Inteligencia Artificial 26(72) (2023), 160-177
doi: 10.4114/intartif.vol26iss72pp160-177

INTELIGENCIA ARTIFICIAL

http://journal.iberamia.org/

An Ensemble Classification Method Based on Deep Neural Networks for Breast Cancer Diagnosis

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Abstract Advances in technology have led to advances in breast cancer screening by detecting symptoms that doctors have overlooked. In this paper, an automatic detection system for breast cancer cases based on Internet of Things (IoT) is proposed. First, using IoT technology, direct medical images are sent to the data repository after the suspicious person's visit through medical equipment equipped with IoT. Then, in order to help radiologists, interpret medical images as best as possible, we use four pre-trained convolutional neural network models including InceptionResNetV2, InceptionV3, VGG19 and ResNet152. These models are combined by an ensemble classifier. Also, these models are used to accurately predict cases with breast cancer, healthy people, and cases with pneumonia by using two datasets of X-RAY and CT-scan in a three-class classification. Finally, the best result obtained for CT-scan images belongs to InceptionResNetV2 architecture with 99.36% accuracy and for X-RAY images belongs to InceptionV3 architecture with 96.94% accuracy. The results show that this method leads to a reduction in daily visits to medical centers and thus reduces the pressure on the medical care system. It also helps radiologists and medical staff to detect breast cancer in its early stages.

Keywords: Breast cancer, image processing, ensemble classification, neural network, deep learning.

1 Introduction

Breast cancer is the most common cancer in women. The need to diagnose this disease in the early stages increases the chance of treatment [1]. The aim of this research is to provide a method for early diagnosis, with accurate and fast screening of breast cancer by reducing human errors and increasing the chance of increasing people's life expectancy and reducing the death rate with the approach of artificial intelligence in medicine. Early and accurate diagnosis of breast cancer is very important to control the spread of the disease and reduce its mortality [2, 3].

Today, researchers use various machine learning and deep learning techniques along with artificial intelligence to analyze medical images. These developed techniques are used to identify diseases that may help medical professionals to diagnose diseases in the early stages and provide accurate, consistent, effective and fast results and reduce mortality [4]. There is also a shortage of health workers to care for all patients. Therefore, it is very important to develop an automated intelligent method that provides immediate and high-accuracy results and essentially enables testing anywhere and anytime. This can be provided by the Internet of Things (IoT) and the retrieved data can be analyzed using artificial intelligence techniques for diagnosis [5-7]. Even if medical imaging centres are established in remote areas, the availability of radiologists remains a problem. Developing or underdeveloped

ISSN: 1137-3601 (print), 1988-3064 (on-line)
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countries are struggling to improve their detection capabilities because current methods are expensive and not readily available.

Hence, an easily accessible automated detection system is essential for prompt screening and diagnosis of breast cancer cases [6]. According to the statistics published by the World Health Organization until April 2023, the total number of confirmed cases of breast cancer worldwide has increased significantly [8]. To deal with this epidemic, researchers are looking for a wide range of technologies such as IoT, artificial intelligence and big data that can help overcome the challenges caused by breast cancer. IoT is an expanding ecosystem that integrates a variety of electronic devices and physical objects capable of exchanging information to communicate and collect data [9, 10].

Recently, several artificial intelligence-based methods have been proposed that use chest radiography and CT-scan to detect visual indicators of breast cancer. In order to limit breast cancer misdiagnosis as well as identify cases in the early stages, one solution is to design a model that can perform biological tests without involving many people [11, 12].

In this paper, an automatic detection system for breast cancer cases using three pre-trained convolutional neural networks is proposed with the help of transfer learning technique in breast cancer diagnosis. By combining the results of deep neural networks, this model seeks to develop an efficient ensemble classification method for breast cancer diagnosis. The proposed model includes a data collection section with the help of devices equipped with IoT technology and sending it to the information repository, then processing the information and extracting knowledge, and finally sending the results to the doctor in question to assess the patient's condition.

The main contribution of this paper is as follows:

- An IoT-based framework of deep learning models is proposed for automatic diagnosis of breast cancer patients.
- The configuration process of an ensemble classification model that uses the transfer learning capabilities of four pre-trained convolutional neural network models and can help researchers to identify cases of breast cancer.
- In order to improve the performance of convolutional neural networks, the technique of data amplification and precise adjustment of the main parameters have been used.

The rest of the paper is organized as follows: In Section 2, some related works will be reviewed. In Section 3, firstly, the used dataset will be introduced and then the data enhancement technique will be reviewed. In Section 4, the proposed model will be introduced. In Section 5, the obtained results are evaluated and compared. Finally, Section 6 deals with conclusions and future work.

2 Related works

This section is dedicated to reviewing some of the works done in the field of breast cancer diagnosis using machine learning approaches. After reviewing the related works, we have summarized them in Table 1.

Oh et al. [13] introduced a smart health care system equipped with IoT to identify and classify chest X-ray images into three classes: cancer, pneumonia and healthy. In the first step, after preprocessing, data enhancement is applied to increase the diversity of the dataset. Then the data is divided into two sets of training and testing, and two pre-trained architectures VGG19 and InceptionV3 are used for classification. They used a set of 4,500 chest X-ray images for their research and finally recorded the best accuracy of 97%.

Mohapatra et al. [14] extracted low-level features from X-ray images using a set of four pre-trained convolutional neural network architectures including NASNet, VGGNet, GoofleNet and DenseNet. Here, fully connected layers are used for classification. This framework has been evaluated on two public datasets and one private dataset, and the results show that the multi-model hybrid convolutional neural network architecture performs better than single-model classifiers.

Murtaza et al. [15] used the CLAHE technique as a pre-processing step for CT-scan images. After that, 100 features were extracted by convolutional neural network and then classified using different machine learning algorithms, and finally a hybrid model is proposed for classifying CT-scan images.

Puglisi et al. [16] used a proposed convolutional neural network to classify Chest X-Ray (CXR) and Computed Tomography (CT) scan images. They used two classification scenarios, two-class and multi-class. For this purpose, 11095 images were used. Finally, the best accuracy in two-class classification was reported as 99.6% and in multi-class classification as 98.2%.

Morid et al. [17] used X-ray and CT-scan images to predict cases of breast cancer based on ReseNet, GoogleNet, AlexNet, DenseNet, Visual Geometry Group (VGG) Network, Inception V3 models, along with a proposed model. The highest accuracy obtained using X-ray images was 97.7% and using CT images reported 97.1%.

