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Deep Learning Based Ultrasound Image Classification for Improved and Better Medical Diagnosis

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Abstract: Ultrasound is the best imaging techniques for detection of abnormalities in the human body. Ultrasound is a medical imaging technique in which a transducer transmits and receives the ultrasound waves to and from the organs of the human body. Ultrasound waves are high-frequency wave ranges from 20 KHz to Giga Hertz. Ultrasound methods are non-invasive, pain-free and patient-friendly techniques. Detection of abnormalities using Ultrasound helps doctors to treat the patient. Abnormalities in liver, Breast, Kidney, Uterus, Heart, Liver, Nerves, Prostate found out using ultrasound techniques has a list of unidentifiable problems in Medical Images in traditional methods. Deep learning plays a vital role in the modern era for much problem identification in medical imaging and other domain.

Keywords: Classification, Convolutional neural network, Linear regression, Medical imaging, Random forest.

I. Introduction

Deep learning with Ultrasound imaging suits for image segmentation, image classification, image registration, image detection/localization. Deep learning has many methods like supervised learning, unsupervised learning, reinforcement learning and semi-supervised learning. In Supervised learning, a label of the images is known. Supervised learning is suitable for classification and regression problems. Naive Bayes, Support vector machine, Random Decision Forest are classification algorithms in supervised learning. In Medical image classification, to identify the cancerous tissues in breast classification algorithms plays a vital role [1, 2]. Linear regression, Generalized regression, Logistic regression are the regression algorithms in supervised learning. Linear line model y = mx+c gives separation between data points to clustering or classification [3].

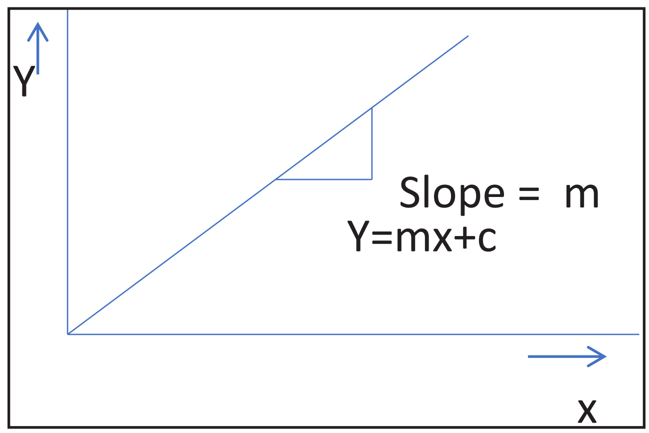


Fig. 1: Linear Model

Logistic Regression: In Logistic Regression the predicted Y value lies between 0 and 1 In the case of linear regression predicted Y value may lie outside of the range 0 to 1. Logistic regression is a S-shaped function preferable for image noise detection. Logistic regression is preferable for 2 classes. If more than 2 classes exist Multinomial regression with different weight vectors are preferred.

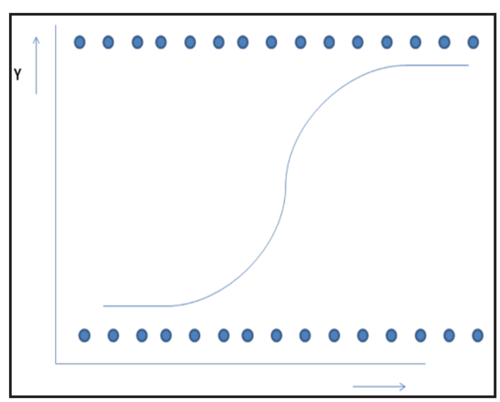


Fig. 2: Logistic Regression

Softmax Layer: Softmax in regression is a mathematical function with an input vector of real numbers normalizes to probability distribution proportional to the exponential of input values.

