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**RadFarm** – Radiofarmaceutyki dla ukierunkowanej  
molekularnie diagnostyki i terapii medycznej

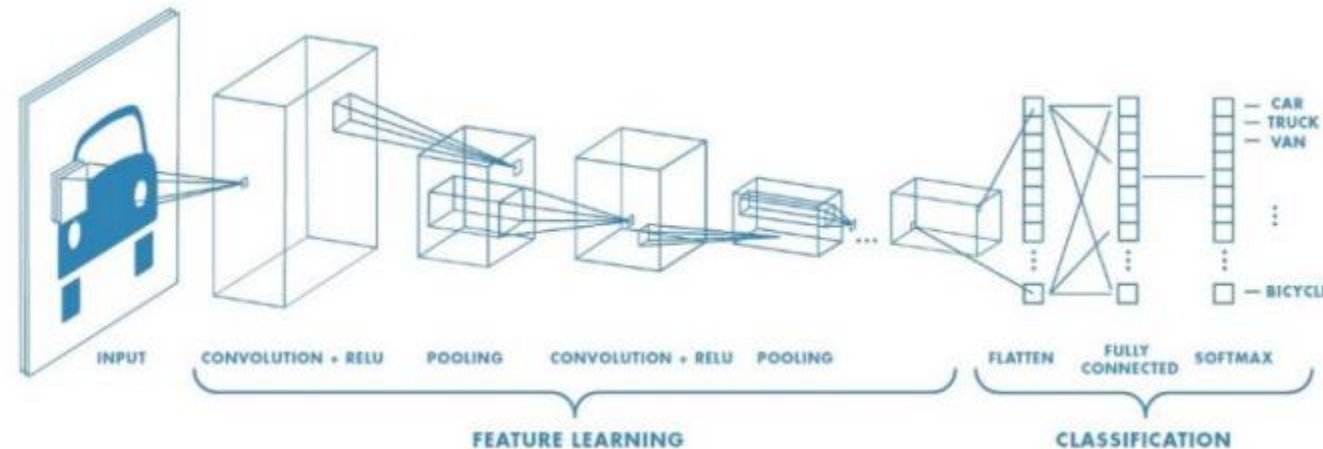
# Convolutional Neural Networks for event classification

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Szkoła Zimowa RadFarm 21.01.2022

# Introduction

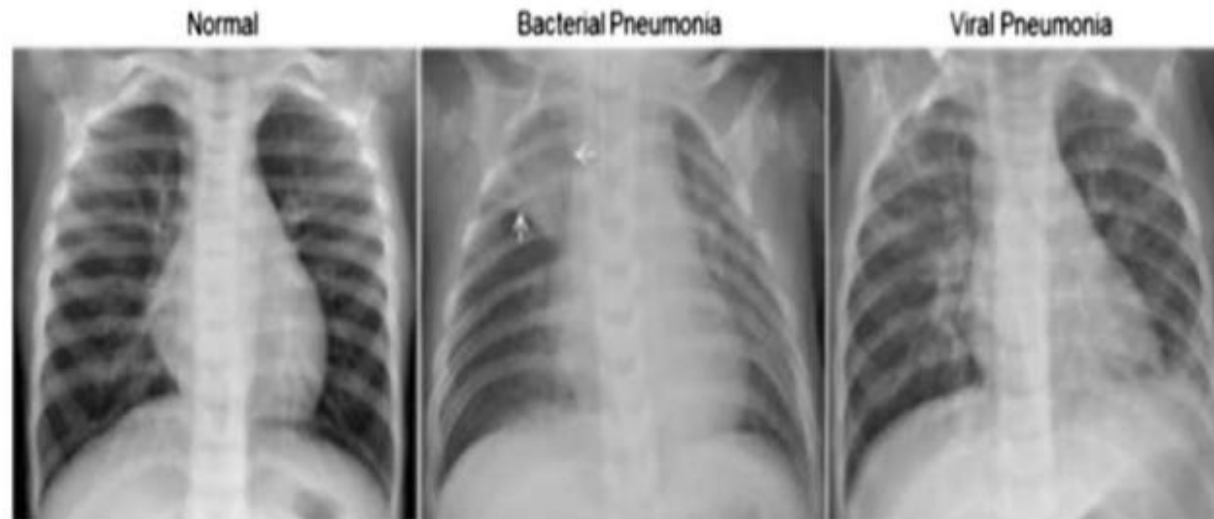
- Convolutional Neural Networks (CNNs) have achieved state of-the-art performance in many areas and are the method of choice commonly used for data recognition or classification.
- CNNs have proven to work most efficiently on 2-dimensional data that are in form of images.



