

Machine Learning Based Breast Cancer Detection and Recognitions Techniques in IoT Environment

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Abstract: Breast cancer is among the worst forms of the disease and one of the major causes of death worldwide. If Breast cancer can be detected and treated before it has spread, it will kill fewer people. Visual inspection is still the best method for diagnosing Breast cancer, despite its flaws. Some researchers believe that deep learning-based technology might help dermatologists detect breast malignancies earlier. Current studies that have used deep learning to categorize Breast cancer are the topic of this literature review. We also detail the most popular DL algorithms and datasets for spotting Breast cancer.

Keywords: Machine learning, IoT, Breast cancer detection

1. Introduction

1.1 Machine learning

Field of ML is rapidly expanding, allowing computers to automatically acquire new skills by analyzing large amounts of data. Machine learning is practice of utilizing algorithms to construct mathematical models and predict future outcomes based on collected data and information [1-3]. Image recognition, voice recognition, email filtering, Facebook auto-tagging, recommender systems, and many more applications are now making use of this technology [4, 5].

1.2 Breast Cancer Detection

Breast cancer detection is a critical component of women's healthcare, aimed at identifying the presence of cancerous cells within the breast tissue at an early and treatable stage. This process encompasses various methods and

technologies. Self-examination is encouraged to empower individuals to monitor their own breast health and report any changes to healthcare providers. Clinical breast examinations performed by healthcare professionals involve physical assessments to detect abnormalities or unusual changes in the breasts.

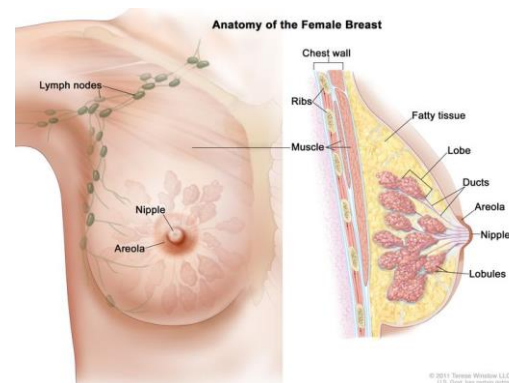


Fig 1. Breast cancer Screening

Mammography, a widely used screening tool, employs X-ray imaging to identify potential tumors or irregularities. Advanced techniques like breast ultrasound and magnetic resonance imaging (MRI) provide detailed images for further evaluation, especially in cases where mammograms may not provide sufficient clarity. Biopsies are employed when suspicious areas are found, involving the removal and analysis of tissue samples. In cases with a strong family history, genetic testing may help assess the risk of developing breast cancer. Early detection through these methods remains pivotal in improving breast cancer treatment outcomes and saving lives. Regular consultations with healthcare providers are essential to establish an effective screening plan tailored to an individual's unique circumstances.

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1.3 Machine learning based Breast cancer detection.

AI for breast cancer diagnosis via machine learning is a significant use case. Images of Breast lesions are analyzed using ML algorithms & DL methods to aid in diagnosis of Breast cancer at an earlier stage. Here's a rundown of how everything falls into place:

- **Data Collection:** Acquiring a big and varied collection of photos of Breast lesions is the first stage in developing a Breast cancer detection system [11-14].
- **Data Preprocessing:** In order to facilitate analysis, the gathered photos are preprocessed.
- **Feature Extraction:** Predictions made by machine learning models need the inclusion of relevant information [15-20].
- **Model Training:** A machine learning model is then developed using the extracted features.
- **Validation and Evaluation:** An independent, performance and accuracy of the trained model are evaluated using a novel dataset.
- **Deployment:** When the model is ready, it may be used in a healthcare system or as a standalone program.

