Section A-Research paper
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Bi-Modal Transfer Learning for Classifying Breast Cancers via Combined B-Mode and Ultrasound Strain Imaging

R.G.Vyshnavi
Assistant Professor, Department of IT
Sridevi Women's Engineering College,Telangana
swecrgv@gmail.com

Palipalli Naga Sindhuja
B. Tech Student , Department of IT
Sridevi Women's Engineering College,Telangana
sindhujapalipalli@gmail.com

Kavali Akshaya
B. Tech Student, Department of IT
Sridevi Women's Engineering College,Telangana
akshayakavali56@gmail.com

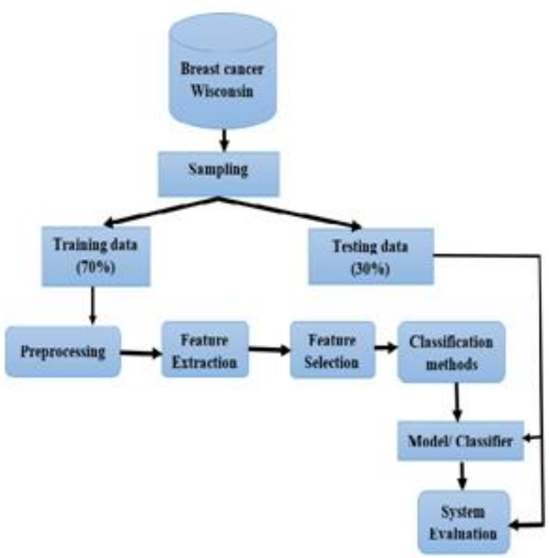
Nigidala Akhila
B. Tech Student, Department of IT
Sridevi Women's Engineering College,Telangana
nigidalaakhila@gmail.com

ABSTRACT: Although precise identification of breast cancer remains difficult, deep learning (DL) may help with more accurate picture interpretation. In this work, we create a highly robust DL model for categorising benign and malignant breast cancers using combined B-mode and strain elastography ultrasound (SE) images. This research comprised 85 individuals, 42 with benign lesions and 43 with cancers, all of which were verified by biopsy. AlexNet and ResNet, two deep neural network models, were trained independently using 205 B-mode and 205 SE pictures (80% for training and 20% for validation) from 67 patients with benign and malignant lesions. These two models were then built to function as an ensemble on a dataset of 56 photos from the other 18 patients, and tested on a dataset of 56 images from the remaining 18 patients. To distinguish benign from malignant tumours, the ensemble model collects the different properties found in the B-mode and SE pictures and also includes semantic information from the AlexNet and ResNet models. The experimental findings show that the proposed ensemble model has a 90% accuracy, which is higher than the individual models and the model trained just on B-mode or SE pictures. Furthermore, the suggested ensemble technique accurately categorised certain patients who were misclassified by existing methods. Because of improved classification accuracy for breast tumours in ultrasound (US) pictures, the proposed ensemble DL model would help radiologists to attain greater detection efficiency.

Keywords *– Breast ultrasound (US) images, ensemble learning, image classification, strain ultrasound elastography.*

1. INTRODUCTION

As a diagnostic technique, ultrasound imaging (US) has a high sensitivity in identifying breast cancer in women with high-risk dense breast tissue [1]. Breast US elastography and B-mode breast ultrasonography, in particular, have been extensively employed for breast cancer detection [2], [3]. Breast US elastography, a revolutionary imaging technology developed in recent decades, displays stiffness in distinct colours to differentiate soft lesions from hard lesions. Soft lesions are often benign, while hard lesions are malignant [4]. Both strain and shear-wave imaging may be used in US elastography. Shear-wave elastography ultrasound (SWE) detects the speed of the shear wave within the tumour, while strain elastography ultrasound (SE) uses tissue displacement to discriminate soft tissue from hard tissue. Both approaches are employed in clinical settings and have higher diagnostic accuracy than independent B-mode imaging. Breast cancer detection in the United States is complicated by a dearth of radiologists, human error, and poor imaging quality. These difficulties have prompted research into computer-aided detection (CAD) systems to help in diagnostic judgements [5]. Many researchers have created CAD systems for breast cancer using typical machine learning approaches [6], [7]. Although traditional machine learning algorithms have shown promising results, they are time-consuming and difficult to build.



