OPTIMIZED ACTIVATION FUNCTION FOR MINIMIZING THE ERROR IN CANCER TUMOR LEARNING WITH NEURAL NETWORK MODEL

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ABSTRACT—Neural Network Learning has a great impact in prophesying the medical analysis. Machine learning allows the electronic machine to learn from the past and to detect the future. Since it’s a distribution of artificial intelligence, this ability is applicable for cancer prediction. Automatic classification of benign and malignant in ultrasound tumor image is bounded within the neural network. The features in a tumor image are well learned with machine learning algorithms like K-Means, Back propagation. Increase learning rate is essential for feature learning. When the number of epochs in neural network learning reaches hundred and fifty with learning rate 0.4, the accurate feature learning would be found with low error rate. Sigmoid activation function is used for optimization and minimizing the error for feature learning. The ultrasound screened image is low quality in nature and the learning about features is a task in predicting. The proposed methodology Optimized Activation Function For Minimizing The Error In Cancer Tumor Learning With Neural Network Model (OACLNM) gives a pathway to find the best features for prediction of cancer.

Keywords— Neural Network, learning rate, breast cancer, ultrasound image, optimization

I. INTRODUCTION

Neural Network Learning is a process of exhibiting the original phenomena of any object into the network to simulate desired output. Likewise, briefly processing the attributes of tumor identification from an Ultrasound screened images is a way step to process over it. A systematic approach for detecting the malignant tumor is a problematic approach. In view of the fact, the data set used to classify the breast cancer tumor is less and noisy in nature. An ultrasound screened image is a basic scanned image of a cancer tumor, which usually has the primary staging properties. Classification of malignant tumor in an ultrasound image is not easy as possible for radiologist to predict the disease symptoms. Thus, automatic prediction is a challenging task for such images. The neural network approach deals the task with learning the entire characteristic of tumor. The basic attributes for characterization of tumor are size, height, width, shape, and calcification. Nowadays, automatic breast cancer detection system is not applicable in our area. Thus to keep on checking the growth of tumor is a must for the people who are affected for cancer. Machine learning technique is a second useful opinion for a radiologist to classify the disease. A system with accurate predictions of tumor growth is well essential. Researchers face a difficulty in facing the human expectation over cancer prediction since the symptoms of cancer is not possible in the early stage. The complexity of the problem should be solved with the number of inputs given for training and testing. Any machine learning technique is depending upon the user input given for training. The classification of malignant or benign cancer depends on the characteristics given as input. Logically, the characteristic of malignant tumor depends on the height, width and shape. The system for automatic prediction of the growing period of tumor should specifically display the alert sign in case of hazard stage. Extraordinarily the ratio for breast cancer among the women’s is growing in speed.

Screening the breast cancer tumor using an ultrasound device seems low in its resolution, thus it makes time to decide the disease. Also, the number of secondary testing devices like biopsy is needed to make sure the tumor is malignant. The system proposed meeting the inadequacy of the missionary part. As a substitution of all the secondary devices the proposed methodology works with similar tasks. Cancer statistics in 2016 reports that even in villages, spreading of malignant tumor is a cause of nature.

A report on October 2016 says for the growth of breast cancer among women’s in Chennai, INDIA is certainly rising up towards 26k per year. Moreover the affected cases may
totally defeat if no proper awareness is done. Several modalities were emerged to detect the breast cancer and diagnosis carried with it; also there are moments that lose their life. The following sections spotlight feature extractions from images and is passed as input to the neural network for self

II. RELATED WORK


Ahmet Mert, Niyazi Kilic et al [7], proposed a concept for the reduction of feature selection properties with Independent Component Analysis (ICA) which selects the original 30 features along with one reduced feature and the classifier accuracy is predicted with k-Nearest Neighbor (k-NN) and Artificial Neural Network (ANN).

The one dimensional feature vector causes Radian Basis Function Neural Network with increase accuracy from 87.17% to 90.49%. The prediction of malignant samples with sensitivity rate from 93.5% to 96.63% for RBFNN and for SVM the rates increase from 96.07% to 97.47%. Analyzing the results, applying ICA for feature reduction for processing with neural network forms to be greater in performance.

