EnsembleCAM: Unified Visualization for Explainable Cervical Cancer Identification

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Introduction

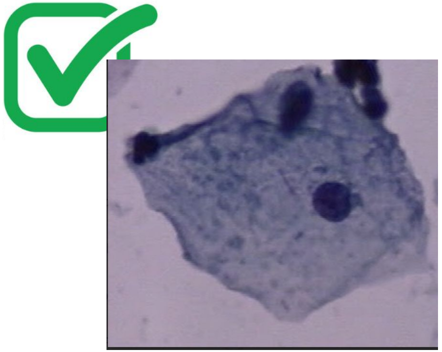
Cervical cancer
ranks as the
4th
most prevalent cancer among women [1].

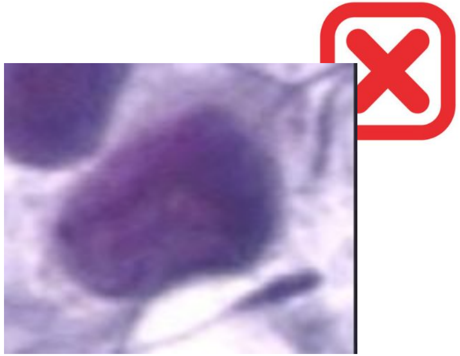
In 2020, an estimated
341,831
women worldwide
died
from cervical cancer [1].

Incidence rates of cervical cancer dropped by more than
50%
from the mid-1970s
to the mid-2000s
due in part to an increase in
screening [1.]

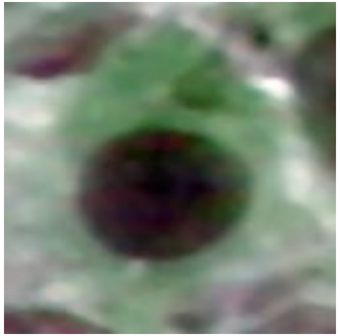
Background

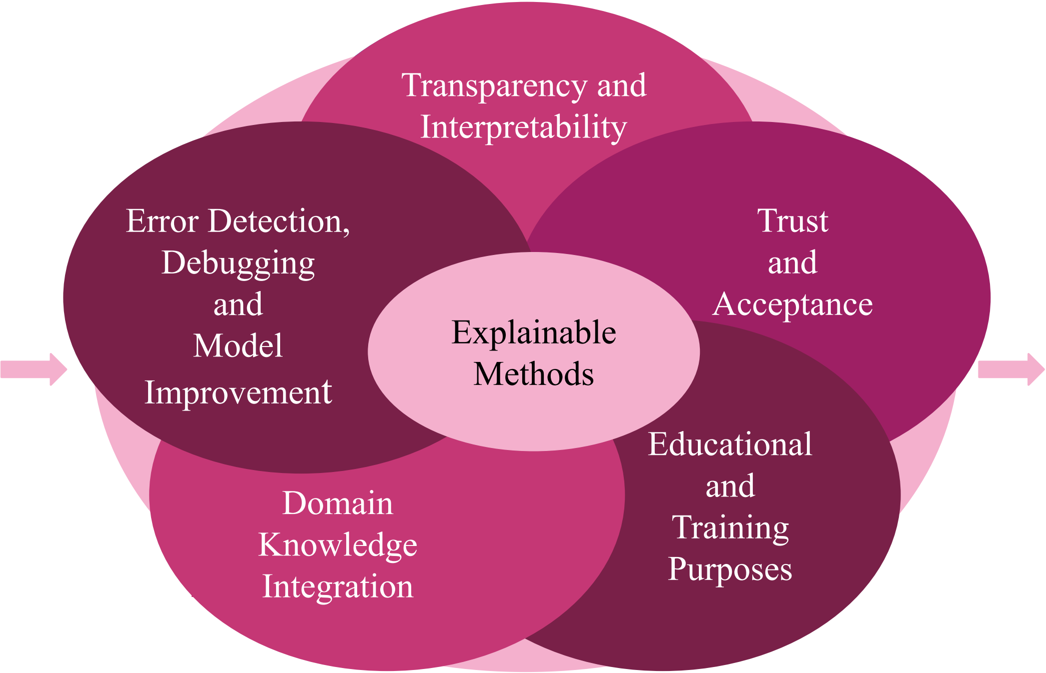
- Conventional Screening Methods:
  - ❏ Pap Smear Test
  - ❏ Liquid Based Cytology
- Limitations:
  - ❏ Time-consuming and laborious.
  - ❏ Prone to subjectivity causing unclear target boundaries [2].
  - ❏ A chance of 1 case to be missed in every 10 to 15 positive cases [3].

