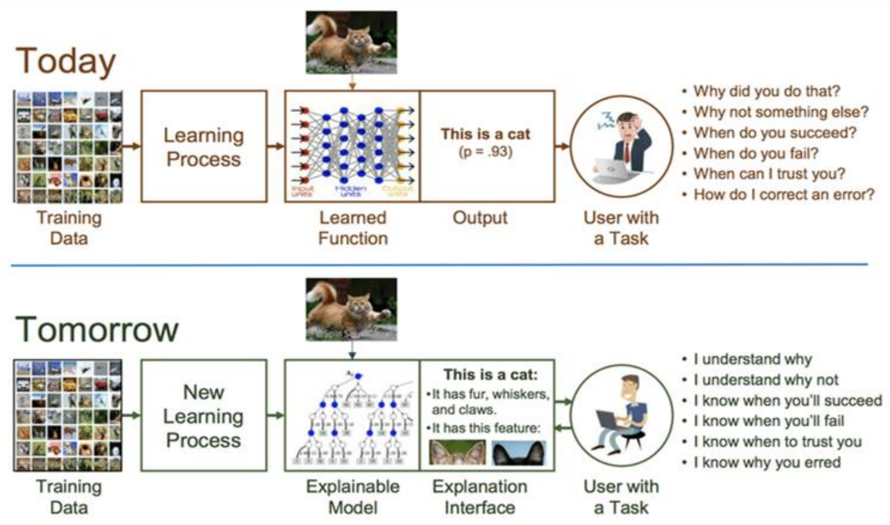
# Towards Explainable Image Classification

Vahidin Hasić, University of Sarajevo, Sarajevo, Bosnia and Herzegovina, vahidin.hasic@etf.unsa.ba

## Motivation

While Deep Neural Networks (DNNs) excel in image classification, their black-box nature necessitates the development of Explainable AI (XAI) methods. Existing XAI techniques face limitations in balancing explainability, fidelity, and efficiency.




Lin, Cheng-Jian & Jhang, Jyun-Yu. (2021). Bearing Fault Diagnosis Using a Grad-CAM-Based Convolutional Neuro-Fuzzy Network. Mathematics. 9. 1502. 10.3390/math9131502.

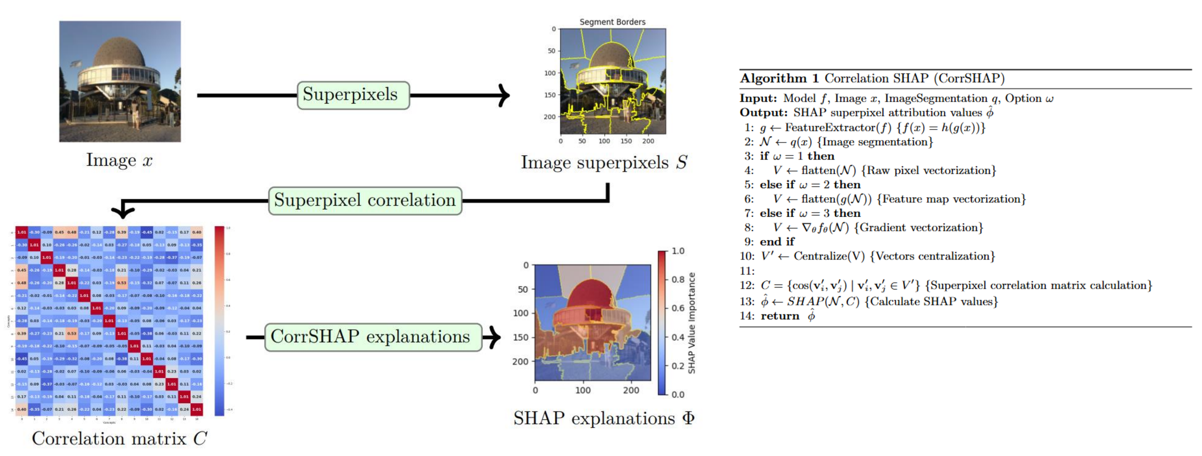
## Thesis Contributions:

- **Perturbation-based explanations –** explaining model predictions by perturbing the input.
- **Concept-based explanations -** explaining model predictions by leveraging human-understandable concepts.
- **Sample-based explanations -** explaining model predictions by leveraging training data.