Jiexiong Tang et al [9], is of Extreme Learning Machine (ELM), predicts an algorithm which trains the hidden layer in forward basis. The efficiency of an algorithm is compared with deep learning and gives better junction than existing learning methods.

III. OACLNN MODEL

The proposed methodology of Neural Network Cancer Prediction Model (NNCPM), is a model for predicting the tumor with attributes like mass shape, age, mass location, mass margin, side, depth, composition (fat, fibrogranular densities, heterogeneously dense, extremely dense), and class. The process is balanced with updating the weights on input to achieve the deserved output. The characteristics of malignant tumor are learned in the training phase and are used for classification.

The training phase is important to build the positive and negative samples for learning the characteristics of breast cancer tumor. Unsupervised learning is using the updated weights until the desired output is reached. The positive samples are benign attributes and negative samples are malignant attributes. The clustered output closed to the malignant attributes. The clustered output closed to the malignant tumor.

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Back Propagation Algorithm (BPA) is based on neural network concepts which apply non-linear transfer function. Sufficient training data are needed to find the relationship of giving input and the character of the tumor.

Automatic prediction of cancer data is obtained by use of ART learning. The following section 2 relates existing works; section 3 consists of a newly developed methodology for optimizing the activation function for feature classification; section 4 discusses the findings of the theme network. Since pattern recognition is the best way for tumor character recognition, it’s been used as a learning algorithm.

The scope of this paper is to bring an activation function with an optimal solution that should minimize the error. The theme is finding the tumor a benign or malignant type cancer.

A. Preprocessing

Any ultrasound screened image should be preprocessed since the nature of the image is noisy. The filtration techniques are for the removal of noise in the image. Preprocessing with the raw data is done by color based filtration [8] The variation in the pixel gives the differentiation of normal and abnormal tumor area shown in Fig.1.

The breast cancer dataset consists of attributes extracted from ultrasound screened images. Being an optimized learning model, the attributes appropriate for cancer detection with minimum error rate should be chosen. Neural Networking is the process which makes out the appropriate output.

Training with 10 attributes of ultrasound images to differentiate the benign, malignant and normal image is symbolically represented in Fig 3.

B. EVALUATION PERFORMANCE

METHODS

(a) K-Means Algorithm

K-Means Algorithm is a cluster based problem solving algorithm used in unsupervised learning. It is used in breast cancer prediction for the purpose of segmenting the foreground and background image. A cluster forms a group of pixel in the ultrasound breast cancer image is combined on the basis of similarity. Moreover, it is used as NP-Hard combinatorial optimization problem.

The vector points used for observation in the case of medical images are represented as $A_1, \ldots, A_n$. Each vector point is assigned to one cluster with respect to its nearest pixel value. The cluster is formed based on the Euclidean distance. The mean value is calculated for each pixel and it’s added to the cluster.

The cluster assignment is calculated as

$$\text{cluster mean}, mK = \frac{\sum_{i=1}^{n} x_i \cdot i = k}{\text{nr}}$$

Initially the grouping of pixels into a cluster is divided in 3 parts. Each part of the cluster varies with certain circumstances. The first cluster has the numerical values with low difference and the next cluster has values with high
difference and final cluster has the difference of median values. Any new entering element into the present cluster should initially find the subtraction formulae and add into neighboring cluster.

The K-Means Clustering algorithm for ultrasound cancer image is stated as,

Clusters C= \{C1, C2, C3\}
Input points X=\{x1, x2, x3 ...xn\}

Step 1: Initialize 3 clusters for grouping the similar values.

[Here the cluster is selected based on the characteristics of ultrasound medical image]

Step 2: The partition of K-clusters are based on the observations with the nearest mean.

Step 3: Calculate each value with the cluster centroid.

Step 4: Place the point to the cluster, which is minimum in the distance.

Step 5: Count the number of values in each cluster using

\[ Cnt_i = \sum_{n=1}^{x} x1...xn \]  

Where, Cnt_i is the total number of elements in each cluster

Step 6: Again calculate the values with newly formed cluster.

Step 7: Until the last values of an image repeat from step 3

Three color groups in Fig 6. is clustered based data from ultrasound images. An ultrasound breast cancer image consists of mass region, normal region and small particle region. The clustering is a variation of pixels in an image that separates the foreground and background objects.

