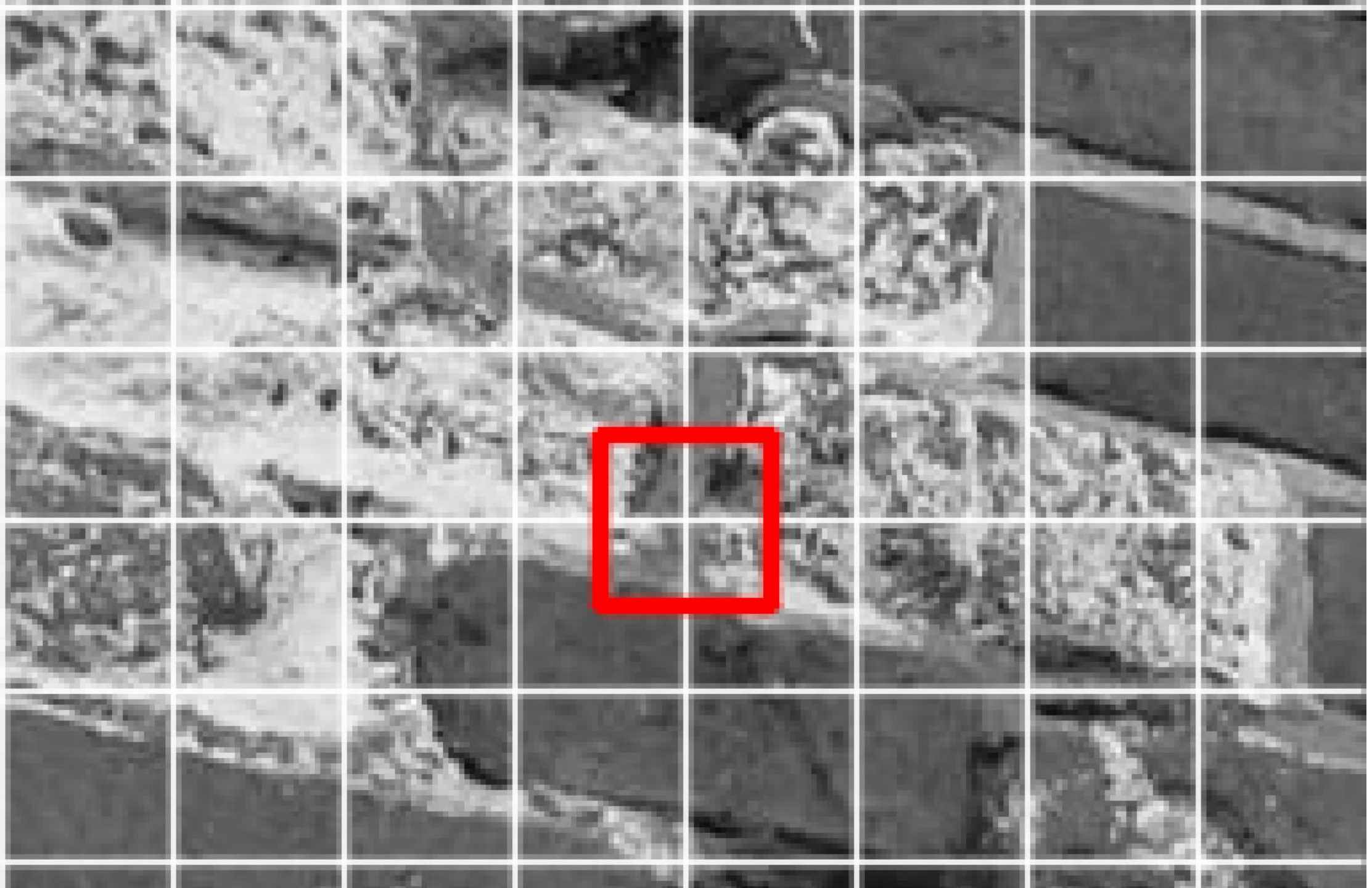

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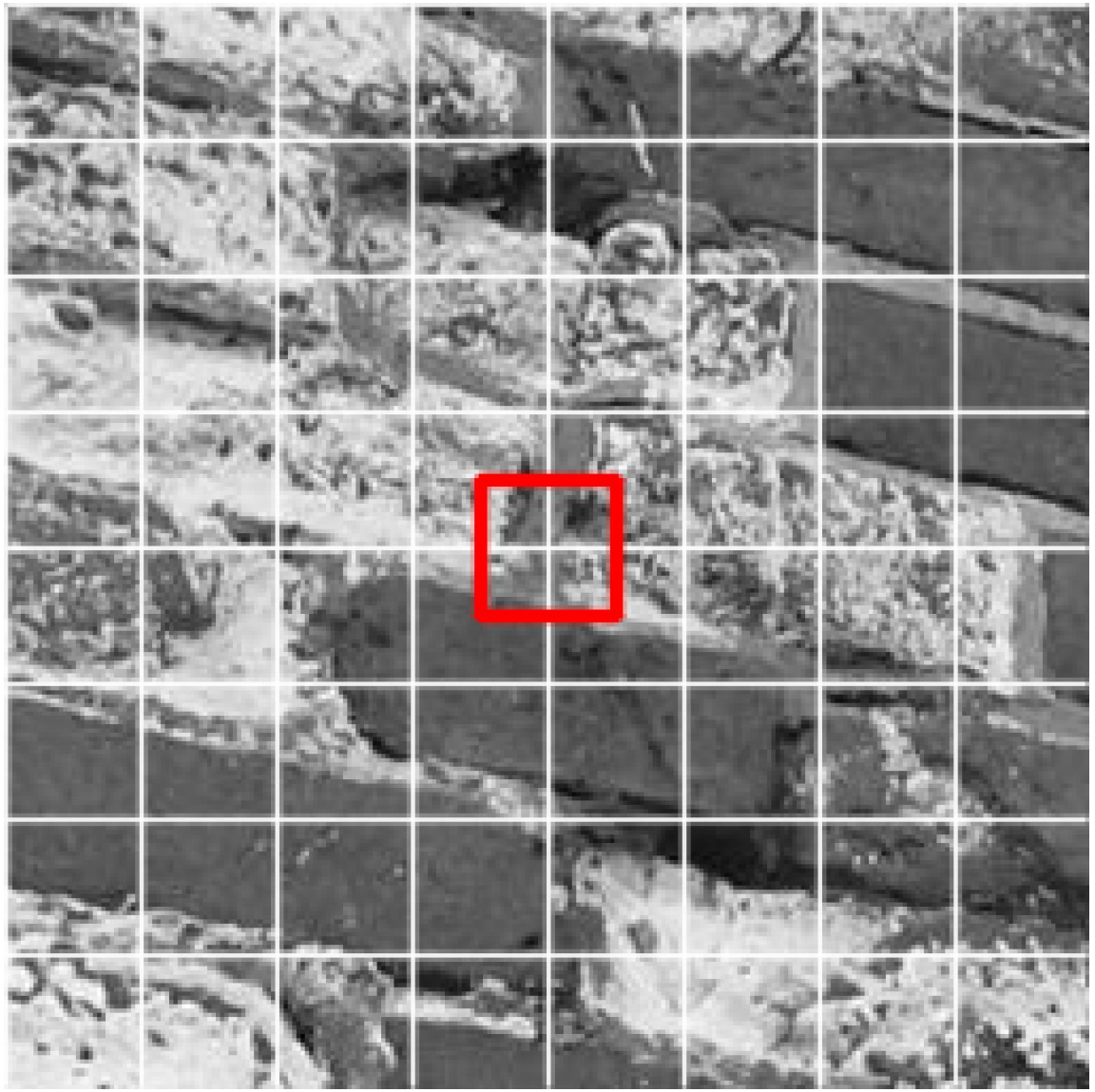

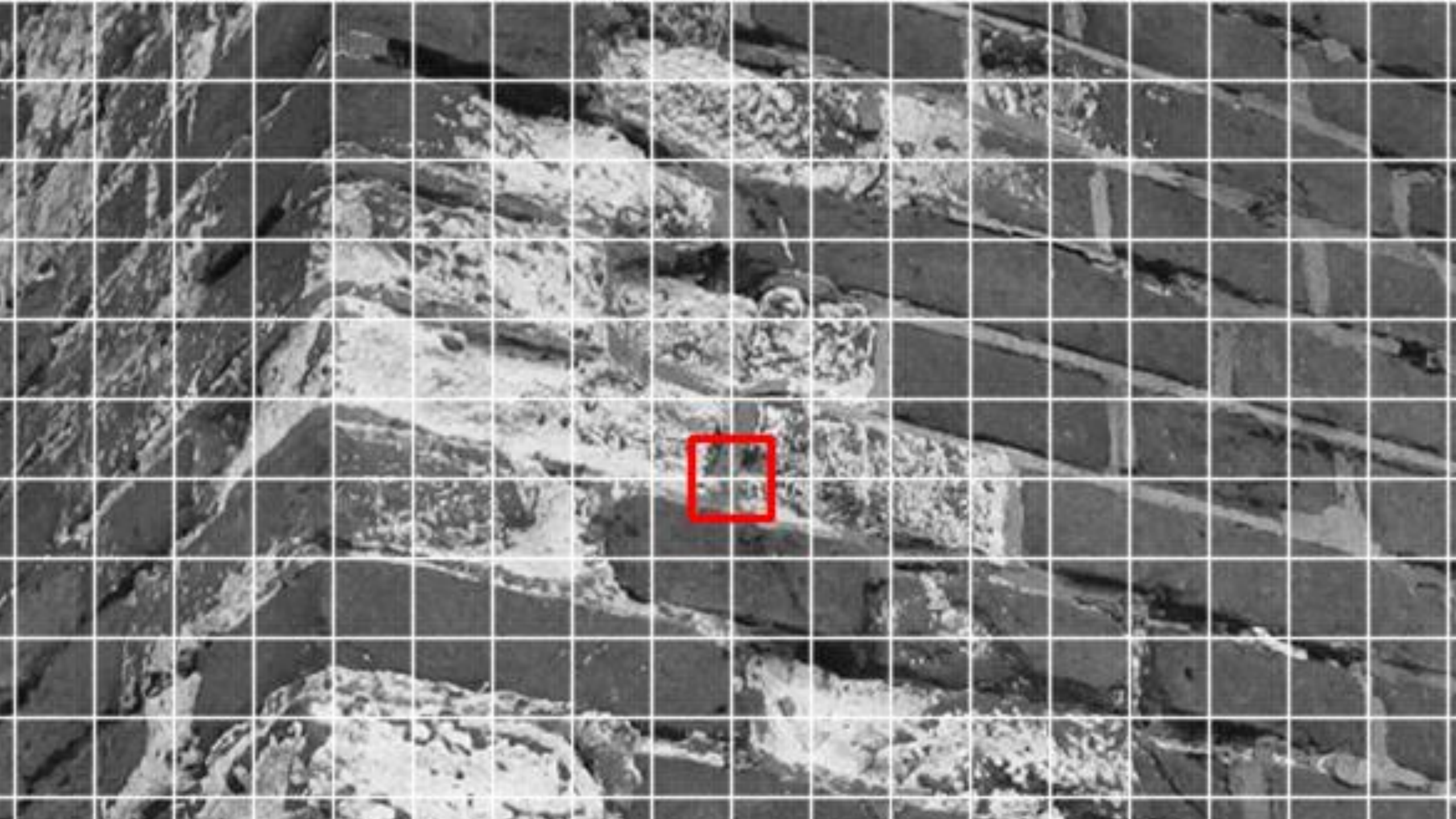

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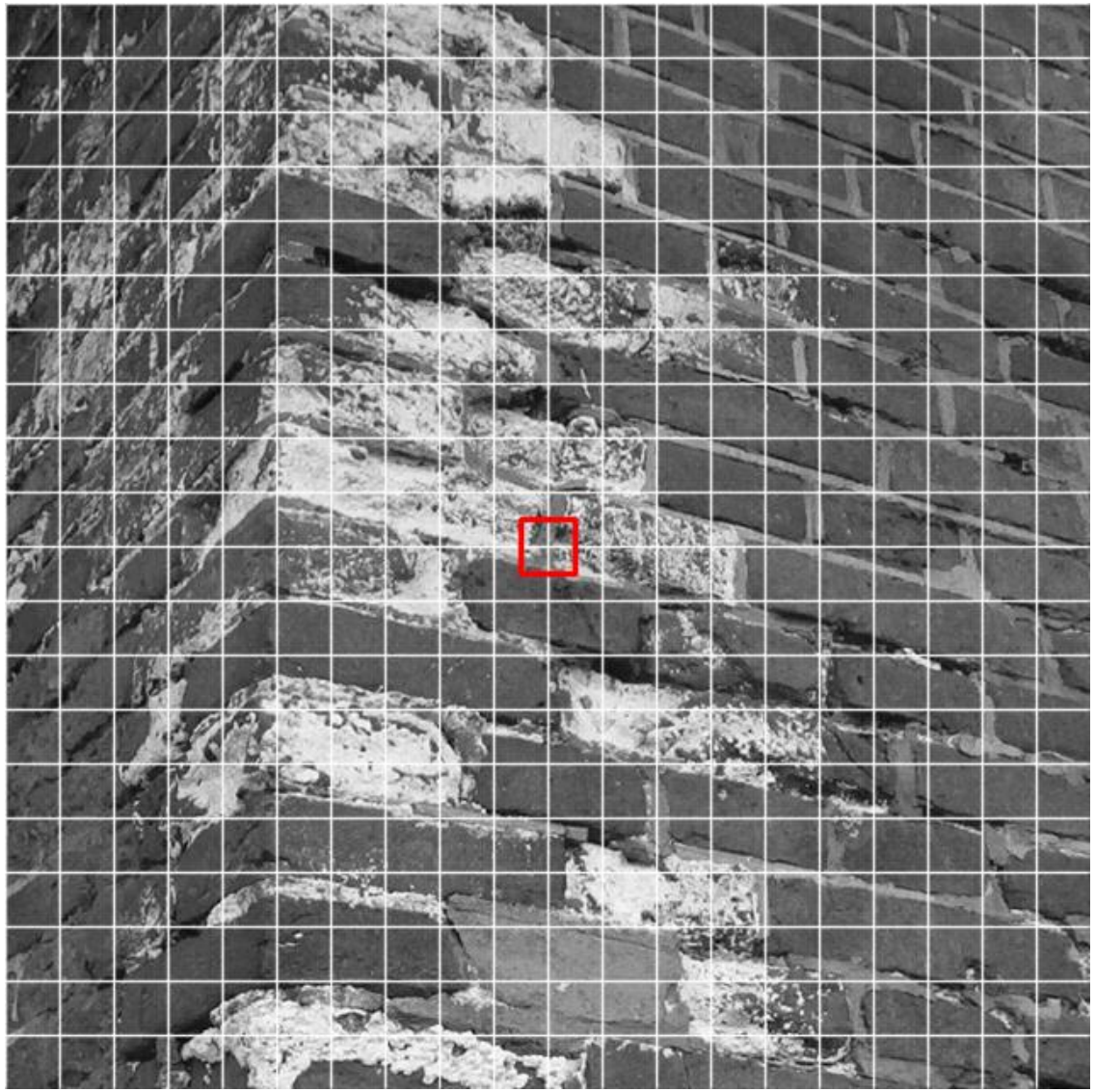

