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Recent Trends on Mammogram Image Segmentation Using Artificial Neural Network

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Abstract: *The main cause of death for women is breast cancer. When this condition is identified early with the aid of mammography, the death rate is decreased. As the number of patients rises, radiologists find it more challenging to complete the diagnostic procedure in the limited time allowed. This study's objective is to investigate the various neural network based techniques that can help radiologists diagnose breast cancer more quickly and accurately (DL). This study compares multiple machine learning and deep learning methods in order to determine the most effective classifier for breast cancer categorization.*

Keywords: Breast Cancer, Classification, Deep Learning, Machine Learning, Mammogram.

Introduction

Different artificial intelligence techniques are utilised to classify difficulties in the field of medical diagnostics, and digital mammography is currently thought of as standard practise for the diagnosis of breast cancer. An essential stage in the classification of mammograms is feature extraction from the picture. Through the use of image processing methods, these features are extracted. There are several ways to extract features from digital mammograms, such as position, shape, and texture features. One of the significant characteristics used in many apps is textures. Mammogram classification has traditionally included a lot of texture features. The ability to discriminate between abnormal and normal cases is one of the textural properties. Artificial intelligence, wavelets, and other classifiers are employed for medical imaging applications [2].

The classification of breast cancer is greatly aided by machine learning. The various diagnosis techniques that have been discussed above all produce pictures. These images are used in machine learning classifications as diagnostic images. A subset of artificial intelligence is called machine learning. Many developers use machine learning to retrain their existing models, which helps them perform better. Machine learning is used for linear data. When the amount of data is small, machine learning provides superior results; but, when the amount of data is large, it does not. Three distinct machine learning techniques are used to train the model. Working with known data, supervised machine learning is guided by a supervisor. Unsupervised machine learning is applied with no supervision. Less people are using reinforcement learning in machine learning. These algorithms use the most relevant data from the past to choose the best course of action. [3].

Deep learning is a branch of machine learning. Unsupervised learning that learns from data is what deep learning is. The data may not be labelled or organised properly. A deep network is one that has more than two hidden layers in a deep neural network. The input layer is on the top layer, and the output layer is on the bottom layer. The hidden layer, which is the intermediate layer, has more layers than a neural network. A node called neurons houses the layer. Deep learning is distinct from machine learning in that it advances you toward your objective more quickly.

II. Literature Survey

This section summarizes earlier work that has been done in the area and is pertinent to the current study. One of two methods can be used to find breast cancer. Deep learning comes after machine learning as the order of priority. Many different types of studies make use of machine learning. However, deep learning overcomes some limitations of machine learning techniques. In this section, you'll study about machine learning and deep learning approaches.

M. FatihAslan et al. [4] proposed a machine learning approach, but they utilised a different classifier. Extreme Learning Machine, SVM, KNN, and ANN were the classifiers employed by the author. To get better results, the classifier was tweaked a little. So far, the results show that the Extreme Learning Machine is the winner.

Ch. Shravya et al. [5] suggested a paradigm for supervised machine learning. Classifiers including Logistic Regression , SVM , and KNN were used in this study. The dataset was obtained from the UCI repository, and the findings were evaluated in light of their overall performance. This shows that SVM was an effective classifier on the Python platform, with an accuracy rate of 92,7%.

SVM classifier was used to examine the performance of the ANN model developed by KalyaniWadkar et al. [6]. According to the author, ANN had a 97% accuracy rate and SVM had a 90% accuracy rate. Without SVM, the accuracy was improved, according to the author.

K. Subashini et al.[7] advocated using ultrasound scans to identify breast cancer. They eliminated noise with DWT, segmented with an active contour model, and classified with a back propagation neural network. S. A research by Julian Savariet. al. [8] suggests using histogram equalisation to improve image quality. When calculating volumetric values, data from the intensity characteristics is gathered and then processed. K-means clustering algorithm is used for categorisation. Noise reduction is achieved using the Gabor filter. The MIAS and DDSM databases are used in this investigation. A minimum of 99% classification accuracy is necessary. Milos Radovic et al. provided the definition of the CAD (computer-aided diagnostic) system. [9] to identify both typical and aberrant breast patterning. They used seven different classifiers to categorise the data, and then compared the results. To focus the study's scope, DWT was used (ROI).

K-means and co-occurrence matrices were described by Leonardo de Oliveira Martins et al. [10] in 2009, and SVM classifier was used to identify the masses. For categorization purposes, images are split into masses and non-masses based on shape and texture characteristics.