**Figure:** CNN architecture used for classification problem (adapted from [1])

# Introduction

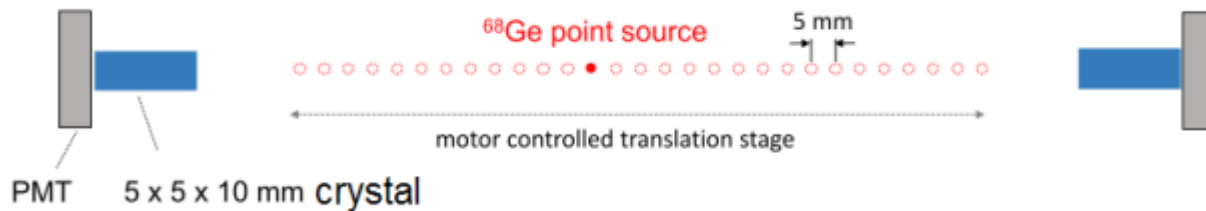
- Advances in CNNs have presented an exciting opportunity in medicine, primarily for solving a variety of image-classification problems.
- In [2] it has been shown that CNN achieves better performance on classification of chest X-ray images than traditional neural networks.



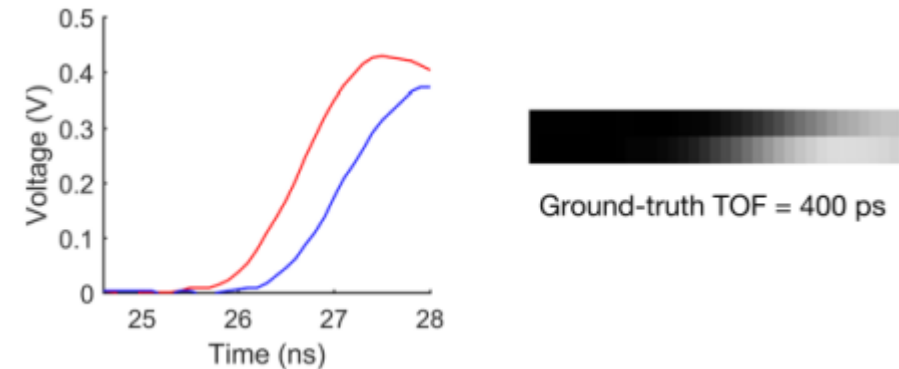
**Figure:** Examples of chest X-rays (adapted from [2])

# Non-image PET data

- For use in the CNNs, the waveform pairs were stored as 2D arrays (2 x 35)
- CNN-based time-of-flight estimation improves timing resolution by 20% compared to leading edge discrimination (see [3] for details).



**Figure:** Detector setup used to acquire coincidence waveforms (top). Rising edges of the waveforms and 2D array (image) of the coincident waveform pair used as the input to the CNN (bottom). Figure adapted from [3].

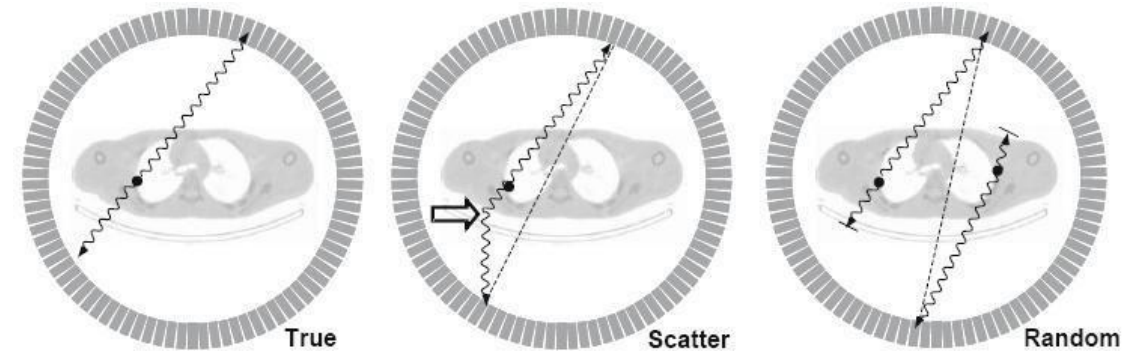


# Non-image PET data

Features selected to describe each coincidence event:

- 1) angular difference between the detection points
- 2) detection times difference
- 3) distance between detection points
- 4) energy difference
- 5) energy sum
- 6) attenuation factor

Development of classification method of coincidence events is crucial since only true events are essential for PET imaging.