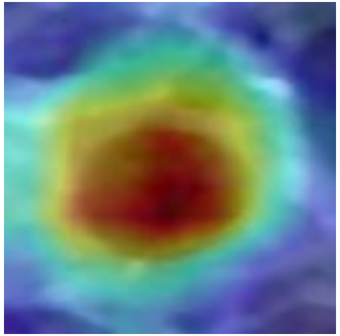




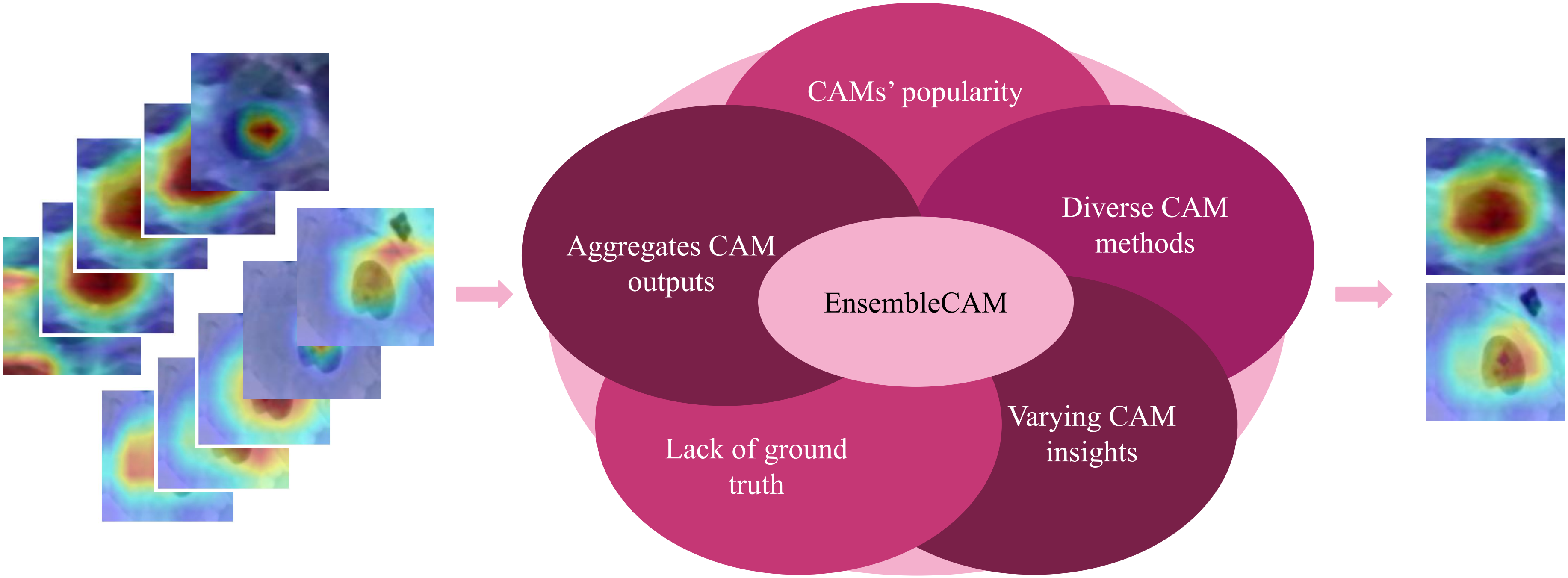
Motivation - Why XAI?







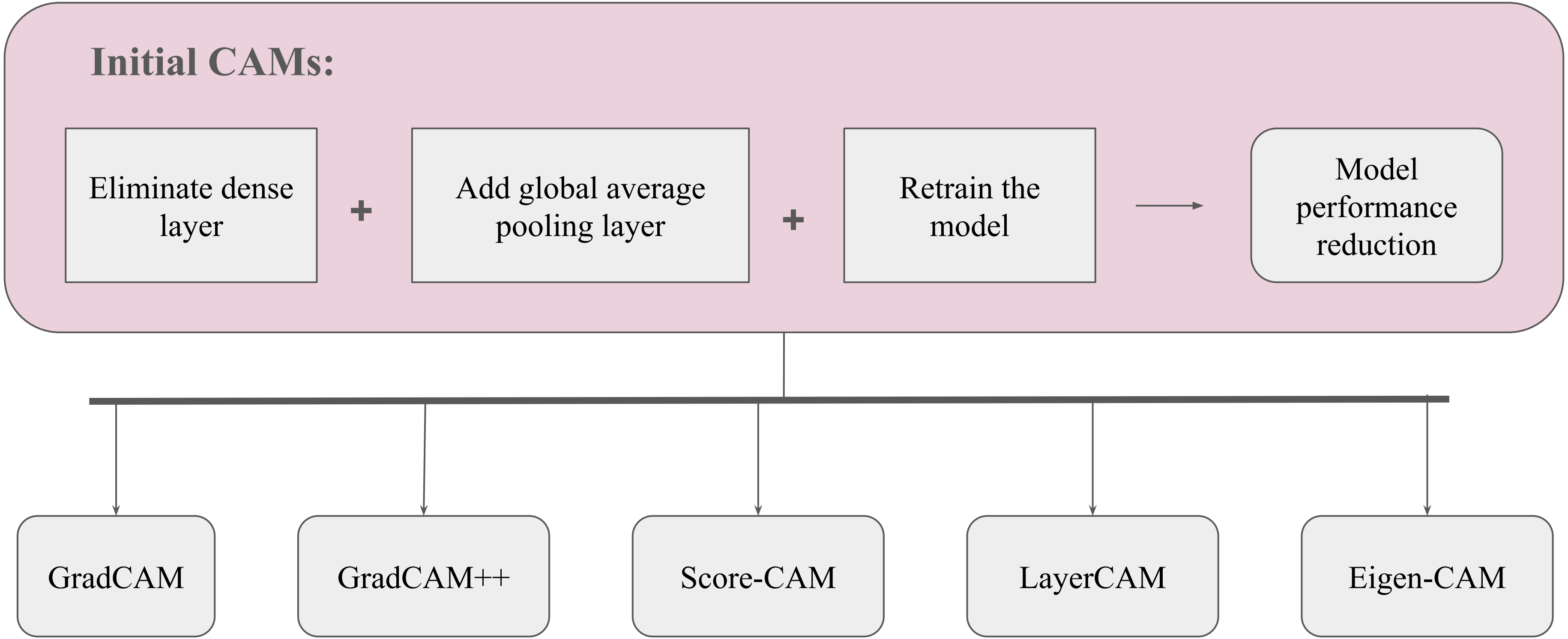
Motivation - Why EnsembleCAM?