**CLEAR-VISION: Credible Learning for Explainable and Reliable Visual Recognition**

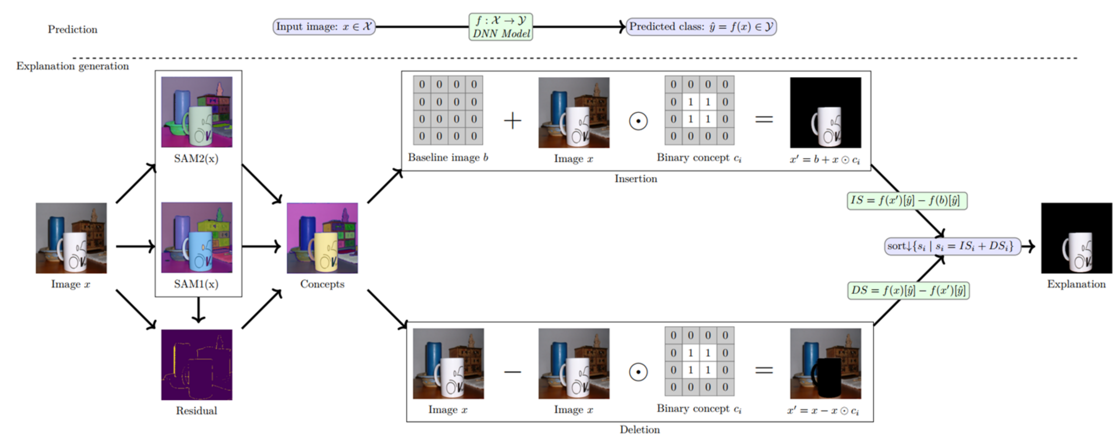
CLEAR-VISION

## Correlation SHAP (CorrSHAP)



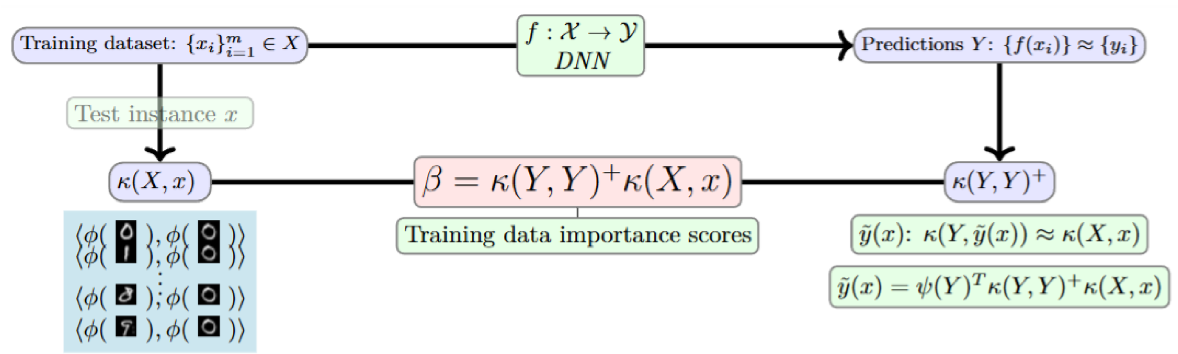

Framework of the proposed CorrSHAP method. The input image is segmented into superpixels. Superpixels are vectorized and centralized into vectors. The correlation matrix between superpixels is calculated using cosine similarity between individual vectors. For each superpixel, we take correlated superpixels, where correlation is higher than the threshold, and perform perturbations on all combinations to calculate superpixel attribution. [1]

