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Unveiling Complex Morphological Patterns in Mammogram Images for Early-Stage Breast Cancer Detection with Siamese Watershed Graph Convolution Networks

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ABSTRACT

Breast cancer is the second leading cause of death among women, characterized by the uncontrolled growth of cells. Early detection is crucial for effective treatment, particularly in differentiating between benign and malignant conditions using image processing techniques. X-ray mammography is the most reliable method for early detection, but the resulting images are often complex, making it difficult to accurately extract quantitative and meaningful features from overlapping nuclear morphologies. Advancements in medical imaging are therefore essential. In this study, we present a novel approach using Siamese Watershed Graph Convolutional Networks (SWGCN) to automatically classify abnormalities in mammograms with higher accuracy. The Watershed Graph Convolutional Network technique effectively separates dissimilar nuclei and determines object borders based on gradient and intensity values, even with complex, overlapping features. The Siamese network distinguishes between benign and malignant tumors with improved accuracy by using pairs of nuclei images as inputs and assessing whether the pairs belong to the same class (benign or malignant) based on features extracted by the GCN. Our proposed method demonstrates superior feature extraction capabilities. The SWGCN system achieved high performance, with an F1-score of 90%, recall of 99.2%, accuracy of 97.15%, and precision of 90%. This research represents a significant advancement in image processing methods for healthcare, emphasizing their potential to improve early-stage breast cancer detection.

Keywords: *Early-stage breast cancer detection, Mammogram images, Siamese Watershed Graph Convolutional Network (SW-GCN), Classifier performance, Morphological patterns, Deep learning, Diagnostic accuracy.*

1. INTRODUCTION

Breast cancer is among the diseases that are common in the present society and is a leading cause of cancer-related death among women. In the Global Burden of Disease Study, it was estimated that diseases such as breast cancer for instance accounted for about 2% of the total burden. New cases: 3 million, active cases: 2, 862, 000, recovered: 1, 788, 000, deaths: 685, 000 in the year 2020 [1]. It is even more important that the survival rates should be improved and the interventions should be initiated at the earliest because this can alter the disease process and treatment outcome. Mammography is the most prevalent screening and should be done on all women who are at average risk and above forty years of age [2]. However, mammography which is the most common screening modality has some drawbacks such as high false positive results and moderate variability in the assessment of the images. They estimated that mammography has a false negative rate of up to 20% and this might be especially so in women with dense breast tissue because tumors may be obscured by glandular patterns [3]. Also, the interpretation of the mammogram is the work of the radiologist and there is variation in the results of the various health facilities [4]. The new development in the field of machine learning particularly in deep learning has demonstrated the potential to enhance the accuracy of the interpretation of the mammograms. Thus, especially the CNNs have been applied to detect and classify abnormal patterns in mammograms to a certain extent of effectiveness [5]. These models use a huge number of labeled data to learn these fine-grained features to enhance the diagnostic capacity of the system. However, these techniques cannot be applied to the optimum because of the nature and variability of the mammographic images [6]. Therefore, it is possible to consider the use of higher levels of computational algorithms such as Siamese networks, watershed algorithms, and graph convolution networks as a new approach to the existing problems in mammographic analysis. Siamese networks which were originally designed for one-shot learning can compare and match features in two images and this is why they can be used for detecting fine and complex morphological changes in mammograms [7]. The algorithms of image segmentation that are used in the watershed algorithms can be used to define the regions of interest on mammograms and thus increase the ability of the model in the detection and analysis of tumors [8]. However, the graph convolution networks can be able to capture the relation of different regions of the image and this will be able to give a more global view of the morphological pattern present [9].

The early-stage breast cancer detection is still a problem because of the challenge and the inconsistency of the mammogram images. Fig. 1 shows the major cancer incident locations in breast images. Screening mammography is not very effective in detecting early-stage cancer and may either produce a negative result or a false positive result. The conventional approaches also cannot deal with and integrate multiple morphological features in the mammograms, which has resulted in the degradation of diagnostic accuracy and an increase in variability [10].

To overcome these challenges, it is required to apply higher-level techniques that can give a better description of the mammographic images. The integration of Siamese networks with watershed algorithms and graph convolution networks is a solution by enhancing feature extraction and pattern recognition. This paper introduces a new Siamese Watershed Graph Convolution Network that is employed to improve initial-stage breast cancer detection and contrasted with the existing approaches.