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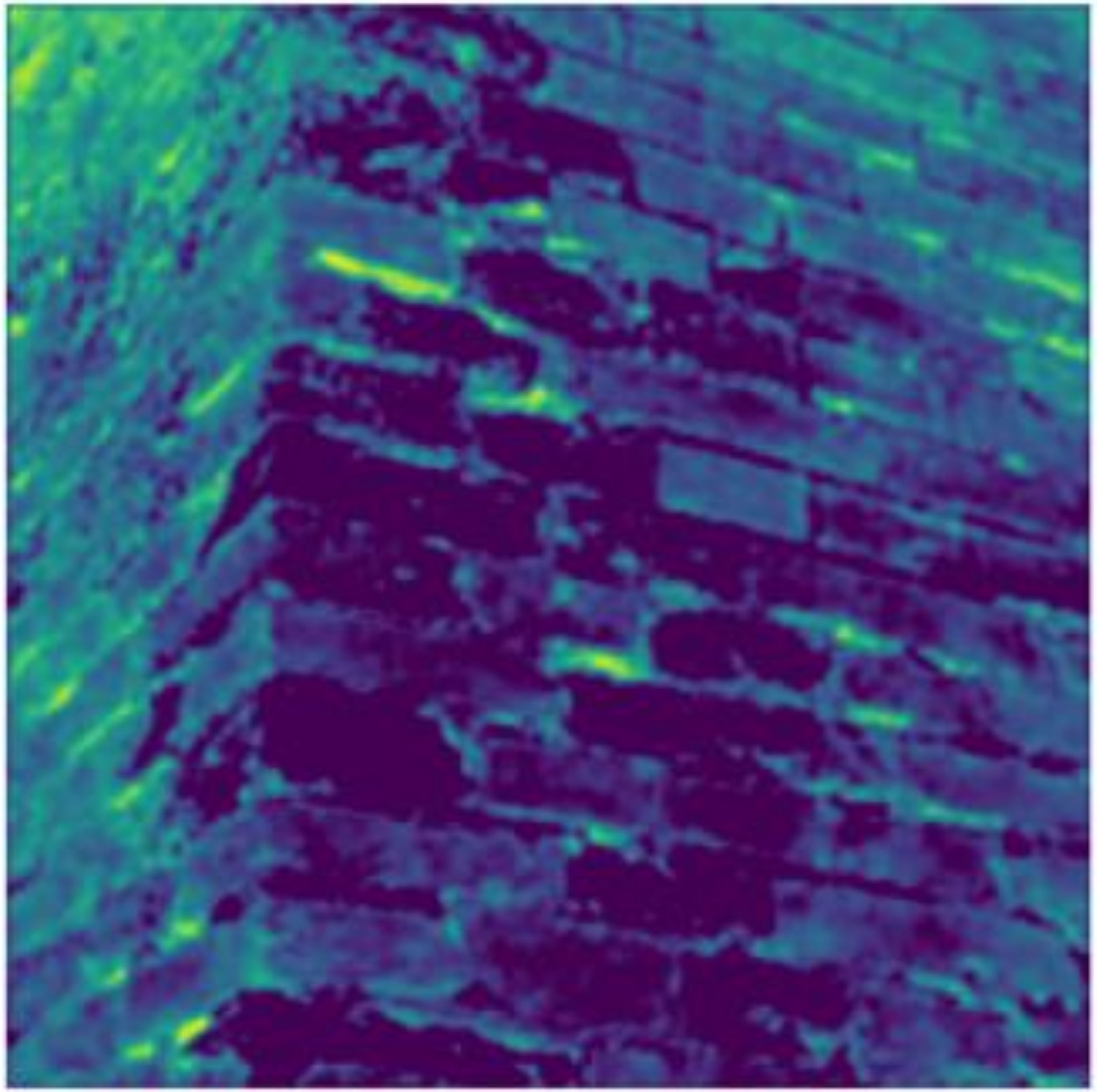
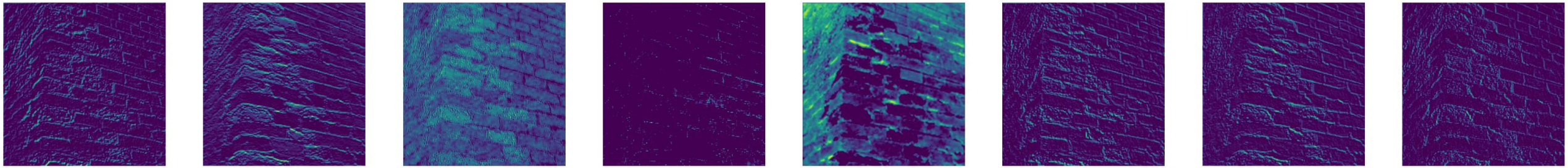
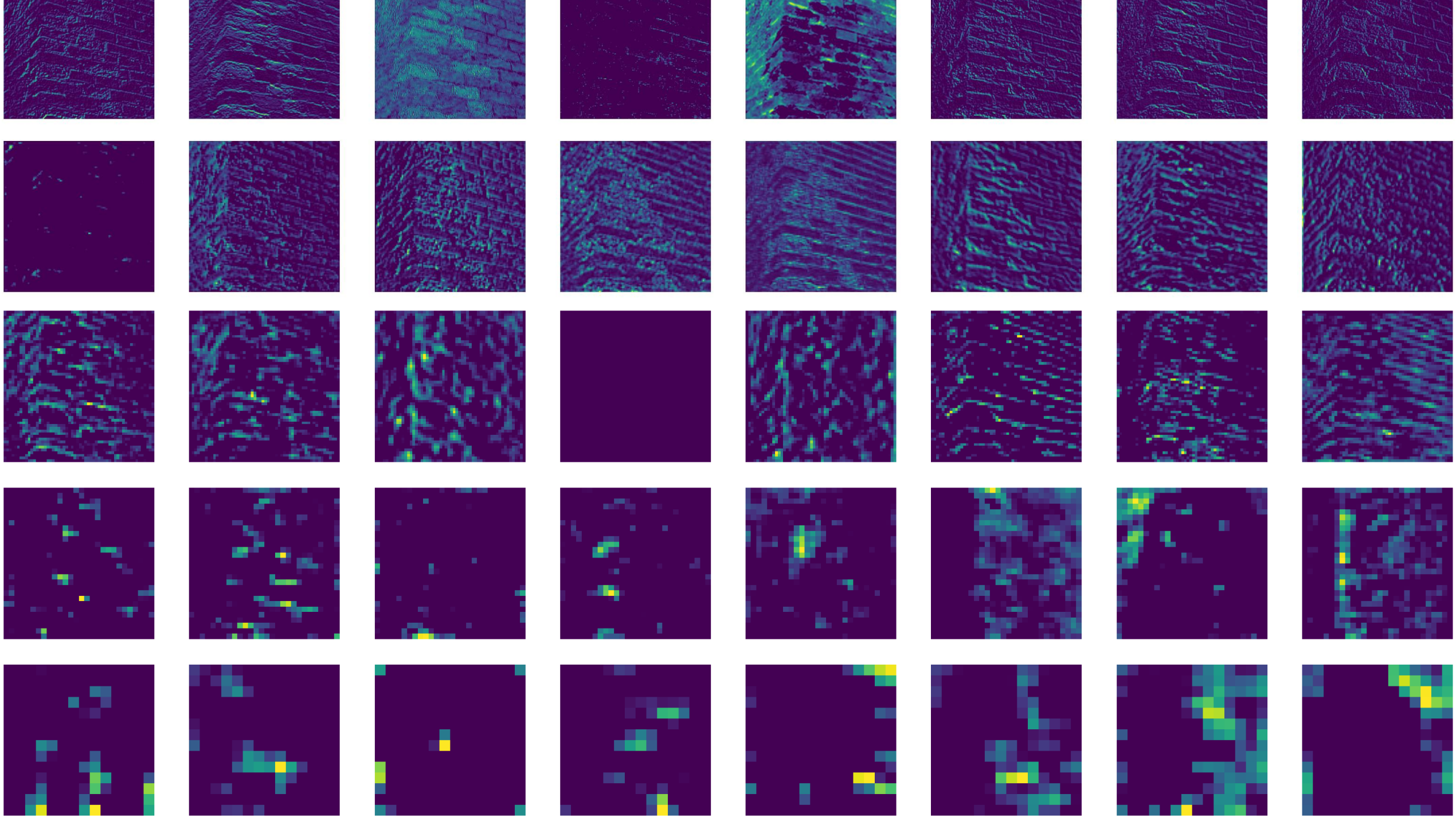