Novelty

- EnsembleCAM, a median-based ensemble method that combines five existing CAMs applied on a cervical cell classification model.
- Qualitative evaluation of heatmaps generated by the individual CAMs and EnsembleCAM.
- Systematic quantitative evaluation of CAM methods and EnsembleCAM.

Related Studies - CAMs

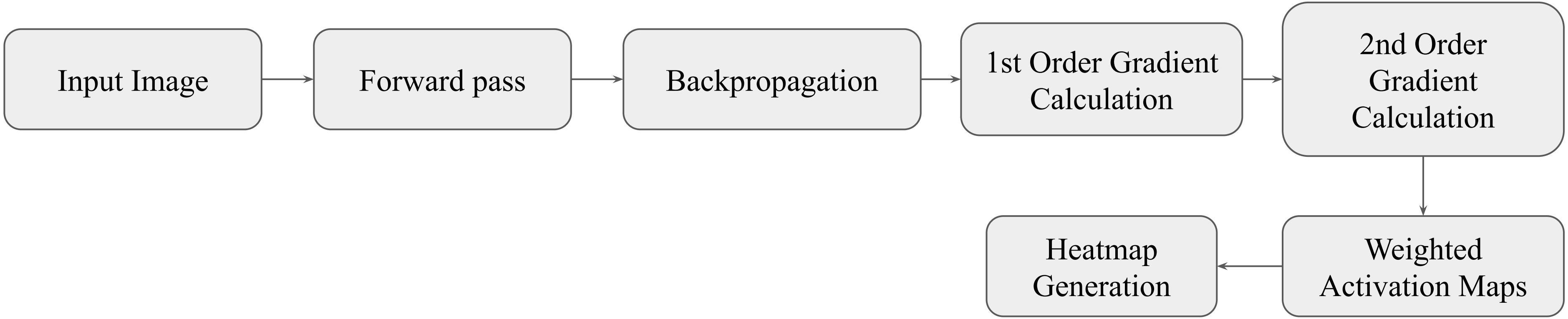


[4]

Related Studies - GradCAM & GradCAM++

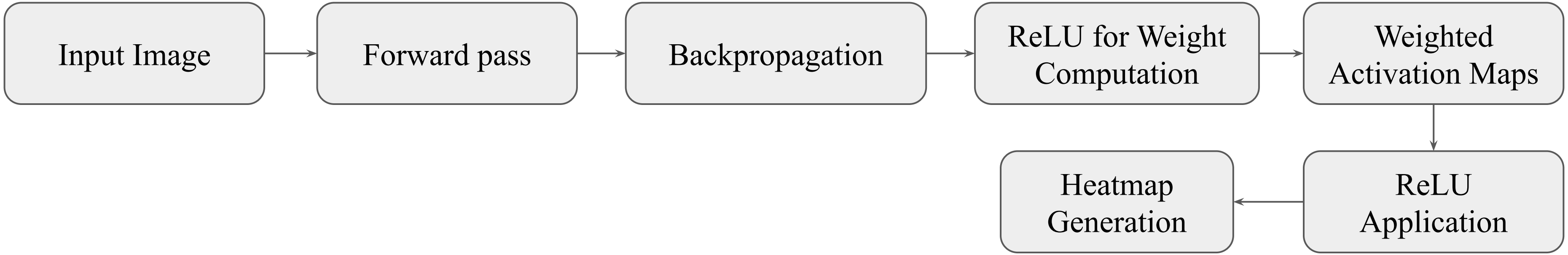
- GradCAM [4]

- GradCAM++ [5]

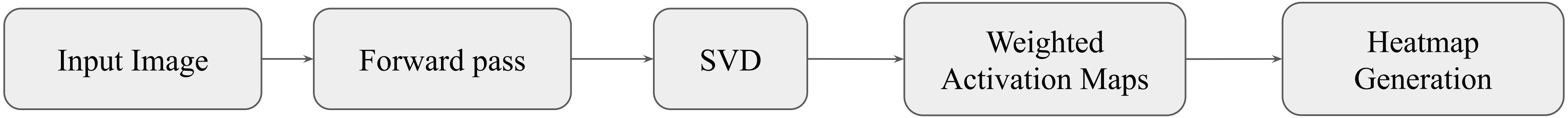


Related Studies - LayerCAM & Eigen-CAM

- LayerCAM [7]

