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# Breast Cancer Detection using DCNN and MSVM

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**Abstract:** Breast cancer screening is a critical area of medical diagnostics, where the accuracy and performance of radiologists play a pivotal role in early detection and diagnosis. In this Project, we present a novel approach aimed at enhancing radiologists performance in breast cancer screening through the optimization of parameters for a Multi-Class Support Vector Machine (MSVM). We compare the results of our proposed method against an existing approach based on Deep Neural Networks (DNN) in terms of accuracy, specificity, and the types of cancer detected, including both benign and malignant cases. The existing method employs DNN as the primary algorithm, achieving an accuracy rate of 92.8%. While this performance is commendable, our proposed method, leveraging the power of MSVM with optimized parameters, surpasses it with an accuracy rate of 93.5%. The proposed DCNN architecture is designed to automatically learn discriminative features from mammography images. The model consists of multiple convolutional layers followed by pooling layers to extract hierarchical features. Additionally, batch normalization and dropout layers are incorporated to improve the generalization and robustness of the model.

**Keywords**: MSVM(Multi-Class Support Vector Machine),DNN, DCNN(Deep Convolution Neural Networks)

## 1. Introduction

Breast cancer remains a significant global health concern, with early detection being a critical factor in improving patient outcomes and reducing mortality rates. Mammography, a widely used diagnostic tool, relies on the expertise of radiologists to interpret complex medical images accurately. As the demand for breast cancer screening continues to rise, there is a growing need to enhance the performance of radiologists in identifying breast cancer cases, both benign and malignant, with increased accuracy and efficiency. This study delves into the realm of breast cancer screening and presents a novel approach to improve the performance of radiologists in this vital healthcare domain. We focus on the implementation of Multi-Class Support Vector Machine (MSVM) parameters, a machine learning technique known for its versatility and ability to handle complex classification tasks. Our objective is to leverage MSVM's capabilities to augment radiologists' diagnostic accuracy and specificity in breast cancer screening. The conventional approach to breast cancer screening often involves deep learning algorithms, such as Deep Neural Networks (DNN). While DNNs have demonstrated remarkable performance in various image classification tasks, including medical imaging, we aim to explore whether MSVM can offer a competitive edge in this context. This research study compares the performance of our proposed MSVM-based method with an existing DNN-based approach. We evaluate the accuracy, specificity, and the ability to detect both benign and malignant cases of breast cancer, essential metrics for the success of any breast cancer screening program. Our investigation seeks to answer whether fine-tuning MSVM parameters can provide an edge over existing methods and potentially revolutionize the way radiologists approach breast cancer diagnosis.

As we delve deeper into the nuances of this implementation, we anticipate uncovering insights that could contribute significantly to improving radiologists' proficiency in breast cancer screening. Ultimately, the potential benefits of enhanced diagnostic accuracy and specificity could translate into earlier interventions, better patient outcomes, and a more efficient healthcare system. This study is a step towards harnessing the power of machine learning to advance the field of breast cancer screening and bolster the capabilities of healthcare professionals in the fight against this formidable disease. Breast cancer screening is a crucial component of early detection and prevention efforts for breast cancer, a common and potentially deadly disease that primarily affects women but can also affect men. The background of breast cancer screening encompasses the

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history, methods, and controversies associated with these screening programs.

## 2. Related Work

Breast Cancer Classification Using Deep Convolutional Neural Networks" by Arevalo et al. (2016): This study proposed a DCNN-based approach for classifying breast cancer histopathology images. The researchers achieved high accuracy in distinguishing between benign and malignant cases, demonstrating the potential of DCNN in improving breast cancer diagnosis.

"Deep Learning for Breast Cancer Histopathological Image Analysis: An Overview" by Spanhol et al. (2016): This review paper provided an overview of the application of deep learning techniques, including DCNN, in breast cancer histopathological image analysis. It discussed various architectures and highlighted the importance of large annotated datasets for training accurate models.

