CSIC 5011 Final Project

SEGMENTING CRACKS USING CLASSIFICATION ALGORITHMS ON THE LOW DIMENSIONAL EMBEDDING OF CRACK DATA

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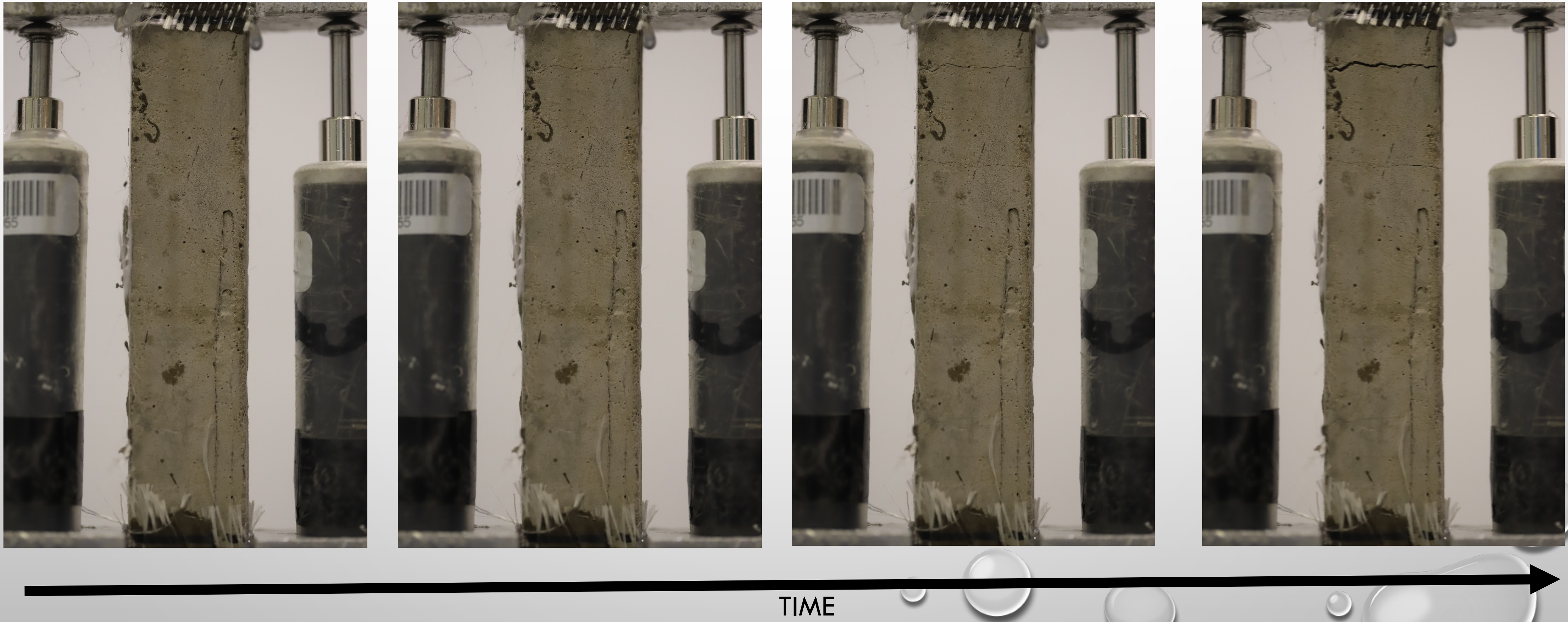
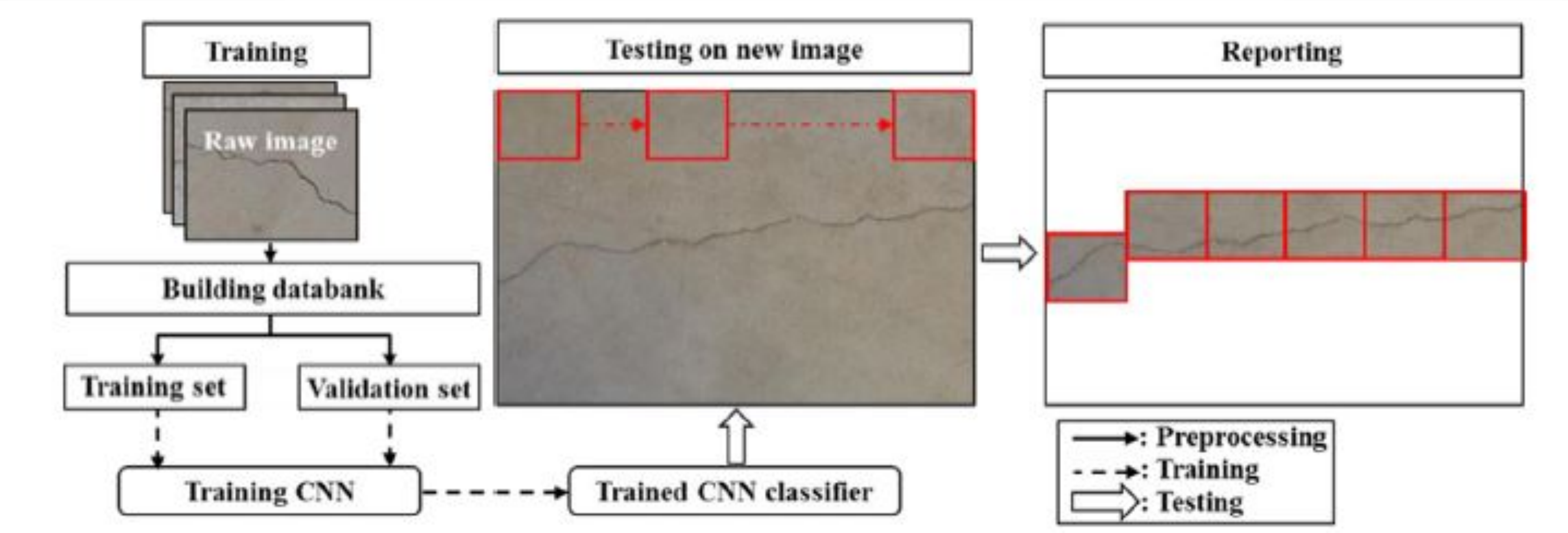
CONTENTS

