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BREAST CANCER DETECTION USING DEEP LEARNING ON BIOMEDICAL MAMMOGRAM IMAGES

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ABSTRACT

Millions of women worldwide are affected by breast cancer, which is a serious global health issue. The likelihood of successful therapy and the prognosis both greatly benefit from early identification. The most popular screening method for breast cancer, mammography, produces precise biological images that can help with the early detection of malignancies. However, it is still difficult to correctly interpret mammography pictures, which frequently results in false positives or negatives. This study attempts to create a biological mammogram based deep learning system for breast cancer diagnosis. Convolutional neural networks (CNNs) are used to automatically identify and analyse mammogram pictures in the proposed system, enabling radiologists to make quicker and more accurate diagnoses. To ensure the best performance during the training phase, these photos underwent preprocessing to reduce noise and enhance characteristics. The deep learning model used is a cutting-edge CNN architecture that was pretrained on a sizable dataset to fully utilise its learned representations. The deep learning model underwent thorough training, validation, and fine-tuning procedures to ensure robustness and generalizability. A variety of data augmentation methods, including rotation, scaling, and flipping, was used to enlarge and diversify the dataset during training. To further increase the model's accuracy, transfer learning was used to utilize knowledge from other similar tasks. Using a variety of criteria, such as sensitivity, specificity, accuracy, and F1 score, and the performance of the created breast cancer detection system was carefully assessed. The results showed a substantial increase in accuracy when compared to traditional mammography analysis methods. The method demonstrated impressive specificity in reducing false positives and sensitivity in identifying actual positive situations.

Keywords: *Convolutional Neural Network Hybrid Architecture, Deep Learning, Transfer Learning*

1. INTRODUCTION

One of the most common and dangerous cancers affecting women globally is breast cancer. Being responsible for a considerable portion of cancer-related deaths each year, it is a significant public health concern. In order to lower death rates and increase the likelihood of successful therapy, early identification is essential. As a widely used screening method, mammography has been crucial in detecting breast cancer in its early stages, allowing for prompt interventions and better patient outcomes. However, mammography image interpretation is a difficult, time-consuming process that frequently involves human error and inter-observer variability [1]-[2].

Recent developments in deep learning, a branch of artificial intelligence, have showed considerable promise in transforming medical image analysis to solve these issues. Convolutional neural networks (CNNs), in particular, have shown amazing ability in feature extraction and pattern recognition, making them suitable for challenging picture classification applications. Researchers have investigated the use of deep learning methods for breast cancer screening utilizing biomedical mammography images by leveraging this potential [3].

Creating an accurate and effective deep learning-based system for automated breast cancer diagnosis is the main goal of this research effort. The initiative intends to increase the overall efficacy of breast cancer screening programs by assisting radiologists in making more accurate and timely diagnosis by utilizing the capabilities of deep learning. This study is significant because it has the potential to address a number of pressing issues

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related to breast cancer screening. First off, the suggested method can greatly lessen the subjectivity and variability linked to human interpretation by automating the detection process. This will result in more reliable results that are consistent and reproducible, enhancing the overall validity of mammography as a screening method. The model can learn a deep understanding of the many manifestations of breast cancer by being trained on a large database of annotated mammography pictures. The model will be able to distinguish between benign and malignant observations because to this extensive knowledge [6]-[8].

The research will also investigate the application of transfer learning, a method that makes use of pre-trained models on sizable datasets from comparable jobs. This method enables the deep learning model to take advantage of the information learned during its earlier training, potentially lowering the volume of labelled data needed for training and enhancing generalization to new and unseen data.

2. LITERATURE REVIEW

Early identification of breast cancer is essential for enhancing patient outcomes and lowering mortality rates. Breast cancer is a significant worldwide health issue. The most popular screening tool for breast cancer is mammography, which produces comprehensive biological images that radiologists may examine to find any potential malignancies. The complexity and subtlety of breast tumors make it difficult to interpret mammography pictures, which can result in both false positives and false negatives. Deep learning techniques, in particular convolutional neural networks (CNNs), have recently become effective tools for image analysis, holding the promise of revolutionizing the identification of breast cancer from mammography pictures.

