Deep Learning for Disease Detection Including Breast Cancer

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Abstract: Among women, breast cancer is the most often occurring reason of cancer-related mortality. Early detection and diagnosis of tumours is the best and most effective approach to stop their spread. Mammography is the imaging method recommended for early breast cancer detection and diagnosis nowadays. Helping radiologists make an accurate diagnosis depends on the classification of masses in mammograms, which still presents a great challenge. In this work, we provide one deep learning approach based on convolution neural networks (CNNs).

Index terms - *breast cancer detection, deep learning, convolutional neural networks, mammography, MobileNet, Inception V3, image classification, computer-aided diagnosis, medical imaging, tumor detection, feature extraction, X-ray imaging, breast mass classification, early cancer diagnosis*

1. INTRODUCTION

Breast cancer is among the most common forms of cancer affecting women currently. Thought to be the highest rate of any cancer kind at 29%, over 246, 660 women were diagnosed with breast cancer in 2016. Second in women's expected mortality, breast cancer makes around 14% of all cancer-related deaths. Breast cancer claims over 40,000 lives annually in the United States. Early detection and correct diagnosis are absolutely vital if we are to raise the survival rate. In clinical practice, mammography is a widely used diagnostic method to search for breast cancer [1]. During a mammography, the patient's breasts are subjected to low X-ray radiation dosages. Mammography can detect breast cancer by use of X-ray absorption rates varying between normal and malignant tissues. On mammograms, cancers might show up as masses, asymmetry, distortions, hypothesised masses, or microcalcifications [2]. Radiologists have trouble precisely detecting and diagnosing breast cancer (i.e., normal and abnormal) given the number of breast images they must evaluate every day and the difficulty of understanding the images—that is, recognising the breast masses and appropriately diagnosing them [3]. Therefore, offering clinicians a second view to help and support their decisions depends on computer-aided detection and diagnosis (CAD [4]. Investigating aspects of machine learning and artificial intelligence using numerous nonlinear processing layers, the fast developing field of deep learning extracts features directly from the data [5]. Deep learning using convolutional neural networks is one of the most powerful machine-learning tools for image classification; it beats almost all other traditional classification methods and even human ability in terms of accuracy [6, 7]. The convolutional approach may cut an image with millions of pixels to a collection of small feature maps by decreasing the quantity of input data while maintaining the most relevant differential properties [8]. We apply two CNN architectures—Mobile-Net and Inception V3—to recognise the whole mammograms. MobileNet is CNN class developed by Google researchers. Mobie-Nets' basic architecture uses depth-wise separable convolution to provide lightweight deep neural networks with simplified design. Rather of employing a single 3X3 convolution layer followed by batch norm and ReLU, the Mobile-Net architecture separates the convolution into a 3X3 depth-wise convolution and a 1X1 point-wise convolution. Originally introducing the Inception architecture in 2014 were Szegedy et al. Computed inside the same network module, the inception module's goal is to generate 1x1, 3x3, and 5x5 convolutions thereby acting as a "multilevel feature extractor." These filters' output stacks along the channel dimension before being delivered into the next tier of the network.

2. LITERATURE SURVEY

2.1 Prediction of pathological complete response after neoadjuvant chemotherapy in breast cancer by combining magnetic resonance imaging and core needle biopsy

https://www.sciencedirect.com/science/article/abs/pii/S0960740420304102

ABSTRACT:

Context

Especially in hormone receptor-negative breast cancer, neoadjuvant chemotherapy (NAC) often produces pathological complete response (pCR). Contrast-enhanced magnetic resonance imaging (cMRI) is the most consistent imaging method for evaluating the pathogenic effect of NAC. Ultrasound is absolutely necessary for obtaining representative specimens from the target lesion using core needle biopsy (CNB). This work aimed to evaluate the prediction accuracy of pCR by adding CNB following NAC in cases with full clinical response (cCR) detected by cMRI.

Techniques

In this prospective multicenter study, we evaluated cCR using cMRI after NAC. Ultrasonic-guided CNB (uCNB) was performed as planned under general anaesthesia using a 14G needle without any clip marks. Comparatively to surgically removed specimens, the uCNB-collected specimens were categorised as (i) no cancer (ypT0), (ii) no invasive carcinoma and merely residual carcinoma in situ (ypTis), and (iii) residual invading carcinoma. Whether the uCNB and the pathological results from the surgical specimens matched each other was investigated.

Findings

Of the 83 persons evaluated, 41 (49.4%) and 17 (20.5%) had ypT0 and ypTis respectively. The related false negative rates (FNR), sensitivity, and specificity were 50.0%, 50.0%, and 100%; for predicting ypT0 by uCNB, they were 50.0%, 50.0%; for predicting ypT0+ypTis, they were 28.0%, 72.0%, and 98.3%; respectively. Concordance rates for ypT0 were 74.7% (62/83) and for ypT0+ypTis they were 90.4% (75/83).

