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Research Article

Data Collection from Thermal Imaging Device in IOT

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Received: 03 June 2022; Revised: 02 July 2022; Accepted: 01 August 2022; Published: 07 October 2022
AID: 001-03-000013

Abstract: Breast cancer, being one of the most prevalent malignancies, poses a formidable threat to human health due to its aggressive nature and elevated mortality rates. The pivotal role of early detection in augmenting patient survival rates is well-established. Presently, mammography serves as the conventional diagnostic approach; however, its cost and exposure to ionizing radiation underscore the need for alternative, cost-effective, and less invasive diagnostic modalities, such as thermography. In light of this, the goal of the current research project is to construct and create a thermal imaging-based breast cancer detection model. The first phase entails developing a customized machine learning model built on convolutional neural networks (CNNs), which is specifically intended to use thermal pictures to detect breast cancer. This model is subsequently fine-tuned through extensive training using a diverse dataset comprising thermal images of breast abnormalities, aiming to achieve a robust detection mechanism. The overarching objective of this study is to facilitate binary classification, distinguishing malignant from benign breast cancer cases, with a particular emphasis on the potential to enhance diagnostic accuracy, especially when confronted with multifarious image attributes. This work employed a wide range of image classification methods to identify breast cancer utilizing thermal image processing techniques. The comprehensive workflow encompassed cancerous image enhancement, precise segmentation, texture-based feature extraction, and the subsequent classification of breast cancer within thermal images, culminating in a successful endeavor. Concomitant with these intricate challenges, a bespoke classifier was devised, capitalizing on machine learning paradigms such as the 2D Convolutional Layer (2D CNN) and Support Vector Machine (SVM). The proposed model was meticulously trained on a representative dataset, meticulously selected from the DMR-IR (Database of Mastology Research). Notably, the empirical results yielded a classification rate of 95% for the proposed 2D CNN classifier, surpassing the SVM and pre-existing CNN counterparts, which registered classification rates of 91% and 71%, respectively. It is crucial to emphasize that there are now just a handful of publicly available datasets for thermography in the field of cancer diagnosis.

Keywords: Thermography; Breast Cancer Detection; Thermal Imaging; Machine Learning; Convolutional Neural Networks (CNN)

1. Introduction

The advent of the Internet of Things (IoT) has catalyzed significant advancements across various sectors, most notably in the realm of healthcare. The IoT revolution has precipitated a paradigm shift in contemporary healthcare practices, amalgamating technological, economic, and social facets into a transformative confluence. Within this transformative landscape, the detection of temperature aberrations within the human body, a ubiquitous indicator of illness, assumes paramount importance. Infrared thermography (IRT), a non-invasive, contactless, and passive alternative to traditional medical thermometers, emerges as a pivotal tool for the observation and monitoring of human body temperature. Notably, IRT extends its utility beyond mere temperature measurement, enabling remote monitoring of body surface heat. Its effectiveness has been established in a variety of fields, including gynecology, dermatology, cardiology, maternal physiology, and neuroimaging, for the early detection and diagnosis of a variety of medical diseases, including breast cancer, diabetic neuropathy, and cardiovascular illnesses. Real-time, high-resolution thermographic images may now be created thanks to technology advancements in the form of improved infrared cameras and data processing methods. Simultaneously, IoT, as an emerging technological frontier, has empowered professionals, physicians, and researchers to usher in revolutionary solutions, particularly within the medical and healthcare domains. IoT leverages smart sensors, computer networks, and remote servers, among other elements, to forge innovative pathways in healthcare delivery [1].

The overarching objective of this research endeavor is to introduce an IoT-enabled medical system that seamlessly facilitates remote diagnosis and detection of various medical anomalies in real-time. The Internet of Things (IoT) technology and infrared thermographic methods are combined in this project to create a dynamic system that can recognize, diagnose, and wirelessly alert users of problems, thereby maximizing the potential of the IoT.

Assuming the integration of IoT technology and infrared thermographic methods in our work, our research endeavors to revolutionize medical diagnostics. The goal is to provide a wireless, real-time solution for remote medical anomaly identification and warning. This cutting-edge device not only improves diagnostic skills but also makes use of the Internet of Things to provide prompt and effective healthcare solutions.

Cancer, a condition in which cells within body tissues proliferate out of control, is extremely dangerous to human health. While cancers can arise in various tissues throughout the body, breast tissue stands as a particularly abundant site. The human body continually generates and divides cells to support growth and vitality, a process that can be disrupted as individuals age. In some instances, these normal cellular turnover falters, resulting in the accumulation of surplus, unnecessary cells. This aberrant cellular growth can manifest as a lump, tumor, or growth. In the context of breast tissue, such cancerous growths are indicative of breast cancer, often accompanied by inflammation.

In recent decades, breast cancer has emerged as a leading cause of mortality among women, prompting governments worldwide, particularly in developed nations, to channel substantial efforts into its detection and treatment. Central to the effective management of breast cancer is the identification of sentinel lymph nodes, which possess a direct lymphatic connection to the malignancy and, consequently, represent potential sites for cancer metastasis from the breast. Accordingly, numerous research endeavors have been dedicated to advancing the field of breast cancer diagnosis and classification [2]. The creation of an adaptive system capable of classifying and detecting breast cancer becomes critically important in light of these requirements. About 22.9% of all invasive malignancies in women are breast cancer, making it a substantial contributor. Multiple diagnostic modalities have been employed in the detection and diagnosis of this disease, with mammography holding a prominent position. Mammography, a screening technique designed to detect breast cancer at its nascent stages, entails the physical examination of the breasts by medical practitioners. Additionally, screening procedures such as thermal imaging, mammography, and other imaging techniques have been deployed. Mammography, owing to its simplicity, cost-effectiveness, and efficiency, has long been regarded as the gold standard for early-stage breast cancer diagnosis. However, it is not without its drawbacks, including radiation exposure and patient discomfort. Importantly, the sensitivity of mammography ranges from 70% to 90%, with a false-negative rate of 10% to 30%, potentially leading to the overlooking of more than a quarter of all malignancies. This limitation is especially important when dealing with big, ill-defined breasts because it can be difficult to distinguish between malignant and healthy tissue in these situations.

