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Research Article

# IoT-Integrated CNN Deep Learning for Automated Breast Cancer Detection and Diagnosis

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**Abstract:** Breast cancer continues to be a primary cause of death in women, requiring prompt and accurate diagnosis to enhance treatment results. Traditional diagnostic techniques depend on manual assessment, which leads to possible misclassification, significant inter-observer variability, and delays in decision-making. Current deep learning models, including CNNs, frequently experience feature loss, gradient declining and restricted adaptability to real-time data. To overcome these restrictions, we present a hybrid framework combining CNN and ResNet that merges deep learning-based feature extraction with real-time data collecting from IoT devices. The proposed approach utilises CNNs for preliminary feature extraction, ResNet for hierarchical learning with residual connections, and IoT for real-time patient monitoring and automatic notifications. The dataset undergoes preprocessing through normalisation, augmentation, and histogram equalisation to improve image quality and learning efficacy. The model is trained with cross-entropy loss and the Adam optimiser, guaranteeing stability and excellent performance. The evaluation results indicate a substantial enhancement compared to baseline models, with an accuracy of 97, an F1-score of 95.3, and a recall rate of 96.4%, exceeding traditional deep learning (90 accuracy) and CNN-based models (80% accuracy). The suggested model similarly minimises mistakes, with RMSE and MSE values declining to 1.2 and 1.6, respectively, signifying reduced misclassification rates. The inclusion of IoT facilitates instantaneous data transmission with little latency, hence improving clinical decision-making and minimising diagnostic delays. This advanced system facilitates automated and precise breast cancer detection, providing an innovative method for early diagnosis, optimised treatment planning, and improved patient outcomes, while ensuring data privacy and security through encryption and commitment to healthcare regulations.

**Keywords:** Breast Cancer Detection, Health Automation, Enhanced Cancer Classification, Convolutional Neural Network (CNN), Residual Neural Network (ResNet), Internet of Things (IoT)

## Introduction

Cancer is considered a major health challenge for humanity. Millions of people lost their lives in mean course of time due to cancer. A tumour which can grow and spread to the other tissues is known as Cancer.

Tumour is divided into two types, namely benign tumour and malignant tumour. Benign tumour cannot spread to the other tissues. Malignant tumour is cancerous and spreads to other tissues through the blood and lymph. Carcinogens are the particles responsible for the formation of cancer. Chemotherapy is the general treatment given to the cancer patients. There is no treatment for certain types of cancer. Cancer is divided into stages from non-invasive stage to metastatic stage where the cells start to multiply rapidly. Survival rate varies according to the stages. Early diagnosis is the most important factor in the treatment for cancer. Sometimes death occurs due to the wrong prediction of cancer. Women are affected by breast cancer on large scales. The survival rate for breast cancer varies upon different regions and the stages. The women above the age group of 50 are more vulnerable to breast cancer than the younger women. Unhealthy lifestyle and previous breast cancer history of the family members are the major factors in the development of breast cancer. Breast mammography is the traditional method used for the detection of breast cancer. The accuracy of mammography for younger women is said to be low than the older women. To overcome this many researchers tried to introduce health automation in detection of breast cancer. Health automation is the process of syncing health care with the technologies. As the traditional methods are inefficient in the cancer detection, health automation with new technologies is introduced for the detection of all kinds of cancer. Radiologists consider these health automation techniques as secondary method of cancer detection as it may also give false predictions. In this research we have used IoT smartly integrated with CNN deep learning to overcome the issues of the previous technologies and provide accurate results than the traditional method for breast cancer detection. Deep learning is an advanced methodology in machine learning. IoT is the connection between devices which we use regularly via the internet to enhance the comfort for the individuals using it. Combining these two technologies will allow us to create a revolution in the breast cancer detection and health automation. Research (Khan et al., 2019) presents an IoMT-based framework for the early identification of breast cancer utilising machine learning and artificial intelligence. It utilises Evolutionary Algorithms for feature selection and an ensemble classifier, attaining 98% accuracy in identifying cancer cells in breast cytology images. Although progress in AI-assisted diagnostics, current CNN-based systems frequently encounter issues with gradient vanishing and constrained generalisation. Most previous studies either fail to integrate with real-time data platforms such as IoT or do not evaluate their models inside clinical procedures. This work addresses the gap by combining ResNet-enhanced CNN with IoT-based monitoring to achieve improved diagnosis accuracy and real-time automation. Industry 4.0 is transforming the healthcare sector in very positive way, it replaces and automates the reputative process with minimum human interactions in a places like caregiving homes (Pang et al., 2018). Natural language processing (NLP) uses 100 operative reports and 100 pathological reports and splits them into 2 sets namely the test sets and training sets to obtain the accuracy in both reports which happens to be 91.9% in operative and 95.4% in pathology, this nearly matches the human accuracy (Chen et al., 2022). Ak (2020) compares Data visualization and Machine learning (ML) diagnostic techniques and shows that linear regression model yields 98.1% accuracy and revealed the potential for new and enhanced outcomes in the detection of breast cancer.