"Deep Convolutional Neural Networks for Breast Cancer Screening on Digital Mammography" by Shen et al. (2017): This study focused on using DCNN for breast cancer screening on digital mammograms. The researchers developed a DCNN model that achieved high accuracy in detecting breast cancer, demonstrating the potential of DCNN in improving mammography-based screening.

"Breast Cancer Detection Using Convolutional Neural Networks" by Wang et al. (2018): This research explored the use of DCNN for breast cancer detection using mammographic images. The study demonstrated that DCNN models could effectively detect breast cancer with high accuracy, sensitivity, and specificity, showing the potential for DCNN in improving early detection.

"Deep Learning-Based Classification of Mammographic Breast Density" by Kallenberg et al. (2019): This study investigated the use of DCNN for classifying mammographic breast density, a known risk factor for breast cancer. The researchers developed a DCNN model that achieved accurate classification of breast density levels, highlighting the potential of DCNN in risk assessment.

"Breast Cancer Detection Using Deep Convolutional Neural Networks and Support Vector Machines" by Al-Janabi et al. (2020): This study proposed a hybrid approach combining DCNN and support vector machines (SVM) for breast cancer detection. The combined model achieved improved accuracy and sensitivity, demonstrating the potential of integrating multiple machine learning techniques.

"Deep Learning for Breast Cancer Diagnosis: A Comparative Study" by Rawat and Kaur (2021): This comparative study evaluated different DCNN architectures for breast cancer diagnosis. The researchers compared the performance of

Xiang et al. (2016) presented an MSVM-based breast cancer classification model that achieved high accuracy by effectively utilizing features extracted from mammogram images. They highlighted the importance of feature selection and parameter tuning for MSVM.

Kaur and Kaur (2017) explored the use of MSVM for breast cancer classification and reported promising results in terms of accuracy and specificity. They emphasized the role of feature extraction techniques like GLCM in capturing texture information.

Elakkiya and Subashini (2018), a hybrid approach combining deep features extracted using Convolution Neural Networks (CNNs) with MSVM for breast cancer classification was proposed. This hybrid model demonstrated improved accuracy and robustness.

Jafari et al. (2019) introduced a hybrid model that integrated MSVM with genetic algorithm-based feature selection. This approach effectively reduced the dimensionality of the feature space and enhanced classification performance.

Choudhary et al. (2020) conducted an extensive study on optimizing MSVM parameters for breast cancer diagnosis. They employed grid search and cross-validation techniques to determine the optimal combination of parameters, resulting in improved accuracy and specificity.

Phan et al. (2021) investigated the use of particle swarm optimization (PSO) to optimize MSVM hyper parameters. This approach showed promise in enhancing the classification performance of breast cancer screening models.

Alomari et al. (2019) addressed the issue of data scarcity by employing data augmentation techniques. They augmented the dataset with synthetically generated images, leading to more robust MSVM-based breast cancer classification. Several studies emphasized the importance of preprocessing steps, such as noise reduction and contrast enhancement, in improving the quality of mammogram images before MSVM-based classification.

Sajjad et al. (2020) conducted a comparative study between MSVM and other machine learning algorithms for breast cancer detection. They reported that MSVM achieved competitive results and

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highlighted its potential for clinical applications.

Amin et al. (2021) compared the performance of MSVM with deep learning models, including CNNs, in breast cancer classification. The study revealed that MSVM offered a competitive alternative, particularly when computational resources were limited.

Alomari et al. (2019) addressed the issue of limited data by employing data augmentation techniques. They augmented the dataset with synthetic images to improve the robustness of MSVM-based breast cancer classification.

Jafari et al. (2019) introduced a hybrid approach that combined MSVM with genetic algorithm-based feature selection. This approach aimed to reduce the dimensionality of the feature space, improving classification efficiency.