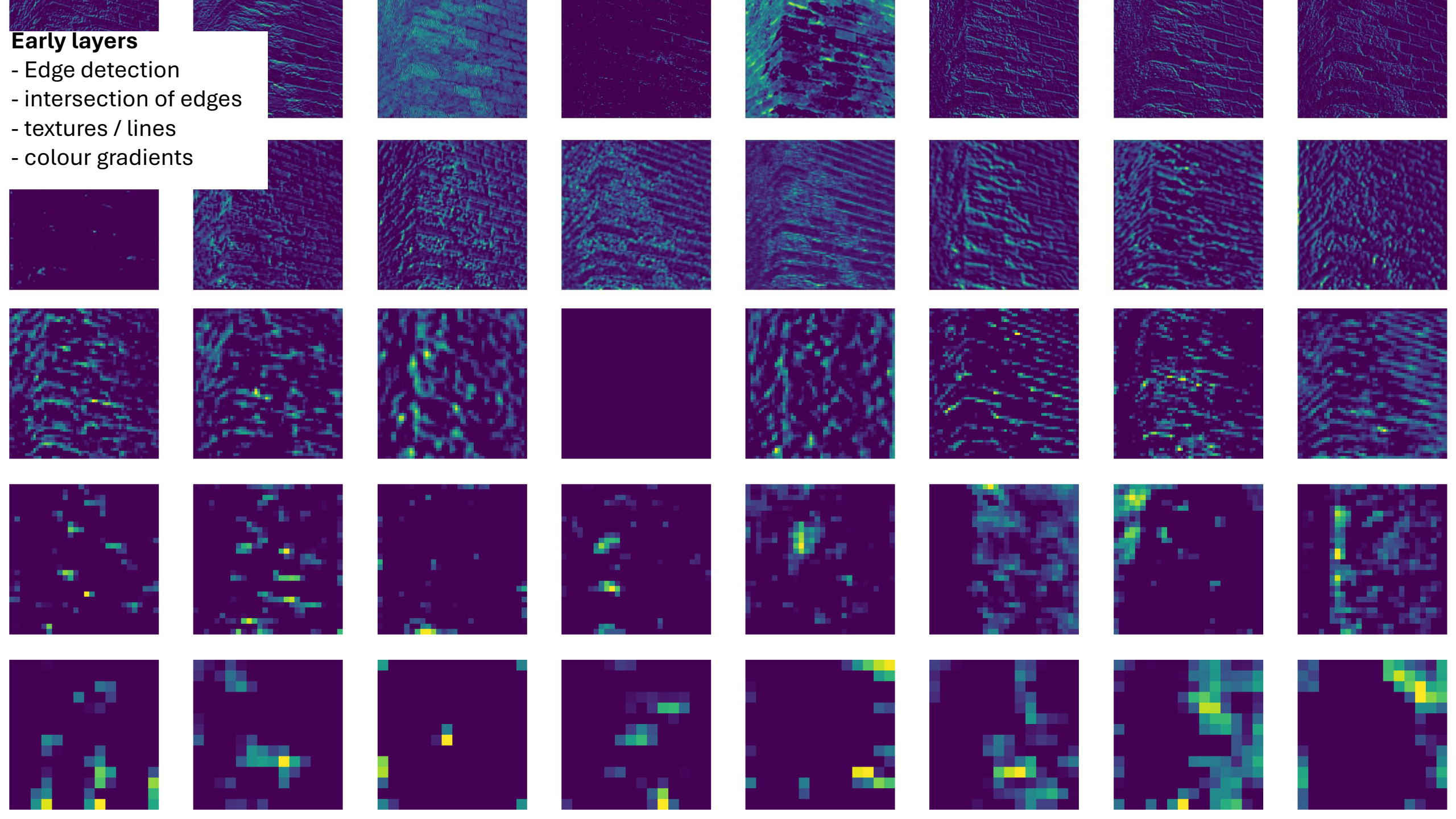
RESULTS

MACHINE LEARNING

block1_conv1



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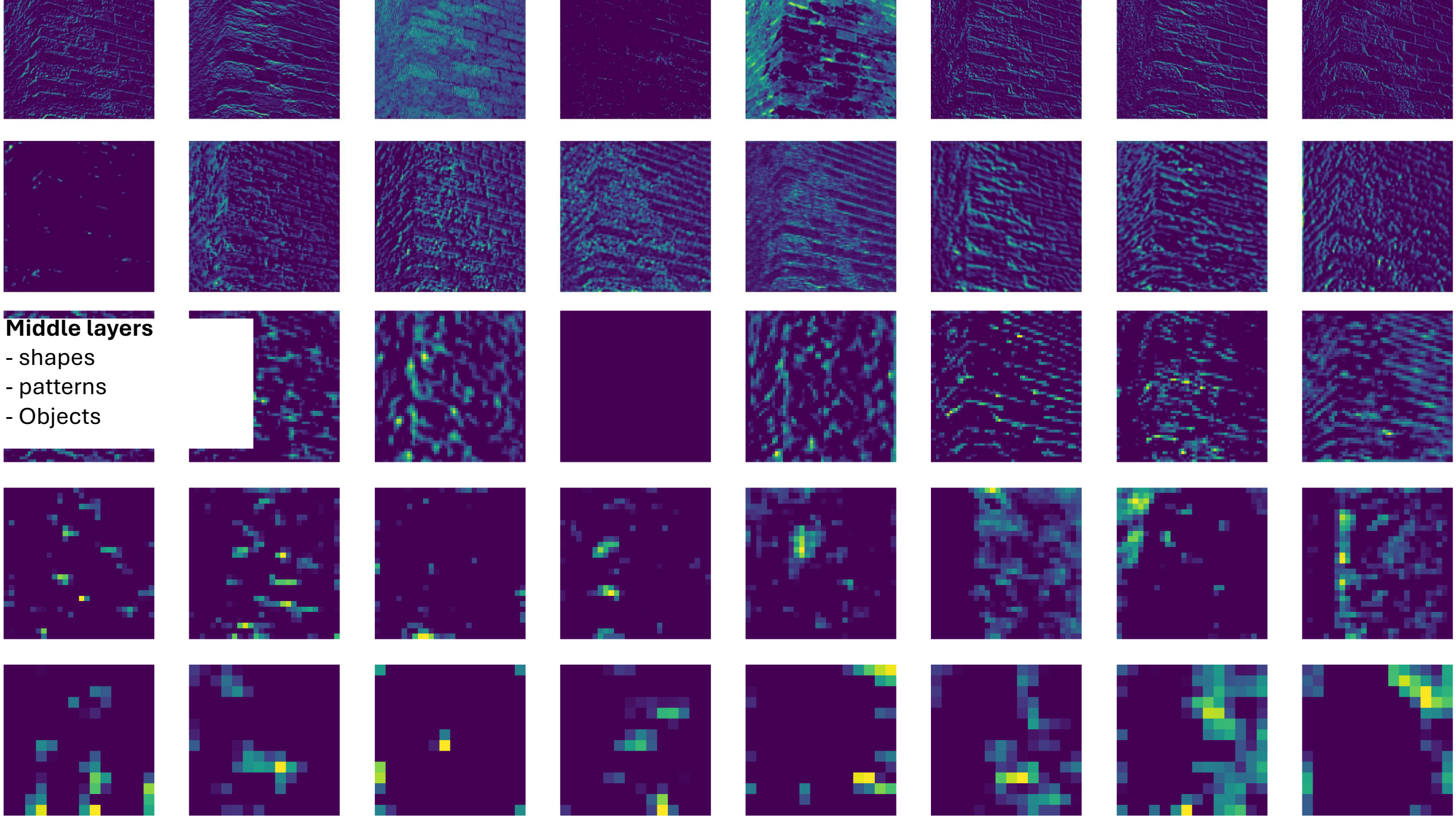
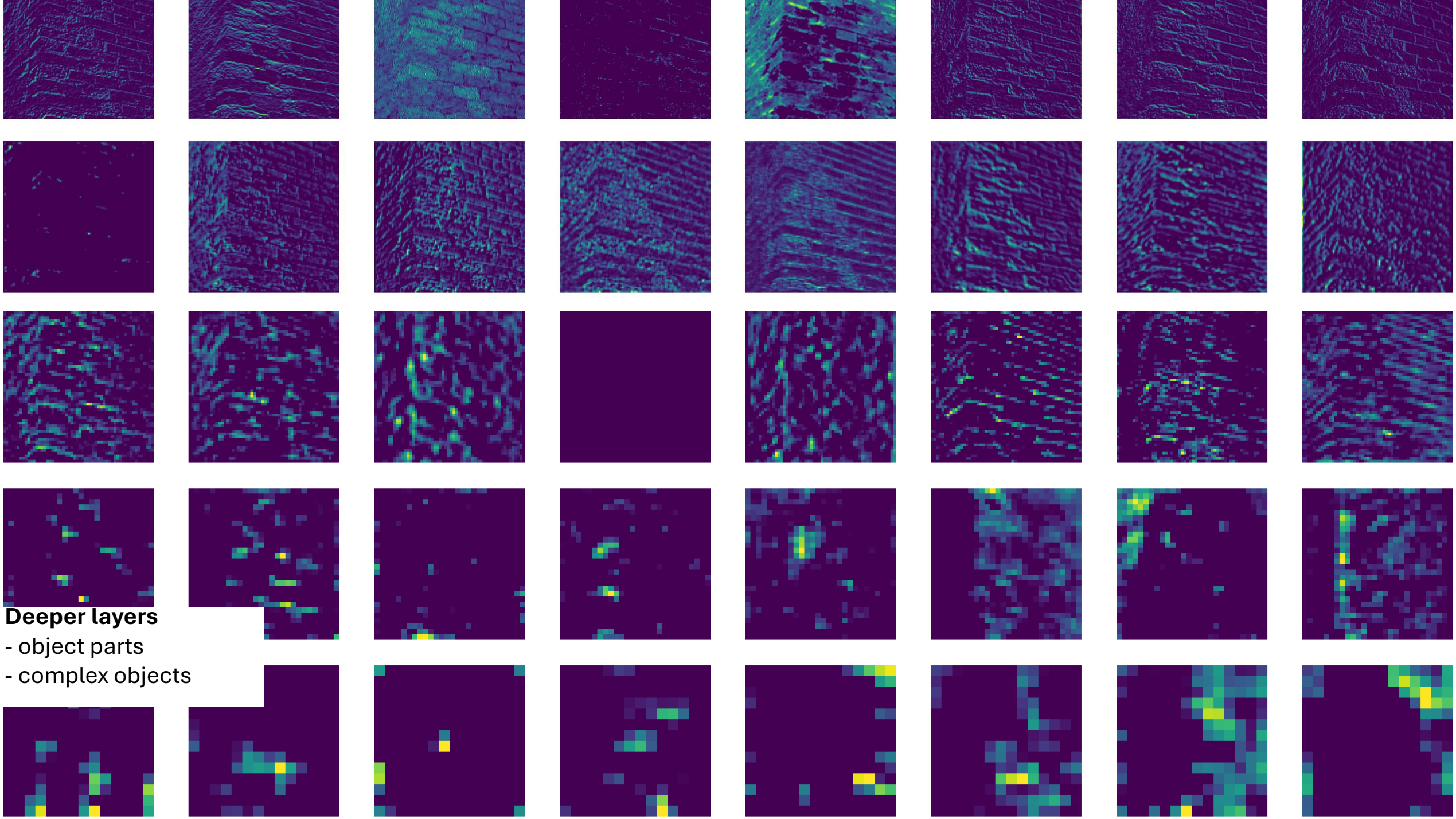
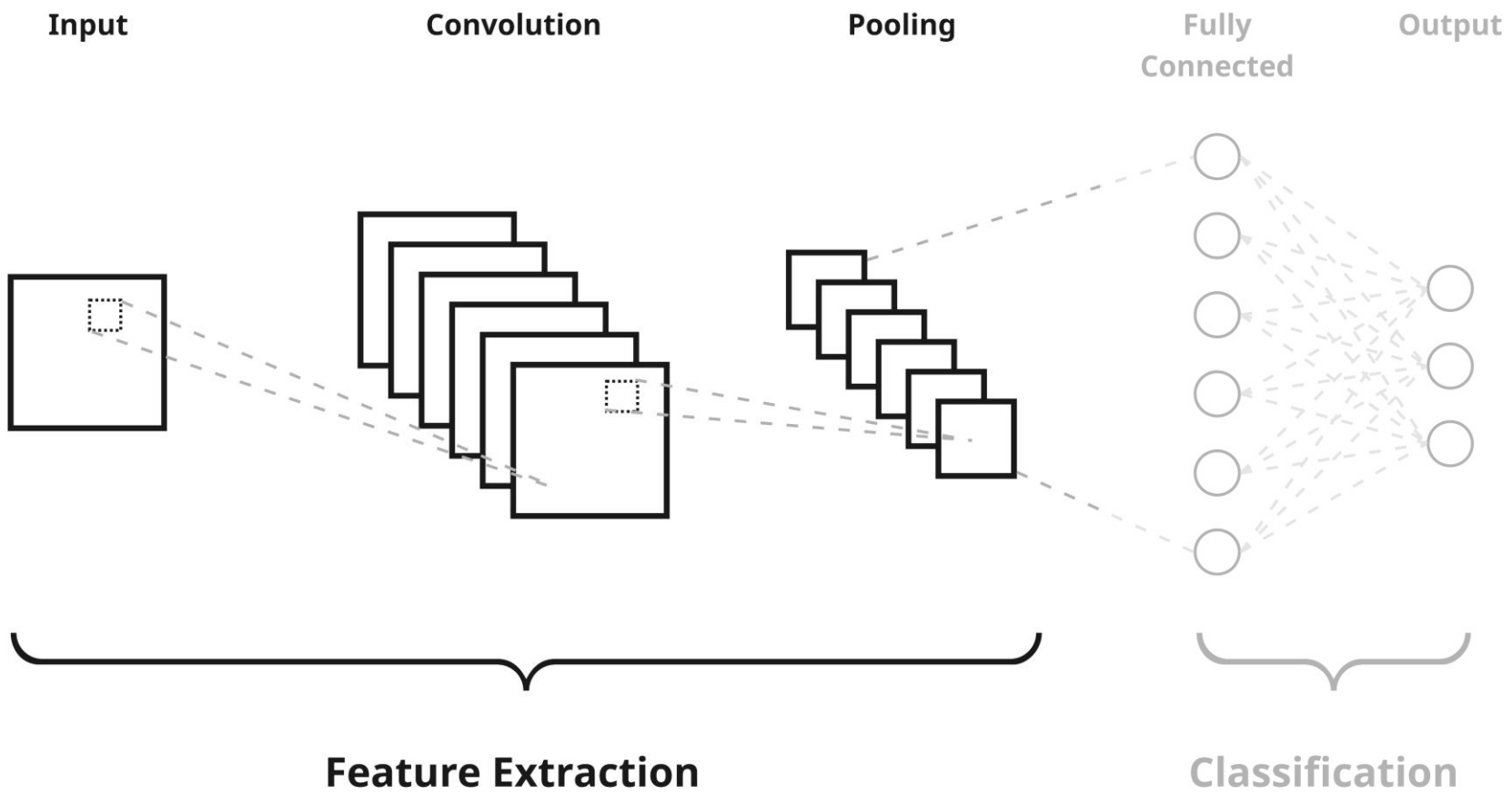

