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Detection Of Breast Cancer From Mammography Images

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Abstract
Early detection is very important in minimizing mortality rates; however, the manual diagnosis using mammogram images is complicated and requires expert intervention. Several AI-based approaches have been reported in the literature, but they still suffer from several challenges, such as poor feature extraction, inadequate training models, and the inability to differentiate between malignant and non-cancerous regions. We introduce a new automatic computational framework for breast cancer classification in this paper. This model employs a novel technique known as haze-reduced local-global contrast to enhance image contrast. The enhanced images are then used for dataset augmentation to increase the range of datasets and enhance the training effectiveness of the selected deep learning model. Then, a pre-trained model named EfficientNet-b0 was used and augmented with extra layers. The enhanced model was separately trained on both the original and improved images with deep transfer learning methods and fixed hyperparameter initialization. In the second phase, a new serial-based method was employed to combine deep features that had been gathered from the average pooling layer.
Keywords: breast cancer, mammogram images, contrast enhancement, augmentation

INTRODUCTION

In a survey conducted by Breast Cancer Treatment (BCC), 42% of NHS trusts stated that they lack the personnel necessary to assist patients in an efficient manner, primarily due to a lack of professional nursing experience in treating breast cancer. This deficiency is one of the primary reasons for the disease's low global survival rates. Lack of breast cancer experts may lead to inequities in access to high-quality care, delayed identification, and decreased adherence to recommended screening and treatment regimens [1]. The techniques used to detect breast cancer are intended to spot anomalies and categorize the condition, which is crucial for a precise diagnosis [2]. Although early detection is essential for lowering death rates, early diagnosis with screening mammography is difficult due to the tiny size of any nodules in comparison to the entire breast. Breast cancer has the highest treatment success rate among cancer types, with approximately 90% of cases being treatable. Additionally, cancer typically does not present early symptoms, leading to its recognition only when significant health complications arise [3].
Mammography analysis serves as the primary diagnostic tool for physicians; however, it is susceptible to biases and fatigue among doctors. Regrettably, the detection rate of mammography is low, with false-negative results ranging from 5% to 30%, influenced by factors such as lesion type, breast density, and patient age [4]. Breast cancer is detected using a range of signal processing methods, such as curvelet transform, microwave imaging, and ultrasound imaging. Computer-aided detection (CAD) technologies are crucial for enhancing therapeutic outcomes because they reduce radiologists' labour and improve detection accuracy. The traditional approach to classifying medical conditions including breast lumps, skin imperfections, and brain malignancies is based on pattern recognition. In the case of breast cancer, mammography features are manually extracted and subsequently entered into a machine learning classifier to be classified. However, correct categorization is challenging due to a variety of image-related issues and abnormalities in tumor areas.

REVIEW OF LITERATURE

The CAD system performs a series of intermediate operations, such as raw image preprocessing, feature learning and extraction, feature selection and reduction, and classification. The researcher is interested in enhancing image quality and filtering out any noise during preprocessing. Preprocessing attempts to increase the visibility of the tumor region to aid in the precise identification of a region of interest (ROI). Numerous traditional methods for ROI recognition have been reported in the literature, including as clustering algorithms, fuzzy algorithms, and saliency-based algorithms. The next important step is feature extraction, when the essential characteristics of each image are calculated. The literature has provided a number of well-established feature extraction techniques, including those based on shape, texture, and point characteristics. To improve accuracy and cut down on computation time, several academics have also focused on feature reduction and selection. Using machine learning algorithms to categorize malignant or non-cancerous parts into relevant groups is the last critical stage in artificial intelligence. [5]. Convolutional neural networks (CNNs) recently manifested immense potential in medical imaging, particularly the detection and classification of malignancies. The size of available training datasets often dictates the performance of deep learning models. Conventional methods have been unable to cope with the intricacies of some datasets, while deep learning methods have performed exceedingly well. Particularly, deep learning takes advantage of CNNs for breast cancer classification [11]. SoftMax, the final layer, functions as a classifier. Deep learning enables automated artificial intelligence methods in the application of medical imaging. In scholarly literature, a variety of deep learning architectures have been put out for the purpose of diagnosing and categorizing medical disorders. To diagnose and classify breast cancer, researchers have created a number of deep learning techniques, but they still run into issues including unbalanced [6].

