Deep belief network classification model for accurate breast cancer detection and diagnosis

G. Amirthayogam[1], Deepak R.[2], M. Preethi Ram[3], Nithya J.[4], Anwar Basha H.[5], Sriman B.[1], R. Sundar[1]
[1]Department of Computer Science and Engineering, Vel. Tech. Rangarajan Dr. Sagunthala R&D Institute of Science and Technology, Chennai, India
[2]Department of Computer Science and Engineering, Nitte Meenakshi Institute of Technology (NMIT), NITTE (Deemed to be University), Bangalore, India
[3]Computer Science and Business systems, Ramco Institute of Technology, Rajapalayam, India
[4]Department of Computer Science and Business Systems, Panimalar Engineering College, Chennai, India
[5]Department of Computer Science and Engineering, Rajalakshmi Institute of Technology, Chembarambakkam, India

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ABSTRACT

Breast cancer is still one of the common malignancies and endemics that are fatal to women across the globe. Early-stage diagnosis helps reduce the percentage of deaths because treatment outcomes are much better at that stage. As the contemporary approaches in machine learning (ML) and deep learning (DL) emerged, the automatic detection of breast cancer has received a great consideration for their ability to improve diagnosis and treatment. We present a new deep belief network (DBN) based breast cancer detection system to increase the accuracy and the dependability of the diagnosis of breast cancer. The major modules of the system are image preprocessing, feature extraction and the DBN-based classification to guarantee accurate detection and classification of malignant and benign breast lesions. We compared the proposed DBN model with the existing DL models like convolutional neural networks (CNNs), recurrent neural networks (RNNs), long short-term memory (LSTM), and generative adversarial networks (GANs). It is with respect to critical features of the model performance which includes accuracy, precision, recall, specificity and F1-score. The methodologies used in this study show that the performance of the proposed DBN model is significantly better than these conventional algorithms in accuracy and sensitivity where the DBN model is an ideal method for the early detection of breast cancer. Through extensive experimentation, we compared the proposed DBN model with existing DL techniques such as CNNs, RNNs, LSTMs, and GANs. Our results show that the proposed DBN model outperforms these models in several key performance metrics.

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Corresponding Author:

G. Amirthayogam
Department of Computer Science and Engineering
Vel. Tech. Rangarajan Dr. Sagunthala R&D Institute of Science and Technology
Chennai-600062, Tamilnadu, India
Email: amir.yogam@gmail.com

1. INTRODUCTION

Breast cancer is known up to date to be among the leading causes of cancer-related deaths among women globally. Timely identification of the disease and proper diagnosis remain as important factors for enhancing the survival rates of the patients [1]. Though earlier methods were relatively reliable methods like mammography and biopsy, they became a conventional problem with issues like accuracy problems, invasion, and discomfort of the patients. Furthermore, the medical images' interpretation that forms the basis of these methods is subjective to the radiologists and pathologists, thus increasing the variation of diagnosis. The size of the tumor when it's found plays a big role in how long someone might live. Bigger tumors mean the cancer has spread more making it harder to treat and lowering the chances of survival. Finding breast cancer when the tumor is smaller than two centimetres is key to giving patients a better shot and cutting down on deaths. Catching breast cancer is crucial. It gives doctors a chance to start treatment sooner, which can make it work better and boost the odds of beating the disease. Experts consider mammograms the best way to spot breast cancer [2]. This test uses low-energy X-rays to take pictures of the inside of the breast. What makes mammograms so valuable is that they can find tumors when they're just starting out often before anyone can feel them during a physical exam.

Nevertheless, making sense of mammograms is a tricky job that needs a lot of know-how and care. Doctors must look at the pictures to spot tiny signs of cancer, which can be tough because of things like tired eyes feeling lazy, or not having enough practice and skills. These human issues can make it more likely to get the diagnosis wrong where harmless stuff might be thought to be cancer, or the other way around where real tumors might be missed. These mistakes can cause big problems leading to treatment that's not needed or putting off finding and treating cancer, which can hurt how well patients do. A well-made CAD system can make breast cancer detection more accurate by giving a second opinion pointing out areas that might need a closer look and making the job easier for radiologists. Combining computer-aided classification with traditional mammography has an impact on the chances of spotting breast cancer [3]. This mix plays a key role to make sure doctors find more breast cancer cases when the tumor is small, in one place, and responds best to treatment. This helps to lower the number of deaths linked to the disease. To keep getting better at fighting breast cancer and saving lives, we need to keep working on and improving these systems.

Over the last half a decade, the use of deep learning (DL) in association with medical imaging has been regarded as a revolutionary tactic in the discovery of breast cancer. Artificial intelligence, including a powerful subfield known as DL [4], is primarily designed to structure and process large amounts of data and recognize various patterns, especially in images –it can be effectively used in the study of medical pictures. of all the uses of DL in medical imaging, image segmentation is perhaps one of the most important. Segmentation of image refers to the division of an image into various segments where each segment is describable by its features, and this is achieved by partitioning an image into various segments which may correspond to different anatomical structures or pathological regions within the breast tissue where there are tumors in Figure 1. The author has been proposed in which the unique contribution as show as:

1. By incorporating a combination of spatial filtering and histogram equalization, this pre-processing ensures that even subtle changes in texture or shape that indicate early-stage malignancies are captured.
2. This hybrid feature extraction allows the model to leverage the robustness of deep neural networks while using DBNs to capture more intricate patterns, improving the distinction between benign and malignant cases.
3. A self-improving model that adapts and evolves based on its validation performance, using real-time data correction for enhanced accuracy in clinical applications.