In summary, the research outlined in this paper aims to address these crucial concerns by presenting a comprehensive approach to breast cancer detection that makes use of thermal imaging, IoT technology, and advanced machine learning techniques, aiming to enhance the overall efficacy of breast cancer detection methodologies and improve diagnostic accuracy, reduce invasiveness, and reduce the burden on patients.

1.1. Research Objective:

The principal objective of this study is to enhance the classification accuracy of a CNN model when applied to breast images, differentiating between malignant and non-cancerous situations. This methodology encompasses the following steps:

- Curating a dataset of cancerous and non-cancerous thermal images, sourced from an open-access online database.
- Designing and training a 2D CNN model tailored for binary classification, distinguishing between malignant and benign cases, using the curated thermographic images.
- Implementing strategies to enhance the model's classification accuracy, consequently reducing the occurrence of false-positive results.

2. Literature Review

Breast cancer remains a leading cause of global female mortality. Advanced engineering techniques and Artificial Intelligence have significantly influenced breast-image classification, with thermal imaging offering an alternative perspective and time-saving benefits for specialists. Despite numerous articles on breast image classification, comprehensive review papers are scarce. This research emphasizes the CNN approach for breast imaging categorization and discusses the use of traditional Neural Networks (NN), logic-based classifiers (e.g., Random Forest, Support Vector Machines, Bayesian methods), and some semi-supervised and unsupervised methods in addition to CNN [20].

Machine learning has greatly improved breast cancer patient care, and this progress has been further accelerated by incorporating machine-learning techniques. However, the computational complexity of current deep-learning-based machine learning classifiers remains a key challenge. This research aims to develop a lighter DNN model that can be constructed more efficiently. Additionally, the reliance on extensive training data in DNN-based cancer image classifiers is a concern. This paper provides a comprehensive overview of breast cancer image classification, encompassing breast thermogram datasets, general image classification methods, feature extraction, noise reduction techniques, performance evaluation criteria, and cutting-edge findings. In cases where expert resources are limited, a machine learning-based diagnostic system can offer immediate disease feedback, enhancing patient care [3].

Back Propagation Algorithm (BPA), Radial Basis Function Networks (RBFN), Learning Vector Quantization (LVQ), and Competitive Learning Network (CL) are neural network models implemented by R. R. Janghel et al., with LVQ emerging as the optimal classifier for breast cancer detection [13]. In another study, the author introduced a hybrid system for recognizing breast cancer tumors, employing three modules: fuzzy feature-based feature extraction, hybrid bees algorithm (BA) - back-propagation (BP) for classifier training during the training phase, and a multi-layer perceptron (MLP) neural network as the classifier, achieving high accuracy [15]. Additionally, they introduced a partially connected neural network technique, demonstrating its comparability to fully connected neural networks across four datasets [14].

The primary technology for breast cancer screening is mammography, but it falls short in detecting tumors in thick breasts or those smaller than 2 mm. To address these limitations, thermography-based breast cancer detection is proposed. This method involves four stages: (1) Image pre-processing using the top-hat transform and adaptive histogram equalization, (2) ROI segmentation through K-means clustering and binary masking, (3) feature extraction using signature boundary, and (4) classification employing the

Extreme Learning Machine (ELM) and Multilayer Perceptron (MLP). The proposed approach is evaluated on the DMR-IR public dataset, considering various experimental scenarios (e.g., integrating geometrical and textural feature extraction) and assessing performance metrics like accuracy, sensitivity, and specificity. Notably, ELM-based results outperformed MLP-based results [5].

A paper purposed the methodology combining thermography and mammography for breast cancer detection is presented. The findings indicate that the thermogram-based detection method exhibited lower sensitivity compared to mammographic technique. However, when both techniques were combined (thermogram and mammogram detection), sensitivity improved compared to previous results [5].

Block Variance, introduced by Sourav Pramanik et al. in their paper, serves as a feature extraction technique. It leverages local texture analysis, applied to diagnose breast cancer using thermograms. Their approach combines gradient descent training with a feed-forward neural network during classification. Testing was conducted on the DMR public database, utilizing 100 photos, including 40 malignant and 60 benign cases. Asymmetric analysis validates the proposed method, which exhibits a high classification accuracy with a false-positive ratio below 0.1. However, it's essential to note that these successful results were obtained with a limited dataset [6].

Gaber et al. proposed an automated segmentation and classification approach for distinguishing normal and abnormal breasts. This automated segmentation relies on the Fast Fuzzy C-mean method optimized with Neutrosophic submodules. The SVM classifier discerns between normal and aberrant images. The approach was assessed for sensitivity and accuracy, but the study's limited sample size of 29 healthy individuals and 34 cancer patients restricts the generalizability of the results [7].

In their study, the authors of [8] investigated seven deep convolutional neural network models (GoogLeNet, AlexNet, ResNet-50, ResNet-101, Inception-v3, VGG-16, and VGG-19) to classify breast thermograms. They employed a learning rate of 1e-4 and allocated 70% of the dataset for training, 30% for verification, with a total of 5 epochs. The dataset included 141 thermal images of healthy individuals and 32 thermal images of breast cancer patients. Evaluation metrics encompassed sensitivity, specificity, area under the ROC Curve, and accuracy. Notably, the InceptionV3 model yielded results with specific values for specificity while sensitivity and accuracy were not provided.

