# UzADL method

# UzADL

- Unsupervised learning method
- Localize defected part
- Binary classification
- Principal stages:
  - Annonte unlabeled images
  - Train based on obtained images
  - Visualize defective regions

# Annonte unlabeled images

- Pre-Processing:
  - Represent images in 4D Tensor
  - $X \in \mathrm{R}^{M \times C \times H \times W}$,
    - M: Total number of images
    - C: Number of channels
    - H: Image height
    - W: Image width
  - This tensor contains all the raw pixel values for the images.
  - Standardization of Pixel Values

# Pseudo-Labeling

- Want to label datas in 2 class (Normal – defected)
- Extract Features from the Images
- Construct the Graph Based on Feature Similarity
  - Create a graph of images
- Form the Adjacency Matrix and Degree Matrix
- Compute the Graph Laplacian Matrix
  - Degree matrix – adjacency matrix

$$\begin{pmatrix} M_1 & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & M_K \end{pmatrix}$$

- Obtain the largest EVL and corresponding EVT
- Save into 1D vector
- Apply a threshold to classify On largest Eigenvectors( e.g. 0)
- Assign label to X0(class N) and X1(class A)

$$V_{\mathrm{GL}} = \begin{bmatrix} 0.7 & 0 \\ -0.7 & 0 \\ 0 & 0.6 \\ 0 & -0.6 \end{bmatrix}$$

**Input:** Tensor $X_{std}$; **Output:** $X_0$, $y_0$, $X_1$, $y_1$;

**Let** $M_{Adj}$ be adjacent matrix of $X_{std}$;

**Obtain** $M_{Deg}$ based on $M_{Adj}$;

**Let** $M_{GL} = M_{Deg} - M_{Adj}$;

**Obtain** EVL and EVT of $M_{GL}$;

**Stack** largest EVTs into $V_{GL}$;

**for** $i$ in $len(V_{GL})$ **do**

    **Cluster** $v_i$ into $c_0$ and $c_1$;

**end for**

$X_0 \leftarrow []$, $y_0 \leftarrow []$, $X_1 \leftarrow []$, $y_1 \leftarrow []$

**for** $j$ in $len(c_0)$ **do**

    **Extend** $X_0$ with $X == c_0[j]$;

    **Extend** $y_0$ with 0;

**end for**

**for** $k$ in $len(c_1)$ **do**

    **Extend** $X_1$ with $X == c_1[k]$;

    **Extend** $y_1$ with 1;

**end for**

**Return** $X_0$, $y_0$, $X_1$, $y_1$.

# Training process

- Use pre-trained ResNet-18 model
- Extract features from the images
- After extracting the features, develop a model of several fully connected layers
- input of this model is the feature vector from ResNet-18.
- Use a sigmoid for last layer
- Use weighted binary cross-entropy loss function
- Use SGD optimizer

