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Advancements in Telehealth: Enhancing Breast Cancer Detection and Health Automation through Smart Integration of IoT and CNN Deep Learning in Residential and Healthcare Settings

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ABSTRACT

The rapid evolution of telehealth, or telemedicine, has spurred crucial technological advancements aimed at addressing the early stages of complex cancer conditions, where conventional diagnostic methods face challenges. This research introduces a cancer detection system that utilizes Internet of Things (IoT)-based patient records and machine learning. The primary objective is to automate real-time breast cancer monitoring and detection in residential institutions and smart hospitals, thus enhancing the delivery of quality cancer healthcare. Background: Traditional diagnostic methods, particularly physical inspection, exhibit inherent limitations in identifying breast cancer at early stages. This research responds to this challenge by leveraging innovative technologies, such as IoT and deep learning-based techniques, to overcome the constraints of conventional approaches. Objective: The primary goal of this study is to develop and implement a cancer detection system that integrates IoT-based patient records and machine learning for real-time breast cancer monitoring in residential and healthcare settings. Method: The research employs a synergistic combination of IoT technology for collecting images of residential users and Convolutional Neural Network (CNN), a deep learning technique, for early cancer prediction. The focus lies on contributing to the overall well-being of individuals who may unknowingly be living with cancer. Result: Simulated outcomes after 25 epochs are presented, emphasizing the training accuracy of the model and its validation accuracy using the proposed VGG16 classifier. Graphical representations of the results indicate consistent performance metrics, with both validation and training accuracy exceeding 99%. Specifically, the training accuracy measures at an impressive 99.64%, while the validation accuracy stands at 99.12%. Main Findings: The study demonstrates the effectiveness of the integrated IoT and deep learning techniques in achieving high accuracy rates for early breast cancer prediction. The findings affirm the potential of this approach to assist dermatologists in identifying breast malignancies at treatable stages. Conclusion: This research establishes a foundational framework for the integration of IoT and deep learning techniques, presenting a promising avenue for advancing early cancer detection in smart healthcare systems. The proposed cancer detection system holds significant potential for improving healthcare outcomes and contributing to the overall well-being of individuals at risk of breast cancer.

Keywords:

Internet of Things; Machine learning;
Breast cancer detection; Deep learning

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1. Introduction

Researchers have increased their interest in developing predictive systems in the contemporary effort to automate health assessments for critical conditions such as breast cancer. One main objective of this initiative is digitizing cancer healthcare delivery through technological innovations like IoT-based sensors and deep learning techniques like the coevolutionary neural network (CNN) to develop effective predictive models and systems. Cancer predictive systems combine hardware components like servers, computers, mobile devices, IoT devices such as actuators, sensors, wearables, and software, creating a repository of real-time data [1]. These predictive models and systems serve as valuable assets capable of providing essential breast healthcare services to assist patients and healthcare professionals in detecting or diagnosing stage 0 or stage 1 of cancer development, respectively, either in the homes where the patient lives or in the hospital where the healthcare professional work. This study seeks to investigate the best processes and methods required to integrate IoT-based with Machine Learning (ML), which can modernize the cancer healthcare landscape within residential environments like hospitals, educational homes and residential homes. The study further proposed a comprehensive real-time cancer monitoring system to help avert the numerous life-threatening risks posed by breast cancer to humanity [2,3]. According to the United Nations (2023) report, it is projected that by 2040, the global annual incidence of cancer is projected to exceed 3 million cases, with an estimated 1 million fatalities. Notably, around 75% of these mortality cases are expected to occur in countries characterized by low and middle incomes. The global community must unite to play a crucial role in enhancing and advancing healthcare systems and services on a broader scale to effectively address the global public health challenge presented by breast cancer to satisfy the objectives of UN SGD goal 3, which is intended to promote the well-being and ensure healthy lives for people of all ages [4].

