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Medical Image Diagnosis by Histogram Feature and Neural Network

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Abstract- Image diagnosis for medical practioner help to understand the patient condition as per symptoms. This analysis is depends on experience of doctor. To improve health services automation is involve for the medical image diagnosis as per type of report / disease. This paper has proposed a mathematical model that extract visual features from the image for the training dataset. Extracted information is further process to normalize data as different feature has different value set. Normalized values were used for the training of neural network and gives an trained model that classify input testing image into infected / normal category. Experiment was done on real dataset of malaria images. Result shows that proposed model has increased the comparing parameter values than other existing model.

Index Terms- Medical image diagnosis, Classification, Content Feature, Machine Learning.

I. INTRODUCTION

There have been dramatic increase in the number of medical data which are taken for treatment planning, diagnosis and other clinical purposes [1]. In the current clinical standards, these measurements (annotations) from medical scans or parameters evaluations are done by expert physicians. These procedures are tedious and prone to intra and inter-observer errors which can readily affect the diagnosis and treatment procedure [2].

The need for using expert-level automated methods (i.e. segmentation and/or classification) and software with high efficacy which can help and ease these tasks and resolve above mentioned problems, is essential. Various soft compting techniques are being used for developing medical diagnosis models. Proposed study tried to emphasis the on the basic concept of medical diagnosis model. Some diseases datasets and its processing case studies which are enlisted below concetrated on the development of medical diagnosis model using soft computing techniques. As imaging equipment becomes more and more prevalent, so too does the demand for computational solutions to process and analyse the complex images being produced increase. As such, the field of medical image computing has grown in parallel with that of medical imaging, and now has many journals and conferences dedicated to its advancement. The overriding goal is to develop computing techniques which can leverage the acquired imaging data to extract the maximum amount of useful information to improve patient outcomes.

In pursuance of this, Machine Learning (ML) algorithms have become ubiquitous with applications all across the medical imaging spectrum: from identifying regions of interest (segmentation), to categorising whole images (classification), to deriving characteristics from images (feature extraction), to aligning multiple images (registration), to create images from the raw data provided by the scanner (reconstruction).

In order to strengthen the medical work, diagnosis learning models were proposed by researchers. Image features were extract from the reports for classification, hence various visual contents edge, histogram, DWT, DCT, etc. [5], were used in the work.

Extracted features were train in different learning models named as CNN, RNN, DNN, etc. [6].

II.LITERATURE SURVEY

Mehedi Masud et. al. in [5] proposed an algorithm that detects a deadly and common disease called malaria specially designed as a mobile healthcare solution for the patients. The main objective of the paper focuses on convolution or deep learning architecture and it proves to be useful in detecting malaria disease in real-time accurately by imputing images and thus reduces the manual labor in the detection of the disease.

Fuhad et. al. in [6], given a deep learning technique by which analysis can be done automatically. By this, the need for trained professionals will be drastically reduced as the model will give accurate and automatic results. This model is based on CNN (Convolutional Neural Network) and can be used in the diagnosis of malaria by taking input in form of microscopic blood images. These techniques include Autoencoder, knowledge distillation, and data augmentations features and are classified in form of k-nearest neighbors or support vector machine. This was further performed by three training procedures namely autoencoder, general distillation, and distillation training to improve the accuracy of the model.

P. A. Pattanaik et. al. in [7] given a comprehensive computer-aided diagnosis (CAD) concept to identify the parasites of malaria in the blood images. The parameters of this model were trained by using artificial neural network techniques followed by a stacked autoencoder. 12500-2500-100-50-2 was the optimum size kept for this CAD scheme out of which the input layer consist of 12500 nodes and the output layer of the softmax classifier possesses 2 nodes. A 10 fold cross-validation system was also used to prove the reliability of this model by comparing it with blood smear images of any new patient.

S. Pereira et. al. in [38] proposed a new rough to fine (CFM) method for brain tumor segmentation. considered hierarchy included preprocessing, deep classification of networks and post-processing. Preprocessing was used to generate image patches for all MR images and the deep learning network output was a grievous image patch. The high-level abstract function extracted from the input using the stacked auto encoder framework for identifying patches of images. After that classification results were mapped into a binary image, the final segmenting result was achieved with a morphological filter. For the analysis of the proposed method, the experiment was used for the brain tumors segment for each patient data package.

s. banerjee et. al. in [39] presented the convolutional neural networks in which multi-succession magnetic resonance images were grouped for tumor detection in brain region. various cnn were given that focused on magnetic resonance image patches, cuts and volumetric multi-planar cuts without any preparation. two existing convnets (vggnet and resnet) models prepared in imagenet dataset, through a calibrating of the last scarcely any layers, likewise test the reasonableness of move examination to the mission. the leave one tolerant out assessment plot was applied to evaluate convnets output. convnets outcomes shown that it accomplished better accuracy in all situations when arranged for a multi-planar volumetric informational collection.