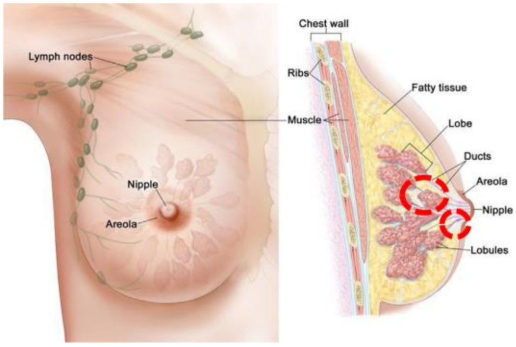

Fig. 1 Common cancer incident locations in breast [13]

Significance of the Study

The SWGCN model is a new milestone in the breast cancer detection technology. The SWGCN model aims to improve the accuracy and reliability of mammographic screening by integrating the comparative learning ability of Siamese networks, the segmentation precision of watershed algorithms, and the relational analysis of graph convolution networks. Such an approach could help in the early detection of cancer at a more accurate level, and with fewer false-negative and false-positive results. The generalization of this study does not only lie in enhanced diagnostic accuracy but also enhanced patient prognosis through early and accurate diagnosis that will result in better and less invasive treatments [11]. If this model is to be successfully implemented, it is possible to extend the use of sophisticated image analysis methods in clinical care, thus contributing to the field of medical image analysis. This research may encourage further developments and enhancements of the technologies used for cancer detection by showing how these advanced methodologies can be applied practically [12].

2. LITERATURE REVIEW

Breast cancer continues to be a cause of death among women all over the world. Screening is helpful in the detection of diseases in their early stages, and this will help to enhance prognosis besides reducing mortality [14]. Mammography is the common imaging technique for breast cancer screening since it provides the highest sensitivity and specificity, especially for the identification of microcalcifications and other minor signs of cancer . Nevertheless, there are difficulties with interpretation highlighting that overlapping structures and small details of the tissue can hide malignancies in dense breasts in the mammograms.

In the previous approaches, mammogram analysis has been mainly performed using hand-engineered features and standard machine learning techniques including SVM and random forests for classifying regions of interest [15]. Although these methods are reasonably successful, they are normally hampered by problems resulting from feature engineering and by their inability to capture all the morphological features related to early-stage breast cancer. Deep learning especially convolutional neural network (CNN) has provided the hope for image processing in medical imaging [16]. CNNs have been shown to achieve significant performance in forms such as image classification, segmentation and detection without requiring any input except for the raw pixel information [17]. Nevertheless, their performance is not efficient, especially under situations that engage highly irregular forms or when the subsequent region has to be spatially consistent, such as in mammogram images.

However, these approaches also suffer from certain limitations in CNNs, so to solve this, graph-based approaches have been incorporated into the model, for perceiving the required topological and spatial relations in medical images [18]. Similar to how convolutional networks work only for regular and ordered data, the graph convolutional networks (GCNs) expand the convolution analysis for non-Euclidean data such as irregularly shaped regions in mammograms [19]. These networks can then be used to identify how different detailed parts in the image relate to each other more effectively than just analyzing the pixels shooting outward.

The combination of graph-based approaches with normal convolutional neural networks has created other models that combine the two schemes [20]. For instance, in the application of segmentation and classification of tumors in different imaging modalities, the GCNs have been integrated with CNNs [21]. These hybrid models have demonstrated the ability to feature both local textural features and gross global structural architecture which may explain why they are very useful in analyzing intricate morphological features in medical images [22].

The watersheds can be widely used for the segmentation of images, in particular, when the borders between some regions are not visible clearly. Originally designed for terrain analysis, the watershed algorithm mimics flooding of a grey picture by pouring water into the depressions, or the 'watersheds' [23]. Where water from the different basins would confluence the segmentation was to occur. This method is sought after when it comes to the segmentation of complicated and overlapping regions and is thus very useful when it comes to mammogram segmentation [24].