**Figure:** Different types of events in PET measurement. Figure adapted from [4].



# Non-image PET data

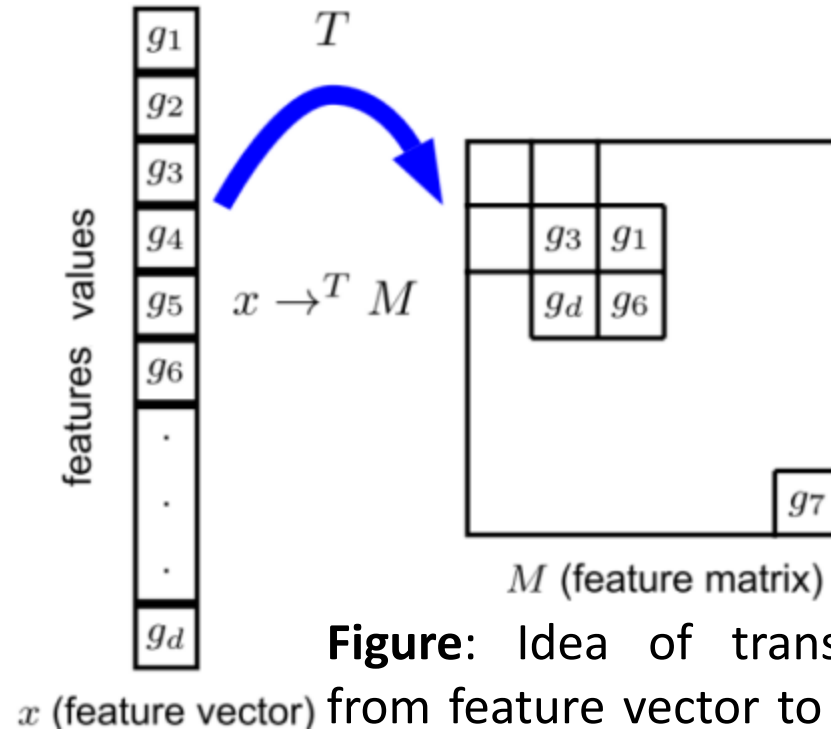
Features selected to describe each coincidence event:

- |  |          |
|--|----------|
| 1) angular difference between the detection points | 144 deg  |
| 2) detection times difference                      | 0.24 ns  |
| 3) distance between detection points               | 77.3 cm  |
| 4) energy difference                               | 35 keV   |
| 5) energy sum                                      | 587 keV  |
| 6) attenuation factor                              | 0.15 [1] |

How to present these numbers as an image?

# Non-image data transformation

- DeepInsight approach: First transform non-image data to a well-organized image form. Then apply CNN for classification.
- This idea increases the versatility of CNN by opening it to non-image data cases.

