2nd PANHELLENIC CONGRESS OF MEDICAL PHYSICS
4-6 OCTOBER 2024| EUGENIDES FOUNDATION

Texture radiomics in the discrimination of cancerous tumors in mammographic images: A comparative evaluation between texture matrices and deep features

Mouratidou Anastasia[1] , Spyridonos Panagiota[2]

[1]Department of Physics, University of Ioannina, Ioannina, Greece

[2]Laboratory of Medical Physics, Faculty of Medicine, School of Health Sciences, University of Ioannina, Ioannina, Greece

1. Background-Aim

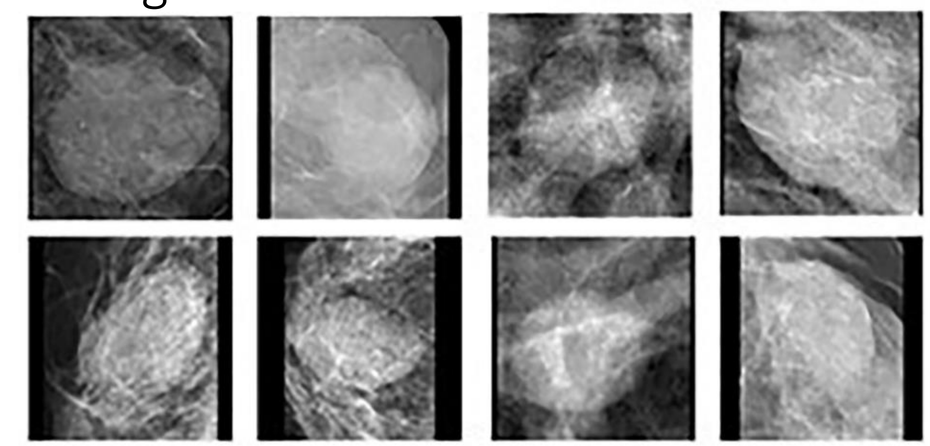
Background:

- Breast cancer is a major global health concern, with early detection and diagnosis being crucial for effective treatment.
- Mammography is a reliable diagnostic tool, but the distinction between malignant and benign areas remains challenging due to the complexity of breast tissue.
- Texture analysis is essential for capturing subtle variations in tissue heterogeneity.

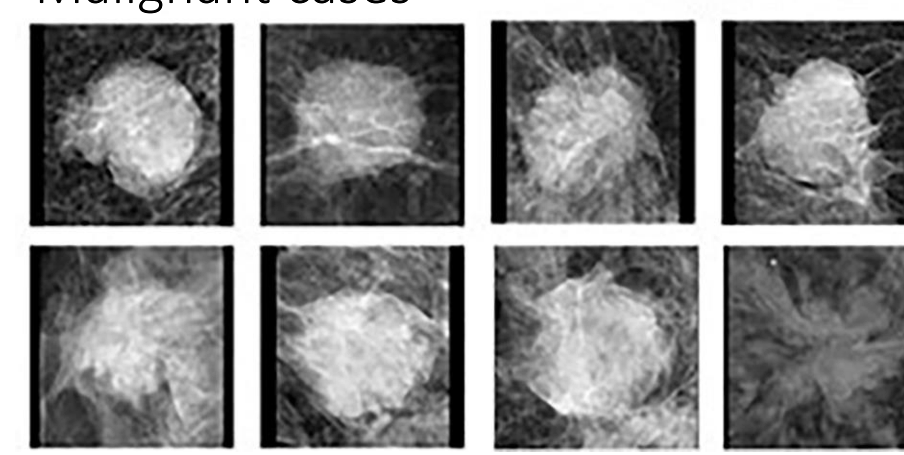
Aim:

- A comparative evaluation of handcrafted texture features and deep features, in the discrimination between benign and malignant breast masses.