Minn et al. [18] have used chest x-ray images to classify people infected with breast cancer by deep learning and using transfer learning. This method investigates five models based on pre-trained convolutional neural networks including AlexNet, VGG16, ReseNet50, ReseNet101 and ReseNet152 on 185 X-ray images including four classes. Due to the small number of images in the dataset, the data augmentation process was used, including rotation of 90, 180 and 270 degrees in different axes. Also, increasing the brightness has been used to improve the classification performance. The best results are obtained if the pre-trained ReseNet152 architecture is trained using larger datasets in an average number of training sessions using the Nadam optimizer function.

Antropova et al. [19] used deep learning-based approaches including deep feature extraction, fine-tuning of pre-trained convolutional neural networks and end-to-end training of an extended convolutional neural network model for image classification. The developed convolutional neural network model consists of 21 layers including convolution layers, maximum integration and fully connected layers and the final classification layer along with batch normalization and ReLU layers.

Saxena et al. [20], a dataset containing 180 breast cancer images and 200 healthy images was used and in order to extract deep features from pre-trained convolutional neural network models (VGG16, VGG19, ReseNet101, ReseNet50, ReseNet18) were used. Finally, the deep features extracted from the ReseNet50 model with the help of SVM achieved 94.7% accuracy, which was the highest score among all the results.

Table 1: Summary of reviewed works

Reference	Methodology	Dataset	Data type	Best accuracy
[13]	VGG19, InceptionV3	4500 chest x-ray images	X-ray	97%
[14]	VGGNet, GoogleNet, DenseNet, NASNet, ResNet, ReseNext, Ensemble model	Chest-xray-cancer- pneumonia dataset	X-ray	Double class: 98.5% Multiclass: 88.9%
[15]	CNN + gaussian naïve base + SVM + Decision tree + RF + Logestic regression	sarscov2-ctscan-dataset	CT-scan	95.4%
[6]	VGG16, ResNet50	15153 radiology images	X-ray	91.3% using ResNet50 algorithm
[16]	Convolutional neural network	11095 medical images	X-ray and CT-scan	Double class: 99.6% Multi-class: 98.2%
[17]	ReseNet50, ReseNet53, GoogleNet, AlexNet, DenseNet201, InceptionV3, ReseNet50+SVM	Dataset collected by Kragujevac	X-ray and CT-scan	97.7% for the X-ray and 97.1% for the CT-scan
[7]	ShuffleNet, mobile net, mobshufnet	5471 CT images, 7439 X-rays images	X-ray and CT-scan	94.7% for the CT dataset and 95.8% for the X-ray dataset
[18]	AlexNet, VGG16, ReseNet50, ReseNet101, ReseNet152	Dataset collected by Kragujevac	X-Ray	95% using ResNet152
[19]	ReseNet18, ReseNet50, ReseNet101, VGG16, VGG19+SVM	sarscov2-ctscan-dataset	X-ray	94.7% using ResNet50 + SVM
[20]	Faster RCNN + ResNet101	11,000 radiographic images	X-ray	98%

3 Dataset

Two datasets of medical images are described for disease analysis of breast cancer and pneumonia. Researchers have used various public datasets such as X-ray images [21, 22] and CT-scan images [23, 24] to diagnose cases of breast cancer. Research shows that the diagnosis of diseased cases is made through CT-scan images with higher accuracy than X-ray images, although the patient receives a lower radiation dose during X-ray imaging than CT-scan. This may be overlooked in the small number of tests, but it is of great importance for expectant mothers. In this paper, two datasets including X-RAY and CT-scan are used to enable the use of various types of medical images for the proposed framework.

3.1 CT-scan dataset

Two datasets of CT-scan images [25] collected from different online sources are combined to create the desired dataset. As shown in Figure 1, there are 5203 breast cancer images and 2418 healthy images in this dataset. Also, in order to make the proposed model work better in the real world, 2618 images of community-acquired pneumonia have been added to this dataset. A total of 10239 CT-scan image data have been used.

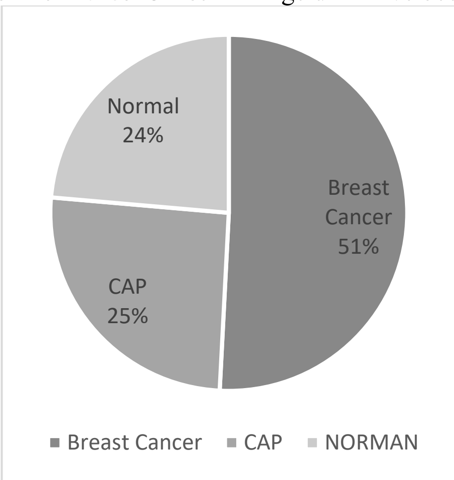

Figure 1: Structure of CT-scan dataset

3.2 X-RAY dataset

X-ray images have been collected from several sources [26-29]. The images are classified into three categories: breast cancer patients, non-breast cancer pneumonia patients, and normal people, and all photos are resized in 256x256 size. A total of 5228 chest X-ray images were used and the data distribution of the X-ray dataset is presented in Figure 2.

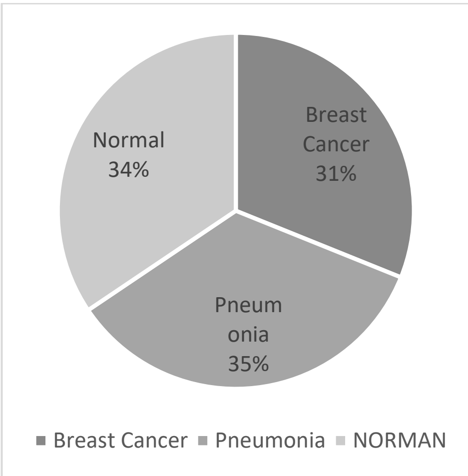

Figure 2. Structure of the X-RAY dataset

3.3 Preprocessing

The huge number of educational images is one of the requirements of deep learning, in this regard, the data augmentation process has been used to increase the classification performance. This process aims to artificially increase the training dataset [27, 30] and the test dataset remains constant. A set of different geometric operations can be used to increase the dataset. In this paper, we have used horizontal flipping and zooming of images. Figure 3 shows some images of all three classes.