Multi-ROI segmentation was provided by P Anjaiah et al.[11] for a sizable collection of mammography pictures. It significantly assists in identifying the greatest textural elements in mammography images. Current ROI segmentation conducts segmentation without being aware of the general form of the mammography model. The proposed multi-ROI segmentation made use of a sizable sample of mammograms to generate the universal shape (or average model parameters) of mammograms. It helps in getting precise texture or form information from a suspicious mammogram for detecting breast cancer.

Machine learning is used in a wide variety of investigations. On the other hand, deep learning solves some shortcomings in machine learning methods. CNNs have been employed in several studies to carry out mammogram-related tasks like breast lesion identification, classifying benign and malignant breast masses, identifying micro-calcifications, and combinations of these tasks.

CNNs were employed by Fonseca et al. to extract mammography characteristics, and a support vector machine classifier was utilised to determine density [12]. Ahn et al. used a CNN architecture with the aid of three additional generated images to categorise the input mammography patches into dense or fatty tissues and estimate the mammographic density by averaging the findings of all patches [13]. Li et al. created a method to categorise mammographic density based on a sliding window segmentation methodology [14]. Manual segmentation maps of dense regions are needed as a reference for these two investigations.

CNNs were suggested by X. Zhang et al. [15] as a method of classifying mammograms and tomosynthesis pictures. They examined information from 3000 tomosynthesis and mammography scans. To distinguish between 2-D and 3-D mammograms, various CNN models were created. Each classifier was assessed using truth-values derived from the histology results of the biopsy and the two-year negative mammography follow-up certified by qualified radiologists. They have created and improved a system that uses mammography and tomosynthesis data along with transfer learning and data augmentation to automatically diagnose breast cancer.

In order to build a deep learning algorithm that can precisely detect breast cancer on screening mammograms, Li Shen et al. [16] employ a "end-to-end" training technique that effectively utilises training datasets with either thorough clinical annotation or just the cancer status (label) of the entire image. Just during the initial training phase are lesion annotations necessary; later phases only call for image-level labels, eliminating the necessity for the inconveniently located lesion annotations. Our all-convolutional network method for classifying screening mammography fared fairly well in contrast to older techniques.

A model was proposed by M. Tardy et al. [17] to address the issue of assessing breast density as an imagewise regression task with the aim of calculating the proportion of fibroglandular tissue. Their approach, which is based on deep learning, offers an estimate that is clinically acceptable while requiring only a few expert annotations. They also discuss feeding the neural network with additional data from the X-ray acquisition parameters.

T. Shen et al. [18] present a mixed-supervision guided technique and a residual-aided classification U-Net model for joint segmentation and benign-malignant classification (ResCU-Net). Through the combination of strong supervision in the form of a segmentation mask and weak supervision in the form of a benign-malignant label through a straightforward annotation procedure, their method effectively segments tumour regions while also projecting a discriminative map for identifying benign-malignant tumour types.

Y. Wang et al. [19] design an efficient feature dimension reduction strategy, train an ensemble support vector machine, and create a multi-network feature extraction model using pre-trained deep convolution neural networks (DCNNs) (E-SVM). The histology images are first preprocessed using scale transformation and colour enhancement algorithms. Second, to extract multi-network characteristics, four pre-trained DCNNs are used (e.g., DenseNet-121, ResNet-50, multi-level InceptionV3, and multi-level VGG-16). Third, a feature selection approach based on dual-network orthogonal low-rank learning (DOLL) is developed for performance improvement and overfitting reduction. Using combined features and a voting technique, an E-SVM is trained to complete the classification task, categorising the images into four groups (i.e., benign, in situ carcinomas, invasive carcinomas, and normal).

A new combined feature CAD method based on DL is proposed by R. Song et al.[20] for classifying mammographic masses into three categories: normal, benign, and cancerous (malignant). Three different types of breast masses were scored using a feature extractor created by the Deep Convolution Neural Network (DCNN). The classifier then receives a combined input of the score features and picture texture features. These characteristics were used to extract this information from mammograms, and the Support Vector Machine (SVM) and Extreme Gradient Boosting (XGBoost) classifiers were trained for the classification task. Although Faster R-CNN has been used in medical imaging, the literature on breast imaging is scant.

Jung et al. [21] proposed a mass detection model to address the issue of excessive class imbalance between the foreground and background. With the help of both a private (GURO) and a public (INbreast) dataset, the network's performance was evaluated. A neural network based on deformable convolutional nets and a region-based fully convolutional network (R-FCN) was proposed by Morrel et al. [22].

III. Conclusion

The purpose of this study is to evaluate the various neural network-based methods that can aid radiologists in making more rapid and precise diagnoses of breast cancer (DL). For the purpose of categorising breast cancer, this study evaluates various machine learning and deep learning techniques to find the most potent classifier.

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