# An Enhanced Collaborative Framework for Medical Imaging Diagnostics Employing Software Computing Techniques

Noor Zaman[a], Mudassir Ilyas[b], Muneer Ahmad[c], Fazdil Mohammad[d], Azween Abdullah[e]

[a,b,c] College of Computer Science & IT, King Faisal University, Saudi Arabia; [d,e] Department of Computer Science, University Technology PETRONAS, Malaysia
[a] nzaman@kfu.edu.sa, [b]qilyas@kfu.edu.sa, [c] mmalik@kfu.edu.sa, [d] mfadzil_hassan@petronas.com.my, [e]azweenabdullah@yahoo.com

**Abstract:** The computer-aided systems (CAD) commonly provide a collaborative means to help medical practitioners in disease analysis and cure for patients. The accuracy of such systems is highly dependent over enhanced identification of regions of interest in medical diagnostics especially in medical images. Despite the existence of several medical imaging diagnostic systems, an enhanced collaborative framework for significant imaging analysis is still required. This paper presents an enhanced collaborative framework for medical diagnostics employing software computing techniques. The major components of this system are preprocessing, segmentation, image enhancement, pattern matching and diagnostic decision. Fuzzy rules have been applied with new wavelet transforms for image enhancement and identification of hotspot regions in a series of images. The system builds a collaborative framework for archiving, extraction and matching of various enhanced images. The medical practitioner makes an initial decision from the retrieved images, collects and fuses the feedbacks from the system and produce a final decision. The integrated software techniques employed in collaborative framework have been tested over real benchmarked datasets of diverse medical images and outperformance of the system was observed as compared with existing conventional medical diagnostic systems. The proposed collaborative framework will be extended in future to address neural network logic with genetic algorithm for enhanced robust solutions for medical diagnostics.

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## 1. Introduction

Image enhancement is the improvement of digital images to perceive the information in images for either computer analysis or human viewers. Medical images of patients help health professionals to judge the disease and its degree. X- Ray, CTScan and MRI are common tools for medical imaging. CAD systems thoughts started in the 1950s but most attempts were unsuccessful, which could be the reason that some physicians and radiologists do not trust these systems. However, recently some techniques such as [1-3] introduced CAD systems for cancer detection such as breast and lung cancer from images. It has been reported that the accuracy of detecting cancer with the help of CAD systems has increased by 19.6% [4]. There have been many applications developed to assist radiologists in diagnosing diseases such as [5-9].

The analysis and diagnosis of many human diseases based on medical imaging has been using 2D images for a long time. Even though, 2D images has helped medical practitioners in diagnosing many diseases, yet 3D images has been reported in many publications to lead to more accurate disease diagnosis [10]. Many experiments have been done to examine the ability of 3D imaging in increasing the detection rate of cancer cells. [11] Examined 3D breast cancer and concluded that it has a promising future since it gives more view of the breast and therefore, cancer cells were detected. The advantage of 3D imaging has also its advantage in dental treatment [12] where it provides better understanding of the symptoms of the patients as well as drafting the best treatment. Moreover, a study to compare cell analysis in 2D and 3D was performed in [13] and concluded that 3D images has more potential in cell analysis. All in all, 3D imaging has a valuable contribution in developing applications with high accuracy in detecting abnormalities especially subtle regions that are hard to be visible in 2D images.

The concepts related with medical image enhancement have been stretched by researchers of the field into two different directions namely; spatial domain which operates directly on pixels and frequency domain which operates on the Fourier transforms. The former addresses enhancement in bringing variations to image characteristics and is commonly applied at user level (a certain fraction of enhancement is achieved that is far from optimal enhancement). CAD uses machine learning algorithms such as artificial neural networks, support vector machines classifiers and others [14]. Another medical imaging technique, content-based image retrieval (CBIR), is used to help physicians in disease diagnosis. This technique works as to select features of all images and store them in a database. When a new query image is introduced as an input, feature extraction will be applied on the new image and the system will compare the extracted features with the stored images in order to find the nearest if not the exact same image and retrieve it [15].

