MIMS: Medical Image Manipulation System using Neural Network

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Abstract - **This paper provides an efficient Medical Image Manipulation System (MIMS) which is applicable to medical field databases in large scan and X-rays. It gives the effects of various attributes on system efficiency and confirms best consequences using dense sampling and spatial content with the Spike Neural Network (SNN) classifier. It uses an unsupervised learning technique for training purpose. In addition, the problems of posterior probability evaluation, the association stuck between neural and usual classifiers, feature parameter selection and also the effect of misclassification overheads are analyzed. It is an efficient step in the similarity based classification, which has its major Medical implication for modern computer aided analysis.**

Index Terms— **Categorization, MIMS, Neural classifier, SNN, Training.**

I. INTRODUCTION

IN recent days there is a great explosion in the number of images that are acquired every day in any modern hospital, due to the increase in digital medical imaging techniques and patient image-screening protocols. The field of content-based image retrieval [1],[2] deals with the analysis of image content and the development of tools to represent visual content in a way that can be efficiently searched and compared. Conventional databases allow for textual searches, in particular using the headers of the DICOM standard.

This paper, focus on building efficient system that can provide better retrieval of X-ray Images that have been extracted by efficient probabilistic models. The brain computations are done by a highly interconnected network of neurons, which communicate by sending electric pulses through the neural wiring consisting of axons, synapses and dendrites.

As shown in Figure the Natural neurons

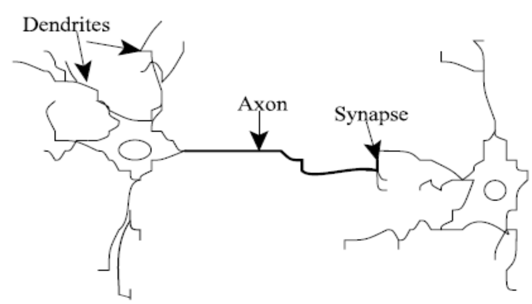

Fig.1 Natural neurons

receive signals through *synapses* located on the dendrites or membrane of the neuron. When the signals received are strong enough (surpass a certain *threshold*), the neuron is *activated* and emits a signal though the *axon*[3]. This signal might be sent to another synapse, and might activate other neurons.

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Artificial neural networks are inspired by the early models of sensory processing by the brain. An artificial neural network can be created by simulating a network of model neurons in a computer.

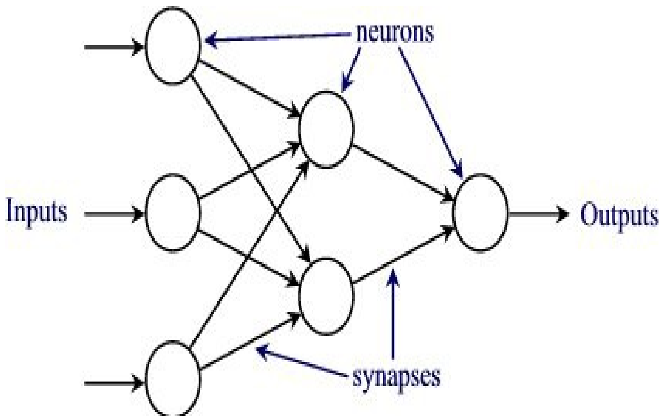

Fig.2 Artificial neurons

By applying algorithms that mimic the processes of real neurons, we can make the network 'learn' to solve many types of problems.

Second, a single image may contain a different number of regions-of-interest (ROI), each of which may be the focus of attention for the medical expert, depending on the diagnostic task at hand. A single chest image may contains the lungs, heart, shoulder blade, rib cage, diaphragm, clavicle, spine and blood vessels, any of which may be the focus of attention, and all of which should be readily accessible within an ideal retrieval system[4].

Clinical decision support techniques such as case-based reasoning or evidence-based medicine can produce a strong need to retrieve images valuable for supporting certain diagnoses. For the clinical decision-making process it can be beneficial or even crucial to find other images of the same modality, the same anatomic region or the same disease. Computer-aided diagnostics for radiological practice, as presented at the Radiological Society of North America (RSNA) are on the rise and create a need for powerful data and meta-data management and retrieval. Besides diagnostics, teaching and research can be greatly enhanced by visual access methods in existing large repositories.