1.1 Internet of Things (IoT)

The term IoT, or Internet of Things, refers to empowering everyday objects to communicate through the internet. As highlighted in sources [5], IoT represents a paradigm in which everyday objects can be endowed with identification, sensing, networking, and processing capabilities, enabling them to interact with each other and various devices and services over the internet to achieve specific objectives. IoT essentially establishes connections among objects, often termed the internet of non-living things, and these non-living entities can be made communicative through sensor nodes [6]. According to [7], IoT can be envisioned as a global network interconnecting various objects. The foundational concept at the heart of IoT involves collecting data from the surrounding environment, which may be challenging for humans to perform [8]. Discussions by [9] have explored the applicability of IoT as it plays a role in monitoring users' heart rate by gathering essential health metrics from individuals seeking medical attention. Moreover, integrating breast cancer into the IoT framework holds significant potential for early detection and monitoring. Although [10-12] have delved into IoT applications in educational settings, none of these works addressed Electronic Health Records (EHRs), nor did they highlight the appropriateness of addressing health-related issues in institutional homes through the implementation of health sensors, as proposed in their research.

1.2 Machine Learning

As its name implies, machine Learning (ML) involves granting computational capabilities to machines or devices designed for efficient work by learning from initial inputted algorithm or

function. As a subset of AI, ML utilizes computational algorithms to analyse extensive datasets, categorize information, and make predictions without explicit instructions [13]. Machine learning encompasses various branches, including supervised learning for labelled dataset predictions, unsupervised learning for pattern discovery in unlabelled data, semi-supervised learning combining both, reinforcement learning for decision-making in dynamic environments, transfer learning leveraging knowledge from one task for another, deep learning with neural networks for hierarchical representations, natural language processing for human language interaction, computer vision for visual data interpretation, and ensemble learning for combining multiple models for improved performance. CNN, a deep learning technique, has the ultimate efficiency in cancer detection [14,15]. CNN, a specialized subset of artificial intelligence (AI), empowers computer systems to learn and enhance their performance autonomously, eliminating the need for explicit programming. Specifically applied to breast cancer, CNN algorithms meticulously analyse intricate datasets, identifying patterns and making predictions that significantly contribute to the early detection and diagnosis of this critical health condition. Incorporating technology into breast cancer detection signifies a ground-breaking paradigm in contemporary healthcare.

1.3 Breast Cancer

The identification of breast cancer through the application of Convolutional Neural Networks (CNN) is a critical aspect of global healthcare, with breast cancer ranking second, following skin cancer, as the most commonly diagnosed cancer in women worldwide. Despite its occurrence in both genders, breast cancer predominantly affects women. Ongoing improvements in health systems have focused on developing effective cancer screening methods, recognizing that early detection significantly improves the chances of successful treatment [16]. Various medical organizations and breast cancer advocacy groups provide guidelines for breast cancer examination or screening, leaving the choice of a preferred method to health professionals and patients based on individual risk factors. Ductal Carcinoma in Situ (DCIS) and Invasive Ductal Carcinoma (IDC) constitute the primary categories of breast cancer [17,18], with DCIS featuring non-invasive abnormal cells confined to ducts, and IDC involving the penetration of cancer cells into surrounding tissues [19]. Figure 1 below shows an image of a breast with a cancer lump.