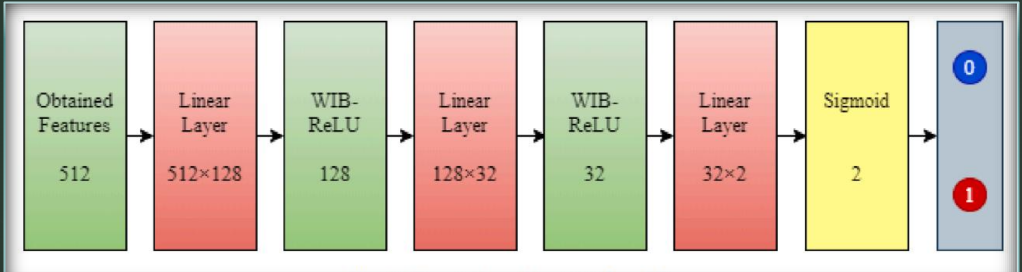
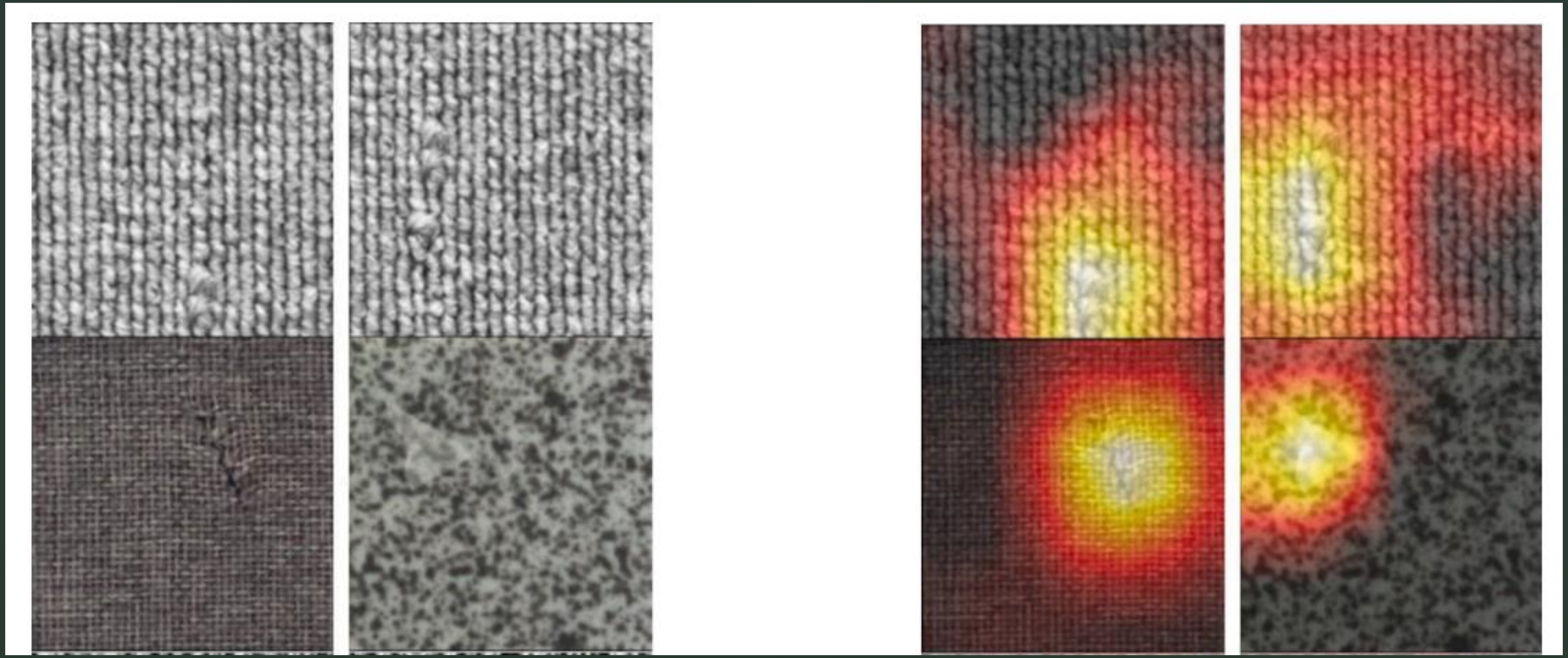


Fig. 2. Description of the DNNM model.

# Defect visualization

- If the model predicts an image as defected:
  - Compute significance of each feature map
    - partial derivative of the pre-final layer’s output
  - It measures how sensitive the output is to changes in each feature map.
  - Apply Global Average Pooling On partial derivative
  - Result shows the importance of each feature map in defected class
  - heatmap highlights the regions in the image that contributed the most to the "defective" classification.

# Heatmap example



# Performance

| Dataset Name | Model Name | AS | PS | RS | F1 | AUC | Time (s) |
|---|---|---|---|---|---|---|---|
| NT | SSBD | 0.942 | 0.926 | 0.978 | 0.952 | 0.870 | 2.034 |
| | LDFC | 0.958 | 0.932 | **0.976** | 0.954 | 0.886 | 1.901 |
| | CTPT | 0.937 | 0.944 | 0.948 | 0.946 | 0.892 | 1.972 |
| | ADIC | 0.832 | 0.819 | 0.829 | 0.824 | 0.792 | 4.281 |
| | UNST | 0.819 | 0.822 | 0.842 | 0.832 | 0.809 | 3.335 |
| | UzADL | **0.984** | **0.971** | 0.973 | **0.972** | **0.899** | **1.224** |
| MVAD | SSBD | 0.970 | 0.968 | 0.960 | 0.964 | 0.910 | 7.920 |
| | LDFC | 0.968 | 0.960 | 0.940 | 0.960 | 0.906 | **5.240** |
| | CTPT | 0.940 | 0.917 | 0.939 | 0.928 | 0.899 | 8.710 |
| | ADIC | 0.858 | 0.820 | 0.880 | 0.850 | 0.826 | 14.003 |
| | UNST | 0.892 | 0.865 | 0.835 | 0.850 | 0.843 | 12.827 |
| | UzADL | **0.990** | **0.992** | **0.990** | **0.991** | **0.913** | 7.164 |
| DW | SSBD | 0.972 | 0.921 | 0.939 | 0.930 | 0.892 | 8.802 |
| | LDFC | 0.980 | 0.899 | **0.997** | 0.948 | 0.905 | 9.124 |
| | CTPT | 0.958 | 0.962 | 0.938 | 0.950 | 0.899 | 9.120 |
| | ADIC | 0.903 | 0.895 | 0.891 | 0.893 | 0.850 | 19.573 |
| | UNST | 0.902 | 0.945 | 0.901 | 0.923 | 0.878 | 17.092 |
| | UzADL | **0.996** | **0.997** | 0.996 | **0.996** | **0.946** | **5.530** |