Deep learning (DL) approaches have recently been used more often in breast imaging in the United States. DL algorithms identify patterns of lesions, such as their direction, border, and echogenicity, to categorise B-mode images using Breast Imaging-Reporting and Data System (BI-RADS) score. The convolutional neural network (CNN) [8] is the most often utilised DL neural network in image categorization. Training a CNN from scratch, on the other hand, requires a big, annotated picture dataset, and gathering a sufficient volume of breast US data is time-consuming and often impossible. As a result, transfer learning (TL) has been proposed as one solution to the scarcity of breast US pictures for training a CNN model [9]. Byra et al. [10] created a TL-based strategy for breast mass classification utilising a pre-trained Visual Geometry Group (VGG)-19 model after grayscale B-mode pictures were transformed to red, green, and blue (RGB) images. Tanaka et al. created an ensemble TL model by integrating two CNN architectures (VGG-19 and ResNet-152) to use the average probability value to identify breast US pictures as benign or cancerous.

2. LITERATURE REVIEW

Role of breast ultrasound for the detection and differentiation of breast lesions:

Breast cancer diagnosis has greatly improved with the invention of high-resolution ultrasound technology. Previously, ultrasonography was thought to be exclusively effective for cyst diagnosis. Meanwhile, it enhances benign and malignant lesion differentiation, local preoperative staging, and guided interventional diagnosis. Mammography has limited sensitivity in thick breasts. Furthermore, women with thick parenchyma have a significantly greater chance of developing breast cancer. Ultrasound may be used to look at thick breast tissue. Recent studies have demonstrated that using high-resolution ultrasonography to identify tiny tumours increases the detection rate by 3-4 malignancies per 1,000 women with no clinical or mammographic abnormalities. Furthermore, the stage distribution of mammographically and sonographically identified carcinomas is comparable. To circumvent the limitations of mammography, ultrasound is now frequently employed for curative diagnosis. Breast density, on the other hand, is not seen as relevant in mammographic screening in Germany. If mammography detects a worrisome lesion, ultrasound is employed. Surprisingly, a screening study began in Austria two years ago in which ultrasonography is always used in situations with thick breasts. According to preliminary data, the discovery of new carcinomas increases in the same order as in prior research. As a result, high-resolution ultrasound may be predicted to enhance cancer diagnosis and distinction.

Ultrasound elastography improves differentiation between benign and malignant breast lumps using B-mode ultrasound and color Doppler:

The purpose of this study was to assess the diagnostic yield of mammography, B-mode ultrasonography (US), ultrasound elastography (UE), and colour Doppler when used alone or in combination to differentiate breast lesions. Patients and procedures: Sixty patients with breast lumps received mammography, B-mode US, colour Doppler evaluation, and UE. The histological evaluation of an excisional sample served as the gold standard for comparing outcomes. Results: Mammography revealed that 36 individuals had thick glandular breasts and 24 had fatty parenchyma. Eleven individuals with thick glandular parenchyma and seven with fatty parenchyma had malignant tumours. Malignant lesions have a considerably higher mean resistive index than benign lesions. Malignant strains had a considerably higher mean strain ratio. The combined use of US and UE produced a higher diagnostic yield than the combined use of US and Doppler, whereas the combination use of US, UE, and Doppler increased diagnostic yield with high sensitivity and specificity and a 95% NPV. The high diagnostic yield of the combination of US, UE, and Doppler was verified by ROC curve analysis. Conclusion: The combined use of B-mode US, UE, and colour Doppler yielded an NPV of 95%, allowing needless invasive diagnostic procedures to be avoided. UE has a good sensitivity and specificity as a standalone diagnostic test. Because of its great sensitivity, mammography might be utilised as a screening test.

Ultrasound imaging technologies for breast cancer detection and management: A review:

Ultrasound imaging is a popular method for detecting and diagnosing breast cancer. We outline ultrasonic imaging technologies and their clinical uses for the care of breast cancer patients in this study. Ultrasound elastography, contrast-enhanced ultrasound, three-dimensional ultrasound, automated breast ultrasound, and computer-aided detection of breast ultrasound are among the technologies available. We outline the research findings found in the literature and explore their potential future paths. We also discuss ultrasound-guided breast biopsy and the integration of ultrasound with other imaging modalities, particularly magnetic resonance imaging (MRI). At the conclusion of this review, we compare the diagnostic performance of mammography, MRI, PET, and CT for breast cancer diagnosis. New ultrasound imaging methods, ultrasound-guided biopsy, and the integration of ultrasound with other modalities are key tools for breast cancer patients' care.