Benign cases



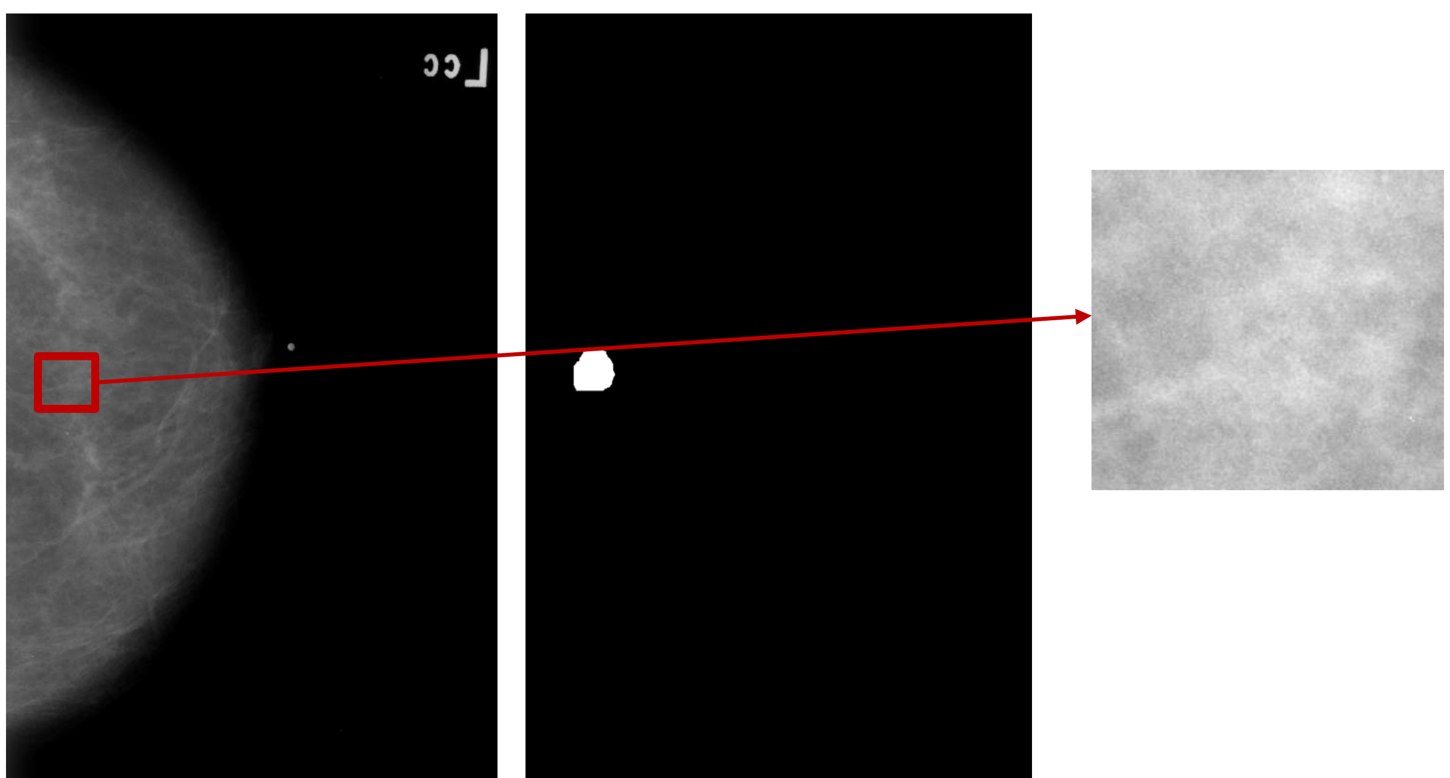
Malignant cases



2. Materials

Dataset

The dataset used is the CBIS-DDSM[1] from the Cancer Imaging Archive (TCIA), an open-access archive of medical images for cancer research.

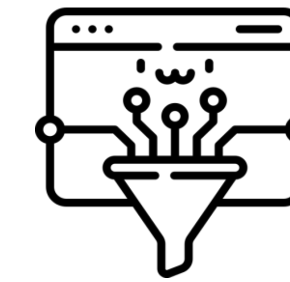


CBIS-DDSM	benign	malignant
training set	681	637
testing set	231	147

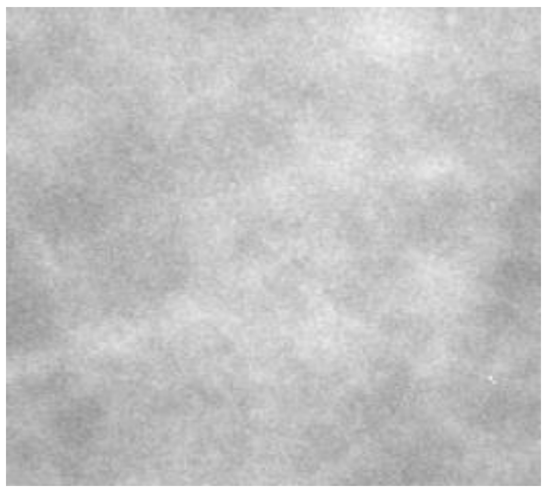
[1]CBIS-DDSM | Curated Breast Imaging Subset of Digital Database for Screening Mammography