So far, many works have been presented on image preprocessing. In this paper, first, the dataset images are changed according to the input size of the training networks, and then all images are converted from color mode (three RGB channels) to black and white images (one gray scale color channel) [31]. In addition, in order to make the network work better, the values of each pixel are changed from the range of 0-255 to the range of 0-1 and then they are divided into three sets of training, validation and testing using random selection of images [32, 33].

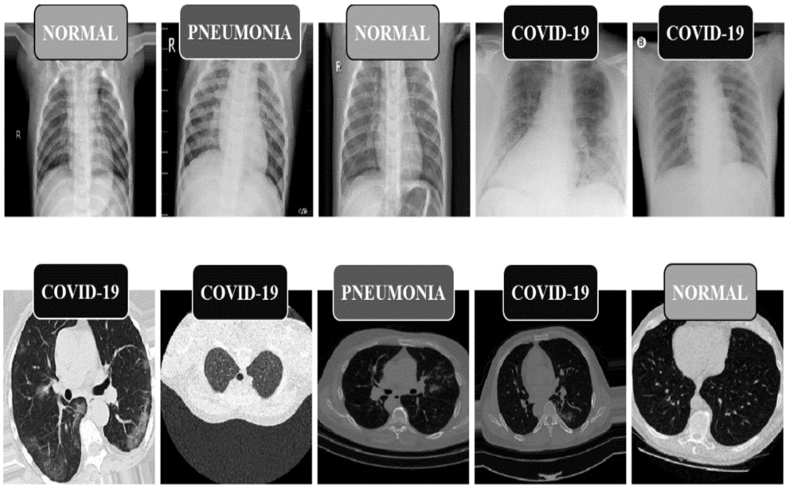

Figure 3: Examples of dataset images after applying the data enhancement process

4 Proposed method

In this section, the framework of the proposed intelligent model based on IoT is described. IoT makes it possible to monitor a large number of patients at home or in a hospital. In addition to the main data used in this paper, it is possible to transfer other patients' biometric data to the main data repository for analysis and knowledge extraction. In [20], an inexpensive IoT system was proposed that automatically uploaded the resulting data to a global network using wireless communication through smartphones. Hence the test results are immediately available anywhere in the world. Such an IoT system is a very important tool for doctors to deal with other diseases.

In this paper, a framework for automatic detection of breast cancer is introduced, which first sends information to the data repository using IoT. Then, using deep neural network algorithms in image processing, the data is processed in order to extract knowledge. In the first step, four pre-trained convolutional neural network models were used after fine-tuning the important parameters of the problem using transfer learning to diagnose cases of breast cancer and used in an ensemble classification. The main goal is to correctly classify and diagnose images into three classes: breast cancer patient, pneumonia patient and healthy. The reason for using the classification of three classes of medical images is to help radiologists to prioritize breast cancer patients in order to quickly treat affected people and protect a healthy society.

The workflow of the proposed model is shown in Figure 4. As can be seen, the data collected with the help of IoT is divided into two parts: training data (70%) and testing data (30%). First, pre-processing and data amplification is done on the data, then the model is trained and finally the results are obtained to determine whether the person is sick or not.

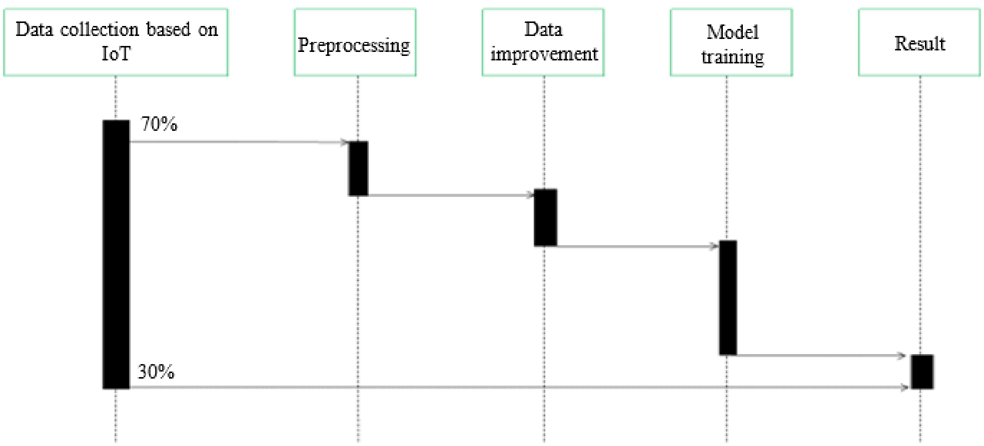

Figure 4. Overview of the proposed model

4.1 The role of IoT in data collection

Today, IoT covers various applications such as transportation, smart cities, surveillance, health care, etc. according to the needs of the society. For example, in the healthcare industry, IoT can play an important role in remote monitoring in the hospital, especially at home for the elderly with chronic diseases. Also, by using IoT and automatic disease detection systems, people with breast cancer can be diagnosed and treated in the early stages. In the future, using this technology, healthcare systems will experience major effects such as reduced response time to detect abnormalities, high quality care, low hospitalization costs, and high life expectancy.

IoT makes it possible to monitor a large number of patients at home or in a hospital. In addition to the main data used, it is possible to transfer other biometric data of patients to the main data repository in order to analyze and extract knowledge. Due to this feature, the treatment staff can easily and quickly obtain the patient's information through the hospital network. In the field of IoT in medicine, artificial intelligence plays a very important role. Because the number of Internet of Medical Thing (IoMT) devices is increasing day by day, and this is where the ability to process data is very important in the success of the devices. To move IoMT data from one point to another, IoT devices in medicine must use different communication protocols. In other words, all these efforts are to bring data to the Internet. The main complication is that once the data reaches the Internet, from that point on, the data reaches different doctors or health services.

Different architectures have been proposed for IoT, but in general, IoT consists of four main layers: 1) Perception layer as the lowest layer in the IoT architecture, which includes sensors, operators and devices, the task of measuring environmental data and it is responsible for measuring the parameters. 2) Network layer is used as middle layer in IoT architecture. This layer is responsible for sending information from sensors and devices to the platform and cloud centers, and in order to achieve this, several technologies are used in it. 3) the platform layer, in which all information is sent; They are stored, collected and processed, and then control commands are issued according to data analysis and artificial intelligence. 4) Finally, the application layer exists as the highest layer in the IoT architecture. This layer refers to a large set of applications that may be designed and implemented for a particular industry or several industries, and is responsible for the graphical display of information. The IoT architecture based on the proposed model is shown in Figure 5.

