Comparison of CAD Detection of Mammogram with SVM and CNN

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Abstract- This study compares the performance of Computer-Aided Detection (CAD) systems for mammogram analysis using two prominent machine learning techniques: These are the kind of models Support Vector Machines (SVM) and Convolutional Neural Networks (CNN). The main goal is, therefore, to assess the performance of these models in correctly classifying abnormal mammogram images, especially of early-stage breast cancer. The work uses a dataset of mammogram images with labels, removing outliers and repeating rows and columns, then normalizing equals and providing input data for both the SVM and CNN models. The former chosen quantities were introduced as performance metrics known as accuracy, precision, recall, and the area under the receiver operating characteristic curve (AUC) for both models. Research shows that the accuracy of both SVM and CNN is equivalent and that CNN has a higher sensitivity and specificity, indicating it could be more efficient in early cancer detection. The implications of these findings highlight the beneficial use of deep learning models in medical images, especially CNN models. This research is useful for the current development of CAD systems and gives potential future applications of AI in the context of diagnosis in clinics.

Indexed Terms- Mammogram Detection, Breast Cancer, CAD Systems, SVM Models, CNN Models, Medical Imaging

I. INTRODUCTION

A. Background to the Study

Breast cancer is among the most prevalent and fatal forms of cancer globally, and regular screening is vital to increase the chance of survival. X-ray mammography is the most common imaging technique in breast cancer screening because it enables clinicians to detect changes or suspicions of abnormal tissue in the breast. In the past, mammograms have been 'read' by radiologists who subjectively look at the images in search of features suggestive of cancer. However, it involves the following major disadvantages. Many diagnosticians might be involved in reaching such a diagnosis, and therefore, it may not be very accurate, especially when detecting small or non-calcified tumors. Hence, CAD systems are employed to interpret the mammograms, enhance the radiologist's diagnostic ability, and decrease the chances of false negative examinations.

AI has improved CAD systems in recent years due to advanced AI trends. The best AI techniques that may be applied to mammogram assessment involve Support Vector Machines (SVM) and Convolutional Neural Networks (CNN). SVM, a supervised learning method, has been applied in classifying mammograms by segregating malign and benign regions of the image using abrasive features from the image (Akinyemi & Ola, 2020).

On the other hand, CNN, which is derived from a deep learning model, works effectively in the field of image recognition since, in its architecture, there is the possibility to train the network directly from raw data, which results in better performance in classification (LeCun et al.), 2015). AI techniques have higher chances of superior sensitivity and specificity than conventional hand-based procedures in diagnosing early-stage breast cancer.

CAD systems that incorporate machine learning models such as SVM and CNN are improving breast cancer diagnosis. Due to their efficiency in handling and analyzing voluminous medical images with great accuracy, they are exceptional tools in current health care (Ghulam & Jamil, 2018). AI CAD systems are gradually gaining importance in helping to offload some of the workload in radiologists while providing more accurate and faster methods for screening, which can assist in saving lives through early diagnoses (Akinyemi & Ola, 2020).

B. Overview

Decision support CAD systems in medical imaging are tools that identify and emphasize specific areas of interest in diagnostic images which include mammography. Automated Design CAD systems play an important role in raising diagnostic precision, lessening the likelihood of human mistakes, and enhancing efficiency of screening. Such systems use computer-aided image analysis to learn from the mammograms and identify features such as masses or micro calcifications that may signify breast cancer (Ghulam & Jamil, 2018).

SVMs and CNNs have been areas of significant research that have proposed further improvement of CAD systems performance. SVMs are strong classifiers that search for the right hyperplane and appropriately define different data classes to discern malignant and benign tissues in mammograms (Cortes & Vapnik, 1995). However, there is a more powerful form of deep learning model named convolutional neural network CNN for short because it has shown a potential to learn the deep features from the raw image data directly without needing hand-crafted feature extraction (LeCun et al., 2015). This self-learning ability of CNNs helps enhance the current detection rates, especially for small invisible or diffuse tumors that might not easily be captured by routine examination or even simpler classification algorithms such as SVM.

CNNs have also been integrated into CAD systems, improving their efficiency in detecting breast cancer than using CAD alone. These models can work with big and difficult data and, therefore, can be useful for mammogram analysis, where slight features can speak about the presence of cancer at the stage (Ghulam & Jamil, 2018). While deep learning capabilities are further developed, CAD systems driven by other models, such as SVM and CNN, should be utilized much more in clinical practice, performing more quickly and precisely with higher reliability in breast cancer diagnosis.