In their paper, the authors proposed a methodology that combines an SVM classifier with a deep CNN, Inception V3, to enhance early-stage breast cancer detection. The study utilized the DMR thermal image database, consisting of 602 normal and 460 aberrant thermal images. Network training employed a learning rate of 1e-4, and the deep convolutional neural network Inception V3 was trained on 80% of the data, with 20% reserved for validation, over 15 epochs. The findings underscored Inception V3's suitability for processing both dense and sparse input, making it a fitting choice for classification tasks [9].

In their study, the authors explored various convolutional neural networks (CNNs) including VGGNet, V-net, End-to-end CNN, Input Cascade CNN, and U-net, among others. They conducted examinations on a cohort of 180 breast cancer patients at a cancer hospital, constituting their database. Parameter learning employed the Adam optimization approach with a learning rate of 10-4 for point-wise classification modeling methods and 10-5 for end-to-end CNN segmentation modeling techniques. Notably, V-net demonstrated remarkable accuracy among the tested models [10].

This paper leverages deep CNNs, specifically Inception V3, for automatic feature extraction and classification purposes. The study also shows how accuracy is impacted by the state of the hardware and software. A technique for automatic screening and categorization of thermal images was developed, involving multiple learning rate values and iterative training of the Inception V3 software with learning rate adjustments. Inception V3, a third-generation model in the Inception series, produced varying accuracy results at each training step, and the classification's average accuracy was computed from epochs 3, 5, and 6. The strategy yielded superior outcomes within the learning rate range of 1e-3 to 2.5e-3, with consistently high accuracy levels [11].

The researchers presented four experiments aimed at identifying the optimal convolutional neural network (CNN) model. The first experiment involved dataset partitioning, allocating 50% for training, 20%

for evaluation, and 30% for testing. CNNs were combined with various optimization algorithms, including Adaptive Moment (ADAM), Root Mean Square Prop (RMSPROP), and Stochastic Gradient Descent (SGD), with SGD emerging as the most effective. In the second experiment, CNN models were altered by swapping out the top layer with either an average pooling layer or a flattening layer. Results indicated that basic CNN models with the flattening layer achieved notably high accuracy levels [12].

In their research, a backpropagation neural network was employed to develop a breast cancer detection technique. By correcting missing attribute values during the data gathering procedure, they improved experimental outcomes. Notably, increasing the number of neurons in the hidden layer correlated with improved accuracy. The optimal configuration involved a neural network with 9 neurons in the hidden layer, achieving superior accuracy compared to the reference paper [16].

Breast cancer is a potentially lethal and aggressive disorder that is defined by distinct cellular abnormalities within the breast. Early detection is pivotal for effective treatment and can mitigate the exorbitant healthcare costs associated with breast cancer. Recent years have witnessed the emergence of computer-aided techniques as a critical facet of automated cancer detection. This paper presents a system for automated breast tumor diagnosis, incorporating an enhanced Deer Hunting Optimization Algorithm (DHOA) for optimization. The methodology combines an improved convolutional neural network (CNN) with a hybrid feature-based strategy. Simulations are conducted using the DCE-MRI dataset, with performance metrics established for evaluation. The research incorporates preprocessing to streamline the categorization process and introduces a novel metaheuristic approach. Furthermore, the feature extraction method incorporates Haralick texture and local binary pattern (LBP), contributing to the method's precision and efficacy, as demonstrated by the obtained findings [17].

This research delves into automated breast cancer diagnosis employing Machine Learning techniques. Recursive Feature Elimination (RFE) was employed to select salient features from a CNN classifier model. Additionally, the study conducts a comparative analysis of five algorithms, namely SVM, Random Forest, KNN, Logistic Regression, and the Naive Bayes classifier. The evaluation utilizes the BreaKHis 400X Dataset, with a focus on measuring system performance based on accuracy and precision. Probabilistic predictions are combined with activation functions like ReLu. The comparative analysis encompasses various machine learning algorithms for breast cancer screening, including CNN, KNN, SVM, Logistic Regression, Naive Bayes, and Random Forest. It is evident that CNN outperforms existing methods in terms of accuracy, precision, and data scalability [18].

The Convolutional Neural Network (CNN) has an enduring and illustrious history in biomedical image analysis. Its origins trace back to Fukushima's introduction of the " necognitron" CNN, which exhibited the remarkable capability to detect stimulus patterns with minimal variations [13]. This pioneering work emerged from Japan. Notably, Wu et al. are credited as the first researchers to employ a CNN model for classifying batches of mammography images into malignant and benign categories. Their approach included a simplified model architecture with a single hidden layer, which reduced model complexity while obtaining good accuracy. Subsequently, Sahiner et al. harnessed CNNs to distinguish between mass and normal breast tissue, demonstrating commendable accuracy in classifying both tissue types [6].

3. Experimental Design and Procedures:

3.1. Dataset Description

In this study, we introduce a 2D CNN model for binary breast cancer classification using thermal imaging. The popular, unrestricted, and openly accessible DMR-IR database of Visual Lab Group at Federal Fluminense University, Brazil is the database's source. Considerations for image capture involve controlled room conditions and patient instructions to avoid physiological changes. The FLIR SC-620 thermal camera, with a resolution of 640 × 480 and thermal sensitivity of 45 mk, was used for 287 women aged 29 to 85. Protocols include dynamic patches of 20 and static images from five angles. Diagnostic confirmation was obtained through mammography, ultrasound, and biopsies, with rigorous authentication by radiologists. The database can be accessed online at [19] using a user-friendly interface.