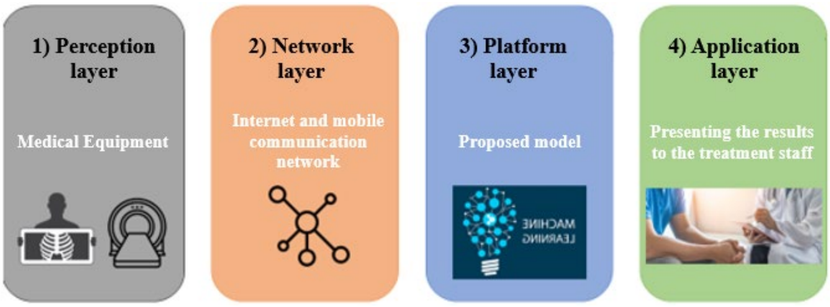

Figure 5. IoT architecture

As shown in Figure 5, IoT is used to collect and transmit real-time data regarding patient status decisions. According to the obtained results, by using the proposed model and informing the doctor about the patient's condition, the patient's treatment can be continued faster.

In breast cancer, artificial intelligence and IoT are gaining more attention in healthcare, where screening and diagnosis procedures can be performed more safely. Thermal imaging and social distance monitoring are also functions that are mainly considered in the breast cancer screening stage. In fact, the purposes of using these devices are to detect body temperature, screen people and also control health. Finally, IoT can help reduce costs and reduce infrastructure complexity [34].

The rapid evolution and adoption of IoT may raise additional security concerns. Therefore, the main challenge is to maintain the privacy of important and sensitive medical data. Numerous attacks, threats and risks can affect different layers of the IoT architecture. Therefore, an IoT ecosystem must be secure and follow strict privacy protocols [35]. In the IoT application, safety plays an important role because it can negatively affect the physiological, psychological and biological state of humans. It may even lead to loss of life. IoT devices with poor security are one of the most effective channels for cybercriminals to expose customer data through communication streams [36]. Hence, medical care centers should develop risk assessment guidelines to ensure data protection.

4.2 Classification model

Convolutional neural network is the most reliable deep learning algorithm [37] and they are used to process a huge amount of data where they do not need to manually extract features. The architecture of a convolutional neural network is divided into two parts, feature learning and classification. In general, these networks are hierarchically composed of three types of layers: convolution layer, integration layer to extract features, and fully connected layer to classify them.

The proposed architecture of these networks includes four stages. First, the images of people suspected of breast cancer who refer to medical centers for chest imaging are sent to the dataset in real time for processing using devices equipped with IoT technology. Then, the images of the dataset are pre-processed and trained by convolutional neural network in the next step. At this stage, four architectures ResNet152, VGG19, InceptionV3 and InceptionResNetV2 have been used using the transfer learning technique along with the precise adjustment of the main parameters of the problem to extract the best features. Also, at the end of each architecture, in order to improve the accuracy of the network, a GlobalAveragePooling2D layer and then three fully connected layers have been used for data classification. In addition, the dropout layer (0.5) has been used to prevent overfitting. After that, the proposed neural networks are evaluated by the test set images. In addition, ReLU and sigmoid activation functions have been used in this network and the weights are generated using the Adam optimizer with an initial learning rate of 0.003. The networks used in 30 rounds of training with a dynamic learning rate have been done in order to increase accuracy and prevent overfitting. According to the teaching process, a reduced learning rate has also been used. During the training process, there is a point where the output of the model does not improve, for this purpose, the early stopping technique has been used based on the lowest amount of validation error. The configuration of neural network models used in Tables 2-5 are shown for ResNet152, VGG19, InceptionV3 and InceptionResNetV2 architectures, respectively. Meanwhile, the structure of these networks is shown in Figures 6-9, respectively.

Table 2: Types of layers and number of parameters used for ResNet152 architecture

Layer type	Output	Number of parameters
resnet152	(None, 7, 7,2048)	58370944
global_ average_ pooling2d	(None, 2048)	0
flatten	(None, 100352)	0
dropout_1	(None, 100352)	0
dense_1	(None, 2048)	1836032
dense_2	(None, 1024)	1049600
dropout_2	(None, 1024)	0
dense_3	(None, 3)	3075

Table 3: Types of layers and number of parameters used for VGG19 architecture

Layer type	Output	Number of parameters
inception_v3	(None, 5, 5,2048)	21802784
global_ average_pooling2d	(None, 2048)	0
flatten	(None, 2048)	0
dropout_1	(None, 2048)	0
dense_1	(None, 1024)	2098176
dense_2	(None, 1024)	1049600
dropout_2	(None, 1024)	0
dense_3	(None, 3)	3075

Table 4: Types of layers and number of parameters used for InceptionV3 architecture

Layer type	Output	Number of parameters
VGG19	(None, 5, 5,2048)	20024384
global_ average_pooling2d	(None, 2048)	0
Flatten	(None, 2048)	0
dropout_1	(None, 2048)	0
dense_1	(None, 1024)	2098176
dense_2	(None, 1024)	1049600
dropout_2	(None, 1024)	0
dense_3	(None, 3)	3075

Table 5: Types of layers and number of parameters used for InceptionResNetV2 architecture

Layer type	Output	Number of parameters
inception_resnet_v2	(None, 5, 5, 1536)	54336736
global_ average_pooling2d	(None, 1536)	0
flatten	(None, 1536)	0
dropout_1	(None, 1536)	0
dense_1	(None, 1024)	1573888
dense_2	(None, 1024)	1049600
dropout_2	(None, 1024)	0
dense_3	(None, 3)	3075