### *Literature Survey*

Recent research contributed to predict Invasive Ductal Carcinoma (IDC) a kind of breast cancer by using CNN model by providing a simple interface for the usage of medical professionals and yielded a high accuracy in the detection of breast cancer (Dequit and Nafa, 2024). Another study aimed to develop an Artificial Intelligence (AI) technology by using Deep Learning model for the automation in detection of breast cancer which outperforms the traditional methods of detection and the Computer-Aided Detection (CAD) systems (Díaz et al., 2024). Popkova and Sergi (2022) created new datasets and an interactive platform for big data analysis in digital public health, especially in response to viral threats like as COVID-19. It combines IoT with AI for intelligent health management, rectifying limitations in technology's practical influence on public health systems. Chelladurai and Pandian (2022) suggested a blockchain-enabled smart e-health system for secure and efficient health data exchange among providers. It guarantees data integrity, fast access, and patient control over electronic health records through the use of smart contracts and cryptographic hash functions. Performance is assessed using trials that measure efficiency and latency. Bai et al. (2021) examined the integration of deep learning in breast cancer screening by Digital Breast Tomosynthesis (DBT). It analysed the rise of DBT as the standard, the contribution of AI in diagnostic imaging, current research on AI-assisted DBT interpretation, and challenges to clinical adoption. The paper examines AutoML's function in healthcare, highlighting its capacity to assist professionals in utilising machine learning without requiring significant knowledge. Waring et al. (2020) examines various researches, highlighting AutoML's capacity to achieve expert-level performance while simultaneously addressing growing issues. Further implementation necessitates additional study and inclusion into medical practices. Saha et al. (2018)

explored IoT-enabled real-time health monitoring, facilitating remote patient monitoring through sensors and automated notifications. It reduces human error, maximises space efficiency, and includes alarm-based medication reminders and alerts for significant health alterations, so improving patient care in both home and hospital settings. Singh and Singh (2020) discussed CAD in breast thermography, highlighting its use as a non-invasive alternative to mammography. It explores image processing techniques, machine learning applications for enhanced accuracy and the potential of numerical simulation to minimise false positives, recommending for future AI developments in real-time diagnosis. Lotter et al. (2021) presented an annotation-efficient deep learning model for breast cancer diagnosis, attaining high precision in mammography classification and DBT. It improves early detection, generalises across the population, and surpasses radiologists, hence enhancing screening precision and accessibility worldwide. Rodríguez-Ruiz et al. (2019) compared the breast cancer detection performance of radiologists with and without the assistance of AI. AI assistance enhanced accuracy (AUC: 0.89 vs. 0.87), increased sensitivity (86% vs. 83%), and indicated a potential for increased specificity, all without extending reading time, so demonstrating AI’s medical value in mammography. Charan et al. (2018) analysed deep learning, particularly CNN, for breast cancer diagnosis utilising the MIAS mammogram dataset. Positive results highlight its effectiveness in distinguishing normal from abnormal cases enabling further improvement of CNN architectures and pre-trained models to enhance accuracy in medical imaging applications. This review evaluates improvements in artificial intelligence for breast cancer detection via digital mammography and tomosynthesis. It compares deep learning methods with traditional CAD systems, focussing AI's enhanced precision and future medical significance. Sechopoulos et al. (2021) discussed solutions and challenges associated with the integration of AI into practical screening operations. Wang (2017) highlighted developments in the detection of early-stage breast cancer, emphasising biosensors, biomarkers, and microwave imaging as cost-effective and fast alternatives to traditional screening techniques. It indicates current advancements in breast diagnostics, highlighting the future potential of microwave imaging for improved early detection. Mambou et al. (2018) reviewed breast cancer detection methods, focussing on the limitations of mammography and investigating infrared digital imaging. The text discusses the function of CAD and deep learning in enhancing diagnostic accuracy and presents a comparative analysis of detection methodologies utilising sophisticated computer vision and AI models. Bazazeh and Shubair (2016) compared three machine learning methodologies SVM, Random Forest, and Bayesian Networks, for breast cancer detection utilising the Wisconsin dataset. It evaluates their performance for accuracy, recall, precision, and ROC area, providing insights into machine learning-based early diagnostic tools. Dinesh and Sudhaman (2016) introduced a real-time image processing system based on IoT and enabled by Li-Fi, utilising a 32-bit ARM processor. The study examines the integration of Li-Fi for high-speed, secure communication, focussing on its applications in traffic monitoring, medical imaging, and biometric security, which enhances connectivity and automation in IoT systems. The review covers recent research on image processing methods that improve security, privacy, and safety in IoT applications. It evaluates techniques that secure image-related data before transmission, resolving issues in feature extraction and information retrieval. Al-Ghaili et al. (2023) presents a detailed architecture outlining effective image processing methods for IoT security. Kapoor et al. (2016) studied the integration of IoT and image processing for agricultural purposes, particularly in recognising environmental or chemical variables influencing the growth of plants. An IoT sensing network gathers essential environmental data and leaf photos, subsequently analysed by histogram algorithms in MATLAB to identify possible growth barriers. Siddiqui et al. (2021) presents a cloud-based deep learning model for the Internet of Medical Things (IoMT) designed for detecting breast cancer stages, demonstrating great accuracy in identifying different carcinoma forms. The method improves early diagnosis, supports current screening techniques, and may decrease breast cancer mortality by intelligent and efficient detection. Suresh et al. (2019) evaluates the limitations of mammography screening through the application of image processing algorithms to improve cancer detection. Segmentation reduces unnecessary areas, enhancing feature estimate. The proposed classifier, which combines decision trees and neural networks, outperforms conventional methods, ensuring higher diagnostic precision. Yu et al. (2017) improved image classification by utilising (CNNs) and including multi-layer features. A mapping function balances semantic and detail-oriented features, enhancing fine-grained image similarity. Studies indicate enhanced retrieval efficiency relative to single-layer features and direct concatenations. Wu et al. (2019) focused on the balance between depth and breadth in residual networks, showing that relatively thin networks can achieve performance comparable to deeper models. Pre-trained models enhance Fully Convolutional Networks (FCNs) for semantic segmentation, attaining competitive outcomes across various benchmark datasets. Suzuki (2017) reviews the influence of deep learning on medical imaging, focussing its transition from feature-based machine learning to direct image analysis. This analysis contrasts the principal models, MTANN and CNN, highlighting the efficiency and excellence of deep learning in computer-aided diagnostics and radiomics applications. Wang et al. (2017) introduced UIE-Net, a CNN-based framework for improving underwater images, targeting colour distortion and visibility loss. It employs a unified training methodology for colour correction and haze removal, employing synthetic datasets for achieving enhanced performance across various underwater environments. This research explores deep learning techniques for the identification of colorectal cancer using ResNet-18 and ResNet-50 architectures. The findings by Sarwinda et al. (2021) indicate that ResNet-50 surpasses ResNet-18 in accuracy, sensitivity, and specificity, attaining over 80% accuracy and 87% sensitivity, so proving its dependability for biological image analysis. Recent models such as Vision Transformers (ViT), EfficientNet, and U-Net have demonstrated encouraging outcomes in medical image categorisation. However, their computational complexity and restricted interoperability with real-time IoT systems present obstacles. Our CNN-ResNet-IoT hybrid achieves a balance between performance and practical implementation by enhancing learning efficiency and minimising latency.