2. Methods

Texture feature extraction workflow



Feature extraction



Input

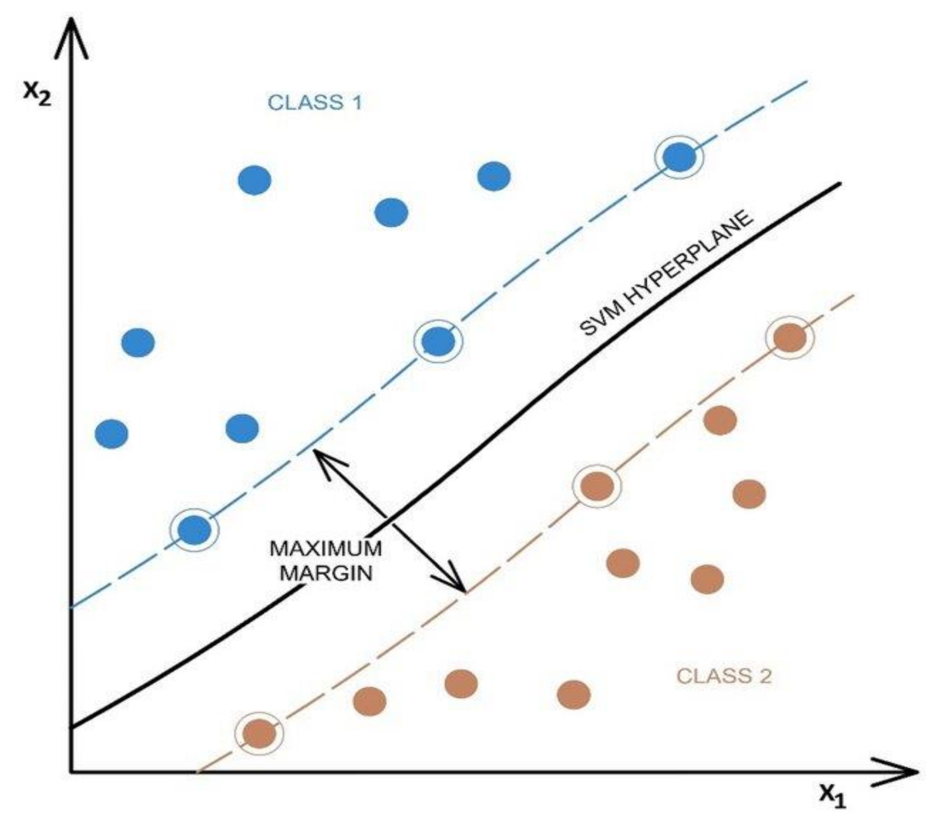
Feature extraction from texture matrices

Classification model SVM[2]

Benign

Malignant

Output

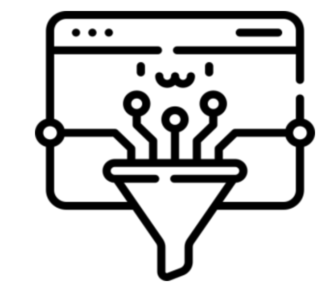


[2] SVM is a powerful and versatile machine learning algorithm, particularly well-suited for tackling high-dimensional problems.