II. METHODOLOGIES INVOLVED

A. Classification:

Image classification is based on the ground truth of manually categorized images[5]. This system use a nonlinear multiclass Spike Neural Network classifier (SNN). Note that histogram intersection has no free kernel parameters, which makes it convenient for fast parameter evaluation.

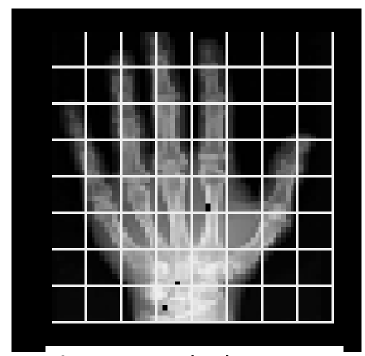

Fig.3: 8x8 Block Division

The two other kernels have a free tradeoff parameter, and require careful optimization. In order to classify multiple categories, it use the one-versus-one extension of the binary classifier, where binary classifiers are trained for all pairs of categories in the dataset. The given unknown image is divided into blocks of patches [6][7], from these patches features will be extracted and inputted to the neurons.

Whenever an unknown image is classified with a binary classifier it casts one vote for its preferred class; the final result is the class with the most votes. Since each binary classifier runs independently, parallelization of both training and testing phases of the Neural Network is straightforward.

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B. Training Neurons

This system uses the Unsupervised Training it only supplies inputs Features. The features given as input are:

(i) Histogram Feature

(ii) Edge Feature.

After getting these features the spike neural network[8] adjusts its own weights so that similar inputs cause similar outputs. The network identifies the patterns and differences in the inputs without any external assistance. The SNN also includes both excitatory and inhibitory facilitating synapses[9] which create a frequency routing capability allowing the information presented to the network to be routed to different hidden layer neurons. A variable neuron threshold level simulates the refractory period. Epoch which is iteration through the process of providing the network with an input and updating the network's weights. Typically many epochs are required to train the neural network

The sizes of these images are related to the size of the patterns in various scales[10]. Large images may include many of the basic images. Our system allows the user to choose the characteristic images automatically and manually. During the training process, the sizes of the characteristic images are calculated automatically.

Here, a small seed image is first randomly chosen in the interested texture. Then, many other images are selected in the same size at random positions in the interested texture. All of these images are compared to the seed image and then, average error threshold is determined for that size.

Finally, all of these operations are carried out for many other seed images located at random positions. Then, the characteristic images with minimum average error values are determined and statistical properties of these images are used to segment the statistical pattern.

C. Retrieval:

Image retrieval requires a way to measure similarity between images [11]. A single training neuron is then used to assign weights to the synapses associated with the classifying neurons according to similarities or "relative occurrence of to emulate the

