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Proposed Cnn Model For Breast Cancer Detection

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A B S T R A C T

Breast cancer is a life-threatening disease for women, and early detection of this disease will lead to a longer lifespan. Breast cancer is a leading cause of death among women worldwide. In this study, we designed a proposed convolutional neural network (CNN) model that consisting of 39 layers. The model begins with feature extraction from input mammogram images using a series of convolutional layers, batch normalization, ReLU activation functions, and max-pooling layers. This is followed by six fully connected layers for classification. Overall, the proposed model includes a three-layer feature extractor and a two-layer decision-making module designed specifically for breast cancer detection. The model achieved impressive performance metrics, with an accuracy of 98%, precision of 95%, recall of 96%, and an F-score of 96.4% if number of epoch equal to 5 and 100% if epoch equal to 10.

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1. Introduction

Breast cancer is a life-threatening disease for women, and early detection of this disease will lead to a longer lifespan. Although a web of distinct manual techniques like mammography, thermography, and magnetic resonance imaging (MRI) are used for the detection of breast tumors, there exist some challenges using these techniques, such as high false-dismissal and false acceptance rates [1]. To overcome these limitations, an automated detection system is proposed. The automated, or computer-aided system for detecting malignant breast tumors usually follows three stages: the pre-processing stage is used to reduce unwanted disturbance, the prominent stage in the CAD system is the feature extraction method to identify abnormalities or normal occurrences in the image, and the classification stage is used to categorize malignant or benign tumors of the breast. In this paper, an analysis is made to scrutinize the proposed convolutional neural network (CNN) model from the literature. [2].

One in 8 women globally develop breast cancer. Men can also be diagnosed but less frequently. Deep learning techniques show promise in detecting cancer and have the potential to save lives. Breast cancer is the second most prevalent illness, affecting around 20-25% of people. Studies have used oversampling, hybrid mammogram, BCDTC,

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and Grassmann points to detect breast cancer. A Convolution Neural Network model compatible with USM images assists radiologists in diagnosing breast cancer. [3]

2. Related Work

The study on *Breast Cancer Detection using CNN* highlights that breast cancer remains one of the leading causes of cancer-related deaths globally. Diagnosing it accurately through hematoxylin and eosin-stained images is a challenging task, often leading to inconsistencies among medical experts. To address these challenges, computer-aided diagnosis (CAD) systems offer a promising solution by improving diagnostic efficiency and reducing associated costs. Traditional classification techniques rely heavily on handcrafted features based on expert knowledge, which can be limiting. As a result, deep learning approaches have gained attention as more robust alternatives. In this work, a Convolutional Neural Network (CNN) is proposed to classify breast biopsy images stained with hematoxylin and eosin. The model categorizes the images into four classes—normal tissue, benign lesion, in situ carcinoma, and invasive carcinoma—as well as performing binary classification to differentiate carcinoma from non-carcinoma. The network is carefully designed to extract information at multiple scales, capturing both nuclear and tissue-level features, which allows for effective integration with whole-slide histology images. The proposed approach achieves an accuracy of 77.8% for the four-class classification task and demonstrates a high sensitivity of 95.6% in cancer detection. [4]

The research titled *"Breast Cancer Detection: A Comprehensive Study on Machine Learning and Deep Learning Techniques"* introduced a unified AI-based system for detecting breast cancer by integrating convolutional neural networks (CNNs) for processing medical images with an artificial neural network (ANN) for analyzing clinical data. The model was trained on a dataset comprising ultrasound and pathology images, along with clinical records from 569 patients. While the CNN handled the classification of breast tissue into benign or malignant categories based on imaging, the ANN evaluated clinical features for the same purpose. This combined strategy notably enhanced diagnostic accuracy, achieving over 96% by leveraging both image and clinical data. To improve the transparency of the CNN's predictions, Class Activation Maps (CAMs) and heatmaps were employed. The study concludes that combining CNNs and ANNs not only improves diagnostic accuracy but also offers an interpretable and effective solution for early breast cancer detection and clinical decision-making. [5]