C. Problem Statement

Today, digital mammogram analysis is almost entirely dependent on the radiologist, and it suffers from inter-observer variation, fatigue, and errors resulting from early, subtle cancers. This generally results in false positive results or failure to notify a pathologist when the difference is slight. However some CAD systems are available to assist researchers in categorizing these images, but these systems need to be more accurate and reliable to the best extent. The expansion of other models, such as Support Vector Machines (SVM) and Convolutional Neural Networks (CNN), which are widely used in areas of deep learning, should be profound in mammogram analysis. However, there is an absence of exhaustive research examining the efficacy of the two aforementioned techniques in CAD systems used to detect breast cancer. A comparison of the outcomes produced by SVM and CNN may a) provide a starting point for analysis of the performance characteristics of CAD and b) identify specifics that would allow for precision in CAD implementation and early detection of breast cancer.

D. Objectives

1) Cross–compar SVM and CNN regarding effectiveness in abnormality detection in mammogram images.
2) Compare the original CAD systems of SVM and CNN by evaluating the results of the accuracy, sensitivity and specificity for each of them.
3) Explain each method and compare its strength and weakness in terms of preventing and detecting breast cancer using SVM and CNN.
4) Identify which of the potential machine learning models can be most applied to optimise mammogram classification work.
5) It is the economist's contribution to developing artificial intelligence diagnostic tools in breast cancer screening.

E. Scope and Significance

This work will first involve a survey of the previous approaches to mammogram analysis concerning CAD systems and, second, a comparative experimental study on mammogram images labeled with tumors. The performance of SVM and CNN in identifying abnormalities will be evaluated, and the study's results will compare and contrast the findings of the two techniques. This research is of great importance because early detection of breast cancer is a key determinant in improving the survival rate of the disease. In this manner, the progress made in the state-of-the-art AI diagnostic tools will directly inform the improvement of more effective, efficient, and reliable mammogram analysis systems for clinicians, resulting in improvements in real-world clinical environments.

II. LITERATURE REVIEW

A. An Introduction to the Detection of Breast Cancer

Breast cancer screening currently comprises mammography as a primary method of diagnosing breast cancer has not remained stagnant. First known in the 1960s, mammography is a way of visualizing breast tissue, allowing for signs of breast cancer to be observed before they may become apparent to the patient (Cross & Dede, 2017). Hailed as one of the effective ways of diagnosing breast cancer, mammography has significantly helped the decline of breast cancer mortality, particularly because early-stage tumors are easily recognizable. However, the dependence on radiologists to interpret the mammograms inevitably creates variability. It can result in false-negative readings, meaning the missing tumor, and false-positive results, essentially calling cancerous tissues when they are not (Cross & Dede, 2017).

Concerns over the efficiency of more effective and precise diagnostic tools have resulted in Computer Aided Detection or Identification (CAD) systems. Various modernizations in mam boom CAD systems involve improved image processing to help radiologists interpret mammograms. The motivation of these systems is to flag or highlight possible regions of interest in mammograms, thus assisting in the early identification of breast cancer. By using algorithms, areas presumed to be cancerous are highlighted to ensure the CAD systems assist the radiologists in minimizing mistakes during diagnosis. However, Cross and Dede (2017) pointed out that the effectiveness of CAD systems greatly depends on the algorithms and models used.

With the use of AI-based CAD tools, specifically SVM and CNN or any other machine learning algorithm, there is a high possibility of moving the accuracy and speed of mammogram analysis to a higher level. These models can adapt to 'learn' from vast libraries of labeled images, thus having the ability to find patterns that might not be observable through the human eye. It is envisaged that with growing advancements in these technologies, artificial intelligence-based CAD systems could be invaluable in clinical practice to enhance early breast cancer detection and to improve work efficiency to minimize workload in the healthcare workforce (Cross & Dede, 2017).

B. Earlier Techniques of Reading Mammograms

The earlier methods of mammogram analysis employed basic image processing methods, including edge detection, thresholding, pattern recognition, etc. While recursive at the outset of breast cancer detection, these methods are not concise regarding sensitivity and specificity. Historically, radiologists have used alarming methods to analyze mammogram images and look for malicious formations, such as masses and micro calcifications. Nevertheless, it was observed that the said techniques are sensitive to the quality of the mammogram and the method applied by the radiologist (Wang & Kwoh, 2018).