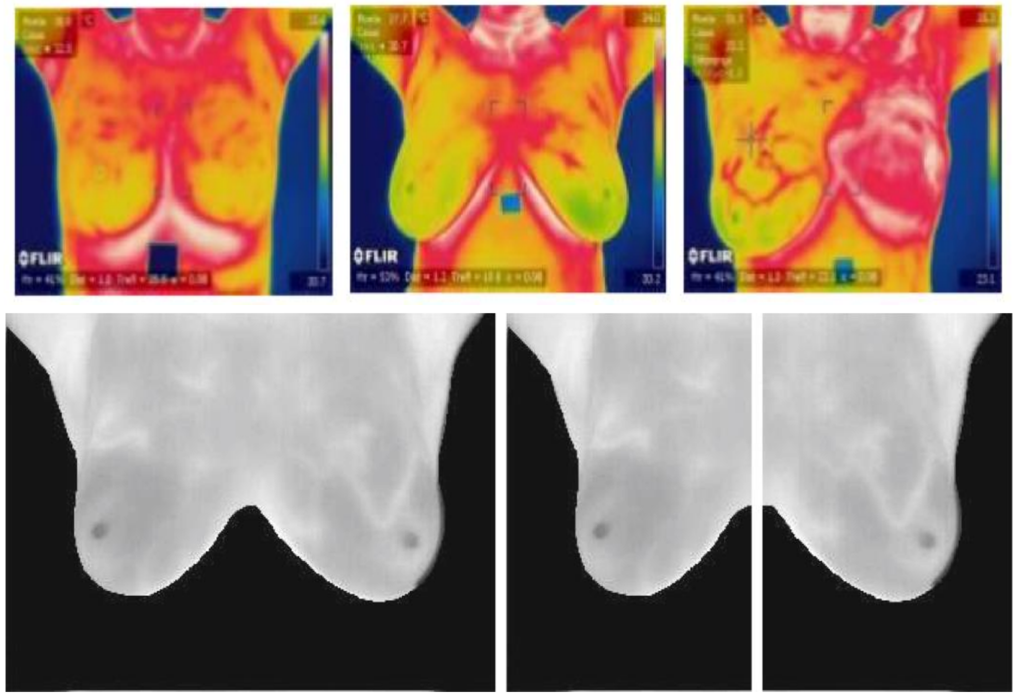

Figure1: Sample of breast cancer thermograms from DMR database.

We have curated image datasets from the DMR-IR dataset and organized them into three distinct sets. The first set comprises 100 images, the second set comprises 500 images. In both of these sets, we allocated 80% of the data for training purposes, reserving the remaining 20% for testing. This training and testing schedule lasted 20 epochs. The third set, on the other hand, consists of 4000 images. Similar to the previous sets, we utilized 80% of this dataset for training and allocated the remaining 20% for testing, albeit with a total of 10 epochs for training and evaluation.

Table 1: Dataset Description

Dataset description	Dimensions	Training	Testing	Total
Batch 1	640 x 480	80%	20%	100
Batch 2	640 x 480	80%	20%	500
Batch 3	640 x 480	80%	20%	4000

3.2. Proposed 2D CNN model architecture

A customized 2D CNN model is being developed to better breast cancer diagnosis. The efficacy of the Convolutional Neural Network (CNN) method in breast cancer diagnosis is attributed to its ability to extract global features through kernel-based operations. These global features have traditionally been leveraged for image classification tasks. In this context, a deep CNN model, drawing inspiration from GoogleNet and incorporating certain elements from ResNet, is employed for feature extraction and binary classification. Specifically, the model utilizes a hidden layering sequence for analyzing benign and malignant tumors. Simulation results underscore the superiority of the 2D CNN variant (CNN 2D-h) as the most effective classifier. This effectiveness stems from its capacity to intuitively categorize thermograms, achieved through filtration and the application of the Rectified Linear Unit (ReLU) activation function, facilitating an instinctive classification of thermographic data. The deployment of a 2D-CNN facilitates the efficient identification of distinctions between benign and malignant tumors, allowing for the rapid and automatic extraction of significant features without the need for preprocessing.

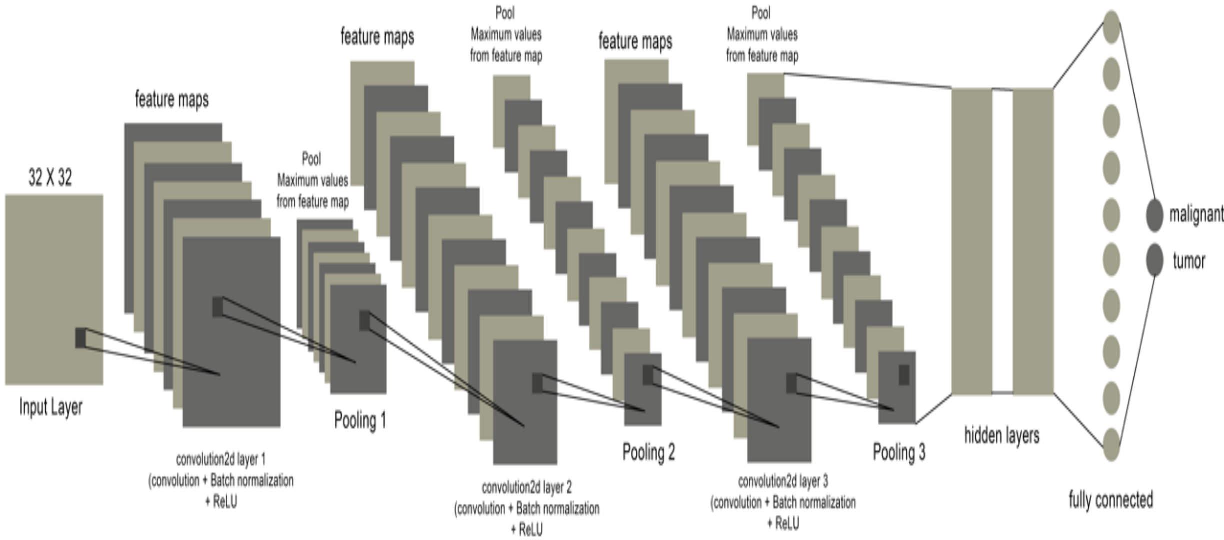

Figure 2: The architectural structure of the CNN process

3.3. Model Architecture

Step 1: The initial phase involves loading the dataset and efficiently batching the data for processing.