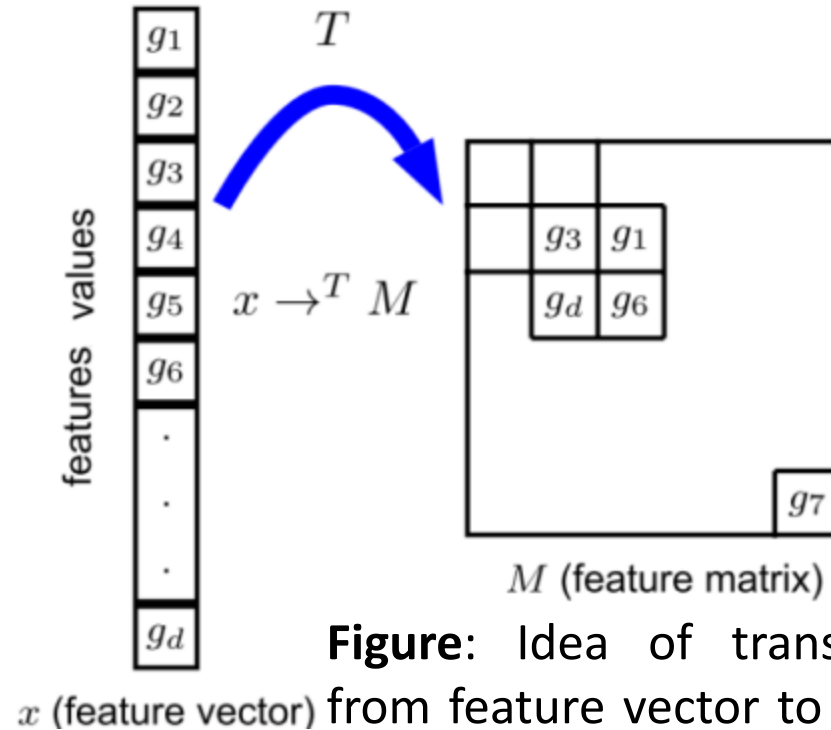


**Figure:** Idea of transformation ( $T$ ) from feature vector to feature matrix (image-form). Figure adapted from [5].

# Non-image data transformation

DeepInsight approach:

- create a feature set – by transposing the data set
- apply similarity measuring technique or dimensionality reduction technique (t-SNE or **kernel PCA**) to obtain a 2D plane – non-linearity techniques
- these points define the location of features



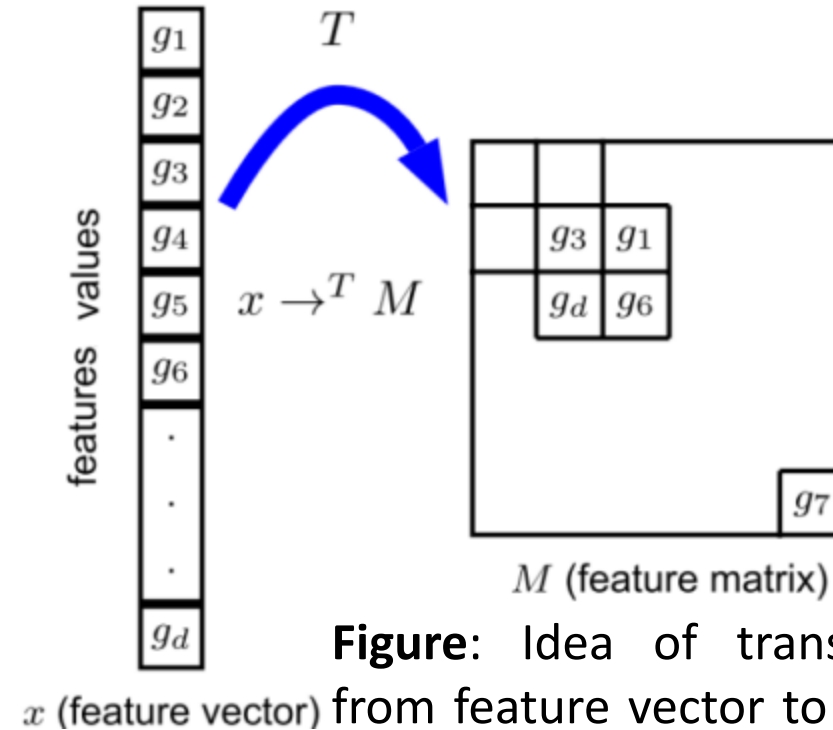
**Figure:** Idea of transformation ( $T$ ) from feature vector to feature matrix (image-form). Figure adapted from [5].