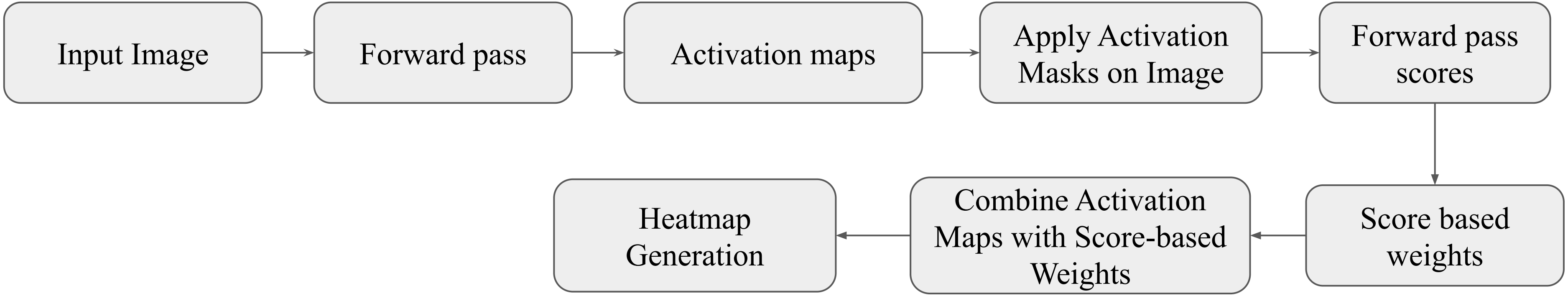


- Eigen-CAM [8]



Related Studies - ScoreCAM

- ScoreCAM [9]

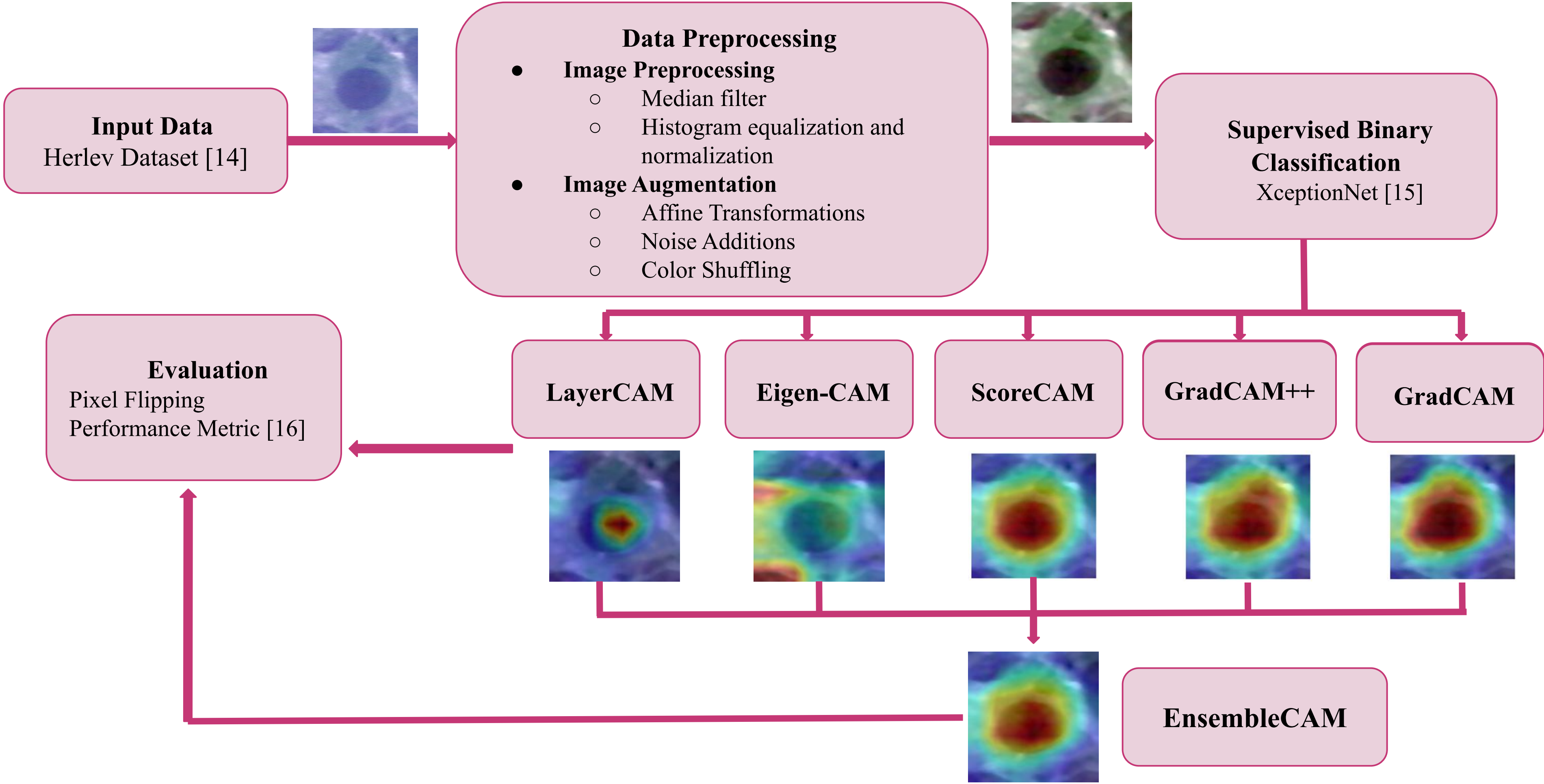


Related Studies - Augmenting / Combining CAMs

Study	Base CAM Methods	Augmentation / Combination Technique
Gao et a. [10]	GradCAM++	● Combined activation maps of geometrically augmented images. ● Bilinear interpolation to enhance saliency map resolution.
Ornek et al. [11]	-	● Novel method using PCA to select main convolutions in the last convolutional layer.
Ornek et al. [12]	GradCAM GradCAM++ LayerCAM Eigen-CAM	● Normalized outputs from the base CAMs are summed. ● Values greater than the fixed threshold of 2 are retained.
Kaczmarek [13]	GradCAM GradCAM++ LayerCAM and 8 more…	● Extensive experimentation to select the best CAMs. ● Normalized outputs from the selected CAMs are summed. ● Adaptive thresholding based on ROAD.