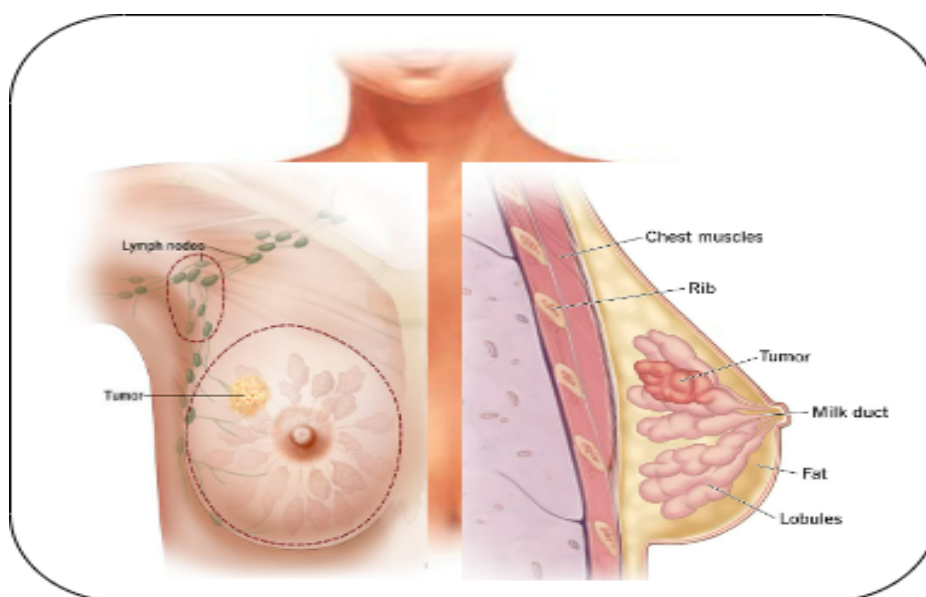


Fig. 1. Cancer Infested Breast

Traditionally, healthcare professionals have employed physical exams involving the manual examination of the breasts for lumps or abnormalities. Additional physical examinations may include observing changes in skin colour or organ enlargement [9]. Another diagnostic method is laboratory tests utilizing physiological samples such as urine and blood. For specific cancer types, an advanced form of laboratory testing called a biopsy may be required to collect necessary physiological samples, as exemplified by the complete blood count for leukaemia cancer diagnosis [20]. Image-based or imaging tests utilize non-invasive methods to examine bones and internal organs for cancer diagnostics. Frequently used imaging techniques encompass bone scans, Computerized Tomography (CT), Magnetic Resonance Imaging (MRI), Positron Emission Tomography (PET), ultrasound, and X-ray [21].

2. Literature Review

Sensors serve as the cornerstone for collecting medical data, and a potential avenue for future research involves enhancing the performance of intricate frameworks for recognizing complex human activities [22,23]. This integration of breast cancer into IoT opens avenues for improving healthcare services and emphasizes the potential for innovative solutions in the early detection and monitoring of critical health conditions [24]. Model training is resource-intensive and time-consuming, underscoring the importance of well-trained models to avoid inaccurate predictions with low probabilities. The integration of CNN principles into breast cancer detection elevates diagnostic accuracy and introduces a sophisticated and adaptable approach to healthcare [25]. This approach facilitates efficient pattern recognition and predictions within the dynamic landscape of medical data, marking a substantial advancement in diagnosing and managing breast cancer in humans [26-28].

In the realm of breast cancer detection, the integration of infrared cameras with CNN technology presents a promising avenue. This involves capturing images of individuals, deploying CNN to identify gender, and utilizing Electronic Health Record (EHR) thermal images to identify cancerous cells in the breast. The challenge lies in the lack of systems capable of zooming in on breast temperature, necessitating the development of an IoT-based system that can detect contactless changes in breast temperature distribution [23]. Previous studies have outlined challenges, including limitations in representative datasets, poor kernel performance, and heavyweight CNN models, prompting future efforts to optimize datasets, employ augmentation algorithms, and implement segmentation techniques with effective kernels to build lightweight CNN models [23,29]. The World Health Organisation (WHO) has it on record that, in 2022 out of the 2.3 million diagnosed with breast cancer 685 000 of them died globally. It is therefore essential to improve the accuracy of various studies regarding breast cancer.