## Any Segment Explanation (ASE)



Any Segment Explanation (ASE) overview. An input image is classified, yielding a certain prediction. It is segmented with the Segment Anything Model. Segments are treated as concepts and are transformed into binary masks. Perturbed images are generated by inserting/deleting concepts. Insertion/Deletion Scores (IS/DS) measure model prediction change. The concepts are ranked by combining IS and DS scores, where the k top-scoring concepts are shown as the explanation. [2]

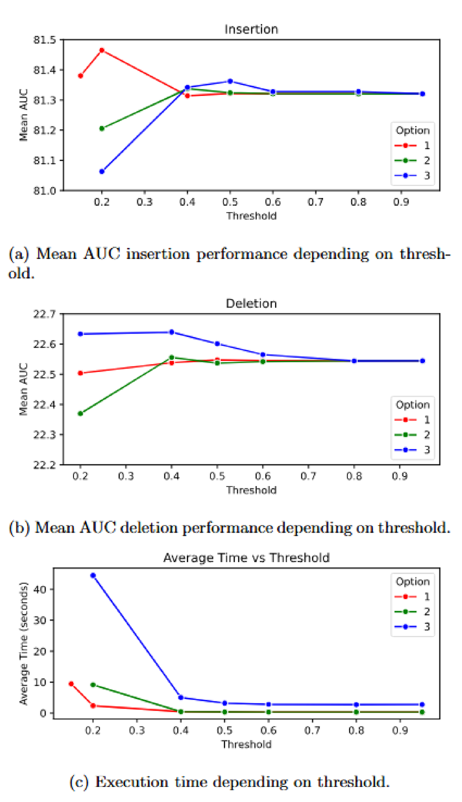
## Kernel Sample Based Explanations (K-SBE)

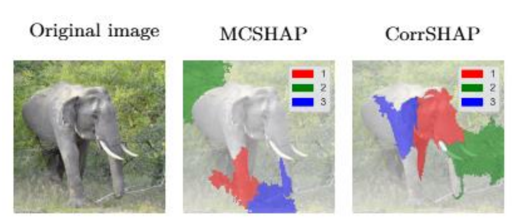



A pretrained model generates predictions Y for a training dataset X, where each image is flattened into a feature vector, forming a matrix X. The output matrix Y has rows for instances and columns for output dimensions. For a test instance x, the kernel matrix $\kappa(X,x)$ and the pseudoinverse $\kappa(Y,Y)^{+}$ are computed. The attribution scores for the training instances are calculated using the dot product $\kappa(Y,Y)^{+} \cdot \kappa(X,x)$. Sorting this vector reveals the importance of each training instance $x_i$ related to the test instance x. [3]

