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Analyzing Breast Cancer Detection Using Machine Learning & Deep Learning Techniques

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Abstract: The most recent statistics show that of all cancers, cancer of the breast is the most common, killing about 900,000 individuals annually. Finding the disease early and correctly diagnosing it can increase the chances of a good result, which lowers the death rate. Early diagnosis can, in fact, prevent the disease from spreading and prevent premature victims from experiencing it. In this work, a comparison is made between advanced deep learning techniques and traditional machine learning for the analysis of breast cancer. We evaluated a deep learning model based on neural networks and traditional machine learning approaches such as Support Vector Classifier (SVC), Decision Tree, and Random Forest. Several demographic and clinical data were included in the diverse dataset of this investigation. This study compared traditional machine learning models (Random Forest, Decision Tree, SVC) with a neural network-based deep learning model in breast cancer analysis using features such as age, family history, genetic mutation, hormone therapy, mammogram results, breast pain, menopausal status, BMI, alcohol consumption, physical activity, smoking status, breast cancer diagnosis, frequency of screening, awareness source, symptom awareness, screening preference, and geographical location. SVC obtained an 86.36%, Decision Tree an 86.18%, and Random Forest an 86.00%. The deep learning model more precisely, a neural network outperformed these results with a highest 93% accuracy. To evaluate their diagnostic usefulness for breast cancer analysis, this study compares deep learning algorithms with more traditional machine learning methods. Accuracy ratings for the machine learning models were 86.00% for Random Forest, 86.18% for Decision Tree, and 88.36% for Support Vector Classifier.

Keywords: Breast Cancer; Deep Learning; Machine Learning; SVC; Neural Networks.

1. Introduction

Breast cancer is the primary cause of death for women aged 40-55 years and is increasingly prevalent in this demographic. The incidence rate for breast cancer is notably higher in women over 50 years old, with approximately 2 cases per 1,000 individuals in this age group. This condition is predominantly observed in obese women and is significantly more frequent in females compared to males. The likelihood of developing breast cancer rises with age, with very few cases occurring before the age of 20. Additionally, a carcinoma in one breast can lead to cancer in the other breast in about 4% of cases. The BRCA-1 gene is responsible for 5-10% of breast cancer cases and can be inherited from one's parents. According to the Centers for Disease Control and Prevention (CDC), breast cancer is the most prevalent cancer among women. A trustworthy source is the Centers for Disease Control and Prevention (CDC). Multiple variables significantly affect the probability of surviving breast cancer. A woman's tumor kind, and two of the most important factors are the severity of the disease and when it was diagnosed. Breast cancer refers to cancer that starts in the cells of the breast. Most breast cancers start in one of the two breast structures called lobules or ducts. Adipose tissue, a kind of fatty tissue, and fibrous connective tissue are other potential sites of breast cancer development. Uncontrolled cancer cells may spread to other parts of the breast and even to the blood vessels under the arms if they are not removed[2]. Many underlying factors can make the data less accurate. Some of the most common mistakes happen because the doctor is distracted or tired or because of the way the breasts are built. Radiologists may have trouble finding the cancerous cells because the images are often complicated, and it can also be hard to figure out what the disease is like in its early stages[3]. Computer-aided diagnosis (CAD) is used to detect breast cancer at an early stage. The whole procedure consists of a total of three steps: Firstly, identifying and pinpointing the location of the potential tumor or not. The preprocessed mammogram is used to identify cancerous cells. The characteristics of the tumor, such as its shape, size, density, weight, and texture, are then determined. On the basis of these features, it is determined whether the tumor type is benign or malignant. The X-ray was the only screening procedure formerly used to identify any kind of malignancy, including breast cancer[4]. A better result depends on screening and early diagnosis. It is important to find a lot of people in the first part so that performance can be improved. It increases the chance of living. Because of this, it is important to look at both the old and new ways of finding breast cancer for screening and diagnosis, with the goal of finding places where it could be improved. There are a number of screening tests that can find breast cancer. These include self- and professional breast exams, sonography, mammograms, MRIs, and others. Imaging methods, which make images, let the doctor look at and identify the tumor without hurting it. Most of the time, mammography is the best way to find cancer early[5]. It is important to find breast cancer early, but it is not the only thing that needs to be thought about when trying to avoid and treat it. The disease also gets worse because of things in the person's genes and the surroundings. But they aren't perfect, so you should use more than one way to figure out what's wrong. our risk of getting breast cancer can also be changed by what you eat, how much you move, and how much alcohol you drink[6].