Most real world problems are in uncertain or imprecise state including medical diagnosis. In such situation conventional computing (hard computing) is not suitable, instead soft computing (SC) [1] is. SC aims at solving problems that are uncertain, imprecise or partially true [16-17]. Fuzzy logic (FL), artificial neural network (ANN or NN), genetic algorithms (GA) and probabilistic reasoning (PR) etc. are techniques refer to soft computing. These techniques can be implemented independently or combined in such a way to complement each other [18-19]. For instance, Nazmy et al. [20] developed an adaptive neuro-fuzzy inference system (ANFIS) for classification of ECG signals. The system has been tested and a 97% accuracy rate was achieved. Raja et al. [21] developed a CAD system using fuzzy-neural (NN-FL) hybrid technique for diagnosing ultrasound kidney images. The algorithm has proven to be capable of classifying kidney diseases and predicting future abnormalities in normal subjects. Benamrane [22] presented an application of NN-FL in detecting tumors in medical images. The system has been tested on MRI images of human brain and was able to perform very well in detecting tumors. Andre´s et.al [23] presented a fuzzy-genetic (FL-GA) breast cancer diagnosis system. The system has been tested and the average accuracy was 97%. In addition, the work of [24] proposed a FL-GA approach for the classification of epilepsy risk level from EEG signals, the accuracy reached more than 90%. Moreover, a system has been developed to predict the lung sounds using neuro-genetic (NN-GA) in [25], and the overall performance of the technique is very good, and the accuracy is high. Another application to analyze digital mammograms is presented in [26]. The system has achieved a very satisfactory performance. Another SC methodology is demonstrated when NN, FL and GA are combined in one system to solve a specific problem. A neuro-fuzzy-genetic (NN-FL-GA) system was proposed in [27] to interpret medical images by classifying and detecting any abnormalities. Other systems in [28] and [29] utilize the same methodology and their results have been reported to be very good.

## 2. Methodology

We have proposed an enhanced collaborative framework for medical diagnostics employing software computing techniques. The enhancement methodology can be described as, Figure 1 depicts the major steps in the proposed enhancement collaborative framework. This framework reflects the behavior of the system and shows how it should diagnose abnormalities in the medical images of the human internal organs. The framework demonstrates the different components of the system that would contribute into the diagnosis process. The major components of this framework can be described below.

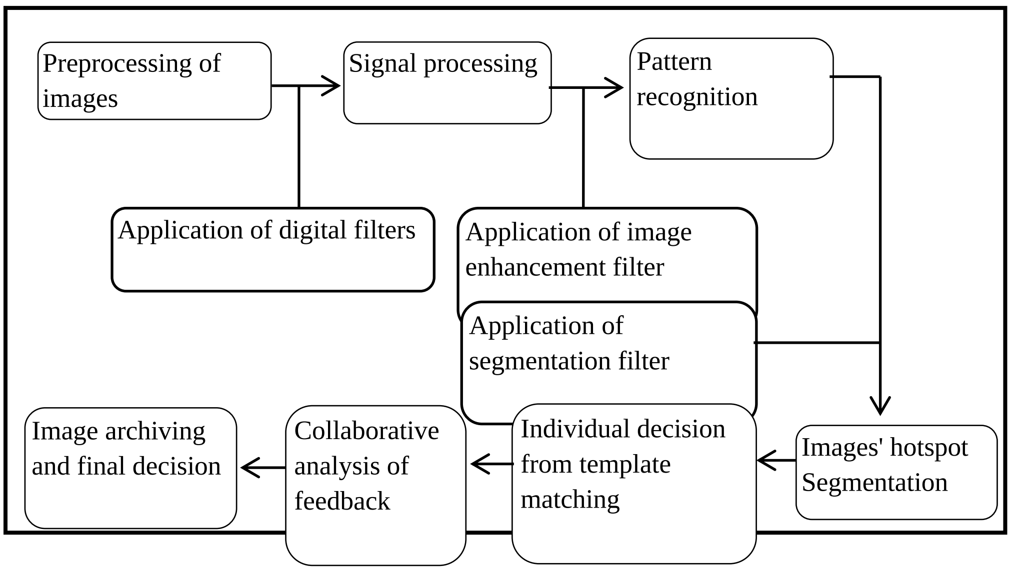


Figure 1 Collaborative enhanced framework for medical imaging diagnostics

2.1. Preprocessing

We have built a new image filter that preprocesses the image data and rectifies the impurities in images. The collected images from different medical imaging tools may include irrelevant data as well as noise due to imperfections in the acquisition process. The filtering stage exploits preset knowledge about the expected data through the use of a combination of threshold based and correlation based methods to filter out the undesired artifacts. This is an essential process which has drastic effects on enhancing the accuracy of the decision making process.

2.2. Signal processing

At this stage, different data features are exposed through various procedures of signal processing. This includes image enhancement functions such as spatial and frequency domains. An image compression technique has been applied in order to reduce the storage needed to save an image and morphological processing which includes tools to highlight region of interest (ROI) of the most important components in an image. It must be noted that sometimes after the use of signal processing techniques further filtering may be applied since some noise cannot be separated from the source data unless some feature extraction is applied.