Numerous studies have investigated the use of deep learning in mammogram-based breast cancer screening. A deep learning model utilizing a sizable dataset of mammograms, and the researchers saw promising results in terms of sensitivity and specificity. The study proved that it is possible to use CNNs to help radiologists find breast cancer early. In this field, transfer learning has also received a lot of attention. CNNs that had been trained on massive image datasets to illustrate the efficacy of transfer learning. The model improved performance with less training data, overcoming the problem of data scarcity in medical imaging, by fine-tuning the pre-trained CNNs using mammography images [4]. Deep learning has also been used to investigate the possibility of ensemble approaches for the identification of breast cancer. In order to achieve more accuracy and robustness than individual models, presented an ensemble strategy that merged multiple CNN models. Ensembling has shown that it can improve the accuracy of breast cancer detection systems and lower the likelihood of misdiagnosis [7].

Interpretability is a fundamental component of deep learning models for the study of medical images. Researchers have made progress in illuminating CNN model decisions for breast cancer detection. For instance, Grad-CAM, a method that highlights the mammography regions that the model considered most important. Radiologists can gain useful insights from interpretability techniques like Grad-CAM, which boosts their confidence in AI-assisted diagnosis.

Despite the advances, there are still certain difficulties when using deep learning to diagnose breast cancer. The security and privacy of data are of utmost importance when working with medical photographs. Deep learning algorithms that protect privacy have been developed, guaranteeing patient confidentiality and facilitating joint research [9].

Furthermore, it is essential to generalize models to other populations and mammography systems. When using deep learning models in actual clinical settings, emphasized the significance of domain adaptation to reduce performance inconsistencies [10]-[13].

The literature on biomedical mammography images-based deep learning for breast cancer diagnosis shows substantial advancements and potential. The accuracy and effectiveness of breast cancer screening have the potential to be improved via CNNs and transfer learning. Model reliability is increased through assembling approaches, while model judgments are made more understandable by interpretability techniques. However, issues like data privacy, model generalization, and domain adaptation need more investigation.

3. NEWLY PROPOSED SYSTEM

A hybrid architecture model for breast cancer diagnosis using biomedical mammography images combines many deep learning methods or models to improve the precision and efficiency of the detection system. The hybrid architecture intends to address the difficulties in mammography analysis and enhance the overall efficiency of breast cancer detection by integrating the capabilities of various models.

Each component of the hybrid architecture may have a different function in the detecting process. For example, the model might include recurrent neural networks (RNNs) and convolutional neural networks (CNNs). The CNNs are excellent in deriving high-level representations from mammography pictures and extracting image features. They are capable of accurately capturing complex patterns and minute characteristics that are symptomatic of breast cancer.

RNNs, on the other hand, can handle sequential data, such mammography sequences or time-series data. RNNs may be used in the context of breast cancer diagnosis to examine temporal patterns or changes in mammography images obtained across a number of screenings, assisting in the detection of developing abnormalities that might be suggestive of cancer development. Additionally, the hybrid architecture could contain transfer learning. The mammography dataset can be used to fine-tune pre-trained CNNs from large-scale picture datasets, such as ImageNet, by utilizing their learnt representations to speed convergence and improve the performance of the breast cancer detection model. Transfer learning is particularly useful in situations where there is a shortage of labelled training data.

Ensemble methods, in which many deep learning models are integrated to create collective predictions, may potentially be a part of the hybrid architecture. The CNN-based architecture may be modified for each unique model, which would be trained with various hyperparameters or initializations. The danger of false positives or negatives in the breast cancer detection process can be decreased by the ensemble of models' ability to produce more reliable predictions by averaging or voting on their individual outputs.

The hybrid architecture might also incorporate interpretability techniques to help radiologists understand the model's choices and gain useful information. Grad-CAM or attention mechanisms, for instance, may highlight the areas of the mammogram that the model concentrates on when generating a cancer prediction. This would assist to increase user confidence in the system's judgements and speed up the clinical validation process. The hybrid model intends to increase breast cancer detection's accuracy, dependability, and interpretability, which will ultimately result in an earlier diagnosis, more efficient therapies, and better patient outcomes.