Detection of breast cancer using Convolutional Neural Networks (CNN) is a critical aspect of global healthcare, with breast cancer ranking second, following skin cancer, as the most commonly diagnosed cancer in women worldwide [14,25,28,30]. Despite its occurrence in both genders, breast cancer predominantly affects women. Ongoing improvements in health systems have focused on developing effective cancer screening methods, recognizing that early detection significantly improves the chances of successful treatment [7]. Various medical organizations and breast cancer advocacy groups provide guidelines for breast cancer examination or screening, leaving the choice of a preferred method to health professionals and patients based on individual risk factors [31].

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In breast cancer detection, integrating infrared cameras with CNN technology presents a promising avenue [28,32,33]. This involves capturing images of individuals, deploying CNN to identify gender, and utilizing Electronic Health Record (EHR) thermal images to identify cancerous cells in the breast. The challenge lies in the lack of systems capable of zooming in on breast temperature, necessitating the development of an IoT-based system that detects changes in breast cancer infestation using distributed contactless systems [23,34,35]. VGG16, VGG19, and ResNet50 are prominent convolutional neural network architectures commonly employed in image classification, with VGG16 and VGG19 emphasizing simplicity and ResNet50 introducing residual connections to address training challenges in deep networks [14,36]. VGG16, VGG19, and ResNet50 have significantly contributed to breast cancer detection [37] by serving as robust convolutional neural network architectures, enabling accurate image classification and aiding in identifying cancerous patterns within medical imaging datasets. Various studies have achieved different accuracy due to the advanced computational powers and scalability of technological innovations, which allow for additional memory powers to enhance performance improvement. Previous studies have outlined challenges, including limitations in representative datasets, poor kernel performance, and heavyweight CNN models, prompting future efforts to optimize datasets, employ augmentation algorithms, and implement segmentation techniques with effective kernels to build lightweight CNN models [23,29,38,39]. While earlier studies indicated 100% accuracy in breast cancer prediction [14], subsequent investigations by Gupta and colleagues [10,11,29,40] reported reduced accuracy ranging from 76% to 96.88%. This study seeks to assess the effectiveness of associated models in identifying the parameters that contribute most significantly to the proposed breast cancer detection system.

3. Proposed Work

The methodology required in the experimental processes for the proposed system involves three major phases. The phases are the pre-processing stage, the model training stage, and the test stage, which have been further illustrated in the flow chat diagram of the proposed framework in Figure 2.

