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Enhancing Ultrasound Image Quality Using Machine Learning Techniques

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Abstract: Machine learning (ML) techniques are becoming more commonplace as a result of their utility in addressing complex issues in several contexts. Using ML methods in ultrasonic imaging applications is nothing new, but there has been a meteoric rise in research into this area over the last several years. Medical diagnostics and non-destructive assessment use ultrasonic imaging extensively, and both have benefited from the use of machine learning methods. In the former, which constitutes the bulk of the review, solutions that pertain to the detection/classification of material defects or specific patterns are reported, while in the latter, studies were categorised according to the body organ examined and the methodology adopted. Finally, the study's analysis is summarised, and the key benefits of machine learning are explored..

Keywords: *Machine learning; deep learning; ultrasound imaging; medical diagnostics; NDE*

1. Introduction

Machine learning (ML) methods, which are founded on the premise that computers can analyse data, recognise patterns, and act autonomously, have revolutionised many fields of study and business in recent years. This study will focus on one particular application of ML—ultrasound imaging—but ML has many other possible uses, including computer vision [1, 2, 3, 4], self-driving vehicles [5, 6], virtual personal assistants [7], voice recognition [8], and more.While using ML approaches in ultrasonic imaging has been around for a while, there has been a sudden uptick in research into the topic in recent years, particularly in the areas of sonar, near-death experiences (NDEs), and medicine. Particular attention is paid in this study to the medical application of the latter two topics.

2. Machine Learning

One of the most active areas of artificial intelligence (AI) research is machine learning (ML), which is defined as the study of algorithms that can learn on their own to improve their performance on a job via exposure to data and repetition. The primary goal of ML methods is to empower systems to learn and acquire expertise on their own, with little human intervention. There has been a lot of research on the possibility of teaching computers how to learn on their own without being given any instructions. The methods employed by ML vary depending on many criteria, such as the nature of the issue, the amount of variables involved, and the optimal model. Both supervised and unsupervised learning are crucial to ML. In supervised learning, an algorithm is taught to produce a desired result by being fed data that has already been labelled with that result. Classification algorithms, which use information about an object to determine which category it belongs in, fall under one category of supervised algorithms, while regression algorithms, which use information about an object to estimate the value of a particular feature, fall under another. These are the most common types of regression algorithms:

• Linear regression, which uses a regression line to create a connection between two sets of data (input and output). There are two distinct kinds of linear regression: simple linear regression, in which there is only one independent variable, and multiple linear regression, in which there are two or more.

• Logistic regression, a statistical method for modelling binary outcomes (i.e., issues with two categories) using one or more explanatory variables. The data and the connection between a binary dependent variable and one or more independent variables may be described in this fashion.

The most common algorithms used to solve categorization issues are listed below.

• Naive Based on a probabilistic model, Bayes allows for the capturing of a model's uncertainty via the calculation

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of probability. By offering usable learning methods and merging observed data, the Bayesian classification helps address predicted challenges. Learning algorithms may be better understood and evaluated with the help of this categorization [32].

Data points may be separated into two classes using the hyperplane that provides the most dissimilarity using a method called support vector machine (SVM). The linear SVM classifier is the simplest kind of SVM classifier, and it works by mapping examples into a space in which the cases belonging to two distinct categories are clearly divided by a gap that maximises the difference. Predictions regarding an example's category may be made based on which side it falls on. There are both linear and non-linear versions of SVM. Results from non-linear SVMs may be particularly useful when data cannot be segregated linearly. The kernel method, where a non-linear function is used in place of the scalar product, maximises the hyperspace. The most common kernel types are polynomial and Gaussian..

• The results from many decision trees are combined into a single prediction in a random forest (RF).

• The goal of K-nearest neighbours (K-NN) is to make a prediction about a new instance based on prior knowledge of the data points that have been classified into distinct groups. In other words, the data set is defined by the collection of data points or instances that belong to a certain class. It works on the principle that instances are more similar to data points the closer they are near each other in terms of those qualities. The method employs a distance measure. It is used for classifying entities into two or more categories based on modelled group differences. It flattens higher-dimensional spaces into ones with fewer characteristics. LDA, like SVM, determines the best hyperplanes based on each user's unique goals. However, SVM computes ideal hyperplanes without assuming anything about the covariance matrices of the classes, while LDA hyperplanes are optimal only when they are identical.