# Non-image data transformation

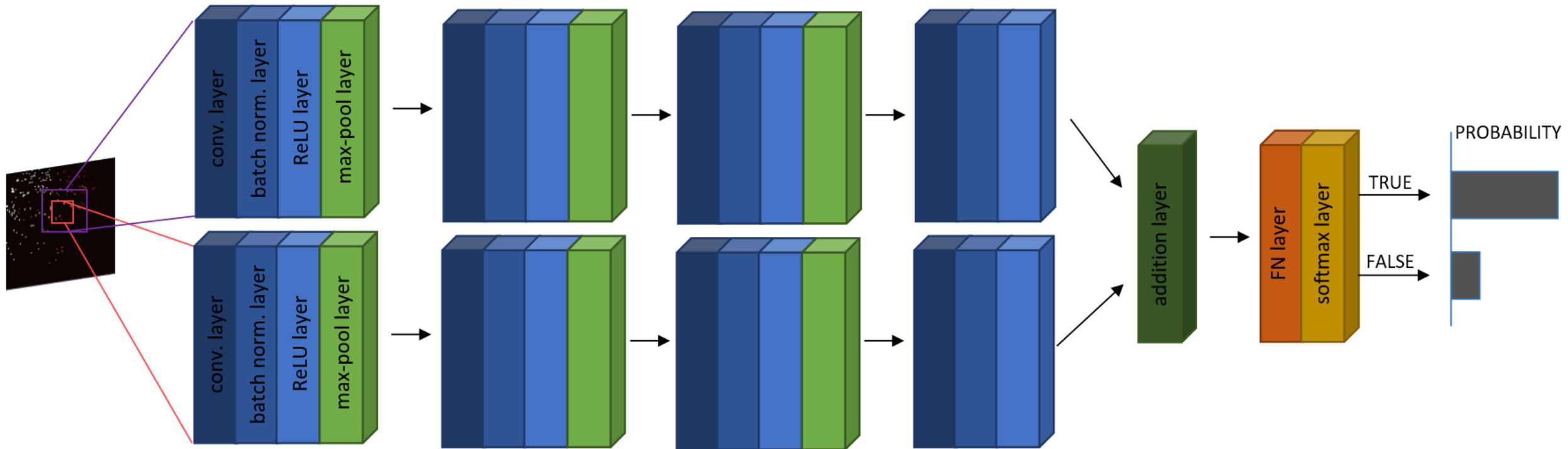
Non-linear finite support (NLFS) PCA approach [6]:

- introduce non-linearity in „feature engineering” step, by application of non-linear function with finite support (e.g. polynomial function)
- apply linear PCA to obtain 2D plane
- these points define the location of features
- this method gives us an opportunity to „manipulate” the number of pixels