Automated breast ultrasound lesions detection using convolutional neural networks:

The identification of breast lesions by ultrasonic imaging is regarded as an essential step in computer-aided diagnostic systems. Researchers have established the ability to automate the first lesion identification throughout the last decade. However, when comparing the performance of such algorithms, the absence of a consistent dataset impedes study. This research analyses three distinct deep learning systems for breast ultrasound lesion detection: a Patch-based LeNet, a U-Net, and a transfer learning strategy using a pretrained FCN-AlexNet. Their performance is compared to four cutting-edge lesion identification systems (i.e., Radial Gradient Index, Multifractal Filtering, Rule-based Region Ranking, and Deformable Part Models). Furthermore, two conventional ultrasound picture datasets obtained from two distinct ultrasound systems are compared and contrasted in this work. Dataset A contains 306 photos (60 malignant and 246 benign), whereas Dataset B has 163 images (53 malignant and 110 benign). Dataset B will be made accessible for research purposes to compensate for the scarcity of public datasets in this sector. Deep learning algorithms show an overall improvement in terms of True Positive Fraction, False Positives per Image, and F-measure when tested on both datasets.

Robust phasebased texture descriptor for classification of breast ultrasound images:

Breast ultrasound (BUS) image classification is a crucial stage in the computer-aided diagnostic (CAD) system for breast cancer. A unique phase-based texture descriptor is provided in this research for efficient and robust classifiers to distinguish benign and malignant cancers in BUS pictures. The phased congruency-based binary pattern (PCBP) suggested descriptor is an oriented local texture descriptor that combines the phase congruency (PC) technique with the local binary pattern (LBP). The support vector machine (SVM) is then used to classify tumours. To validate the effectiveness of the proposed PCBP texture descriptor, we compare it to three different state-of-the-art texture descriptors, and tests are performed on a BUS image database containing 138 examples. After performing the receiver operating characteristic (ROC) analysis, seven criteria are used to assess the classification performance using various texture descriptors. Then, to test the PCBP's resistance to lighting fluctuations, we train the SVM classifier on texture features derived from original BUS photos and apply this classifier to texture features recovered from BUS images with varying illumination circumstances (i.e., contrast-improved, gamma-corrected and histogram-equalized). To assess classification results, the area under the ROC curve (AUC) index is utilised. Conclusions and findings Regardless of gray-scale changes, the suggested PCBP texture descriptor gets the greatest values (i.e. 0.894) and the fewest variances in terms of the AUC index. The experimental findings show that classifications of BUS pictures using the suggested PCBP texture descriptor are efficient and robust, which might be beneficial for breast ultrasound CADs.

3. METHODOLOGY

Deep learning (DL) approaches have recently been used more often in breast imaging in the United States. DL algorithms identify patterns of lesions, such as their direction, border, and echogenicity, to categorise B-mode images using Breast Imaging-Reporting and Data System (BI-RADS) score. The convolutional neural network (CNN) is the most often utilised DL neural network in image categorization. Training a CNN from scratch, on the other hand, requires a big, annotated picture dataset, and gathering a sufficient volume of breast US data is time-consuming and often impossible. As a result, transfer learning (TL) has been proposed as one remedy to the scarcity of breast US pictures for training a CNN model. Byra et al. created a TL-based strategy for breast mass classification utilising a pre-trained Visual Geometry Group (VGG)-19 model after grayscale B-mode pictures were transformed to red, green, and blue (RGB) images.

Disadvantages:

1. Accurate breast cancer diagnosis remains a big difficulty.
2. Lower detection efficiency as a result of improved classification accuracy for breast tumours in ultrasound (US) pictures.

We describe a novel method for classifying benign and malignant lesions in breast US pictures utilising ensemble TL using a mix of B-mode and SE images. To extract characteristics for improved diagnosis, we stack B-mode and SE pictures (termed B-SE for concision). For strong prediction performance, two classification models are integrated into one better classifier. The CNN model is trained using an ImageNet dataset (huge annotated natural pictures), and then fine-tuned (optimised) using a small, annotated breast US dataset. We chose AlexNet by Krizhevsky et al. and deep residual network (ResNet) by He et al. since both models are widely known for their low false-positive rates and high accuracy in medical picture categorization.

Advantages:

1. Because of improved classification accuracy for breast tumours in ultrasound (US) pictures, the proposed ensemble DL model would allow radiologists to attain greater detection efficiency.
2. The experimental findings show that the proposed ensemble model has a 90% accuracy, which is higher than the individual models and the model trained just on B-mode or SE pictures.

