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A Comparative Analysis of Implicit Augmentation Techniques for Breast Cancer using Multiple Views

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Overview

- This study focuses on implicit augmentation techniques to address class imbalance in Breast Cancer (BC) diagnosis. We evaluate nine methods using two feature sets, deep GoogleNET, and Haralick features, across Craniocaudal (CC) and Mediolateral Oblique (MLO) mammogram views. This work provides a statistical analysis recommending optimal combinations of image view, deep features, or handcrafted features using two classifiers to enhance diagnostic accuracy.

Dataset Details

Table: Training and test samples are categorized as positive (Tr Pos/Ts Pos) or negative (Tr Neg/Ts Neg) for both datasets.

Setups	Tr Pos	Tr Neg	Ts Pos	Ts Neg
S_{CC}	98	1216	19	308
S_{MLO}	99	1204	20	298
S_{CC+MLO}	158	2420	39	606
WBC	170	286	42	71

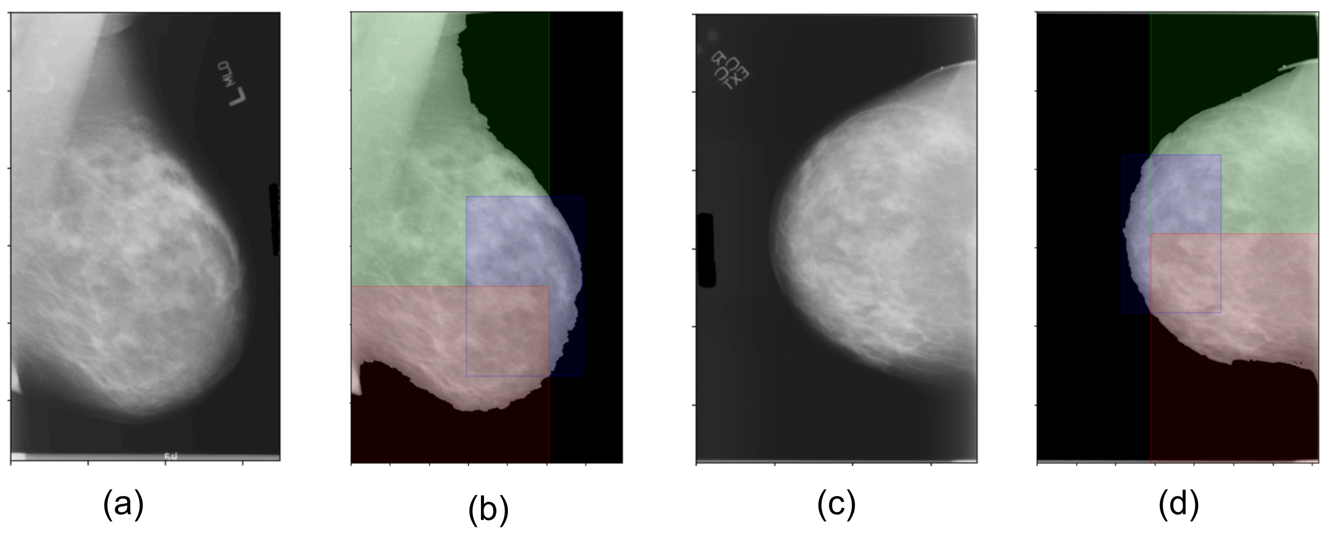


Figure: (a) Left MLO View (b) Segmentation of Left MLO image (c) Right CC View (d) Segmentation of Right CC image.