Rodrigues, Paulo Sergio "Explainable AI and susceptibility to adversarial attacks a case study in classification of breast ultrasound images" in this article they utilized ResNet-50 pre-trained model of convolutional neural network (CNN in order to classification images into two classes by change the last layers of model that called fully connected layer from 1000 classes to two classes benign and malignant. They achieve accuracy reach to 97% .[6]

3. Proposed Model

3.1. Data set collection stage: The proposed CNN model was trained and evaluated using a breast Ultrasound Image Dataset obtained from an online source[7], as shown in figure (1) . This dataset contains 250 breast cancer images, 100 benign and 150 malignant. The dataset was randomly split into two subsets, allocating 70% for training and the remaining 30% for testing

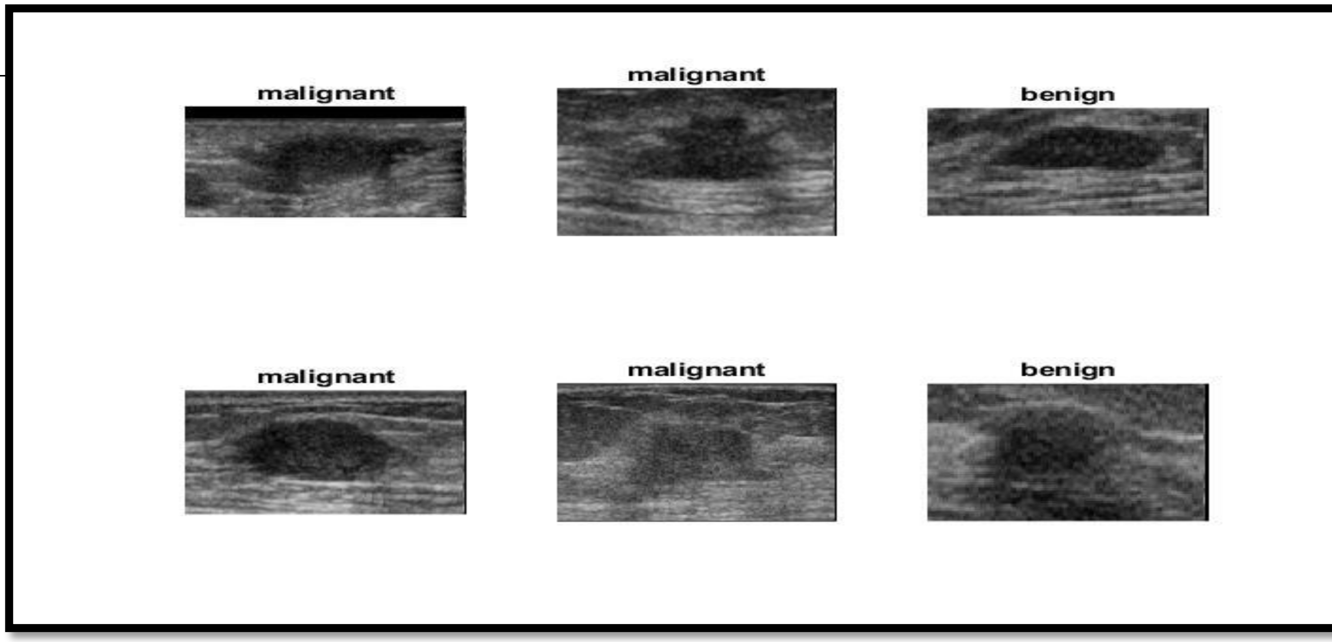

Fig. 1: examples from the dataset

3.2 Data Pre-Processing Stage: Pre- Processing enhances AI model development by removing noise and augmenting data in this stage two steps are implemented**:**

3.2.1 Image resize: To ensure consistency, all images input into the AI algorithm must be of a uniform size. This involves adjusting the width and height of each image, either by enlarging or shrinking them [8]. In this case, the images are resized to 300×300 pixels. Standardizing image dimensions helps optimize processing efficiency and reduces computational time.

3.2.2 Data augmentation: Techniques used to increase dataset size, improve data diversity, reduce model bias, and enhance model learning capability in computer vision. For an image, a bounding box or ROI (Region of Interest) can be classified or segmented into a specific object based on the target task. The input image can be resized to an arbitrary reference size according to the desired input model, making it potentially more robust against various input resolutions during the test time. [9]

3.3 Data splitting: after preprocessing stage the dataset must separate in to two parts one part use for training that represent 70% and the second part used for testing that represent 30% .