## *Proposed System*

A wide variety of technology is employed for breast cancer detection and health automation. Health automation is essential in our rapidly evolving environment. New sensors are being integrated into everyday devices to track individuals' health. In today's society, many individuals neglect their physical well-being; thus, the integration of medical sensors with technology is an essential factor to this problem.

Breast cancer incidence is increasing, and conventional diagnostic technologies often lack precision. The introduction of health automation in breast cancer detection is essential to decrease mortality rates among women. The proposed method integrates a CNN-ResNet-IoT hybrid model to improve breast cancer detection and health automation. It employs deep learning for feature extraction from histology images, utilising ResNet's residual learning to enhance accuracy. The integration of IoT facilitates real-time monitoring, improving the system's adaptability through automated data collecting and cloud-based processing. The CNN layers detect essential picture patterns, whereas IoT connectivity facilitates uninterrupted patient monitoring. Data preprocessing methods, including normalisation, augmentation, and histogram adjustment, enhance image quality, facilitating effective learning. This advanced framework assists radiologists in precise cancer identification, promoting early diagnosis, reducing manual labour, and enabling prompt medical measures. The flow chart for the proposed system is given in Figure 1 shown the system employs a MQTT-based protocol for efficient communication between edge devices and the cloud server. Real-time images gathered by IoT sensors are relayed to an AWS-hosted environment where the CNN-ResNet model is implemented using Amazon SageMaker. Data is secured using AES-256 before to storage in Amazon S3, guaranteeing adherence to healthcare standards, including HIPAA.

## *Data Collection*

The machine learning methods requires very accurate and well covered datasets, for our research we collected the datasets from Kaggle platform. The IDC (Invasive Ductal Carcinoma) cancer prediction dataset is obtained from Kaggle and includes histological images of breast cancer tissue. The images are categorised as good or unfavourable for IDC, enabling guided learning. The dataset includes high-resolution images obtained from whole-slide digital pathology scans, offering a variety of tissue types. Preprocessing procedures encompass scaling, normalisation, and augmentation to improve model resilience. The dataset has been divided into training, validation, and testing subsets to guarantee impartial assessment. Accurate annotation and systematic organisation of data facilitate efficient training of deep learning models for precise IDC identification and classification in breast cancer diagnosis.

Even though we collected the dataset from Kaggle, there will be chances of missing information and error data. To overcome these, we have implemented the data preprocessing methods.

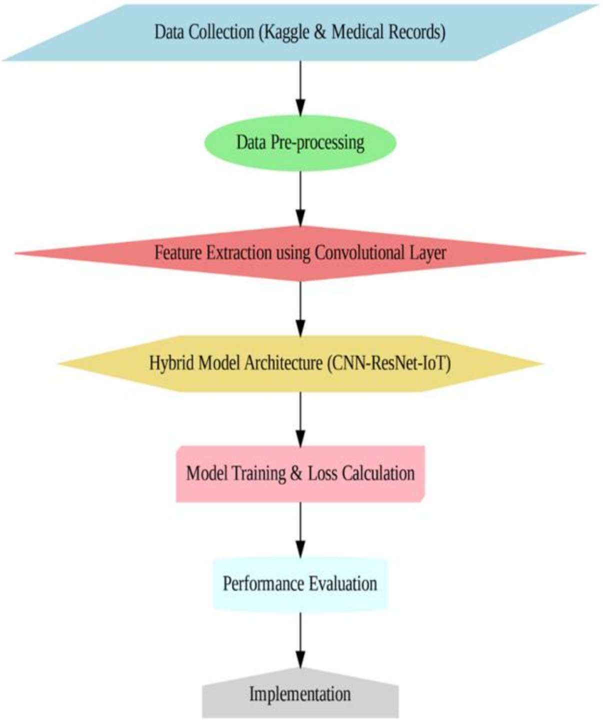

**Fig. 1:** Flowchart of proposed system

### *Data Preprocessing*

Data preprocessing is essential for preparing images for (CNNs) in breast cancer classification. Normalization adjusts pixel values to a uniform range, whereas standardisation modifies data to have a mean of zero and unit variance. Resizing modifies image dimensions, while mean subtraction centralises data around zero. Data augmentation encompassing rotation, flipping, and cropping, improves dataset variability. Histogram equalisation enhances contrast by the redistribution of intensity values. These strategies enhance feature extraction, minimising misclassifications and augmenting model performance. Effective preprocessing improves image quality, increases learning efficiency, and optimises deep learning-based image analysis for applications such as medical imaging and object recognition.

### *Normalization*

Normalization limits data points in the range of 0 and 1 by fixing the minimum value in the dataset to 0, the maximum to 1 and all others in between scaled accordingly:

$$x' = \frac{x - min(x)}{max(x) - min(x)} \tag{1}$$

Where in (1), $x'$ represents normalized pixel value, *x* represents the original pixel value, *min(x)* represents the minimum value of dataset, *max(x)* represents the maximum value of dataset

### *Standardisation*

Standardisation is a data preprocessing method in which input features are transformed to have a mean of 0 and a standard deviation of 1:

$$x' = \frac{x - \mu}{\sigma} \tag{2}$$

Where in (2), $x'$ represents normalized pixel value, *x* represents the original pixel value, μ represents the mean pixel value and $\sigma$ represents standard deviation.