Methodology

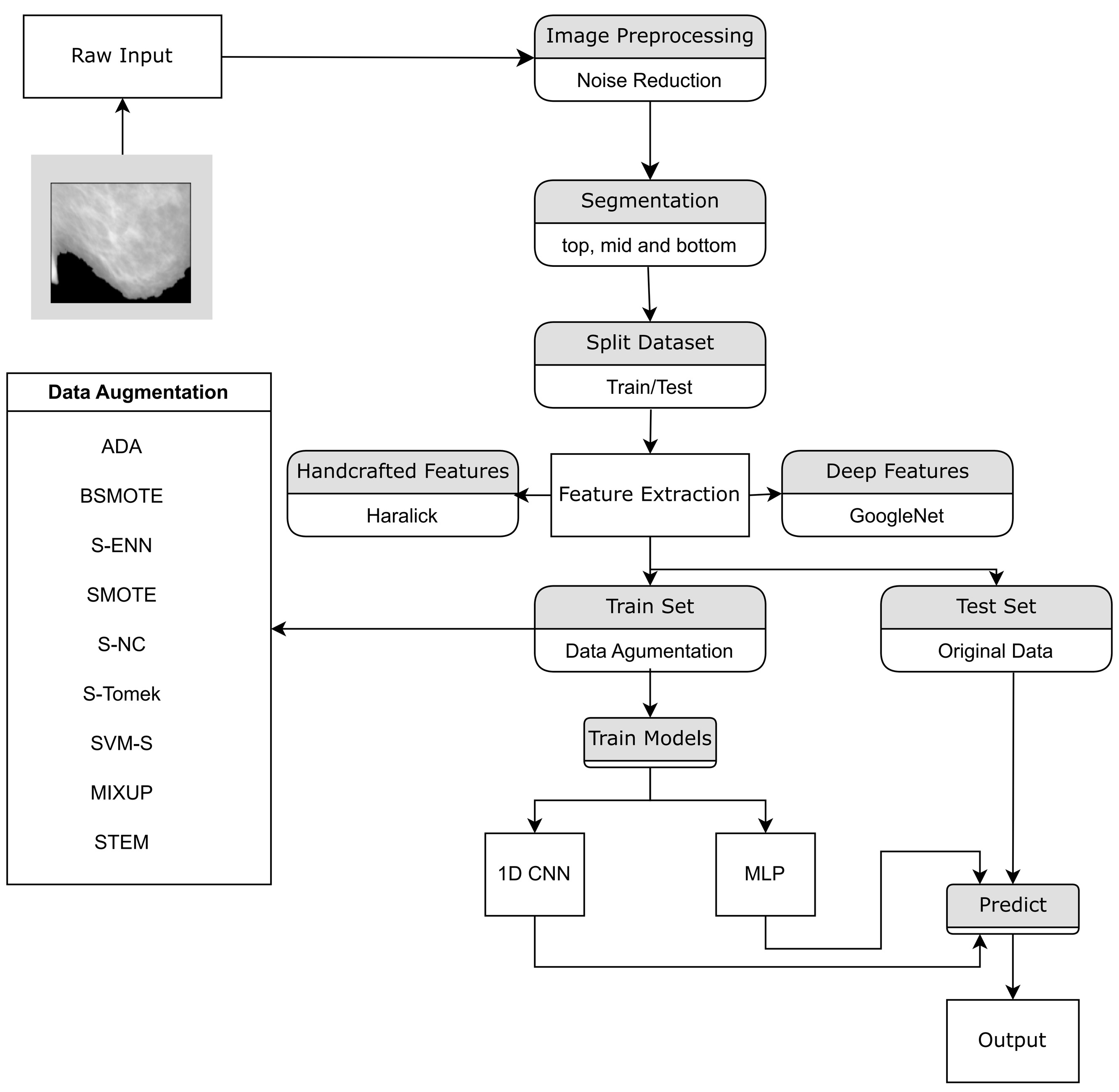


Figure: The workflow illustrating our comparative analysis of data-level augmentation approaches.