Unsupervised learning involves discovering latent patterns in data without labelling the results. Here are some of the most important unsupervised learning algorithms:

The dimensionality of a dataset that contains many variables that are strongly or weakly correlated with each other can be reduced using principal component analysis (PCA), while the inherent variation in the dataset is preserved to the greatest extent possible using k-means clustering. Principal components are created by transforming the original variables into a new set of orthogonal variables, where the retention of variance in the original variables reduces as one moves down the order.

Deep learning (DL), a subfield of machine learning, seeks to accomplish the automated discovery of high-level abstract structures inside data via the use of hierarchical modelling. The foundation of the deep learning approaches that are used the most often is comprised of neural networks. These networks draw their inspiration from the structure of the human brain and nervous system. It is constructed consisting of processing units called nodes, which are connected to one another and layered in layers (input, hidden, and output respectively). Every node in the network receives its inputs, multiplies them by their weight, and then adds the products together. Following this, a transformation is applied to the sum by the activation function, which is commonly a sigmoid, tanh, or rectified linear unit (reLU). The output of the function is the data that is sent into the processing unit of the layer that comes after it. The resolution to the issue may be found in the very last piece of output. The convolutional neural network known as UNet was developed specifically for the purpose of processing medical photos. A UNet is a kind of network that has the form of a U and is designed such that each layer of convolution in the encoder is connected to the matching convolution layer in the decoder. Each possible permutation results in a quality that is exclusive to the classes that are being separated. Unet is a deep learning system that recognises and categorises repeated image sequences by using convolutional neural network layers and max-pooling architectures.

There are a total of eight layers in Alexnet, the first six of which are convolutional and the last three of which are completely connected. Alexnet is an example of a convolutional neural network, or CNN. Because of its complex framework and many model parameters, AlexNet is better able to recognise a greater variety of characteristics than conventional CNNs.

One kind of CNN design is known as ResNet. This architecture makes use of a skip link in order to cut across a number of layers. The use of a skip connection is helpful and should be done so in order to eliminate errors in training that are brought on by degradation (also known as accuracy saturation), which occurs when a significant number of layers are employed.

3. Literature Review

Shuojie Wen et.al (2023) The suggested CNN model was evaluated using data from ultrasound scans of phantom breasts, simulated breasts, and real breasts. Two deep-learning-based tracking techniques (MPWC-Net++ and ReUSENet) and two traditional tracking methods

(GLUE and BRGMT-LPF) were used to evaluate its performance.

Qi Chen et.al (2022) Because of mechanical noise, electromagnetic interference, human disturbance, etc., medical pictures may be blurred or distorted throughout the collection process. This may lead to subpar imaging, which in turn can undermine clinicians' conviction in their diagnoses. An essential adjunct to coronary angiography diagnosis is intravascular ultrasound (IVUS). IVUS pictures are susceptible to distortion for a variety of causes, and significant distortions may reduce diagnostic certainty.

Zixia Zhou et.al (2019) claims that four alternative algorithms, including conventional gray-level-based approaches and learning-based approaches, are compared to Our suggested technique. The findings verify that the suggested method achieves the best option for enhancing the quality of portable ultrasound pictures and providing helpful diagnostic information. The potential for this technology to improve access to healthcare for all people is enormous.

Ultrasound Samples database

B-mode ultrasound pictures of the thyroid and B-mode ultrasound images of the breast are used in this analysis. Two different sets of ultrasound pictures of the thyroid are used in this study. The first set comes from a private database of 40 photos obtained from JSS Hospital, Mysuru with approval from the local ethics council. Twenty of the nodules in these 40 photographs are benign, whereas the other twenty are cancerous. These pictures have been labelled by a radiologist with more than 15 years of expertise, and they have been verified to be accurate by a biopsy. Twenty benign, twenty malignant, and thirty borderline thyroid nodule photos are chosen from this database. According to the thyroid imaging and data system (TIRADS), 15 of the 30 borderline nodules have a malignancy risk of between 5 and 10%, whereas 15 have a malignancy risk of between 10 and 80%. Among 30 suspicious nodules, 15 were found to be benign and 15 were found to be malignant when biopsies were performed. Well-defined margins and a consistent texture characterise the benign thyroid lesions shown in Fig. 1 from the confidential database seen by the seasoned radiologist.