Materials and methods

Approximately 1.7 million women were diagnosed with breast cancer in 2012, and it was the most prevalent malignancy globally. Breast cancer risk is determined by several factors such as age, history, and family history. With 2.1 million breast cancer cases reported annually, women contribute a significant share of cancer mortality. It has been estimated that 627,000 women lost their lives due to cancer in 2018—15% of all female cancer deaths [7]. A model based on deep learning is commonly employed for computer visualization-based breast cancer classification and diagnosis. It is therefore imperative to enhance a physician's ability to detect by utilizing a computer-aided detection (CAD) system reliant on deep learning techniques. Mammogram images were initially pre-processed for visualization [8]. A deep learning model was subsequently trained using the already pre-processed photos to derive relevant information. The features of the final layer were then classified using SoftMax, a convolutional neural network (CNN) classifier. In the proposed framework, classification accuracy of mammography images was improved by this selected model.

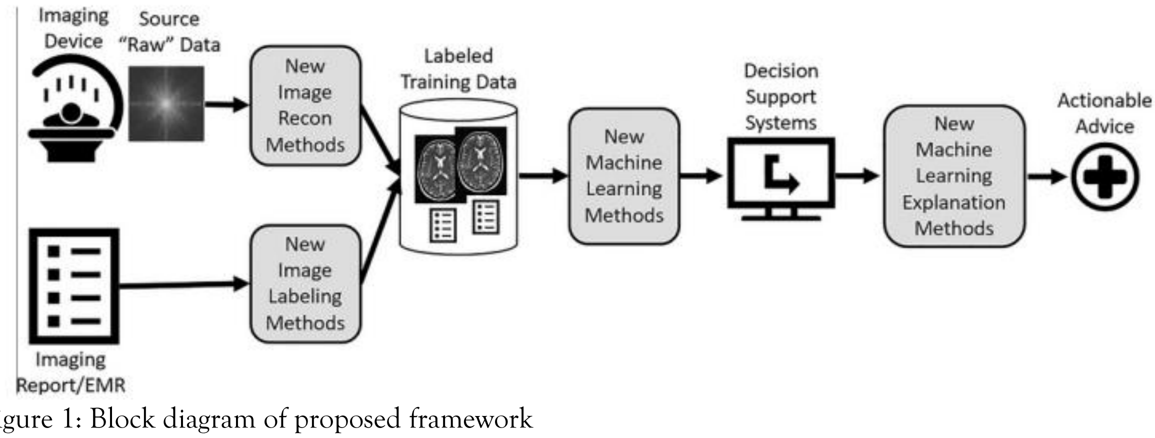

Figure 1: Block diagram of proposed framework

The previously described research focused on data augmentation, tumor detection using CNN and thresholding techniques, manual hyperparameter value selection, and the model's information integration [12]. It was observed, although, that they failed to take a few crucial actions that could improve accuracy. These procedures involve optimizing the retrieved characteristics and enhancing contrast. For weight optimization in deep learning models, the SGD and ADAM optimizers are frequently utilized. However, following the feature extraction process, we included a feature optimization approach to cut down on computation time, lessen overfitting, and increase accuracy. Focus is on the architecture of the system in this section, where the proposed framework for classifying breast cancer based on images taken

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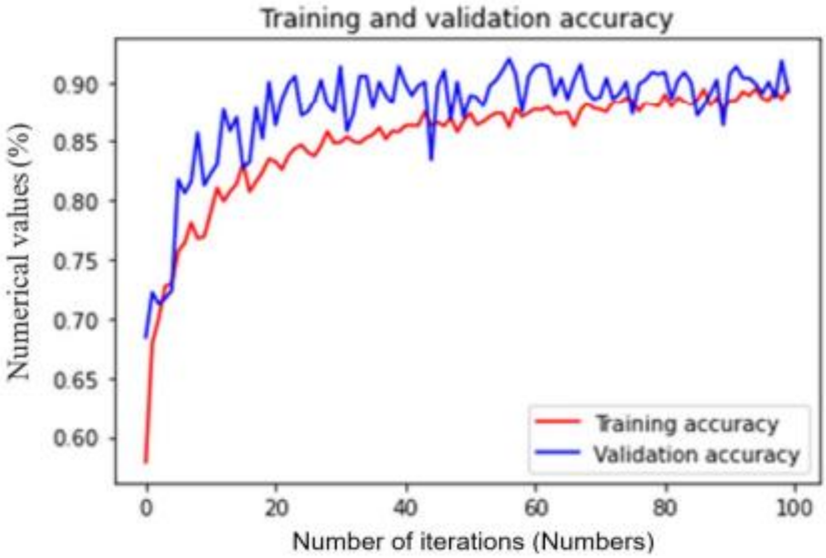
from a mammography is explained. CBIS-DDSM and IN breast datasets are utilized for experiments, as illustrated in the figure provided [10]. Both datasets are initially applied with a contrast enhancement technique followed by the process of data augmentation. The original as well as enhanced datasets are utilized to train the modified EfficientNet-b0 model with a deep transfer learning strategy [9]. An average pool layer is utilized to extract features and the most relevant features are obtained with a hybrid optimization strategy. The selected features are grouped and classified into categories using machine learning classifiers sequentially [13].