L. Sun et. al. [40] built up a DLF (Deep Learning Framework) for brain tumor sections and has anticipated the endurance of glioma by methods for Magnetic Resonance Image. This paper utilized different 3 Dimension CNN engineering sets for MRI tumor detection rule. This diminished model inclination and improved execution efficiencies. They selected solid endurance properties utilizing a decision tree and cross approval. An irregular backwoods model was in the long run evolved to assess the patients by and large endurance.

S. Podnar et. al. in [41] built up a prescient Machine Learning Model for the analysis of brain tumors. Routine blood tests must require substantially more data than even the most prepared specialists by and large acknowledge. They built up an AI prescient model in which neurological patients were tried for mind tumors normally. Review assessment of 68 sequential brain tumors and 215 control patients for the nervous system science administration has affirmed the model.

III.PROPOSED MODEL

Proposed Spiking Neural Based Medical Image Diagnosis (SNMID) for disease detection was done by this section. This work was divide into two modules first was training of neural network by extracted image feature set and other was testing of trained neural network. Whole working steps for training of proposed model was shown in fig. 1, while testing of trained model was show in fig.2. Various annotation used in the work was detailed in table 1.

1. Pre-Processing

Input image dataset need to be preprocessed first as training dataset should be of same dimension and format. As training dataset have labeled images either infected or normal, hence images labels were store in separate desired vector D. In this step of proposed model dimension of each image was resize into fix mxn dimension. All input image was transform into gray format. To increase the work efficiency input image I is blocked into bxb size. So image has B number of blocks where

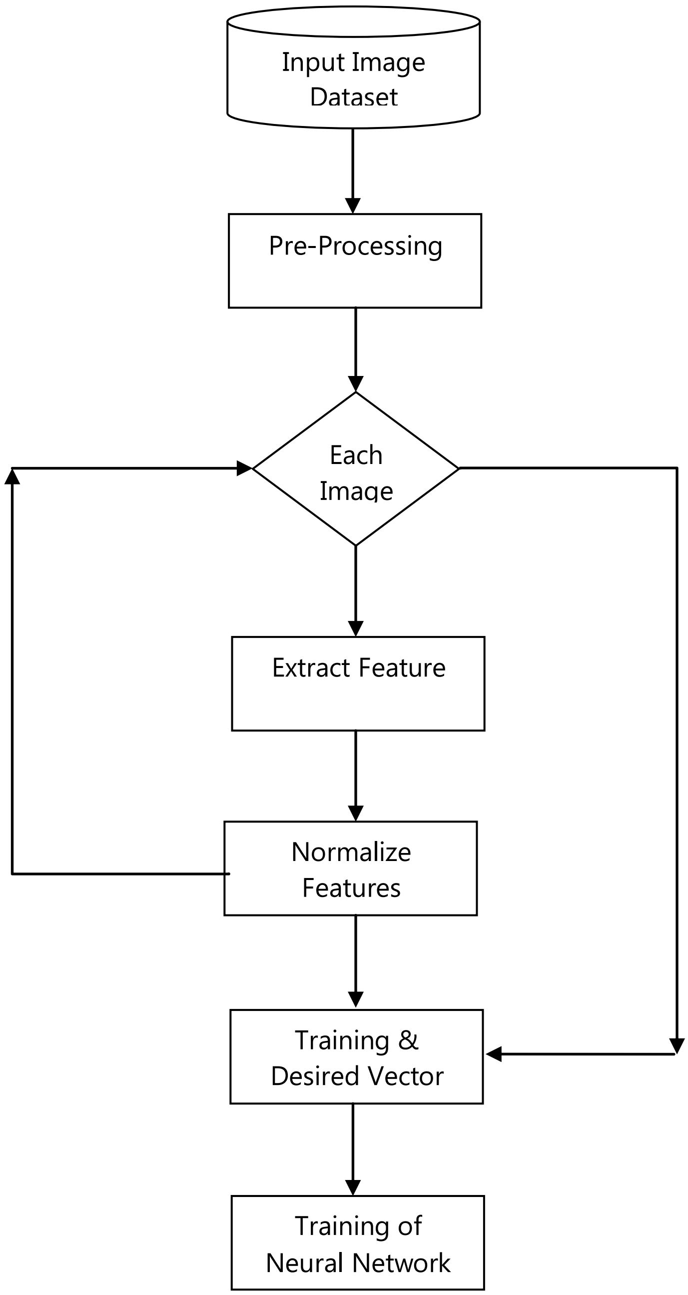
$$B = (mxn)/(bxb) \text{---------Eq. 1}$$

Each block was treat separately for feature extraction and training of neural network in the model. D vector for each block of same image have 0 or 1 value, where o0 is for normal condition and 1 is for infected condition.