1.4 Recognition techniques in IoT for Breast cancer

IoT can be harnessed for breast cancer recognition and early detection through various techniques and applications. These techniques involve the use of IoT devices and technologies to collect and analyze data related to breast health. Here are some recognition techniques in IoT for breast cancer:

1. **Wearable Devices and Sensors:** Wearable IoT devices, such as smart bras or patches equipped with sensors, can continuously monitor and collect data related to breast temperature, texture, or breast changes.
2. **Remote Monitoring:** IoT-enabled breast health monitoring systems can remotely track and analyze breast health data.
3. **Imaging and Scanning Devices:** IoT can enhance the capabilities of breast imaging devices.
4. **Machine Learning and AI:** IoT devices can leverage machine learning and artificial intelligence algorithms to process and analyze breast health data.
5. **Telemedicine and Teleconsultations:** IoT-enabled telemedicine platforms allow patients to connect with healthcare providers remotely.
6. **Predictive Analytics:** IoT-driven predictive analytics models can assess a person's risk of developing breast cancer based on historical data, genetics, and lifestyle factors.
7. **Data Privacy and Security:** Given the sensitivity of health data, IoT systems for breast cancer detection

must prioritize robust data privacy and security measures to ensure the confidentiality and integrity of patient information.

2. Literature Review

B. Sahu et al. (2023) introduced the breast cancer prediction model utilized [1]. P. Manikandan et al. (2023) reviewed the machine learning architecture for the SEER breast cancer classification [2]. A. Alshehri et al. (2023) predicted the presence of breast cancer using machine learning [3]. A. Pati et al. (2023) focused on the IoT and deep transfer learning enabled by fog computing for breast cancer diagnosis [4]. A. Sivasangari et al. (2022) introduced AI and connected devices to screen for breast cancer [5]. P. Malathi et al. (2022) did research on IoT-based mammography screening for breast cancer in women [6]. N. Behar et al. (2022) reviewed a new method for identifying and categorized breast cancer [7]. S. Salvi et al. (2021) introduced early detection of breast cancer applying ML with IoT techniques [8]. A. Sood et al. (2018) presented neural networks for the diagnosis of breast cancer [9]. S. Ekici et al. (2020) reviewed the thermography with CNN for the detection of breast cancer [10]. D. Singh et al. (2020) introduced the image thermography's historical, contemporary, and future use in the diagnosis of breast cancer at an early stage [11]. M. Abdaret al. (2019) looked the precise diagnosis of breast cancer, use the CWV-BANN-SVM ensemble learning classifier [12]. D. A. Omondigbe et al. (2019) focused on the methods for classification of breast cancer using ML with WDBC Dataset, this study will examine SVM, ANNs, and NBs [13]. P. Jasbi et al. (2019) introduced the targeted plasma metabolomics for the diagnosis of breast cancer. In this work, they describe a targeted metabolic profiling technique using LC-MS/MS to find metabolic marker candidates for early and advanced breast cancer [14]. M. Swellam et al. (2019) presented the breast cancer diagnosis and the role of circulate micrnas[15]. N. Liu et al. (2019) reviewed the development of a revolutionary intelligent classification model for the detection of breast cancer. Ultimately, they hoped that our study would help clinical doctors make more informed judgements in the future by applied our findings to a real-world diagnostic system [16].

3. Problem Statement

Implementing ML-based breast cancer detection and recognition techniques within IoT environment presents a promising avenue for early diagnosis and monitoring. However, it also brings forth a set of intricate challenges. One of the foremost concerns is data privacy and security, as these systems collect sensitive medical information. Safeguarding patient data from unauthorized access and ensuring compliance with healthcare regulations is of

paramount importance. Moreover, quality & quantity of data pose significant hurdles, with the need for diverse, well-annotated datasets that encompass various breast conditions and demographics. IoT's real-time requirements necessitate optimizing machine learning models for low latency and resource-efficient processing, which can be especially challenging given the resource constraints of IoT devices. Ensuring robustness to environmental factors, model interpretability, and scalability further compound the complexities.

4. Proposed Work

The existing model is shown in the proposed work's training phase. An experimental breast cancer dataset is being considered for use in training. Images in the dataset are now being resized and compressed as part of the dataset's preprocessing.