Middle layers
- shapes
- patterns
- Objects


Deeper layers
- object parts
- complex objects

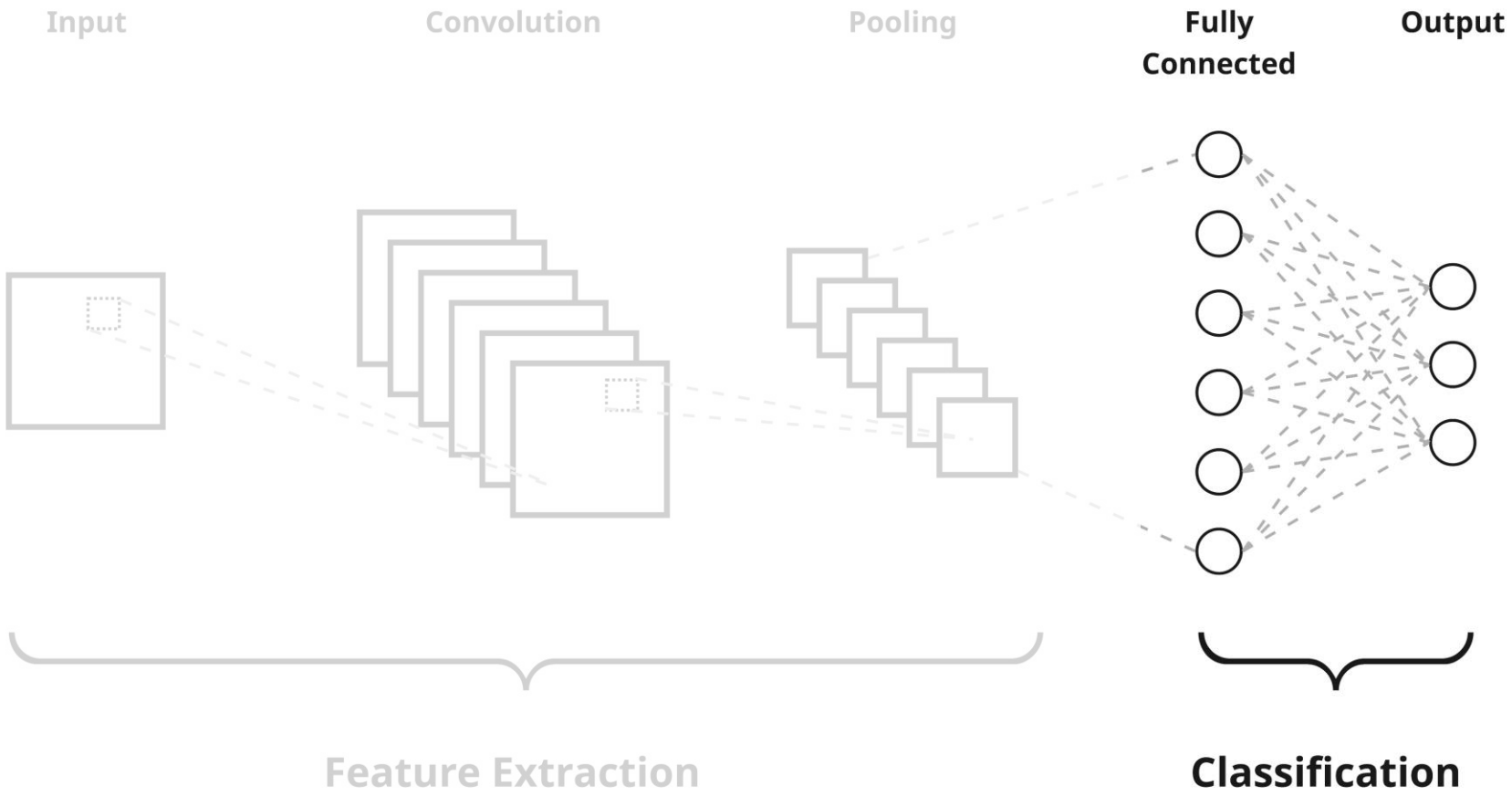
RESULTS

MACHINE LEARNING - CNN



RESULTS

MACHINE LEARNING - CNN



RESULTS

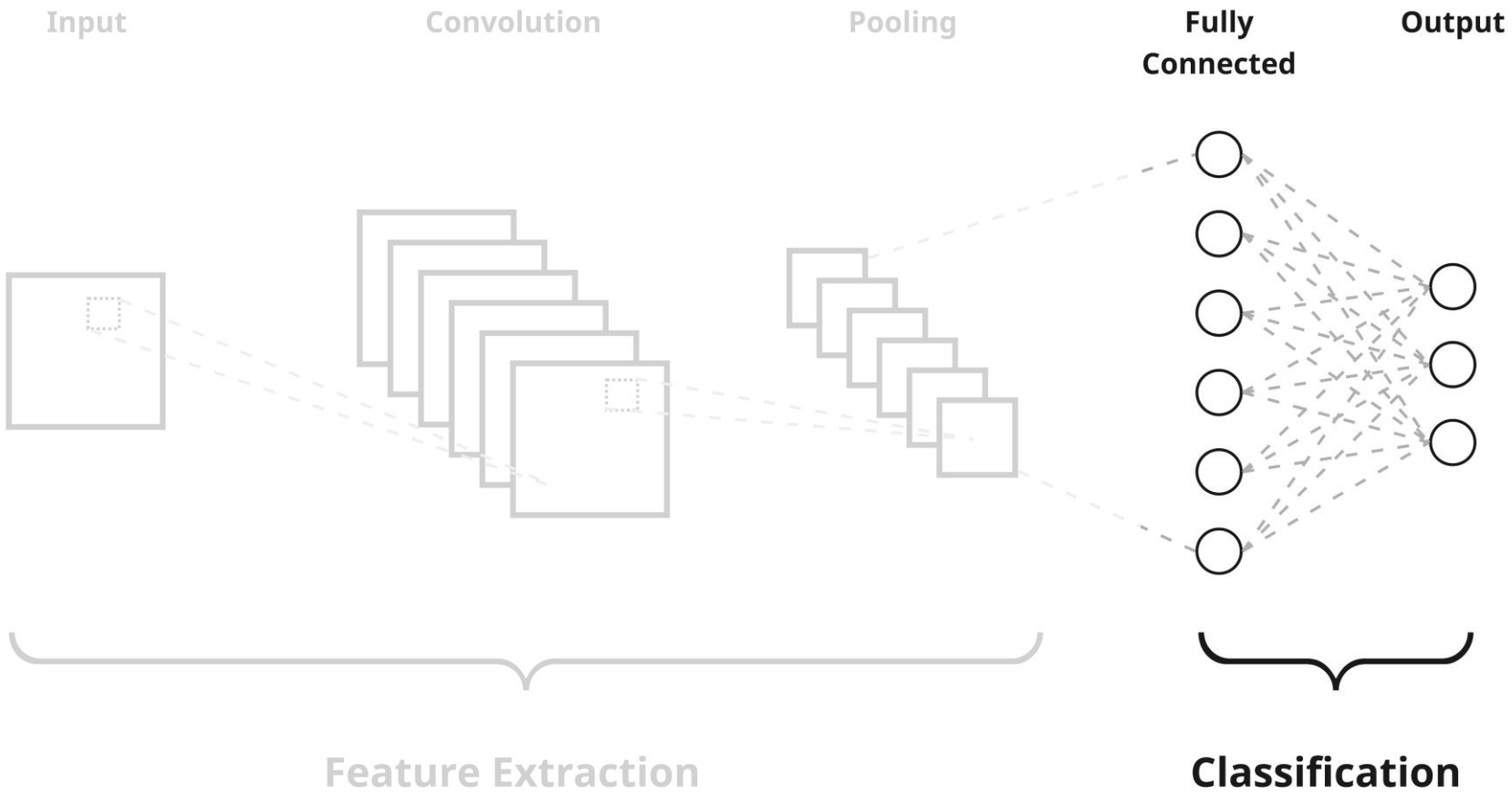
MACHINE LEARNING - CNN

Efflorescence

91%

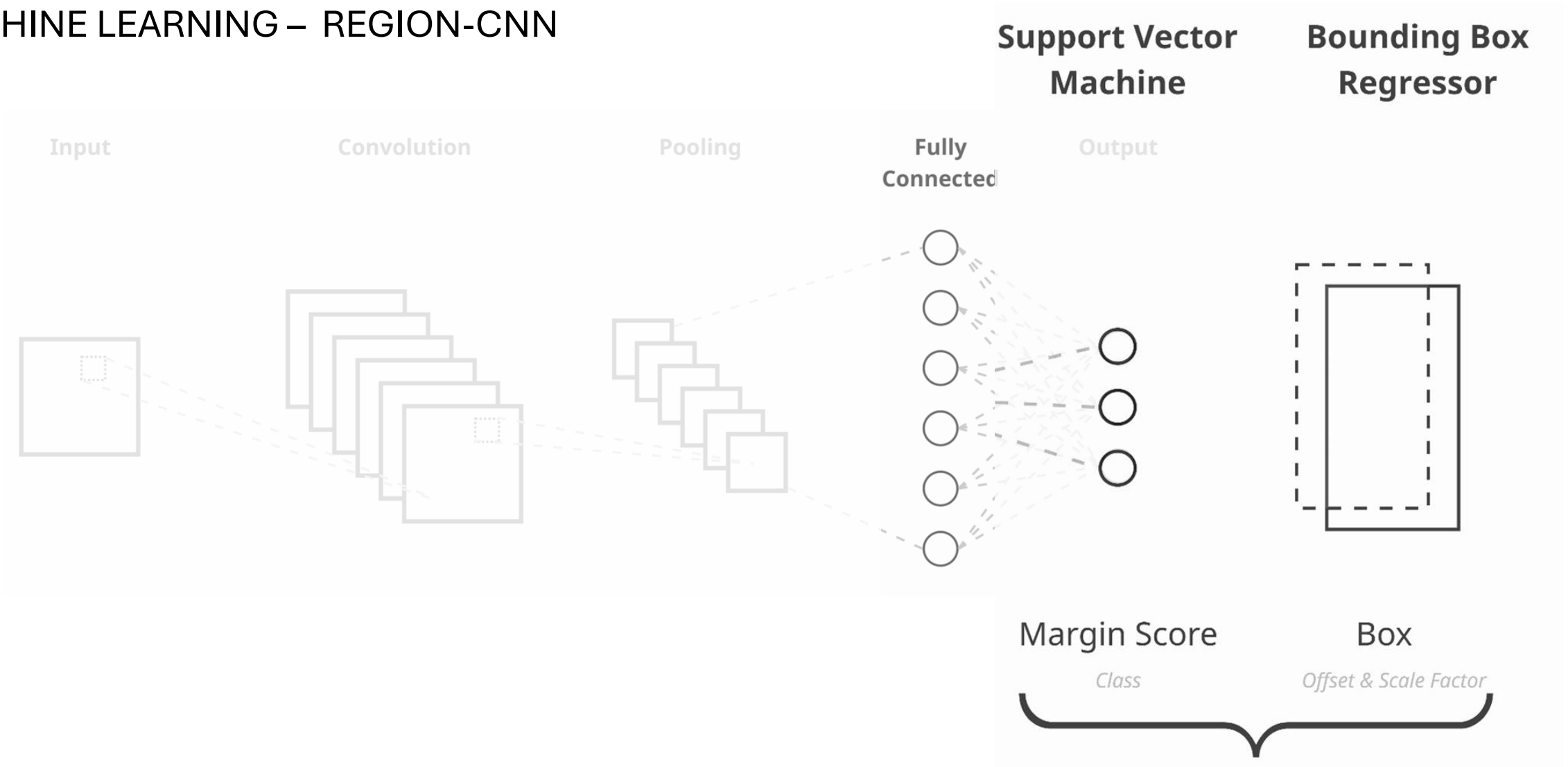
RESULTS

MACHINE LEARNING - CNN



RESULTS

MACHINE LEARNING – REGION-CNN



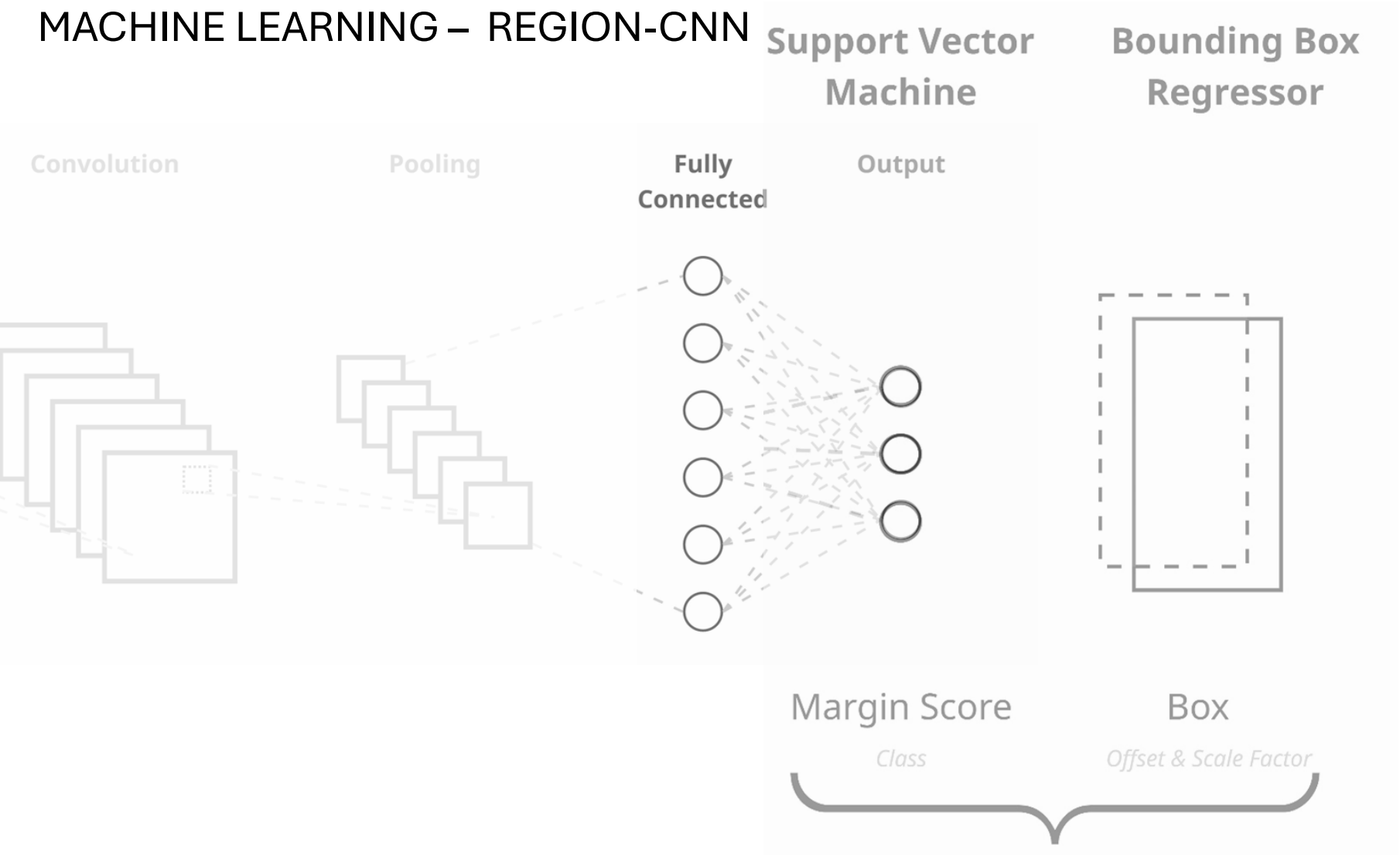
RESULTS

MACHINE LEARNING – REGION-CNN

Efflorescence
91%

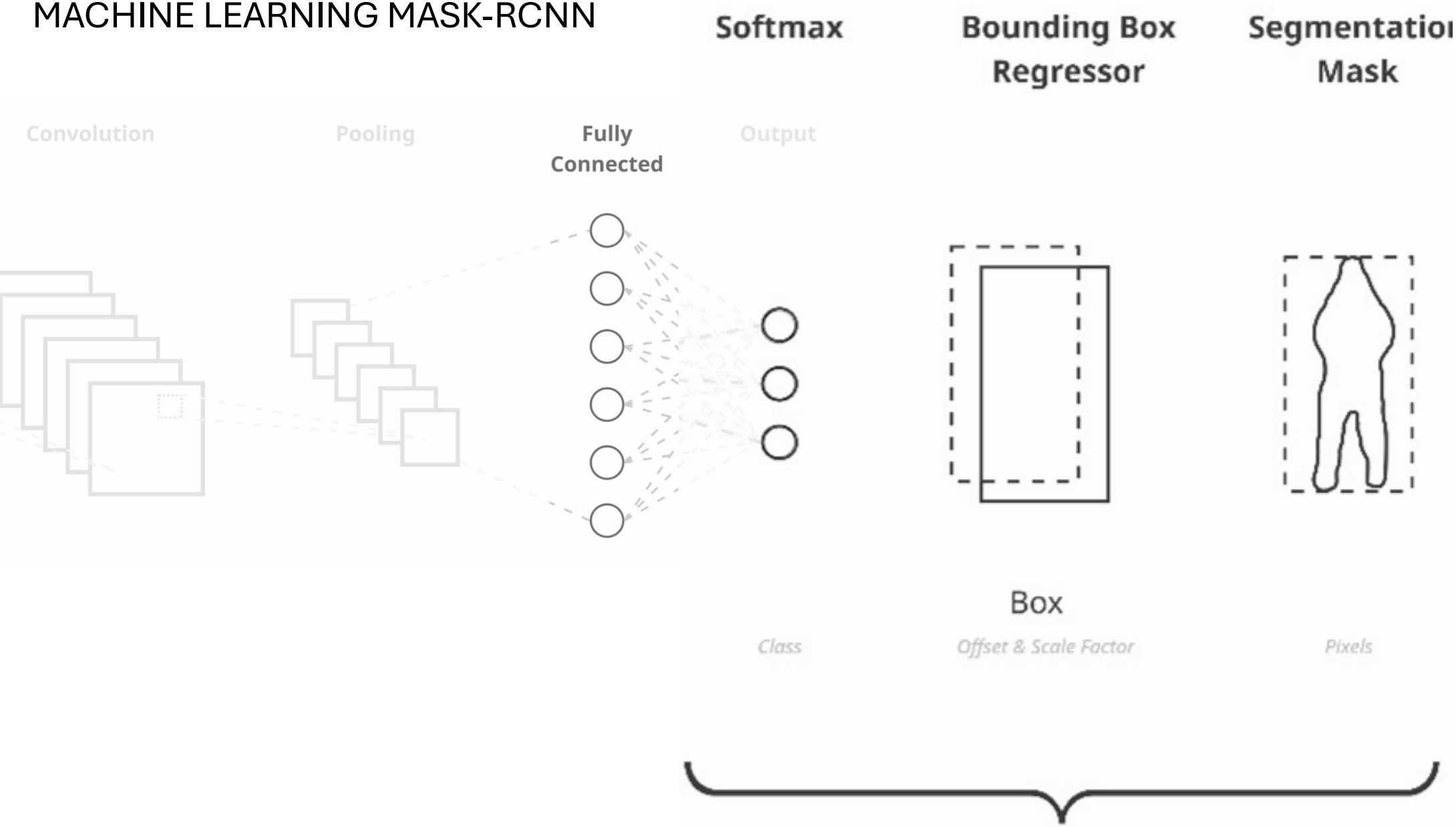
RESULTS

MACHINE LEARNING – REGION-CNN



RESULTS

MACHINE LEARNING MASK-RCNN



RESULTS

MACHINE LEARNING MASK-RCNN

Efflorescence
91%

RESULTS

MACHINE LEARNING

- Scale variations
- lightning conditions
- Image quality and resolution
- Perspective and angle
- Color inconsistencies
- Uncontrolled backgrounds

METHODOLOGY

EXPERIMENTS & HYPOTHESIS

H1: Integrating thermal imaging as an additional channel (to detect moisture presence like rising damp or leakage) improves efflorescence detection accuracy compared to using only RGB data.

H2: Including **similar damage classes** (graffiti, lichens, encrustation) in the model improves the ability to distinguish efflorescence from **visually similar damage types**.

H3: Including **co-occurring damage types** (e.g., powdering, scaling) as a separate class in the model improves the detection of efflorescence and show statistical significance.

H4: Variations in **image quality, angle, and distance negatively affect model performance** in detecting efflorescence.

METHODOLOGY

EVALUATION METRICS

EPOCH:
One full pass through the entire dataset during training.