## Results

### Correlation SHAP (CorrSHAP)



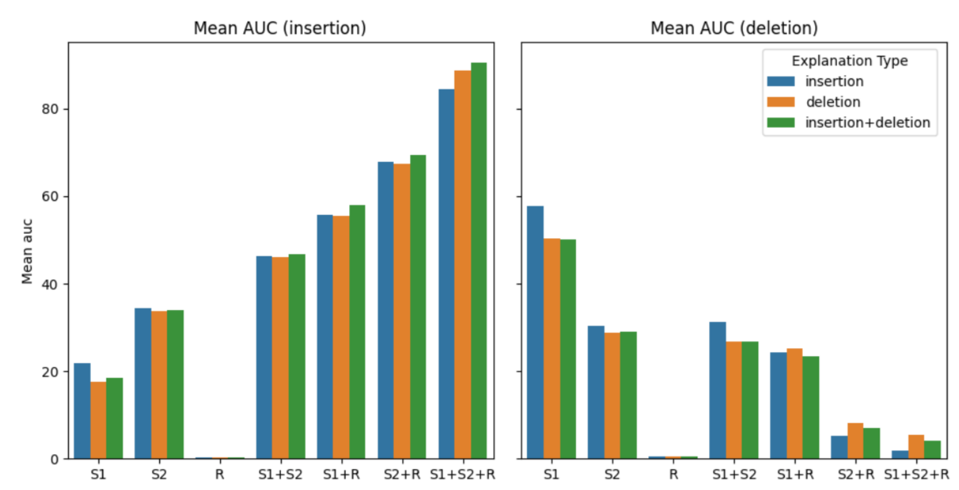

Model prediction: elephant

| Model | Superpixels | CorrSHAP 1 | CorrSHAP 2 | CorrSHAP 3 | MCSHAP |
|---|---|---|---|---|---|
| **Area Under the Curve (AUC) Insertion ↑** | | | | | |
| MobileNet-v2 | Quickshift | 80.4 | 80.37 | 80.29 | **80.89** |
| | SLIC | **78.12** | 78.13 | 78.15 | 77.79 |
| ResNet-18 | Quickshift | 60.21 | 60.23 | 60.21 | **61.60** |
| | SLIC | 54.66 | 54.65 | 54.65 | **55.41** |
| ResNet-50 | Quickshift | **82.63** | 82.61 | 82.63 | 82.27 |
| | SLIC | **81.20** | 81.20 | 81.20 | 80.66 |
| ViT-b16 | Quickshift | 80.83 | 80.83 | 80.74 | **81.84** |
| | SLIC | 76.36 | 76.33 | 76.41 | **76.82** |
| **Area Under the Curve (AUC) Deletion ↓** | | | | | |
| MobileNet-v2 | Quickshift | **20.14** | 20.14 | 20.16 | 20.93 |
| | SLIC | **19.48** | 19.48 | 19.48 | 21.40 |
| ResNet-18 | Quickshift | 8.25 | 8.25 | 8.25 | **8.03** |
| | SLIC | 9.06 | 9.06 | 9.06 | **9.01** |
| ResNet-50 | Quickshift | **22.79** | 22.79 | 22.79 | 24.16 |
| | SLIC | **22.36** | 22.36 | 22.39 | 23.79 |
| ViT-b16 | Quickshift | 17.20 | 17.17 | 17.13 | **16.86** |
| | SLIC | 20.53 | 20.53 | 20.53 | **20.48** |
| **Execution Time (seconds) ↓** | | | | | |
| MobileNet-v2 | Quickshift | **0.42** | 0.54 | 1.15 | 16.13 |
| | SLIC | **0.74** | 0.89 | 1.86 | 14.98 |
| ResNet-18 | Quickshift | **0.43** | 0.50 | 1.09 | 7.85 |
| | SLIC | 0.66 | **0.51** | 1.91 | 13.82 |
| ResNet-50 | Quickshift | **0.46** | 0.58 | 2.76 | 25.16 |
| | SLIC | **0.78** | 0.93 | 5.93 | 36.49 |
| ViT-b16 | Quickshift | **0.40** | 0.52 | 5.41 | 7.26 |
| | SLIC | **0.73** | 1.01 | 10.53 | 18.00 |

Performance analysis as a function of the threshold. **Option 1** - raw pixel vectorization, **Option 2** - feature map vectorization, and **Option 3** - gradient vectorization. Lower AUC deletion, higher AUC insertion scores, and lower execution time indicate superior performance. The execution time decreases sharply until 0.5 threshold, without sacrificing method faithfulness. Further reductions of threshold yields diminishing returns in performance.