2. Methods

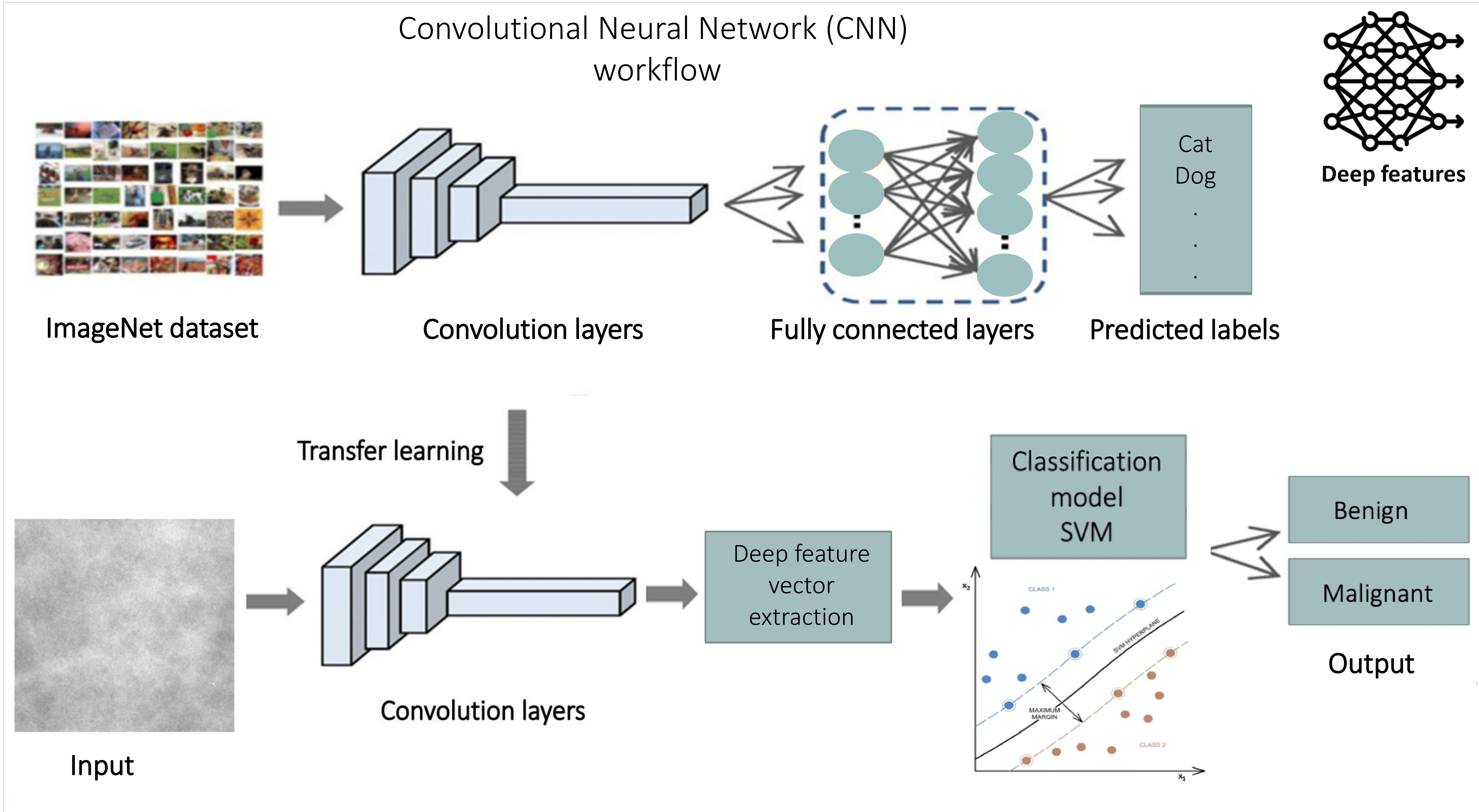
Handcrafted texture features :

Texture matrices	Number of Features
Gray Level Co-occurrence Matrix (GLCM)	23
Gray Level Run Length Matrix (GLRLM)	16
Gray Level Size Zone Matrix (GLSZM)	16
Neighboring Gray Tone Difference Matrix (NGTDM)	5
Gray Level Dependence Matrix (GLDM)	15
Total	75