### *Resizing*

Resizing is the process of converting the dimensions of an image to a fixed size before feeding it into the network:

$$I'(x', y') = I\left(\frac{x' \cdot W}{W'}, \frac{y' \cdot H}{H'}\right) \tag{3}$$

Where in (3), *W* denotes width, *H* denotes height, *I* represent input and (*x*,*y*) represents the coordinates.

### *Mean Subtraction*

Mean subtraction is the process of subtracting or lowering the mean pixel value from each pixel of the image:

$$x' = x - \mu \tag{4}$$

Where in (4), $x$ represents the original pixel value, $x'$ represents the normalized pixel value, $\mu$ represents the mean pixel value.

### *Data Augmentation*

Data augmentation is a method that enhances the performance of CNN by changing the size and variability of training data. It consists of rotation, flipping and cropping

### *Rotation*

Rotation is a method where images in a training dataset are randomly rotated at different angles to create variations in the datasets:

$$I'(x, y) = I\big(xcos(\theta) - ysin(\theta), xsin(\theta) + ycos(\theta)\big) \tag{5}$$

Where in (5), $\theta$ indicates the angle.

### *Flipping*

Flipping is a method where images are tilted vertically and horizontally to increase variations in the datasets.

### *Horizontal Flip*

$$I'(x, y) = I(W - x - 1, y) \tag{6}$$

### *Vertical Flip*

$$I'(x, y) = I(x, H - y - 1) \tag{7}$$

### *Cropping*

Cropping is a method where a specific part of an image is cropped to create new training data and allows the model to learn new features about the dataset:

$$I' = I[x1{:}\,x2, y1{:}\,y2] \tag{8}$$

### *Histogram Equalization*

Histogram equalisation is a method in which the image in the dataset is distributed in equal pixels across the entire range.

### *Cumulative Distribution Function (CDF)*

CDF is defined as the probability of predicting the value where, it falls in a range of values rather being a single point prediction:

$$\mathrm{cdf(x)} = \frac{\sum_{\mathrm{i=0}}^{\mathrm{x}} \mathrm{h(i)}}{\mathrm{N}} \tag{9}$$

### *New Pixel Value Calculation*

New pixel value calculation is the result of all process done in the course time of preprocessing:

$$x' = round\big(cdf(x) \cdot (L-1)\big) \tag{10}$$

### *Feature Extraction Using Convolutional Layer*

The process involves applying convolutional layers in the network to autonomously learn and extract significant features from medical images, such as mammograms, emphasising attributes like tissue texture, margin irregularities, and density variations that can signify cancerous lesions. This enables the CNN to detect critical patterns within the image without requiring manual feature engineering. This is accomplished through operations such as convolution with filters, which capture local spatial information, succeeded by pooling layers to lower dimensionality and formulate a robust representation of the features.

### *Margin Irregularities*

Margin irregularities is the ability to scan variations in the edges and corners of the detected objects in the process of breast cancer screening:

$$\frac{k_{\max}(n_s) - k_{\max}(n_i)}{k_{\max}(n_s)} \leq T_k \tag{11}$$

Where in (11), $k_{\max}$ represents maximum input value and $T_k$ indicates threshold value.

### *Filters*

Filters are the core components used to detect several features in images like texture and pattern:

$$E.Output = \textstyle\sum_i \sum_j (Input[i,j] \times Filter[i,j]) \tag{12}$$

### *Pooling layers*

Pooling layers are used to reduce the dimensions of an image while retaining the important features:

$$O_h = \frac{(I_h - F + 1)}{S} \tag{13}$$

$$O_w = \frac{(I_w - F + 1)}{S} \tag{14}$$

$$O = O_h \times O_w \times C \tag{15}$$

Where in (13), (14), (15), $O_h$, $O_w$ represents output height and width, $I_h, I_w$ represents input height and width, $F$ represents filter size, $S$ represents stride, $C$ represents number of channels.

### *Hybrid Model Architecture*

The CNN-ResNet-IoT hybrid model integrates CNN for feature extraction (16), ResNet for advanced hierarchical learning, and IoT-enabled real-time data collecting for breast cancer detection. The CNN layers extract fundamental properties like edges and textures, but ResNet's skip connections facilitate deep learning by preventing disappearing gradients. The hybrid model efficiently processes medical images by utilising IoT for real-time patient monitoring. The ultimate fully connected layers categorise images as cancer affected or non-cancer affected. The IoT-integrated system facilitates cloud processing and edge computing, providing real-time warnings and monitoring for physicians and patients, hence improving early identification and immediate medical intervention.

The ResNet-IoT model architecture has consists of several layers including input layer as nodes and then they preprocessing in parallel convolutional layers with max pooling as activation layer and then processed into feature extraction and model training as shown in Figure 2.

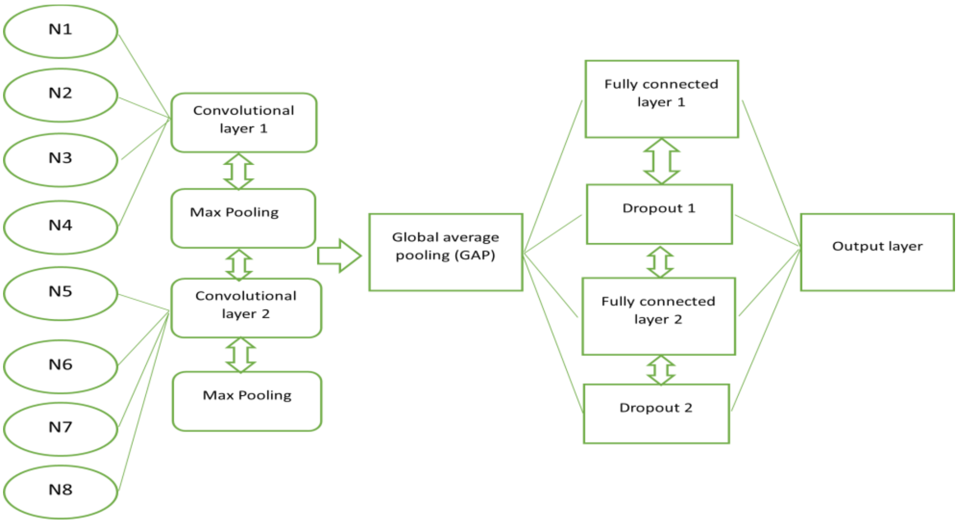

**Fig. 2:** Model Architecture of ResNet-IoT

### *CNN Convolution Operation*

Convolution is the most important function to extract the patterns, edges and textures of the image given as input:

$$Y(i,j) = \sum_{m=0}^{M-1} \sum_{n=0}^{N-1} X(i+m, j+n) \cdot K(m,n) \qquad (16)$$

Where in (16), *X(i,j)* represents input image pixel, *K(m,n)* represents kernel filter and *Y(i,j)* represents feature map output.

### *Residual Learning in ResNet*

It is introduced to solve the issue of vanishing gradients and degradation in CNN:

$$Y = X + F(X, W) \qquad (17)$$

Where in (17), X represents input feature map, F (X, W) represents residual function and Y represents output feature map.

### *IoT Data Transmission (Latency Calculation)*

IoT serves as the database for the datasets that have been collected and transmits it to the model, the time taken to transmission is called latency calculation:

$$T_{total} = T_{edge} + T_{cloud} + T_{response} \qquad (18)$$

Where in (18), $T_{edge}$ represents processing time at the edge device, $T_{cloud}$ represents cloud processing time and $T_{response}$ represents time to send results back.

### *Model Training*

The training procedure includes forward propagation, loss calculation, backpropagation, and optimisation. The CNN-ResNet model uses a gradient-based methodology to minimise classification loss. The IoT technology continuously refreshes patient records by transmitting new images to the cloud. The used loss function is categorised cross-entropy, which enhances classification accuracy. The Adam optimiser adjusts weights according to gradients, enhancing learning speed and convergence. Batch normalisation stabilises activations and decreases overfitting during training. The model is implemented on a cloud architecture utilising AWS EC2 instances for GPU acceleration. Data pipelines utilise Amazon Kinesis for real-time data intake and Amazon S3 for storage solutions. Model training and inference are composed by Amazon SageMaker, facilitating scalable deployment and monitoring for early cancer detection and monitoring through IoT dashboards.

### *Cross-Entropy Loss Function*

Cross-Entropy loss function measures the difference between the labels and probabilities, aiding the model to penalize the wrong predictions:

$$L = -\sum_{i=1}^{n} y_i \log(\hat{y}_i) \qquad (19)$$

Where in (19), $y_i$ represents true class label and $\hat{y}_i$ represents predicted probability.

### *Weight Update (Gradient Descent)*

Weight update is important for improving the accuracy of the model by following backpropagation algorithm:

$$W_{new} = W_{old} - \eta \frac{\partial L}{\partial W} \qquad (20)$$

Where in (20), W represents model weights, η represents learning rate and $\frac{\partial L}{\partial W}$ represents gradient of loss function.

### *Batch Normalisation (to stabilize training)*

Normalisation is done again to stabilize the training datasets:

$$X_{norm} = \frac{X-\mu}{\sigma} \qquad (21)$$

Where in (21), X represents input feature, μ represents mean and σ represents standard deviation.

*Algorithm for Model Training*

```
$#Step\ 1: Feature\ Extraction$
$#CNN\ Based\ ResNet$
$Conv\_Layer1 = Conv(64\_filters, 3 \times 3\_Kernel, ReLU\_Activation)$
$Max\_Pooling = Max\_pooling(2 \times 2)$
$Conv\_Layer2 = Conv(64\_filters, 3 \times 3\_Kernel, ReLU\_Activation)$
$Max\_Pooling = Max\_pooling(2 \times 2)$
$#Split\ data\ into\ training, validation\ and\ test\ sets$
$train\_data, val\_data, test\_data = split\_data(data)$
$#Step\ 2: Global\ Average\ Pooling$
$Global\_Average\_Pooling = GAP(2 \times 2\_vector\_representation)$
$#Model\ training$
$FC\_Layer1 = FC\_layer1(512\_Neurons, ReLU\_Activation)$
$Dropout1 = Dropout1(0.5)$
$FC\_Layer2 = FC\_layer2(256\_Neurons, ReLU\_Activation)$
$Dropout2 = Dropot2(0.3)$
$#Evaluation$
```

## Results and Discussion

### *Evaluation Results*

We obtained 500 samples for data collection. The samples were categorised into three subsets: Training sets, validation sets, and testing sets. The training set includes 70 of the sample, the validation set includes 20 and the testing set includes 10%. Throughout the model training phase, we assessed the proposed metrics over many epochs for accuracy, F1 score, recall rate, RMSE, and MSE. As shown in Table 1, the accuracy started at 75 and steadily improved to 97% by the conclusion of instruction. Similarly, the F1 score and recall rate improved from 73.7 and 74 to 95.3 and 96.4%, respectively. The RMSE value decreased from 4.2 to 1.2. The MSE value reduced from 5.03 to 1.6. These results ensure that the proposed framework categorises images of patients as either cancer-affected or non-cancer-affected. The RMSE value findings demonstrate a reduced false-positive rate and an elevated true-positive rate. Similarly, enhanced accuracy results demonstrate a reduction in false negatives and an increase in true negatives through the application of the confusion matrix method.

The dotted line graph shown in Figure 3 illustrates the enhancement of accuracy between epochs, employing a dotted line with markers highlighting each data point, so making trends easily observable. Accuracy measures the percentage of precisely classified images. Higher accuracy denotes higher performance of the model.