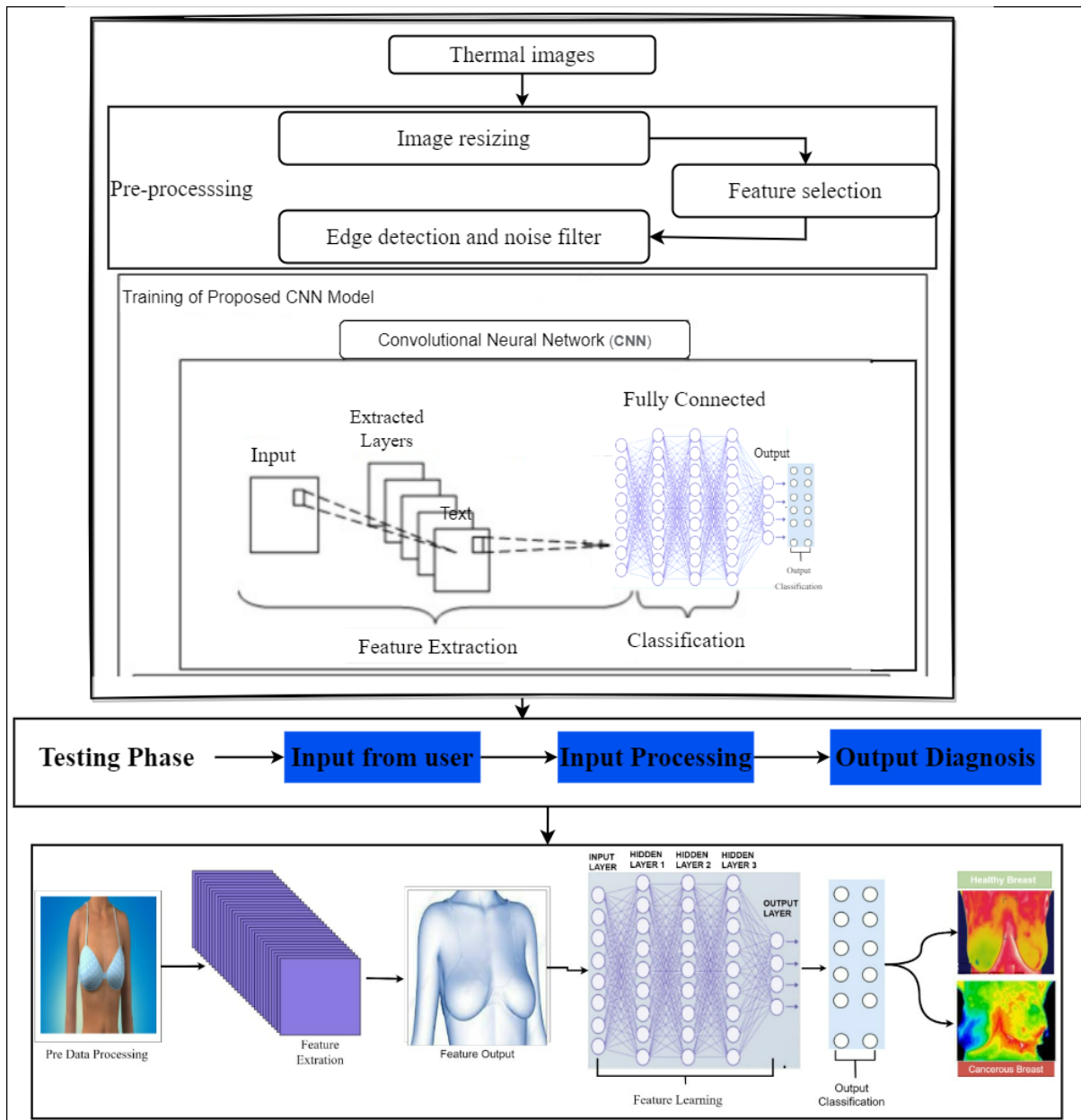


Fig. 2. Flow Chat of the Implementation Process in the Proposed Research

The proposed model incorporates the aspect of the existing model during training the model. An experimental breast cancer dataset for training purposes was collected in the form of IoT thermal camera images and stored by the Kaggle dataset repository. During the dataset pre-processing, images undergo resizing and compression. This pre-processing step ends with an edge detection and noise filter, which functions as distributed computing at the end of the *body area network* to improve the effectiveness and promptness of health detection systems to apply edge detection and the images are subsequently divided into a detectable edge portion and a non-detectable edge portion and the images are then segmented into a distinguishable edge section and a non-distinguishable edge section. At the training of the proposed model sections, various ensemble techniques that deployed some combination of layers in the CNNs model were employed for image labelling. The results were assessed to determine the most efficient CNN model for categorizing breast cancer images, which prompted the initiation of the current study.

The testing stage saw a split data ratio of 80:20, representing 80% of the dataset for training the model and 20% of the dataset being used to test the efficiency of the model, respectively. The picture of the model's performance was shown in the last part of the flow chat. While prior research incorporated ensemble models such as CNN and Resnet50 model [14], performance enhancement was not thoroughly addressed. The study identifies potential efficiency improvements in the training, testing, and validation processes, highlighting the opportunity for increased accuracy in breast cancer image classification of the VGG 16 with parameter turning of the epochs and randomness outperforming both CNN and ResNet50 models.

4. Results and Discussion

The evaluation of the proposed model in this study involved utilizing classifiers with performance metrics, employing an 80:20 ratio for the universal split between the training and test datasets. The model's training involved fine-tuning parameters and utilizing the three most effective classifiers in the third phase of the training process. A comparative analysis is presented in Table 1, contrasting the techniques deployed in the study.