3.4 Building CNN proposed model : The Convolutional Neural Network (CNN) algorithm is among the most widely recognized models in the deep learning domain. It offers several advantages over traditional neural networks, including reduced parameter counts and fewer neurons, which contribute to shorter training times [10]. The CNN architecture used in this study comprises multiple layers—starting with an input layer, several hidden layers, and an output layer. Typical hidden layers in CNNs include convolutional layers, pooling layers, flattening layers, and fully connected layers. In this study, a customized CNN architecture was developed. This section focuses on constructing the foundational layers of the proposed model. The initial design phase involves determining the number of convolutional layers required. For instance, with input images sized at 300 × 300 pixels, multiple convolutional and pooling layers are necessary to extract meaningful features and reduce dimensionality. The final model consists of 39 layers, beginning with feature extraction using convolutional layers, batch normalization, ReLU activation functions, and max-pooling layers, followed by six fully connected layers for classification. Figure (2) shows the block diagram of proposed model.

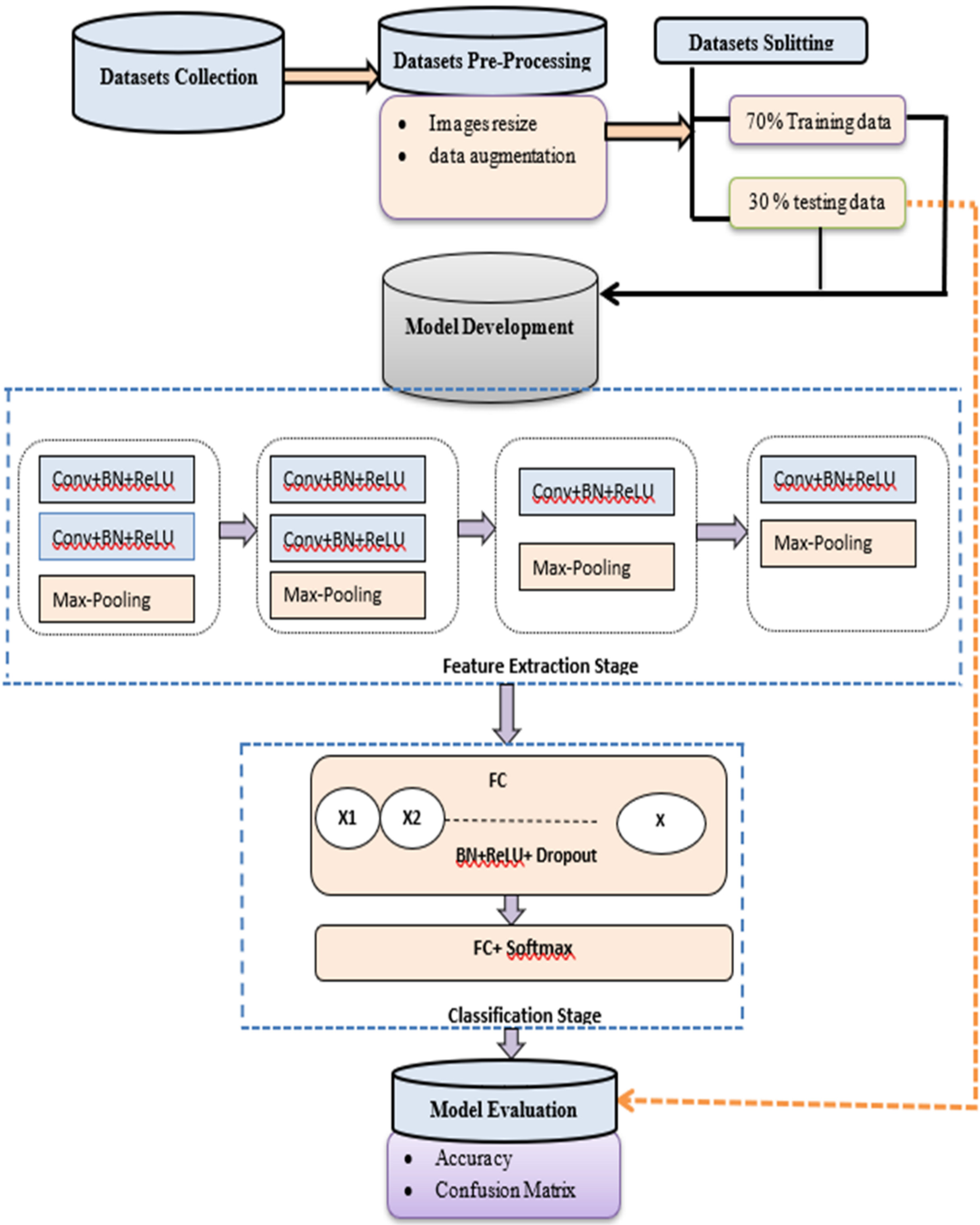

Fig. 2: Block diagram of proposed CNN model

4. Evaluation Model

The model performance evaluation is a necessary step in determining model applicability and effectiveness. After developing the model, its algorithms and deep learning techniques should be evaluated based on certain performance evaluation techniques. Evaluation metrics are used to measure the performance of the model using standard analysis of metrics such as accuracy, precision, recall, and F1 score. By evaluating these parameters, a model's performance can be analyzed.[11]

Accuracy is the measuring of codes and is one of the factors that are frequently used to study the performance of models. It can be calculated using this formula