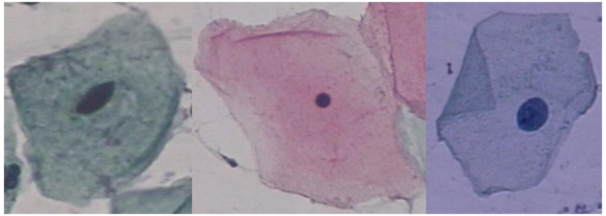
Methodology

Process Overview

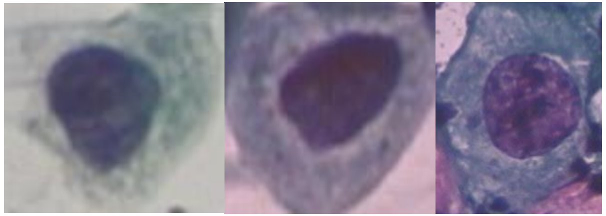


Dataset

- The dataset used for the study is Herlev dataset.
- It originally consists of 7 classes.
- For the scope of the study, we reclassified the dataset into 2 classes.
  - Normal class - Images without cancer cells
  - Abnormal class - Images with cancer cells



Normal Class



Abnormal Class

Image Preprocessing

- All images are resized to same size which is 224x224 pixels.
- Used median filter for noise reduction in images.
- Used histogram equalization and normalization to enhance the contrast [17].

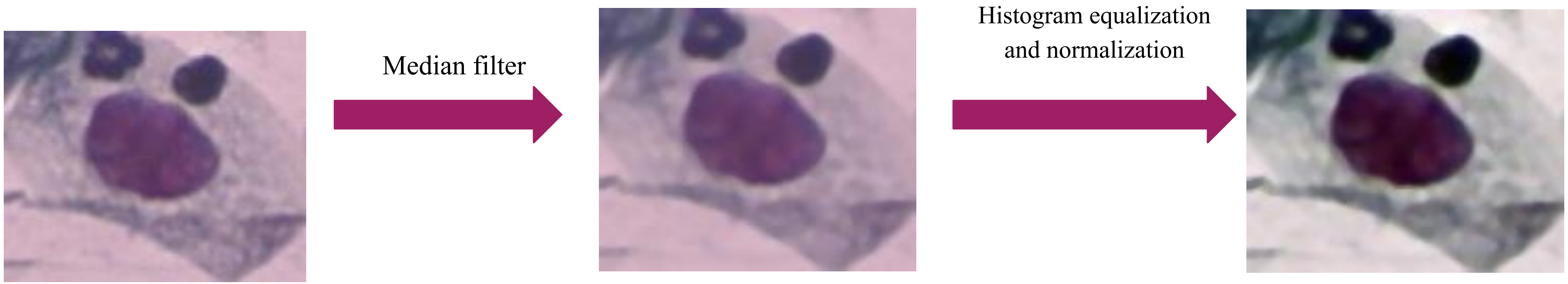
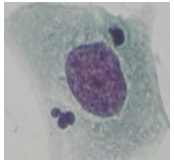
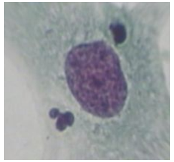
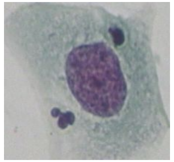
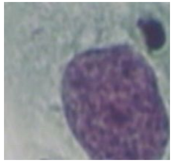
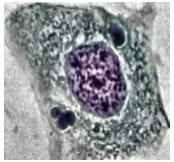
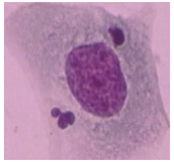
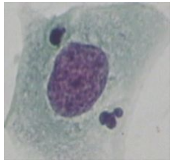
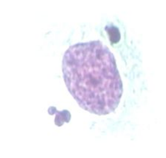
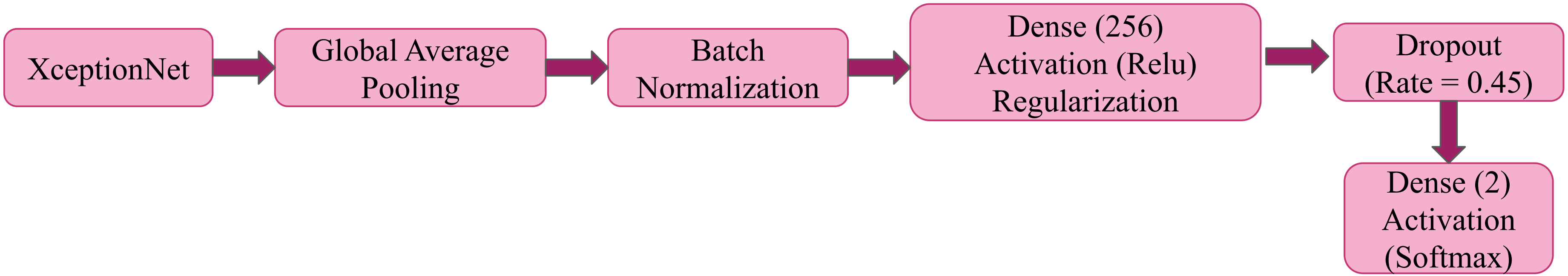