Table 1
Results of Diverse CNN Ensemble Methods in Cancer Identification

Methods	F-1 Score	Precision	Recall	Accuracy	AUC	Error Rate
VGG19	85.23	87.17	86.34	85.01	89.21	0.149
Resnet50	96.14	94.24	95.92	98.28%	94.32	0.0568
VGG16	99.00	98.85	99.50	99.12%	99.34	0.008

In the analysis presented in Table 1, considerable enhancements were experimented with to improve the results obtained by all benchmarked papers discussed in Table 1. All ensemble algorithms used deployed three (3) network layers: two (2) hidden layers and a Fully Connected (FC) layer at the output layer. The analysis indicated that among the VGG19, Resnet50, and VGG16 models indicates that, the VGG16 with various parameter turning in this study obtained the F1-Score of 99.0%, Precision of 98.85%, Recall = 99.50%, and accuracy was 99.12%. Analysing the accuracy with other proposed models shows a 2.8% improvement than [18], the next best performing model. The error rate of 0.0087 represents 0.87%. These performance metrics indicate the VGG16 outperformed the existing CNN and the Resnet50. The analysis further indicates that VGG16 obtained as low as a 1% error rating during the system predictions. The outstanding AUC of 0.9934, equivalent to 99.34%, surpasses the Area Under the Curve (AUC) achieved by the state-of-the-art models proposed for breast cancer detection systems.

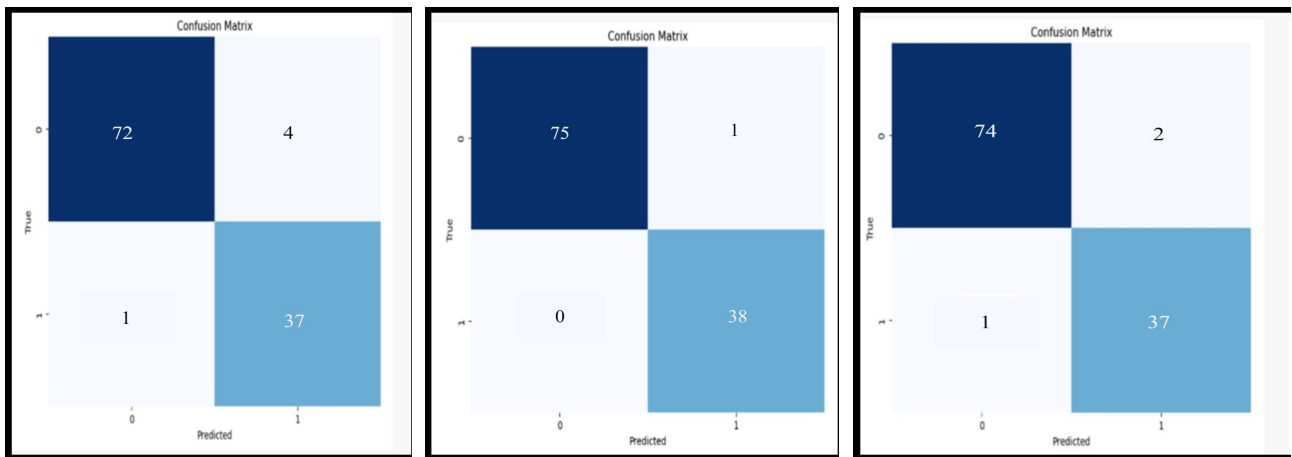


Fig. 3. Graphical presentation of confusion metrics of traditional classifiers for (a) VGG19, (b) Resnet50, and (c) VGG16

Figure 3 indicates the graphical representation of the confusion metrics used to train the ensemble CNN algorithms established in studies. Figure 3(a) indicate the VGG19, Figure 3(b) indicates the Resnet50 classifier, and Figure 3(c) indicates the VGG16, which was the best-performing classifier and has the capabilities to perform better regarding the prediction of breast cancer, in institutional homes.