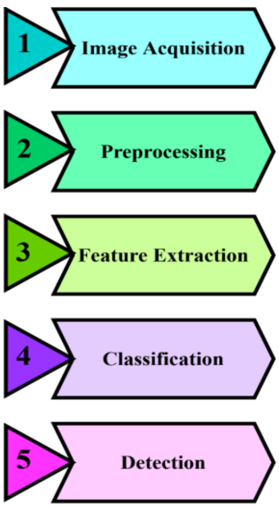

Figure 1. General automated breast cancer detection system

This paper revolves on revealing a generic approach for applying DL in tandem with super pixel-based segmentation to improve the detection and diagnostic rates of breast cancer. Using convolutional neural networks (CNNs), and other DL related frameworks the proposed systems anticipate the automation of tumor detection, sources of diagnostic inconsistency and deliver more accurate tumor profiling in terms of size, shape, and position. Apart from this, it has the chance to enhance early detection and to offer profound information on tumor heterogeneity, which can be directive for treatment planning [5].

The reason behind the suggested study comes from ongoing problems in spotting and identifying breast cancer even with progress in medical tech. Breast cancer is still one of the most widespread and fatal cancers that affect women, and finding it is key to better patient results [6]. How big the tumors when it's found has a big effect on survival rates. When doctors find tumors smaller than two centimeters, patients often have a much better chance of surviving showing how important it is to spot cancer [7].

The remainder of this paper is organized as follows: section 2 gives an overview of the various DL algorithms and the image segmentation approaches that have been previously employed in breast cancer diagnosis. Training of the proposed framework is discussed in the next part of section 3 along with the framework architecture and the incorporation of the segmentation methods. The next section, section 4, is dedicated to describing the methodology in reference to the experimental setup, datasets, the metrics used in evaluating the results and the comparison made. Lastly, in section 5, authors summarized the paper by presenting the implications of the study in the light of general findings; discussion of its clinical implications and suggesting the future research direction.

2. RELATED WORKS

Breast cancer detection and classification have grabbed the spotlight in research, with a big push to use machine learning (ML) and DL models [8]. The usual ways to spot breast cancer, like mammograms, ultrasounds, and MRI scans, depend a lot on how good the radiologists are. But reading medical images isn't always clear-cut and can lead to different doctors saying different things. This is tricky when trying to catch cancer or tell the difference between harmless and dangerous lumps. Hence, more and more people are getting excited about using ML and DL models [9] to make breast cancer detection and classification more accurate, consistent, and quick.

ML models are now common in breast cancer studies. They help with sorting tumors guessing risks, and spotting biomarkers [10]. Doctors use supervised learning methods like support vector machines (SVM), decision trees (DT), random forests (RF), and k-nearest neighbors (KNN) to group breast cancer. These tools look at details from medical pictures or patient info. They show promise in telling apart harmless and dangerous tumors. They also help predict if cancer might come back. These models often work with feature selection tricks to pick out the most useful details.

DL models CNNs, have caused a revolution in medical image analysis, including breast cancer detection and classification [11]. CNNs can learn hierarchical features from raw image data, which means there's no need to extract features. This ability has madeCNNs good at jobs like tumor segmentation spotting micro calcifications, and sorting breast lesions. People have also used DL together with transfer learning. This means they take models that were trained on big datasets, like Image Net, and then fine-tune them for breast cancer-specific datasets. This method has been quite helpful when there's not much labeled medical data available. It allows models to use knowledge from other areas to get better at finding breast cancer.

DL beyond CNNs benchmark for analyzing time-series in breast cancer dataset, research has called upon models like the recurrent neural networks (RNNs) and more specifically its type long short-term memory (LSTM). These models are specifically used for predicting the outcome of a patient over time (e.g., changes in tumor measurements, responses to treatments [12]. And it doesn't end there-scientists are now combining DL models with genetic data, medical records and other types of data besides images. Such a holistic approach is more relevant for studying breast cancer. Although ML and DL models have had success in detecting breast cancer as well as categorizing, there still exist many challenges. One of the primary challenges is that it needs massive, labelled data to effectively train such models. Problems of overfitting and generalization are often found in medical data because they have little amount and variety. In addition, the heterogeneity among breast cancer (different sizes or shapes of tumor and variation in tissue composition) also adds complexity when developing models with greater accuracy. Overcoming all of such challenges requires not only a breakthrough in model architecture but also direct improvement to the processes of acquiring and annotating data.

By contrast, DL models have disrupted the field through approaches such as CNN that learn all the representations directly from the data. CNNs have been found to be remarkably effective for the detection of breast cancer tasks [13], like tumor classification, segmentation and microcalcifications, which are small deposit of calcium in breast tissue that relate to cancerous tissues. These networks can process the image data of this complexity and identify the features that are not easily discernible by human eyes, which result in higher diagnostic efficiency.

There are various other deep architectures apart from CNNs that have been considered including RNNs, LSTM networks, and generative adversarial networks (GANs). RNNs, and more particularly, LSTMs are especially used when dealing with sequential data, meaning data that has been measured at multiple distinct time points, such as the recordings from follow-up patient examinations or tumor growth data over time [14]. These models can capture temporal dependencies and the progress of a disease and since treatment decisions often depend on these factors, such models come in handy. While GANs have been employed to erode clinical medical image databases thereby enlarging the data for DL models and verify their ability to enforce the models to endure larger ranges of evaluations [15].