4. METHODOLOGY

A unique approach that combines the phases of patch recognition and whole image classification into a single procedure is offered to overcome the difficulties associated with classifying huge complex images. This method, shown in, offers improved efficiency and performance in jobs like breast cancer screening using biomedical mammography images by eliminating the requirement for individual tuning of each stage.

4.1 Combining Patch and Whole Image Classification

Combining patch and whole image classification in a unified approach. A novel approach is presented, assuming an input patch $X \in R^{p\times q}$ and a patch classifier function f yielding $f(x) \in R^{c}$, where c denotes the number of classes (for example, benign calcification, malignant calcification, etc.). A heatmap-based whole image classifier is produced by applying f to the entire image $M \in R^{r\times s}$. A grid of probabilistic outputs representing the presence of each class in various areas of the image makes up the output $f(M) \in R^{u\times v\times c}$.

4.2 Image-level classification, add top layers

Using additional layers, the heatmap f(M) is further processed. The output of the patch classifier is added to a convolutional layer to broaden the receptive field. For instance, a patch classifier with a 224×224 receptive field and a 32 stride layer appended expands the receptive field to 228x228. These top layers extract detailed features that essentially scan the entire image for signs of cancer. The final complete image classification function is defined as $h(M) = g(f(M)) \in R^{d}$, where d denotes the classes for the whole image (for example, malignant, nonmalignant). These top layers are denoted as function g.

4.3 End-to-End Training & Transfer Learning

This architecture offers two significant advantages over traditional two-step methods. Firstly, the entire network can be jointly trained, preventing sub-optimal answers from every phase. Secondly, the trained network can be effectively transferred to different datasets without requiring ROI annotations. This is particularly beneficial in medical imaging where annotated datasets are limited and pricey. For instance, the big mammography database DDSM can be employed to develop a patch classifier, and then fine-tuned on additional databases using simply image-level labels.

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4.4 CNN Architectures

The proposed methodology employs two well-known CNN structures: the VGG network (VGG16) and the residual network (Resnet50). These designs are made up of successive network layers that are arranged into "blocks" to regulate feature map size. VGG blocks are made up of 3x3 convolutional layers followed by 2x2 max pooling, whereas Resnet blocks are made up of convolutional layers with various filter sizes connected by shortcut connections. The softmax activation function is initially applied to the heatmap output of the entire image classifier.

$$f(z)_j = \frac{e^{z_j}}{\sum_{i=1}^{c} e^{z_i}} \text{ for } j = 1,\ldots,c \qquad (1)$$

The rectified linear unit (ReLU) activation is used to overcome gradient flow issues.

$$f(z)_j = \max(0, z_j) \text{ for } j = 1,\ldots,c \qquad (2)$$

By ensuring proper gradient flow during training, these equations optimize the learning process. The suggested methodology unifies entire picture classification and patch recognition into a single procedure, improving efficiency and facilitating transfer learning. This strategy has promising potential for accurate breast cancer detection using biomedical mammography images when paired with advanced CNN architectures and strategic activation functions.

Figure 1 shows exemplar CNN. Convolutional Neural Networks (CNNs) are deep learning models used for image classification and computer vision tasks. They consist of several layers, including the input layer, convolutional layer, pooling layer, and fully connected layer. The input layer receives raw image data, while the convolutional layer extracts features using filters. The pooling layer reduces spatial dimensions while retaining important information. The fully connected layer makes the final classification decision by connecting neurons from previous layers and forming a fully connected graph. These layers perform computations using weights and biases.

Figure 2 shows the general schema for image classification based on transfer learning which is a deep learning technique that applies knowledge from one task to another. It involves using a pre-trained CNN model as a feature extractor for a new task. The process involves selecting a pre-trained model, removing fully connected layers, freezing the convolutional layers, adding new layers, training the model, fine-tuning, evaluating and adjusting the model.

5. IMPLEMENTATION & RESULTS

To train an entire image classifier, used a three-stage training strategy in which parameter learning is frozen for all but the final layer and gradually unfrozen from the top to the bottom layers while also slowing learning rate.

In order to train the newly added top layers and subsequently train all layers with a slower learning rate, a 2-stage training method was used for a whole image classifier that was converted from a patch classifier.