BACKGROUND



BACKGROUND

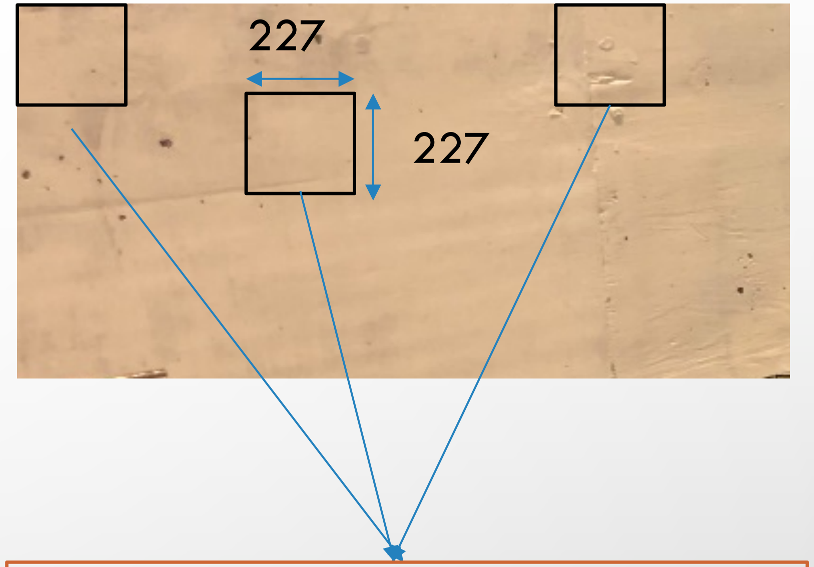


Training
Raw image
Building databank
Training set
Validation set
Training CNN
Testing on new image
Trained CNN classifier
Reporting
: Preprocessing
: Training
: Testing

PROBLEM STATEMENT

Crack Segmentation through classification of embedding as an alternative to techniques based on **'learning'**