Multi-resolution analysis has been performed employing a new wavelet transform known as Daubechies wavelet filter. This methodology consisted of a series of steps namely, (1) transformation of RGB image to a gray scale image, (2) filtration of transformed image by low pass and high pass band discrete filters of third order, (3) application of soft threshold factor to decomposed wavelet coefficients obtained in high frequency spectral regions of signal and (4) synthesis of denoised signal. Another application of Prewitt operator in signal convolution helped in uniform smoothing in one direction and edge detection in other direction.

2.3 Pattern recognition decision making

Customized GA-NN-FL algorithms have been applied to the input filtered and signal processed images to perform pattern recognition into predefined medical categories. The parameters of the algorithms have been provided in a dynamic real-time fashion by the decision making task. The machine learning algorithms have been utilized to medical knowledge bases, historical data, and the classified images generated by the pattern recognition module and those that are classified by specialists to produce final decisions on the medical conditions associated with the currently analyzed images.

More specifically, in this module, the acquired images have been filtered at the beginning in order to reduce the noise that has affected them during the acquisition process.


Figure 2: Image de-noising using wavelets transform

At this stage, a new multi-resolution decomposition processing filter has been applied on the image(s) using discrete wavelet transform (DWT) where if it is assumed that an image at its original resolution is represented as level 0 then $f(z) = Po$; this results in creating a multi-resolution representation for the $f(z)$ where wavelet transform should be applied in different resolution.

### 2.4 Feature extraction

After the images have been pre-processed, a feature extraction has been applied to extract the most important features that helped in the classification process. Principle Component Analysis (PCA) was used for dimension reduction and feature extraction. At this stage, a mixed technique of PCA with wavelet transform was applied to extract the features and segment the image(s). The operation has been done in which 2D-Discrete wavelet transform decompose an image to reduce its resolution.

### 2.5 Application of hybrid genetic algorithm approach

The next step after feature extraction is to use features as an input to the learning algorithm that is a hybrid technique of NN-FL-GA. In this technique, the GA optimizes the initial weights of the neural network. The output of the neural network is processed through fuzzy rules. The role of fuzzy in this algorithm is to deal with uncertainty and imprecision.

### 2.6 Feedback and decision fusion module

In this process, distributed radiologists meet online and discuss the cases that the intelligent system was not able to diagnose. These cases are considered to be as new cases to the system and therefore, they are forwarded to these radiologists. The role of the radiologists is to collaborate and take a diagnostic decision and send their feedback to the intelligent system which used this feedback to learn these new cases. This process helped in increasing the knowledge base of the system and helped in diagnosing more cases in the future without the intervention of human.

## 3. Results and discussions

We have applied the proposed methodology to wide range of medical image datasets of differernt types including MRI and CT-Scan images.

**Table 1:** Noise percentile with different clusters of image datasets

| Noise percentile | Clusters of Image Datasets | | | | | |
|---|---|---|---|---|---|---|
| | 100 | 200 | 500 | 5000 | 10000 | 20000 |
| 2 percentile | 2.4272 | 2.5852 | 2.7926 | 2.971 | 3.1738 | 3.3474 |
| 5 percentile | 6.0675 | 6.4615 | 6.9775 | 7.421 | 7.9255 | 8.358 |

| | | | | | | |
|---|---|---|---|---|---|---|
| 10 percentile | 12.144 | 12.967 | 14.064 | 15.03 | 16.122 | 17.053 |
| 15 percentile | 18.2055 | 19.395 | 20.9565 | 22.305 | 23.838 | 25.1535 |
| 20 percentile | 24.272 | 25.856 | 27.934 | 29.724 | 31.762 | 33.512 |
| 25 percentile | 30.345 | 32.34 | 34.9675 | 37.245 | 39.83 | 42.045 |
| 30 percentile | 36.408 | 38.778 | 41.889 | 44.568 | 47.607 | 50.211 |
| 40 percentile | 48.584 | 51.904 | 56.352 | 60.296 | 64.808 | 68.708 |
| Avg. Cumulative | 60.855 | 65.62 | 72.45 | 78.5 | 86.285 | 92.795 |

Table 1 describes the noise percentile against clusters of different image datasets. First dataset contains 100 image segments, second set contains 200 segments at 2 percentile and 5 percentile noise percentiles respectively. Similarly clusters of various other segments with noise percentile level is shown.