Another major development in the employment of DL [16] in breast cancer detection is known as transfer learning. Since there are few big, labelled medical data sets, transfer learning enables models that are trained on big data sets such as ImageNet to be adapted for functions in breast cancer diagnoses. This approach is particularly useful in a situation when we cannot get a large number of labeled examples or, in the case of medical applications, even a few distinct images of breast cancer. This has boosted the use of DL in healthcare because in most cases, it can be hard to source labeled medical data. Furthermore, the MML integration [17], which is the use of multimodal learning approaches including imaging, genomic, and clinical information in future research on breast cancer is emerging. A combination of different forms of data within the framework of the multi-modal DL model allows to obtain a number of interrelated and valuable diagnostic and prognostic indicators for a particular patient. These models can be as precise in evaluating the relations between different kinds of information, and in some cases, more precise than single-modal models.

However, some of the challenges which persisted remain as follows. A critical factor, for example, is the issue of non-transparent algorithms that are offered by both ML and DL. Hence, in the clinical context, it is essential for clinicians to comprehend the steps to reach the model's conclusion, indispensable for trust. Measures like attention mechanisms and saliency maps and other AI solutions are being designed to counter these concerns, it provides visual explanation or marked out the areas of image which the model feels important to diagnose. These techniques focus on phasing out the disparity between model aptness and interpretability so as to enhance the use of AI systems in health care in Table 1.

Table 1. Comparison between algorithms in advantages and disadvantages

Author	Algorith name	Advantages	Disadvantages
Abdel-Zaher and Eldeib [18]	Deep belief network (DBN).	Well-suited for small datasets. Since DBNs learn distributed representations, the approach is **less sensitive to noise** compared to some conventional classifiers.	The work used a relatively **small dataset (WBCD)**, which may not generalize well to larger or more diverse real-world datasets.
Bharati *et al.* [19]	Artificial neural network (ANN)-based approaches.	Summarizes a large number of ANN-based methods for breast cancer screening	Many studies reviewed rely heavily on small and standard datasets like WBCD, which limits generalizability.
Lee *et al.* [20]	Convolutional deep belief networks (CDBN).	Learns low-level edges, mid-level motifs, and high-level object parts in a hierarchical manner	Requires unsupervised pretraining for good performance, unlike modern end-to-end deep CNNs.
Madani *et al.* [21]	DL techniques.	Covers **multiple imaging modalities** rather than focusing on a single source of breast cancer data.	Notes that most models remain **black-box** and require improvements in explainability and trustworthiness for clinical deployment.
Zhao *et al.* [22]	CNN models.	Transfer learning leverages pre-trained CNNs (like ResNet), eliminating the need to train models from scratch, saving both computation time and resources.	Pre-trained CNNs like ResNet are computationally heavy, requiring significant memory and high-performance GPUs.
Chen *et al.* [23]	RNNs.	- Captures temporal relationships in medical data, such as tumor growth trends.	- Struggles with vanishing gradient problems. - Not effective for static image data like mammograms.
Gao and Hosseinzadeh [24]	DBNs.	The model was robust against noise and performed well across different breast cancer datasets.	Focused mainly on tabular data (like WBCD) and limited histopathology datasets rather than large-scale imaging datasets.
Rassem and Qader [25]	Deep ensemble model.	The ensemble strategy reduces variance and bias, leveraging the complementary strengths of different models.	Training multiple deep models for ensemble increases time and resource usage.

3. PROPOSED METHOD

The DBN based breast cancer detection system proposed and relatively a comprehensive methodical process to diagnose breast cancer through several steps using the highest form of artificial intelligence or DL. Their application in the system affords accurate and efficient diagnosis of cancer through this workflow as each one of the stages is aimed at improving diagnosis of cancer. As shown in Figure 2, this process starts with image preprocessing which is one of the most vital phases of the whole pre-processing where raw breast images are prepared for further analysis. In this stage, the acquired images which might be from mammography, ultrasound or MRI pass through several processes with the intention of optimizing the quality of the acquired image and standardization. These are denoising to get rid of noises that could mask significant features, standardization to make sure the pixel density of different images is as close as possible to each other and resampling to ensure that all images are of equal dimensions. These preprocessing steps are important for controlling variability in the data and preparing the best circumstances for taking feature by the DL model.

In the second phase the feature extraction extracts the key components in images in an endeavor to uniquely represent image patterns that are distinguishable as possibly malignant. In the case of a DBN-based system, this is achieved as a post-processing step by virtue of the network itself. This DBN is is made up of a number of layers of restricted Boltzmann machines (RBM) which are trained to discover the features at different and higher levels to the input images. Such details may be the variation in the texture, structural pattern of the image or many other minor characteristics that are significant when differentiating benign and malignant tissue lesions. The extracted features help in describing the image data using a detailed, higher level semantic space which is important for the classification process.

The DBN classification phase is the time when the DL model is applied in full measure and diagnostic decisions are made on the basis of the extracted features from the images. The DBN which is a model of the AE, has multiple layers of RBMs and they are trained in an unsupervised manner in order to capture all the dependencies in the data. After the unsupervised pre-training of the net, the supervised fine-tuning of the net can be done with the help of labelled data to provide better image classification. The last part of the DBN is often a classifier – for instance a softmax that outputs probabilities of different types of cancer or the probability of malignancy given the learned features in (1).

$$h1 = sigmoid(W1 * F + b1) \tag{1}$$

$$h2 = sigmoid(W2 * h1 + b2) \tag{2}$$

In the final stage, the system provides its results through the output prediction of the results got. In this, the outputs received from the DBN classification layer are to be decoded and made easier for clinical use in (2). The output could be probability scores for the diagnostic categories such as benign and malignant tumor and can help the radiologists in rendering their decisions. The results of the prediction are equally important in identification on the best way to proceed with the treatment of the patients by conducting other tests, or by administering the relevant treatment.