(b) Wavelet Transformation

The feature extraction of any ultrasound breast cancer image is learned with Discrete Wavelet transformation (DWT). It is the tool for extracting the actual features in an image. DWT mainly used to give the information about the frequency of the object in an image which is further used for classification. The operation is carried by applying DWT on each RGB pixel value for Low-Low (LL), Horizontal (LOW-HIGH), Vertical (HIGH-LOW), diagonal (HIGH-HIGH) components. The pixels are separated with odd and even values. The obtained values are then processed for sampling by performing low and high pass filters.

The following are the pixels for calculating components.

\[ lh=LOW_{\text{odd}}(i,j)-LOW_{\text{even}}(i,j) \]
\[ ll= LOW_{\text{even}}(i,j)+\text{round}(lh(i,j)/2) \]
\[ hh=HIGH_{\text{odd}}(i,j)-HIGH_{\text{even}}(i,j) \]
\[ hl=HIGH_{\text{even}}(i,j)+\text{round}(hh(i,j)/2) \]

Now the separated components in Fig 5. with all kinds of filter converge in the form by inverse wavelet transform.The ultrasound breast cancer image is processed with wavelet transformation for feature learning. The LL, LH, HL, HH bands of an image splits into four quadrants and filtration techniques implemented to extract the cancer features.

C. QUALITY MEASUREMENTS

The quality measurements are given as the input to the neural network for learning. The effective characteristics of cancer tumor can be easily automatically learned by the system. Objective measurements are

(a) MEAN

The MEAN is a statistical measurement for finding the mean value among the pixel values of an image. It’s a kind of spatial filtering used for noise removal. The mean value is placed at the center of destination processed image and other neighboring pixel similar are near to its values are along with it.

The mean value calculation is as follows:

\[ X(m,n)=\frac{1}{MN} \sum_{i<j \in X} M(i,j) \]  

Where, X(m,n) is the destination meaned image,
M is the number of rows in an image
N is the number of Columns in an image
M(i,j) is the original image.
(i,j) is the pixel value of each cell in an image

(b) MEDIAN

The median is used to partition high intensity pixel values and low intensity pixel values. Logically, it is used to get the middle pixel value from the original image and replace with an original image.

\[ \text{MEDIAN}(i,j) = \left( \frac{M(i,j)}{n} \right) \text{th term is the median} \]  

(c) MODE

This kind of quality measurement is used to find the pixel values which are occurring frequently. The process of classification is done by mode quality. In the case of breast cancer image, it particularly separates the tumor based on its pixel value among the entire pixels. Midpoint filtering is the basis of Mode operation which satisfies the brightness value.

(d) STANDARD DEVIATION (SD)

Standard Deviation is the principle of finding the bright area in a cancer breast image. The pixel value distribution is learned by SD. The formula for Standard Deviation is

\[ SD = \sqrt{\frac{\sum (X-X_{\text{mean}})^2}{N-1}} \]  

(e) MEAN ABSOLUTE ERROR (MAE)

Mean Absolute Error is the error value which states the difference of each element of the original image and degraded image

\[ \text{MSE}=\text{sum}(\text{abs}(x(:)-y(:)))/\text{numel}(x) \]  

(f) PEAK SIGNAL TO NOISE RATIO (PSNR)
PSNR is used to find the image quality of a processed image. The Mean Square Error (MSE) between the original image $X(i,j)$ and calculated image $\hat{X}(i,j)$ is

$$\text{MSE} = \frac{1}{MN} \sum_{M=1}^{M} \sum_{N=1}^{N}[X(i,j) - \hat{X}(i,j)]^2$$ (8)

(g) LAPLACIAN MEAN SQUARE ERROR (LMSE)

The edge measurement of any image is calculated with LMSE. If the value of LMSE is less, the image is said to be good quality. Since one of the characteristic of cancer is a representation of the shape, the LMSE is major part of finding the appearance of a malignant image.