After pictures have been compressed, edge detection is then performed. After pictures have been preprocessed,

they are split into a detectable edge portion and a non-detectable edge portion. In order to acquire a more precise number, researchers have suggested a hybrid ensemble model that takes into account both the CNN model and the Resnet50 model. CNNs are the deep learning technology used for labelling images. To determine which CNN model would be most effective for tumour classification in images of breast cancer, we conducted the present investigation. We were successful in our predictions because we trained a CNN. In this study, we introduce a hybrid model, which we call the ResNet50 model, for classifying images of breast cancer. Even though previous research used ensemble models that included of cnn and vgg 16, not much consideration was put into enhancing performance. There is potential for improvement in the efficiency with which training, testing, and validation may be completed, despite the fact that these research did assist increase accuracy.

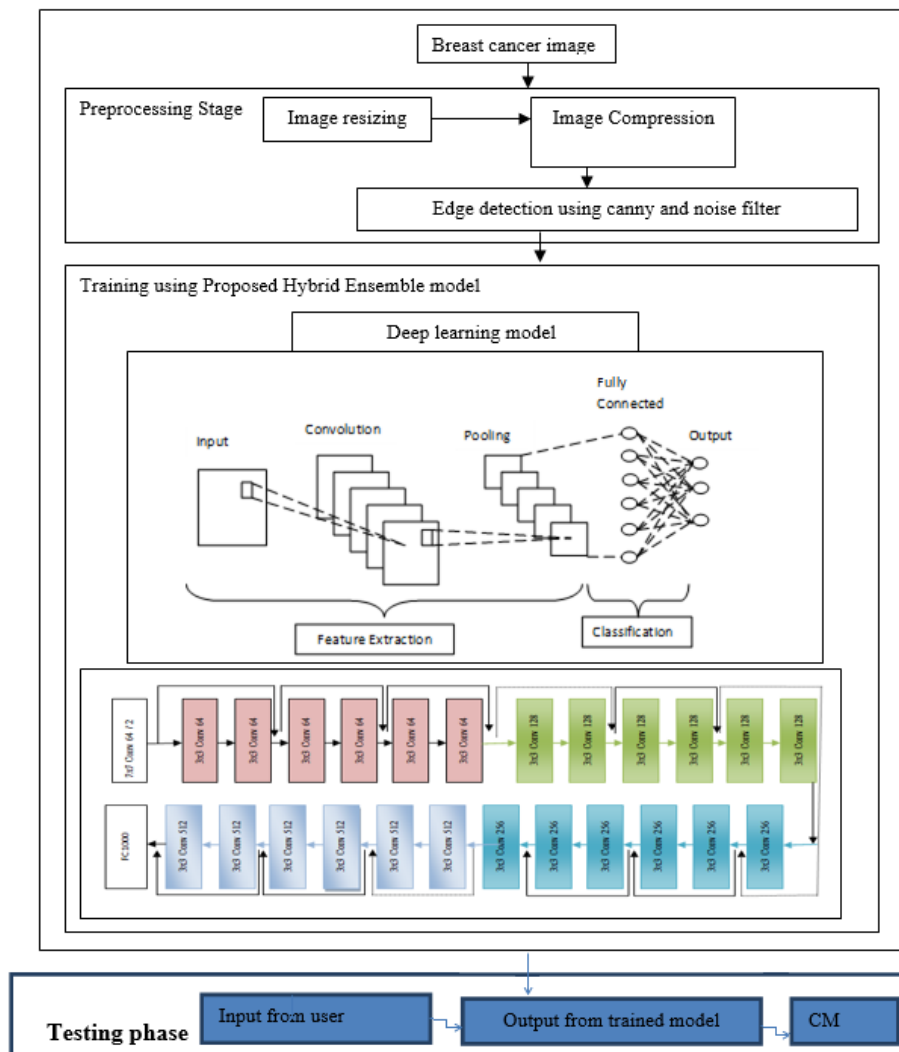


Fig 2. Flow chart of implementation of Proposed Work

5. Result and Discussion

Time spent simulating the process of finding breast cancer. Comparisons of accuracy and performance have been made to guarantee that the suggested model is of appropriate quality. The recall, precision, accuracy, & F1-score of a simulated deep learning-based categorization are shown. This was done so that the suggested model might be trusted.