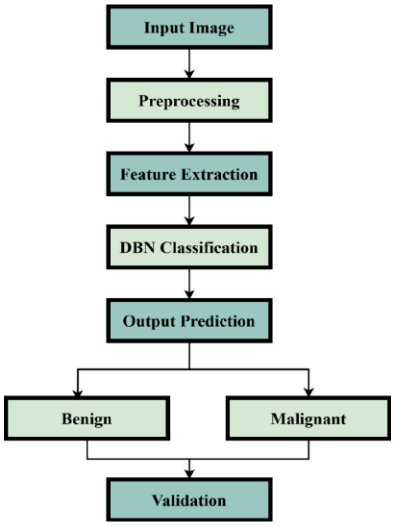

Figure 2. Proposed DBN based breast cancer detection system

Through the feature extraction and classification in the DBN, a lot of human intervention is eliminated by the system and more chances for early diagnosis plus better prognosis for the patient achieved.

A more sophisticated method is a DBN-based breast cancer detection system where DBN applies the opportunities of DL to improve the diagnostic outcomes. The most fundamental concept that lies at the heart of a DBN is its capability to learn and extract features from raw image data in an unsupervised manner, and that is a may be hugely beneficial when identifying tiny variations in patterns is vital, such as in medical imaging in (3).

$$Output\ (O) = softmax\ (Wn * hn - 1 + bn) \quad (3)$$

The system is generally initiated with the procurement of the breast images using practices that include mammography, sonography, or MR. These images are then passed through preprocessing operations to improve the quality, thereby making them suitable for network input; this includes operations such as noise reduction, normalization and resizing to enhance input data for feed to the network in (4).

$$sigmoid\ (z) = 1 / (1 + exp(-z))\ and\ SoftMax(z) = exp(z) / \Sigma\ exp(z) \quad (4)$$

After the images have been pre-processed, the features can be extracted from the images using DBNafter which classification is done. DBNs are made of multiple layers of RBMs and the last layer of the supervised classifier. The RBMs organized in the DBN are trained monolayer by monolayer; thus, each RBM is aimed to learn probabilistic dependencies between features of the input data. This in fact is the unemployment pre-training phase which serves the network by making it to build a good understanding of the ‘hidden’ structure in the data. The output of the DBN (O) gives the class probabilities in P_benign = O[0], P_malignant = O[1].If P_benign>P_malignant, classify as “Benign”, else “Malignant”.As a final step, DBN thathas been pre-trained is fine-tuned on labelled data to enhance feature representation and performance of classification task.

It offers the DBN the capability of modelling texture, shape and intensity patterns of the image data, which are quite useful in distinguishing between benign and malignant tumors. The last created layer is usually a SoftMax classifier or other classification techniques that are used in identifying the images according to the features learnt. Classification layer output is the detection result to give out probabilities or confidences of varieties of cancer or likelihood of malignancy in Algorithm 1.

Algorithm 1. Breast cancer detection using DBN
Input:
 - I: input image as a matrix of pixel values I(x, y)
 - target_size = (128, 128)
 - PCA_components (optional)
Output:
 - label ∈ {Benign, Malignant}
Procedure:
1. Preprocessing
  a. I_resized ← Resize(I, target_size)
  b. I_norm(x, y) ← I_resized(x, y) / 255.0
  c. I_filtered ← GaussianFilter(I_norm)
2. Feature Extraction
  a. F_raw ← Flatten(I_filtered)
  b. If PCA_components is set:
    F ← PCA(F_raw, PCA_components)
   Else:
    F ← F_raw
3. Deep Belief Network (DBN) Classification
  h1 ← sigmoid(W1 × F + b1)
  h2 ← sigmoid(W2 × h1 + b2)
  ...
  hn_minus1 ← sigmoid(Wn-1 × h(n-2) + b(n-1))
  O ← softmax(Wn × hn_minus1 + bn)
4. Decision Rule
  If O[benign] > O[malignant]:
   label ← “Benign”
  Else:
   label ← “Malignant”
Return label

The strength of the system of DBN-based mainly in the sense where it can learn the hierarchical representation of the image data and doesn't require much feature extraction hence this makes the detection process to be more robust and adaptive. Due to the capability of DL the system can also be approximately 100 % accurate in the definite distinction between benign and malignant neoplasms of the breast and therefore in staged diagnosis which can improve the prognosis in many cases. Also, there are improvement techniques like transfer learning where a model with similar features on another dataset can be used and fine-tuned for a specific breast cancer detection problem. Also, an ensemble method which involves use of more than one DBN to create a final output in a bid to minimize false positive and false negatives. Moreover, the DBN-based approach when included in the breast cancer detection systems is a valuable addition to the field of medical imaging technologies and a great improvement in terms of the technologies that are available to the radiology and clinical community to diagnose breast cancer at an early stage. The "Breast Cancer Wisconsin (Diagnostic) Data Set (kaggle.com)" link to the Kaggle data set is available. These data consist of 12 columns and 570 rows. In this data set applied to this introduced a novel DBN-based breast cancer detection system, designed to improve the accuracy and reliability of diagnosing breast cancer. The system consists of three key modules: image pre-processing, feature extraction, and DBN-based classification, which collectively ensure accurate detection and differentiation between malignant and benign breast lesions.