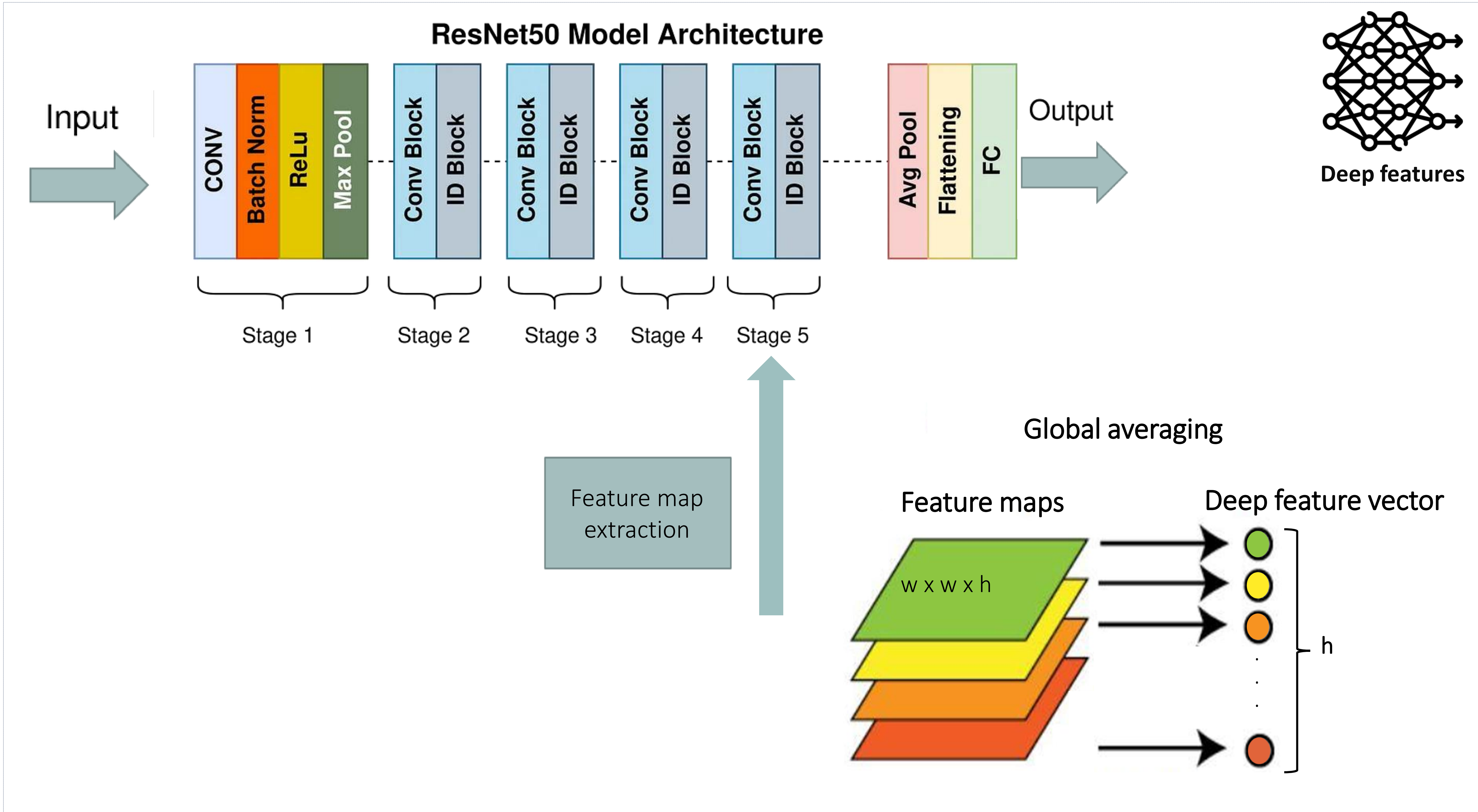
Feature extraction

2. Methods



Convolutional Neural Network (CNN) workflow
Deep features
Cat
Dog
ImageNet dataset
Convolution layers
Fully connected layers
Predicted labels
Transfer learning
Deep feature vector extraction
Classification model SVM
CLASS 1
SVM HYPERPLANE
MAXIMUM MARGIN
CLASS 2
Benign
Malignant
Output
Convolution layers
Input