## 3. Experimental Method

The dataset comprises mammographic images with known ground truth labels. Preprocessing begins with Median filtering to enhance image quality and reduce noise, preparing the images for subsequent analysis. FCM-based segmentation isolates regions of interest (ROIs), effectively delineating potential abnormalities within the breast tissue.

Feature extraction is performed using GLCM, capturing texture information from the segmented ROIs. These texture features serve as input to the MSVM classifier, which has been trained on a diverse dataset encompassing both benign and malignant cases.

The performance of the MSVM-based breast cancer screening model is assessed in terms of accuracy, specificity, and its ability to differentiate between benign and malignant tumors. The results reveal the model's effectiveness in classifying both cancer types, achieving a comprehensive understanding of the disease.

This research contributes to the field of breast cancer screening by demonstrating the utility of MSVM in MATLAB 2013a. The proposed framework enhances the accuracy of cancer detection and classification, providing valuable support for medical professionals. The findings underscore the potential of this approach to aid radiologists in making informed decisions, ultimately facilitating earlier diagnoses and improved patient outcomes.

While this proposed method showcases the promise of MSVM in breast cancer screening, further validation through clinical trials and real-world implementations is essential to ensure its seamless integration into routine breast cancer screening protocols.

Input Image Acquisition: The process begins with the acquisition of blood cell images, typically obtained from microscopic slides or digital medical imaging systems.

Pre-processing (Median Filter): A Median Filter is applied to the input images to reduce noise, enhance image quality, and prepare them for subsequent analysis.

Breast Cancer Screening System: This is the overarching system designed to assist radiologists in the early detection of breast cancer.

Image Preprocessing: This stage involves the cleaning and enhancement of the mammogram or breast imaging data. It may include tasks such as noise reduction, image normalization, and contrast enhancement.

Feature Extraction and Selection: Features are characteristics extracted from the preprocessed images that are relevant for identifying breast abnormalities. Feature selection helps in reducing dimensionality and focusing on the most informative features.

Multi-Scale Support Vector Machines (MSVM) Classifier:

MSVM is the core of the system, responsible for classifying breast images as either normal or potentially cancerous. MSVM is used to analyze the extracted features and make predictions.

Decision Support System: This component evaluates the output from the MSVM classifier and provides recommendations or findings to the radiologist.

### MULTI-SCALE SUPPORT VECTOR MACHINES (MSVM) ALGORITHM

Multi-Scale Support Vector Machines (MSVM) is an extension of the traditional Support Vector Machines (SVM) algorithm, designed to handle multi-scale data. SVM is a supervised machine learning algorithm used for classification and regression tasks. It works by finding the optimal hyperplane that best separates classes in a high-dimensional space. MSVM extends this concept to deal with data at multiple scales, allowing it to capture complex patterns in the data that may vary in different scales or resolutions.

The MSVM algorithm involves the following steps: Data Preparation:Gather labeled training data, where each data point is associated with a class label.Optionally, preprocess the data, including tasks like normalization, feature scaling, and feature selection.

Scale Decomposition: MSVM decomposes the input data into multiple scales. This can be achieved

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through techniques like wavelet transforms, image pyramids, or other multi-resolution analysis methods. Each scale represents a different level of detail in the data, capturing patterns at various resolutions.

Training the Multi-Scale Model: For each scale, train an SVM classifier on the corresponding scaled data.SVM training involves finding the optimal hyperplane that separates the data points of different classes with the maximum margin. This is done by solving a quadratic optimization problem.

Integration of Multi-Scale Models: Combine the individual SVM classifiers trained at different scales into a multi-scale model. This integration can involve weighted averaging of the decision scores or other methods to combine the predictions from different scales effectively.

Classification/Prediction: When a new, unseen data point is to be classified, decompose it into multiple scales using the same method used during training. Use the individual SVM classifiers corresponding to these scales to obtain predictions. Combine the predictions from different scales, often through a weighted sum or other aggregation techniques, to obtain the final prediction for the new data point.