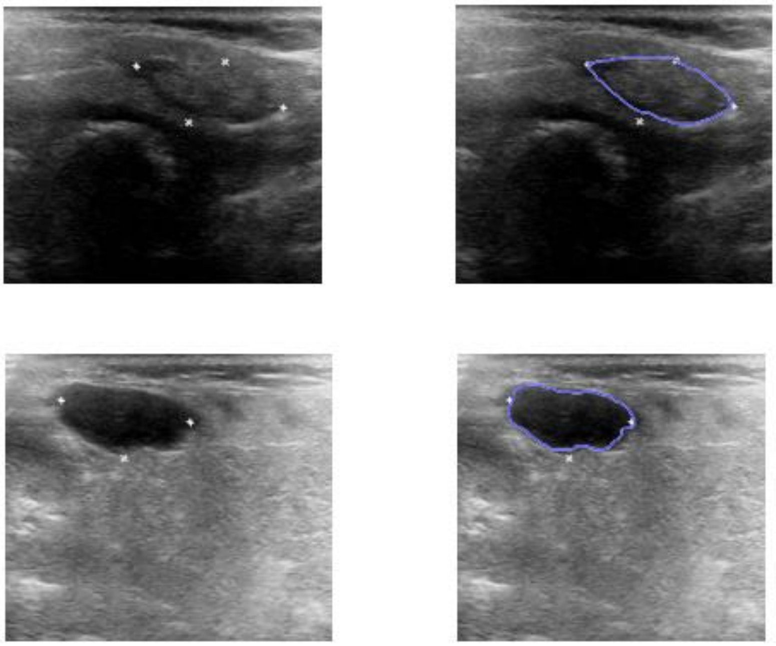

Fig 1 Benign thyroid lesions and their delineations

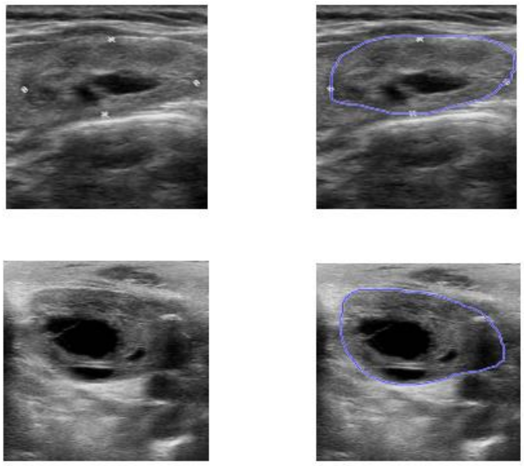

Fig. 2 Malignant thyroid lesions and their delineations

Figure. 2 shows some of the malignant thyroid lesions from the private database with cystic changes