DATA COLLECTION: PROCESSING



Grey Scaling and Annotating, Flattening

Crack Dataset I_{nxd}

n is number of segments 10000 with 5000 'D' damaged image and 5000 'ND' Not damaged Image

d dimension of each image (227x227)=51529

DATA COLLECTION : EXAMPLE

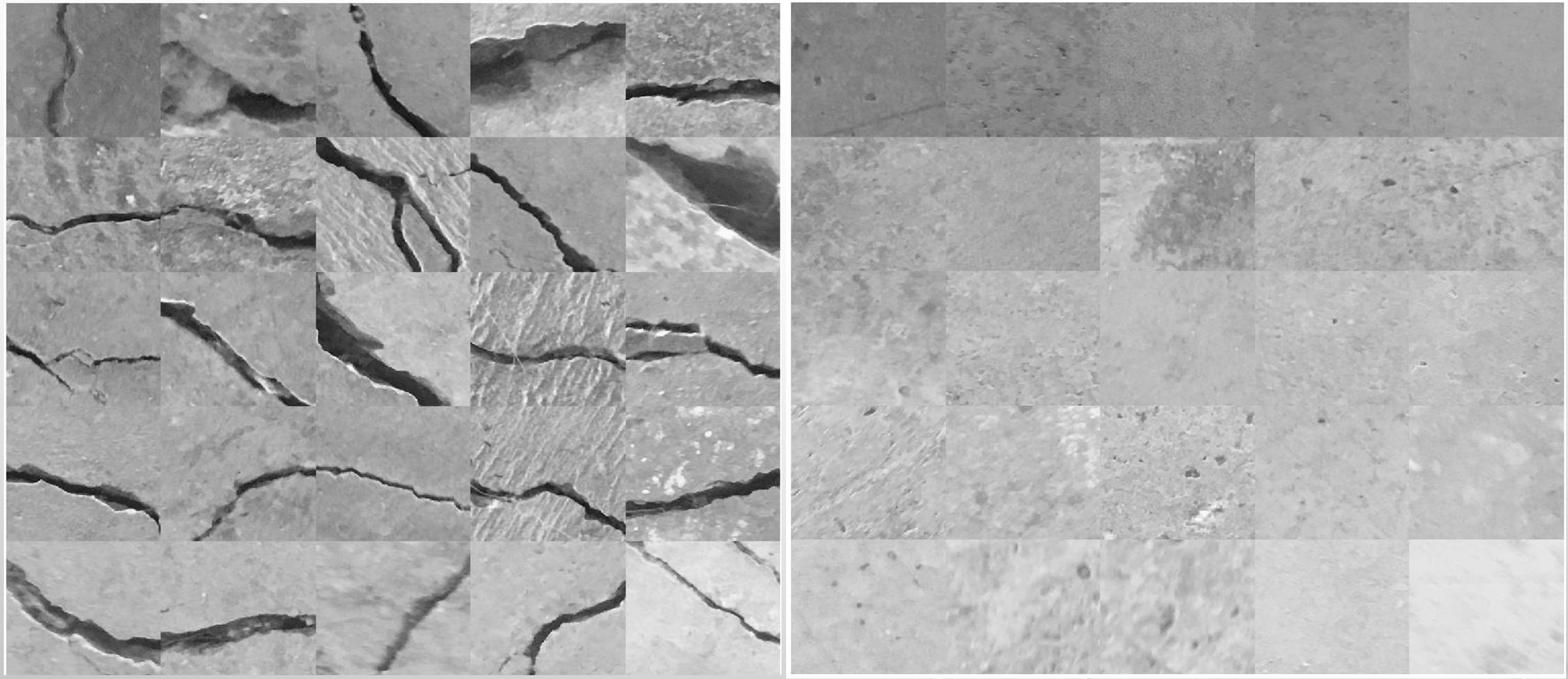


Figure 1 Some images of our dataset with annotation a) D(Damaged) b) ND (Not Damaged)

METHODOLOGY : DIMENSIONALITY REDUCTION

➢ Linear Dimensionality Reduction:

Data Matrix: $X = [x_1, x_2, \dots x_n]^T \in R^{n \times p}$

SVD of $Y = X - \frac{1}{n} 1 1^T X = U \Sigma V^T$

1) PCA: Top k right Singular vectors

2) MDS: Top k left Singular vectors

- Dual of Each other
- MDS tries to preserve the Euclidean distance $D_{ij} = \left|\left|x_i - x_j\right|\right|^2$