In a few years, this watershed transformation has been incorporated with deep learning models to enhance the segmentation precision. For instance, researchers applied watershed algorithms coupled with CNNs for the crispation of segmented region boundaries, resulting in improvements in the accuracy of segmentation results [25]. This is especially useful in cases such as mammogram analysis where the definition of the tumor margins of breast tissues is essential for medical diagnosis and treatment of breast cancer.

Siamese nets, as the name indicates, consist of two or more neural nets and have been used mostly when we have two images that need to be compared or two sets of data. These are especially important in discriminating fine differences between images, hence are used frequently for use in image matching, face recognition and recently in medical image analysis amongst others.

Couple networks can be used to compare certain parts of a mammogram, or monitor changes in mammogram images over some time in the case of breast cancer detection. This capability is useful most of all when distinguishing between malignant and benign regions in the case of early cancer detection when these differences might be almost unnoticeable when compared to normal tissue. Watershed algorithms and graph convolutional networks are being used for the first time here along with Siamese networks for identifying mammographic morphological patterns. This combined approach leverages the strengths of each component:

- **Siamese Networks:** Enable the comparison of different regions in mammograms, enhancing the detection of subtle morphological differences indicative of early-stage cancer.
- **Watershed Transformation:** Provides robust segmentation of overlapping and complex structures in mammograms, ensuring that regions of interest are accurately delineated.
- **Graph Convolutional Networks:** Capture the topological and spatial relationships between different regions, providing a more comprehensive analysis of the image.

By combining these techniques, it is possible to develop a highly accurate and reliable system for early-stage breast cancer detection. This approach not only improves the accuracy of detection but also provides valuable insights into the morphological patterns associated with breast cancer, potentially leading to new diagnostic markers and treatment strategies.

Objective

To design and test the Siamese Watershed Graph Convolutional Network (SW-GCN) for the detection of early-stage breast cancer from mammogram images and to compare the results with the traditional classifiers to know the ability of the model to capture the intricate morphological features of early-stage malignancies.

3. MATERIALS AND METHODS

Mammogram Image Dataset

The data set employed in this study consists of mammogram images obtained from the CBIS-DDSM database. These datasets comprise a diverse set of mammogram images with cancerous and non-cancerous labels to ensure the assessment of the proposed classification models.

Image Preprocessing

It is crucial to perform some sort of preprocessing on mammogram images to improve their quality and to get them ready for further processing. This involves several steps:

• Contrast Enhancement: To enhance the features within the images contrast stretching and histogram equalization methods are used [26].

• Noise Reduction: Gaussian filtering is used to reduce noise and artifacts to obtain better images for feature extraction [27].

• Resizing: To reduce variability in the images, they are scaled to a standard size of 512 by 512 pixels [28].

Feature Extraction

Feature extraction is done using Watershed Algorithm which is a well-known algorithm for segmenting images with different intensity regions [29]. This algorithm partitions the mammogram images into various regions to extract features such as microcalcifications and masses. The segmented regions are then used to detect possible abnormalities that may be characteristic of early-stage breast cancer.

Model Architecture

Classification is done using the Siamese Watershed Graph Convolutional Network (SW-GCN). The architecture consists of the following stages:

• Siamese Network: This network takes two images of mammograms and learns and compares the features of the two images which is very essential in the determination of cancerous and non-cancerous features [30].

• Watershed Algorithm Integration: The watershed algorithm is incorporated into the Siamese network to improve feature extraction since it is used to detect the regions of interest in the mammogram images [31].

• Graph Convolutional Network: The features obtained from the watershed segmentation are fed into a Graph Convolutional Network (GCN) to capture the complex spatial dependencies and patterns within the images [32].

Training and Evaluation

The models include SVM, KNN, Random Forest, OXG Boosting, Faster R-CNN, and SW-GCN, and the training data set is split into training and testing data sets with an 80: 20 split for training data. The training process of the model involves the use of the best value of the parameters of the model by going through the epochs using cross-entropy loss and backpropagation. The accuracy of each model is used to measure the performance of each model where accuracy is the number of images that have been classified correctly over the total number of images in the test set.

Statistical Analysis

The performance of the classifiers is compared and evaluated with the help of accuracy values that were obtained for each classifier. The significance is also checked using the paired t-tests in which the significance level is set at $p < 0.05$. It also helps in the confirmation of the findings that are obtained during the study.