Result and discussion

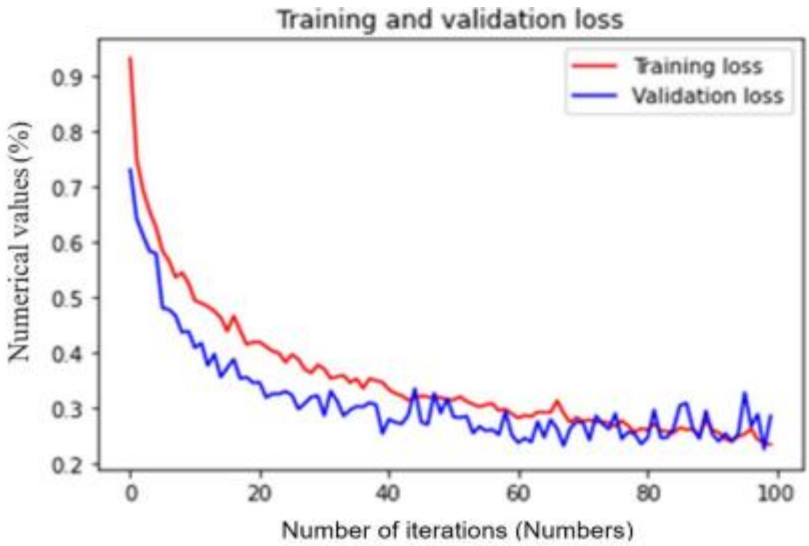
The limited number of image datasets is beneficial for training traditional machine learning techniques, such as form features (HOG), point features, color features, and the like. On the other hand, deep learning models generally need larger sets to be generated or obtained.

Figure 2: (a) Normal mammogram image and (b) Cancer affected mammogram image

Since there aren't many publicly accessible datasets on breast cancer, we employed data augmentation in this study. This technique not only expands the dataset but also improves the durability of the deep learning model and lessens overfitting problems. By rotating the original image at angles of 0°, 90°, 180°, and 270°, and then flipping the four resulting images horizontally, eight more photographs were produced for each patch that was discovered. An summary of the images after augmentation is provided.



(a)



(b)

Figure 3: (a) & (b) Accuracy and loss graph

EfficientNet uses a compound coefficient to scale the size and shape of its convolutional neural network suitably. It scales the network's depth, width, and resolution proportionally through this coefficient [14]. The EfficientNet approach utilizes a predetermined list of scaling coefficients to change the network's resolution, width, and depth equally, whereas the traditional approach solves these parameters freely. As per this compound scaling hypothesis, as input image sizes are larger, the network needs additional layers to extend its receptive field and additional channels to collect finer information in bigger images. Squeeze-and-excitation blocks and MobileNetV2 inverted bottleneck residual blocks are components of the basic EfficientNet-b0 architecture [15].

CONCLUSION

This study presents a novel paradigm for using mammography pictures to classify breast cancer. The structure incorporates critical processes, beginning with picture gathering and categorization. The initial step is to implement a contrast enhancement strategy. The improved images are utilized to train the deep learning model (EfficientNet-b0), and the performance is compared to the deep feature accuracy of the original images. The accuracy obtained by the proposed enhancement method is better than the original but failed to reach the previously set accuracy benchmarks, as per the results. Therefore, a new fusion technique is introduced. By integrating the features of the original and enhanced photos, this technique greatly enhances accuracy. The added processing time of this technique resulted in the introduction of a novel feature selection technique called Equilibrium-Jaya controlled Regula Falsi. Processing time for both data sets is significantly reduced by applying this selection approach.

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