PRECISION:
High precision = few false alarms

$$Precision = \frac{TP}{(FP + TP)}$$

RECALL
Of all the actual cases of efflorescence in the image, how many did the model successfully find

$$Recall = \frac{TP}{FN + TP}$$

Intersection over Union (Iou):
compares predicted and ground truth masks/ boxes by the overlap area divided by the union area

$$IoU = \frac{Area\ of\ Overlap}{Area\ of\ Union}$$

mAP:
A standard score used in object detection that combines precision across different thresholds.
(mAP@0.5 means the prediction is considered correct if it overlaps at least 50% with the true area.)

$$\text{mAP}_{@0.5} = \frac{1}{\text{K}} \sum_{\text{i}=1}^{\text{K}} \text{AP}_{\text{i}}$$

METHODOLOGY

EVALUATION METRICS

EPOCH:
One full pass through the entire dataset during training.

PRECISION:
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Of all the actual cases of efflorescence in the image, how many did the model successfully find

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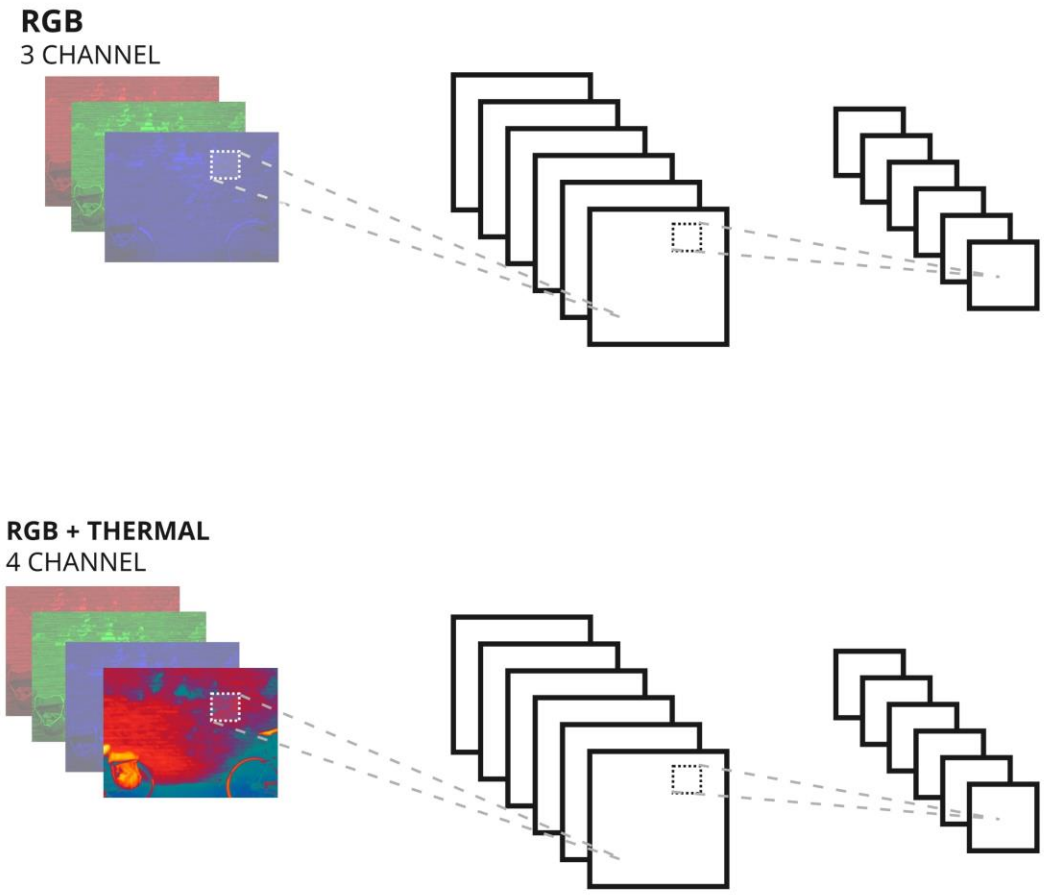
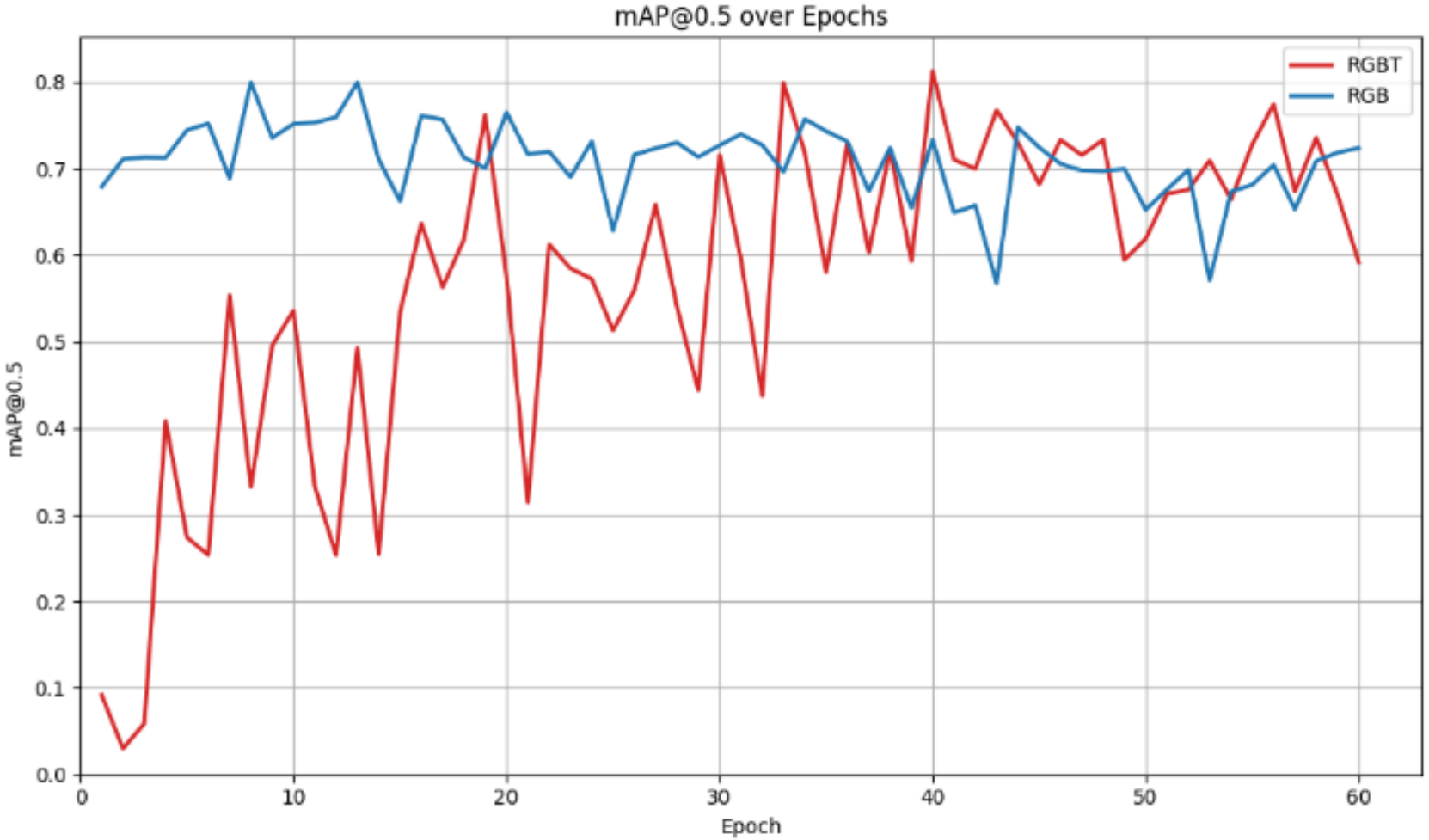
RESULTS

H1: THERMAL IMAGING VS RGB – SET UP



RESULTS

H1: THERMAL IMAGING VS RGB

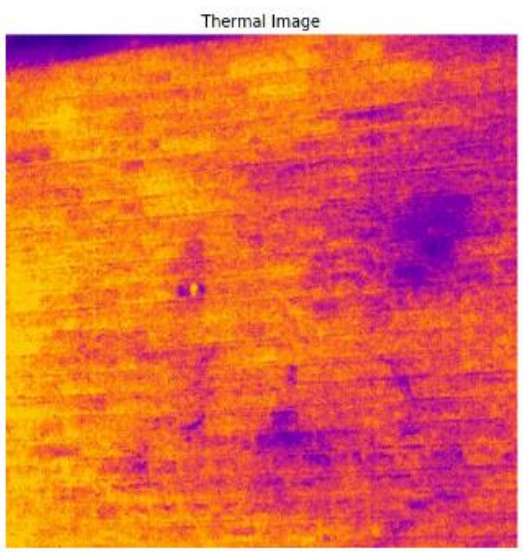


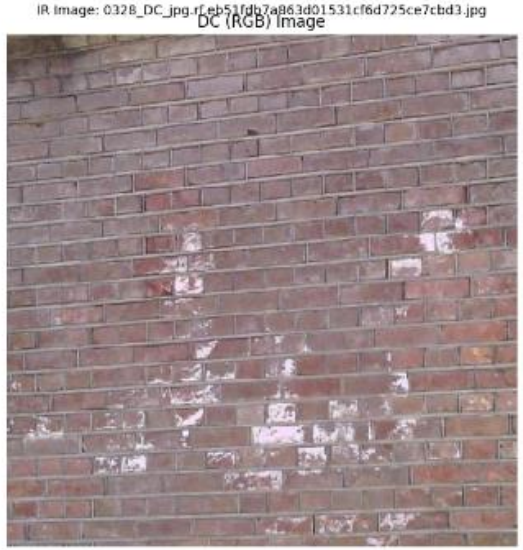
RESULTS

H1: THERMAL IMAGING VS RGB

RGB

RGBT





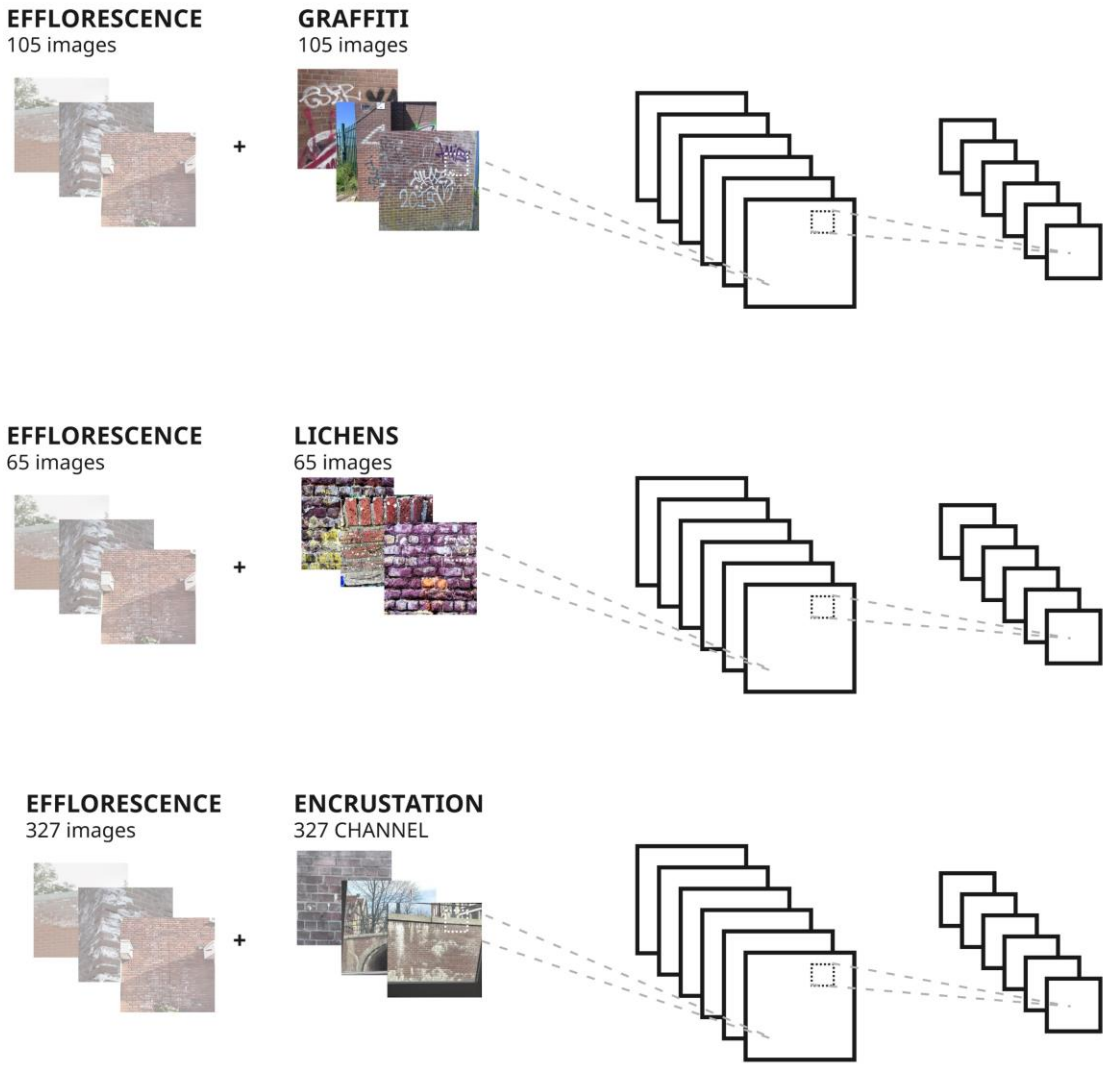
RESULTS

H1: THERMAL IMAGING VS RGB

- RGB learns faster and stabilizes earlier.
- RGBT achieves higher precision
- RGBT performs better for contexts where false positives are costly)
- RGBT may benefit from more thermal-specific augmentation, better channel normalization, or architectural tuning