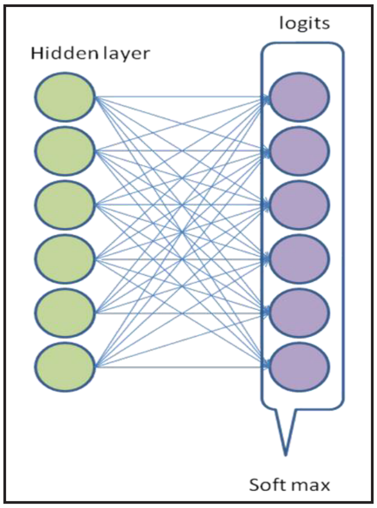


Fig. 3: Softmax Function

II. Literature Review

A. Support Vector Machine

Support vector machine is an algorithm which has a plane that separated the various support vectors. The distance between the support vectors is known as margin. Accuracy of the algorithm can be classified based on the higher distance between the support vectors. Multiple hyperplanes exist but it is inaccurate as the same vectors may be classified with various hyperplanes. The hyperplane need not be a linear line it can be a circle or triangle or rectangle or any other shape based on either the data is linear or non-linear.

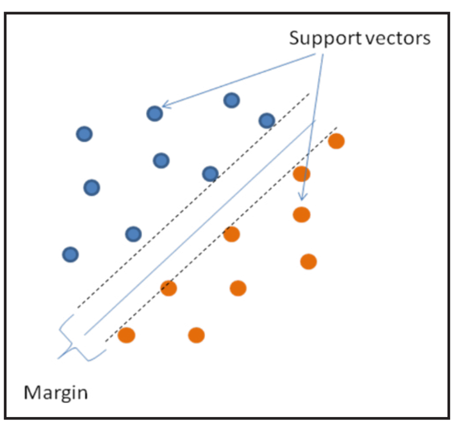


Fig. 4: SVM

B. Bayes Theorem

It is the working principle behind the Naive Bayes algorithm. where An and B are occasions and P(B). Bayes theorem is meant for finding the conditional probability. If a random variable is dependent then it is known as marginal probability, if the variable is independent then the event is done. If the probability depends on more than two variables then it is known as joint probability. If the probability depends on one or more variable it is known as conditional probability.

$$P(A \mid B) = \frac{P(B \mid A)P(A)}{P(B)}$$

In Gaussian Naive Bayes, consistent qualities related with each element are thought to be conveyed by a Gaussian appropriation. Gaussian dissemination is additionally called Normal circulation.

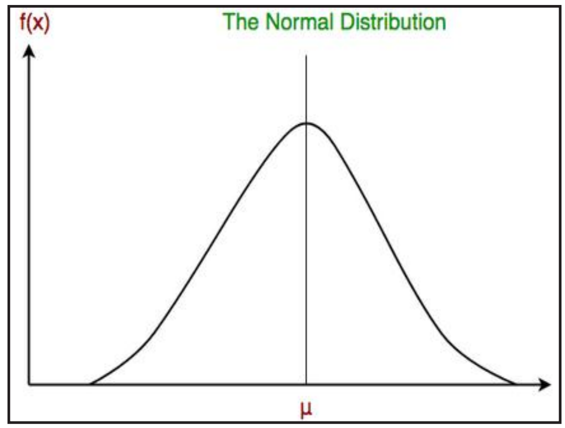


Fig. 5: Normal Distribution

At the point when plotted, it gives a chime formed bend which is symmetric about the mean of the component esteems as demonstrated as follows: In random decision forest algorithm, The learning methods are based on the conditions true or false. A tree is constructed based on the human organ for classification or regression. Each tree will denote an organ and the imaging view with the underlying abnormality or normal organ.

The decision is based on the learning made by the algorithm with the previous data. Overfitting problem is avoided in the random forest as there are many decision trees in this algorithm for various classifications. Larger trees give a more accurate result. Random forest algorithm works well for huge data sets. Scaling problem is minimized in this algorithm. This algorithm takes more time to construct trees for huge data.