The comparison with the original and of LMSE is as follows

\[
\begin{array}{ccc}
n-1,n-1 & x-1,n & x-1,n+1 \\
 x,n-1 & x,n & x,n+1 \\
x+1,n-1 & x+1,n & x+1,n+1 \\
\end{array}
\]

(h) ROOT MEAN SQUARE ERROR (RMSE)

Frequently, Root Mean Square Error is used to measure the error rate of error occurred on the production stage. To get the optimized result for classifying benign or malignant the error value gives the variance of input and output images.

$$\text{RMSE} = \sqrt{\text{mean}(X(i,j) - \hat{X}(i,j))^2}$$ (9)

(i) IMAGE FIDELITY (IF)

Image Fidelity (IF) is used to find the brightness of an image without losing its information. Image Fidelity can help to find the position of the tumor. Since the

$$\text{Image Fidelity} = 1 - \frac{\text{Difference of original image and preprocessed image}}{\text{Image}}$$ (10)

D. TRAINING NEURAL NETWORK

Machine learning is the process of defining a pattern of interest with neural network. The ultimate aim of this research is to classify the input images within the basis of benign and malignant. Neural network plays an important role in the classification. The decision of preferred class is based on the activation function. This research focus on back propagation algorithm in neural network for training since the expected output is known to the user the training algorithm is termed as “supervised learning”. The activation nodes used by back propagation algorithm are entirely differentiable. In machine learning, the hidden and output values are being continuously processed with small increment by adjusting its weights for the learning process. The neural network is capable of solving any kind of problems once the pattern is being trained.

The problem recognized for training is to classify whether the given image data are benign or malignant. Only two outputs are to be displayed by use of several attributes.

Training in neural network starts with normalizing the input data. Since the neural network to be trained before it is used, the input data should be normalized (i.e) the value should be represented within 0-1. The standard minimum, maximum normalized formula is represented as,

$$\text{Normalized Formulae} = \frac{x - \text{MinX}}{\text{MaxX} - \text{MinX}} \times (\text{MAXX} - \text{MINX}) + \text{MINX}$$ (11)

The objective of performing minimum and maximum normalized techniques is to covenant with linear transformation on the ultrasound cancer pre-processed data. From the formulae (11), MinX, MaxX are the attributes to map a range of values. Consider a situation, prediction in breast cancer data, to be benign or malignant. In this case, the attribute chosen is class, which contains two option ranges: benign (1-5), malignant (6-10). MinX is 5 and MaxX is 10. The value that crosses 5 will be normalized as malignant.

The neural network learning with training dataset will be concluded when the optimized result is obtained. The back propagation network scheme updates the weights until the required outcome is gained.

E. OPTIMIZED ACTIVATION FUNCTION

The neural network for performing the classification task is done through activation function. Since back propagation algorithm implements the cancer detection, sigmoid activation function depicts the flow of the algorithm. The value of sigmoid function ranges from 0 to 1 in case of the binary sigmoid function. The standard sigmoid function is expressed as,

$$f(x) = \frac{1}{1 + \exp(-\sigma x)}$$

Here, $\sigma$ is the gradient parameter.

![Standard Sigmoid Function](Fig 6. Standard Sigmoid Function)
To reduce the error rate in the hidden layer, an optimized activation function is used. The hidden layer consists of values which are grouped together using clustering techniques. The optimal function with a penalty value describes the range of hidden values.

Penalty function for activation function is to the smooth process of focusing on output class. Triumph over the limitations of existing methodology towards optimization comes into growth by adding penalty function for error occurrence. Thus, adding the penalty will give the least number of hidden units for getting the desired output. Three penalty parameters are included into the sigmoid function to smooth the hidden process. The parameters used are $\omega=0.1$, learning rate $\eta=0.4$ and the maximum number of epochs $\beta=150$.

Since there is a 2 output class, the hidden function is grouped into two phases. After adding the penalty value to the activation function $f(x)$, the expression is processed as

IV. RESULT & DISCUSSION

Optimizing the activation function for obtaining the cancer indication is the approach of the proposed methodology. Various observations and calculations gone through are discussed below. The raw input images are preprocessed before training and testing phase. The tables designate the output for attributes, learning rate with minimizing the error for prediction.