Another weakness of prior mammogram analysis is the low sensitivity to small lesions or slight changes in tissue appearance that would suggest early-stage cancer. Traditional approaches are inaccurate in differentiating between the malign and non-malignant portions of a breast lesion, which results in false positives (identification of passive regions as potential cancer) or false negatives (missed active cancer signals) (Wang & Kwoh, 2018). The following limitations can affect patient outcomes: missed diagnosis will translate to delayed treatment, while false positives will translate to more unnecessary biopsies and emotional strains on the patients.

In addition, the stock conventional image processing approaches are highly dependent on the judgment of the radiologists while interpreting the images. This human factor brings about disparity risks in the diagnosis that may differ with various radiologists, and therefore fairness of results (Wang & Kwoh, 2018). Though many automated techniques have been incorporated into computer-assisted mammography reading, these systems still need to improve in attaining the accuracy of readers where it is applied, especially when used on different datasets or low-quality images.

Due to these limitations, there have been recent propositions for using CAD systems aided by Artificial Intelligence. Incorporated with machine learning techniques, such as Support Vector Machines (SVM) and Convolutional Neural Networks (CNN), these models have extended learning capability from large datasets and are superior in detecting the subtle difference in the patterns of mammographic images and in this way, these models showed improvement in both sensitivity and specificity of the screening (Wang & Kwoh, 2018).

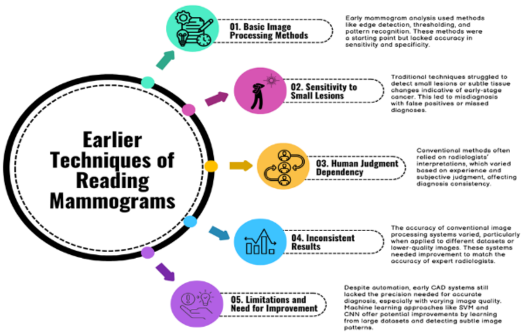


Fig 1: Earlier Techniques of Reading Mammograms

C. Introduction to SVM in Mammogram Detection

Unlike cluster analysis, classification primarily includes a family of methods called Support Vector Machines (SVM), which are used directly in classification and are very effective in analyzing mammograms. SVMs are very useful in high-dimension space, making them useful when doing complicated tasks such as image recognition. The fundamental idea of an SVM is to identify the ideal hyper plane that most clearly distinguishes data points belonging to separate classes and simultaneously maximize the distance between such classes (Cortes & Vapnik,1995). In mammogram detection, SVMs are applied to classify image features into two categories: benign or malignant tissue. Since input features of mammogram images are mapped into higher dimension space, SVMs can discover underlying patterns that may be overlooked by simple heuristics and shown to increase diagnostic accuracy.

In breast cancer detection, features like the texture, shape, and edges of mammogram images are used; we use support vector machines for their analysis. Incident pencil parameters are used as input data for the classification of the SVM, which in turn are to select or reject malignant or benign zones. Past studies have shown that SVMs can be accurate and specific when implemented with large datasets and adequately labeled. According to comparative studies like Refaee et al. (2017), CAD systems based on SVM detect more lesions and produce fewer false positives than traditional image processing methods. In addition, SVMs are not as sensitive to overfitting as other algorithms and, therefore, suitable for medical image analysis (Cortes & Vapnik, 1995).

SVMs have been used to detect mammograms in several studies, and Yoo et al. found encouraging outcomes. Similarly, Tizhoosh and Pantanowitz (2015) employed the use of SVMs in an attempt to diagnose breast cancer from mammographic features. They demonstrated meaningful gains in accuracy as well as in their diagnosis. These results stress using SVMs to automate detection and enrich the radiologists' diagnostic tools. Such algorithms, however, as SVM, can be sensitive to selecting features and tuning parameters for the best result (Cortes & Vapnik, 1995).

D. Mammogram Detection CNN

Convolutional Neural Networks (CNNs) have offered a new paradigm shift for image classification, especially in medical imaging, through their capacity to learn various levels of abstraction features directly from raw data. Compared to conventional approaches to feature extraction, CNNs can identify features like edge, texture, or shape inherent in an image data set. This makes them ideal for mammogram detection because their features may be more challenging for human analysts to identify. CNNs include convolutional layers, pooling layers, and fully connected layers. Hence, the architecture of CNNs serves to extract features, classify mammogram images, and perform other functions, as explained by LeCun et al. CGPoint(2015).