### Any Segment Explanation (ASE)

| | | ASE(ours) | EAC* | DeepLIFT* | GradSHAP* | IntGrad* | KernelSHAP* | FeatAbl* | LIME* |
|---|---|---|---|---|---|---|---|---|---|
| Insertion ↑ | ResNet-50 | **91.10** | 83.400 | 75.235 | 64.658 | 68.772 | 64.544 | 70.187 | 76.638 |
| | MobileNet-v2 | **90.67** | 74.651 | 34.197 | 47.848 | 48.662 | 60.837 | 59.197 | 61.282 |
| | ViT-b16 | **89.86** | 89.594 | 54.455 | 68.125 | 69.480 | 75.152 | 65.656 | 76.161 |
| | ResNet-18 | **78.03** | 73.558 | 47.799 | 38.877 | 36.806 | 50.547 | 43.448 | 50.592 |
| Deletion ↓ | ResNet-50 | **8.99** | 23.799 | 25.262 | 40.996 | 36.214 | 26.583 | 37.332 | 25.307 |
| | MobileNetv2 | 6.61 | **6.002** | 26.381 | 14.679 | 13.382 | 7.766 | 8.866 | 7.344 |
| | ViT-b16 | **6.24** | 17.298 | 40.784 | 30.948 | 29.903 | 21.825 | 34.191 | 19.254 |
| | ResNet-18 | **2.57** | 6.596 | 8.588 | 11.273 | 11.555 | 6.638 | 8.352 | 6.776 |

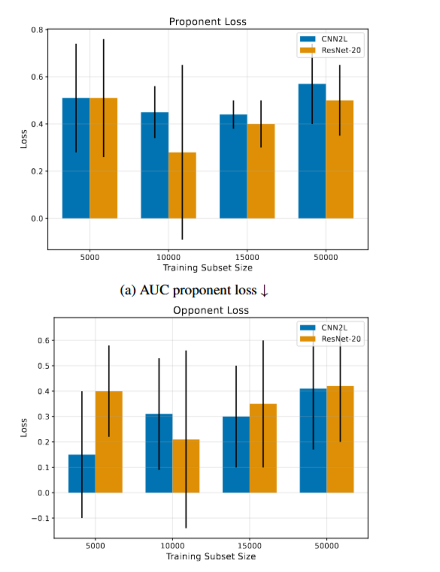



Ablation study of concept insertion and deletion using MobileNet v2 on 100 randomly sampled ImageNet-1k images. Performance is measured by the area under the curve (AUC). S1 and S2 refer to segmentation algorithms SAM1 and SAM2, respectively, while R denotes the residual region. Results demonstrate improved performance when combining segmentation methods and concept insertion and deletion.

### Kernel Sample Based Explanations (K-SBE)

| | Execution time (s) ↓ | | | | | Mean AUC DEL accuracy proponent ↑ | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | K-SBE (ours) | TracIn | Gen-Rep NTK-final (tracing) | Influence Function | Random | K-SBE (ours) | TracIn | Gen-Rep NTK-final (tracing) | Influence Function | Random |
| CIFAR-10 | **0.00926** | 4144.23 | 104.72 | 124.25 | *0.00079* | 2.60 ± 5.00 | **3.80 ± 5.22** | 1.00 ± 3.22 | -4.00 ± 5.26 | -3.60 ± 5.15 |
| CIFAR-100 | **0.02838** | 3944.29 | 398.54 | 234.49 | *0.00035* | **3.80 ± 6.44** | 2.40 ± 5.44 | 2.20 ± 3.47 | 3.00 ± 4.36 | 1.40 ± 4.90 |
| FMNIST | **0.00805** | 2794.05 | 394.94 | 265.05 | *0.00046* | **2.60 ± 5.39** | -7.00 ± 5.30 | -2.00 ± 2.33 | -4.40 ± 3.84 | -3.80 ± 3.89 |
| MNIST | **0.00355** | 2793.02 | 125.66 | 139.20 | *0.00031* | **0.00 ± 0.79** | -2.60 ± 3.55 | -0.60 ± 1.42 | -1.40 ± 3.01 | -0.60 ± 2.92 |

