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KNN Based Medical Image Diagnosis by Content Features

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Abstract- Medical science works in different field for increasing the understanding of living organism. Medical image is great tool to understand the status of different disease. To improve the diagnosis of health reports researcher introduce automation. Infected patient reports are clustered separately from healthy patient reports according to the approach provided in this study. The input report is parsed to pull out two content features: a co-occurrence matrix feature and a discrete wavelet transform (DWT) coefficient. The report's in-depth diagnosis is provided through feature extraction from blocked images. The extracted characteristics are then utilized to determine which feature set best groups infected and uninfected reports into distinct clusters. The model uses a K-Nearest Neighbour (KNN) clustering technique to locate the cluster's centers.

Keywords- Data analysis, Digital image processing, Information Extraction, visual processing.

I. INTRODUCTION

Medical imaging is the process of producing visible images of inner structures of the body for scientific and medicinal study and treatment as well as a visible view of the function of interior tissues. This process pursues the disorder identification and management. This process creates data bank of regular structure and function of the organs to make it easy to recognize the anomalies. This process includes both organic and radiological imaging which used electromagnetic energies (X-rays and gamma), sonography, magnetic, scopes, and thermal and isotope imaging.

There are many other technologies used to record information about the location and function of the body. Those techniques have many limitations compared to those modulates which produce images. Annually billions of images have been done globally for different diagnostic purposes. About half of them use ionizing and nonionizing radiation modulates [1]. Medical imaging produces the images of the internal structures of the body without invasive procedures. Those images were produced using fast processors and due to conversion of the energies arithmetically and logically to signals [2]. Those signals later are converted to digital images. Those signals represent the different types of tissues inside the body. Ever since the first images from inside the human body were taken using X-Rays in 1895, the field of medical imaging has progressed at a considerable rate. While traditional X-Ray imaging has stood the test of time and is still used today, it has been joined by ultrasound, Computed Tomography (CT), Magnetic Resonance Imaging (MRI), Positron Emission Tomography (PET), and Single Photon Emission Computed Tomography (SPECT), among others.

Each of these imaging modalities fills an important and often complementary niche in clinical practice providing greater insight into the human body in both health and disease than would have ever been possible without them. The modern-day clinician now has a large amount of techniques at their disposal allowing for highly detailed images of individual brain structures, as well as precise measures of brain activity and processes such as metabolism and the accumulation of proteins. 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 popular with applications all across the medical imaging spectrum: from identifying regions of interest (segmentation), to categorizing whole images (classification), to deriving characteristics from images (feature extraction), to aligning multiple images (registration), to creating images from the raw data provided by the scanner (reconstruction).

II. RELATED WORK

H.N. et. al.in 2017 [5] proposed using a blind source separation technique for the extraction of MRSI data from the tissue-specific profiles and their distribution. A novel algorithm is used for the detection of the tumor, necrotic, and normal tissues from the MRSI signals. In which firstly this algorithm uses the window method for the peaks enhancing a reducing the length, which later builds the 3-D MRSI tensor. Thus, for finding the tissue-specific spectral profiles of the NCPD (nonnegative polyadic decomposition), there occurs the decomposition of the tensor using this NCPD by allowing in mode 1 and mode 2 common factor to retrieve tissues.

Alexander Zotina et. al. in 2017 [6] describes the solution of the image clarity and clearance by using the minimum number of the configuration parameters upon input image. For this, they acquired the medical specialist procedure by distributing into two sets of digital procedures. In which in set one they concentrate upon the quality of image and segmentation of object of concern that is tumor by forming the edge map. In the set two, they made the analysis of data by calculating those parameters obtained by the diagnosis.

M. Li. Et. al. in 2019 [7] experiments the two-methods combination of the multi-modal combination fusion and convolution neural network detection method. In this paper, there wa use of the 2D CNN and 3D CNN multimodal extension by getting brain lesion for different characteristics in 3D. By solving the 2CNN of raw input for the different modal information at raw input faults. To eliminate the problem of over fitting there was the addition of real normalization layer in the convolution and pooling layer to improve the convergence speed. Resulting in the improvement of loss function, so weighted loss function is added in the lesion area to develop the feature learning.

Hong huang et. al. in 2019 [8] for the image segmentation method uses the FCM clustering algorithm with a rough set theory. The authors construction the attribute table by the values obtained from the FCM segmentation result and the image is divided into small areas on the basis of the attributes. Weighted values are obtained by value reduction and used for the calculated difference between the region and similarity of the region. Later was realized through equivalence difference degree. This final value of equivalence degree is used to evaluate the segmentation of images and merge regions. The method has the limitations up to only MRI images of brain and CT, artificially generated images.