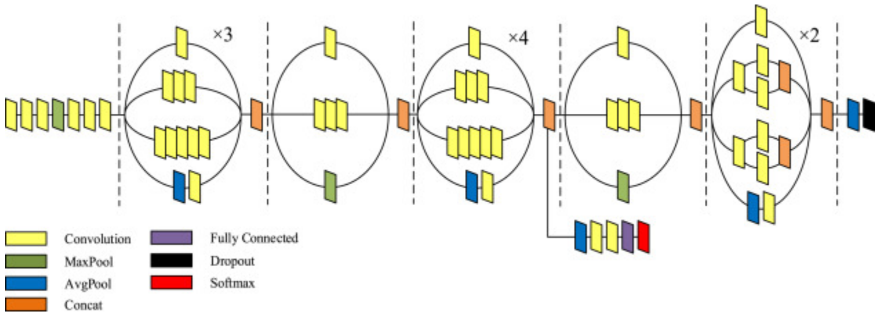

Figure 6. InceptionV3 neural network structure in the proposed model

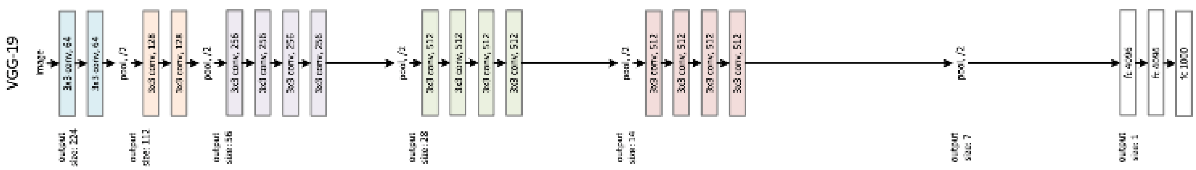

Figure 7. VGG19 neural network structure in the proposed model

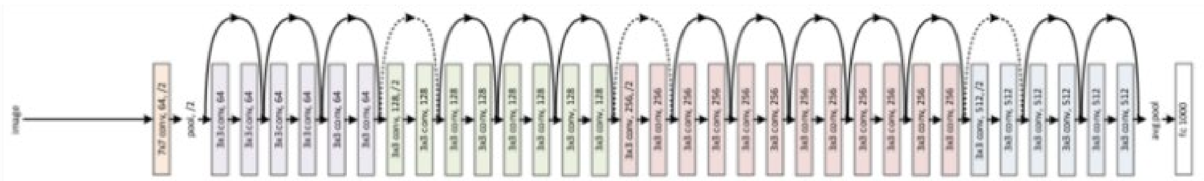

Figure 8. ResNet152 neural network structure in the proposed model

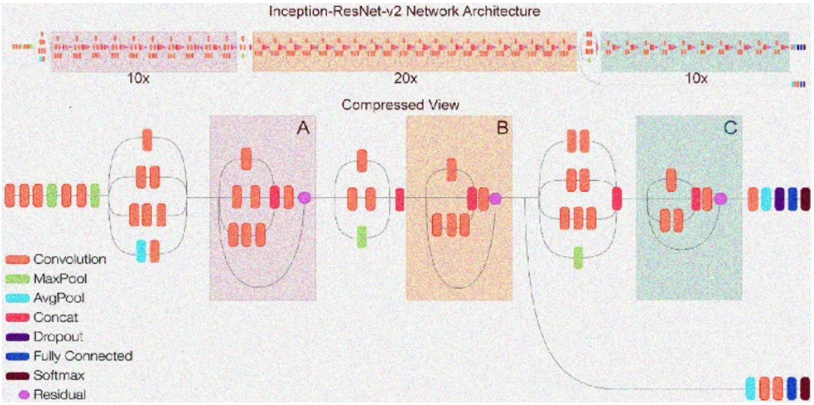

Figure 9. InceptionresnetV2 neural network structure in the proposed model

Ensembles can help us improve machine learning results by combining multiple models. Basically, ensemble models consist of several separate trained supervised learning models and their results are combined in different ways to achieve better predictive performance than a single model. In this paper, the output of all neural network models is combined by voting technique to get the final predictions. In the voting technique of ensemble learning, several models of different types are built and some simple statistical analysis such as calculating the mean or median is used to combine predictions. This prediction is used as an additional input for training to build the final prediction. Figure 10 shows the schematic representation of ensemble classification.

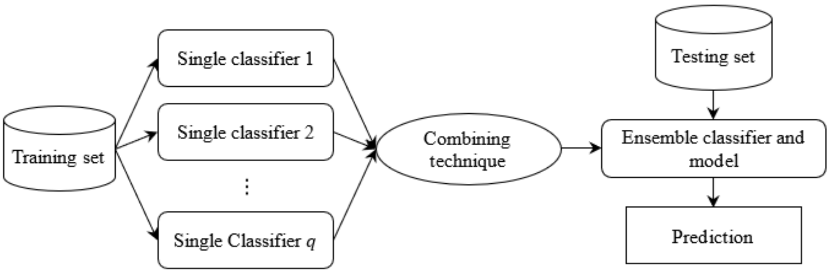

Figure 10. Overview of ensemble classification

5 Experiment results

In this section, we evaluate the performance of the proposed method. First, we describe the evaluation criteria used. Then, in the next section, we describe the performance of the proposed classification in two X-RAY and CT-scan datasets and compare it with other works.

5.1 Evaluation criteria

Classical criteria including accuracy, precision, recall and F-measure have been used to evaluate the proposed model. The function of these metrics is given in Equations. (1–4) respectively. Also, the objective function is formulated in Equation (5).

$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN} \tag{1}$$

$$Precision = \frac{TP}{TP + FP} \tag{2}$$

$$Recall = \frac{TP}{TP + FN} \tag{3}$$

$$F\_score = \frac{2 * (Precision * Recall)}{(Precision + Recall)} \quad (4)$$

$$CCE = -\sum_{k=0}^{m-1} y_k \log(\hat{y}_k) \quad (5)$$

where, True Positive (TP) indicates a correct prediction (true positive class), True Negative (TN) indicates a correct prediction (negative true class), False Positive (FP) indicates a false prediction (negative true class), and False Negative (FN) indicates false prediction (true positive class).