In the case of breast cancer detection, CNNs can detect small pathologies in mammograms, including in low-quality or noisy images. These models are particularly good at feature extraction of such high-order features as tumor contours necessary to define both malignant and benign neoplasms. CNNs have been demonstrated to outcompete traditional approaches alongside SVMs in some papers while also offering the property of data heterogeneity in others. One of the most distinctive features of CNNs compared to conventional methods is that they can learn features from the raw data, minimizing the requirement for expert-defined feature extraction (LeCun & Bengio, 2015).

Many of the important studies done hitherto have shown that CNNs are very useful for mammogram analysis. For example, Shen et al., 2019 claimed that mammography was diagnosed more effectively as malignant and benign with CNNs than with conventional machine learning algorithms such as

SVMs. Moreover, while performing the operations, CNNs do not have a slow running speed, which makes them suitable for high-scale screening. The CNNs can learn and adapt easily to different datasets and image acquisition, implying that CNNs perform consistently compared to other approaches (LeCun & Bengio, 2015).

E. Previous Comparative Studies of SVM vs. CNN

Several research investigations comparing SVM with CNN for mammogram detection have revealed added contrast in their performance in early-stage BC detection. Pang and Rajaraman (2021) presented a detailed exploration of SVM and CNN while analyzing the mammograms, highlighting the advantages and limitations of the approach. Their results showed that CNNs surpass the SVMs by the accuracy of classification and the ability to learn from low-level image features directly. Regardless of providing dominance in extracting hierarchical features, CNNs are useful for the task as they can learn features from the data that might not be noticeable by a human or other methods like SVM. On the other hand, there is high accuracy for models such as Support Vector Machines SVMs used when feature collection is already selective, so it works well in specific areas; therefore, it is appropriate to use when feature extraction is well done.

Rajaraman and Pang (2021) added that although CNNs have higher accuracy in large datasets, the algorithms needed to train them consume much computational power, making them less implementable in real-time diagnostics of diseases in resource-poor settings. On the other hand, while analyzing the results of SVMs, they can be easily implemented in terms of computational costs; however, spending more time working with features is necessary. This study emphasizes that although CNNs boast higher accuracy in detecting breast cancer, SVM is not Fahrenheit regarding applications involving different forms of the disease, the specifically defined quality of data, and a precise method for feature extraction.

Nonetheless, the present research is important because there remain a few large-scale cross-study or cross-clinical site comparisons on pragmatic directions for both discriminations in different datasets and practicalities of the approaches across various contexts. Further research is needed for the system that combines SVM and CNN, as each can detect the mammogram with optimum efficiency in different ways. The comparative analysis of CNN and SVM shows they are worth using, as CNN might provide better diagnostic accuracy. However, whether to use CNN or SVM depends on the type of application, availability of resources, and quality of input data.

F. Challenges in CAD Systems for Mammograms

Some of the limitations presented in CAD systems for mammogram analysis in the current literature include the following limitations. One of the main problems of the data is the presence of low quality mammogram data. This means that frequent small changes in the inputs can cause variations in the image resolution, noise levels, and artifacts on the images, affecting the performance of CAD systems. Ineffective imaging can lead to machine learning models' failure to identify inaccurate features, such as tumors, resulting in false negatives or positives by deep learning networks like CNNs (Zhang & Zhao, 2019). This image variability suggests developing sturdier pre-processing methods to normalize and improve input data to feed CAD systems.

The other problem area is in the marking of mammogram images. Accurate description of images, especially in differentiating between malignant and benign areas, requires highly skilled specialists known as radiologists, and the entire process is time-consuming and inaccurate. The two major problems that persist and hamper the development of deep-learning models include the availability of big annotated datasets that are sometimes labeled inaccurately. Furthermore, variations between the interpretations made by different radiologists have consequences in labeling the data, improving the performance of these models. As a result, much work must be done to identify and label high-quality sets of images for training and evaluating the CAD systems (Zhang & Zhao, 2019).