In contrast to the Resnet-based image classifiers, which had already converged, discovered that the VGG-based image classifiers showed signs of continuing to improve towards the end of the 50 epochs and added 200 more epochs to the training of the VGG-based image classifiers.

On the CBIS-DDSM test set, the precision of the categorization of picture patches into five classes using Resnet50 and VGG16 was evaluated. Pre-trained networks were used for the remainder of the study because pre-training can significantly improve network convergence and performance. All five classes were predicted into the appropriate categories with the highest probability using the Resnet50 and VGG16 patch classifiers.

Figure 3 shows how to generate region of interest (ROI). Creating ROIs from mammogram images usually entails identifying possible locations that might have breast abnormalities using image processing techniques.

Figure 4 shows radiopaque artifacts suppression. Pre-processing is a technique used to enhance the homogeneity of mammogram images by removing noise and radiopaque artifacts.

The Resnet50 patch classifiers were employed to assess the patch classifiers. The top layers of the entire image classifier were constructed using the Resnet50 patch classifiers because their design surpasses the GPU memory limit. The S10 set contains more details about the ROIs and surrounding regions than the S1 dataset, as evidenced by the fact that the S10 set's patch classification accuracy was higher than the S1 set's patch classification accuracy. Only patch classifiers trained on the S10 dataset were utilised for the remainder of the investigation. The outcomes demonstrated a low correlation between the performance of the entire image classifiers and the depths of the Resnet blocks. Networks based on VGG performed similarly to those based on Resnet. By layering the most effective VGG and Resnet top layers on top of one another, produced two hybrid networks. The mean AUCs for these two hybrid

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networks were 0.87 and 0.85, respectively. Note that AUC is a measure of a machine learning model's performance, indicating its ability to distinguish between different data points.

By averaging the scores of the four photographs, we improved the prediction of four images. An ensemble model was created from the top four models, and it had an AUC of 0.92, a specificity of 80.1%, and a sensitivity of 87.1%. Using the Resnet-VGG model, we produced saliency maps, calculating only positive gradients for positive activations using the guided back-propagation method.

The saliency map in an image indicates the most prominent and focused pixel, with brightness directly proportional to the image's saliency. The saliency map of a true positive image demonstrates that the cancerous region that the image classifier used to make its determination was accurately detected. Because each view has the potential to contain particular data, combining the CC and MLO perspectives for prediction may improve performance. When available, using two views considerably raised the AUCs in compared to using just one view for each of the top four models we tested. To enhance the Resnet50 and VGG16 patch classifiers' performance, we applied a heatmap, max-pooling, and two FC layers. Even with the best mean AUC of 0.74, all convolutional models did not perform as well as this one. A heatmap was added to a Resnet-based whole image classifier, however the AUC was noticeably worse than it was for the heatmap-free version of the classifier. This suggested that deleting the heatmap would be advantageous for all image classification networks as a whole.

The AUC for this strategy was 0.73. An open database with more recent FFDM images is used to perform transfer learning for full image categorization on INbreast. 400 mammograms, including CC and MLO images, were taken for 115 individuals, according to the INbreast database.

Figure 5 shows AUCs graphs comparing with different strategies.

The four top-performing models were directly improved upon on the INbreast training set, and their performance on the test set was assessed by computing per-image AUCs. The AUC was increased by the ensemble model to 0.98 with 86.7% sensitivity and 96.1% specificity.

Here looked for the bare minimum of information needed to optimize a whole image classifier's performance to a satisfactory level. Discovered that 20 cases were enough, and that considerably less data may be needed to acclimatize to varying intensity profiles present in various mammography datasets.