Step 2: Subsequently, the dataset is partitioned into distinct training and validation subsets.

Step 3: It is noteworthy that each category of thermal images comprises varying quantities, specifically 100, 500, or 1000 images.

Step 4: The subsequent step involves specifying the training options for the Convolutional Neural Network (CNN).

Step 5: The CNN is then trained utilizing the designated training dataset.

Step 6: Following training, the model is employed for the detection of both positive and negative cases.

Step 7: The validation of each image is meticulously carried out, and the accuracy of the model's predictions is computed.

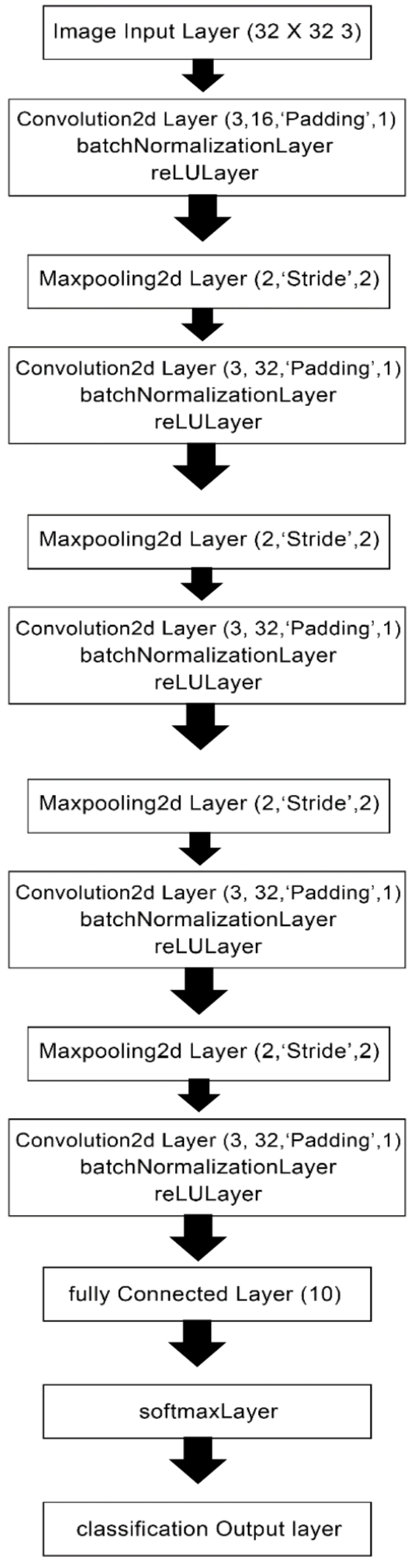

Figure 3: Proposed 2D CNN Model Layered Architecture

3.4. Features of the 2D CNN Model

The introduced 2DCNN model has the following fundamental characteristics:

3.4.1. 1x1 Convolution 2D Layer

This layer serves to reduce data size within the network, enhancing both depth and breadth. 1x1 convolution, also known as the "Network Inside Network," analyzes pixel-wise combinations in an image, resulting in a 1x1 output. While it may not learn internal linear patterns, it captures similarities across image channels, aiding dimension reduction and enhancing network learning.

3.4.2. 1x1 Batch Normalization Layer

Batch normalization fosters independent learning at each layer and scales input layers. It serves as a regularizer to prevent overfitting while promoting effective learning. This layer in the CNN 2D-h model uses normalization algorithms to equalize input/output between the convolution layer and the activation function (ReLU).

$$x_{\ normalized} = \frac{x - m}{x_{max} - x_{min}}$$

4.3.3. 1x1 ReLU Layer

The output of each kernel operation undergoes rectification using the ReLU function, known for its effectiveness. It sets values less than or equal to zero to zero, allowing positive values to pass. The ReLU parameter can be tuned to optimize model performance.

$$\sigma\ (\mathrm{x}) = \ \max\ (0, \mathrm{x})$$

3.3.4. Max-Pooling 2D Layer

A pooling layer, placed after ReLU, selects the maximum element within filter-covered areas of a feature map. This technique condenses notable characteristics from the preceding map, taking just the highest values within a kernel size into account. When a 2x2 kernel is applied to the entire image, the result is a 4x4 output.

3.3.5. 1x1 Fully Connected Layer

Data from preceding layers is consolidated for image classification. The output from the previous max-pooling layer is flattened before entering the Fully Connected layer.

3.3.6. Softmax Layer

The SoftMax function computes classification probabilities by transforming the output of a fully connected layer to a value between 0 and 1. It calculates data classification loss using normalized exponential functions. Neurons in the previous layer fully link to the SoftMax layer.

$$\mathrm{f}_{\mathrm{j}}^{\mathrm{l}} = \sigma\left(\sum_{\mathrm{i}=1}^{\mathrm{N}^{\mathrm{l}-1}} \mathrm{f}_{\mathrm{i}}^{\mathrm{l}-1} * \mathrm{k}_{\mathrm{i,j}} + \mathrm{b}_{\mathrm{j}}^{\mathrm{l}}\right)$$

The layer before the Soft-Max Layer is denoted by:

$$\mathrm{h}_p^{end} = \omega^{end} * h_p^{end-1} + b^{end}$$

Given that we are using binary classification, the normalized Soft-Max regression result can be represented as:

$$\bar{\mathrm{y}}_p = \frac{\exp\ (h_p^{end})}{\sum_{p=1}^{2} \exp\ (h_p^{end})}$$

3.3.7. Classification Output Layer

This final stage leverages SoftMax probabilities to classify inputs into mutually exclusive classes. Post-training, the network classifies the validation set, achieving a 95% success rate in our 2D CNN model.