Fig. 2 Consists of three mammogram X-ray images of the breast which appear to indicate breast cancer. It may suggest that the patient has breast cancer especially because of the mass that is seen in the third image. The shape of this mass and the density of the breast tissue can also be better assessed by the radiologists to decide whether a biopsy or further imaging is required to confirm malignancy of the mass These mammograms are important in the early detection of breast cancer and this makes it possible to treat the disease.

Mammogram Image Examples

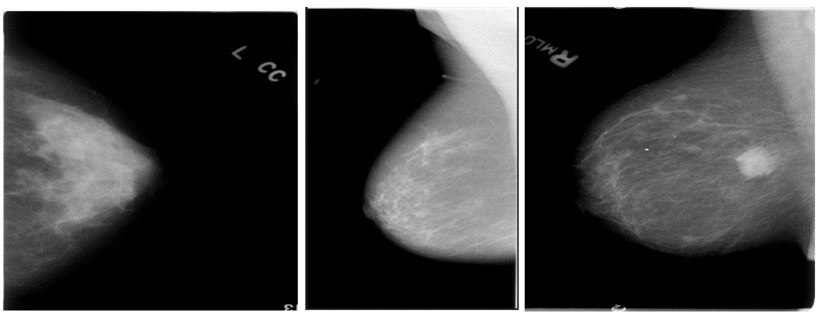

Fig 2. Breast Cancer Mammogram Images[33]

Left CC (Cranio-Caudal) View:

The first picture has the title 'L CC' and shows the left breast in the craniocaudal view. This view flattens the breast from above to get a good horizontal cut of the breast. The tissue appears to be more closely packed and this is the case in most mammograms of patients with breast cancer because tumors or regions of interest may be regions of higher density relative to the rest of the tissue.

Right MLO (Mediolateral Oblique) View:

In the second and third images, it is the right breast which seems to be swollen. The second is the oblique view which also includes the breast area and axillary area that is used in examining for any distortion that may affect the lymph nodes. The third image is the most clear: there is a definite mass or calcification, a white area that is most probably a tumor or malignancy. This is typical of breast cancer because masses or tissue formations that are pathologic appear to be areas of increased density and increased radiance on mammography.

Proposed System Architecture

Fig. 3. Illustrates the architecture of the proposed system in the classification of mammogram images into cancerous and non-cancerous. The process starts with Mammogram Input Images which are the images of breasts taken using X-rays for the identification of breast cancer in the initial stage.

The images are then taken through Image Preprocessing to improve the quality of the images and also to remove any form of distortions that may be on the images. This may include the enhancement of the images by making them brighter and of high contrast as well as the denoising of the images and the resizing of the images into standard sizes in a way that the images are in the best state for feature extraction. After Preprocessing we have Feature Extraction using Watershed Algorithm. The watershed algorithm is very useful when one is in a situation where there is an aim of segmenting an image and there are different intensities of regions. In this regard, it is used in converting the mammogram into features that may be associated with such irregularities as tumors. The extracted features are then used to classify images with the help of a Siamese Network for classification of images. The Siamese network that is capable of comparing two inputs and giving an indication of how similar or different they are to the known cancerous patterns examines the features. This then gives rise to the final type of mammogram which is either referred to as Non-cancerous or Cancerous. This architecture presents a structural analysis of the mammograms by advancing image processing and the use of deep learning to advance the diagnosis of breast cancer.