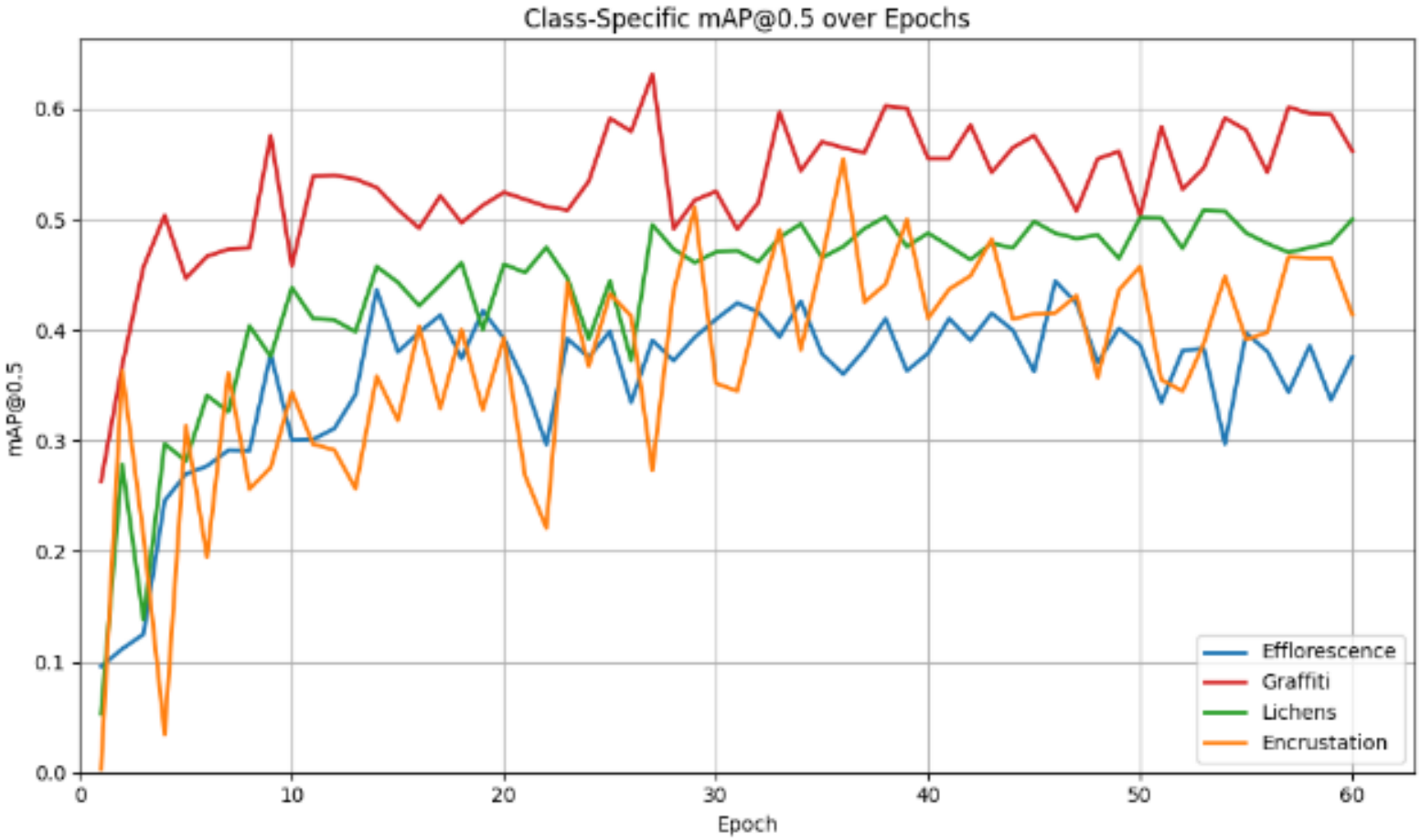
RESULTS

H2: SIMILAR CLASSES



RESULTS

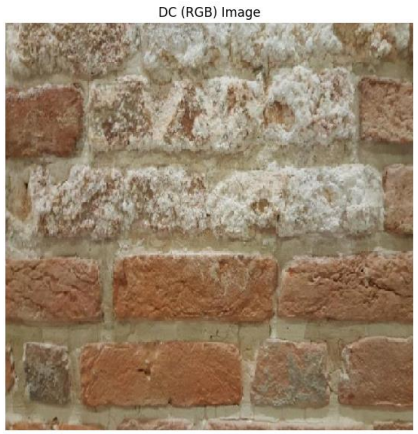
H2: SIMILAR CLASSES

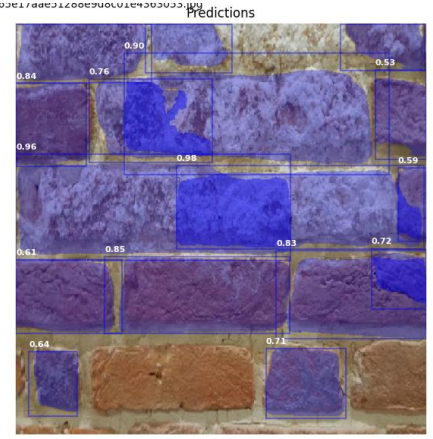


RESULTS

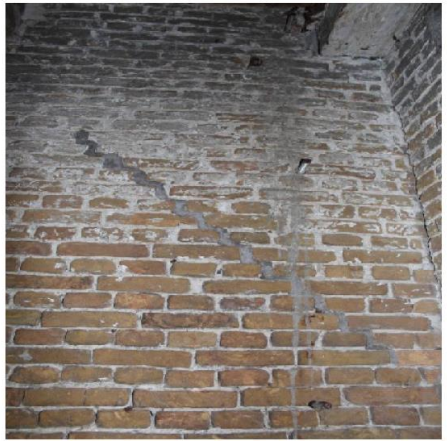
H2: SIMILAR CLASSES

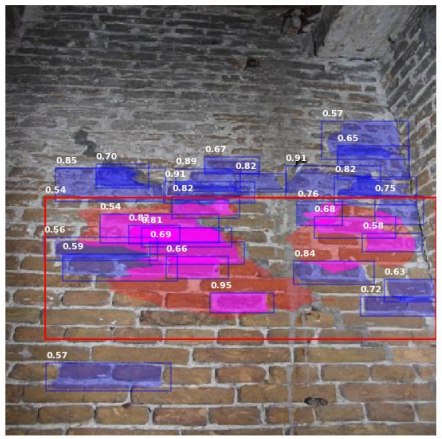
GRAFFITI





ENCRUSTATION

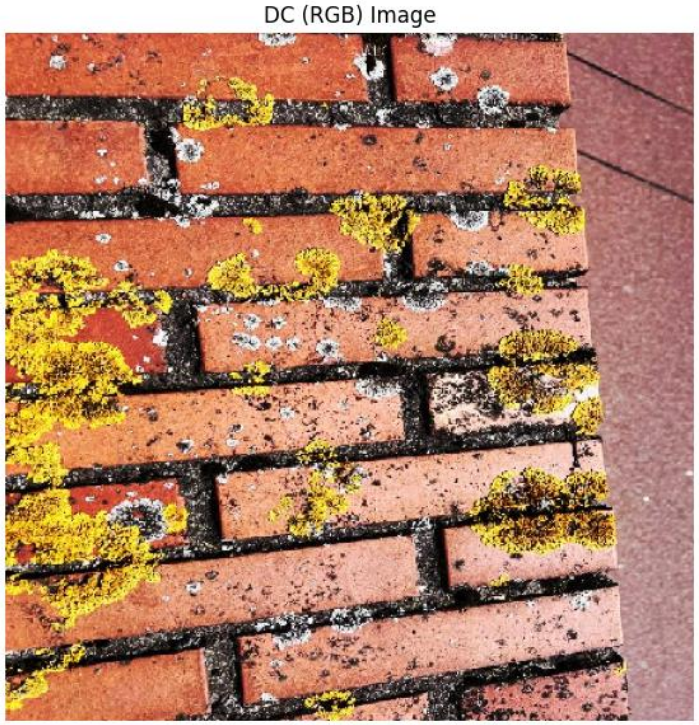


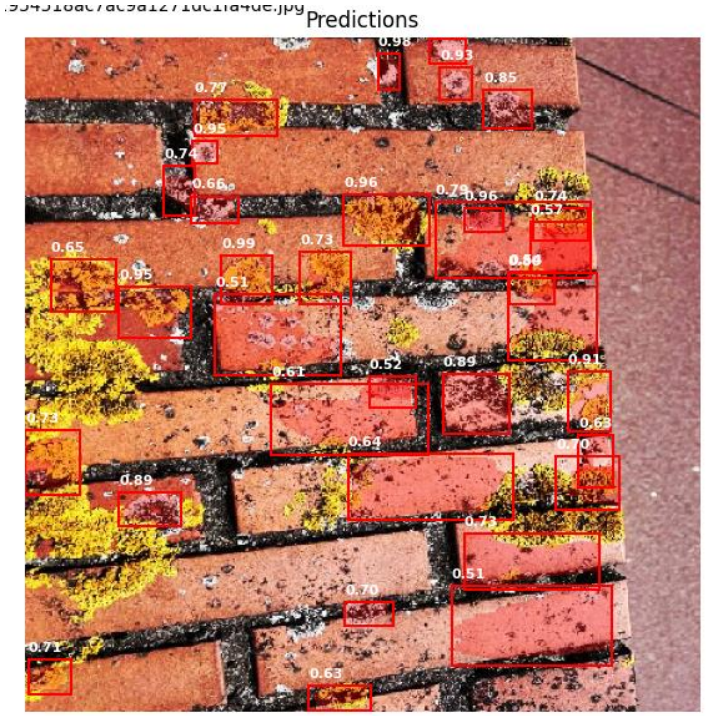


RESULTS

H2: SIMILAR CLASSES

LICHENS





RESULTS

H2: SIMILAR CLASSES

Graffiti

- Strong color contrast & defined edges
- High precision early in training

Lichens & Encrustation

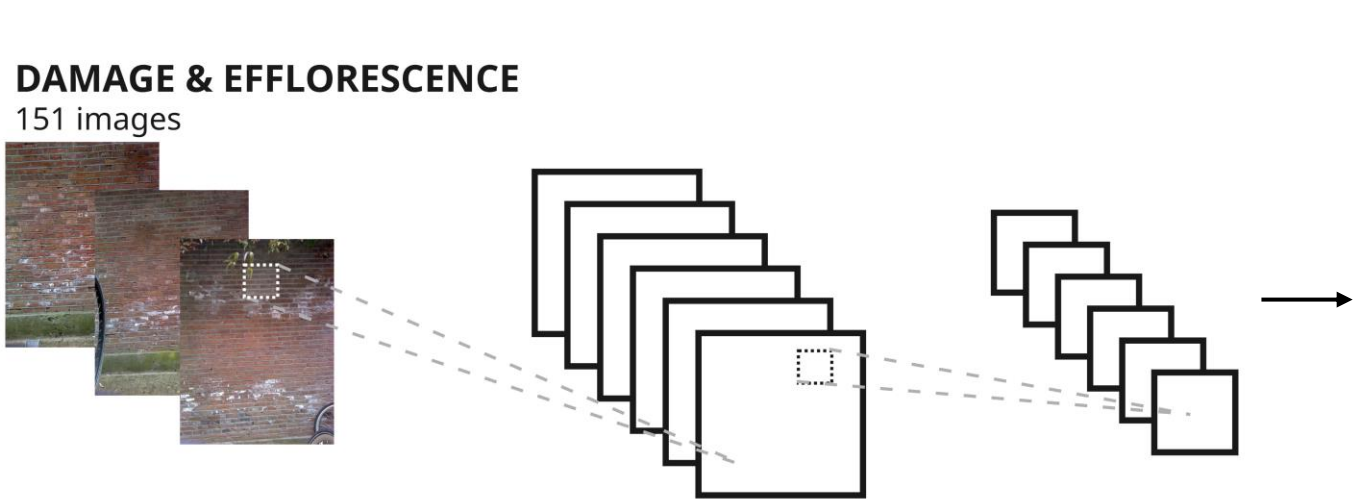
- High precision but unstable causes under detection
- Models perform conservative, predict when confidence is high

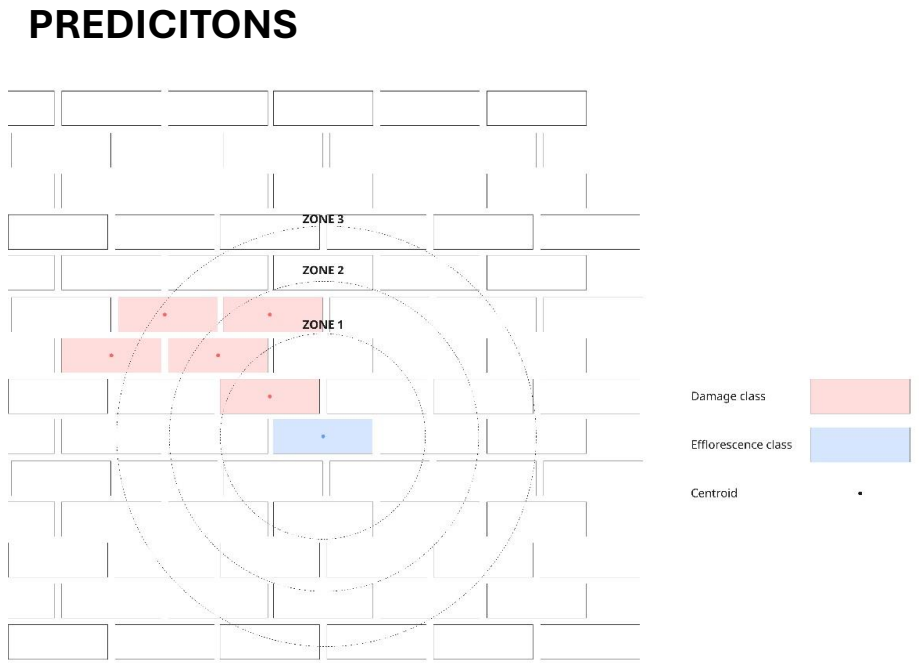
Loss behavior

- Graffiti & efflorescence: mask/class losses converge clearly
- Lichens & encrustation: segmentation struggles with irregular/diffuse shapes