Results

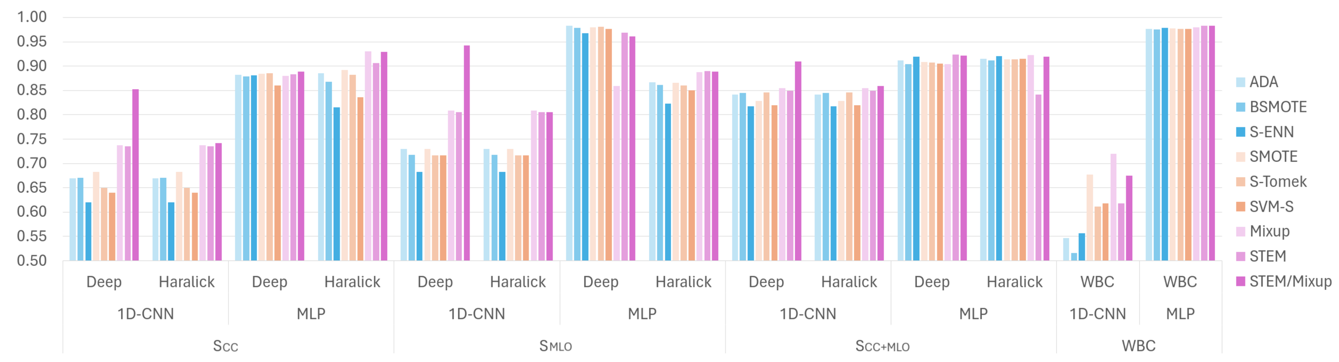
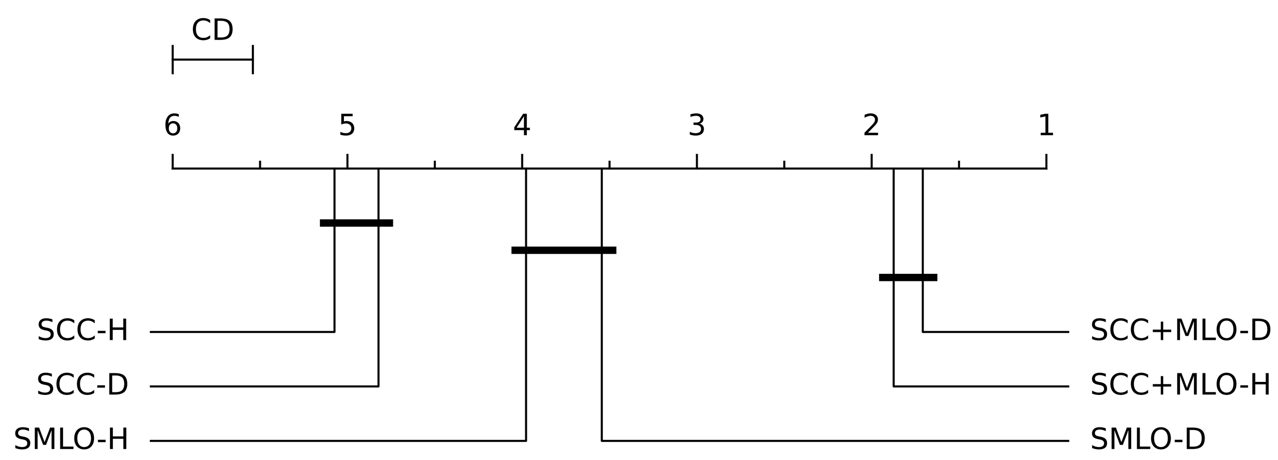
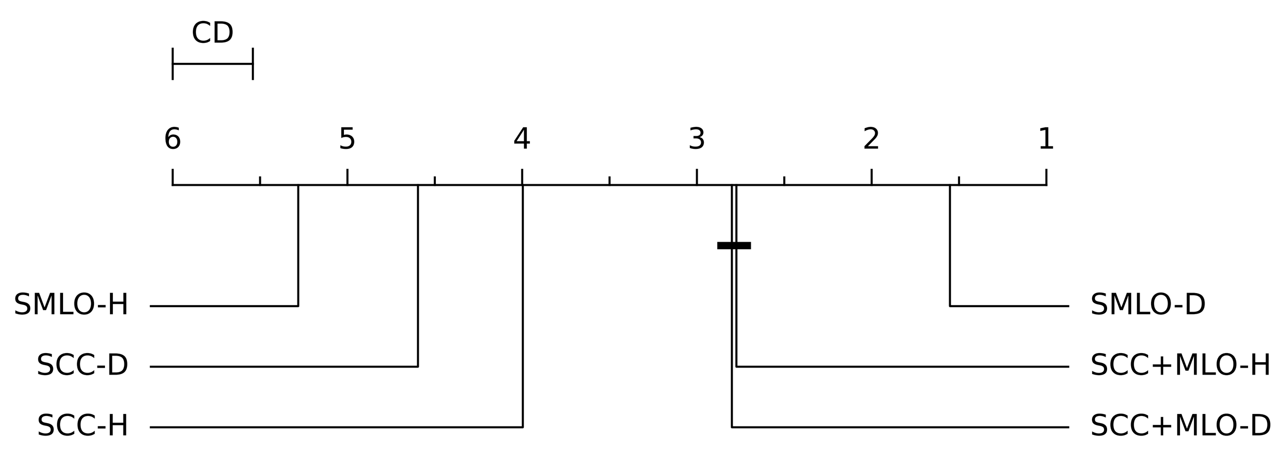


Figure: The Area Under the Curve (AUC) is the performance metric for 1D Convolutional Neural Network (1D-CNN) and Multilayer Perceptron (MLP) classifiers as shown across data setups. The x-axis represents data setups, the y-axis indicates AUC scores, and the legend highlights the applied augmentation techniques.



(a) 1D-CNN



(b) MLP

Figure: A Nemenyi Plot compares the performance of dataset setups on the $DDSM$ dataset across nine augmentation methods using 1D-CNN (a) and MLP (b). Setups ranked 1 (best) to 6 (worst) within the Critical Distance (CD) show no significant difference at $\alpha = 0.05$, with D for deep features and H for Haralick features.

Table: The STEM/Mixup combination was added to explore the diversity of generated samples using 1D-CNN and MLP classifiers. Where D and H are used for Deep and Haralick features respectively.

Setups	1D-CNN	MLP
$S_{CC} - D$	STEM/Mixup	STEM/Mixup
$S_{CC} - H$	STEM/Mixup	Mixup
$S_{MLO} - D$	STEM/Mixup	ADASYN
$S_{MLO} - H$	Mixup	STEM
$S_{CC+MLO} - D$	STEM/Mixup	STEM
$S_{CC+MLO} - H$	STEM/Mixup	Mixup
WBC	STEM	STEM/Mixup

Conclusion

- This study explores data augmentation's impact on Deep Learning for BC diagnosis. Experiments on DDSM and WBC datasets show that Mixup and STEM are the most effective techniques for 1D-CNN architectures. Key insights include the effectiveness of MLP classifiers with deep features from MLO views and the use of Haralick features for CC views.

Contact Us

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