<table>
<thead>
<tr>
<th>Class</th>
<th>Training Data</th>
<th>Testing Data</th>
<th>Validation Data</th>
</tr>
</thead>
<tbody>
<tr>
<td>Class 1 Benign</td>
<td>150</td>
<td>50</td>
<td>135</td>
</tr>
<tr>
<td>Class 2 Malignant</td>
<td>300</td>
<td>150</td>
<td>265</td>
</tr>
<tr>
<td>Class 3 Normal ultrasound data</td>
<td>600</td>
<td>560</td>
<td>560</td>
</tr>
</tbody>
</table>

Benign class consists of 150 data of different patients, which is filtered by 50 testing data. The validation after processing, the systems of benign satisfies 135 images and is chosen for further processing.

Malignant class is about 300 screened images which are the peak input for neural network cancer learning. Testing data for malignant tumor is about 150 and to learn specified attributes 265 validated output data is chosen.

Normal ultrasound data can be any input image taken from the ultrasound screened image. The information chosen for testing data is validated for processing.

Cancer prediction attributes in Table II for neural networking are shape, age, mass location, mass margin, composition, side, depth, height, nodes, and calcification. The error rate indicates if it reaches the desired predicted value, the classification of malignant data between the normal data would be predicted accurately.

<table>
<thead>
<tr>
<th>S.No</th>
<th>Cancer Attribute Name</th>
<th>Error rate</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Mass shape</td>
<td>0.06</td>
</tr>
<tr>
<td>2</td>
<td>Age</td>
<td>0.00</td>
</tr>
<tr>
<td>3</td>
<td>Mass location</td>
<td>0.03</td>
</tr>
<tr>
<td>4</td>
<td>Mass margin</td>
<td>0.05</td>
</tr>
<tr>
<td>5</td>
<td>Composition</td>
<td>0.1</td>
</tr>
<tr>
<td>6</td>
<td>Side</td>
<td>0.1</td>
</tr>
<tr>
<td>7</td>
<td>Depth</td>
<td>0.02</td>
</tr>
<tr>
<td>8</td>
<td>Height</td>
<td>0.09</td>
</tr>
<tr>
<td>9</td>
<td>Nodes</td>
<td>0.02</td>
</tr>
<tr>
<td>10</td>
<td>Calcification</td>
<td>0.07</td>
</tr>
</tbody>
</table>

The comparison table illustrates the classification performance of ultrasound cancer image. It is found to be 0.92% for prediction of using neural network concepts. The training and testing phase process reaches high performance metric compared to existing methods.
Fig 2. Histogram Specification of Ultrasound image

Fig 4. Clustering of Ultrasound screened image data

Fig 5. DWT bands for an ultrasound screened image
Fig 1. OACLNM Model for cancer prediction

Fig 3. Neural network architecture for cancer tumor classification
TABLE IV: LEARNING RESULTS OVER CANCER ATTRIBUTES

The above declared table determines the learning rate of cancer attributes for several images. The attributes need the mentioned learning rates for the system to learn the symptoms.