5.1 Simulation of conventional VGG16 based ensemble model

Images of breast cancer have been simulated and categorized using an ensemble of VGG16 and a CNN model. Data used for training & for testing has been divided 80:20. Accuracy during training and validation are shown in the following figure.

Epoch	Train Loss	Train Acc	Test Loss	Test Acc
Epoch 01/25 - Train Loss: 2.1882 - Train Acc: 98.8088 - Test Loss: 1.8529 - Test Acc: 98.9872				
Epoch 02/25 - Train Loss: 2.1882 - Train Acc: 98.8088 - Test Loss: 1.8529 - Test Acc: 98.9872				
Epoch 03/25 - Train Loss: 2.1882 - Train Acc: 98.8088 - Test Loss: 1.8529 - Test Acc: 98.9872				
Epoch 04/25 - Train Loss: 2.1882 - Train Acc: 98.8088 - Test Loss: 1.8529 - Test Acc: 98.9872				
Epoch 05/25 - Train Loss: 2.1882 - Train Acc: 98.8088 - Test Loss: 1.8529 - Test Acc: 98.9872				
Epoch 06/25 - Train Loss: 2.1882 - Train Acc: 98.8088 - Test Loss: 1.8529 - Test Acc: 98.9872				
Epoch 07/25 - Train Loss: 2.1882 - Train Acc: 98.8088 - Test Loss: 1.8529 - Test Acc: 98.9872				
Epoch 08/25 - Train Loss: 2.1882 - Train Acc: 98.8088 - Test Loss: 1.8529 - Test Acc: 98.9872				
Epoch 09/25 - Train Loss: 2.1882 - Train Acc: 98.8088 - Test Loss: 1.8529 - Test Acc: 98.9872				
Epoch 10/25 - Train Loss: 2.1882 - Train Acc: 98.8088 - Test Loss: 1.8529 - Test Acc: 98.9872				
Epoch 11/25 - Train Loss: 2.1882 - Train Acc: 98.8088 - Test Loss: 1.8529 - Test Acc: 98.9872				
Epoch 12/25 - Train Loss: 2.1882 - Train Acc: 98.8088 - Test Loss: 1.8529 - Test Acc: 98.9872				
Epoch 13/25 - Train Loss: 2.1882 - Train Acc: 98.8088 - Test Loss: 1.8529 - Test Acc: 98.9872				
Epoch 14/25 - Train Loss: 2.1882 - Train Acc: 98.8088 - Test Loss: 1.8529 - Test Acc: 98.9872				
Epoch 15/25 - Train Loss: 2.1882 - Train Acc: 98.8088 - Test Loss: 1.8529 - Test Acc: 98.9872				
Epoch 16/25 - Train Loss: 2.1882 - Train Acc: 98.8088 - Test Loss: 1.8529 - Test Acc: 98.9872				
Epoch 17/25 - Train Loss: 2.1882 - Train Acc: 98.8088 - Test Loss: 1.8529 - Test Acc: 98.9872				
Epoch 18/25 - Train Loss: 2.1882 - Train Acc: 98.8088 - Test Loss: 1.8529 - Test Acc: 98.9872				
Epoch 19/25 - Train Loss: 2.1882 - Train Acc: 98.8088 - Test Loss: 1.8529 - Test Acc: 98.9872				
Epoch 20/25 - Train Loss: 2.1882 - Train Acc: 98.8088 - Test Loss: 1.8529 - Test Acc: 98.9872				
Epoch 21/25 - Train Loss: 2.1882 - Train Acc: 98.8088 - Test Loss: 1.8529 - Test Acc: 98.9872				
Epoch 22/25 - Train Loss: 2.1882 - Train Acc: 98.8088 - Test Loss: 1.8529 - Test Acc: 98.9872				
Epoch 23/25 - Train Loss: 2.1882 - Train Acc: 98.8088 - Test Loss: 1.8529 - Test Acc: 98.9872				
Epoch 24/25 - Train Loss: 2.1882 - Train Acc: 98.8088 - Test Loss: 1.8529 - Test Acc: 98.9872				
Epoch 25/25 - Train Loss: 2.1882 - Train Acc: 98.8088 - Test Loss: 1.8529 - Test Acc: 98.9872				