| | Train subset | Mean AUC DEL logits proponent ↑ | | | | |
|---|---|---|---|---|---|---|
| | | K-SBE (ours) | TracIn | Gen-Rep NTK-final | Influence Function | Random |
| CIFAR-10 | 5000 | **1.06 ± 0.50** | 0.68 ± 0.44 | 0.01 ± 0.36 | -0.27 ± 0.30 | -0.31 ± 0.34 |
| | 10000 | **1.34 ± 0.41** | 0.32 ± 0.40 | 0.13 ± 0.28 | 0.11 ± 0.23 | 0.11 ± 0.22 |
| | 15000 | **1.32 ± 0.34** | 0.73 ± 0.30 | 0.16 ± 0.21 | -0.31 ± 0.12 | -0.33 ± 0.12 |
| | 50000 | 0.62 ± 0.21 | **0.77 ± 0.32** | -0.03 ± 0.17 | -0.57 ± 0.15 | -0.58 ± 0.14 |
| CIFAR-100 | 6000 | 0.31 ± 0.62 | **0.90 ± 0.57** | -0.58 ± 0.43 | 0.40 ± 0.40 | 0.46 ± 0.41 |
| | 12000 | 0.99 ± 0.33 | **1.13 ± 0.49** | -0.11 ± 0.33 | 0.24 ± 0.28 | 0.26 ± 0.30 |
| | 18000 | **1.12 ± 0.38** | 0.44 ± 0.30 | -0.01 ± 0.24 | 0.24 ± 0.15 | 0.24 ± 0.18 |
| | 60000 | 0.77 ± 0.15 | **0.81 ± 0.24** | 0.18 ± 0.21 | 0.08 ± 0.16 | 0.06 ± 0.16 |
| FMNIST | 5000 | **0.97 ± 0.17** | -1.44 ± 0.30 | -2.38 ± 0.27 | -2.58 ± 0.26 | -2.62 ± 0.27 |
| | 10000 | **0.08 ± 0.11** | -1.68 ± 0.31 | -1.87 ± 0.31 | -2.90 ± 0.21 | -2.92 ± 0.22 |
| | 15000 | **0.12 ± 0.14** | -1.82 ± 0.30 | -2.05 ± 0.30 | -3.03 ± 0.20 | -3.06 ± 0.21 |
| | 50000 | **0.41 ± 0.09** | -2.54 ± 0.35 | -2.79 ± 0.31 | -3.89 ± 0.25 | -3.88 ± 0.26 |
| MNIST | 6000 | **0.67 ± 0.18** | -2.98 ± 0.36 | -3.60 ± 0.37 | -4.08 ± 0.40 | -4.09 ± 0.39 |
| | 12000 | **1.24 ± 0.15** | -4.50 ± 0.30 | -4.71 ± 0.31 | -5.65 ± 0.31 | -5.73 ± 0.31 |
| | 18000 | **0.76 ± 0.15** | -3.66 ± 0.28 | -4.16 ± 0.24 | -5.06 ± 0.27 | -5.12 ± 0.27 |
| | 60000 | **0.59 ± 0.10** | -4.18 ± 0.32 | -5.02 ± 0.32 | -5.72 ± 0.27 | -5.75 ± 0.28 |




Quantitative comparison of proposed K-SBE against: TracIn, Generalized Representer and Influence Function. We evaluate efficiency (execution time in seconds, lower is better) and explanation faithfulness (delta accuracy, higher is better). Random data attribution (italicized) provides the lowest possible execution time. K-SBE drastically outperforms other methods in execution time, approaching the theoretically lowest possible execution time, while outperforming other state-of-the-art methods in the faithfulness of the explanations.

## Open research questions

- How can compensatory mechanisms restore SHAP completeness and symmetry in non-exhaustive sampling?
- How can contextualized verbal and visual explanations be generated for multi-class image classification?
- How can custom kernels be designed and developed to optimize the performance of sample-based explanations?

## Supervisor

- Asst. Prof. Dr. Senka Krivic, Faculty of Electrical Engineering, University of Sarajevo, Sarajevo, Bosnia and Herzegovina

## References

[1] Accepted at World Conference on eXplainable Artificial Intelligence (XAI 2025).
[2] Accepted at International Conference on Artificial Neural Networks (ICANN 2025).
[3] Submitted to International Conference on Computer Vision (ICCV 2025).