RESULTS

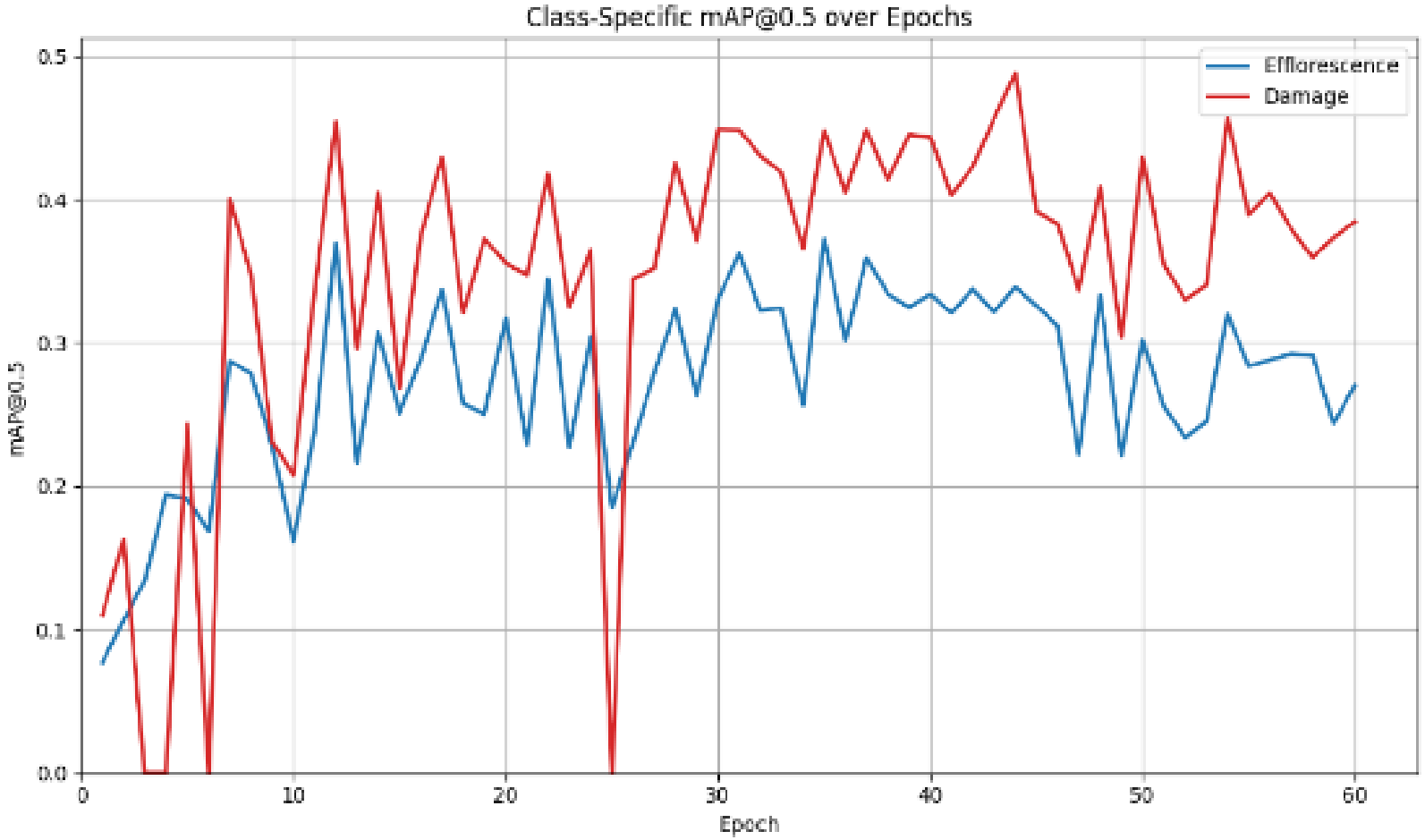
H3: DAMAGE CO-OCCURANCE – SET UP





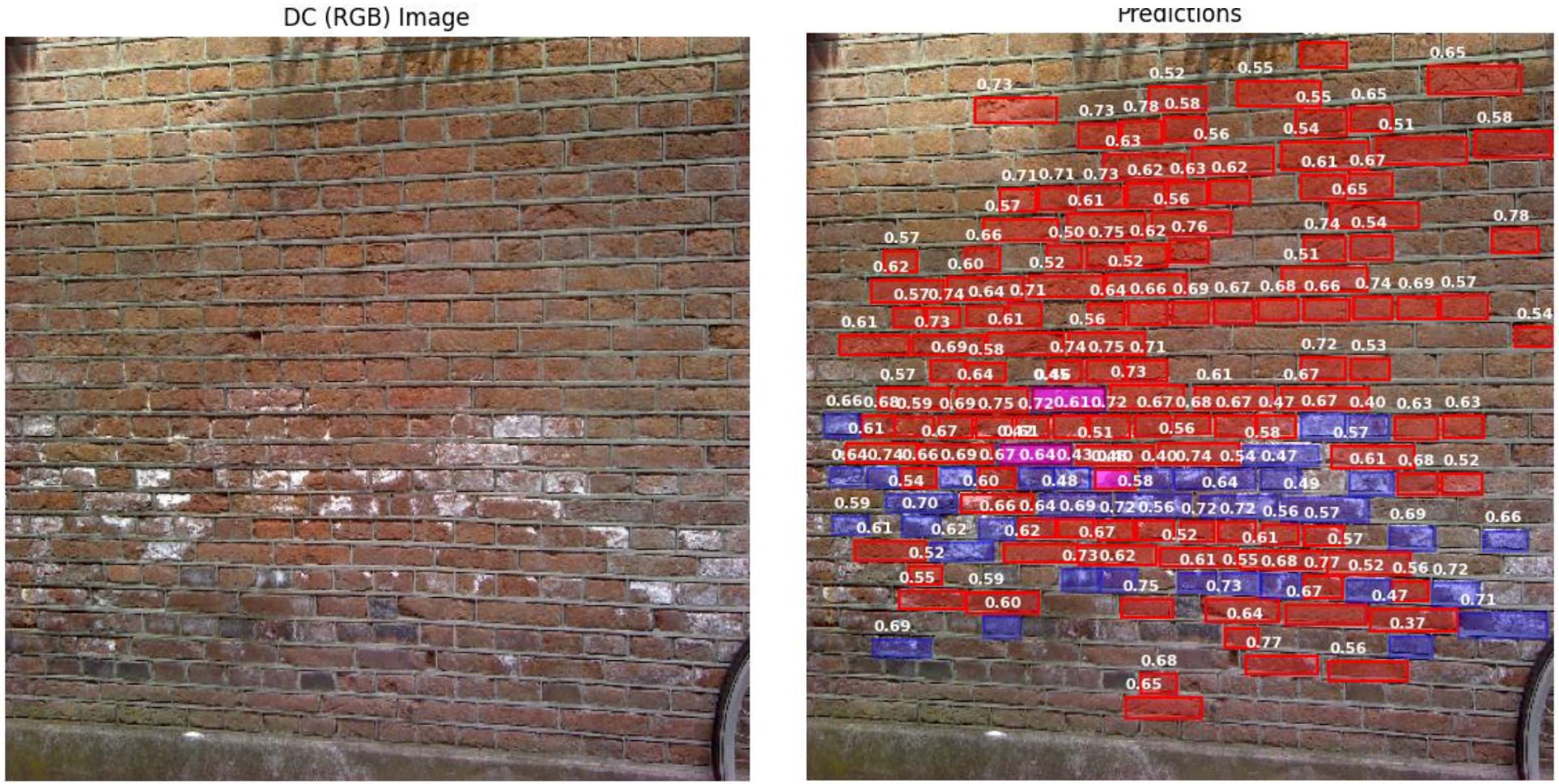
RESULTS

H3: DAMAGE CO-OCCURANCE



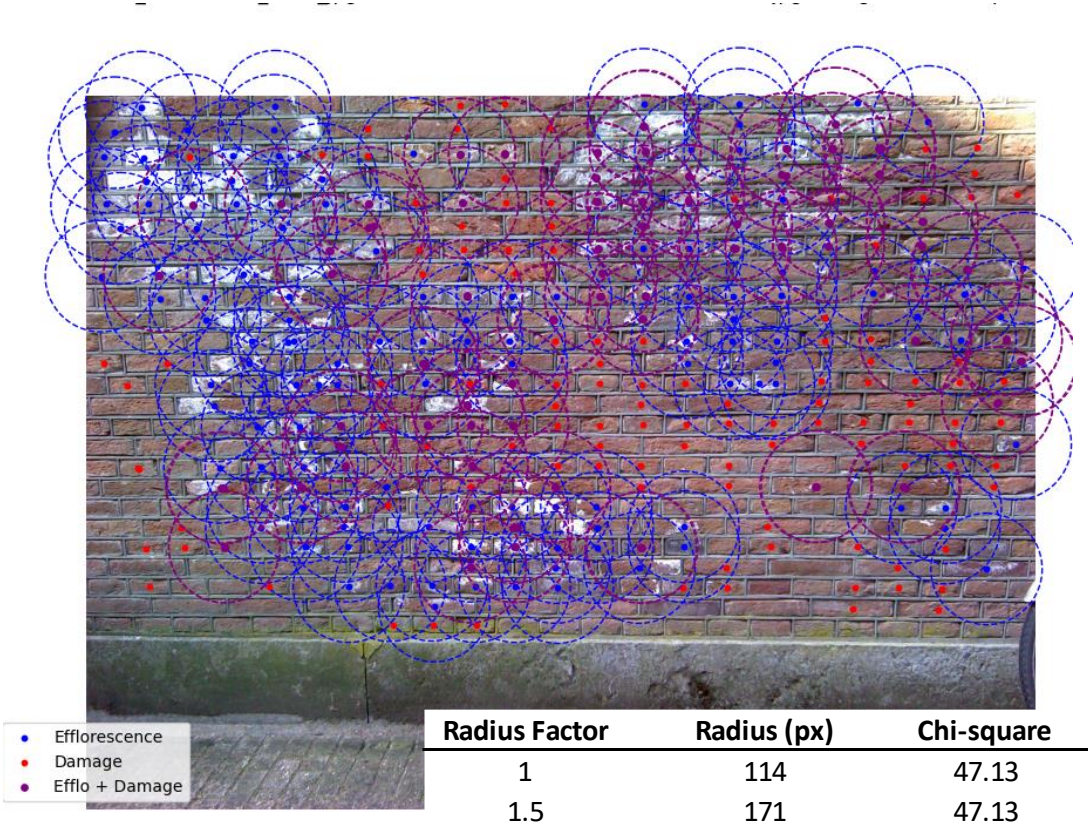
RESULTS

H3: DAMAGE CO-OCCURANCE



RESULTS

H3: DAMAGE CO-OCCURANCE



Radius Factor	Radius (px)	Chi-square	p-value
1	114	47.13	< 0.00001
1.5	171	47.13	< 0.00001
2	228	47.13	< 0.00001
5	570	6.77	0.00927

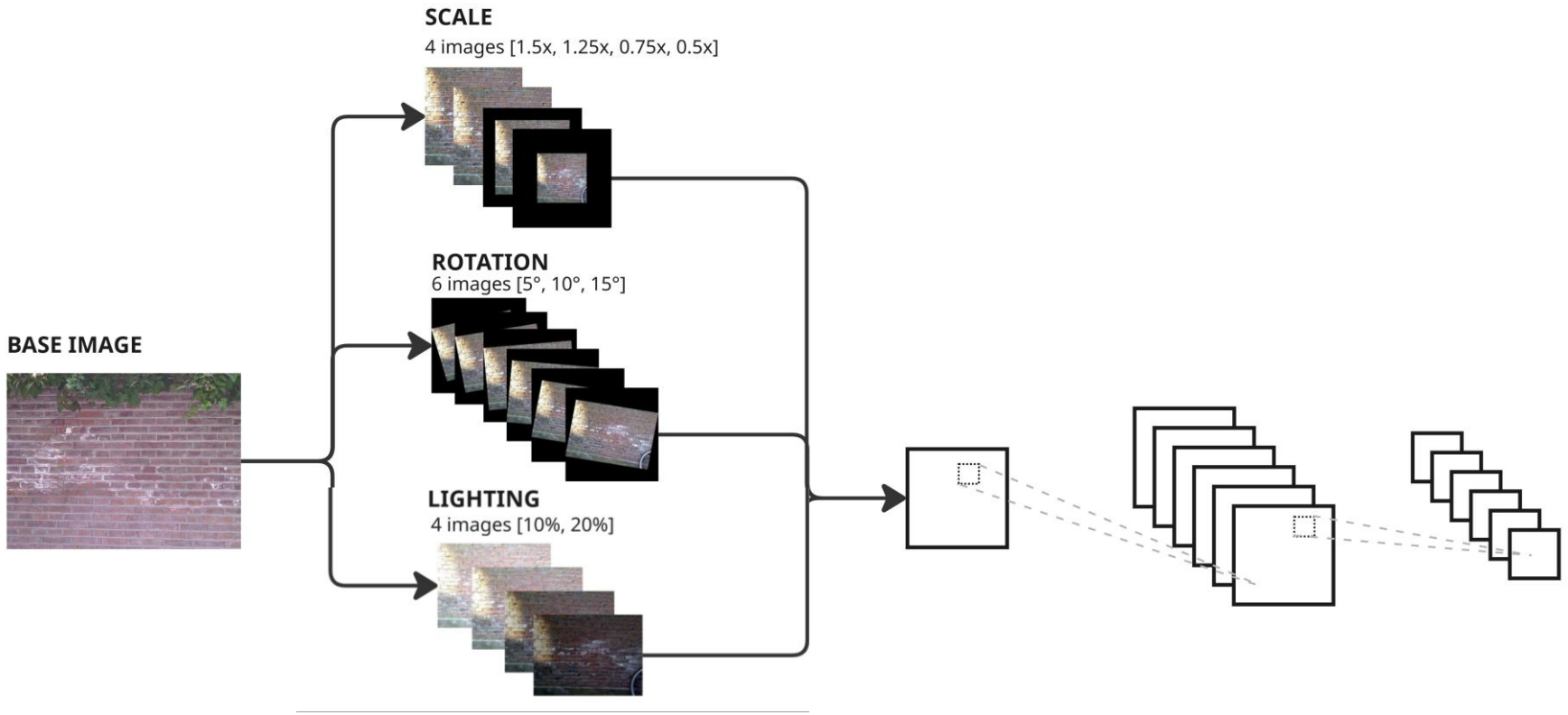
RESULTS

H3: DAMAGE CO-OCCURANCE

- Efflorescence and damage had limited convergence and moderate segmentation
- Damage outperforms efflorescence in mAP
- Class imbalance which caused high loss, unstable precision/recall
- Indicates model struggles to learn two co-occurring patterns in the same region