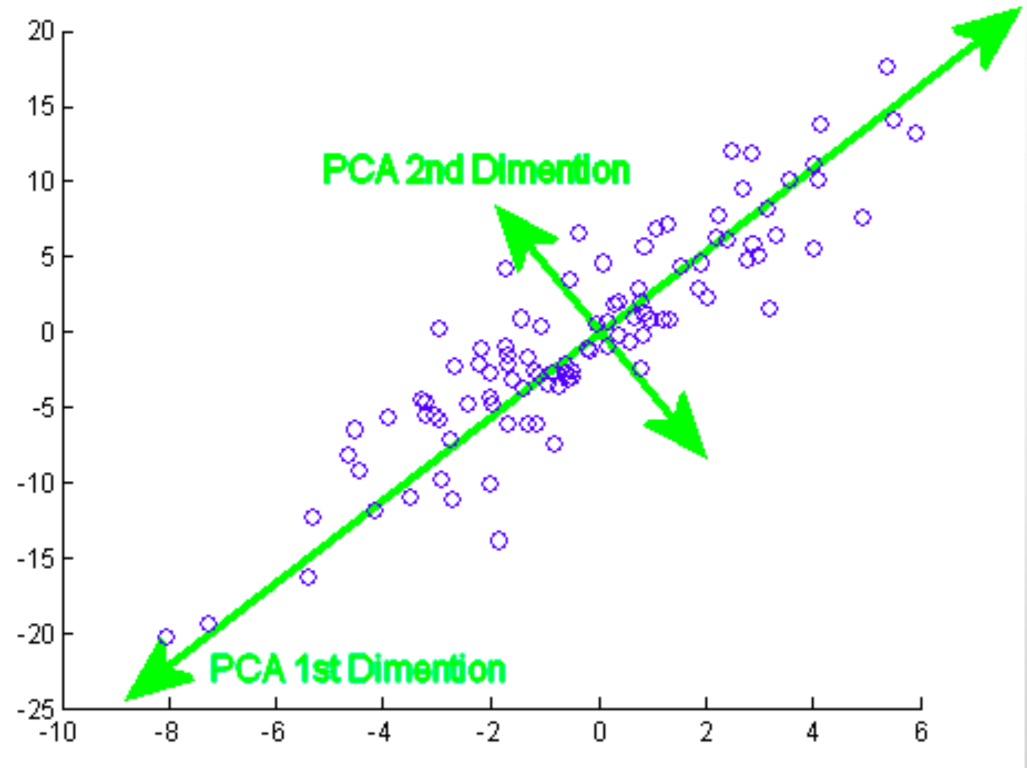


Image Source: https://towardsdatascience.com/pca-is-not-feature-selection-3344fb764ae6

Nonlinear Dimensionality Reduction

- ISOMAP: Preserve Geodesic Distances

Data $\longrightarrow$ Neighborhood Graph ($G = (V, E, d_{ij})$) $\longrightarrow$ Kernel $\longrightarrow$ Spectrum

K-nearest neighbors: Euclidean Distance

Shortest path distance : $d_{ij} = \min_{\mathrm{P}=(\mathrm{x_i},..\mathrm{x_j})} (||x_i - x_{t11}|| + \cdots + ||x_{t_{k\_1}} - x_{t_1}||)$