Table 6. Results obtained on X-ray and CT-scan datasets

Dataset	Method	Precision	Recall	F-score	Accuracy
X-ray	ResNet152	0.95	0.95	0.95	94.55
	InceptionResNetV2	0.97	0.95	0.95	95.98
	VGG19	0.93	0.93	0.93	93.31
	InceptionV3	0.97	0.97	0.97	96.94
CT-scan	ResNet152	0.99	0.99	0.99	99.31
	InceptionResNetV2	0.99	0.99	0.99	99.36
	VGG19	0.99	0.99	0.99	98.73
	InceptionV3	0.99	0.99	0.99	99.17

Table 7. The results obtained for each class using the proposed models

Dataset	Method	Class	Precision	Recall	F-score
X-ray	ResNet152	Breast Cancer	0.98	0.98	0.98
		Pneumonia	0.96	0.89	0.93
		Normal	0.90	0.97	0.94
	InceptionResNetV2	Breast Cancer	0.99	0.98	0.98
		Pneumonia	0.89	0.89	0.94
		Normal	0.98	0.98	0.95
	VGG19	Breast Cancer	0.98	0.96	0.97
		Pneumonia	0.92	0.90	0.91
		Normal	0.92	0.94	0.91
	InceptionV3	Breast Cancer	1.00	0.98	0.99
		Pneumonia	0.94	0.94	0.96
		Normal	0.98	0.98	0.96
CT-scan	ResNet152	Breast Cancer	0.99	0.99	0.99
		CAP	1.00	1.00	1.00
		Normal	0.98	0.99	0.99
	InceptionResNetV2	Breast Cancer	0.99	0.99	0.99
		CAP	1.00	0.99	1.00
		Normal	0.99	0.98	0.99
	VGG19	Breast Cancer	0.99	0.98	0.99
		CAP	1.00	1.00	1.00
		Normal	0.97	0.98	0.97
	InceptionV3	Breast Cancer	0.99	0.99	0.99
		CAP	1.00	0.99	1.00
		Normal	0.98	0.97	0.98

5.2 Evaluation of models

In this classification model, there are three types of data: breast cancer patients, pneumonia patients and healthy people. In the proposed approach, four convolutional neural network models named ResNet152, VGG19, InceptionV3 and InceptionResNetV2 are used under transfer learning technique. This approach is trained on two datasets of X-RAY and CT-scan, and in order to improve the performance of the network after data pre-processing, data enhancement technique is used. Here, 70% of the data is used for training the network, 20% for testing and the remaining 10% for validation. Training has been done in 30 steps and using a decreasing learning rate. Meanwhile, the performance of the model during training along with early stopping is based on the lowest validation error rate.

In order to avoid the problem of overfitting, the generalization technique has also been used. In addition, to obtain the best accuracy, the hyper-parameters have been set on four convolutional neural network models. Also, the obtained results are shown in general in Table 6 and for each class in Table 7. The best performance for X-RAY dataset is related to InceptionV3 architecture with 96.94% accuracy and for CT-scan dataset it belongs to InceptionResnetV2 architecture with 99.36% accuracy. This shows the high efficiency of the proposed framework to help the treatment staff to identify infected cases in the early stages of the disease. Also, according to the results obtained from two sets of data, it can be concluded that CT-scan images have more details than X-ray images in order to diagnose breast cancer diseases. In addition, the InceptionV3 model learns faster than other models, reaches an early termination point, and requires fewer training rounds. Figure 11 shows the classification results of X-RAY images in the form of confusion matrix and Figure 12 is related to CT-scan images.

The matrix in the fusion shows the performance of the proposed model in such a way that the real class of the images of the test set is given in the rows and the class predicted by the proposed model is given in the columns. The data that is on the main diameter is the correct prediction and the rest of the data in other cells is the wrong prediction.

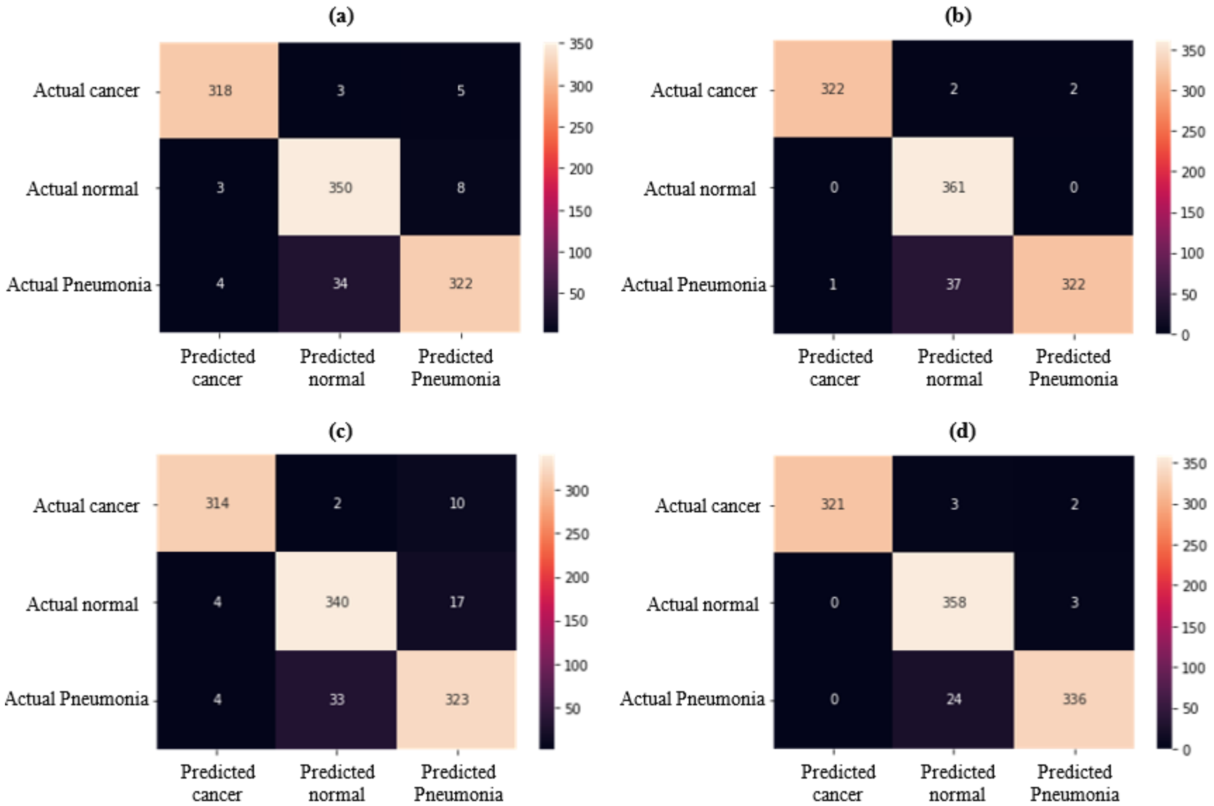

Figure 11: Confusion matrix in X-ray dataset. a) ResNet152 network, b) InceptionresNetV2 network, c) VGG19 network and d) InceptionV3 network