The use of deep learning and machine learning methods to find and identify breast cancer at early stage. These algorithms can have used to find the hidden insights in data. These models mostly used to predict the presence or risk of breast cancer. This study based on predictive analysis that used machine learning and deep learning models for prediction of risk of breast cancer disease in survey data. This study is a comparison of deep learning and machine learning models.

The structure of this document is as follows: Section 1 provides an introduction to the topic. Section 2 details the literature review. Section 3 details the methodology. Section 4 presents the results and their evaluation. Section 5 describes the conclusion of this study.

2. Literature Review

One of the study developed a machine learning (ML) model for breast cancer detection there is still a need to investigate and improve several problems. One of the most common malignancies that affect women globally is breast cancer, and successful treatment depends on early diagnosis detection. The authors highlight the importance of ML techniques for breast cancer detection. This study work describes many problems still exists that need to be investigate for future work. The authors discuss the limitation of machine learning methods that need to be further analysis. They used standardized methods for data collection[7].In another study work the deep learning technology was used in conjunction with ultrasound imaging diagnosis. Using a supervised technique, the tumor zones were separated from the breast ultrasound (BUS) pictures. block-based technique for segmenting regions[8]. By creating a combination feature model based on strain elastography and the depth feature of ultrasonic imaging, the best diagnostic result was obtained. The proposed idea is mentioned in [9]. An effective approach called the noise filter network (NF-Net) was presented to address the problem of noisy labels in the training of breast cancer classification models. A CAD system was created for tumor diagnosis, as described in reference [10]. This system implemented an image fusion method that merged diverse representations of picture content and utilized ensemble techniques with various convolutional neural network (CNN) architectures on ultrasound images. This network incorporated clinically-validated breast lesion characteristics, referred to as BIRADS features, into a semi-supervised deep learning framework (SSDL) designed for specific tasks. The goal of this integration was to achieve precise diagnosis of ultrasound images, particularly when training data is limited. The study mentioned in reference [11] introduced a novel BIRADS-SSDL network. The researchers in [12] analyzed and discussed the effectiveness of several classification techniques. Employing eight distinct classification techniques and a 10-fold cross-validation approach. In the validation process, the classification approaches were used to eight distinct NCD datasets. To evaluate accuracy, the area under the curve was computed and examined for these measurements. According to the authors, the NCD datasets contain noisy data and irrelevant attributes. Despite this, K-Nearest Neighbors (KNN), Support Vector Machines (SVM), and Neural Networks (NN) showed resilience in handling the noise. Furthermore, they suggested that the problem of irrelevant attribute can be overcome by the implementation of pre-processing techniques, leading to an improvement in the accuracy rate. The researchers in [12] analyzed and contrasted the effectiveness of several classification techniques. Using a range of imaging modalities, the authors of [13] examined recent work that applied deep learning to breast cancer. Datasets, architecture, applications, and assessments were the main points of attention as they organized these investigations. They focused in on creating deep learning frameworks for MRI, ultrasound, and mammography three distinct modalities used in breast imaging. They used CNN for classification and sensitive datasets in their study. [14-15], however, the time needed to detect diseases is shortened by the deep machine learning basis models [16] It takes a lot of expertise and experience to interpret what they observe, and it takes time. Imaging methods can be very helpful when performing breast biopsies [17], Clinical Breast Examination is recommended as a straightforward diagnostic method for breast lesions based on cost, but it necessitates a clinician's expertise [18], as breast cancer is a serious disease [19-21]. Mammography systems optimize lesion to background contrast, improving the sensitivity of the approach for cancer detection, helped by computer-aided detection [22]. This interdisciplinary approach can be extended to healthcare, where blockchain can provide a secure framework for AI-driven diagnostic tools [32-33]. The paper mentions the use of AI-enabled algorithms for diagnosing, classifying, and predicting diseases, which not only improve patient health outcomes but also apply precision and personalized medicine [34]. The paper addresses challenges such as the need for large annotated datasets and the variability in disease symptoms across different plant species. These challenges are also prevalent in breast cancer detection, where large, diverse datasets are crucial for training robust models [35] .Ultrasound [23–25], MRI [26], and mammography are useful imaging technologies. Thus, imaging technologies have an indisputable role in the identification of disease [27-31]. AS it provides the volume, location and position of abnormality in breast cancer [36-39]. Convolutional neural networks are widely used in computer vision applications such as picture segmentation, object detection, and classification [40].