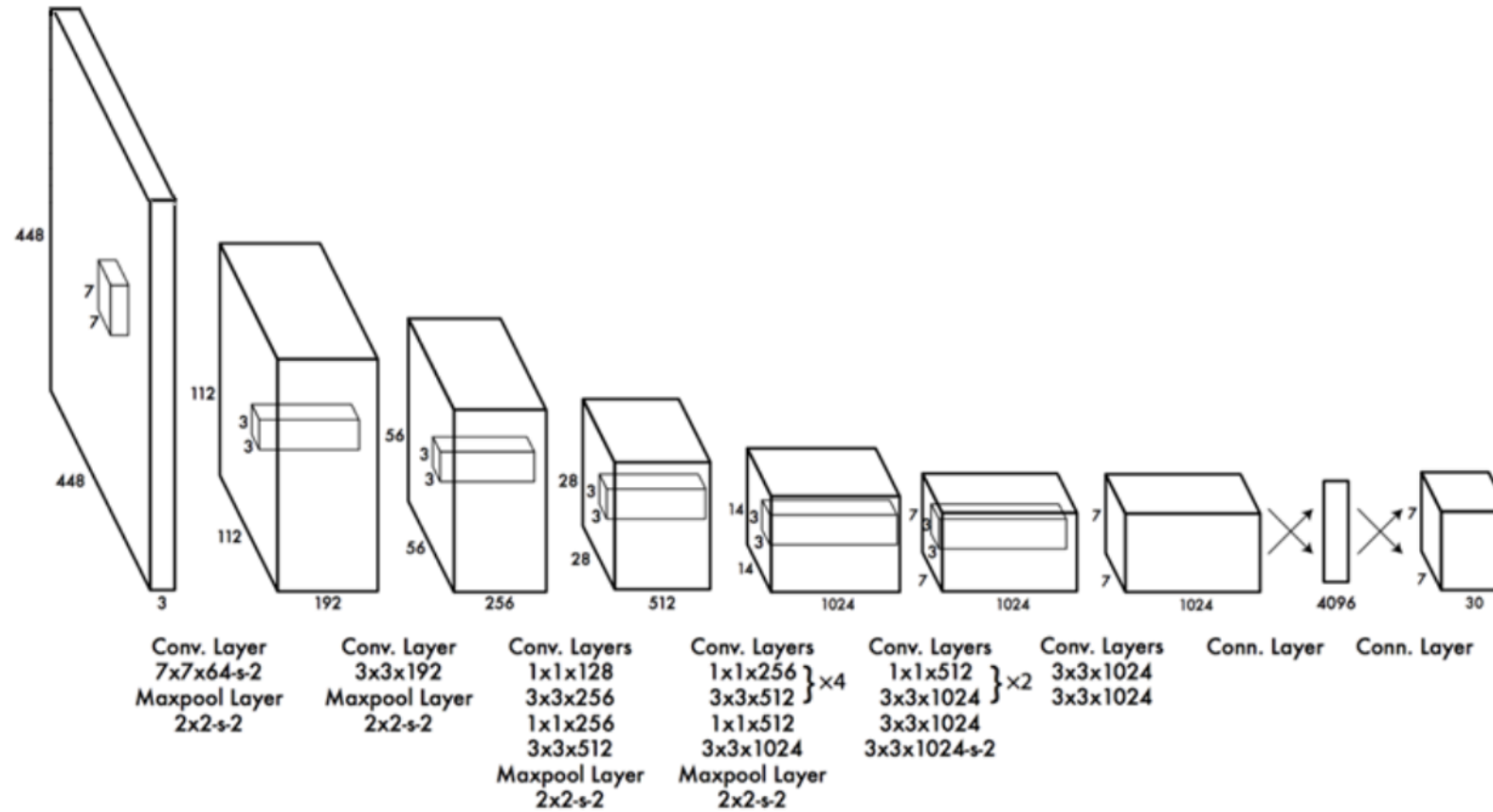


**Figure:** Idea of transformation ( $T$ ) from feature vector to feature matrix (image-form). Figure adapted from [5].

# CNN DeepInsight



# CNN YOLOv1



# Bayesian optimization

Bayesian optimization aims to find model hyperparameters that give the best result on the validation set. The biggest advantage over random search or grid search is that previous ratings affect subsequent ratings. The algorithm "spends" time selecting the next hyperparameter to make fewer evaluations.

In the DeepInsight network architecture, the optimized hyperparameters are: number and size of filters, momentum, L2-regularization value and initial learning rate.

# Metrics

In order to compare results two metrics were chose:

- PPV (positive predictive value) – precision

$$PPV = \frac{\textit{number of true positives}}{\textit{number of true positives} + \textit{number of false positives}}$$

- TPR (true positive rate) – sensitivity

$$TPR = \frac{\textit{number of true positives}}{\textit{number of true positives} + \textit{number of false negatives}}$$

The goal of the research is to maximize positive predictive value while maintaining true positive rate at 95%.