3.3.8 Hidden Layers

To establish a deep neural network, hidden layers can be added. Our proposed 2D CNN incorporates three hidden layers, with the last layer of one batch connecting to the first layer of the next.

Table 2: Structural Information of Proposed Methodology

Structural Information	Proposed Model
Input Image Size	32x32
Number of Convolution Layers	5
Number of Pooling	5
Number of Fully Connected Layers	3
Number of Normalization Layers	5
Number of Activation Functions (ReLu)	5
Total Number of Layers	27
Rearranged Layers	Classification, Softmax, and Last Fully Connected

3.9 Performance analysis of 2D CNN:

A number of performance measures, including accuracy, specificity, sensitivity, recall, precision, and F-score, are calculated as part of performance analysis. The confusion matrix, which includes information on the number of true positives, false negatives, false positives, and true negatives (FN), is used to calculate these parameters.

4. Results and Discussion

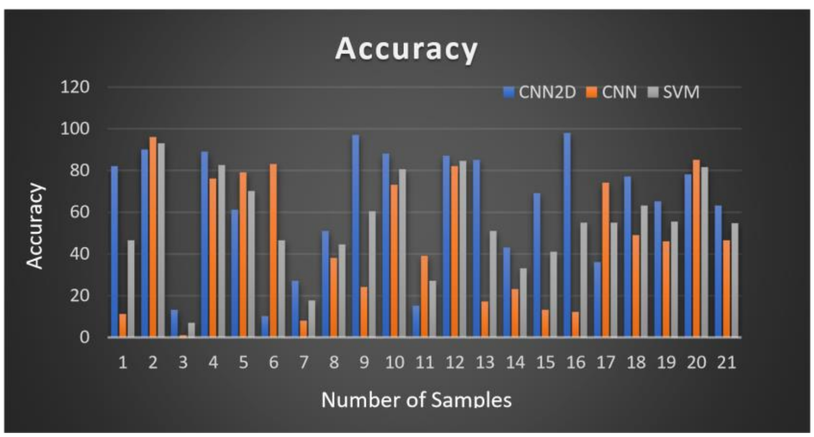

Figure 4: Accuracy results with batch 1

Figure 4 shows the accuracy results with 20% dataset that indicate the roughness of graph lines due to the short number of images and the maximum number of training samples. As we increase the number of images, then the smoothness of the graph increases automatically.

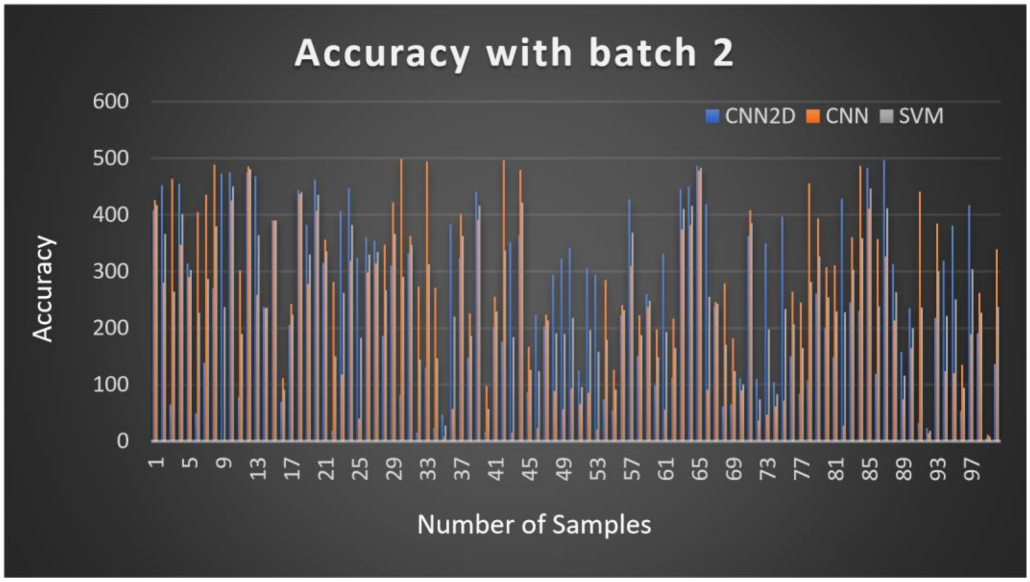

Figure 5: Accuracy results with batch 2

Figure 5 shows the accuracy results with batch 2 that indicate the roughness of graph lines due to the short number of images and the maximum number of training samples