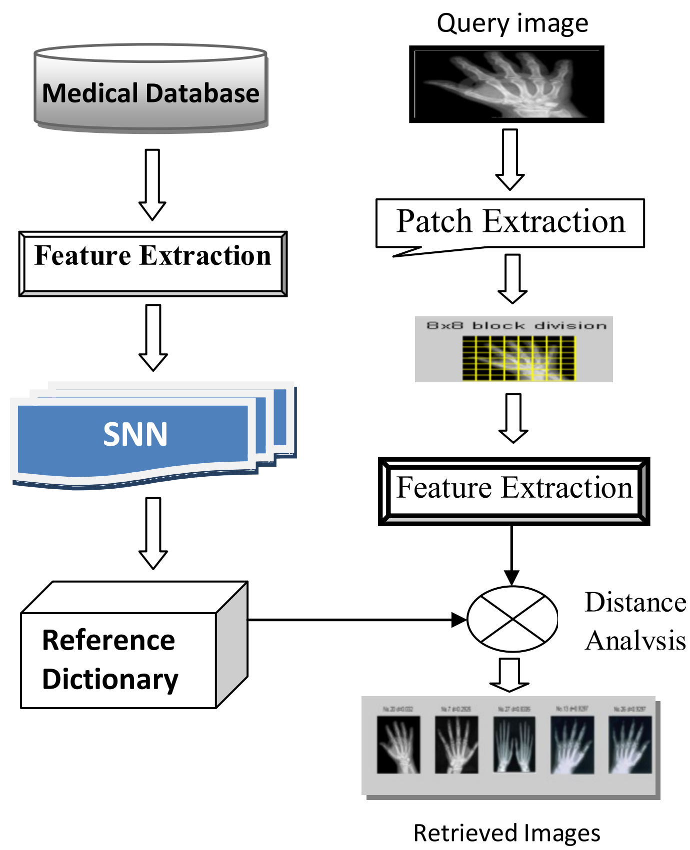

Fig.4 System Architecture

absolute and relative recovery periods similar data values" in the input data for all classes[12]. Variable firing thresholds were also used inherent in a biological neuron. Using the image representation described in the previous section, the distance between images is defined as the sum of the bin-to-bin distance of the representing histograms.

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D. Database Used

The IRMA database has worked on algorithm development teams for many years, and in the past several years has been a source for the ImageCLEF medical annotation competition.

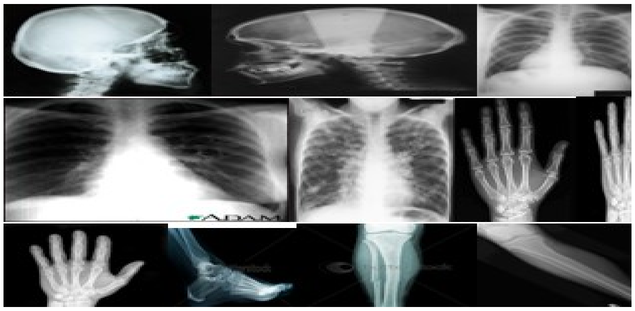

Fig.5 Database Images

Images in the IRMA database [13] consist of scanned X-ray images, gray scale, 512 pixels long. The X-ray images are noisy with irregular brightness and contrast, and may contain dominant visual artifacts such as artificial limbs and X-ray frame borders. Images in the archive are labeled according to the IRMA coding system, with each category described by four axes:

1) A technical axis that describes the image modality;
2) a directional axis that defines body orientation,
3) an anatomical axis that describes the body region examined
4) a biological axis that describes the biological system being examined.

The axes have a hierarchical description. Technical axis: X-ray, plain radiology, analog; Directional axis: Sagittal, mediolateral; Anatomical axis: Lower extremity (leg), hip, left hip; Biological axis: Musculoskeletal systems.

III. EXPERIMENTAL RESULTS

For sample, a hand image is gives as query to the system

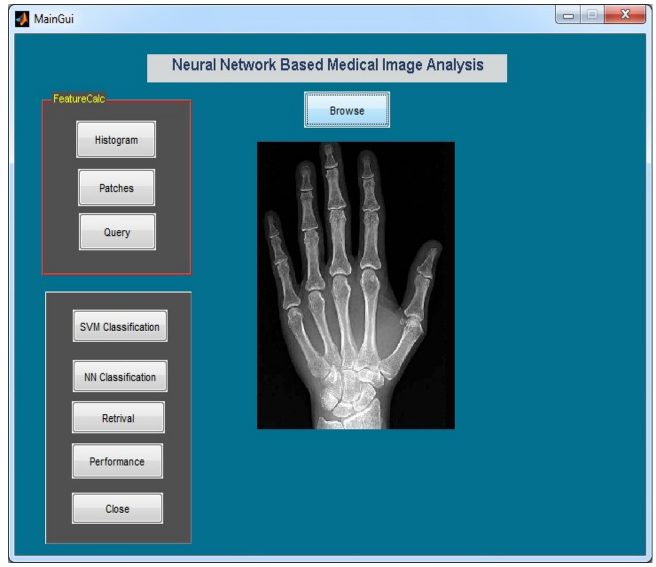

Fig.6 Query Image

The result produced by the system is given below; almost it provides an accurate result than any other systems.