In conclusion

uCNB was insufficiently accurate to predict pCR in cCR patients identified by cMRI. For improved prediction, other modalities, such as clip locations and/or larger core needles, would be needed.

2.2 Results of a nationwide survey on Japanese clinical practice in breast-conserving radiotherapy for breast cancer

https://pmc.ncbi.nlm.nih.gov/articles/PMC6373682/

ABSTRACT: The Breast Cancer Group of the Japanese Radiation Oncology survey Group undertook a statewide questionnaire survey on the clinical use of postoperative radiation for breast-conserving therapy of breast cancer. These 18 questions addressed subjects including the annual patient count, planning technique, contouring structure, field design, dose-fractionated regimen, hypofractionated radiotherapy application, boost irradiation, radiotherapy for synchronistically bilateral breast cancer, and accelerated partial breast irradiation. 293 Japanese hospitals in all answered the web survey. The results showed the following: Although some facilities used a different age criterion (>70 years) to omit a tumour bed boost, the most common criteria for boost irradiation are based on the surgical margin width (5 mm) and age (40 or 50 years); almost all institutes delivered 10 Gy in five fractions to the tumour bed and 50 Gy in 25 fra. Treatment planning is carried out using rather similar field designs and delivery methods. This poll found that 43% of facilities have hypofractionated radiotherapy accessible; the most often used regimens were 10.64 Gy in 4 fractions for boost irradiation and 42.56 Gy in 16 fractions for whole-breast irradiation. Nearly of the facilities treated both breasts at once for synchronised bilateral breast cancer; accelerated partial breast irradiation was not usually accessible in Japan. This survey provided a summary of the present clinical use of radiation in Japan for breast-conserving treatment of breast cancer.

2.3 Breast cancer screening (BCS) chart: a basic and preliminary model for making screening mammography more productive and efficient

https://pubmed.ncbi.nlm.nih.gov/28505346/

ABSTRACT: Background: To increase the effectiveness of screening mammography, the breast cancer screening (BCS) chart is recommended as a fundamental and initial tool.

Methods: Under this case-control study, conducted in 2016, we gathered 1422 women between the ages of 30 and 75, 506 of whom had breast cancer (cases) and 916 of whom did not (controls). We produced the BCS figure using a multivariate logistic regression technique. We used the disease's dangers to project every individual's particular risk of breast cancer. The expected risk probabilities were then categorised and coloured as follows: 05% (green), 05-09% (yellow), 10-14% (orange), 15-19% (red), 20-24% (brown), and ≥25% (black).

Results: The BCS graphic displays the risk probability of breast cancer based on age, body mass index, late menopause, benign breast disease, and a positive family history of breast cancer among first-, second-, or third-degree relatives. Using this chart one may classify themselves as having a low risk of breast cancer (green), a medium risk (yellow and orange), a high risk (red and brown), or a very high risk (black).

Conclusions: This chart is a versatile and user-friendly tool that may identify high-risk individuals and improve the effectiveness and efficiency of the screening program.

2.4 Representation learning for mammography mass lesion classification with convolutional neural networks

https://pubmed.ncbi.nlm.nih.gov/26826901/

ABSTRACT: Context and goal: Currently, there is no solution for automatically classifying lesions from breast imaging. In order to circumvent the need to create specialised hand-crafted image-based feature detectors, this research presents a novel representation learning framework for mammography-based breast cancer detection that incorporates deep learning techniques to automatically learn discriminative features.

Methods: A new biopsy-proven benchmarking dataset was constructed from the cases of 344 patients with breast cancer. It included 736 film mammography (mediolateral oblique and craniocaudal) views, as well as 426 benign and 310 malignant lesions that were manually segmented as mass-related lesions. The two primary steps of the developed technique are (i) preprocessing to improve image details and (ii) supervised training to build the classifier for breast imaging lesions as well as the characteristics. Unlike other studies, we take a hybrid method in which the representation is learnt in a supervised manner using convolutional neural networks rather than by creating specific descriptors to describe the content of mammography pictures.

Results: Our method outperforms state-of-the-art image descriptors like histogram of orientated gradients (HOG) and histogram of the gradient divergence (HGD), as shown by experimental results using the developed benchmarking breast cancer dataset. The performance increased from 0.787 to 0.822 in terms of the area under the ROC curve (AUC). It's interesting to note that this model actually performs better than a collection of manually created features that utilise extra data from the radiologist's segmentation. Ultimately, the optimal descriptor for mass lesion categorisation was produced by combining the two representations—learned and hand-crafted—achieving an AUC score of 0.826.

Conclusions: A new deep learning framework was created to automatically classify breast mass lesions in mammograms.