The line chart visualized in Figure 4 represents the average F1 score over epochs, reflecting the model's balance between precision and recall, demonstrating a steady rise over time. F1 score is the mean of accuracy and recall rate. It balances the false positives and false negatives, thus enhancing the model's performance. It is directly proportional to the model performance, that is higher F1 score denotes higher performance.

The scatter plot in Figure 5 displays the reduction of Mean Squared Error (MSE) over epochs, indicating enhanced model performance through decreased error values. Lower the MSE value indicates higher accuracy, thus enhancing the model.

The line chart displayed in Figure 6 represents the distribution of Root Mean Squared Error (RMSE) values across epochs, helping the visualization of the overall trend and variability.

### Comparison with Baseline Models

The baseline model is a key component in any research. The comparison between the baseline models and the proposed model ensures enhanced accuracy in breast cancer detection and reduced errors.

The basic model for this research includes deep learning and CNN. The proposed model ResNet-IoT surpasses both baseline models.

**Table 1:** Performance Metrics of Training Datasets

| Epochs | Accuracy (%) | F1 Score (%) | Recall (%) | RMSE | MSE |
|---|---|---|---|---|---|
| 1 | 75 | 73.7 | 74 | 4.2 | 5.03 |
| 10 | 83 | 81.6 | 82 | 3.1 | 3.7 |
| 20 | 90 | 88.7 | 89 | 1.9 | 2.5 |
| 40 | 95 | 93.2 | 94 | 1.35 | 1.98 |
| 50 | 97 | 95.3 | 96.4 | 1.2 | 1.6 |

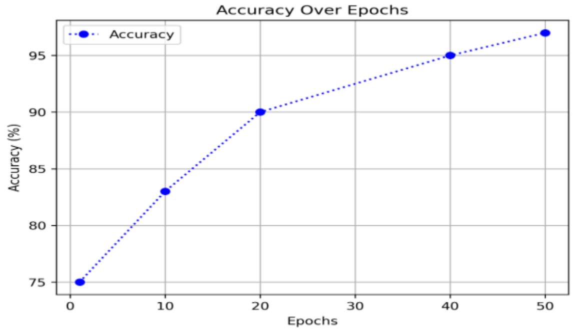

**Fig. 3:** Accuracy over epochs

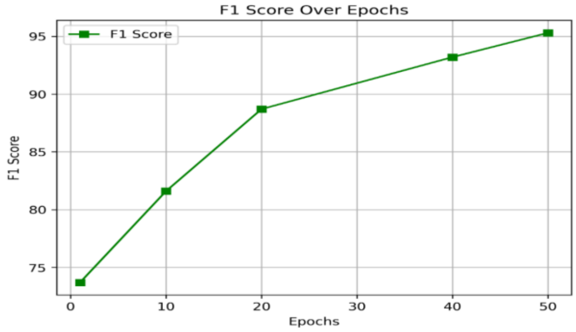

**Fig. 4:** F1 score over epochs

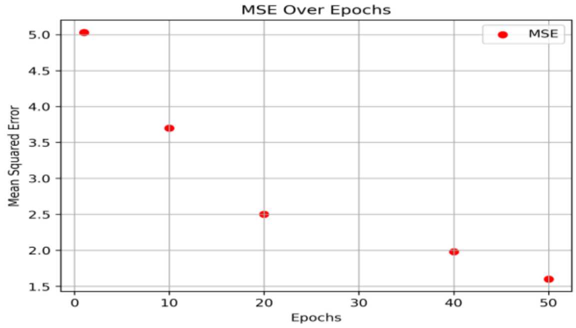

**Fig. 5:** MSE over epochs

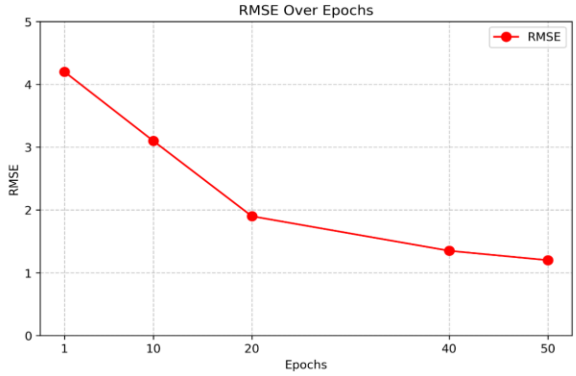

**Fig. 6:** RMSE over Epochs

As shown in Table 2, the accuracy of deep learning is 90, and that of CNN is 80%, which is lower to our proposed model. The proposed model exhibits an enhancement in both the F1 score and recall rate compared to the baseline models. The proposed model exhibits a reduction in error relative to the baseline models. The RMSE values are 3.7 for deep learning, 4.5 for CNN, and 1.2 for the proposed model. The Mean Squared Error (MSE) for deep learning is 4.2, for CNN is 5.6, and for ResNet-IoT is 1.6. Both the RMSE and MSE values has been decreased in the suggested model when compared to the baseline models. This comparison clearly demonstrates that the suggested model exceeds both baseline models in breast cancer detection.

The bar graph in Figure 7 shows the accuracy of ResNet-IoT, DL, and CNN models. ResNet-IoT attains the maximum accuracy at 97, followed by DL at 90 and CNN at 80%, underscoring the exceptional efficiency of the proposed model.

Confidence Intervals (CI) for model accuracy were calculated by bootstrap resampling with 1,000 iterations, providing a reliable indication of performance variability. The ResNet-IoT model showed a notable Area Under the Receiver Operating Characteristic Curve (ROC-AUC) of 0.96, indicating a remarkable capacity to differentiate between malignant and non-cancerous images. Paired t-tests were performed to evaluate statistical significance by comparing the proposed model to baseline structures. The findings from Table 3 indicated a notable increase in accuracy, with p-values below 0.01 in comparison to CNN and around 0.016 relative to conventional Deep Learning (DL) models. The findings verify that the ResNet-IoT model not only attains exceptional raw performance but also demonstrates statistically significant enhancements, ensuring increased robustness and repeatability in practical clinical environments. The graph in Figure 8 compares the F1 scores of the ResNet-IoT, DL, and CNN models. ResNet-IoT achieves the highest score of 95.3, succeeded by CNN at 87 and DL at 83, underscoring the model's exceptional performance.