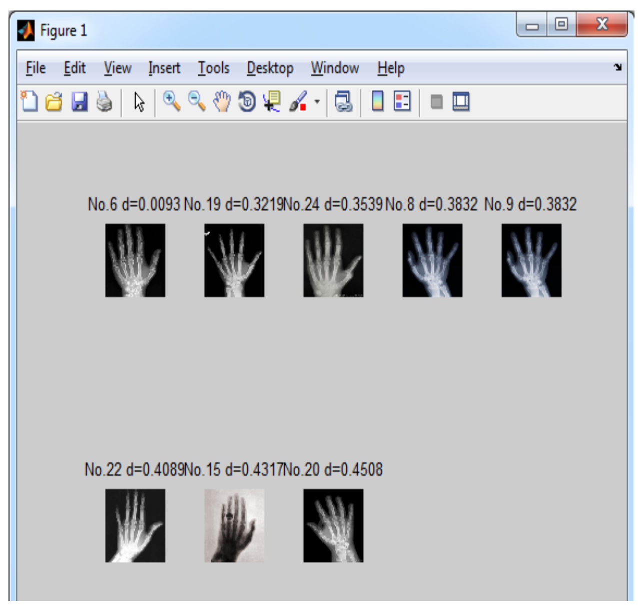

Fig.7 Retrieved Related Images

Performance

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As per result obtained in our system some of the performance evaluation aspects are given below.

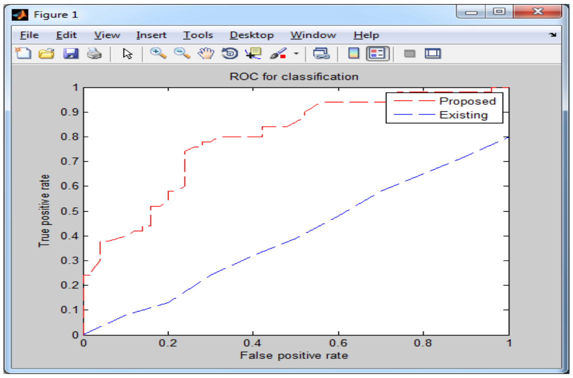

Fig.8 ROC's True positive rate Vs False positive Rate

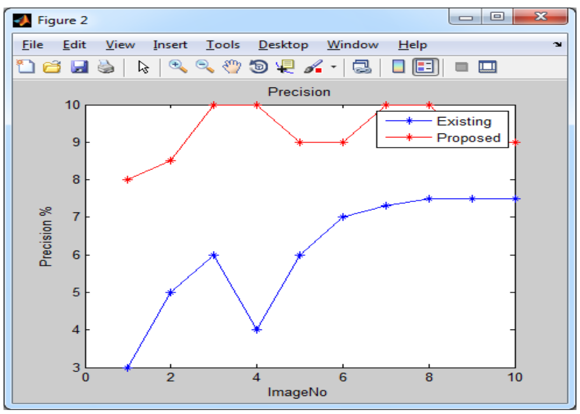

Fig.9 Percentage of Precision

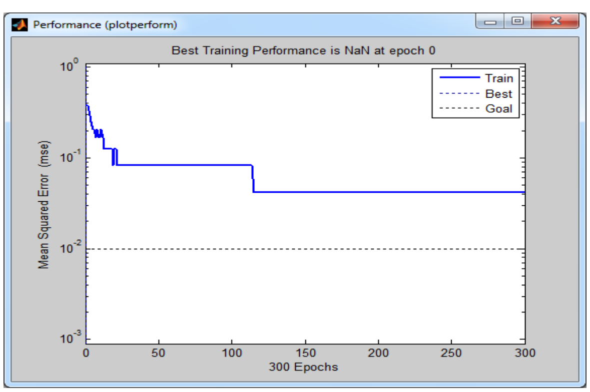

Fig.10 Mean squared Error(MSE) Vs Epoche

IV. CONCLUSION

This paper provides a Patch based approach and Spike Neural Network classifier for medical image categorization and retrieval. This methodology builds a visual dictionary, and represents an image as a histogram of visual words in multiple scales. Thus the system is trained using unsupervised learning to achieve high accuracy in the classification of Medical images. Mean square error is very much reduced by automatic weight adjustment. Thus it provides better result than other SVM classified system and textual based search.

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