The writers of [41] use several machine learning techniques to suggest a natural network method to find whether a mammogram picture is of a benign, malignant, or normal breast. It looks into what. After running the simulation, researchers concluded that CNN is the best classifier because it uses morphological and filtering processes to put digital mammograms into intuitive groups. Although predicting human diseases is a very difficult task for medical professionals as well as the technologists who assist them with diagnosis and therapy. Table 1 represents the previous study findings with methodology, results and research gap.

Table 1. Summary of Findings from Prior Research

Study	Methodology	Results/Findings	Research Gaps
[7] ML Model for Breast Cancer Detection	Standardized data collection methods. Used various ML techniques like SVM, Random Forest, etc.	Highlighted the importance of ML in early breast cancer detection. Noted limitations in current ML methods for diagnosis.	Need for more robust models to handle noisy and incomplete data. Improve generalizability across diverse datasets.
[8] DL with Ultrasound Imaging	Supervised learning approach. Block-based technique for segmenting tumor	Achieved optimal diagnostic results using combined features.	Refinement needed in segmentation techniques for better precision. Address variability in ultrasound images.

	zones. Combined strain elastography and depth features.	Improved accuracy of breast cancer detection in ultrasound images.	
[9] Noise Filter [11]Network (NF-Net)	Implemented noise filtering in DL models. Integrated BIRADS features. Used a semi-supervised learning approach (SSDL).	Improved accuracy in diagnosing breast lesions from ultrasound images with limited data.	Explore advanced noise reduction techniques. Need validation on larger, more diverse datasets.
[10] CAD System for Tumor Diagnosis	Employed image fusion and ensemble techniques. Applied various CNN architectures. Used BIRADS features for semi-supervised learning.	Enhanced tumor detection through diverse image representations.	Need better integration of multimodal imaging data. Address challenges in dataset scarcity and diversity.
[11] BIRADS-SSDL Network	Developed a novel BIRADS-SSDL network. Used ensemble learning techniques. Focused on ultrasound images.	Achieved accurate diagnosis despite limited data availability.	Further work needed to improve handling of noisy labels and irrelevant features. Validation needed across different imaging modalities.
[12]Classification Techniques Analysis	Compared 8 classification techniques. Employed 10-fold cross-validation. Analyzed AUC for NCD datasets.	KNN, SVM, and NN showed robustness with noisy and irrelevant data. Suggested pre-processing to enhance accuracy.	Explore more advanced pre-processing techniques. Investigate model performance with more complex datasets.
[13]DL in Breast Imaging	Reviewed DL frameworks for MRI, ultrasound, and mammography.	Highlighted the potential of DL in improving breast cancer diagnosis	More comparative studies needed across different modalities. Address data imbalance and heterogeneity.

	Used CNN-based classification.	across imaging modalities.	
[14] ML Techniques for Mammogram Classification	Applied SVM, CNN, and Random Forest. Used morphological and filtering processes.	CNN identified as the best classifier for benign, malignant, and normal breast classification.	Further analysis needed on the impact of data quality and preprocessing. Explore additional ML techniques for improved accuracy.