<table>
<thead>
<tr>
<th>Age</th>
<th>Learning rate</th>
<th>Mass Location</th>
<th>Learning rate</th>
<th>Margin</th>
<th>Learning rate</th>
<th>Calcification</th>
<th>Learning rate</th>
</tr>
</thead>
<tbody>
<tr>
<td>1-20</td>
<td>0.0</td>
<td>45°</td>
<td>0.03</td>
<td>&lt;0.3mm</td>
<td>0.5</td>
<td>1</td>
<td>0.7</td>
</tr>
<tr>
<td>21-35</td>
<td>0.0</td>
<td>90°</td>
<td>0.03</td>
<td>&lt;0.3mm</td>
<td>0.2</td>
<td>0</td>
<td>0.4</td>
</tr>
<tr>
<td>36-65</td>
<td>0.0</td>
<td>45°</td>
<td>0.03</td>
<td>&lt;0.3mm</td>
<td>0.2</td>
<td>0</td>
<td>0.4</td>
</tr>
<tr>
<td>65 above</td>
<td>0.0</td>
<td>180°</td>
<td>0.03</td>
<td>&lt;0.3mm</td>
<td>0.2</td>
<td>0</td>
<td>0.4</td>
</tr>
<tr>
<td>36-65</td>
<td>0.0</td>
<td>60°</td>
<td>0.03</td>
<td>&gt;0.3mm</td>
<td>0.5</td>
<td>1</td>
<td>0.7</td>
</tr>
<tr>
<td>21-35</td>
<td>0.0</td>
<td>120°</td>
<td>0.03</td>
<td>&gt;0.3mm</td>
<td>0.5</td>
<td>1</td>
<td>0.7</td>
</tr>
<tr>
<td>36-65</td>
<td>0.0</td>
<td>85°</td>
<td>0.03</td>
<td>&lt;0.3mm</td>
<td>0.2</td>
<td>0</td>
<td>0.4</td>
</tr>
<tr>
<td>21-35</td>
<td>0.0</td>
<td>90°</td>
<td>0.03</td>
<td>&gt;0.3mm</td>
<td>0.5</td>
<td>1</td>
<td>0.7</td>
</tr>
<tr>
<td>65 above</td>
<td>0.0</td>
<td>90°</td>
<td>0.03</td>
<td>&lt;0.3mm</td>
<td>0.2</td>
<td>0</td>
<td>0.4</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Shape</th>
<th>Learning rate</th>
<th>Side</th>
<th>Learning rate</th>
<th>Height</th>
<th>Volume</th>
<th>Learning rate</th>
<th>Nodes</th>
<th>Learning rate</th>
</tr>
</thead>
<tbody>
<tr>
<td>Irregular</td>
<td>0.4</td>
<td>L</td>
<td>0.4</td>
<td>5ml</td>
<td></td>
<td>0.2</td>
<td>Yes</td>
<td>0.4</td>
</tr>
<tr>
<td>Regular</td>
<td>0.3</td>
<td>R</td>
<td>0.4</td>
<td>3mm</td>
<td>0.1</td>
<td>No</td>
<td></td>
<td>0.4</td>
</tr>
<tr>
<td>Normal</td>
<td>0.2</td>
<td>M</td>
<td>0.4</td>
<td>2mm</td>
<td>0.1</td>
<td>No</td>
<td></td>
<td>0.4</td>
</tr>
<tr>
<td>Regular</td>
<td>0.3</td>
<td>L</td>
<td>0.4</td>
<td>5mm</td>
<td>0.1</td>
<td>No</td>
<td></td>
<td>0.4</td>
</tr>
<tr>
<td>Irregular</td>
<td>0.4</td>
<td>R</td>
<td>0.4</td>
<td>54x47mm</td>
<td>0.2</td>
<td>Yes</td>
<td></td>
<td>0.4</td>
</tr>
<tr>
<td>Irregular</td>
<td>0.4</td>
<td>T</td>
<td>0.4</td>
<td>7.8x6.4cm</td>
<td>0.2</td>
<td>Yes</td>
<td></td>
<td>0.4</td>
</tr>
<tr>
<td>Normal</td>
<td>0.2</td>
<td>B</td>
<td>0.4</td>
<td>2.5mm</td>
<td>0.1</td>
<td>No</td>
<td></td>
<td>0.4</td>
</tr>
<tr>
<td>Irregular</td>
<td>0.4</td>
<td>B</td>
<td>0.4</td>
<td>54x47mm</td>
<td>0.2</td>
<td>Yes</td>
<td></td>
<td>0.4</td>
</tr>
<tr>
<td>Regular</td>
<td>0.3</td>
<td>T</td>
<td>0.4</td>
<td>1.2mm</td>
<td>0.1</td>
<td>No</td>
<td></td>
<td>0.4</td>
</tr>
</tbody>
</table>
V. CONCLUSION

Collection of cancer data is massively available for research. Prediction of cancer symptoms supported by the attribute selection is a challenging task. The proposed work is implemented by neural network attributes for identifying cancer in ultrasound screened image. Systematic learning is important to classify the benign and malignant image. This methodology initially clusters the image into 3 basic groups by K-Means Algorithm and the attributes or features of cancer are selected and calculated with wavelet transform. Malignant attribute classification is most required input for cancer classification. Automatic classification of cancer images must be enhanced by training the system with suitable attributes through a network. Minimizing the error for attribute learning is the major theme of this work. This work contributes the attributes with error rates as mass shape(0.06), age(0.00), mass location(0.03), mass margin(0.05), composition(0.1), side(0.1), depth(0.02), height(0.09), nodes(0.02), calcification(0.07). The error rate is minimized by adding penalty value to the activation function, thus minimizing the error rates for finding the cancer symptoms which are suitable for automatic cancer prediction with neural networking principle.

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