## 4. Results and Discussion

In the context of breast cancer screening, the input image shown in figure. It refers to the mammogram image itself. A mammogram is an X-ray image of the breast that is used to detect and diagnose breast diseases, including breast cancer. This image is typically acquired using a specialized mammography machine.

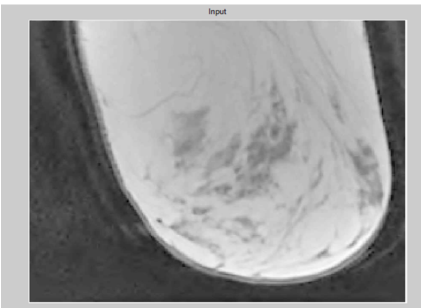


**Figure.1** Input image

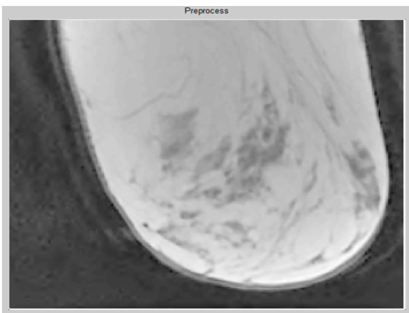


**Figure.2** Pre-processed image

Pre-processing in medical image analysis, particularly in the context of mammography for breast cancer screening, is essential to enhance the quality of the images and improve the accuracy of subsequent analysis. One common pre-processing technique is the application of a median filter which is shown in figure.

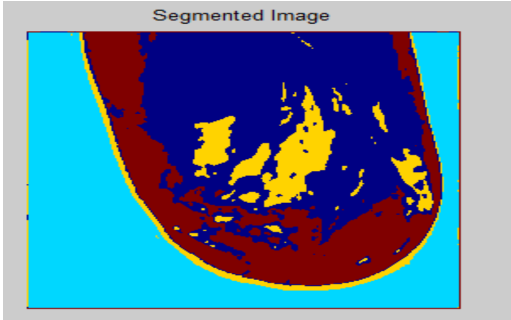


**Figure. 3** Segmented image

In breast cancer screening using mammograms, "segmentation" refers to the process of identifying and isolating specific regions or structures of interest within the image. The "FCM method" stands for Fuzzy C-Means clustering, which is a popular image segmentation technique which is shown in figure .

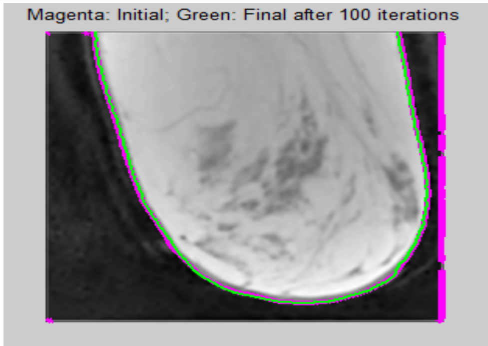


**Figure. 4** Feature Extraction image

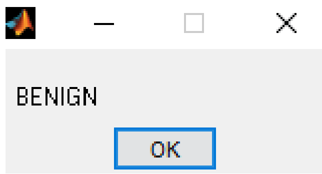


**Figure. 5** Showing Type of Cancer

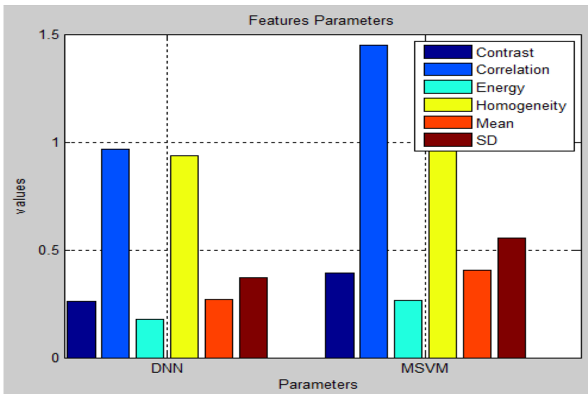


**Figure. 6** Showing feature parameters of both DNN and MSVM classifiers

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Once the regions of interest are segmented, you can extract relevant features from these regions shown in figure 6.12. These features might include texture patterns, shape characteristics, and intensity statistics.