2.5 DeepSplice: Deep classification of novel splice junctions revealed by RNA-seq

https://ieeexplore.ieee.org/document/7822541

ABSTRACT: Alternative splicing (AS) allows a single multi-exon gene to generate numerous mRNA transcripts under control. Large-scale RNA-seq data availability allows one to anticipate splice junctions and splice locations using spliced alignment to the reference genome. This greatly increases the ability to understand the many splicing variations and decipher gene architecture. Current ab initio aligners are sensitive to false positive spliced alignments, nevertheless, due to sequence errors and random sequence matches. These erroneous alignments might lead to a lot of misleading positive splice junction predictions in later studies of splice variant identification and abundance estimations. This work shows how properties of splice junction sequences

from experimental data may be found using deep learning techniques. DeepSplice is a new splice junction classification tool based on deep convolutional neural networks that (i) performs better than most advanced methods for splice site prediction, (ii) shows great computational efficiency, and (iii) lets users apply the tool to their own self-defined training data.

3. METHODOLOGY

i) Proposed Work:

Convolutional neural networks (CNNs), a deep learning method quite successful in image-based classification problems, are used in the suggested system. CNNs automatically learn spatial hierarchies of features from input pictures, unlike conventional machine learning algorithms as SVM, Naïve Bayes, and KNN which demand hand feature extraction. This qualifies them especially for uses in medical imaging, including mammography analysis. Layers of linked neurones make up the network; each neurone does calculations and forwards data to the following layer. CNNs may recognise complicated patterns linked with breast tumours by use of layers including convolution, pooling, and fully connected layers.

Inspired on the human visual cortex, CNNs are meant to identify picture characteristics at several degrees of abstraction. This method uses CNN models such as MobileNet and Inception V3 to extract deep characteristics straight from the data, thereby classifying breast cancer from mammography pictures. These designs provide precision and speed together and are light and strong. The system seeks to identify the best appropriate CNN model for the prediction of breast cancer, so enhancing patient outcomes via accurate and efficient detection and so supporting radiologists in early diagnosis.

ii) System Architecture:

Mammogram pictures enter the architecture for deep learning breast cancer diagnosis first preprocessed to improve image quality. Resizing pictures to a standard dimension, eliminating noise, and normalising pixel intensity to ready the images for feature extraction are part of this preparation stage. After that, a Convolutional Neural Network (CNN)—which is especially meant to automatically extract features from visual data—gets these processed images. Working together, the CNN's many layers—convolution layers, ReLU activation functions, pooling layers, and fully linked layers—capture low-level and high-level information of the tumour areas.

Following feature extraction, the CNN feeds the softmax layer the extracted characteristics through to classify the tumour as either benign (non-cancerous) or malignant (cancerous). The system makes use of cutting-edge CNN models such MobileNet and Inception V3, which thanks to their effective design and capacity to learn intricate picture aspects great accuracy and speed. Performance criteria include accuracy, precision, recall, and F1-score help to analyse the output at last to determine how effectively the system forecasts breast cancer. Apart from improving detection speed, this automated design helps radiologists to produce more accurate and dependable diagnosis.

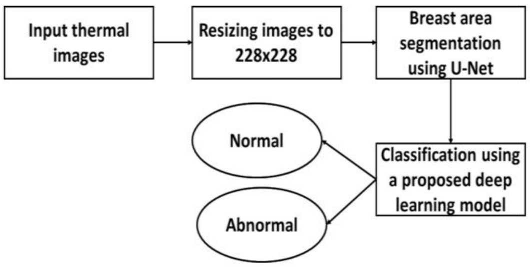

Fig 2. Flowchart of the proposed method.

Fig.1. Proposed Architecture

iii) MODULES:

a) Image Acquisition Module

- Collects mammogram images from medical datasets or real-time inputs.
- Converts images into a compatible format for further processing.

b) Preprocessing Module

- Resizes and normalizes images to ensure consistency in input data.
- Enhances contrast and removes noise to improve feature visibility.

c) Feature Extraction Module (CNN Layers)

- Applies convolution and pooling layers to extract important visual patterns.
- Identifies low-level (edges, textures) and high-level (shapes, tumor areas) features.

d) Classification Module

- Utilizes CNN models like MobileNet and Inception V3 to classify images.
- Determines whether the tumor is benign or malignant based on extracted features.

e) Result Prediction Module

- Displays the classification result to the user (Benign/Malignant).
- Shows the confidence score or prediction probability to indicate model certainty.

f) Performance Evaluation Module

- Measures model effectiveness using metrics such as accuracy, precision, and recall.
- Displays the confusion matrix to visualize true vs. predicted classifications.

iv) ALGORITHMS:

a) **CNN** – CNNs, or convolutional neural networks, are widely used. Perhaps the most well-known deep learning architecture is this one. Convnets' widespread awareness and efficacy are the reasons behind the most recent rise in interest in deep learning. AlexNet launched CNN's pastime in 2012, and since then, it has expanded rapidly. Researchers advanced from eight-layer AlexNet to 152-layer ResNet in just three years. These days, CNN is the go-to mannequin for every issue involving photographs. They completely outperform the rivals in terms of precision. It is also effectively used for herbal language processing, recommender systems, and other applications. CNN's primary advantage over its predecessors is that, aside from human oversight, it automatically recognises the crucial components. For instance, it learns unique characteristics for each category on its own given a large number of images of cats and puppies. CNN also has a high computational efficiency. It performs parameter sharing and utilises unique convolution and pooling algorithms.