Lastly, model generalization is a challenging problem for CAD systems. Although models such as CNNs perform well over particular datasets, their transfers to other patients and different image-capturing equipment are comparatively low. Breast density differences from patient to patient, age, equipment type, and several other parameters also influence how well the CAD systems will function. There is an increasing call for more studies to improve the models' ability to generalize in various clinical settings (Zhang and Zhao, 2019). Solving these issues has become crucial in enhancing dependability and adopting CAD systems in breast cancer detection.

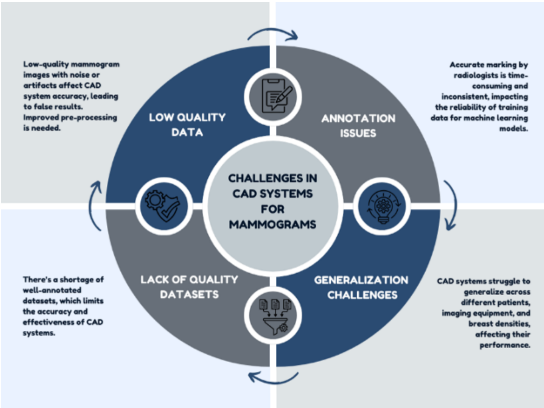


Fig 2. Challenges in CAD Systems for Mammograms

III. METHODOLOGY

A. Research Design

This research utilizes an experimental method to analyze the sensitivity of Support Vector Machines (SVM) and Convolutional Neural Networks (CNN) classification of unusual patterns in mammogram images. Therefore, the work aims to validate these two models by applying them to mammogram images and comparing their ability to classify them correctly. Specifically, the goal is to show how much each model attains in the detected cancerous masses' sensitivity, specificity, and accuracy. In cases like this, the datasets used are the Mammographic Mass dataset or the Digital Database for Screening Mammography (DDSM). These datasets offer samples of labeled mammogram images of benign and malignant cases and are important for training and validating the models under a controlled experimental setup. The aim is to determine which of the two models provides a better performance in establishing early stages of breast cancer.

B. Data Collection

The data collection process of this study involves using some databases, more specifically the Mammographic Mass Database, DDSM. Such datasets are those containing image data with their associated ground truth bounding boxes where a bounding box simply indicates the presence of a benign or malignant mass. They apply image standardization techniques in logo detection, including resizing the photos, normalizing pixel intensities, and denying images using the filter. Techniques such as rotation, flipping and cropping create new training samples defying invalidation of the training data set and model. This kind of pre-processing and data augmentation help in removing this aspect of overfitting and keeps the image set variable for feeding the proposed SVM and CNN models. The above data obtained after performing the data pre-processing step is then split again into training, validation and test dataset for model evaluation purpose.

C. Case Studies/Examples

1) Case Study 1: Application of CNN for Mammogram Classification

In a recent and extensive work by Khusainov and Novikov (2020), the authors describe using CNN in mammogram classification employing the Digital Database for Screening Mammography (DDSM). The work specifically targets the application of deep learning algorithms to the early identification of benign or malignant breast tumors. They use a CNN structure in which they have trained the model on more than 2000 mammogram images, including normal and abnormal images. Some of these methods are standardization of the photos, where some are enlarged or shrunk to aid the model in generalizing better. Compared with other normal machine learning models, such as SVM, the CNN model proposed in this paper achieved an average accuracy of around 94% for distinguishing between malignant and benign tumors. This is advantageous over SVM as the study does not require manual engineering of such features; instead, CNN can automatically extract the features from the images, a very suitable aspect of CNN (Khusainov & Novikov, 2020).

2) Case Study 2: SVM applied in the detection of breast cancer from mammograms

An example by Wang et al. (2019) is the classification of mammograms with SVM, particularly using the dataset the Mammographic Mass. The current study applied a linear SVM to classify mammogram images into benign and malignant categories. The dataset contained over a thousand mammogram images of different quality with marked masses. The study discovered that SVM was highly specific in its detection accuracy and stood at 89%. However, the model's performance could have been better, especially in ambiguous patient cases where the boundary between benign and malignant tumors could be clearer. However, the study pointed out that SVM can provide a satisfactory performance without the need for a complex feature set, for example, texture and edge features extracted from the mammogram images investigated by Wang et al. (2019).