$$B = -\frac{1}{2} HDH^T = U\Lambda \mathrm{U}^{\mathrm{T}}$$

$$X_k = U_k \Lambda_k^{1/2}.$$

TSNE

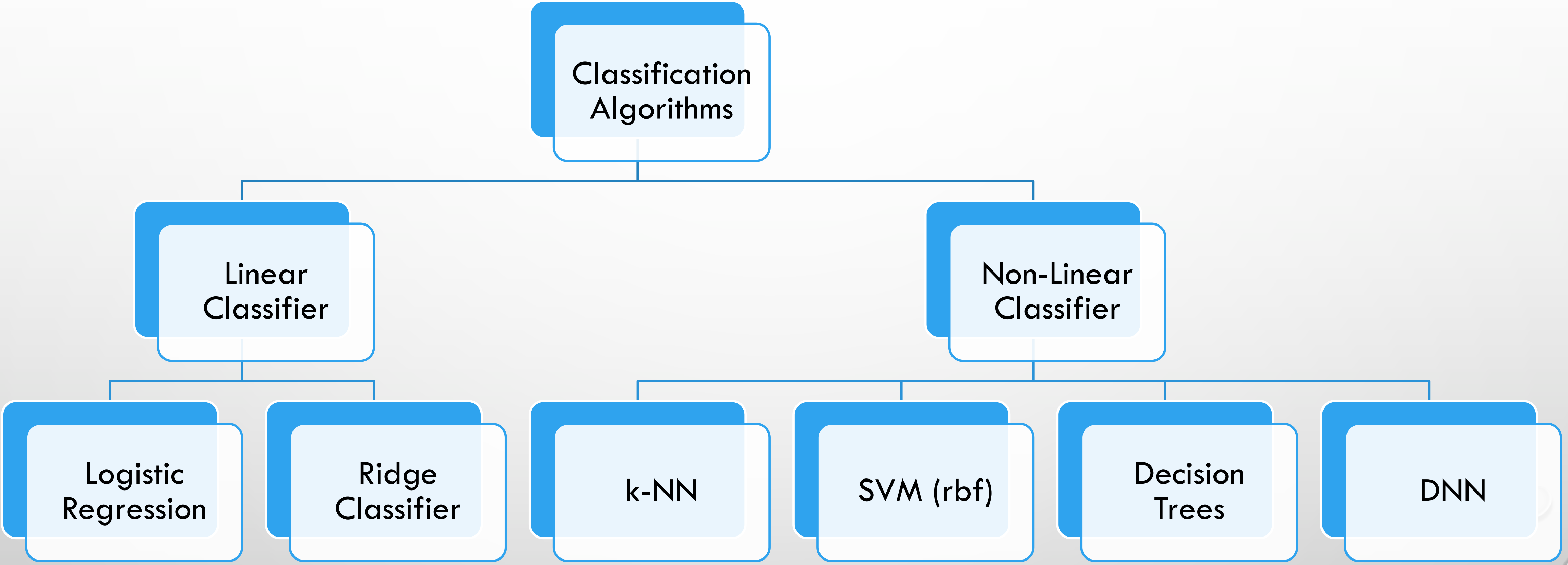
- Efficient 2D embedding for visualization
- Uses Probabilistic distances between datapoints

- Original Space: $p_{j|i} = \dfrac{\exp\left(-\frac{\|x_i - x_j\|^2}{2\sigma_i^2}\right)}{\sum_{k\neq i} \exp\left(-\frac{\|x_i - x_k\|^2}{2\sigma_i^2}\right)}$, $\quad p_{ij} = \dfrac{p_{j|i} + p_{i|j}}{2n}$

- Low Dimensional Space: $q_{ij} = \dfrac{\left(1 + \|y_i - y_j\|^2\right)^{-1}}{\sum_{k\neq i}\left(1 + \|y_i - y_j\|^2\right)^{-1}}$

- Optimization problem: $\min KL(P||Q) = \sum_{i\neq j} p_{ij} \log\left(\frac{p_{ij}}{q_{ij}}\right)$: Use SGD