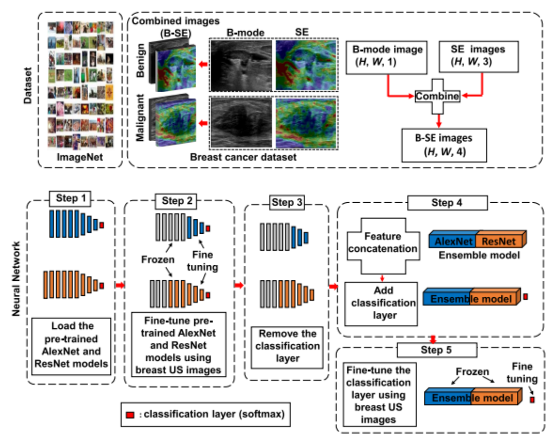


Fig.2: System architecture

MODULES:

To carry out the aforementioned project, we created the modules listed below.

- Data exploration: we will put data into the system using this module.
- Processing: we will read data for processing using this module.
- Splitting data into train and test: Using this module, data will be separated into train and test models.
- ResNet50, InceptionV3, SqueezeNet, VGG16, VGG19, Inception ResNetV2, MobileNet, MobileNetV2, DenseNet121, DenseNet169, DenseNet201,

ResNet50V2, ResNet101V2, ResNet152V2, AlexNet, and Ensemble Model MobileNet + AlexNet were used to build the model. Calculated algorithm accuracy

- User signup and login: Using this module will result in registration and login.
- User input: Using this module will result in predicted input.
- Prediction: final predicted shown

4. IMPLEMENTATION

ALGORITHMS:

ResNet50: ResNet-50 is a 50-layer convolutional neural network. A pretrained version of the network trained on over a million photos from the ImageNet database may be loaded. The pretrained network can categorise photos into 1000 different item categories, including keyboards, mice, pencils, and other animals.

InceptionV3: Inception-v3 is a convolutional neural network design from the Inception family that uses Label Smoothing, Factorized 7 x 7 convolutions, and an auxiliary classifer to transport label information further down the network (along with the use of batch normalisation for layers in the sidehead).

SqueezeNet: SqueezeNet is an 18-layer deep convolutional neural network. A pretrained version of the network trained on over a million photos from the ImageNet database may be loaded. The pretrained network can categorise photos into 1000 different item categories, including keyboards, mice, pencils, and other animals.

VGG16: VGG16 is an object identification and classification method that can classify 1000 photos from 1000 distinct categories with an accuracy of 92.7%. It is a common picture classification technique that works well with transfer learning.

VGG19: VGG-19 is a 19-layer convolutional neural network. A pretrained version of the network trained on over a million photos from the ImageNet database may be loaded. The pretrained network can categorise photos into 1000 different item categories, including keyboards, mice, pencils, and other animals.

Inception ResNetV2: ResNetV2 is an Inception-ResNet-v2 convolutional neural network trained on over a million photos from the ImageNet collection. The network has 164 layers and can identify photos into 1000 item categories, including keyboards, mice, pencils, and a variety of animals.

MobileNet: A convolutional neural network (CNN) built for mobile and embedded vision applications. They are based on a simplified design that use depthwise separable convolutions to construct lightweight deep neural networks with reduced latency for mobile and embedded devices.

MobileNetV2: MobileNet-v2 is a 53-layer deep convolutional neural network. A pretrained version of the network trained on over a million photos from the ImageNet database may be loaded. The pretrained network can categorise photos into 1000 different item categories, including keyboards, mice, pencils, and other animals.

DenseNet121: The densenet-121 model is one of the DenseNet set of image classification models. The authors trained the models on Torch* before converting them to Caffe* format. The ImageNet picture database was used to train all DenseNet models.

DenseNet169: The DenseNet-169 architecture utilised to achieve the suggested approach. Convolutional layers, maxpool layers, dense layers (completely linked layers), and transition layers are all part of the architecture. Throughout the construction, the model employs the ReLU activation function, with the last layer using SoftMax activation.

DenseNet201: DenseNet-201 is a 201-layer deep convolutional neural network. A pretrained version of the network trained on over a million photos from the ImageNet database may be loaded. The pretrained network can categorise photos into 1000 different item categories, including keyboards, mice, pencils, and other animals.