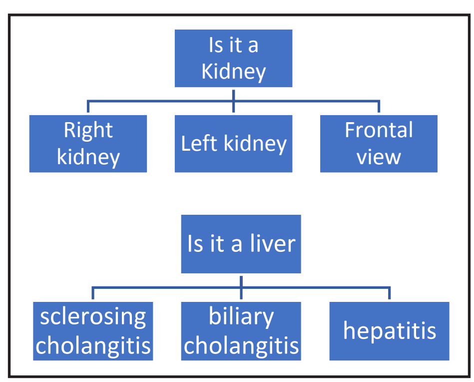


Fig. 6: Random Forest Tree

C. Convolutional Neural Network

It has more number of convolutional layers. Convolution is the process of subsampling as a result of which fully connected networks are formed. Multiple layers constitute convolutional neural networks. The convolutional layer has an input which has nxnxc where c is the no. of channels and n is the width and height of the layer. A convolutional neural network has a feature map that describes the various features of the images finally. The various layers in CNN are max-pooling, subsampling, downsampling. In a single depth slice, for 2x2 kernel maximum value of kernel is obtained as a 2x2 matrix.

CNN identifies the object based on size, texture, height, depth, width. Activation function layer will be applied element-wise like Relu function, sigmoid function, etc. After applying the activation function the output remains unchanged. After obtaining the feature map by the flattening process the values are listed in a single column. AlexNet, GoogLeNet, ResNet are some of the convolutional neural networks in which the stride moves over all the kernel chosen. It is best preferred for the classification methods. Based on the convolution operation the CNN works. The various layers in CNN are pooling layer, fully connected, convolution layer. CNN has a feature learning part, classification part and input part.

Images are often affected with noise preferably the speckle noise in ultrasound images. It is a multiplicative noise. It can be denoised based on wavelet or anisotropic filters or cluster-based filters etc. Impulse noise is often affected while transmission of images. Impulse can be either random or fixed based on the grayscale value that exists in the image pixels. Certain deep learning algorithms are used here for denoising.

III. Results and Discussion

Pre-trained denoising neural network like DnCNN is the Denoising convolutional neural network. Gaussian noise is removed with this DnCNN.

Fig. 7: DnCNN

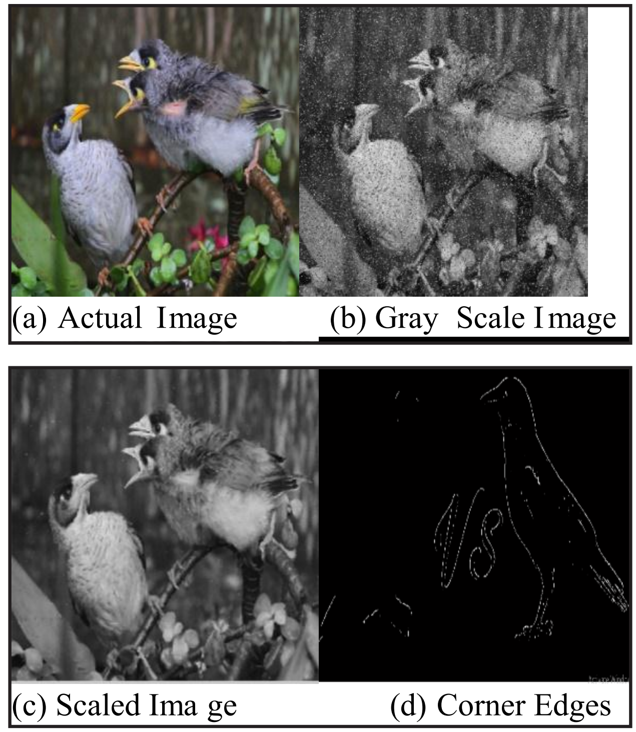


Fig. 8

When the impulse noise of 0.5% is applied to actual image the filter is applied and the edge image is obtained.