$$Accuracy = TP + TN / TP + TN + FP + FN \quad \ldots\ldots(1)$$

Where TP refers to true positives, TN refers to true negatives, FP refers to false positives, and FN refers to false negatives.

Precision measures the performance of machine learning models, especially in classification tasks. It calculates the ratio of true positives to total predicted positives. It can be calculated using this formula

$$Precision = TP / (TP + FP) \quad \ldots\ldots(2)$$

Recall is used to evaluate model sensitivity when having a particular condition, this metric represents the model's ability to recognize it. By using a large number of tests to seek out all positively labeled disease cases, it minimizes the number of false negatives. It can be calculated using this formula

$$Recall = TP / (TP + FN) \quad \ldots\ldots(3)$$

Systems with high recall but low precision tend to generate a large number of results, but the majority of these predicted labels will be incorrect when compared to the true labels in the training data. On the other hand, systems with high precision but low recall behave differently—they produce fewer results, but most of their predicted labels will be correct compared to the training labels [12]. To evaluate a system's performance effectively, it can be useful to summarize its performance with a single metric. This can be achieved by calculating the F1-score, which is the harmonic mean of the recall and precision. The F1-score can be considered as an "average" between the two metrics, which considers how comparable the two values It can be calculated using below formula

$$F1\text{-}score = 2 * (Precision * Recall)/(Precision + Recall) \quad \ldots\ldots(4)$$

5. Result

The proposed model was evaluated and demonstrated strong performance. Initially, it was tested using a fixed number of (5) epochs. The results achieved were impressive, with an accuracy of 98%, precision of 95%, recall of 96%, and an F1-score of 96.4%, as illustrated bellow in the confusion matrix Figure (3).