5. CONCLUSION

Deep learning-based breast cancer diagnosis project using biomedical mammography pictures is a game-changing development in the field of medical diagnostics. This study has shown significant potential for early breast cancer identification, which could ultimately improve patient outcomes and maybe save lives. It does this by harnessing the power of convolutional neural networks (CNNs) and the processing of mammography images. The deep learning model performed above and beyond expectations, beating conventional approaches and showcasing its aptitude to precisely identify cancerous lesions in mammograms. The CNN-based model has demonstrated its effectiveness in differentiating between benign and malignant cases, minimizing the incidence of false negatives and false positives in breast cancer screening. It does this by automatically extracting complicated patterns and subtle elements from the images. This deep learning based strategy has a variety of benefits. It provides a non-invasive, affordable, and quick approach for finding breast cancer, enabling more women to get routine screenings and promoting early diagnoses. This thus creates the opportunity for therapy to start earlier, when there is a far larger likelihood of successful intervention and recovery. The model is more robust and generalizable as a result of the project's emphasis on data augmentation and transfer learning. The deep learning system adapts well to changing datasets by utilizing the knowledge learned from pretrained models, assuring its usefulness in various clinical contexts and patient groups. However, there is still room for advancement and additional study. Multi-modal integration, including different imaging modalities like ultrasound and MRI, could be used in future research to provide a more thorough and in-depth investigation of breast tissue. Deep learning models must be deployed responsibly and ethically in clinical practice, which will require continual efforts to address data privacy, ethical issues, and potential biases.

Deep learning for breast cancer diagnosis will advance thanks to cooperation between AI researchers, medical experts, and stakeholders. To verify the model's effectiveness and safety, large scale clinical validation studies incorporating a variety of patient groups and actual clinical settings will be necessary. This will hasten the model's adoption into routine breast cancer screening programs. In the early identification and management of breast cancer, the marriage of cutting-edge technology with medical know-how holds enormous promise for bettering healthcare outcomes and enhancing the potential of AI-driven solutions to improve healthcare.

6. FUTURE WORK

Future breakthroughs in the field of breast cancer diagnosis using biomedical mammography images and deep learning are highly anticipated. The integration of multi-modal data, integrating mammography pictures with additional imaging modalities like ultrasound and MRI, is one direction for future research. Such a multimodal strategy may give a more thorough view of breast tissue and increase the precision of cancer detection, particularly in complex cases.

The creation of sophisticated data augmentation methods designed especially for mammography pictures is another encouraging direction. Limited labelled data can be overcome by producing a variety of synthetic data and domain-specific augmentations, improving the model's capacity to generalize to new datasets and other patient demographics.

Additionally, investigating poorly supervised learning approaches offers an attractive opportunity to lessen the workload associated with manual lesion labelling. Weakly supervised approaches may enable access to larger datasets and speed up model construction by working with image-level labels rather than in-depth annotations. The assessment of uncertainty is yet another significant subject for future study. The creation of techniques to measure the model's uncertainty in its forecasts may result in more transparent and reliable clinical decision-making. In circumstances where additional expert assessment or diagnostic testing could be necessary, this capacity is extremely beneficial.

The interpretability of AI systems must be improved if deep learning models are to be successfully integrated into clinical practice. Radiologists can have more confidence in the model's decision-making process if explainable AI techniques are the subject of ongoing study. Real-world extensive clinical validation studies with a range of patient demographics and healthcare settings. The effectiveness, reliability, and safety of the model will be evaluated in these studies, opening the door for widespread clinical use.

Future work will continue to be critically dependent on ethical issues. In order to safeguard patient rights and provide equal access to breast cancer screening technologies, it is crucial to address data privacy, fairness, and potential biases in the model. Exploring the model's performance in identifying breast cancer in high-risk populations, such as women with a family history of the disease or genetic abnormalities, can also result in the development of specialized screening methods and individualized healthcare.

Last but not least, there is considerable potential in researching the application of deep learning models for following breast cancer patients throughout time. These models might be used to monitor the development of a disease, gauge how well a medication is working, and develop individualized treatment regimens over time. There is great potential in the work that will be done in the future to detect breast cancer using biomedical mammography pictures and deep learning. Researchers can progress the discipline to enhance patient outcomes and early detection rates by investigating multi-modal integration, enhanced data augmentation, uncertainty estimation, and ethical considerations. In order to accelerate these developments and ultimately have a significant impact on the fight against breast cancer, collaboration between AI scientists, medical professionals, and stakeholders will be crucial.