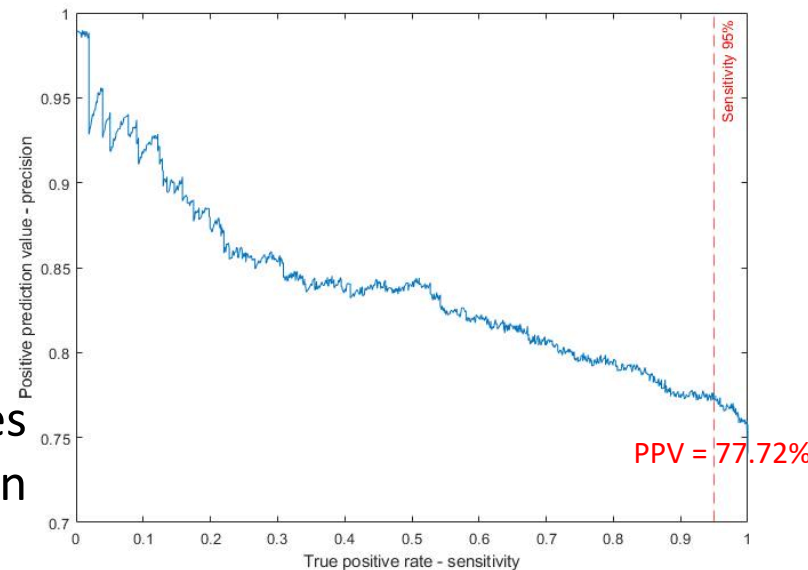


# Results: kernel PCA

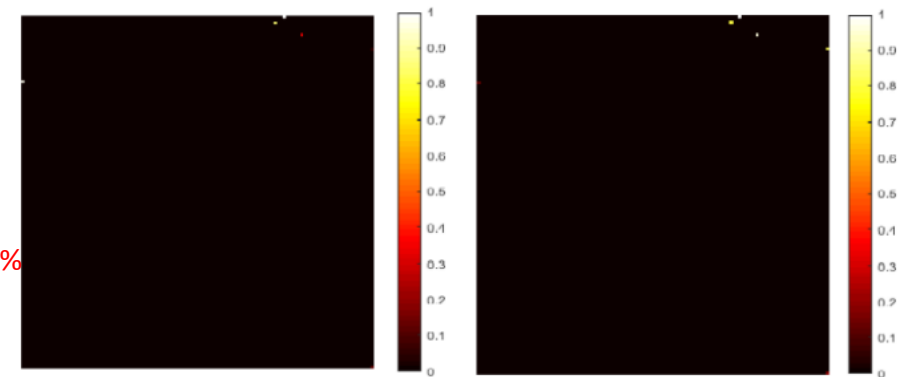
Features selected to describe each coincidence event:

- 1) angular difference between the detection points
- 2) detection times difference
- 3) distance between detection points
- 4) energy difference
- 5) energy sum
- 6) attenuation factor

**Figure:** DeepInsight produces 77.72% classification precision on this dataset

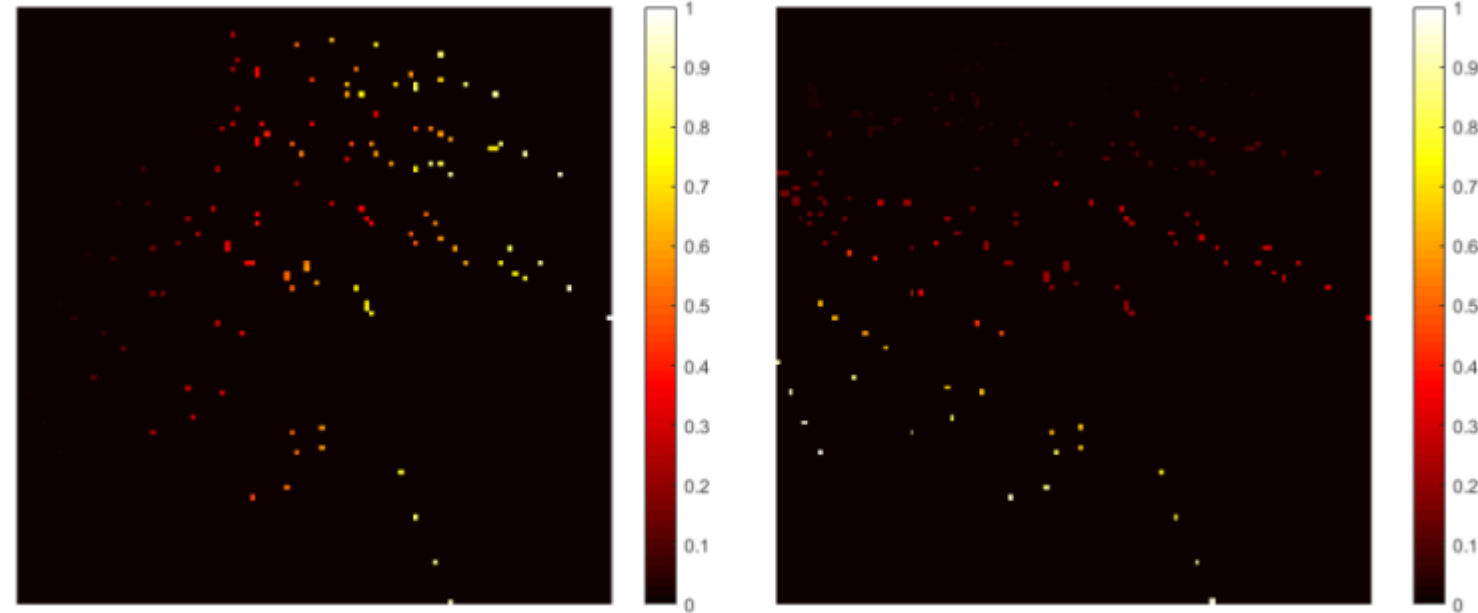


**Figure:** two exemplary images of different coincidence event types. Data processed using DeepInsight approach with kernel PCA transform (6 features -> 6 pixels).