N. Noreen et. al. in 2020 [9] utilizes the techniques of multilevel feature extraction and concatenation to detect early diagnosis of the tumor. In this project uses the two models that are Inception V-3 and DensNet201 for the creation of the two different modes for the identification and diagnosis of tumors. At initially the features of the inception model were extracted from the pre-trained inception model V3 and concatenated also for the tumor detection. Later passed through the SoftMax classifier for the classification of the brain tumor. Similarly done with the DensNet201 for the extraction of features from the Dens Netblock and concatenation completed and later passing through SoftMax classifier for determining the tumor. Thus, both modes are check by three class tumor datasets which is publicly available.

Hari Mohan Rai et. al. in 2020 [10] develops the deep neural network with a minimum number of layers and less complexity in the design of U-Net for diagnosing tumor. There the motive of classification of normal and abnormal images of the MRI images from the data sets of 253 images. Before this MRI images were resized, cropped, pre-proceed, and augmented for the accurate result and fast training for the deep neural network.

Mehedi Masud et. al. in [11] 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 [12], 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 Auto encoder, 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 auto encoder, general distillation, and distillation training to improve the accuracy of the model.

P. A. Pattanaik et. al. in [13] 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 auto encoder. 12500-2500-100-50-2 was the optimum size kept for this CAD scheme out of which the input layer consists 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.

III. PROPOSED METHODOLOGY

Explanation of proposed CICM (Chest Image Classification Model) is done in this section of paper. In order to increase the understanding of the model fig. 1 shows flow diagram of the work. Explanation of each block of the model is done in this section. Some of notations used in the paper for increasing the understanding of the model.

1. Image Pre-Processing:

Input image have noisy data that need to be correct by applying some filter to correct the pixel value. For noise removal proposed model apply weiner filter. Further image is resize as per the working environment of the model and convert image into specific format. So if I is input image then Ip is preprocessed image obtain after applying resizing, gray conversion and weiner filter.

$$\mathbf{I_p = Image\_preprcessing\ (I)}$$

2. Remove Noise:

Wiener filter removed an additive noise and reduced mean square error, as it’s linear estimation of original image.

3. Feature Extraction:

Pre-processed image is block into fix nxn size pixel values. Features are extracting from the blocked image. In order to improve the work efficiency proposed model has extract histogram and DWT feature from the image. CCM of 16 pixels is use in the model. DWT partition image into four block and out of those low frequency region of the image are used for the classification of the model.

4. Co-occurrence Matrix (CCM):

With a specific end goal to get the surface of the image one of the vital technique is co-occurrence matrix. Here co-occurrence matrix exhibits the surface property by the relationship of the neighboring pixels [14]. It quantificational explains the surface component. In these paper four elements is chosen including contrast, energy, inverse difference, entropy.

$$ID = \sum_{i=1} \sum_{j=1} \frac{1}{(1+(i-j)^2} I(i,j)$$

$$Entropy = -\sum_{i=1} \sum_{j=1} I(i,j) \log[I(i,j)]$$

$$Energy = \sum_{i=1} \sum_{j=1} (I(i,j))^2$$

$$Contrast = \sum_{i=1} \sum_{j=1} (i-j)^2 * I(i,j)$$

where I(i, j) the intensity value in cell (i, j).

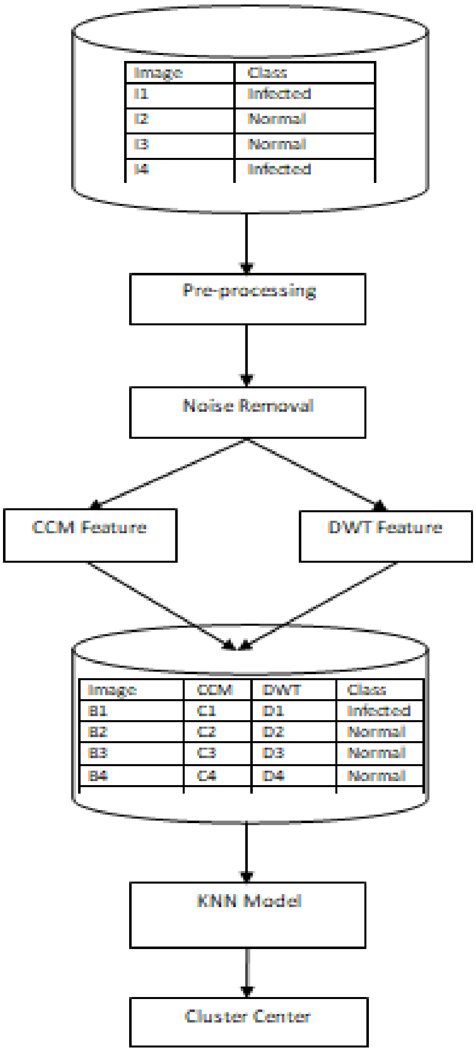

Fig 1. Block Diagram of proposed work.