Image Augmentation

Original		**Optical distortion**, Grid distortion, Elastic transformations		Addition of **gaussian noise**, gaussian blur	
Translation, Scaling, **Rescaling of a random part**		**CLAHE**, image histogram equalization		Conversion to grayscale, shuffling color channel, addition of color jitter, **shifting RGB intensities**	
Vertical flip, **Horizontal flip**, Rotation by a random angle from 0 to 180 degrees		**Random modification of brightness, contrast of the image**		**Sharpening the image**	

Classification Model

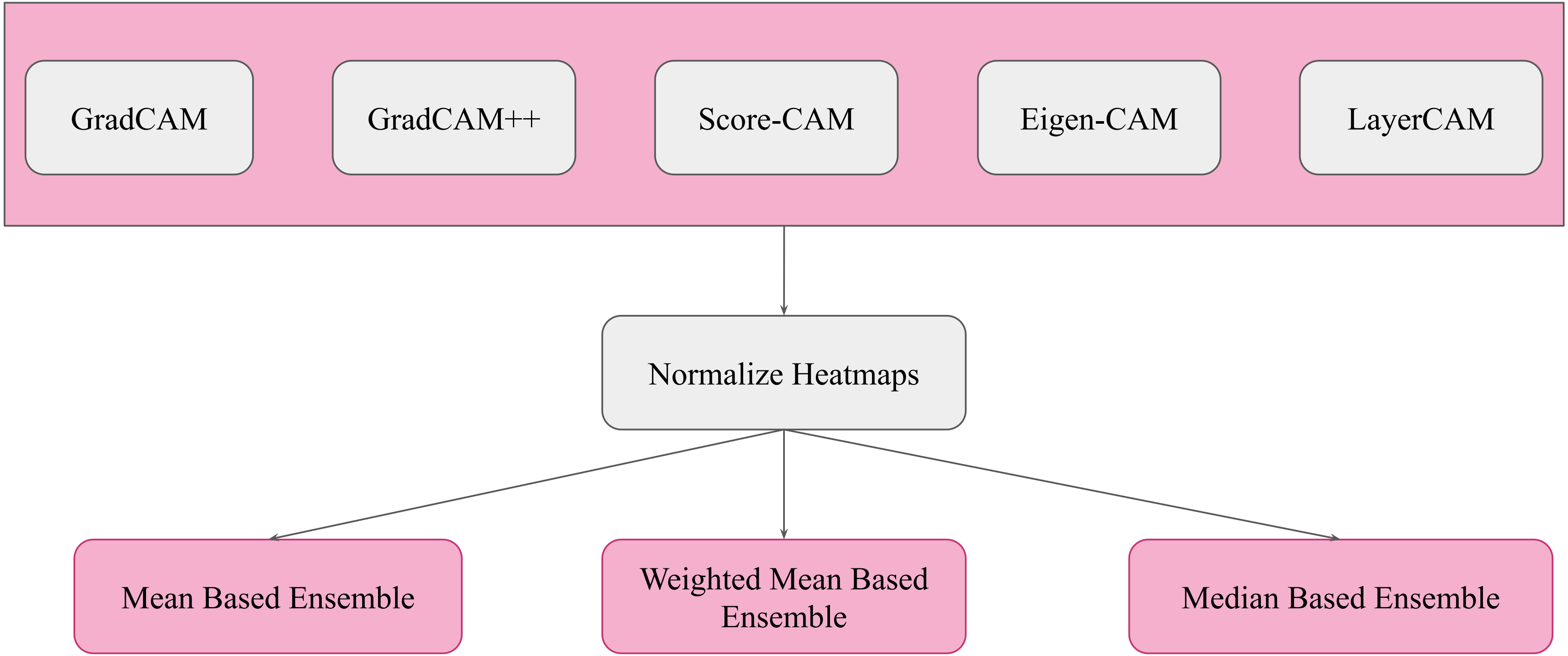


Baseline	Hyperparameters		
	Batchsize	Learning Rate	Epochs
XceptionNet	16	0.001	20

Performance of Classification Model

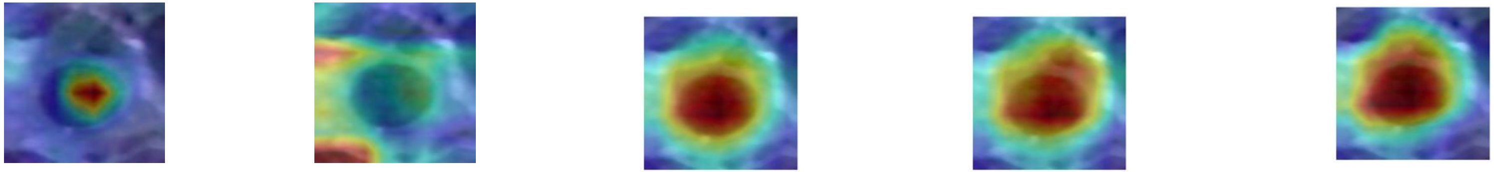
Baseline	Accuracy	Precision	Recall	F1 Score
XceptionNet	0.89	0.90	0.89	0.88