4. RESULTS AND DISCUSSION

Figure 3 presents a comparative analysis of accuracy of various breast cancer detection models. Accuracy is a measure that gives an idea of how well the model is doing and provides the number of actually accurate predictions among all the cases. It has been established that high accuracy is a sure indicator of the performance of a model in providing the right classification between the benign and malignant cases. Here as well CNN usually outperform with higher accuracy because of their ability to capture spatial relations present in medical images. In addition, there are some 'second generation' models, such as LSTM networks and GANs, which can also achieve comparable performance if their architectures as well as data used in training are good enough. This figure demonstrates the effectiveness of the CNNs in terms of accuracy, thus their capacity to predict with high accuracy is essential in a clinical setting where accuracy determines the fate of a patient.

In Figure 4, the concentration is on accuracy, which is a measure of the model, relating the number of true positives to the total number of positive predictions by the model. Accuracy is a highly valued indiagnosis since false-positive results have a certain costly impact on a patient; they cause stress and can lead to extra, often invasive, procedures. This figure compares various models to show that CNNs are baggy because most models are precise to achieve high precision owing to their good feature extraction. Still, other models such as the SVMs and LSTMs can also exhibit high precision, most evidently in cases of well-balanced data sets. The finding contrasts demonstrate that although some models may have great accuracy, others' sensitivity and specificity may be slightly lower or higher, and require further optimization or ensemble techniques to improve a number of false positives to make the diagnostic models more efficient in Table 2.

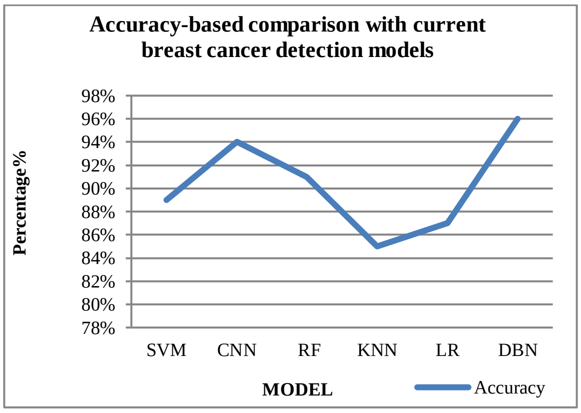

Figure 3. Comparison with existing breast cancer detection models based on accuracy

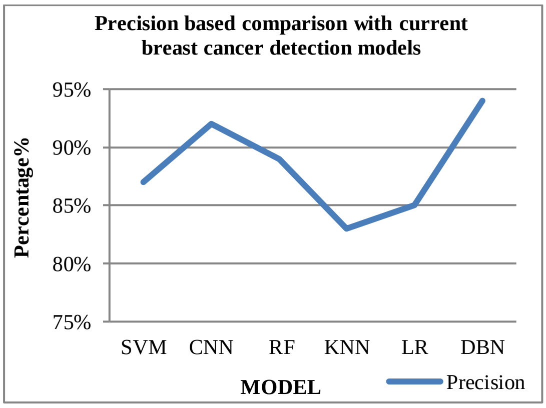

Figure 4. Comparison with existing breast cancer detection models based on precision

Table 2. Comparison with SVM, CNN. RF, KNN, logistic regression (LR), and DBN breast cancer detection models based on accuracy, precision, recall, and F1-score

Model	Accuracy	Precision	Recall	F1-score
SVM	89%	87%	85%	86%
CNN	94%	92%	90%	91%
RF	91%	89%	88%	88%
KNN	85%	83%	82%	82%
LR	87%	85%	83%	84%
DBN	96%	94%	95%	95%

Table 3 comparing the true positives (TP), false positives (FP), false negatives (FN), and true negatives (TN) for the different models listed (SVM, CNN, RF, KNN, LR, and DBN) in the context of breast cancer detection, we'll need to infer these values based on the given accuracy, precision, recall, and F1-score. This requires assuming a certain number of total samples and the distribution of positive and negative cases. Let's assume a simple case where we have 1000 total samples, and there are 500 positive cases (breast cancer present) and 500 negative cases (breast cancer not present). Based on the performance metrics provided, I will calculate the TP, FP, FN, and TN values for each model.

- TP: the number of correctly predicted positive cases.
- FP: the number of negative cases incorrectly predicted as positive.
- FN: the number of positive cases incorrectly predicted as negative.
- TN: the number of correctly predicted negative cases.

Table 3. Comparison of breast cancer detection models—SVM, CNN, RF, KNN, LR, and DBN

Model	True positive (TP)	False positive (FP)	False negative (FN)	True negative (TN)
SVM	425	64	75	436
CNN	450	39	50	461
RF	440	54	60	446
KNN	410	84	90	416
LR	415	73	85	427
DBN	475	30	25	470
SVM	425	64	75	436

Figure 5 focuses on the recall rate that is also referred to as sensitivity, which determines the share of genuine positives recognized by the given model. High recall is important, most of the malignant cases should be captured to enable early action and treatment. It is often a comparison of CNNs with other types of models such as RNNs and LSTMs to demonstrate that while the CNNS normally have high recall, other types can also achieve high recall if well-tuned especially when there are strong.