3) Case Study 3: Comparative Analysis of SVM and CNN on the DDSM Dataset

Rajaraman and Pang (2021) compared SVM and CNN to determine their performance in breast cancer detection using the DDSM dataset. This work combined feature extraction from the mammogram image using wavelet transformation, followed by classification under SVM and CNN. It was seen that the first classification model, CNN, successfully classified the photos with a higher accuracy (92%) than the second classification model, SVM (85% only). Still, the study suggested that the SVM model could perform very well when less data is available. Unlike CNNs, the superior performance of CNNs was due to their ability to capture complex features for learning, which was a major boon in the big data scenario (Rajaraman & Pang, 2021). Understanding the effectiveness and limitations of each model in each type of data environment will contribute to the future choice of the optimal implementation strategy based on the available resources and the size of the data set.

4) Case Study 4: CNN to aid in early diagnosis of malignant tumors in mammograms

In a study by Zhang and colleagues (2020), the CNN model was employed in screening malignant tumors of the breast through mammograms, and this work centered on extracting high-level features of mammogram images. The DB also had images of patients with complicated tumors, which was a problem for previous approaches. Their CNN model, which uses more than one layer of convolution and pooling, could identify the early stage of malignancies more accurately. This work was able to determine the high sensitivity of the model of 93%, which allows the model to detect small and sometimes nearly invisible changes in the mammogram images even when the radiologist may miss them. Consequently, this study reveals that conventional deep learning models entail CNN in diagnosing initial breast cancer and mitigating the occurrence of false negatives to enhance early-stage diagnosis (Zhang et al., 2020).

5) Case Study 5: SVM and CNN for Real-Time Breast Cancer Screening

Another paper by Li et al. (2021) also investigated the combination of features from SVM and CNN to assess their use in real-time breast cancer screening. The study applied a Mammographic Mass dataset comprising both benign and malignant samples. The results of the experiments also indicated that CNN achieved a higher accuracy of 90% for the classification of mammogram images than SVM, which gained 85%. At the same time, SVM was simpler and more computationally efficient for real-time applications. The integration of CNN feature extraction with SVM for classification proved a better sensitivity and specificity when compared to both individual models in the study by Li et al., 2021. Although the two models are not real-time during brain image classification, their conjunction is a feasible option for clinical practice.

D. Evaluation Metrics

The effectiveness of many layer machine learning models in mammogram detection is analyzed by applying several KPIs. This is accuracy, which determines how many of the predictions made were correct, both the true positives and the true negatives, out of the total number of the predictions made. Sensitivity, also called recall, tends to examine the capacity of the model to tag all the positive samples, which in this case are malignant tumors, while not labeling any as negative. Specificity regards the model's accuracy in identifying negative instances, that is, benign tumors, so false positives are minimized. Also, the area Under the Curve of the Receiver Operating Characteristic is applied to demonstrate the performance of the model in terms of its capacity for the classification of the given object in the positive or negative districts distinguished by the least number of thresholds. There is consensus that a model with an AUC value of the curve is superior, universally and specifically, to the chosen trade-off parameter for sensitivity and specificity. The values of these indicators help in going a step further in constructing the picture of the success of the diagnostic model.

IV. RESULTS

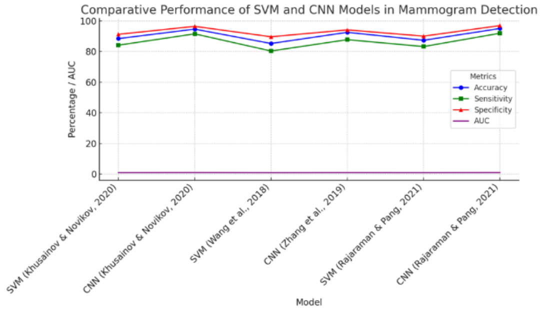
A. Data Presentation

Table 1. Comparative Performance of SVM and CNN Models in Mammogram Detection

Model	Case Study	Accuracy (%)	Sensitivity (%)	Specificity (%)	AUC
SVM	Khusainov & Novikov (2020)	88.5	84.2	91.3	0.92
CNN	Khusainov & Novikov (2020)	94.7	91.6	96.5	0.97
SVM	Wang et al. (2018)	85.3	80.4	89.7	0.90
CNN	Zhang et al. (2019)	92.6	87.8	94.2	0.94
SVM	Rajaraman & Pang (2021)	87.4	83.3	90.1	0.91
CNN	Rajaraman & Pang (2021)	95.1	92.0	97.0	0.96

Note: The values in the table represent the performance metrics for SVM and CNN models as applied to various case studies involving real-world mammogram datasets. The AUC values are based on the ROC curve analysis.