3. Methodology Framework

The methodology framework of our work contain following steps

- Developed a comprehensive survey to collect relevant demographic and clinical data.
- Recruited participants from various healthcare facilities and online platforms.
- Gathered data on age, family history, genetic mutations, hormone therapy, mammogram results, breast pain, menopausal status, BMI, lifestyle factors (alcohol consumption, physical activity, smoking status), breast cancer diagnosis, screening frequency, awareness source, symptom awareness, and screening preference.
- Employed imputation techniques to fill in missing data.
- Normalized numerical features to bring them to a common scale.
- Categorical variables into numerical format using one-hot or label encoding.

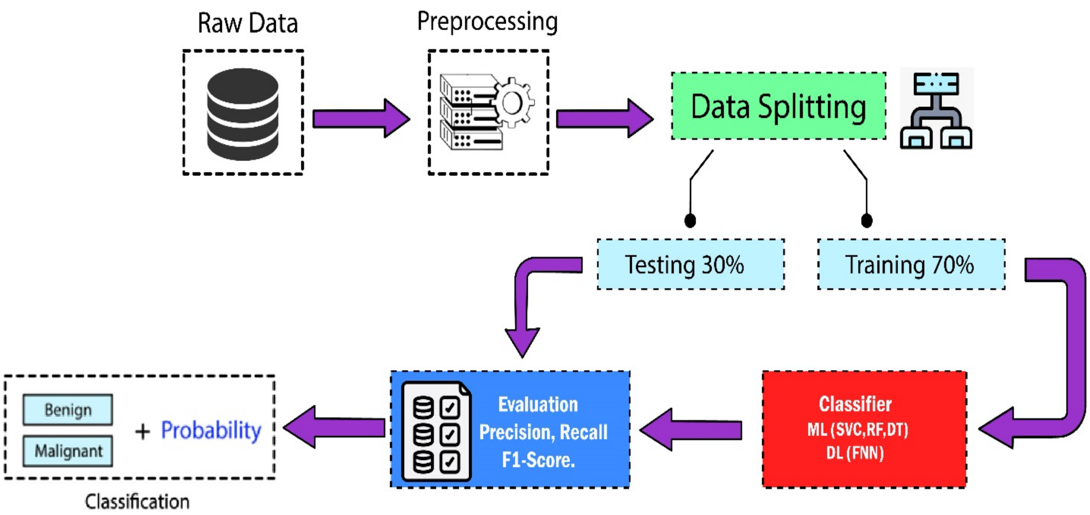

Figure 1. Deep Machine Learning Model for Breast Cancer Detection

3.1. Data Collection

We collected data through structured surveys distributed among females and conducted qualitative interviews with healthcare providers to gather detailed insights into breast cancer screening practices.

3.2. Dataset Features

The dataset features of the proposed work are presented in Table 2.

Table 2. Dataset Features

Variable	Description	Category
Age	Age of the individual	Young (<40), Middle-aged (40-60), Old (>60)
Family History	Presence of breast cancer in the family	Yes, No, Unknown

Genetic Mutation	Presence of known genetic mutations linked to breast cancer	Present, Absent, Unknown
Hormone Therapy	History of hormone therapy	Yes, No, Unknown
Mammogram Results	Results from recent mammograms	Normal, Abnormal, Unknown
Breast Pain	Presence and intensity of breast pain	Mild, Moderate, Severe
Menopausal Status	Menopausal status of the individual	Pre-menopausal, Post-menopausal, Unknown
Alcohol Consumption	Frequency and quantity of alcohol consumption	Low, Moderate, High
Physical Activity	Level of physical activity	Sedentary, Moderate, Active
Smoking Status	Smoking habits	Non-Smoker, Former Smoker, Current Smoker
Breast Cancer Diagnosis	Target variable indicating breast cancer diagnosis	Negative, Positive
Frequency of Screening	Frequency of undergoing breast cancer screening	Yearly, Biennially, Irregular/No screening
Awareness Source	Source of breast cancer awareness	Healthcare provider, Media/advertisement, Family/friends
Symptom Awareness	Awareness of breast cancer symptoms	Lump in breast, Breast pain/discomfort
Screening Preference	Preference of breast cancer screening method	Mammogram, Self-examination, Clinical examination
Geographical Location	Location of residence	Urban, Suburban, Rural

3.3. Model Selection

Proposed study is based on machine learning and deep learning models, which are described below

3.4. Traditional ML Models

The machine learning models we used in our work is described below.