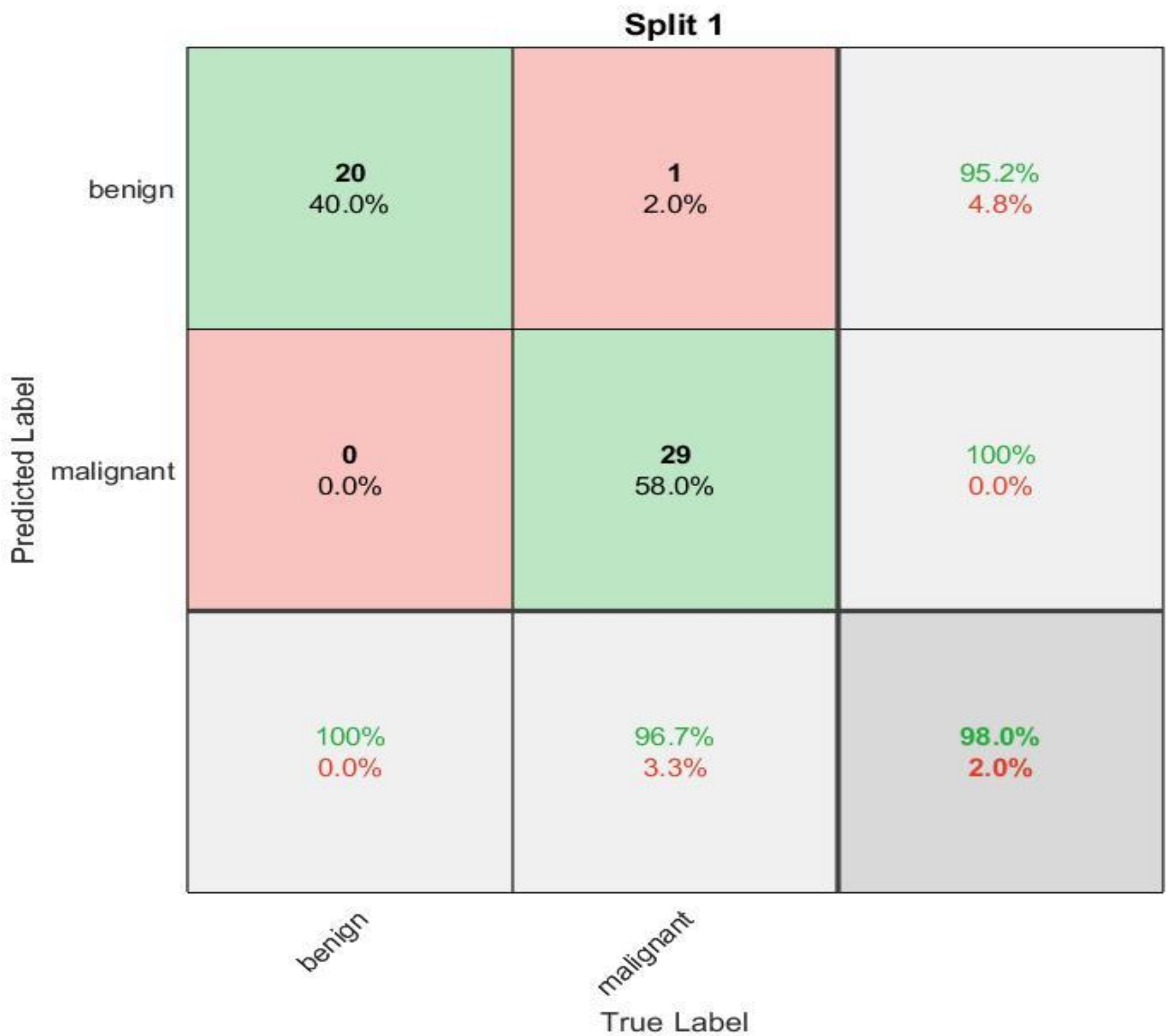

Fig. 3 : Confusion matrix (epoch = 5)

Whereas if set the number of epoch to (10) the resultants have been increasing for metrics above as shown in Figure (4). The experiments have been carried out on MATLAB 2020b platform with windows10 operating system.