5. DWT (Discrete Wavelet Transform):

In this work DWT frequency feature is use[15]. This block of image is obtain by filtering the image rows from the low pass filter then pass same to the low pass filter but here column are filter for the analysis. This block contain flat region of the image which do not have any edge information, so this is term as approximate version of the image. Low frequency region of images is taken for the image classification.

$$B \leftarrow \text{Block}(n, I_p)$$

$$[\text{ID Entropy Energy Contrast}] \leftarrow \text{CCM}(B)$$

$$LL \leftarrow \text{DWT}(B)$$

$$F \leftarrow [[\text{ID Entropy Energy Contrast}], LL]$$

During training input image has two class label first is infected and other is no infected hence each of blocked feature set is flag with same label.

6. K-Nearest Neighbor:

Features extract from the image blocks are arrange in the vector where CCM 16 values are arrange first and later values of DWT-LL coefficients are arrange. Each training vector have desired class value to classify the image. As input images have two class, hence KNN has k=2. For finding the distance of the cluster center this work uses Euclidian distance formula.

7. Testing of Proposed Model:

Trained KNN model is test for the testing. Pre-processing steps are common as done in training. CCM and DWT features are extract from the blocked image image [16]. Now each blocked image features are pass in the trained KNN modle to predict the image class (Infected/Normal)

IV. EXPERIMENT AND RESULTS

Implementation of proposed model is done on MATLAB software 2016a. Experiment is performed on machine having configuration of 4 GB RAM, i3 6^{th} generation processor. Further validation of model is done by comparing proposed model with CNNMID techniques proposed in [17] and ADCN in [18]. Dataset was taken from [19].

Table 1. Skin cancer detection models recall value comparison.

Testing Image Set	ADCN [23]	KNNSCD	MLMID
100	0.8049	1	0.7727
200	0.7143	0.9345	0.7826
300	0.6929	0.9012	0.7868
400	0.7012	0.9282	0.6907

Table 2. Malaria detection models recall value comparison.

Testing Image Set	ADCN [23]	KNNSCD	MLMID
100	0. 7115	0.9184	0.96
200	0.6061	0.598	0.97
300	0.4895	0.5034	0.8867
400	0.4624	0.4378	0.7313

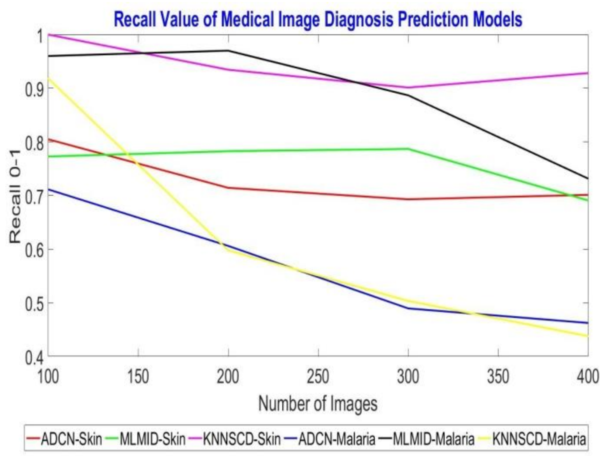

Fig 2. Average precision value based comparison of medical image diagnosis models.

Table 1, 2 and fig. 3 shows the precision evaluation parameters values. It is found that at different number of image dataset proposed model MLMID has improved the performance. Results shows that use of error back propagation neural network has increased the recall parameter by 19.99%. Similarly KNNSCD model has improved the skin image performance of recall value of correct class prediction by 19.42% as compared to MLMID and 22.59 as compared to ADCN. Hence use of KNN model for skin disease is better as compared to ANN model in MLMID.

Table 3. Skin cancer detection models f-measure value comparison.

Testing Image Set	ADCN [23] [23]	KNNSCD	MLMID
100	0.75	1	0.8193
200	0.678	0.918	0.8182
300	0.6567	0.9139	0.8106
400	0.6461	0.923	0.7486

Table 4 Malaria detection models f-measure value comparison.

Testing Image Set	ADCN [23]	KNNSCD	MLMID
100	0.7255	0.9	0.9697
200	0.603	0.6784	0.9282
300	0.4795	0.5920	0.8553
400	0.4444	0.5364	0.7206

Table 3 and 4 shows the f-measure evaluation parameters values. It is found that at different number of image dataset proposed model MLMID has improved the performance of model. Results shows that use of error back propagation neural network has increased the f-measure values are improve by 25.09%. KNNSCD model has improved the skin image performance of f-measure value of correct class prediction by 14.86% as compared to MLMID and 27.27 as compared to ADCN.