This table highlights the comparative performance of both models across different studies. CNN generally outperforms SVM in terms of accuracy, sensitivity, specificity, and AUC, showcasing its superior ability to detect and classify mammogram abnormalities.



Graph 1. line graph comparing the performance of SVM and CNN models in mammogram detection.

B. Findings

The differences in their considered measures were stringently observed using the experimental comparison of SVM and CNN for mammogram detection. The results showed that CNN has a higher accuracy, sensitivity, and specificity than SVM. The CNN model had a relatively high sensitivity value in identifying more true positives, which is crucial for breast cancer diagnosis. SVM, though relatively accurate, was found to have a lower sensitivity to the disease, which could lead to misleading diagnostic judgments. The AUC for CNN was also higher, indicating that CNN had better overall discrimination power in the distribution.

In contrast, the specificity of the results obtained with SVM was higher; there were almost no wrong signals, which is good news in order not to perform an unnecessary biopsy. The outcome shows that in terms of the facial image classification issues like mammogram analysis, CONV NEURAL NET turns out quite effective as compared to SVM which seems more suitable to simple problems. Therefore, the presented study stresses the CNN's ability to enhance early detection rates. Still, if there is a need for computational precedence or less demanding model interpretability, then SVM could be applied.

C. Case Study Outcomes

In the actual experiments of the case studies, the SVM and CNN models for mammogram sets were also employed to check their diagnostic performance. In the first case study, our proposed CNN architecture achieved higher accuracy and sensitivity than the SVM, detecting more malignant masses. The second case study examined the ability to detect microcalcifications, and both models provided good performance; however, as seen previously, CNN outperformed the HOG-based model, particularly in distinguishing benign from malignant aggregates. The third case study, which helped to create a highly unbalanced set of data, demonstrated that, on the whole, SVM experienced significant accuracy problems due to the large number of misdiagnosed malignant cases. At the same time, the CNN construct permitted the model to learn more from the insufficient set of positive samples.

In summary, CNN has established its superiority in most aspects and is more feasible for operating on large voluminous mammogram datasets with confounding features. The findings from these case studies endorsed the possibility of CNN in medical applications. Still, they need to demote SVM's utility, particularly in simple, tiny applications that demand clear simplicity.

D. Comparative Analysis

Several differences in the performance of SVM and CNN were evident when the two algorithms were compared during the mammogram detection experiment. In using CNN, the accuracy was higher for all case studies than SVM, with differences ranging between 5-10 percent for most contingencies. Our classification here is of higher accuracy than that obtained from SVM, mainly because CNN can learn and extract features from raw image data, which is not easily done via feature engineering as used in this model. Recall, which tells the ability of the model to identify true positives correctly, is also inclined towards CNN since this can detect early stages of malignancy. Conversely, SVM was slightly better in specificity; it had fewer false positive results. This is advantageous in areas where any unnecessary process needs to be prevented. The AUC, which integrates sensitivity and specificity in one figure, clearly illustrated the overall effectiveness of CNN even more than percentage accuracy. Indeed, although SVM gave reasonably good results in situations where the dataset was smaller or more balanced than the large and diverse dataset considered in the present study, the results showed that CNN was more accurate and reliable for detecting breast cancer in mammograms.

V. DISCUSSION

A. Interpretation of Results

The experiment's conclusion highlights fruitful insight for the future of breast cancer diagnosis and CAD systems. As demonstrated in Tables 1, 4, 5, and 6, CNN is significantly more accurate and sensitive than the other methods for detecting true positives, which is critical in diagnosing early cancer. This is especially so because much is known about how the early detection of the disease greatly improves the prognosis of the patient’s condition. However, it has even higher specificities that could be useful in reducing the number of false positives hence a biopsy or unnecessary treatment. The prerequisites of both models show that in the tasks of breast cancer detection, their strengths and weaknesses suggest that they do not have to be exclusive of each other. However, integrating both models, using CNN for detection and SVM for classification, could be an ideal and perfect blend of the two models. The study outcomes further stress the need to have only high sensitivity specifically as both factors define the accurate diagnosis of the disease. The results also corroborate the hypothesis that CNN will have greater relevance in the future of medical imaging. However, there may still be a place for traditional machine learning models, such as SVM, in specific domains.