CLASSIFICATION ALGORITHMS



2D VISUALIZATION RESULTS

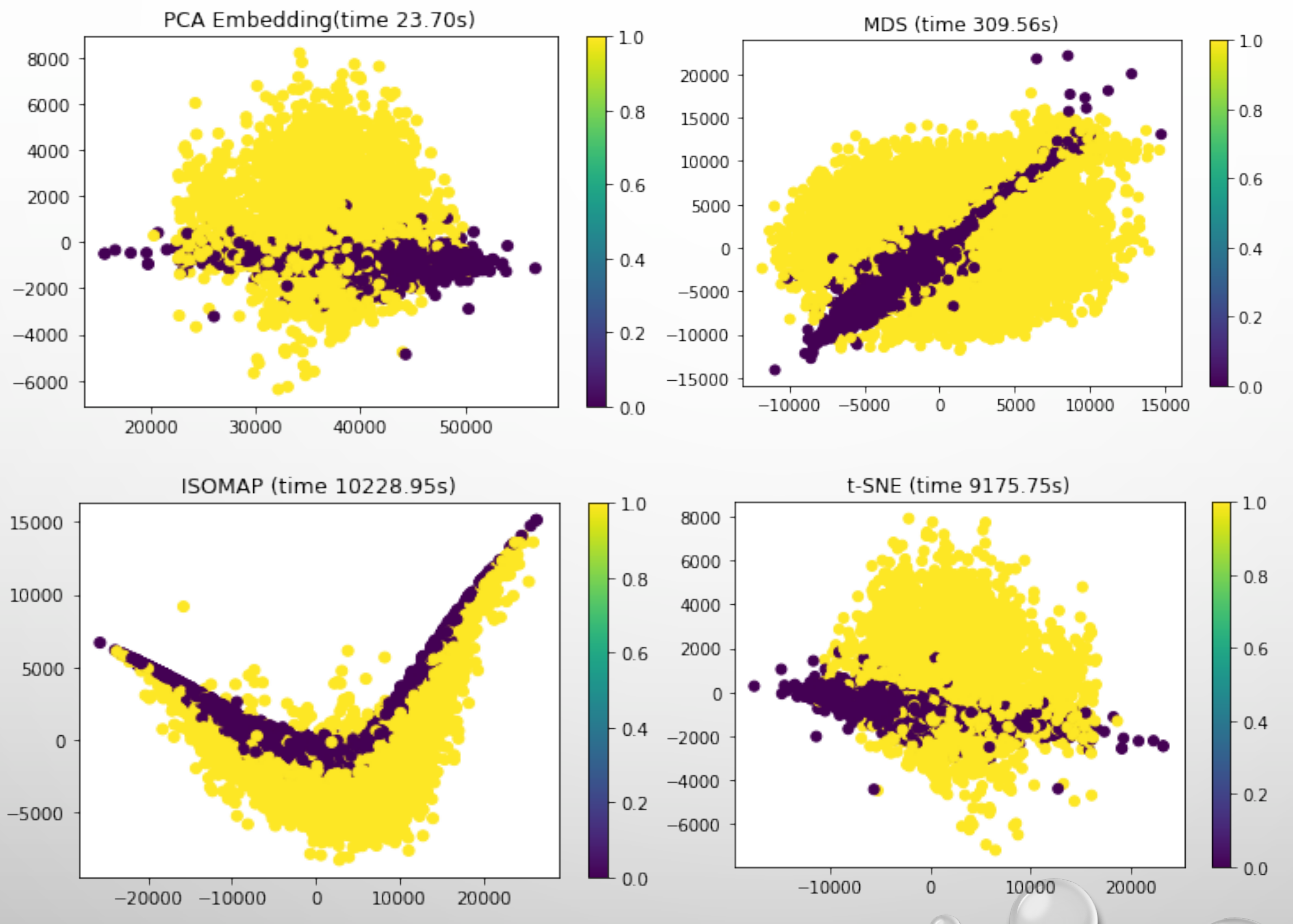


Figure 2 2D Embedding for a) PCA b) MDS c) ISOMAP d) t-SNE

Legend:

1(yellow): Damaged (cracks)

0 (purple): Not Damaged (No Cracks)

CLASSIFICATION RESULTS

(accuracy, precision)

Classifier/Techniques	PCA	MDS	ISOMAP	t-SNE
KNN (k=5)	(0.85,0.85)	**(0.95,0.95)**	**(0.92,0.92)**	(0.84,0.84)
Decision Tree	(0.81,0.81)	(0.93,0.93)	(0.91,0.91)	(0.80,0.80)
Logistic Regression	(0.8,0.8)	(0.69,0.69)	(0.74,0.74)	(0.80,0.80)
Ridge Classifier	(0.8,0.79)	(0.70,0.69)	(0.73,0.73)	(0.78,0.79)
SVM-rbf	**(0.87,0.86)**	(0.94, 0.94)	**(0.92,0.92)**	**(0.87,0.85)**
DNN	**(0.87,0.86)**	**(0.96,0.96)**	**(0.93,0.93)**	**(0.86,0.86)**

Non-linear Classifiers perform better

SENSITIVITY RESULTS

HYPERPARAMETERS:

A. Order of the data set :

Changes the rows of distance matrix

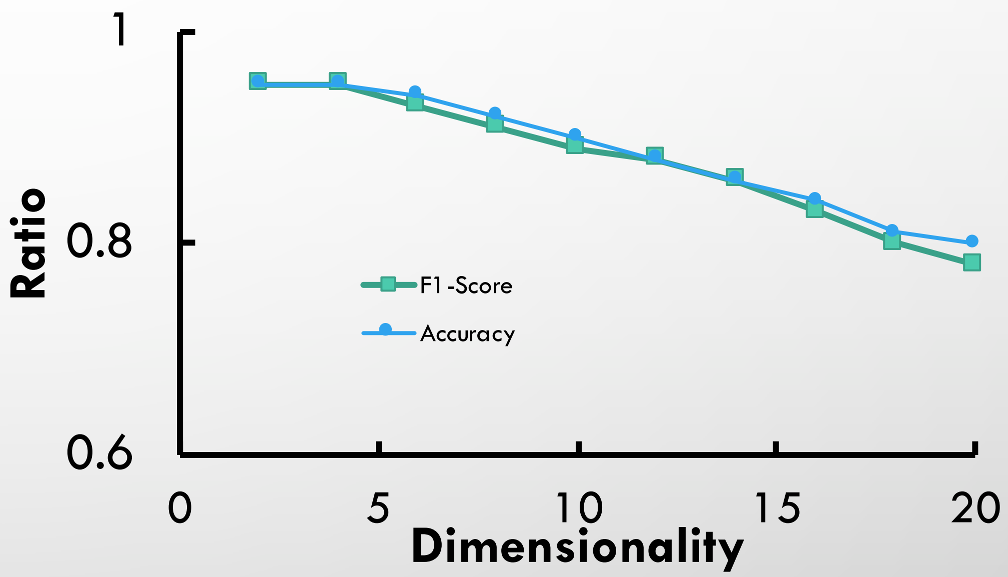
Does not affect spectral roots (eigenvectors/values)

Accuracy/Precision is not affected

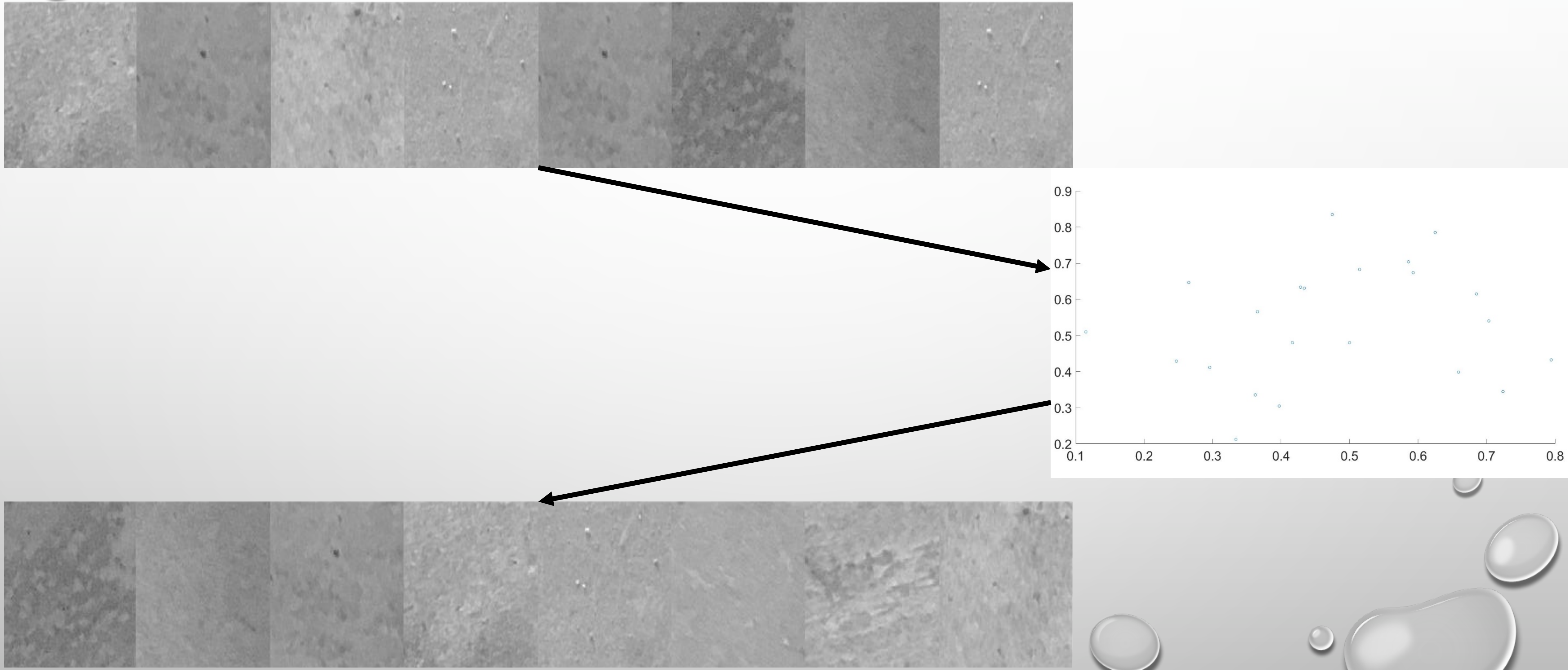
B. Effect of Dimensionality:

Measures separability for embedding created by top K eigenvectors

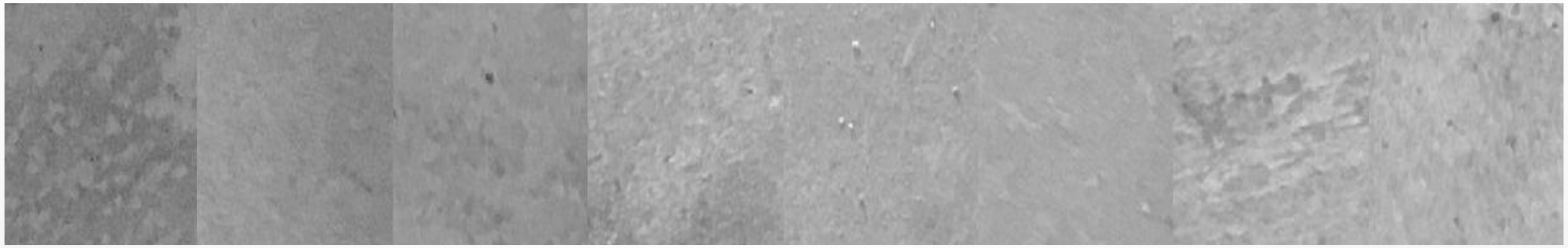
Separability decreases with increasing dimension



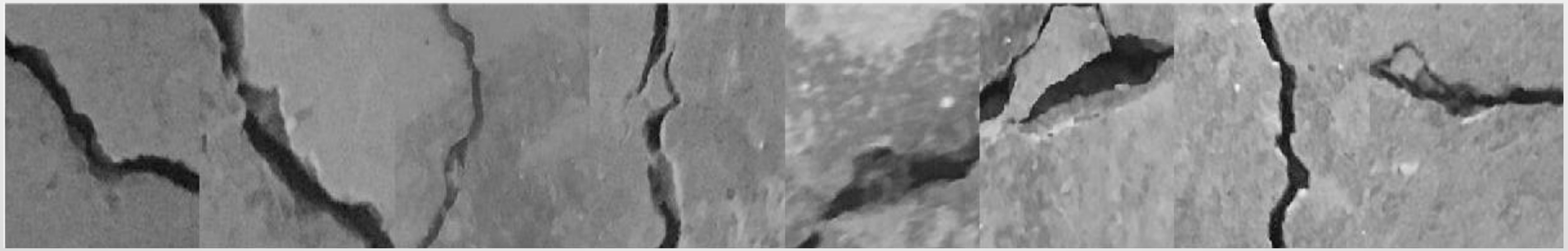
ORDERING IMAGES



ORDERING IMAGES



Non-damaged segments are qualitatively ordered according to their relative brightness i.e. discoloration. This is related to overall quality of the finished structure. Darker is higher Quality



Damaged segments are qualitatively ordered according to their total damaged area. The damaged area controls the urgency of repair. NOTE: Though such correlation is fainter as compared to ND images

CONCLUSIONS AND FUTURE DIRECTION

We applied various dimensionality reduction techniques to segregate damaged and non-damaged images.

1. MDS + Non-Linear classifiers show the best accuracy and precision on our dataset.
2. With increasing dimensionality accuracy of Non-Linear classifiers deteriorates but Ordering of images does not have any effect on the accuracy of the classifier.
3. Ordering of D images with MDS shows a (fainter) correlation with the **amount of damage** as compared to that for ND images which reveals **discoloration of the concrete surface.**
4. LLE, HLLE and LTSA could not be applied due to the curse of dimensionality.

In future more exhaustive selection of embedding techniques and classifier will be used.

LINKS

1) Presentation Video: https://youtu.be/z2LLNTQGVY8
2) GitHub Project : https://github.com/AVKDAS/Crack-Segmentation/tree/master

REFERENCES

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