2. Methods

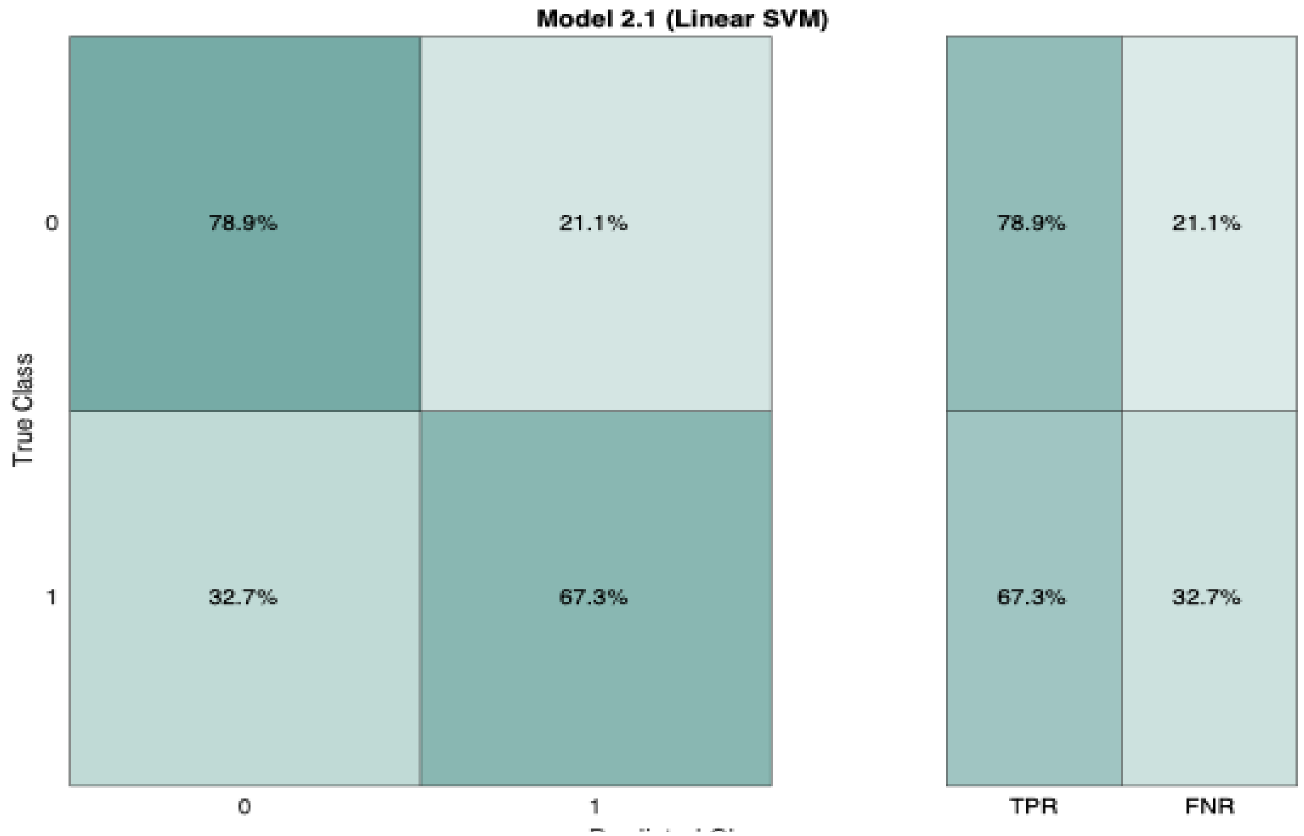


ResNet50 Model Architecture
Input
CONV
Batch Norm
ReLu
Max Pool
Conv Block
ID Block
Conv Block
ID Block
Conv Block
ID Block
Conv Block
ID Block
Avg Pool
Flattening
FC
Output
Deep features
Stage 1
Stage 2
Stage 3
Stage 4
Stage 5
Feature map extraction
Global averaging
Feature maps
Deep feature vector
w x w x h
h