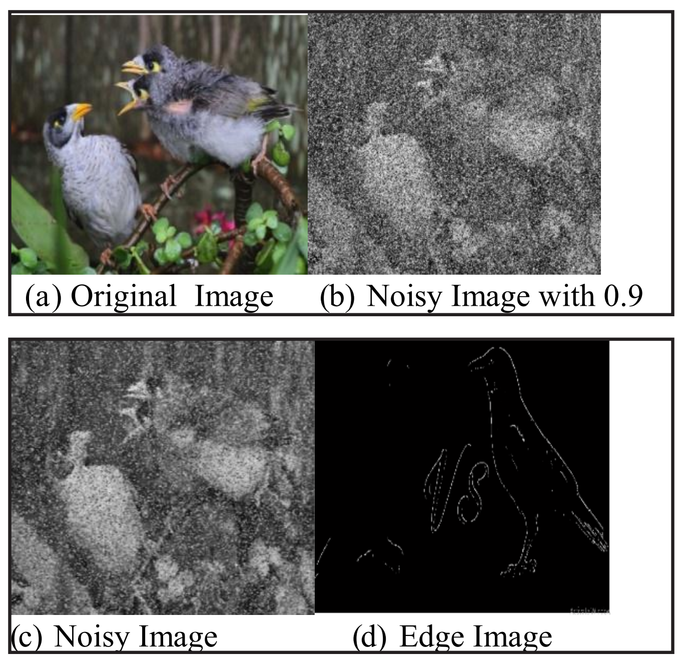
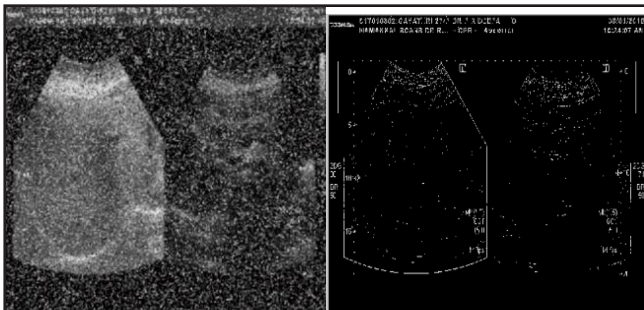


Fig. 9

When the impulse noise of 0.9% is applied to actual image the filter is applied and the edge image is obtained.

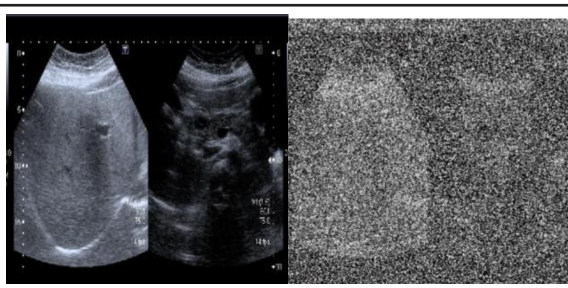
(a) Original Image (b) Gray Scale Image



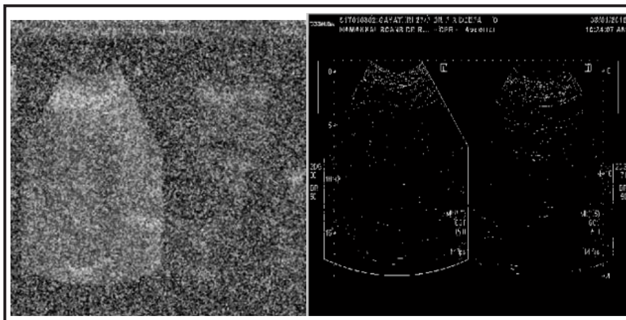
(c) Median Image (d) Edge Image

Fig. 10

Results obtained for 0.5 % of the variance of impulse noise.



(a) Original Image (b) Gray Scale Image



(c) Median Image (d) Edge Image

Fig. 11

When the impulse noise of 0.7% is applied to actual image the filter is applied and the edge image is obtained.

IV. Conclusion

Thus the noise reduction using various filters has been done for various levels of impulse noise. Using deep learning, denoising can be performed with better values for Signal to Noise Ratio, Mean Square Error, Similarity values based on the result obtained.

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