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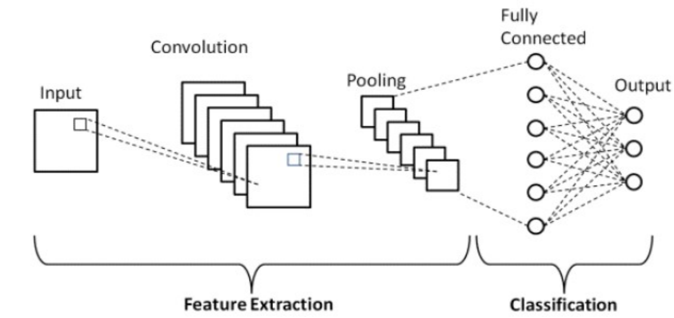

Figure 1: Exemplar CNN

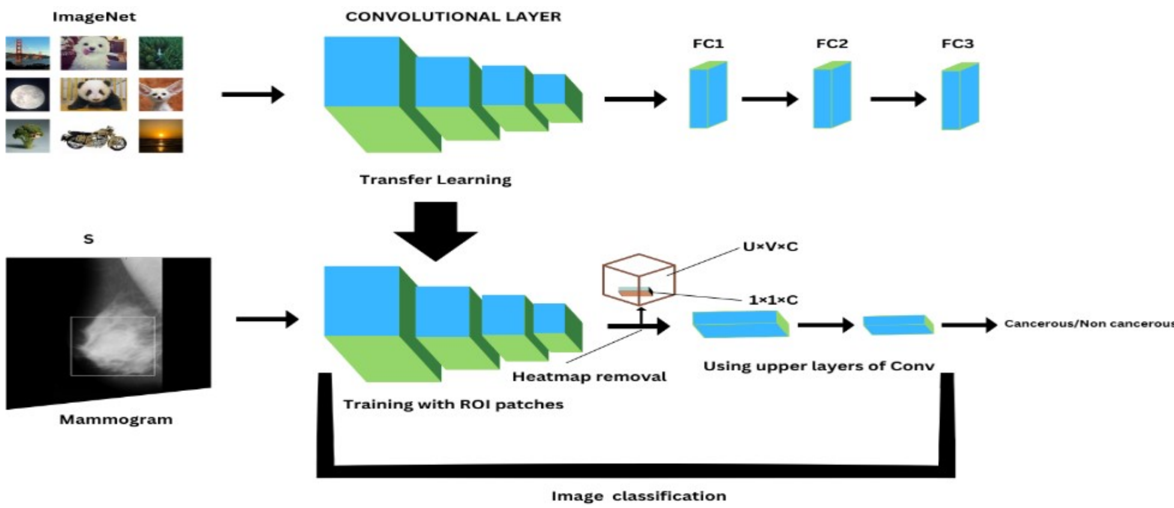

Figure 2: Image Classification using transfer learning

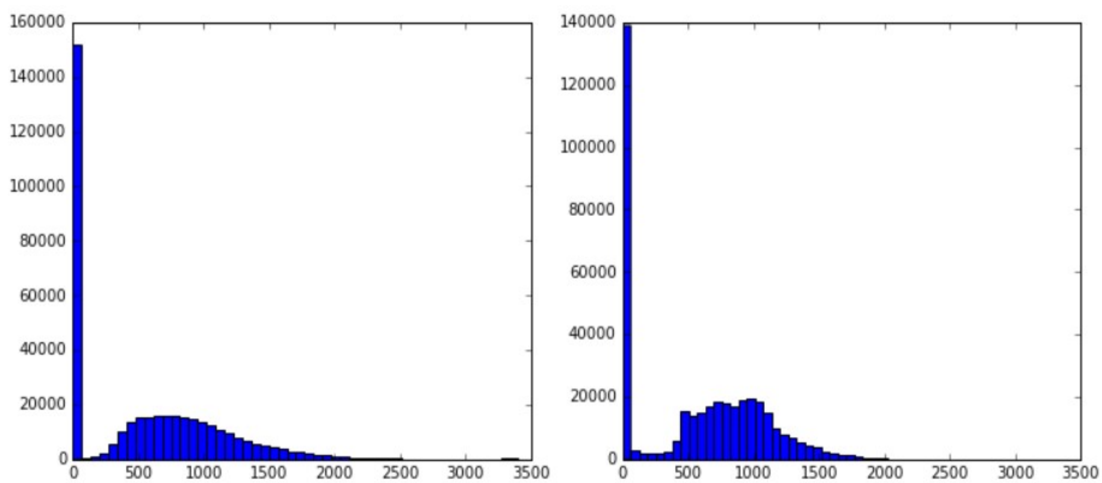