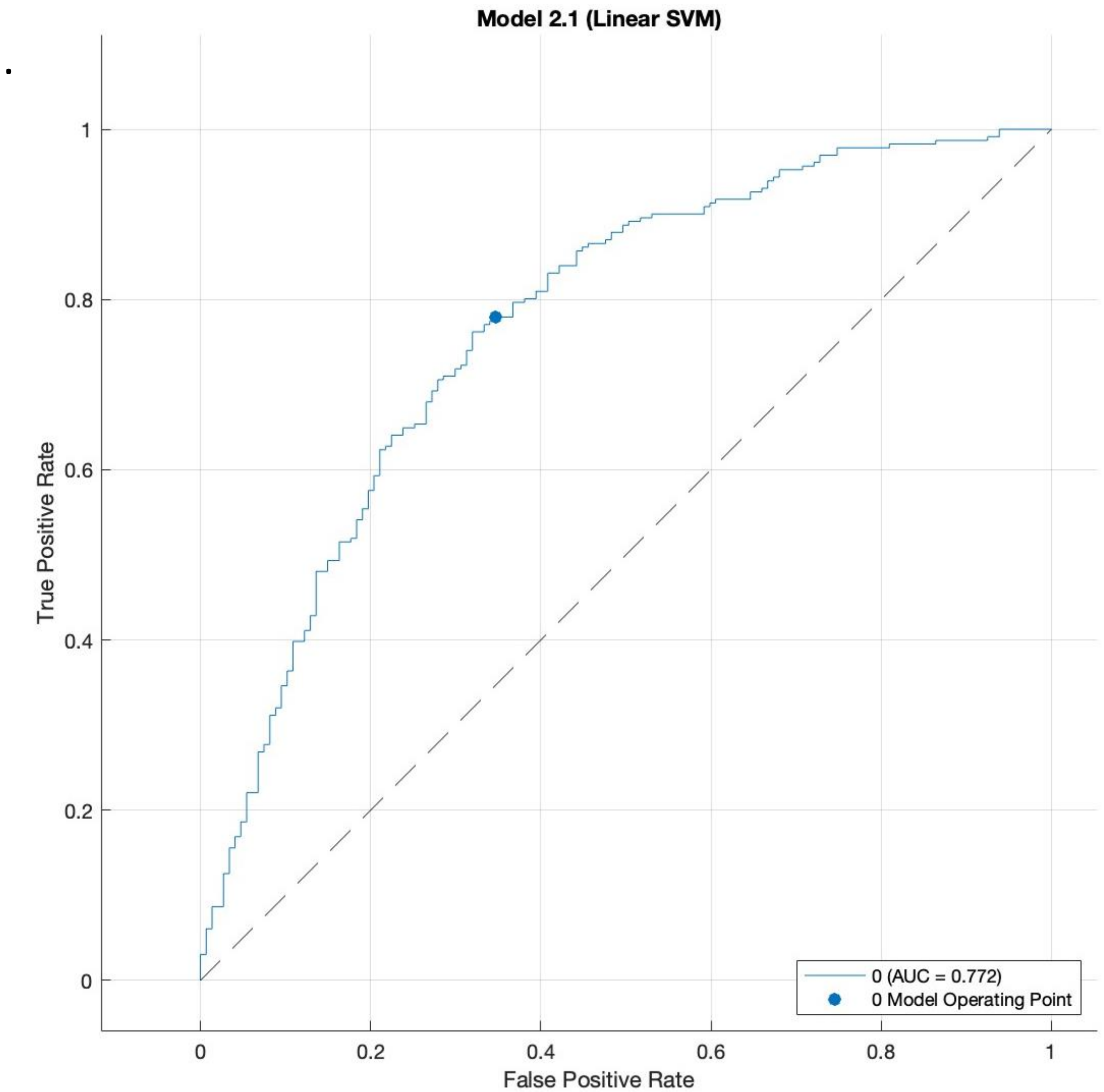
3. Results

Method	Features	Specificity	Sensitivity	AUC
Texture features	72	64,1%	63,3%	0,67
Deep features	2048	78,9%	67,3%	0,77

a.



b.