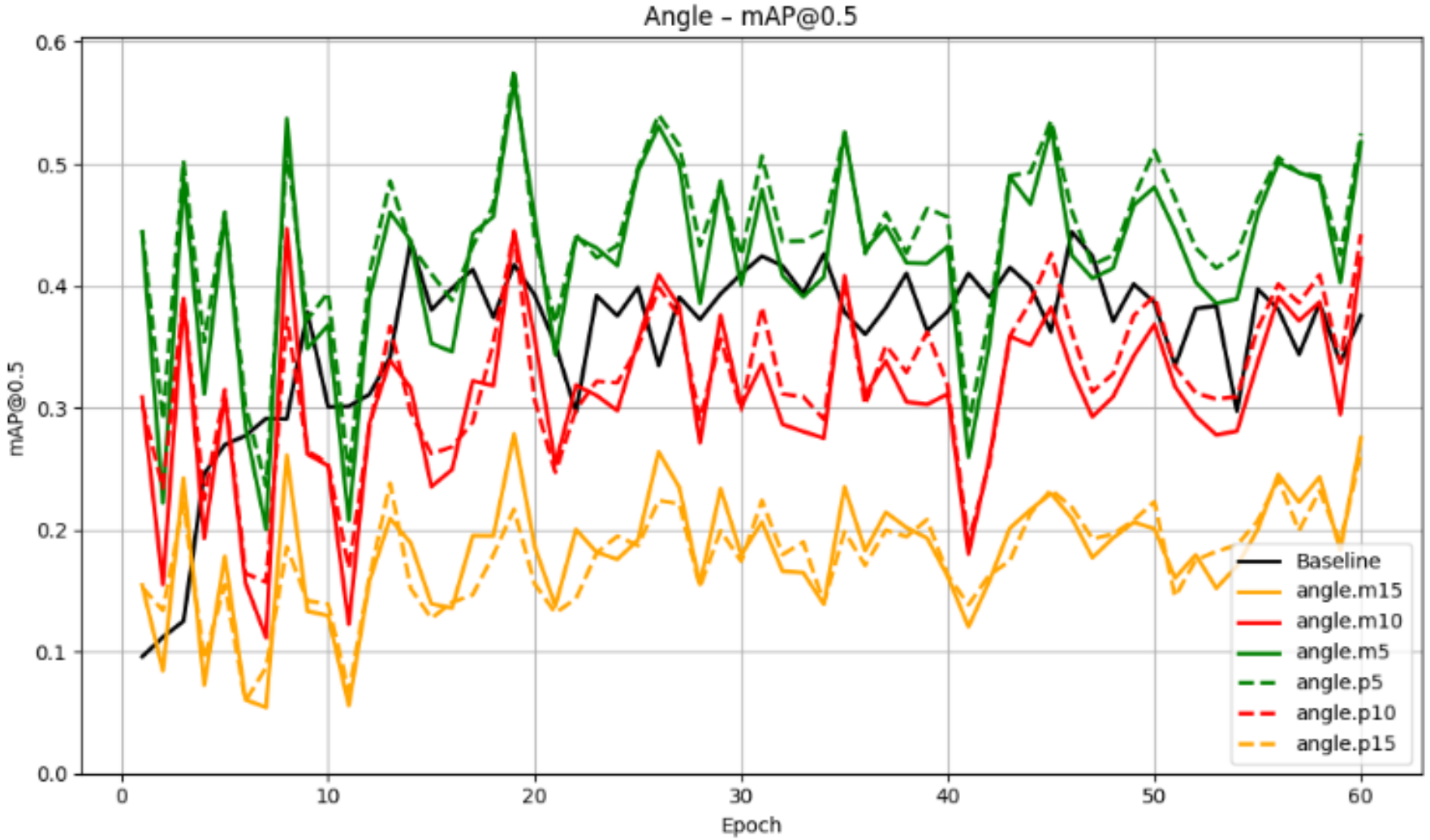
RESULTS

H4: IMAGE QUALITY– SET UP



RESULTS

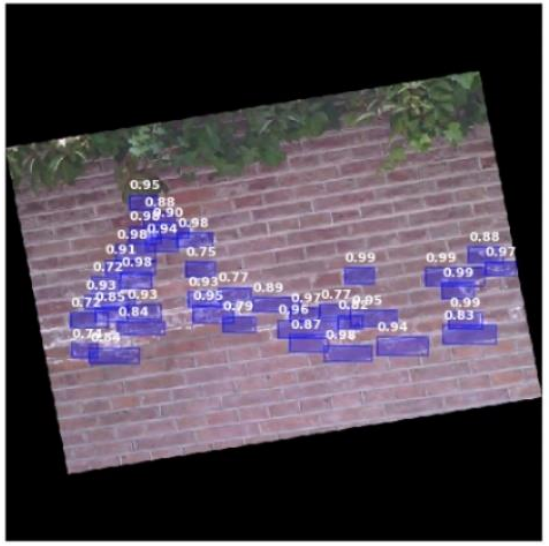
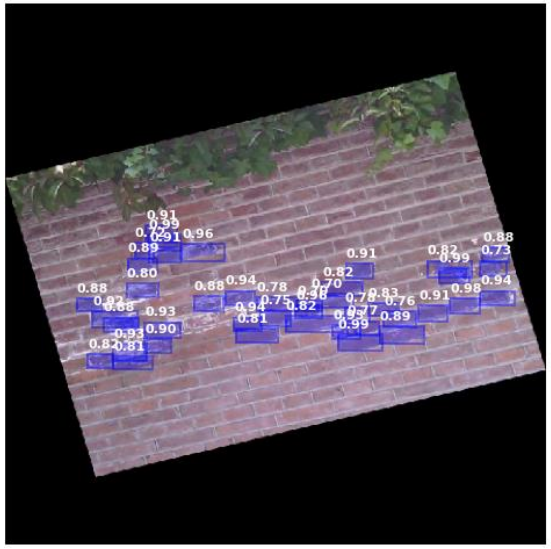
H4: IMAGE QUALITY – ANGLE SHIFT



RESULTS

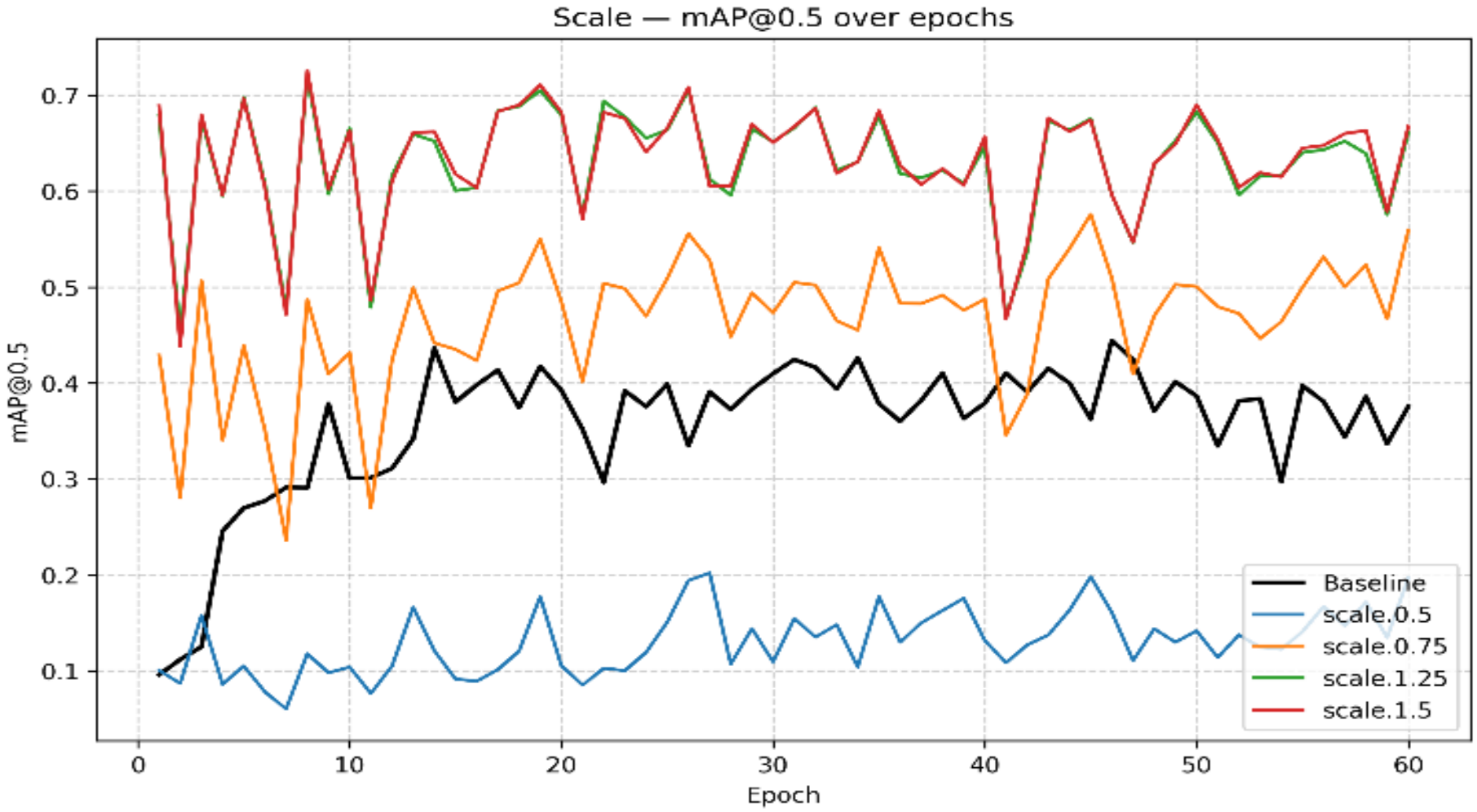
H4: IMAGE QUALITY – ANGLE SHIFT

Rotation

Base image	5°	10°	15°
			

RESULTS

H4: IMAGE QUALITY – SCALE

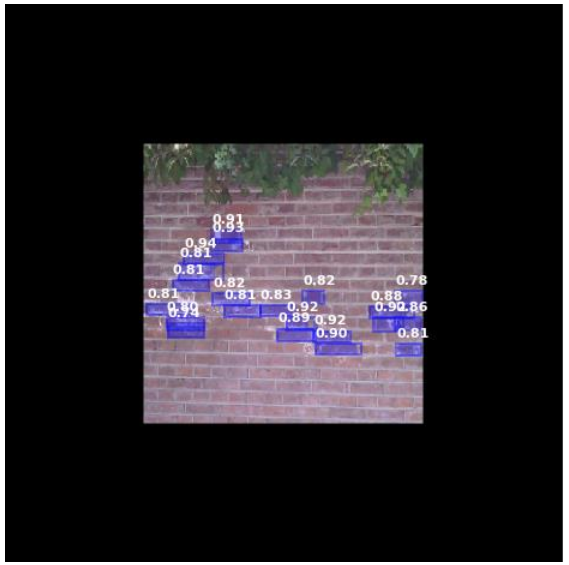


RESULTS

H4: IMAGE QUALITY – SCALE

SCALE

0.5x



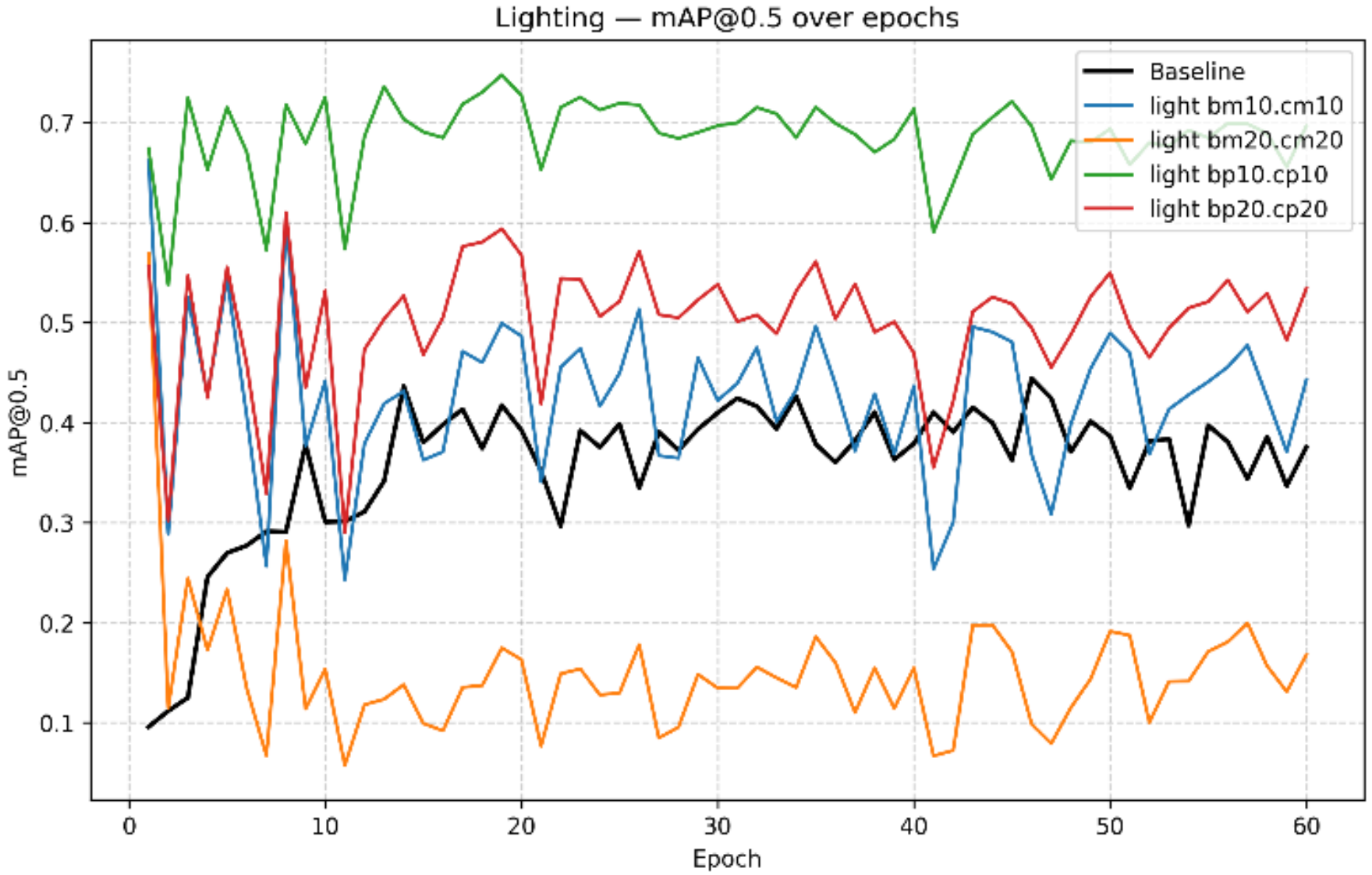
0.75x

1.25x

1.5x

RESULTS

H4: IMAGE QUALITY – LIGHTING



RESULTS

H4: IMAGE QUALITY – LIGHTING

LIGHTING

-20% -10% +10% +20%

RESULTS

H4: IMAGE QUALITY – LIGHTING

- Mild rotations are tolerated, but deviations beyond ±10° disrupt mask alignment due to perspective distortion. Rotation-aware augmentations or architectures are needed.

- Upscaling (1.25×–1.5×) improves confidence and density of predictions, while downscaling (0.5×) degrades segmentation accuracy. High-resolution inputs are critical.

- Darker inputs (−20%) collapse detection, while slight increases in brightness (+10%) enhance performance. Model lacks lighting invariance and depends on training luminance/contrast.

CONCLUSION & RECOMMENDATIONS

MAIN RESEARCH QUESTION

> *How can **deep learning** models be applied to **improve** the **detection** of **efflorescence** in **masonry** buildings in the Netherlands?*

- Deep learning can support reliable efflorescence detection on masonry
- Mask R-CNN best suited for precise masks, contextual learning
- Performance drops with poor resolution, decreased lighting, or steep angles
- Misclassification with lichens/encrustation remains a challenge
- Thermal fusion raises precision but lowers recall, needs refinement
- Reliable deployment requires diverse, high-quality annotations

LESSONS LEARNED & FUTURE WORK

DISCUSSION

TECHNICAL

- More powerful hardware and **deeper backbones** (resnet101) and larger batch sizes.
- Increase **training epochs** and incorporate different **learning strategies** like active learning, mix precision training.
- Try **frame works** (Swin transform, Segformer etc)

DATASET & ANNOTATION

- Expand dataset with additional classes like **efflorescence in the joint.**
- **Additional damage types** according to **MDCS** and maybe differentiate between brick types to adjust performance
- Apply / research towards **data augmentation strategies** tailored to **weathering**.
- Train models with a **dataset** consisting of images taken **over time**

LESSONS LEARNED & FUTURE WORK

DISCUSSION

COLLABORATION AND APPLICATION

- Evaluate models with **expanding on urban level mapping** and **drone-based** inspection
- Continue **open data** and **code sharing**
- Promote the creation of **public datasets** from **MDCS** to enhance research capabilities
- Provide educational materials or **labeling guidelines** for **consistent annotations**

ENVIRONMENTAL / CONTEXTUAL

- Incorporate **geospatial** and **environmental metadata**
- Include **5th channel depth** information from **pointclouds** for additional features
- **Standardized image acquisition protocols** for MDCS future proofing
  Additional thermal patterns to **distinguish capillary** action vs leakage

THANK YOU

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