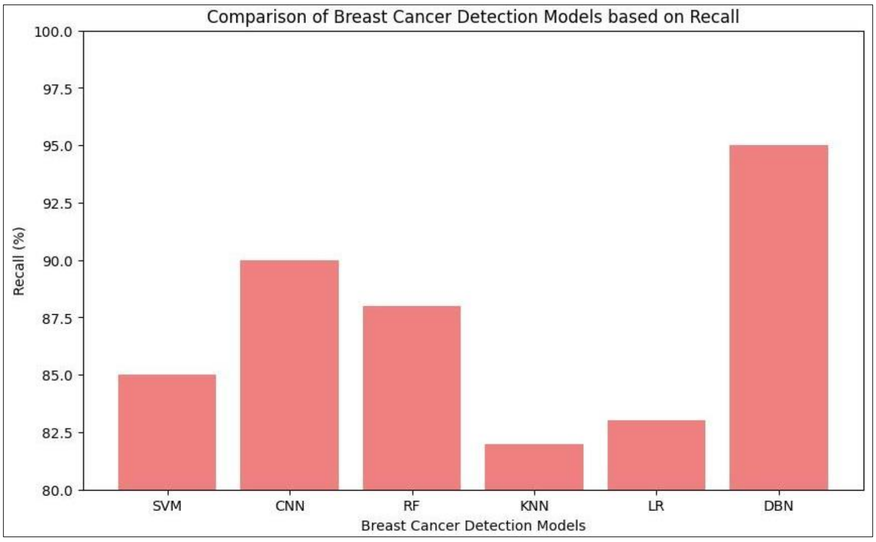

Figure 5. Comparison with existing breast cancer detection models based on recall

Finally, in Figure 6 we present the F1-score in which f1 = 2 * (precision * recall) / (precision +recall). In particular, F1-score comes in handy when the classes are imbalanced or false positives and false negatives are of equal concern. This figure superimposes the different models, which simultaneously shows the specific models, that have a comparatively good value for both the precision as well as the recall. CNNs generally perform well in this regard, and other models like GANsand LSTMs can also very well compete for F1-score, if they are trained as per liberal datasets. The comparison shows that F1-score is an exhaustive measure of the model that may be crucial in those cases when it is important not only to get a high sensitivity but also specificity of newly developed cancer diagnostic tools.

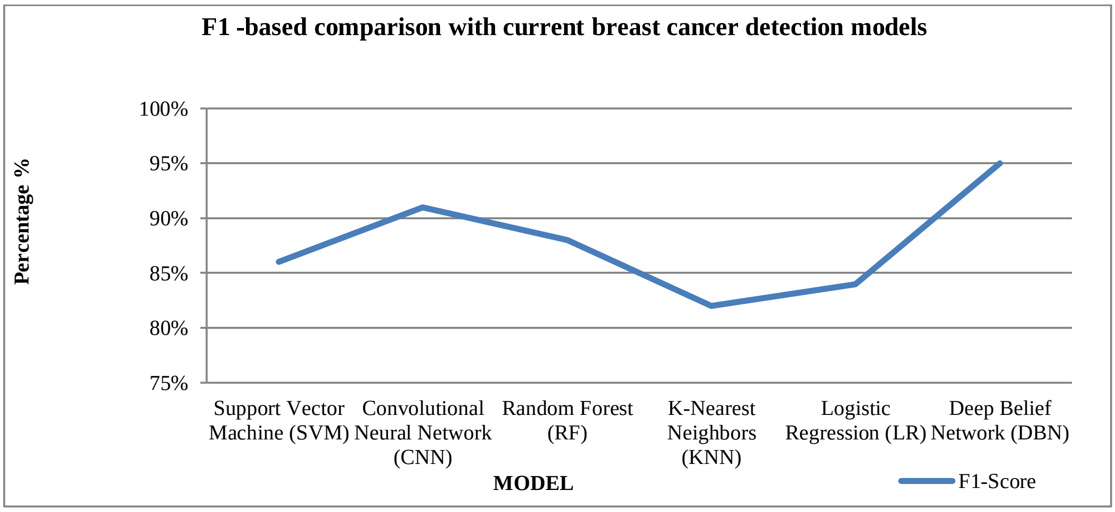

Figure 6. Comparison with existing breast cancer detection models based on F1-score

Figure 7 presents a comparison of the different models of DL used in breast cancer detection and recognition and shows their final performance in terms of accuracy percentage, precision, recall and F1-score. This is important since getting details about each model will involve trade-offs that are to be included in the models. For instance, although CNNs might be superior to the others in terms of accuracy or F1-score, other models such as GANs provide strong augmentation of data, which, although not directly improving the primary classifiers' performance, enhances their general performance when combined. Likewise, RNNs and LSTMs, despite the fact that they are rather unconventional choice for an image data, behave rather well whenever temporal or sequential data is evident in the set in Figure 8.