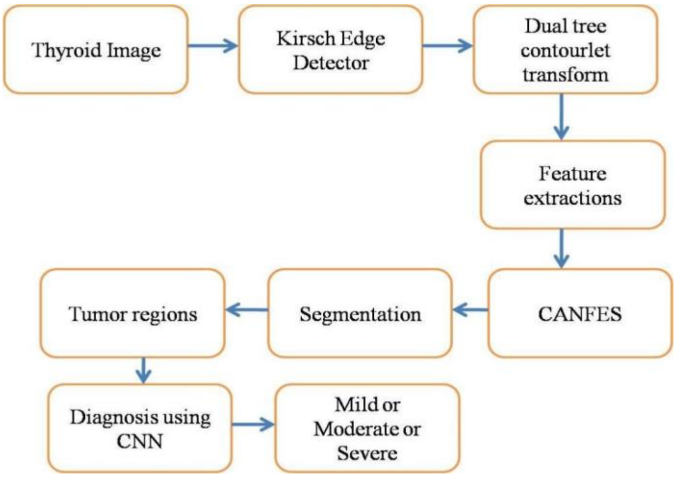

Fig. 3 Proposed tumor detection and diagnosis of ultrasound thyroid images

Layer	Type	Number of Convolutional filters	Filter size	Stride
Layer 1	Convolutional layer	16	3*3	1*1
Layer 2	Convolutional layer	32	3*3	1*1
Layer 3	Convolutional layer	64	3*3	1*1
Layer 4	Pooling layer	-	2*2	2*2
Layer 5	Convolutional layer	256	3*3	1*1
Layer 6	Pooling layer	-	2*2	2*2
Layer 7	Fully connected Neural Networks	-	-	-

Table1 Specifications of the proposed CNN architecture

The characteristics of the proposed CNN architecture are outlined in Table 1. These specifications include the number of layers, the kind of layer, the number of filters, the size of the filters, and the specifics of the stride of each layer.

Thyroid image sequences	Se	Sp	Acc	Pr	F-Score	DSI
1	97.6	98.1	99.5	97.7	97.8	99.1
2	98.1	98.6	99.6	98.1	98.5	98.5
3	98.6	98.9	98.9	98.8	98.4	98.7
4	98.1	97.9	99.5	98.6	98.9	98.5
5	98.3	97.6	99.8	98.9	97.1	98.1
6	97.8	98.1	99.1	98.5	98.7	98.6
7	97.9	98.5	99.4	97.3	98.2	97.7
8	98.3	98.8	99.8	97.7	98.7	98.2
9	98.5	96.9	97.9	98.1	99.1	98.8
10	98.7	98.7	98.6	96.6	98.5	98.1
Average	**98.1**	**98.1**	**99.2**	**98.1**	**98.3**	**98.4**

Table 2.Tumor segmentation results using proposed machine learning approach on 10 numbers of abnormal thyroid images

Cases	Number of ultrasound thyroid images	Correctly diagnosed thyroid images by proposed method	Diagnosis rate (%)
Mild	67	66	98.5
Moderate	116	114	98.2
Severe	17	16	94.1
Total	200	196	98

Table 3 Performance evaluation of Diagnosis system for ultrasound thyroid images

Both the suggested CNN design and the standard CNN architecture are used to diagnose the tumour areas that have been divided in thyroid imaging into mild, moderate, and severe instances. According to Table 4, it is abundantly obvious that the suggested CNN design is capable of achieving a high diagnosis rate in comparison to the standard CNN architecture.

Cases	Number of ultrasound thyroid images	Correctly diagnosed thyroid images by proposed method	Correctly diagnosed thyroid images by conventional LeNET method	Diagnosis rate (%)	
				Proposed method	Conventional LeNET method
Mild	67	66	61	98.5	91.0
Moderate	116	114	110	98.2	94.8
Severe	17	16	14	94.1	82.3
Total	200	196	185	98	89.3

Table 4 Performance comparisons between proposed and conventional CNN architecture

4. Conclusion

Our study proposes a computer-aided approach utilising machine learning and neural networks with deep layers to identify and isolate thyroid cancers in ultrasound scans. Based on the ground-truth ultrasonic thyroid gland images, the proposed tumour segmentation method utilising machine learning technology demonstrated a sensitivity of 98.1%, specificity of 98.1%, accuracy of 98.4%, precision of 98.1%, F-Score of 98.3%, and Dice Similarity Index of 98.4%. The proposed methodology for identifying the thyroid tumour area involves labelling 198 anomalous photographs as such, while 155 normal images are classified as healthy. In a standard scenario, the TTDR is approximately 99.3%, while in an atypical circumstance, it is roughly 99%. According to the proposed methodology, the estimated True Positive Detection Rate (TTDR) for the identification and diagnosis of thyroid tumours is 99.15%. The success rates of diagnosis vary depending on the severity of the case, with rates of 98.1 percent for mild cases, 98.1 percent for intermediate cases, and 94.1 percent for severe cases. The proposed methodology for detecting and diagnosing thyroid tumours has an estimated diagnostic accuracy of approximately 98% overall.

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