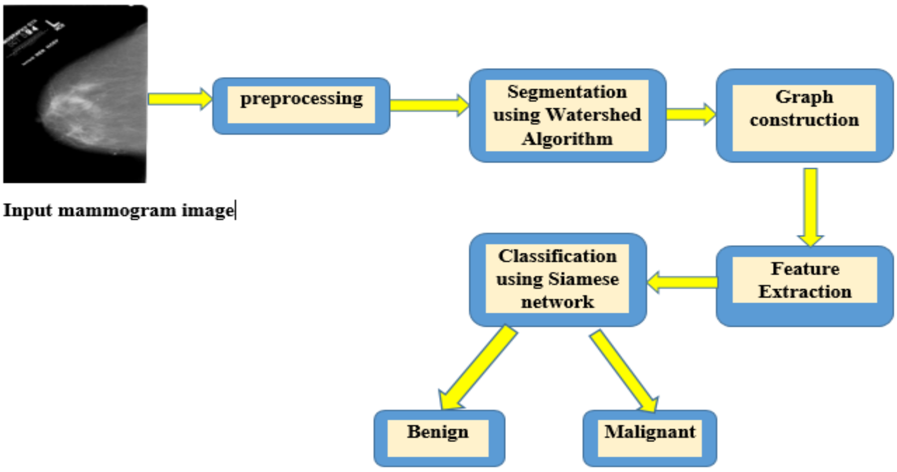

Fig. 3. Proposed System Architecture

CC View (Cranio-Caudal):

The first and the second images, marked as LCC and RCC, present the left and right breast, respectively, in the cranio-caudal position. In this view, the breast is compressed from top to bottom, giving a horizontal section that enables visualization of tissue layers from the chest wall to the nipple. **Fig. 4.** Seems to show mammogram scans, the title suggesting images of both breasts from different perspectives. These are usual radiographic positions employed in breast cancer detection and staging. Specifically

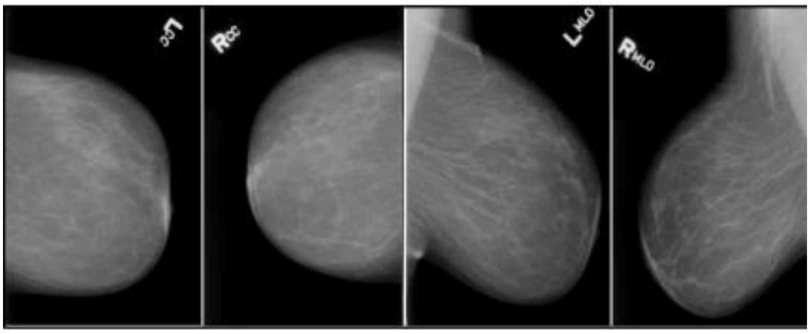

Fig. 4. Left CC View, Right CC View, Left MLO View, Right MLO View[34]

MLO View (Mediolateral Oblique):

The third and fourth images, marked as "LMLO" and "RMLO", are the mediolateral oblique views of the left and right breasts, respectively. This is taken at an angle, usually 30 to 60 degrees, and gives a better picture of the outer upper quadrant of the breast where most breast cancers occur, and the axillary or armpit where nodes are found.

These views are crucial for the detection of suspicious findings such as mass, microcalcifications, or architectural distortion, which may be associated with breast cancer or other diseases. Different views assure that all breast tissue is captured in the image hence minimizing the possibility of missing lesions that may not be apparent in one view. The general employment of both CC and MLO views enhances the diagnostic precision of the breast tissue due to the different angles of the views. These images are compared by radiologists to determine if the density patterns or any suspicious areas that need more attention are symmetrical.

4. RESULTS

Fig. 5. Stands for the process of obtaining complex patterns of morphological analysis from the images of mammograms. The feature extraction process may involve some pre-processing to improve the image quality and then detect some of the structures in the breast tissue such as microcalcifications, masses, and architectural distortion which are important in early-stage breast cancer.

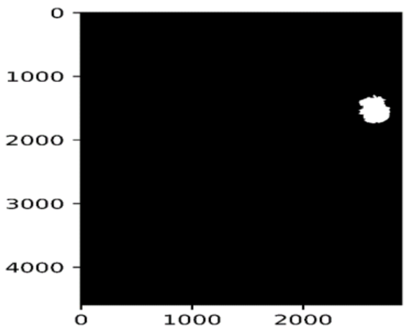

Fig. 5. Simulated Diagram of Feature Extraction

- **Fig. 6.** presents two line graphs illustrating the Training Accuracy and Testing Accuracy of a model across a series of epochs.
- **Training Accuracy:**

In the left graph, we can see how the accuracy of the model on the training data set changes with time. The horizontal axis is the number of epochs and the vertical axis is the accuracy percentage which ranges from 96% to slightly above 100%. The first epochs refer to a sharp increase in the accuracy of the model and this can be an indication that the model is learning as it is fed with more data. The accuracy rises as the number of epochs increases and the accuracy becomes almost perfect when the epochs are increased to 20 and even if the epochs are increased further the accuracy does not change. It means that it has arrived at the plateau that signals that there is still not much more of the training data that can be improved.