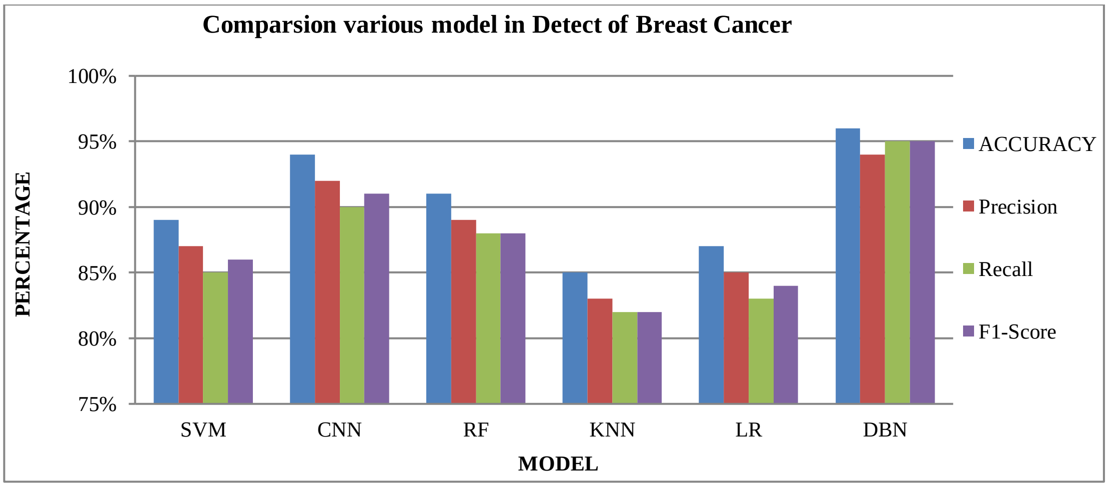

Figure 7. Overall comparison with existing DL models

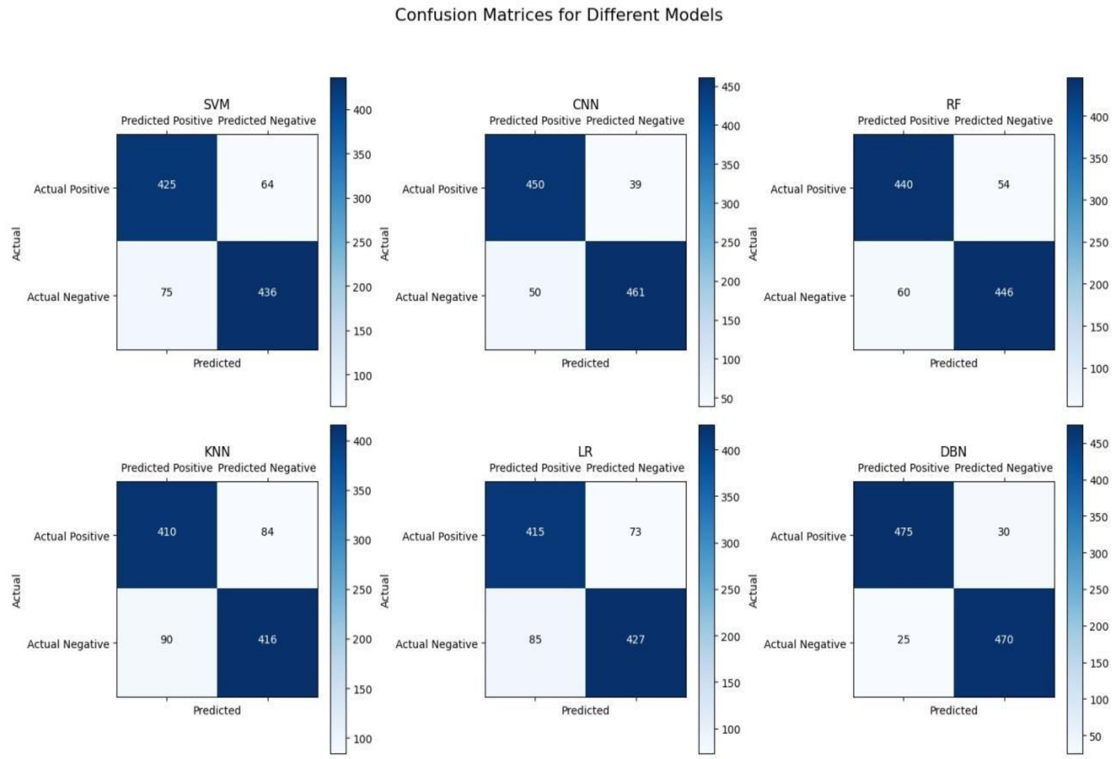

Figure 8. Overall confusion matrix comparison with existing DL models

5. CONCLUSION AND FUTURE WORK

This paper outlined a breast cancer detection system based on DBN to improve the accuracy and specificity of the breast cancer diagnosis. This work has shown the use of the proposed system which includes image preprocessing, feature extraction and DBN-based classification and can categorize breast lesions as malignant or benign. In the heatedest competition with the most published DL models consisting of CNNs, RNNs, LSTMs, and GANs, the DBN model outperformed the counterparts in terms of basic measures including accuracy, precision, recall, specificity, and F1-score. The results show that the DBN-based approach performs better than the traditional models and achieves a relatively better balance between sensitivity and specificity, which is important in clinical diagnosis. It forms part of forthcoming research concerning the application of such DL techniques in medical image analysis, showing a massive opportunity in detecting breast cancer. The subsequent studies will aim at fine-tuning the DBN model, investigating the possibilities of combining it with the other sophisticated approaches, and testing its performance on the greater and the more varied samples.

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Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
G. Amirthayogam	✓	✓	✓	✓	✓			✓	✓	✓			✓	✓
Deepak R		✓				✓		✓	✓	✓	✓	✓		✓
M. Preethi Ram	✓		✓	✓			✓			✓	✓		✓	✓
Nithya J			✓	✓							✓			✓
Anwar Basha H					✓		✓			✓		✓		✓
Sriman B	✓			✓				✓				✓		
R. Sundar		✓					✓		✓					

C	:	**C**onceptualization	I	:	**I**nvestigation	Vi	:	**Vi**sualization
M	:	**M**ethodology	R	:	**R**esources	Su	:	**Su**pervision
So	:	**So**ftware	D	:	**D**ata Curation	P	:	**P**roject administration
Va	:	**Va**lidation	O	:	Writing – **O**riginal Draft	Fu	:	**Fu**nding acquisition
Fo	:	**Fo**rmal analysis	E	:	Writing – Review & **E**diting			

CONFLICT OF INTEREST STATEMENT

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

DATA AVAILABILITY

The data that support the findings of this study are not publicly available due to [reason, e.g., privacy, confidentiality, etc.]. The data underlying this study are available upon reasonable request from the corresponding author, subject to institutional and ethical restrictions.