Table 5 Skin cancer detection models accuracy value comparison.

Testing Image Set	ADCN [23]	KNNSCD	MLMID
100	77.551	100	84.6939
200	71.2121	94.07	84.1584
300	69.5364	93.32	83.2215
400	67.1875	92.265	78.3133

Table 6 Malaria detection models accuracy value comparison.

Testing Image Set	ADCN [23]	KNNSCD	MLMID
100	71.4286	89.7951	97
200	60.101	71.9416	92.5
300	48.8215	66.8823	85
400	46.25	63.5409	71.5711

Accuracy value of medical image diagnosis of skin cancer and malaria is shown in table 5 and 6. These tables show that in all image dataset and at different image sizes proposed MLMID model has improved the detection accuracy.

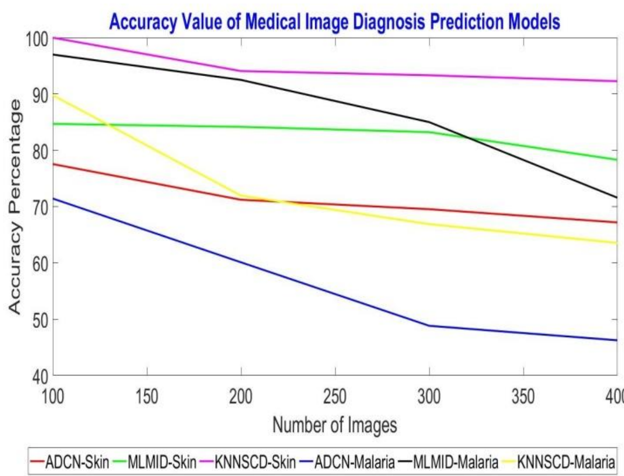

Fig 3. Accuracy value based comparison of medical image diagnosis models.

Fig. 3 shows that proposed work accuracy is improved at all set of testing images. KNNSCD model has improved the skin image performance of accuracy value of correct class prediction by 12.97% as compared to MLMID and 24.8 as compared to ADCN. Hence use of KNN model for skin disease is better as compared to ANN model in MLMID. Fig. 5.4 shows that in case of malaria disease detection MLMID perform better as compared to KNNSCD model.

Table 7. Skin cancer detection models execution time (seconds).

Testing Image Set	ADCN [23]	KNNSCD	MLMID
100	70.148	67.889	60.4566
200	130.563	116.227	102.889
300	210.776	193.718	174.191
400	298.88	260.506	220.123

Table 8. Malaria detection models execution time (seconds)

Testing Image Set	ADCN [23]	KNNSCD	MLMID
100	78.989	71.025	58.922
200	150.207	137.687	77.568
300	236.084	217.872	189.77
400	320.226	284.735	252.428

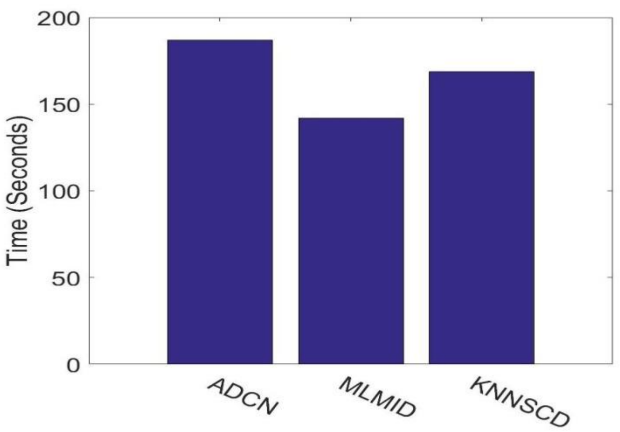

Fig 4. Accuracy value based comparison of medical image diagnosis models.

Time required to detect the class of input image was estimate for both dataset of skin and malaria. Table 7 shows skin image testing time in seconds and table 8 shows malaria image testing time in seconds. It was found that both proposed models has reduced the execution time of detection as compared to ADCN model. Use of CCM, DWT and Histogram feature is responsible for the deduction as time for the feature extraction was these feature is low. While in previous model convolution operation takes time.

V. CONCLUSIONS

Learning through machine processing is becoming increasingly important in the field of medical image analysis. Different classification, detection, and segmentation challenges have been addressed by applying machine learning-based algorithms. The performance of medical image analysis has been significantly improved, particularly as a result of the widespread application of deep learning approaches.

In this work, three features are extracting from the image and neural network has learned the extracted features of each image block wise. Block wise work has improved the learning of neural network as compared to whole image feature learning. Experiment is done on two real medical images dataset skin cancer and malaria. Result shows that accuracy of proposed MLMID is improved by 25.09%, similarly recall parameter by 19.99% while f-measure values are improve by 25.09%.

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