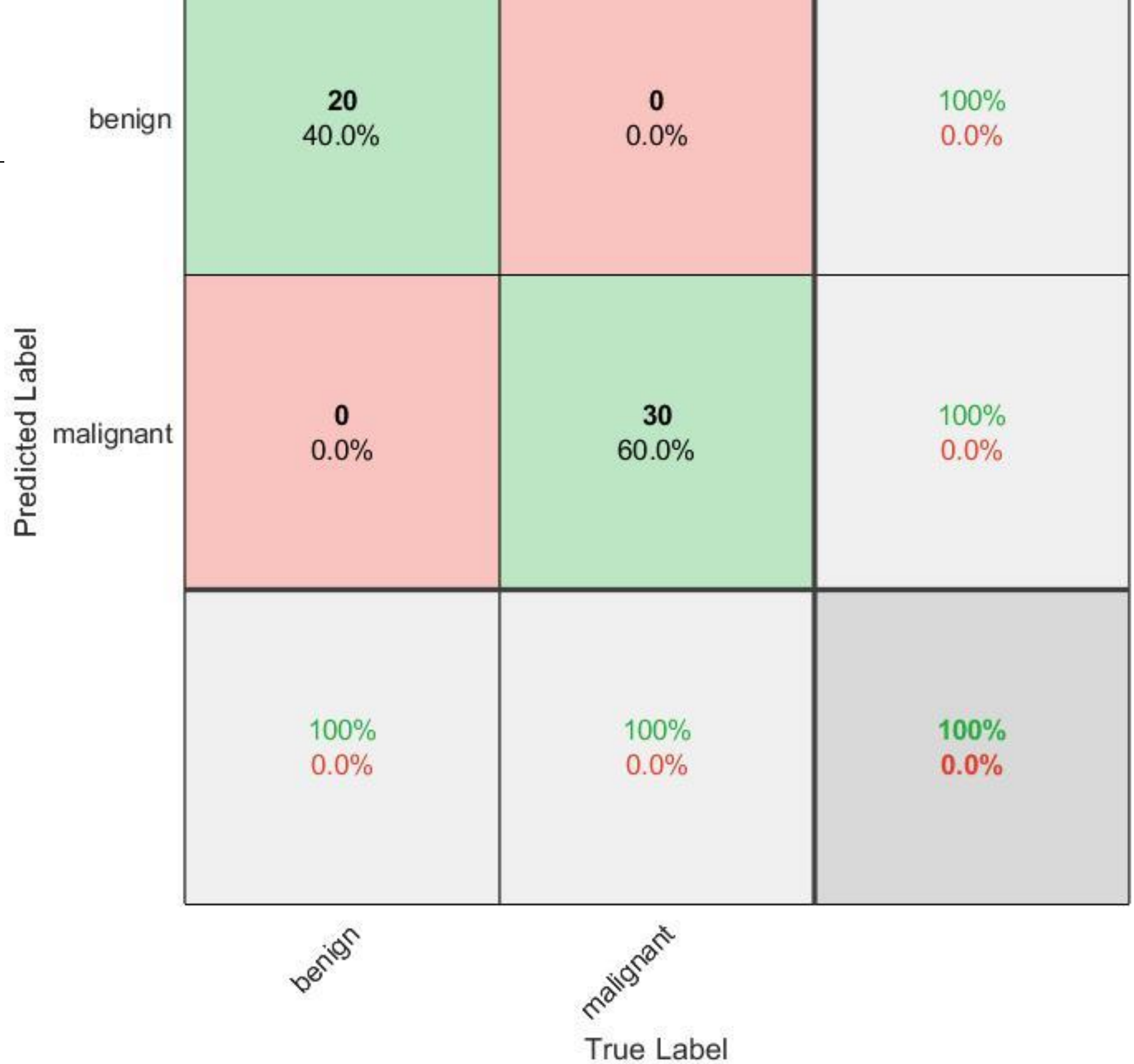

Fig. 4 : Confusion matrix (epoch = 10)

Finally we comparing our proposed model with one of the related works that mentioned above where selected Rodrigues, Paulo Sergio "Explainable AI and susceptibility to adversarial attacks a case study in classification of breast ultrasound images" this study tested on same dataset that we used in our study called (Ultrasound Image) they reached to obtain 97% accuracy. In other hand, we achieved accuracy 98 % if epoch = 5 and 100% if epoch = 10 .

5. Conclusion and Future Work

To conclude, the research work is aimed to design a system that will help radiologists diagnose breast Ultrasound Image from the other cases easily and quickly. The proposed CNN model has been designing with a three-layer feature extractor and a two-layer decision-making layer for breast cancer detection based on mammogram images. To validate the proposed model on a comparatively large dataset of mammograms, two setups, binary and multiclass, were used. The proposed model showed effective results in both steps, first accuracy was 98% when set epoch to 5 and this increasing by increase number of epochs until reached to 100% and epochs equal to 10.

There are many suggestions for improving the proposed system. The following are the most important recommendations for future work:

1. The proposed model can be used for other medical applications and diagnosis such as diagnosing pneumonia, brain cancer, lung cancer, and other respiratory disorders.
2. This model can be developed by integrating it with other well-known CNN models such as VGG16, DenceNet-201, Google Net, Res Net, …etc.
3. Utilizing other classifiers with the proposed system, such as decision tree and studying their effects on classification results.

This model can modify by adding or removing layers and changing the values of hyperparameters such as batch size, learning rate and the number of epochs.

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