Ensemble Explanation Generation



Mean Based Ensemble

LayerCAM | EigenCAM | ScoreCAM | GradCAM++ | GradCAM



$$\frac{[L_{ij}]_{m\times n} + [E_{ij}]_{m\times n} + [S_{ij}]_{m\times n} + [GP_{ij}]_{m\times n} + [G_{ij}]_{m\times n}}{5}$$

$$\downarrow$$

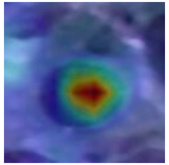
Mean Based Ensemble

Weighted Mean Based Ensemble

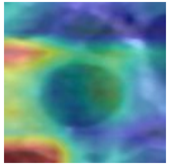
Higher entropy -> Complex explanation

Lower entropy -> More focused explanation

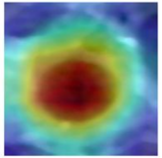
LayerCAM



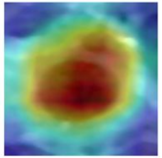
EigenCAM



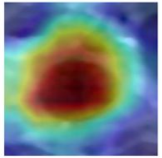
ScoreCAM



GradCAM++



GradCAM

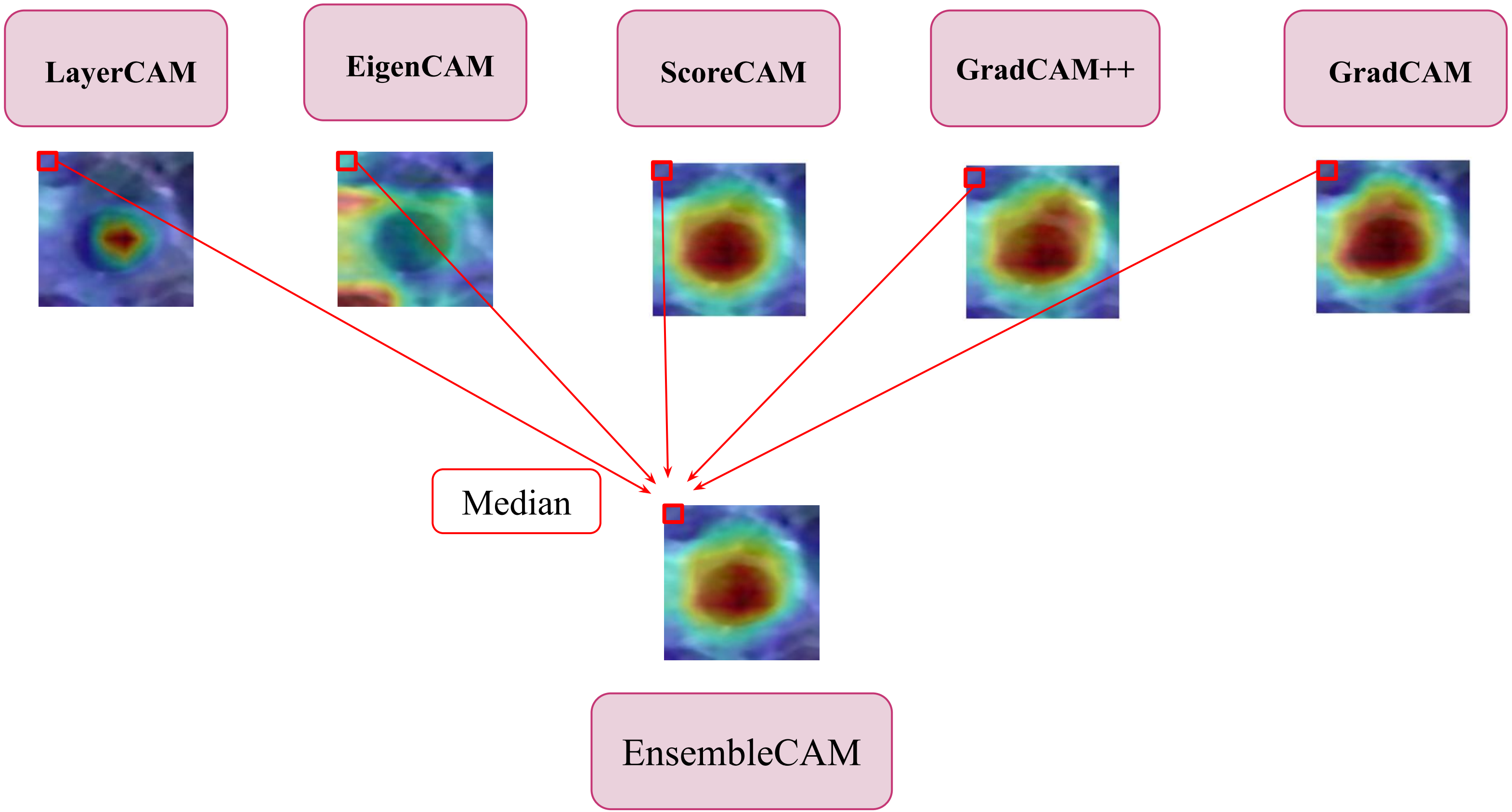


$$\frac{\frac{1}{e_L}[L_{ij}]_{m\times n} + \frac{1}{e_E}[E_{ij}]_{m\times n} + \frac{1}{e_S}[S_{ij}]_{m\times n} + \frac{1}{e_{GP}}[GP_{ij}]_{m\times n} + \frac{1}{e_G}[G_{ij}]_{m\times n}}{\frac{1}{e_G} + \frac{1}{e_{GP}} + \frac{1}{e_S} + \frac{1}{e_E} + \frac{1}{e_L}}$$