The outcomes presented above, including F1-score, Precision, Recall, Accuracy, and AUC, were generated by the CNN model utilizing the corresponding confusion matrix functions denoted as TP, TN, FP, and FN predictions during the model training. The classifier metrics were calculated using the subsequent formulas.

$$\text{Accuracy} = \frac{TP+TN}{TP+FP+FN+TN} \quad (1)$$

$$\text{Error rate} = \frac{FP+FN}{TP+FP+FN+TN} \quad (2)$$

$$\text{Recall} = \frac{TP}{TP+FN} \quad (3)$$

$$\text{Precision} = \frac{TP}{TP+FP} \quad (4)$$

$$\text{F1 Score} = 2 * \frac{\text{Recall} * \text{Precision}}{\text{Recall} + \text{Precision}} \quad (5)$$

This study presents the simulated outcomes after 25 epochs for the training accuracy of the model and its corresponding validation accuracy of the proposed VGG16 classifier. The result plotted in the graph indicated that validation and training accuracy remain above 99%. While training accuracy is 99.64%, the validation accuracy is 99.12.

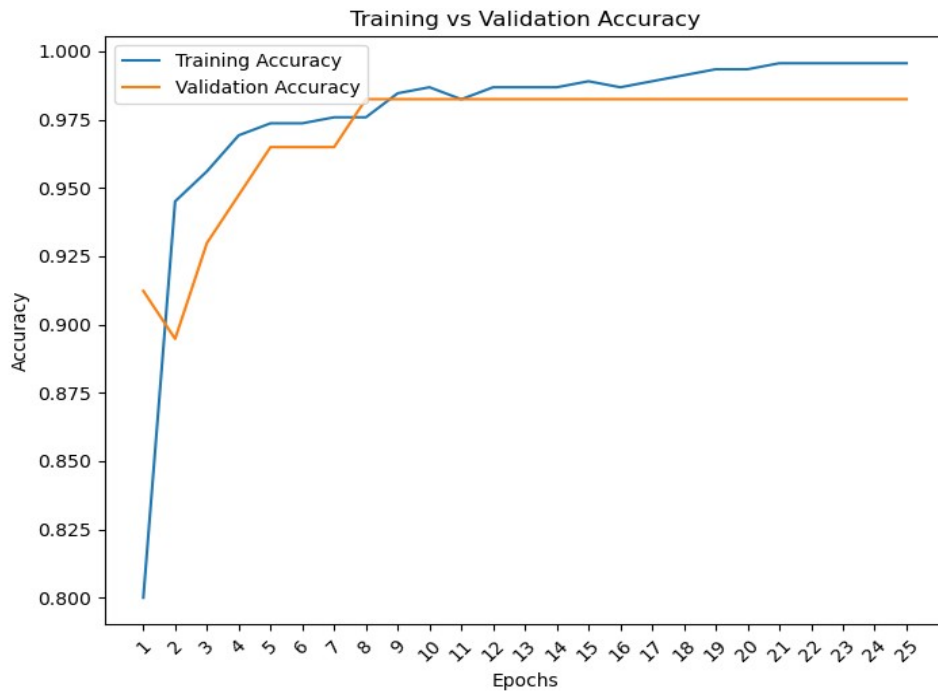


Fig. 4. Performance Metrics for Training and Validation Accuracy

The Iterations which pertain to the number of batches necessary to accomplish a single epoch are displayed below—the results of 25 iterations of training and validation loss. Applying the specified formula guarantees error rates during training and validation phases to be below 1%. The graph is illustrated in the Figure 5 below.