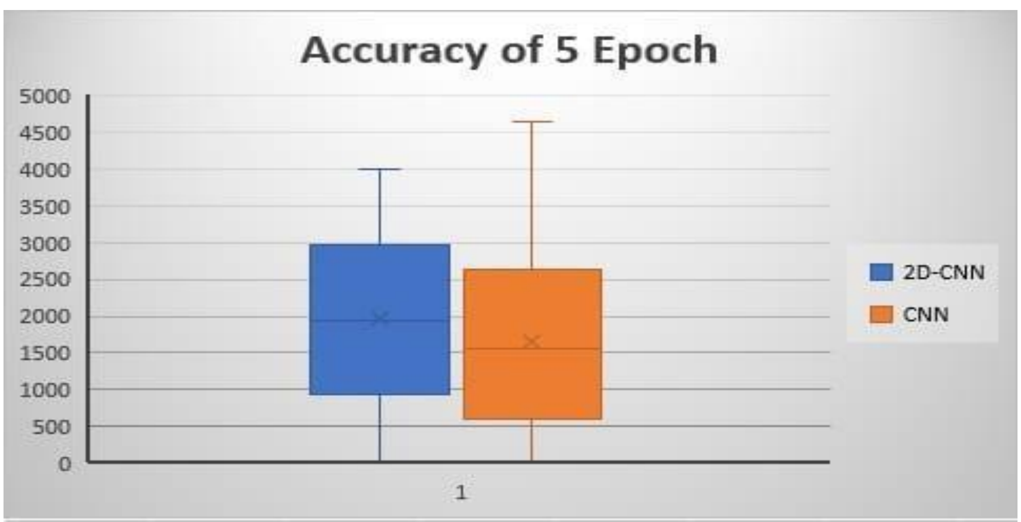

Figure 6: Accuracy results of epoch 5 with batch 3

Figure 6 presents the most favorable accuracy results achieved with a batch3 size of 4000 images at epoch 5. This illustration provides a noteworthy indication that the irregularities observed in the graph's lines can be attributed to the limited quantity of images and the saturation of training samples, particularly at the maximum threshold. It is noteworthy that the introduction of a greater number of images results in a concomitant enhancement of the graph's inherent smoothness.

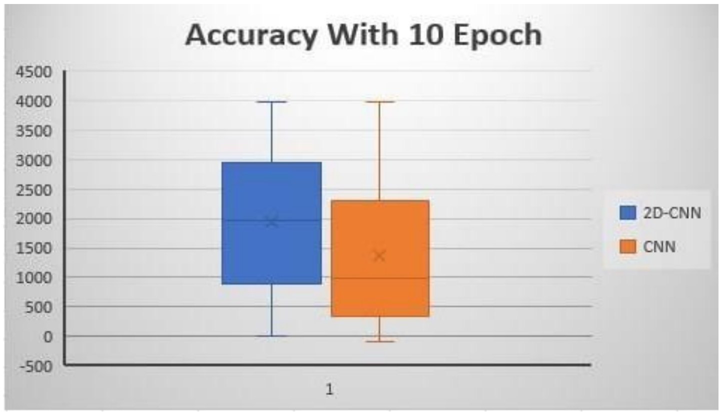

Figure 7: Accuracy results of epoch 10 with batch 3

Figure 7 depicts the most optimal accuracy results achieved with a batch 3 size of 4000 images at epoch 10. This presentation provides valuable insights, suggesting that the irregularity observed in the graph lines can be attributed to the limited number of images and the saturation of training samples. Notably, the augmentation of the image dataset leads to an inherent improvement in the graph's smoothness.

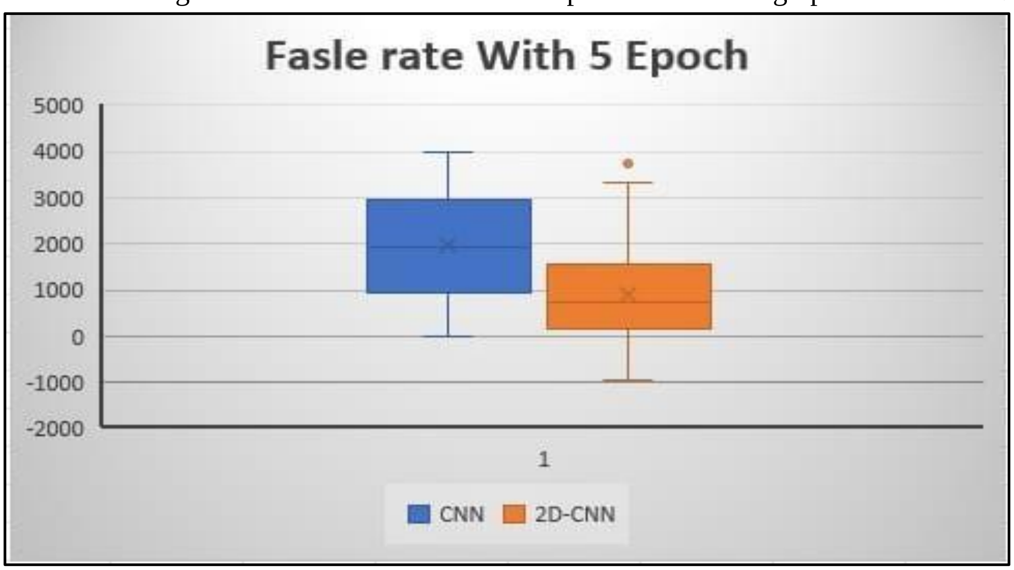

Figure 8: False results of epoch 5 with batch 3

Figure 8 illustrates the most favorable outcomes in terms of false results, specifically with a batch3 size of 4000 images at epoch 5. This portrayal conveys a critical insight: as the quantity of images within the dataset rises, there is a concomitant escalation in the false rate. Furthermore, it is noteworthy that this augmentation in the number of images inherently contributes to the heightened smoothness exhibited by the graph.