$\downarrow$

Weighted Mean Based Ensemble

EnsembleCAM: Median Based Ensemble



Evaluation metrics

Classification Models →

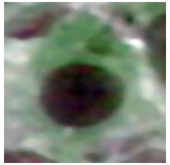
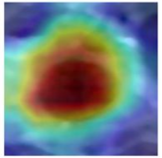
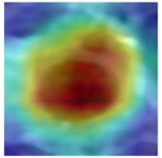
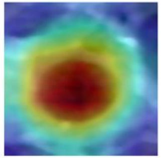
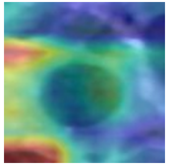
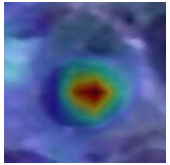
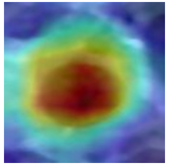
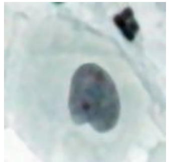
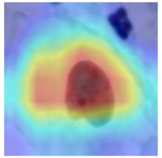
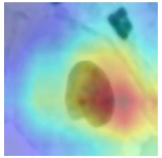
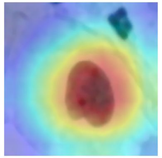
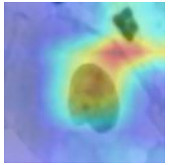
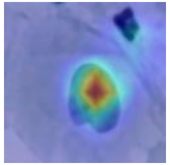
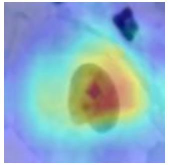
- Accuracy
- Precision
- Recall
- F1 score

XAI methods →

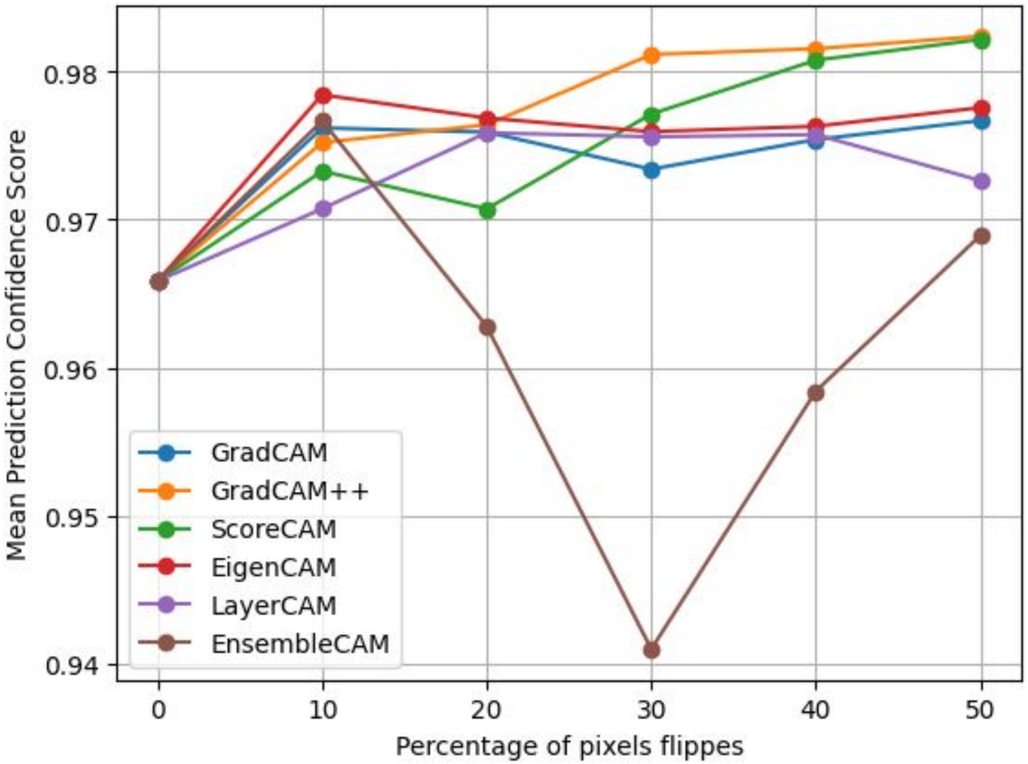
- Pixel flipping performance metric

Performance of EnsembleCAM

Qualitative Evaluation

No.	Original Image	GradCAM	GradCAM++	ScoreCAM	Eigen-CAM	LayerCAM	**EnsembleCAM**
Normal							
Abnormal							

Quantitative Evaluation



Conclusion

- Trained an XceptionNet model to classify cervical cell images into normal and abnormal categories.
- Applied five different CAM methods to generate activation maps for explaining model decisions.
- Exhibited higher activation values concentrated around crucial regions, such as the nucleus, indicative of cervical malignancy.
- Proposed a new ensemble visual explanation method named EnsembleCAM.
- EnsembleCAM outperformed individual CAM methods in explaining the decisions of the classification model.

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