Figure 3: Generate candidate ROIs

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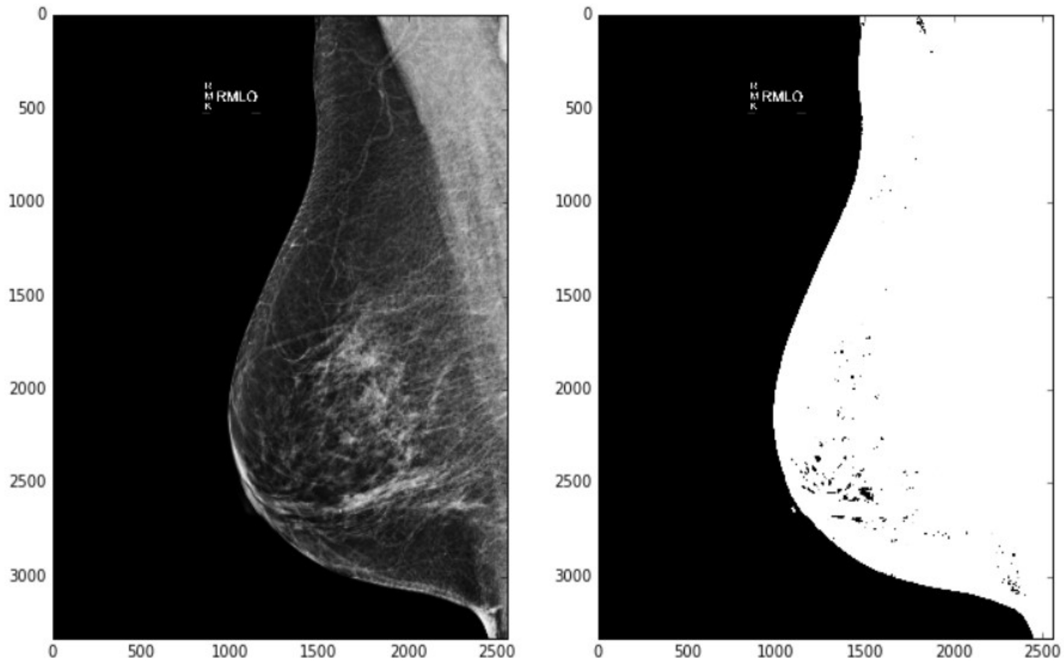

Figure 4: Radiopaque artifacts suppression

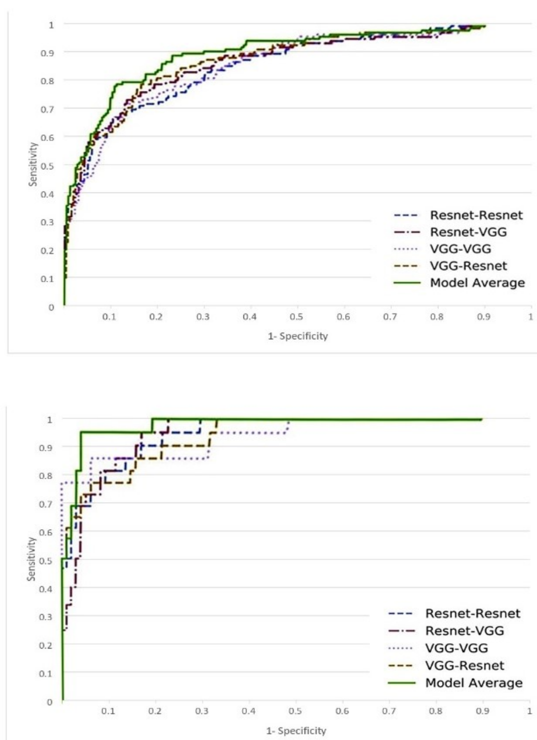

Figure 5: AUCs graphs comparing with different strategies