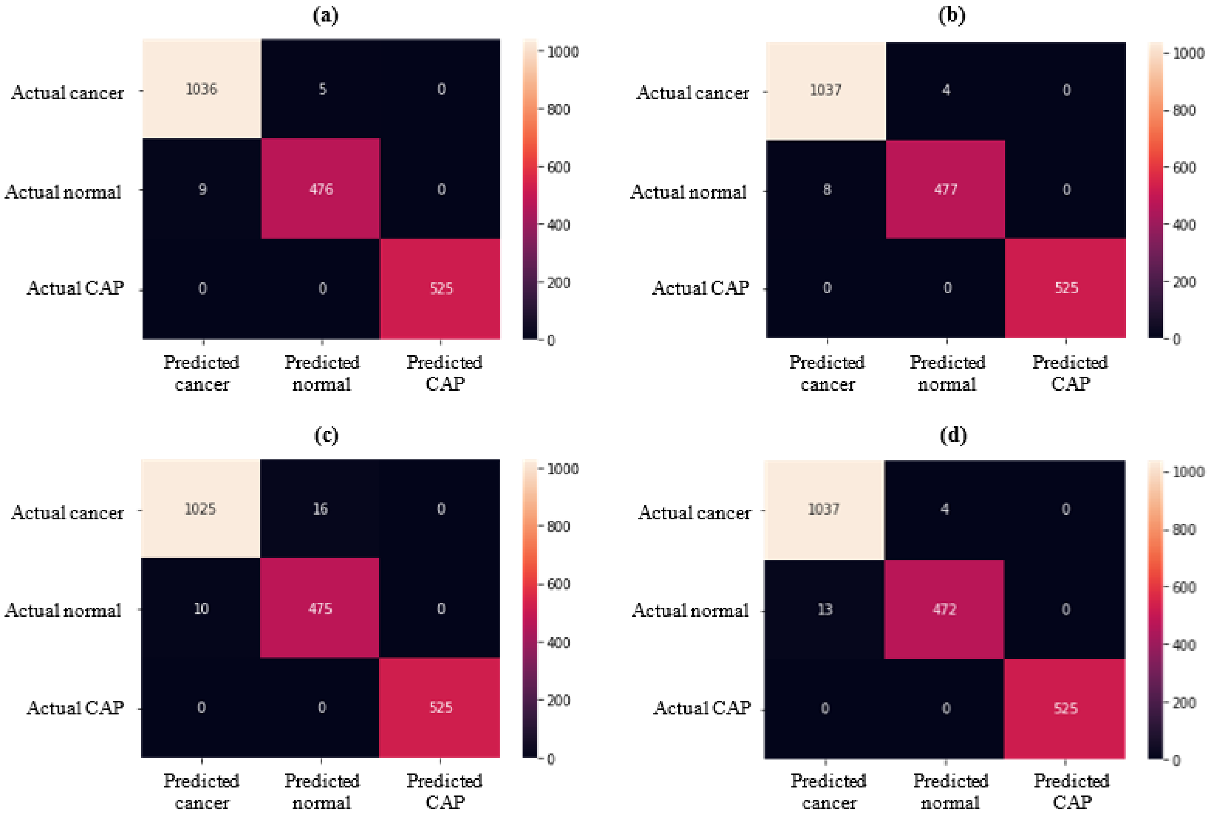

Figure 12: Confusion matrix in CT-scan dataset. a) ResNet152 network, b) InceptionresNetV2 network, c) VGG19 network and d) InceptionV3 network

5.3 Comparison and discussion

A comparative analysis has been done to show the effectiveness of the proposed approach. The results obtained by the proposed approach using X-ray and CT-scan images have been compared with some existing techniques, as shown in Table 8. Also, the introduced dataset was trained on some networks used in related works and the results for the set of X-ray images in Table 9 and for the set of CT-scan images in Table 10 were compared with the results obtained from the proposed models. Also, the time complexity in seconds per round for each model is shown in Tables 9 and 10. The results show that the proposed approach accurately classifies images in all classes with high accuracy. Therefore, it can be concluded that the fine-tuning of the pre-trained CNN architecture can be used as one of the useful techniques in the medical field to classify chest X-ray images. The evaluation results are given in [38, 39]. Today, the use of machine learning methods in disease diagnosis has been welcomed by many. The combination of artificial intelligence with IoT helps to accelerate this in such a way that the diagnosis of all types of medical tests, including radiology and pathology, in real time based on IoT leads to the improvement of the quality of medical services. Therefore, with the use of appropriate equipment and the desired infrastructure, the possibility of processing medical data with high precision is not far from expected.

As shown in Table 8, the effectiveness of the proposed approach using X-ray and CT-scan images has been compared with some techniques in the table of related works. The results show that the accuracy of the proposed approach based on deep convolutional neural network models (ResNet152, InceptionV3, VGG19, InceptionResNetV2) under ensemble is higher than other methods. This shows the high efficiency of the proposed approach in identifying patients in the early stages of breast cancer.

As shown in Table 9, the X-ray dataset was trained on some networks used in related works and the results obtained with the results of the proposed approach based on deep convolutional neural network models (ResNet152, InceptionV3, VGG19, InceptionResNetV2). has been compared. The results show that the proposed approach accurately classifies images in all classes with high accuracy. Therefore, it can be concluded that fine-tuning the parameters of deep convolutional neural network models can be used as one of the useful techniques in the medical field for the classification of chest X-ray images. Also, the time complexity in seconds per round has been calculated for each convolutional neural network approach, which is shown in Table 9.

Table 8: Comparison of the results obtained from X-ray and CT-scan datasets with other related works

Reference	Method	Data type	Data size	Result
[13]	VGG19	CXR	4500	%86
	InceptionV3			%95
[14]	Ensemble classification	CXR	15688	%88
[15]	AlexNet	CXR	5436	%86
	VGG16			%87
	ResNet50			%91
	ResNet101			%93
	ResNet152			%95
[16]	VGG16	CXR	380	%85
	VGG19			%89
	ResNet18			%88
	ResNet50+SVM			%94
	ResNet101			%87
[17]	Ensemble classification	CXR	15760	%98
Proposed method	ResNet152	CXR	5228	%94.5
	InceptionV3			%96.9
	VGG19			%93.3
	InceptionResNetV2			%95.9
[17]	-	CT-scan	6354	%98
[19]	-	CT-scan	8055	%97
	ResNet50			%96
	ResNet101			%95
	GoogleNet			%96
	AlexNet			%93
	DenseNet201			%96
[13]	ShuffleNet	CT-scan	5471	%91
	MobileNet			%92
	MobShufNet			%93
Proposed method	ResNet152	CT-scan	10239	%99.3
	InceptionV3			%99.1
	VGG19			%98.7
	InceptionResNetV2			%99.3