Fig 3 Training and validation process of conventional VGG16

Below, we give the 25-epoch simulated results for training and validation accuracy. The following graph guarantees a validation and training accuracy of less than 99%.

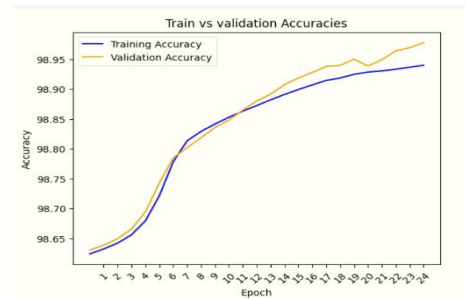


Fig 4 Training and validation accuracy

Below, we give the 25-epoch simulated results for training and validation accuracy. The following graph guarantees a validation and training accuracy of less than 99%.

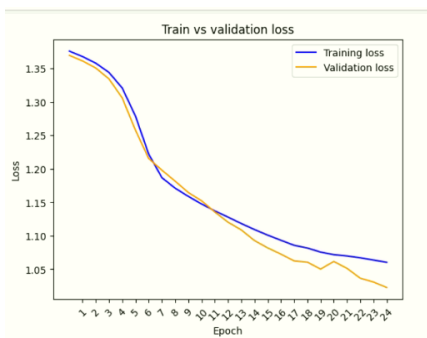


Fig 5 Training and validation Loss

5.2 Simulation of Proposed work

The proposed approach integrates Resnet with a CNN that takes edge information into account. The suggested model is trained and validated by further simulation.

Epoch	Train Loss	Train Acc	Test Loss	Test Acc
Epoch 01/25 - Train Loss: 0.1882 - Train Acc: 99.8088 - Test Loss: 0.1529 - Test Acc: 99.9872				
Epoch 02/25 - Train Loss: 0.1882 - Train Acc: 99.8088 - Test Loss: 0.1529 - Test Acc: 99.9872				
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Epoch 10/25 - Train Loss: 0.1882 - Train Acc: 99.8088 - Test Loss: 0.1529 - Test Acc: 99.9872				
Epoch 11/25 - Train Loss: 0.1882 - Train Acc: 99.8088 - Test Loss: 0.1529 - Test Acc: 99.9872				
Epoch 12/25 - Train Loss: 0.1882 - Train Acc: 99.8088 - Test Loss: 0.1529 - Test Acc: 99.9872				
Epoch 13/25 - Train Loss: 0.1882 - Train Acc: 99.8088 - Test Loss: 0.1529 - Test Acc: 99.9872				
Epoch 14/25 - Train Loss: 0.1882 - Train Acc: 99.8088 - Test Loss: 0.1529 - Test Acc: 99.9872				
Epoch 15/25 - Train Loss: 0.1882 - Train Acc: 99.8088 - Test Loss: 0.1529 - Test Acc: 99.9872				
Epoch 16/25 - Train Loss: 0.1882 - Train Acc: 99.8088 - Test Loss: 0.1529 - Test Acc: 99.9872				
Epoch 17/25 - Train Loss: 0.1882 - Train Acc: 99.8088 - Test Loss: 0.1529 - Test Acc: 99.9872				
Epoch 18/25 - Train Loss: 0.1882 - Train Acc: 99.8088 - Test Loss: 0.1529 - Test Acc: 99.9872				
Epoch 19/25 - Train Loss: 0.1882 - Train Acc: 99.8088 - Test Loss: 0.1529 - Test Acc: 99.9872				
Epoch 20/25 - Train Loss: 0.1882 - Train Acc: 99.8088 - Test Loss: 0.1529 - Test Acc: 99.9872				
Epoch 21/25 - Train Loss: 0.1882 - Train Acc: 99.8088 - Test Loss: 0.1529 - Test Acc: 99.9872				
Epoch 22/25 - Train Loss: 0.1882 - Train Acc: 99.8088 - Test Loss: 0.1529 - Test Acc: 99.9872				
Epoch 23/25 - Train Loss: 0.1882 - Train Acc: 99.8088 - Test Loss: 0.1529 - Test Acc: 99.9872				
Epoch 24/25 - Train Loss: 0.1882 - Train Acc: 99.8088 - Test Loss: 0.1529 - Test Acc: 99.9872				
Epoch 25/25 - Train Loss: 0.1882 - Train Acc: 99.8088 - Test Loss: 0.1529 - Test Acc: 99.9872				