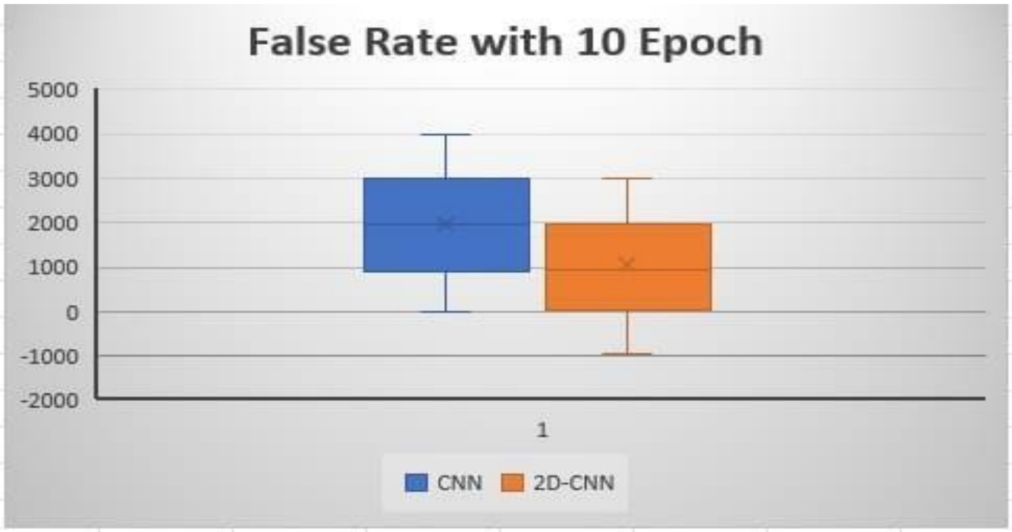

Figure 9: False results of epoch 10 with batch 3

Figure 9 presents the optimal false results obtained with a batch 3 size of 4000 images at epoch 10. This observation underscores the direct relationship between the size of the dataset and the false rate, indicating that an increase in the number of images in the dataset results in a corresponding increase in the false rate. Furthermore, it is noteworthy that as the number of images is augmented, there is a natural enhancement in the graph's overall smoothness.

The reliability of the model is severely impacted by the growing false rates with more data. Increased false negatives could jeopardize the model's efficacy, while elevated false positives could distort decision-making. In order to overcome these obstacles, a careful balance must be struck, requiring model tuning, data quality assessment, and a sophisticated comprehension of the trade-offs between false positives and false negatives in the particular situation.

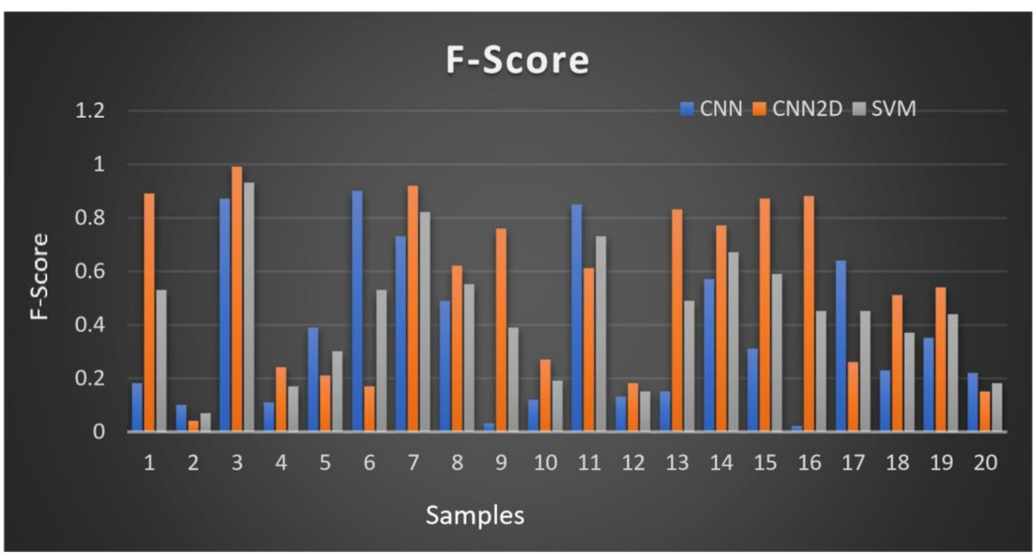

Figure 10: F-score results

In **Figure 10**, we depict the F-score measurements for 20 individual epochs. It is observed that the Convolutional Neural Network (CNN) exhibits a notable 46% increase in false-negative rates, which renders it less effective in terms of F-score. The variability observed in F1 scores throughout models and sample sizes could be attributed to differences in model sensitivity, features of the dataset, and the complex interaction of hyperparameters. In order to reduce these swings and improve overall predictive accuracy, careful tuning and investigation of model complexities are essential. This phenomenon can be attributed to the fact that CNN requires additional processing time when dealing with larger training datasets, ultimately impacting the overall image detection time. Similarly, Support Vector Machine (SVM) also demonstrates a 33% increase in false-negative rates, indicating its limited effectiveness in achieving a high F-score. In contrast, the proposed technique exhibits a more promising and effective performance, delivering improved results in this context.

5. Conclusion:

In the domain of cancer detection, various methodologies leveraging extensive datasets have been employed to prognosticate the status of query images. Thermal imaging, a crucial modality, significantly enhances predictive capabilities in cancer detection systems. This study introduces a novel approach utilizing a 2D Convolutional Neural Network (CNN) architecture with three optimized hidden layers, demonstrating superior outcomes compared to traditional CNN models. The proposed model exhibits enhanced classification efficacy when applied to thermal image datasets. Implemented entirely within the Matlab environment, our approach operates on a segmented dataset comprising a substantial volume of breast cancer images, encompassing various states and thousands of images. Despite a dataset reduction to 600 images, our proposed model achieves exceptional results, surpassing comparative techniques. Specifically, it attains a remarkable binary classification accuracy rate of 95% and an F-score of 94%. In contrast, conventional CNN and Support Vector Machine (SVM) models, discussed in the conclusion but not presented in the results, display classification accuracy rates of 71% and 91%, respectively. CNN and SVM also exhibit F-scores of 68% and 89%, respectively. Our findings suggest that the combination of our methods with other approaches could yield more refined models, elevating the standards for medical picture categorization. The crux of this endeavor lies in the meticulous refinement of the layering process, a pivotal facet of feature detection. Consequently, further precision and accuracy in layering are imperative. The development of an enhanced CNN layering technique, capitalizing on precise intensity value ranking, demands increased reliability to continue advancing the frontiers of medical image classification. To expedite the review and typesetting process, authors must follow the Microsoft Word template provided for preparing their manuscripts. This template must be strictly adhered to when formatting the manuscript for submission.

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