Table 9: Comparison of the results obtained using the X-ray dataset using some deep learning models

Reference	Method	Number of layers	number of parameters	Time complexity in each round	Result
[19]	VGG16	16	More than 138 million	210	%96.4
[20]	ResNet50	50	More than 23 million	190	%94.6
Proposed method	ResNet152	152	More than 60 million	610	%94.5
	InceptionV3	189	More than 23 million	196	%96.9
	VGG19	19	More than 143 million	270	%93.3
	InceptionResNetV2	449	More than 55 million	85	%95.9

Table 10: Comparison of the results obtained using the CT-scan dataset using some deep learning models

Reference	Method	Number of layers	number of parameters	Time complexity in each round	Result
[19]	VGG16	16	More than 138 million	80	91.7%
	ResNet50	50	More than 23 million	75	99%
Proposed method	ResNet152	152	More than 60 million	250	99.3%
	InceptionV3	189	More than 23 million	110	99.1%
	VGG19	19	More than 143 million	360	987%
	InceptionResNetV2	449	More than 55 million	380	99.3%

As shown in Table 10, the CT-scan dataset was trained in [19] and the results were compared with the results of the proposed approach. The results show that the proposed approach classifies images with higher accuracy than [19]. This shows the high efficiency of the proposed approach in classifying CT-scan images.

Table 11: Results of peer ranking test

Dataset	Statistic	p-value	Result
X-ray	3.0	0.39163	H0 is accepted
CT-Scan	2.7	0.44023	H0 is accepted

Table 12: Ranking of architectures in STAC

Dataset	Architecture	Rank
X-ray	VGG19	1
	ResNet152	2
	InceptionResNetV2	3
	InceptionV3	4
CT-Scan	VGG19	1
	InceptionV3	2
	InceptionResNetV2	3
	ResNet152	3

Table 13: Pair-by-pair comparison of algorithms

Dataset	Architecture	Statistic	Adjusted p-value	Result
X-ray	VGG19 vs InceptionV3	1.64317	0.60209	H0 is accepted
	VGG19 vs InceptionResNetV2	1.09545	1.00000	H0 is accepted
	ResNet152 vs InceptionV3	1.09545	1.00000	H0 is accepted
	VGG19 vs ResNet152	0.54772	1.00000	H0 is accepted
	InceptionResNetV2 vs ResNet152	0.54772	1.00000	H0 is accepted
	InceptionResNetV2 vs InceptionV3	0.54772	1.00000	H0 is accepted
CT-Scan	VGG19 vs InceptionResNetV2	1.36931	1.00000	H0 is accepted
	VGG19 vs ResNet152	1.36931	1.00000	H0 is accepted
	InceptionResNetV2 vs InceptionV3	0.82158	1.00000	H0 is accepted
	ResNet152 vs InceptionV3	0.82158	1.00000	H0 is accepted
	VGG19 vs InceptionV3	0.54772	1.00000	H0 is accepted
	InceptionResNetV2 vs ResNet152	0.00000	1.00000	H0 is accepted

To compare the investigated algorithms, a statistical test using Statistical Tests for Algorithms Comparison (STAC) is considered [40, 41]. STAC is a web-based site for comparing methods considering statistical tests. If the data has a normal distribution, the parametric test can be used. Otherwise, if the distribution of the data is not known, the nonparametric test is used.

The purpose of the statistical test is to compare the accuracy of the algorithms, so the algorithms are compared one by one. First, the accuracies in Table 3 are normalized between [0, 1], then the values are given as input to the STAC environment. The rank-sum test is applied and the post-hoc parameter is set to holm and the significance level is set to 0.05, as shown in Table 11. H0 is accepted when the p-value is greater than the significant level.

Table 12 shows the ranking of architectures in STAC. As shown, for the X-ray dataset, InceptionV3 has the lowest score and VGG19 the highest score, and for the CT-Scan dataset, VGG19 has the highest score and InceptionResNetV2 and ResNet152 have the lowest score. Another output is obtained for the pair-by-pair comparison of the algorithms, which is shown in Table 13.

6 Conclusion

Human collaboration with smart technologies has been shown to significantly improve performance. Also, it has been proven that humans and artificial intelligence together provide 6.2% more detection ability for breast cancer diagnosis. In general, IoT is an integrated platform to facilitate interactions between humans and a variety of physical and virtual platforms. Considering the critical conditions of breast cancer, it can play a vital role in the field of medical care and as a result, reduce the pressure on the medical systems. Today, due to the advancement of technology, internet of medical things along with artificial intelligence techniques such as machine learning and deep learning have provided new possibilities that include a wide range of applications in the field of medical care. Medical devices and sensors using the Internet connection can collect valuable data that can be processed in later stages with the help of artificial intelligence techniques and their knowledge can be extracted.

Breast cancer diagnosis through chest images is a challenging issue and many problems still need to be overcome. In this paper, an intelligent health care system is proposed that uses IoT technologies for the initial assessment of breast cancer using neural network with the help of chest medical images. This system uses smart sensors to collect data. These data are stored in the data repository and used to evaluate the condition of patients. First, in the first stage, chest medical images are sent to the data repository using devices equipped with IoT technology. Then, in the next step, the medical images are pre-processed to extract knowledge and sent to the deep learning network, which detects breast cancer. Using the capabilities of technologies such as IoT and artificial intelligence is of great importance due to the lack of treatment staff compared to daily visits and also maintaining the health of society. It is important to note that deep convolutional neural network architectures tend to overfitting when trained with a larger number of courses. In order to prevent it, we have used methods such as early termination and data augmentation.

The proposed model provided the best accuracy of 96.94% for X-RAY images and 99.36% for CT-scan images. Empirical knowledge about applications of convolutional neural networks states that increasing the number of samples and the quality of the dataset has a direct impact on the accuracy obtained. The proposed method based on deep learning will be useful in medical diagnosis research and health care systems. It is also a precise tool for medical experts to screen for breast cancer.

In future works, more images will be collected and deeper models for breast cancer detection will be investigated. Also, the development of a graphical interface to help radiologists identify breast cancer can be the goal of future studies.

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