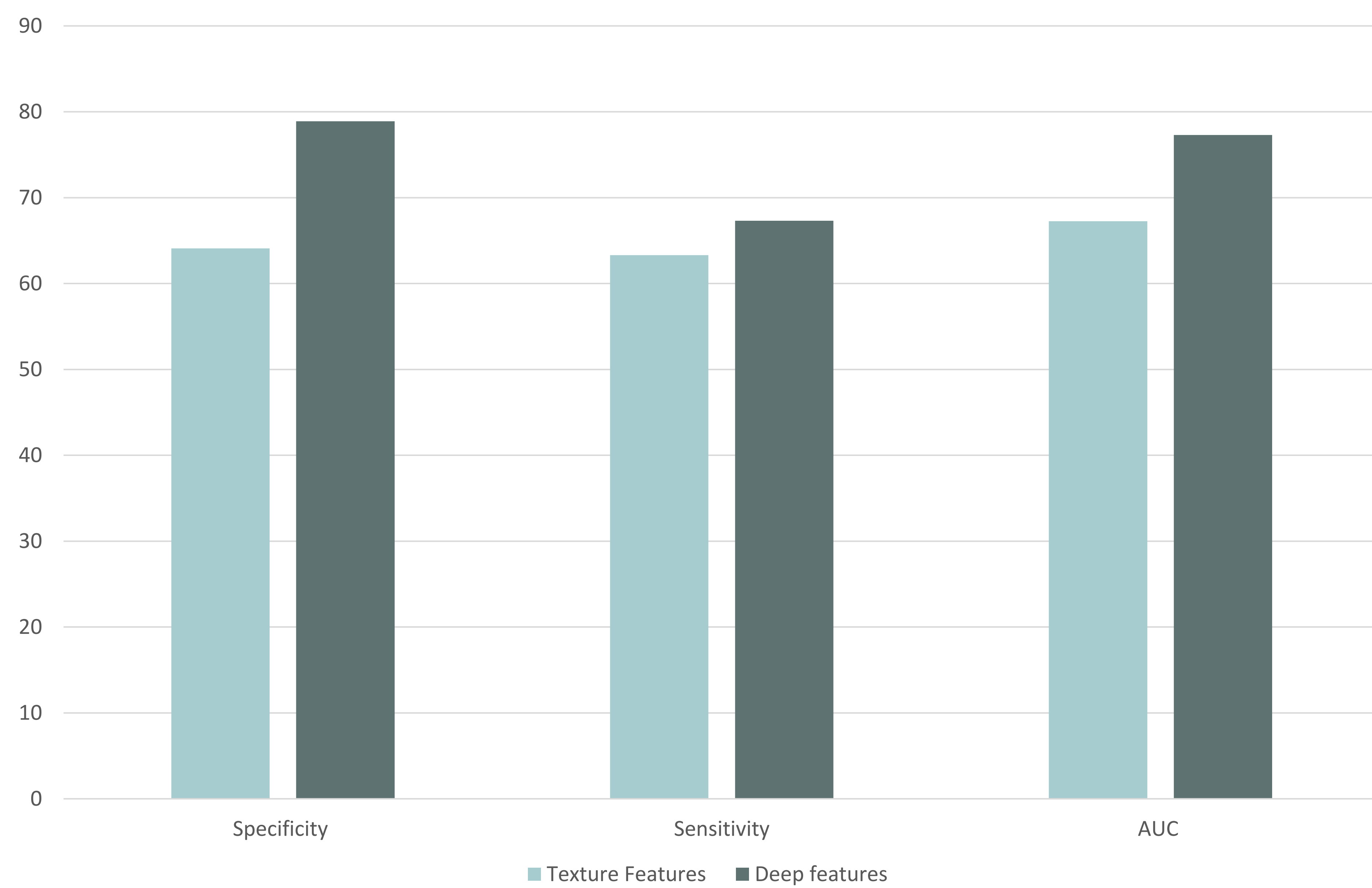


Deep features results

a. Validation confusion matrix
b. ROC curve

4. Conclusions

Deep features lead to more accurate classification compared to texture-based features, while the extraction of texture features is significantly more time-consuming. Deep features can adapt to the complexity of breast tissue textures, providing superior performance in mass classification. Future studies should concentrate on the effective use of feature encoding, combining different networks, layers and features.



5. References

1. Sawyer-Lee, R., Gimenez, F., Hoogi, A., & Rubin, D. (2016). Curated Breast Imaging Subset of Digital Database for Screening Mammography (CBIS-DDSM) [Data set]. The Cancer Imaging Archive. https://doi.org/10.7937/K9/TCIA.2016.7O02S9CY

2. M.K. Ghalati, A. Nunes, H. Ferreira, P. Serranho, R. Bernardes, Texture Analysis and Its Applications in Biomedical Imaging: A Survey, IEEE Rev. Biomed. Eng. 15 (2022) 222–246. https://doi.org/10.1109/RBME.2021.3115703.

3. A.S. Razavian, H. Azizpour, J. Sullivan, S. Carlsson, CNN Features Off-the-Shelf: An Astounding Baseline for Recognition, in: 2014 IEEE Conf. Comput. Vis. Pattern Recognit. Work., IEEE, 2014: pp. 512–519. https://doi.org/10.1109/CVPRW.2014.131.

4. K. He, X. Zhang, S. Ren, J. Sun, Deep Residual Learning for Image Recognition, Proc. IEEE Comput. Soc. Conf. Comput. Vis. Pattern Recognit. 2016-Decem (2015) 770–778. https://doi.org/10.1109/CVPR.2016.90.

5. S. Deep Deb, M.A. Rahman, R.K. Jha, Breast Cancer Detection and Classification using Global Pooling, 2020 11th Int. Conf. Comput. Commun. Netw. Technol. ICCCNT 2020. (2020). https://doi.org/10.1109/ICCCNT49239.2020.9225375.

6. J.M. Moguerza, A. Muñoz, Support Vector Machines with Applications, Stat. Sci. 21 (2006) 322–336. https://doi.org/10.1214/088342306000000493.