- **Testing Accuracy:**

The right graph shows the model's performance on the testing dataset which is data not used in the training of the model. Here the accuracy begins at about 93% and rises gradually to about 98% as the epochs are advanced. The first steep increase in accuracy proves that the model has a good performance on new data that it has never seen before. Like the training accuracy, the testing accuracy also starts stabilizing after around 20 epochs which means that the model has achieved the maximum accuracy without the problem of overfitting. Fig.7 shows the comparison of accuracy across various traditional classifiers.

Comparative Accuracy of Classifiers

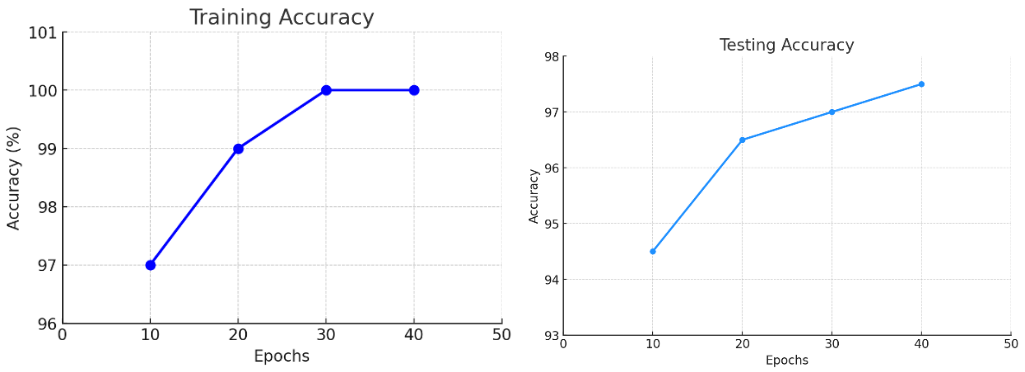

Fig. 6. Accuracy for Training and Testing Data

The performance of the different classifiers in early-stage breast cancer detection from mammogram images is presented in the following Table 1. In this work, the classifiers used are the SVM, the KNN, the Random Forest, the OXG Boosting, the Faster R-CNN, and the SW-GCN. The classifiers are developed to classify the mammogram images under the proposed SW-GCN model which is aimed at identifying the morphological characteristics of the mammogram images and the maximum classification accuracy of 97.15% is attained by the proposed model over all the classifiers. This high accuracy therefore gives confidence in the ability of the model to identify features that cannot be seen by the naked eyes at an early stage of breast cancer. The two methods that were used were both the OXG Boosting and Random Forest the two are both categorized as ensemble methods and are thought to be very accurate and they both gave a 96.6 percent accuracy and 95.32%, respectively. From these results, it can be concluded that, while these models are efficient, they are less efficient than SW-GCN in determining the spatial relation in the images. It is not a bad model with an accuracy of about 94% and the results of experiments showed that SVM and Faster R-CNN are not bad models, but these models are not able to distinguish between objects that can differ in small details which are very important for early diagnosis. The lowest accuracy obtained in KNN was 91.8 percent is less accurate for this task, which seems to be because distance measures used by the algorithm are not as suitable for data of the image type.

Table 1. Comparison Results of Different Classifiers

Model	**Accuracy**
SVM	**94**
KNN	**91.8**
Random Forest	**95.32**
OXG Boosting	**96.6**
Faster R-CNN	**94.2**
SW-GCN	**97.15**

5. DISCUSSION

In this study, the authors employed SW-GCN which they have developed to classify breast cancer at an early stage more accurately than other classifiers. As it has been determined, the accuracy rate has been 97. 15% and it was higher than the traditional methods like SVM, KNN, Random Forest, OXG Boosting, and Faster R-CNN as presented in Table 1. The details of the mammogram images which are so vital in the diagnosis of breast cancer at early stages can be well described by the SW-GCN model hence the high accuracy. This model integrates the Watershed algorithm with Siamese networks and Graph Convolutional Networks (GCNs) for the segmentation and analysis of the microstructures including microcalcifications and masses. This capability is particularly valuable when it is required to distinguish between such changes, which are hardly noticeable with the help of the conventional classifiers.