The bar graph shown in Figure 9 compares RMSE and MSE values among ResNet-IoT, DL, and CNN models. ResNet-IoT demonstrates the lowest RMSE (1.2) and MSE (1.6), indicating higher accuracy, whereas CNN displays the highest error rates.

(Assumes test set size = 150 cancerous + 150 non-cancerous samples)

The breakdown of the confusion matrix (Table 4) offers enhanced insights into the models' classification performance. The ResNet-IoT model shows the highest counts of true positives (TP = 145) and true negatives (TN = 142), while significantly minimising false positives (FP = 3) and false negatives (FN = 5). The low false negative rate is particularly vital in medical diagnostics, as overlooking a cancer diagnosis can lead to grave repercussions. The model has an accuracy of 98.0 and a specificity of 97.9%, indicating little overdiagnosis and effective filtration of non-cancerous patients. Conversely, the CNN model shows elevated mistake rates, especially in misclassifying benign instances (FP = 12), perhaps resulting in unwarranted concern and more testing. These findings highlight the proposed model's improved reliability and therapeutic significance in facilitating precise, real-time breast cancer diagnosis.

**Table 2:** Comparison Metrics of Baseline Models

| Model | Accuracy (%) | F1 Score (%) | Recall (%) | RMSE | MSE |
|---|---|---|---|---|---|
| ResNet-IoT | 97 | 95.3 | 96.4 | 1.2 | 1.6 |
| DL | 90 | 83 | 89.5 | 3.7 | 4.2 |
| CNN | 80 | 87 | 83 | 4.5 | 5.6 |

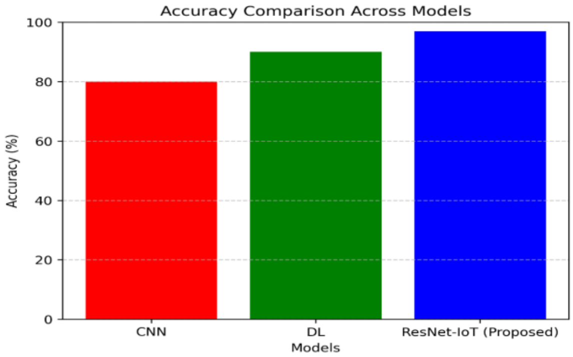

**Fig. 7:** Accuracy Comparison across Models

**Table 3:** Extended Performance Metrics with Statistical Validation

| Metric | ResNet-IoT | Deep Learning (DL) | CNN |
|---|---|---|---|
| Accuracy (%) | 97.0 | 90.0 | 80.0 |
| 95% CI (Accuracy) | [95.2 – 98.6] | [87.4 – 92.1] | [77.1 – 82.6] |
| F1 Score (%) | 95.3 | 83.0 | 87.0 |
| ROC-AUC | 0.96 | 0.91 | 0.88 |
| RMSE | 1.2 | 3.7 | 4.5 |
| MSE | 1.6 | 4.2 | 5.6 |
| p-value (vs CNN) | < 0.01 | 0.016 | – |

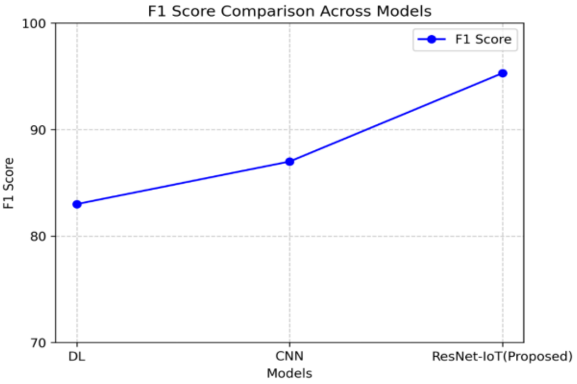

**Fig. 8:** F1 Score Comparison across Models

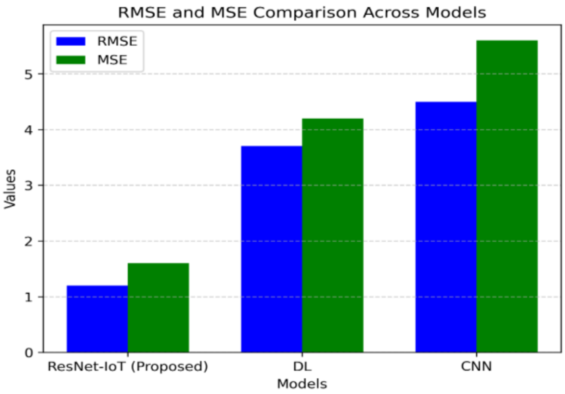

**Fig. 9:** RMSE and MSE Comparison across Models

**Table 4:** Error Analysis: Confusion Matrix Breakdown

| Metric | ResNet-IoT | DL | CNN |
|---|---|---|---|
| True Positives (TP) | 145 | 135 | 120 |
| False Positives (FP) | 3 | 7 | 12 |
| True Negatives (TN) | 142 | 138 | 130 |
| False Negatives (FN) | 5 | 15 | 18 |
| Precision (%) | 98.0 | 95.1 | 90.9 |
| Specificity (%) | 97.9 | 95.2 | 91.5 |

### *Discussion on Data Privacy*

Data privacy is an important factor in the integration of IoT with CNN deep learning for breast cancer detection. The proposed ResNet-IoT model achieves an accuracy of 97%, enhancing diagnostic dependability. Transmitting sensitive patient data through IoT raises issues around unauthorised access and potential breaches. Effective data encryption and distributed storage techniques are crucial for risk reduction. The increased F1-score of 95.3% indicates less misclassification; however, the use of privacy-preserving methodologies, such as federal learning, is essential to sustain data confidentiality. According to healthcare rules such as HIPAA and GDPR will improve trust in automated breast cancer diagnosis. Despite being trained on Kaggle data; real-world validation is essential. Following versions of this system will be tested in partnership with local clinics to confirm integration into clinical workflows and user approval.