3.4.1. Support Vector Classifier (SVC)

Selected for its effectiveness in binary classification tasks. SVC is widely used in machine learning for distinguishing between two classes or among multiple classes, such as classifying diseases present or not, emails as spam or not and recognizing handwritten digits.

3.4.2. Decision Tree (DT)

Chosen for its interpretability and ability to capture non-linear relationships. The decision trees provide a graphical representation of decisions and their possible consequences, making them easy to understand and interpret even for non-experts. Each decision path is explicit, which helps understand how the model makes predictions and identifies which features are most influential. Decision trees can handle classification (e.g., categorizing items) and regression (e.g., predicting numerical values) tasks, making them versatile tools in machine learning. Used for categorizing data into two or more classes, such as classifying emails as spam or not or categorizing medical images. Anomaly Detection employed to identify unusual patterns or outliers in data, crucial for fraud detection, quality control, and security monitoring.

3.4.3. Random Forest (RF)

Used for its robustness and ability to handle overfitting through ensemble learning. Random Forest is widely used for classifying data into two or more classes, such as categorizing emails as spam, predicting customer churn, or classifying images. Effective for datasets with non-linear relationships and high-dimensional features. Useful for reducing the dimensionality of datasets by selecting the most relevant features. It provides more stable and reliable predictions than individual decision trees by averaging the results from multiple trees. Random Forest can be used to impute missing values in datasets by using the predictions from multiple trees to estimate the missing data points. Random Forest can make quick predictions and handle large datasets efficiently, making it suitable for real-time applications such as recommendation systems and online advertising. Random Forest can model complex interactions between features without requiring explicit specification of these interactions, making it useful for tasks where relationships between variables are intricate.

3.5. Deep Learning Model

The deep learning model neural network is described mentioned below.

3.5.1. Neural Network (NN)

Implemented for its capability to learn complex patterns and interactions within the data. A computational model inspired by the human brain, consisting of interconnected nodes (neurons) that process information. Forms the backbone of many deep learning models, capable of learning from data and making predictions. Able to capture and model complex, non-linear relationships in data. Applicable to various tasks like image recognition, speech processing, and game playing.

Key Components of Neural Network

The key components of the neural network are described below.

Neurons

Basic Units

The fundamental units of computation, similar to biological neurons, responsible for processing and transmitting information.

Activation Functions

Functions like ReLU, sigmoid, or tanh applied to the input to introduce non-linearity.

Layers

The layer of neural network is described below

Input Layer

The subsequent layers are used to pass and receive the raw data.

Hidden Layers

Intermediate layers where computations and feature transformations occur.

Output Layer

Produces the final output or prediction of the network.

Type of Neural Network

Feedforward Neural Networks (FNNs)

Information flows in one direction from input to output, without looping back. Used for tasks like regression and simple classification. Structure and framework of neural network is depicted in Figure 2.