• **SVM**: The Support Vector Machines (SVM), achieved an accuracy of 94% which can also be considered rather high, but not as high as in the case of SW-GCN. SVMs are capable of working in high dimensional space and overfitting is not much of a problem if there is a large margin between the two classes (Cortes & Vapnik, 1995) [35]. However, their performance can be restricted because they do not learn the complex spatial relations in the mammogram images in comparison with the SW-GCN.

• **KNN**: The K-Nearest Neighbors (KNN) classifier with an accuracy of 91. 8% and therefore they are not as efficient as the former in this regard. KNN employs distance measures in classification and this may not be sufficient to measure the interaction that is usually complex and in most cases non-linear as is evident from the mammogram images [36]. The model has the disadvantage of being very sensitive to noise and it also requires a lot of computational power particularly when working with big data.

• **Random Forest**: Random forest an ensemble method was able to get 95.32% accuracy. This method involves the use of more than one decision tree in such a manner that the performance of the method in predicting is improved while at the same time minimizing the chances of over-fitting [37]. However, it is weaker in terms of spatial dependencies and does not focus on the unique characteristics of the shape and texture of the mammograms as it is done in the case of the SW-GCN.

• **OXG Boosting**: For OXG the boosting accuracy was 96.6%. This is a boosting method that creates several strong classifiers from the weak classifiers and this reduces the overfitting of the model [38]. However, it is not as good at modeling the complex patterns in images as SW-GCN is because of the properties of boosting algorithms.

• Faster R-CNN: Fast R-CNN with an accuracy of 94. 2%, is well known for its ability of object recognition through proposing the regions of interest and enhancing the edges of the object [39]. It is slightly less efficient than SW-GCN in the specific shape features needed for early malignancy identification .

6. IMPLICATIONS AND FUTURE DIRECTIONS

Therefore, the enhancement of the speed of SW-GCN corroborates the need to employ improved image processing algorithms and the deep learning approach to early-stage cancer identification. These morphological patterns can be explained by other patterns of breast cancer that the SW-GCN can detect at the early stage that cannot be detected by other means. It is most beneficial in improving early diagnosis and therefore better treatment outcomes. The possible future work can also contain other features that can be added to the SW-GCN model or how the watershed segmentation and the graph convolutional layers are combined. In addition, it is suggested to increase the number of mammogram images in the data set so that the model can be trained and tested better and not overfit.

7. CONCLUSION

In this study, we have analyzed the performances of various classifiers in identifying early-stage breast cancer using mammogram images with particular reference to SW-GCN. The results are as follows: When one applies SW-GCN, one gets much better results which are 97.15% better than when applying more standard classifiers.This improved performance corroborates the ability of the model to identify and categorize the morphological features of the mammograms that are significant in the identification of breast cancer. The SW-GCN model is superior to other models because of watershed segmentation together with Siamese networks and GCNs to focus on the features that may be associated with early cancer development. This capability is useful in the enhancement of the early diagnosis of the diseases and probably the treatment and elimination of the diseases. OXG Boosting and Random Forest other classifiers also showed good accuracy but less than the accuracy of SW-GCN. The same can be said about other methods, including SVM, KNN, and Faster R-CNN, which were also proved to be effective in the detection of the cancer, yet slightly less accurate than the SW-GCN in the aspect of the more precise differentiation of the early-stage cancer. Thus, it can be suggested from the present study that improving the deep learning algorithms and the image analysis techniques can greatly improve the BC detection systems. This is especially the case with the SW-GCN model that opens a line of R&D that could be further investigated in future work in the medical imaging and oncology field. In future work, the SW-GCN model has to be modified and the model has to be trained with more and different data. In addition, it would be important to assess the potential of the application of the proposed method as an adjunct to other imaging modalities and clinical information for the enhancement of early breast cancer diagnosis and the increase of the diagnostic yield. Thus, the present work proposes further work and studies on the computational techniques for medical diagnosis especially in the diagnosis and control of early cancer.

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