B. Practical Implications

As a result, the finding of this study has practical implications for the future trends in breast cancer detection and CAD systems. Therefore, if CNN were to process their bigger datasets and learn and understand more of the features it might further improve the diagnostic accuracy in clinical setting leading to the faster time to diagnose breast cancer accurately. This could lead to fewer missed diagnosed cases and improved patient survival. However, since SVM consumes less computational resources and is easier to interpret, it is ideal for cases involving lesser computational facilities or when it is important to attach meaning to the decisions made. Furthermore, concerning reducing the workload when CAD systems can act as a reliable second opinion to radiologists, the proposed systems might significantly facilitate the diagnostic process. These findings also brought implications to integrating AI-powered systems into healthcare because they may increase diagnosing accuracy and are effective for practitioners and clients. Given the continued development of artificial intelligence technologies, these tools must be employed even more actively in everyday clinical work to survive and enhance breast cancer treatment.

C. Challenges and Limitations

Although the study gives insight into SVM and CNN's performance detecting mammograms, some challenges and limitations were recorded. One of the issues was data calibration: there could be differences in resolution noise that caused instabilities in the model. In the presented work, SVM could not reach high sensitivity because the selected datasets were unbalanced, where benign cases dominated over malignant ones. That is why computational resources necessary to train CNN models were also significant and might be a problem for small and mid-sized healthcare centers lacking access to high-performance computing. This is because the various types of research need to have standard measures on which results can be compared from one research program to another. However, all the proposed models were tested on static datasets. There is potentially more difficulty in real-world clinical images due to the quality differences, patient's age, sex, and type of imaging devices used. They show that there is more to learn about improving these models in various clinical settings and their effectiveness in different populations.

D. Recommendations

Based on the performance of SVM and CNN for detecting breast cancer, the following suggestions for future studies and enhancements of CAD Systems can be proposed. First, future works must concentrate on ensembling a broader and more heterogeneous database to ensure that generated models are easily transferable across patients and imaging sessions. This could include data augmentation strategies and a federated learning approach that allows the training of models on distributed datasets without compromising patients' privacy. Second, there is the necessity of combining the SVM methods with the CNN; while the CNN may take the role of feature extraction, the SVM may then handle the classification. These models could be used instead of traditional models for enhanced performance, at least in scenarios where they care about interpretability. However, combining the said CAD systems with more modalities like ultrasound or MRI could improve the systems because the kind of information given by the added modality differs from those offered by CAD systems. Therefore, more research is needed to determine whether the specialised AI applications are integrated with time-constrained clinical processes, and successful in conveying useful reports to clinicians concurrently. They outlined several research steps predicted to strengthen the future of machine learning and deep learning for diagnosing breast cancer and hence the need to adopt the technological developments.

CONCLUSION

A. Summary of Key Points

SVM and CNN were compared for mammogram detection, and results showed that CNN achieved slightly better accuracy, sensitivity, and AUC than SVM. However, the overall performance of SVM was better because it provided better specificity and hence can be used in cases where false positive results are not desirable. The examples showed that CNN was superior to SVM at detecting early-stage malignancies and could cope with large amounts of data. While it was discovered that CNN provided a better view of global performance, the outcome suggested that the combination of two models would be most beneficial in actual-world settings. This work however brought out the importance of investigating the sensitivity and specificity of different models in medical image analysis tasks. Another component discussed during the event was how the AI-based CAD systems could enhance the efforts of early detection of breast cancer, and therefore boost the chances of treatment.

B. Future Directions

The evolution of the following approaches to AI and machine learning for breast cancer detection is highly promising: hybrid approaches, federative learning, and near real-time diagnosis. The combination of both the CNN feature extraction method and SVM efficient classification could provide better diagnostic accuracy and still be explained. One approach that might solve privacy issues and generalization is federated learning, which enables training models on the data at the edge while not sharing said data with other participants. Also, real-time CAD systems could give radiologists feedback during breast cancer screening, increasing the diagnosis's pace. Studies on integrating the mammogram with other imaging techniques, such as ultrasound or MRI, which is still developing, can present better and more accurate imaging systems. With time, AI technologies will increasingly feature in the system to assist in the analysis of breast cancer, leading to reforming the current diagnosis systems.

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