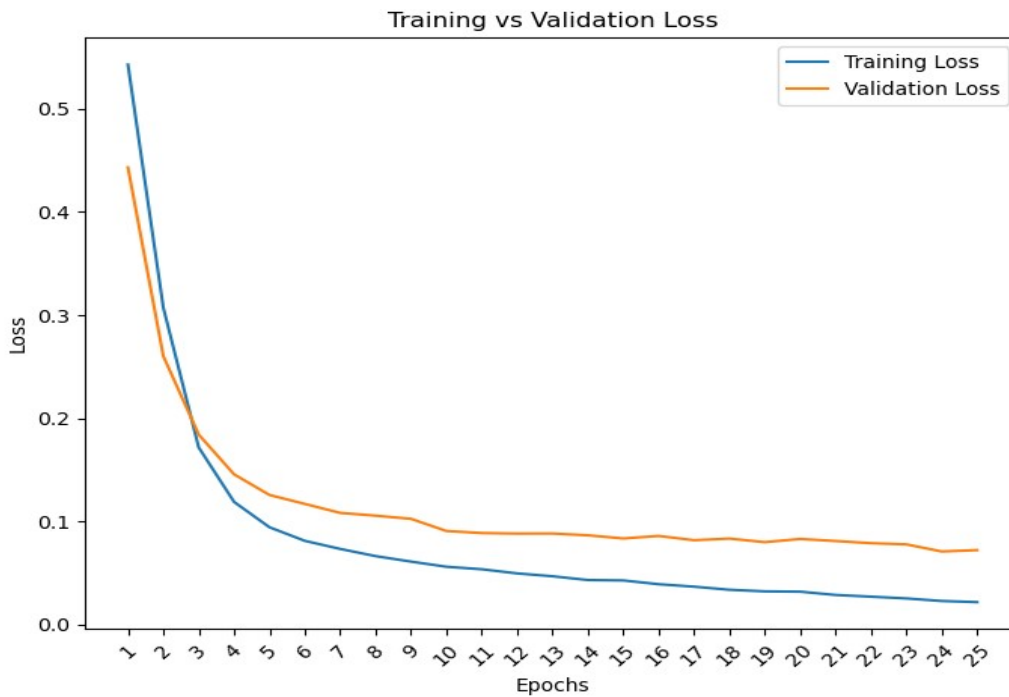


Fig. 5. Analysis of Loss in Training and Validation Phases

5. Conclusion

Traditional healthcare delivery lacks artificial intelligence to automate healthcare systems for effective breast cancer detection and diagnosis, hindering the provision of vital records for cancerous individuals. Many cancer patients are unaware of their status due to delayed symptoms or lack of physical examinations, particularly in underdeveloped and developing countries. Breast cancer, a global disease-causing significant mortality, lacks a comprehensive detection framework that integrates the essential pillars of cancer treatment: early detection, timely diagnosis, and treatment. If left unattended, this challenge threatens the realization of the United Nations Sustainable Development Goal (SDG) 3 and could become a global concern. The intensified global pursuit of effective remote healthcare delivery, particularly during pandemics, has diminished providers' and seekers' emphasis on physical healthcare provision. The proposed system aims to enhance healthcare by automatically scanning and interacting on telehealth platforms within institutional homes or health facilities through a contactless remote system.

The cancer detection system, employing IoT-based and Convolutional Neural Network (CNN) technology in schools and other institutional homes, automates cancer detection for a healthier environment among residential users. The research recognizes the possibility of enhancing efficiency in the training, testing, and validation processes, emphasizing the potential for heightened accuracy in breast cancer image classification using VGG 16. Through parameter tuning of epochs and randomness, VGG 16 demonstrates superior performance compared to both CNN and the ResNet50 model. We, therefore, affirm the performance of the VGG16 classifier in the development of breast cancer detection systems in smart hospitals, institutional homes, and educational institutions.

6. Future Work

The future plan we propose is to develop a holistic breast cancer predictive system called BCancerGyefo, which will deploy the proposed model that integrates IoT-based thermal image cameras.

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