ResNet50V2: ResNet-50 is a 50-layer convolutional neural network. A pretrained version of the network trained on over a million photos from the ImageNet database may be loaded. The pretrained network can categorise photos into 1000 different item categories, including keyboards, mice, pencils, and other animals.

ResNet101V2: ResNet-101 is a 101-layer convolutional neural network. A pretrained version of the network trained on over a million photos from the ImageNet database may be loaded. The pretrained network can categorise photos into 1000 different item categories, including keyboards, mice, pencils, and other animals.

ResNet152V2: ResNet can learn residual representation functions instead of learning the signal representation directly, resulting in an extremely deep network with up to 152 layers. ResNet uses skip connections (also known as shortcut connections) to fit input from one layer to the next without modifying the input.

AlexNet is a neural network with eight layers and learnable parameters. The model is composed of five layers, the first of which is a max pooling layer, followed by three fully connected layers, and each of these levels, save the output layer, uses Relu activation.

MobileNet + AlexNet Ensemble Model:

Ensemble modelling is a process in which numerous varied models are developed to predict a result, either by using a variety of modelling techniques or by employing a variety of training data sets. The ensemble model then combines each base model's forecast, yielding a single final prediction for the unseen data.

5. EXPERIMENTAL RESULTS

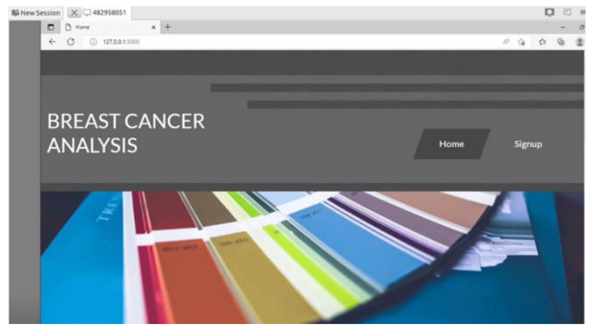


Fig.3: Home screen

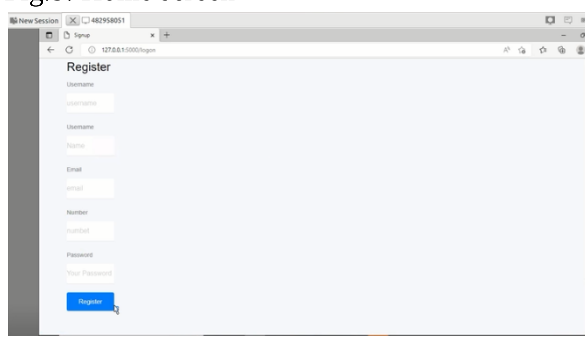


Fig.4: User signup

Fig.5: User signin

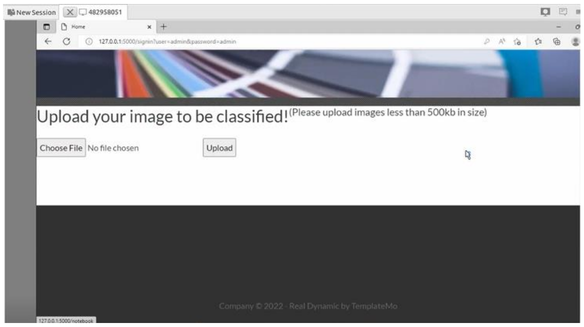


Fig.6: Main screen

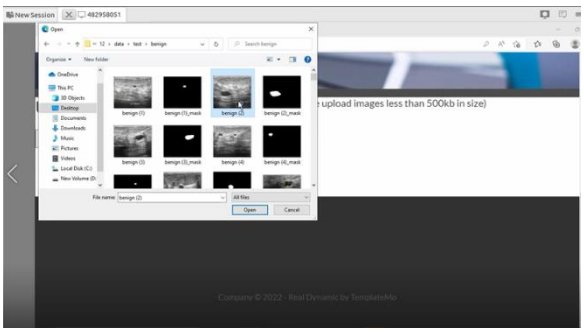


Fig.7: User input

Fig.8: Prediction result

6. CONCLUSION

In this paper, we use clinical B-mode and SE pictures to create a TL-based CAD system that classifies breast masses as benign or malignant by integrating the AlexNet and ResNet CNN models. The two fine-tuned CNN models detect a variety of characteristics in ultrasound picture data. The experimental findings show that the proposed ensemble model, which uses both B-mode and SE pictures, can accurately categorise the vast majority of images with high sensitivity and specificity. We want to test the model's sensitivity and specificity in real-world applications in a prospective research.

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