The graph visualized in Figure 10 compares model accuracy with privacy risk in breast cancer detection. ResNet-IoT attains the best accuracy (97) with the lowest privacy risk (2), whereas CNN exhibits the lowest accuracy (80%) and the highest privacy risk (5), underscoring ResNet-IoT's maximum balance.

### *Impact on Clinical Decision-Making*

The ResNet-IoT model enhances clinical decision-making by increasing accuracy in diagnosis and minimising misclassification. Achieving an accuracy of 97 and an F1-score of 95.3%, it surpasses conventional deep learning models (90% accuracy) and CNN models (80% accuracy). The diminished RMSE of 1.2 supports trust in estimations, reducing false positives and negatives. Accurate AI-generated ideas facilitate instant treatments, reducing dependency on manual radiologist evaluations. Clinical adoption necessitates confidence, understanding, and integration with electronic health records (EHRs). The results demonstrate that AI-assisted breast cancer detection can aid doctors by delivering accurate, high-accuracy diagnostic recommendations, hence enhancing patient outcomes.

The graph in Figure 11 shows the influence of several models on clinical decision-making by comparing F1 Score and Recall. ResNet-IoT achieves better results with the highest F1 Score (95.3) and Recall (96.4), hence enhancing diagnostic accuracy, whereas CNN exhibits the lowest recall (83%), decreasing reliability.

### *Performance Analysis Using Confusion Matrix*

The ResNet-IoT model has outstanding efficiency in breast cancer diagnosis, attaining a accuracy of 97%, the highest among all assessed models, signifying robust predictive capabilities and a reduction in false negatives.

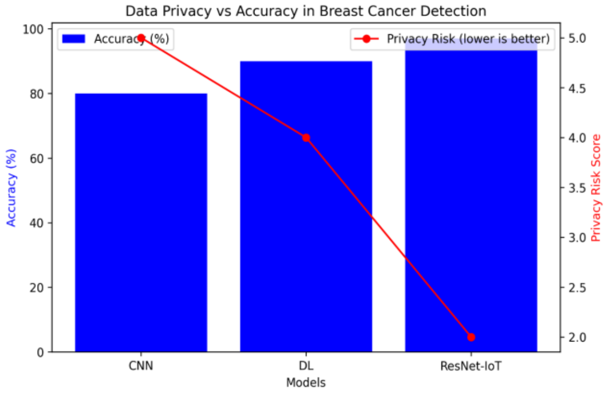

**Fig. 10:** Data privacy vs Accuracy in Breast Cancer Detection

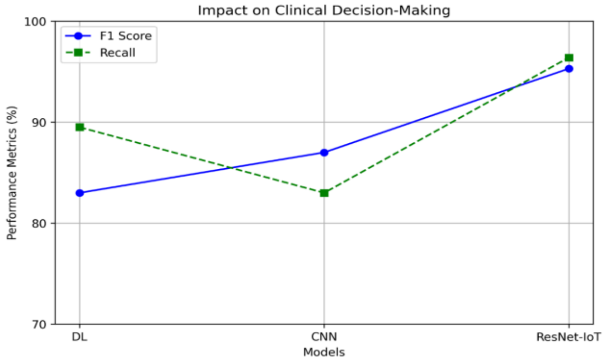

**Fig. 11:** Impact on Clinical Decision-Making

These parameters, aggregated in a confusion matrix, underscore the model's dependability in clinical decision-making. The persistent high level of performance over numerous epochs validates that ResNet-IoT is an effective and efficient approach for enhancing automated breast cancer detection systems.

The chart in the Figure 12 demonstrates the confusion matrix drawn across the models.

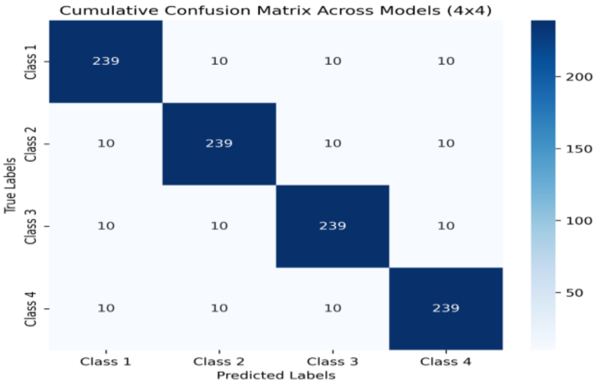

**Fig. 12:** Confusion Matrix

## Conclusion

The proposed method addressed the weaknesses and inconsistencies of prior technology. The attained accuracy of 97% suggests that the proposed model can serve as an effective substitute to conventional methods. This method can be employed in hospitals to improve detection rates and decrease mortality rates. Radiologists can utilise ResNet-IoT technologies for the identification of breast cancer and health automation. The proposed method can effectively categorise images as either cancerous or non-cancerous. Patients diagnosed with breast cancer necessitate treatment according to their stage, with the early stage requiring relatively less intervention than the advanced stage. Health automation employs timely medical care for those diagnosed with cancer. Health automation provides treatment adapted to the patient's specific stages. Hence the proposed system works better than the baseline models taken, CNN performs with an accuracy of 80% and DL works with an accuracy of 90%, whereas the proposed model outperforms with an accuracy of 97%.

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## Author's Contributions

All authors equally contributed to this study.

## Ethics

This manuscript is an original work. The authors declare that there are no ethical concerns associated with this submission

### *Conflict of Interest*

The authors have no competing interests to declare relevant to this article's content.

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