2.Histogram Feature- Blocked image was processed further for getting the image histogram feature having p number of bins. This p is either {8, 16, 32,..256} range. This can be understand if p=8 then image values were divide into 8 bins [14]. So for gray image pixel value range from 0 to 255 then 8 bins are from [{0-31}, {32-63}, {64-95}, ...{233-255}]. So output of histogram feature is a vector having p elements, count of block for each bin pixel present. Sum of p vector is equal to bxb cells.

$$H_{i,B}=Histogram(B, p) \text{--------Eq.2}$$

Where $H_{i,B}$ is matrix of p number of columns and B number of rows for i^{th} image. Blocked image was process further to get DWT feature from the block of bxb dimension [15]. Input block was transform into frequency domain having four sub-matrix of b/2xb/2 dimension. Proposed model utilize all set of transform frequency domain value of block as a DWT feature in the work.



3.Normalize Features- Feature set obtain from a histogram as a vector and DWT as a matrix have different coefficient range. So first of all this step prepare a single vector N of both feature with total p+B number of elements. For each block normalize feature vector was prepared as per spike data of 0 / 1. Each element in the N vector having non zero value was set as 1. Elements with value 1 act as spike in the N vector and other act dead coefficient value in the signal.

4. Training Vector

Normalized vector obtained from the step was combined with other desired output vector of the block D. Tv is vector having [N, D] values obtained from above steps. In training both N and D was passed while in testing only N was passed.

5.Training of Neural Network

- Let us assume a three layer neural network.
- Now consider i as the input layer of the network. While j is consider as the hidden layer of the network. Finally k is consider as the output layer of the network.
- If w_{ij} represents a weight of the between nodes of different consecutive layers.
- So the output of the neural network is depend on the below equation sigmoidal function shown in equation 5:

$$Y_j = \frac{1}{1+e^{-x_j}} ------- Eq.(5)$$

where, $X_j = \sum x_i \cdot w_{ij} - \theta_j$, $1 \le i \le n$; n is the number of inputs to node j, and θ_j is threshold for node j. Where each value obtained from the previous weight matrix multiplication is passed through the sigmoidal function 5. Therefore small variation in the output value was done by this function.

IV.EXPERIMENT AND RESULTS

Whole work was implemented on MATLAB software. It was utilized on account of its rich library which has numerous inbuilt functions that can be specifically use in this work. This section of paper show experimental setup and results. The tests were performed on an 2.27 GHz Intel Core i3 machine, equipped with 4 GB of RAM, and running under Windows 7 Professional.

Results

Table 1 Precision value based comparison of classification models.

Testing Set	Proposed Model	Previous Model
20	0.9047	0.9
40	0.8576	0.85
60	0.8733	0.8
80	0.8347	0.725
100	0.7933	0.74

Table 1 shows that precision value of proposed model is higher as compared to previous image diagnosis model. Use of error back propagation neural network for the training of histogram and DWT feature has increases the work precision value by %.

Table 1 Recall value based comparison of classification models.

Testing Set	Proposed Model	Previous Model
20	0.9944	1
40	0.9327	0.7727
60	0.9179	0.75
80	0.8598	0.7632
100	0.7203	0.6981

Table 2 shows that proposed model uses histogram feature and frequency feature for training of neural network has increases the work recall at different dataset testing size. It was obtained from the table that proposed model has increase the recall percentage by % as compared to previous model.

Table 3 F-measure value based comparison of classification models.

Testing Set	Proposed Model	Previous Model
20	0.9474	0.9474
40	0.8936	0.8095
60	0.895	0.7742
80	0.847	0.7436
100	0.755	0.7184

Table 3 shows that recall value of proposed model is higher as compared to previous image diagnosis model. Use of error back propagation neural network for the training of histogram and DWT feature has increases the work recall value by %.

Table 4 Accuracy value based comparison of classification models.

Testing Set	Proposed Model	Previous Model
20	94.9785	94.4444
40	89.7832	78.9474
60	89.7578	75.8621
80	84.9253	74.359
100	74.2597	70.4082

Table 4 shows that proposed model uses histogram feature and frequency feature for training of neural network has increases the work accuracy at different dataset testing size. It was obtained from the table that proposed model has increase the percentage by % as compared to previous model.

V.CONCLUSIONS

There have been dramatic increase in the number of medical images which are taken for treatment planning, diagnosis, and other clinical purposes. In the current clinical standards, these measurements (annotations) from medical scans are done by expert physicians. Extracted information is further process to normalize data as different feature has different value set. Normalized values were used for the training of neural network and gives an trained model that classify input testing image into infected / normal category. Result shows that proposed model usies histogram feature and frequency feature for training of neural network has increases the work accuracy at different dataset testing size. It was obtained from the table that proposed model has increase the recall percentage by % as compared to previous model.

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