Fig 6 Training and validation process of proposed work

Below, we give the 25-epoch simulated results for training and validation accuracy. The following graph guarantees a validation and training accuracy of above 99%.

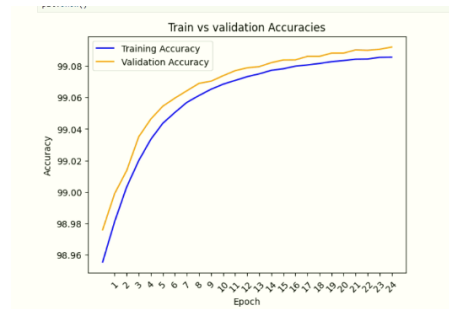


Fig 7 Training and validation accuracy

25 iterations of training and validation loss are shown below. Error rates in training and validation below 1% are assured using the following formula.

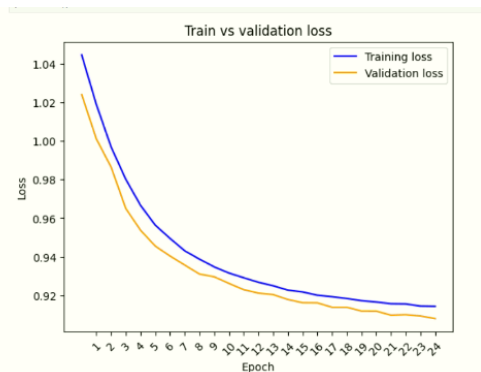


Fig 8 Training and validation Loss

5.3 Comparative Analysis of Accuracy

Scatter graphs showing the difference between accuracy parameters of traditional VGG-CNN-based model & suggested RESNET-CNN-based model were generated as follows.

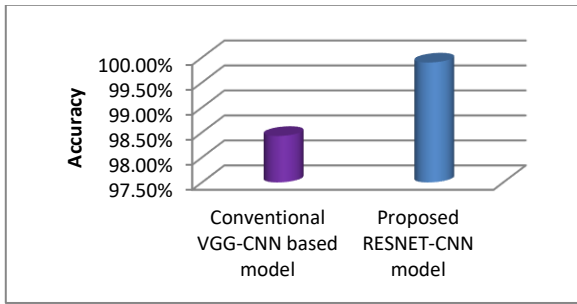


Fig 9 Comparison of accuracy for Conventional model to Proposed -CNN model

6. Conclusion and Future Scope

Last but not least, IoT-based breast detection and identification approaches based on ML are a game-changer for the field of dermatological early diagnosis and surveillance. These systems hold the potential to make breast cancer diagnosis faster, more accessible, and more accurate. However, they come with a set of complex challenges, including data privacy, data quality, real-time processing, resource constraints, interpretability, and regulatory compliance, which must be meticulously addressed to ensure their effectiveness and safety. Future scope for these technologies is highly promising. As IoT infrastructure becomes more commonplace and ML algorithms continue to improve, we can anticipate several advancements. Firstly, improved algorithms and models will likely enhance accuracy and generalization across diverse breast types and conditions.

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