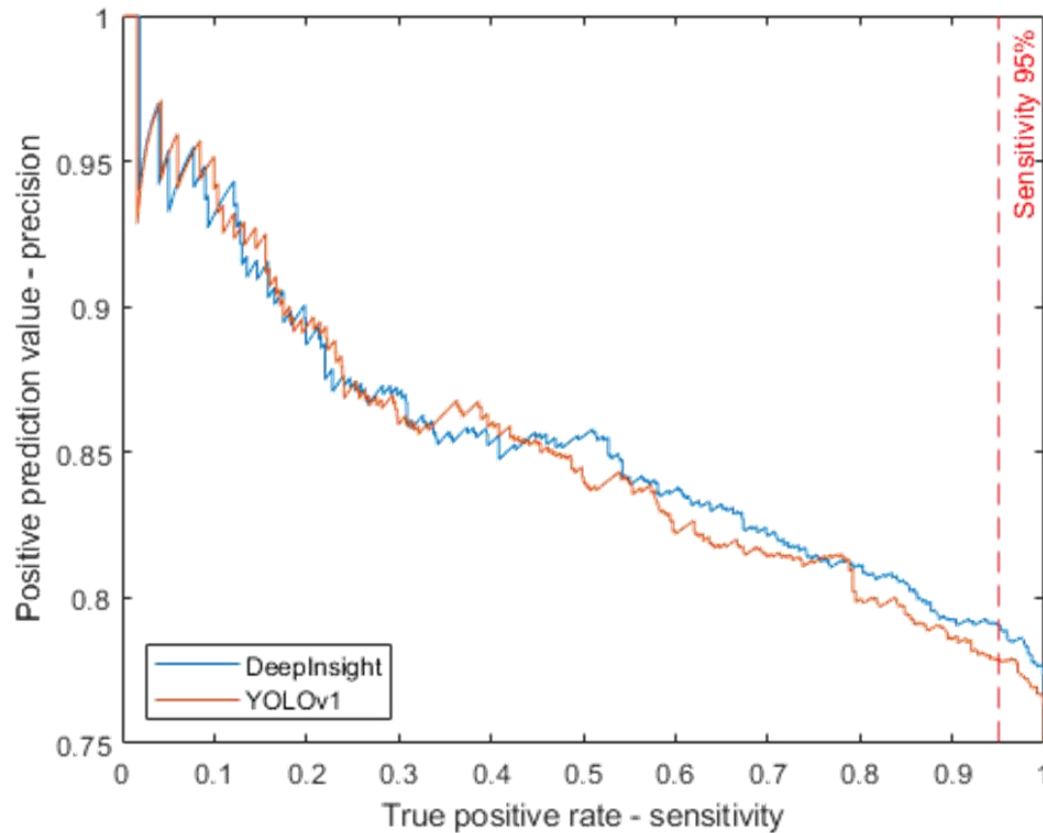
# Results: NLFS PCA

Polynomial degree	1	2	3	4	5
New dimensionality	6	27	83	209	461
Pixel overlap	0.0%	0.0%	1.9%	3.3%	10.6%



**Figure:** Two exemplary images of different coincidence event types. Data processed using proposed approach (6 features -> 209 pixels)

# Results: NLFS PCA



Classification method	Precision (sensitivity = 95%)
Linear discriminant analysis	76.2%
Self-organizing map	77.7%
Multilayer perceptron	78.5%
DeepInsight „raw”	77.7%
YOLOv1	77.9%
DeepInsight „modified”	<b>79.0%</b>

# Summary

## IN PROGRESS

- writing article comparing results of different CNN architectures using simulated data

## TO DO

- waiting for ,real' data from Jagiellonian University to test my method on real samples

# Idea of position reconstruction (z) using CNN

NUMBER OF MODULES = 2	NUMBER OF THRESHOLDS = 4
NUMBER OF <u>SiPMs</u> = 8	NUMBER OF SLOPES = 2
TOTAL NUMBER of ELEMENTS for SINGLE HIT = $2 * 8 * 4 * 2 = 128$	