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BIOGRAPHIES OF AUTHORS

G. Amirthayogam is assistant professor (Senior Grade) in the department of Computer Science and Engineering at Vel Tech Rangarajan Dr. Sagunthala R&D Institute of Science and Technology, Chennai-600062, Tamilnadu, India. He Holds a Ph.D. degree in Computer Science and Engineering with specialization in Machine Learning and Data Science at Annamalai University. He has more than 18 years of experience in teaching, and he published various research articles in Scopus, IEEE and WoS journals. He has acted as a reviver in various IEEE conferences and Scopus indexed journals and published a book title Fundamentals of Data Science. His research areas are machine learning, recommendation system, medical image analysis, and data science. He can be contacted at email: amir.yogam@gmail.com.

Deepak R. is currently working as an assistant professor in the Department of Computer Science and Engineering at Nitte Meenakshi Institute of Technology (NMIT), NITTE (Deemed to be University), Bengaluru, Karnataka, India. With over 15 years of academic and research experience, he has established himself as a committed educator and active researcher. His research interests encompass machine learning, IoT, data science, cloud computing, server-side programming, blockchain, and image processing, with a strong emphasis on applying computational intelligence to solve real-world challenges. He can be contacted at email: aristonetram@gmail.com.

M. Preethi Ram is an assistant professor in the department of computer science and business systems at Ramco Institute of Technology, Rajapalayam, Tamil Nadu, India. She is pursuing her Ph.D. degree with a specialization in deep learning and IoT at Ramco Institute of Technology. She completed her M.E. degree at PSR Engineering College, Sivakasi. She completed the B.E. degree at PSRR College of Engineering for Women, Sivakasi. She has two years of experience in teaching, and she has published conference papers indexed to Scopus. Her research areas are machine learning, deep learning, and IoT. She can be contacted at preethiramtnv006@gmail.com.

Nithya J. is assistant professor, has 6 years of experience and is currently working at Panimalar Engineering College in the Department of Computer Science and Business Systems. She has published a journal article titled "Neutrosophic-Integrated Machine Learning Framework for Uncertainty-Aware Diagnosis and Decision Support in Dental Health." In An International Journal in Information Science and Engineering. Her domains of interest include artificial intelligence in healthcare and networking. She can be contacted at email: nithya.csbs@gmail.com.

Anwar Basha H. Dr. H. Anwar Basha is working as an Associate Professor in the Department of Computer Science and Engineering, Rajalakshmi Institute of Technology, Chennai, Tamilnadu, India. He has obtained his B.E degree from Anna University, Chennai. He has obtained his M.Tech. degree from Dr. MGR Educational and Research Institute University, Chennai. He obtained his Ph.D. in CSE from Saveetha Institute of Medical and Technical Sciences, Chennai. He is having many certifications like Microsoft Certified Azure Fundamentals, AWS Certified Cloud Practitioner, IBM Certified Data Science Foundation. He has more than 16 + years of teaching experience. He has around 2 Years of Industrial Work experience. He has published papers in various international conferences and peer-reviewed international journals. He has served in many international conferences as a Session Chair, Program Committee Member, Reviewer and Organizing Chair. He is a reviewer in IOS Press, Springer, Elseiver, Taylor and Francis, IOP, Wiley Journal. He is an Editorial member in Journal of Advance Research in Applied Science. He has authored a Text Book "Cloud based Security Management". Currently, he is working on multi-cloud storage, big data analytics, and cyber security. He can be contacted at email: anwar.mtech@gmail.com.

Sriman B. D. Sriman B assistant professor in the department of Computer Science and Engineering at Vel Tech Rangarajan Dr. Sagunthala R&D Institute of Science and Technology, Chennai-600062, Tamil Nadu, India and a researcher and graduate in Computer Science and Engineering from SRM Institute of Science and Technology (SRMIST), with a focus on blockchains, distributed systems, data privacy, and security, particularly in the context of social network user privacy. His current research aims to scale and extend the functionality of permissionless blockchains. He is working on protocols for atomic cross-chain transactions and adding transactional support to smart contracts, with the goal of contributing to a global asset management system built on permissionless blockchain infrastructures. Additionally, he is developing client-side caching protocols to address server-side load imbalances in large-scale distributed caching systems. His work also addresses the fault-tolerance problem in ORAM stores and focuses on building client-centric tools to preserve privacy in social networks. M.Tech. in Computer Science and Engineering, SRM Institute of Science and Technology (SRMIST). He can be contacted at email: srimanb@veltech.edu.in.

R. Sundar is associate professor in the department of Computer Science and Engineering at Vel Tech Rangarajan Dr. Sagunthala R&D Institute of Science and Technology, Chennai-600062, Tamilnadu, India. He Holds a Ph.D. degree in Computer Science and Engineering at Sathyabama University. He has published papers in International Journals and Conference proceedings. He has also attended more than 12 conferences at National and International levels. He can be contacted at email: abcesundar@gmail.com.