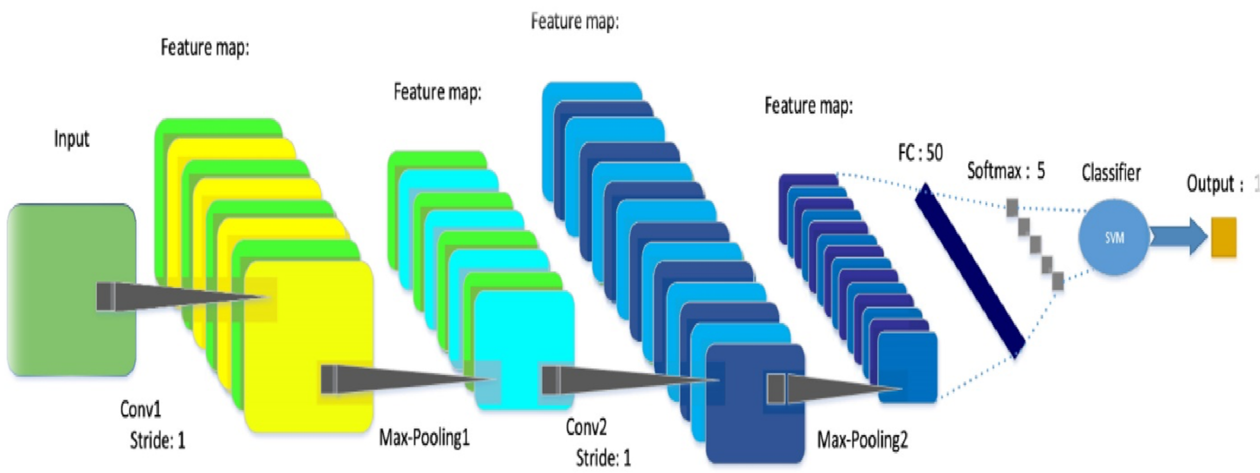

Figure 1. Neural Network Framework

4. Results

Results and Finding including precision, recall and f1 score and accuracy are mentioned in below Table 3. SVC achieved an accuracy of 88.36%. Decision Tree Reached an accuracy of 86.18%. The random forest classifier obtained an accuracy of 86.90%. Neural Network Outperformed with a highest accuracy of 93%.

Table 3. Results & Findings

Classifier	Accuracy	Precision (%)	Recall (%)	F1 Score (%)
Decision Tree	86.18	0.78	0.77	0.77
Random Forest	86.90	0.79	0.77	0.78
SVC	88.36	0.85	0.75	0.78
Neural Network	93.0	0.98	0.87	0.92

It is prevalent in results that Neural Network Obtained Highest Precision, Recall, and F1 Score.

A confusion matrix is a tabular representation of actual versus predicted classifications by a machine learning model. Used to evaluate the performance of classification models by showing the correct and incorrect predictions across different classes. Provides detailed insights into the performance of a classifier beyond simple accuracy. Helps identify specific types of errors made by the model, such as false positives and false negatives. Table 4 depicts confusion matrix.

Table 4. Confusion Matrix

	Predicted Positive	**Predicted Negative**
Actual Positive	True Positive	False Negative
Actual Negative	False Positive	True Negative

Our work comparison with other authors' work is mentioned in table 5 below.

Table 5. Comparative Analysis

Aspect	Other Authors' Research Gap	Our Work Comparison
Research Focus	Limited ML vs. DL comparison	Comprehensive ML and DL comparison
Data Analysis	Insufficient feature engineering, validation, and outlier detection	Rigorous analysis including feature engineering, validation, and outlier detection
Decision Support	Lack of real-world challenges and clinical validation	Addressed implementation challenges and clinical validation
Comparative	Focus on metrics, lacking efficiency and interpretability	Compared ML and DL with metrics, efficiency, and interpretability

Framework	No scalability or clinical workflow integration	Enhanced framework with scalability and workflow compatibility

5. Conclusion

The neural network achieved the highest accuracy of 93%, surpassing all other models in performance. This study rigorously evaluated the importance of each feature in predicting breast cancer outcomes, providing an in-depth interpretation of the results to identify key predictors of breast cancer diagnosis. The findings demonstrated that the neural network-based deep learning model significantly outperforms traditional machine learning models in breast cancer analysis. This research highlights the potential for integrating deep learning and machine learning techniques into clinical practice, promising substantial improvements in the early diagnosis and treatment of breast cancer. The study underscores the critical role of advanced algorithms in enhancing diagnostic accuracy and patient outcomes. Furthermore, the results indicate that these technological advancements could lead to the development of more precise and personalized treatment plans. Future research will focus on optimizing feature selection and utilizing large datasets with various machine learning and deep learning methods to further refine predictive accuracy and clinical applicability. By continuously improving these models, the aim is to support clinicians in making more informed decisions, ultimately improving the prognosis and management of breast cancer.

Conflicts of Interest: The authors declare no conflict of interest

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