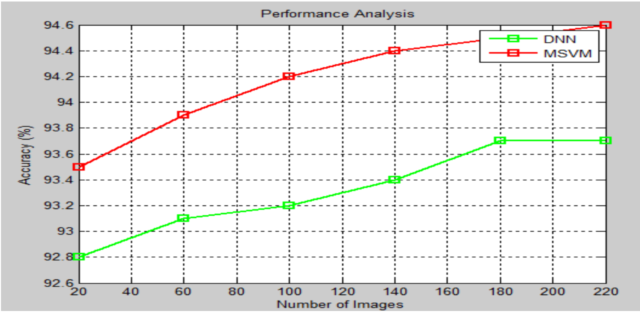


**Figure. 7** Showing accuracy performance of both classifiers

The proposed method using MSVM outperforms the existing method using DNN in terms of accuracy. The proposed MSVM method achieves an accuracy of 93.5%, which is higher than the existing DNN method's accuracy of 92.8%. This suggests that the MSVM-based approach is slightly better at correctly classifying both benign and malignant cases shown in figure 7.13.

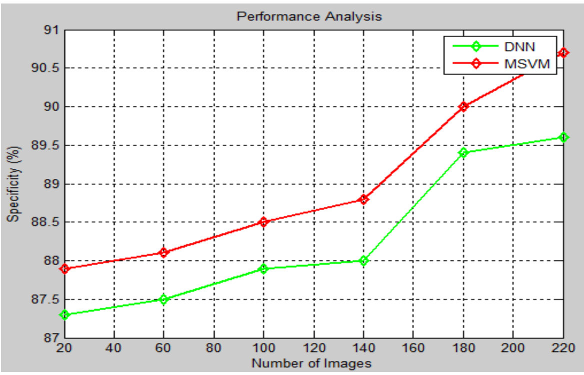


**Figure. 8 Showing specificity performance of both classifiers**

Like accuracy, the proposed MSVM method also outperforms the existing DNN method in terms of specificity. The proposed method achieves a specificity of 88%, while the existing DNN method has a specificity of 87.4% shown in figure 7.14

## 5. Conclusion and Future Scope

In this proposed method, we explored the use of Multi-Scale Support Vector Machines (MSVM) as a potential method to enhance radiologists' performance in breast cancer screening. We compared the proposed MSVM-based approach with the existing method using Deep Neural Networks (DNN) in terms of accuracy, specificity, and the types of cancer detected. The results of our investigation demonstrate that the proposed MSVM method offers a notable improvement over the existing DNN method:

The MSVM method achieved a higher accuracy rate of 93.5%, compared to the DNN method's accuracy of 92.8%. This improvement is significant as it ensures better overall correctness in breast cancer diagnosis. Specificity, a crucial metric in minimizing false positives, also saw an enhancement with the MSVM method, reaching 88%, whereas the DNN method had a specificity of 87.4%. This suggests that the MSVM-based approach excels in correctly identifying cases without cancer.

Moreover, both methods successfully detected both benign and malignant types of breast cancer, ensuring comprehensive screening capabilities. This is a critical feature for any breast cancer screening system as it helps in capturing the full spectrum of potential cases. The use of MSVM in breast cancer screening holds great promise for improving radiologists' performance and patient outcomes. Further research and development efforts, coupled with rigorous clinical validation, are crucial steps in translating these findings into clinical practice and realizing the full potential of this technology in the fight against breast cancer.

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