This makes CNN styles broadly appealing by enabling them to function on any device. This sounds like perfect bliss all around. We are working with a very efficient and eco-friendly mannequin that uses automated feature extraction to achieve superhuman accuracy (yep, CNN models can currently classify photographs more accurately than people). With any luck, this article will help us uncover the methods and mysteries of this amazing technology.

4. EXPERIMENTAL RESULTS

The experimental results of the proposed breast cancer detection system demonstrate the effectiveness of deep learning models, particularly Convolutional Neural Networks (CNNs), in accurately classifying mammogram images. Both MobileNet and Inception V3 architectures were trained and tested on a labeled dataset containing benign and malignant breast tumor images. The models were evaluated using performance metrics such as accuracy, precision, recall, and F1-score. Inception V3 achieved higher accuracy due to its ability to capture multi-scale features, while MobileNet performed efficiently with lower computational cost. The results indicate that the proposed deep learning approach not only improves diagnostic accuracy but also provides faster predictions, supporting radiologists in making reliable decisions for early breast cancer detection.

Accuracy: The ability of a test to differentiate between healthy and sick instances is a measure of its accuracy. Find the proportion of analysed cases with true positives and true negatives to get a sense of the test's accuracy. Based on the calculations:

Accuracy = TP + TN /(TP + TN + FP + FN)

$$Accuracy = \frac{(TN + TP)}{T}$$

Precision: The accuracy rate of a classification or number of positive cases is known as precision. Accuracy is determined by applying the following formula:

Precision = True positives/ (True positives + False positives) = TP/(TP + FP)

$$\Pr e\,cision = \frac{TP}{(TP + FP)}$$

Recall: The recall of a model is a measure of its capacity to identify all occurrences of a relevant machine learning class. A model's ability to detect class instances is shown by the ratio of correctly predicted positive observations to the total number of positives.

$$Recall = \frac{TP}{(FN + TP)}$$

mAP: One ranking quality statistic is Mean Average Precision (MAP). It takes into account the quantity of pertinent suggestions and where they are on the list. The arithmetic mean of the Average Precision (AP) at K for each user or query is used to compute MAP at K.

$$mAP = \frac{1}{n}\sum_{k=1}^{k=n} AP_k$$

$$AP_k = \text{the AP of class } k$$

$$n = \text{the number of classes}$$

F1-Score: A high F1 score indicates that a machine learning model is accurate. Improving model accuracy by integrating recall and precision. How often a model gets a dataset prediction right is measured by the accuracy statistic..

$$F1 = 2 \cdot \frac{(Recall \cdot \Pr e\, cision)}{(Recall + \Pr e\, cision)}$$

Fig 2. Upload data

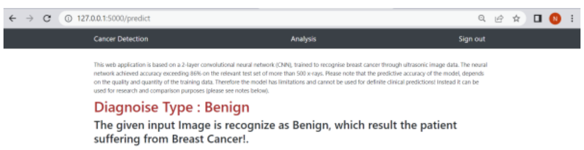

Fig 2. Predicted output

5. CONCLUSION

Here we proposed a computer-aided diagnostic (CAD) system based on convolution neural networks. Convolution neural networks are applied to differentiate between normal and aberrant mammograms. Early cancer diagnosis and treatment advice are always ideal. We leverage the Inception V3 architecture to identify breast cancer with 83% accuracy.

6. FUTURE SCOPE

Deep learning's future breadth of use for breast cancer detection has enormous potential to raise diagnosis accuracy and efficiency even further. Integration of more sophisticated CNN architectures, including ResNet or DenseNet, will help to further improve feature extraction and lower overfitting going forward. Furthermore enhancing the generalisation and robustness of the model would be adding a larger range of mammography pictures, including those with varying age groups, ethnicities, or varieties of breast tissue. Combining multimodal data—that is, combining MRI or ultrasound pictures with mammograms—allows a more complete analysis and helps to lower false positives or negatives. Eventually, especially in rural locations with limited access to medical specialists, real-time deployment of these models on mobile or cloud platforms for faster and more accessible diagnosis might greatly affect world healthcare.

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