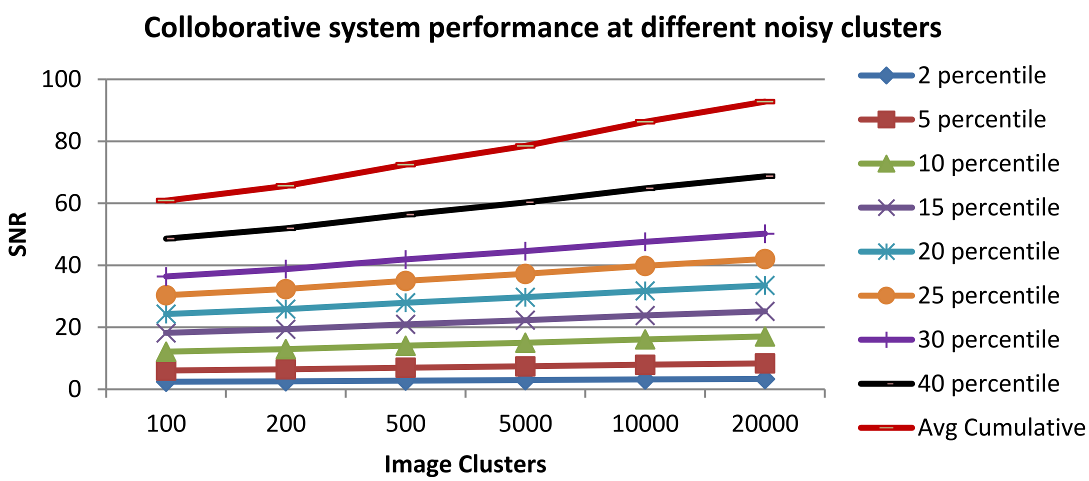


Figure 3: Colloborative system performance at different noise levels

Figure 3 presents a colloborative system performance at different noise levels. It can be seen that system performance is quite smooth and uniform at intial noise percntiles. There is a minute difference at system performance at noise level 2 and 3 depicting similar behaviour. The performance is robust even at high noise percentiles.

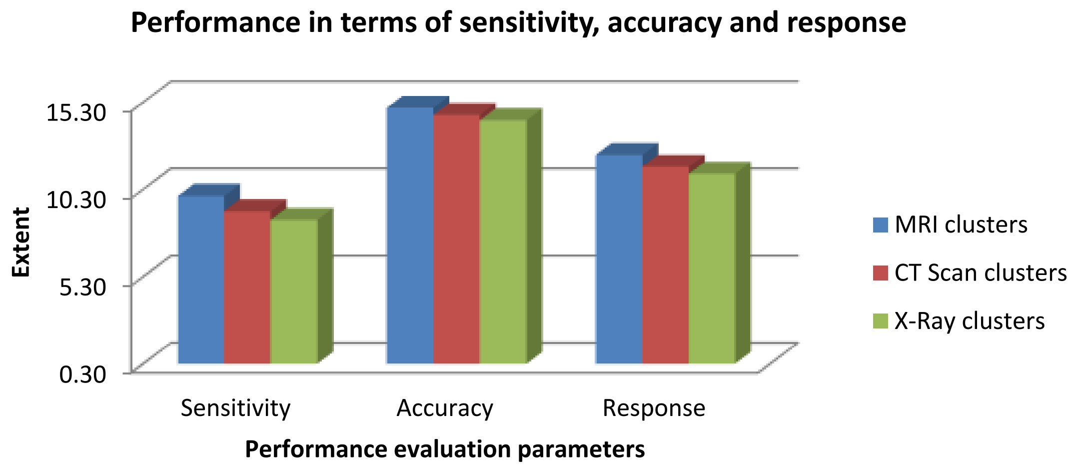


Figure 4: Performance analysis in terms of performance analysis parameters

Figure 4 describes the performance analsis of proposed system in terms of system sensitivity, accuracy and response against clusters of various image datasets comprising of MRI, CT Scan and X-Ray images. It can be observed that MRI segments in such clusters have been more accurately identified by system than other clusters. The system respnse time and sensitivity is also signifiant at different cluster types.

4. Conclusion

This paper describes an enhanced collaborative framework for medical diagnostics using software computing techniques. The major components of the system are described as preprocessing, segmentation, image enhancement, pattern matching and diagnostic decision. We have taken aid from fuzzy rules and new wavelet transforms for image enhancement and identification especially hotspot regions of images. A collaborative framework has been designed for different image processes e.g. archiving, extraction and matching of various enhanced images. The proposed system significantly helps the medical practitioner for a disease assessment and decision from the retrieved images. The system collects and fuses the feedbacks and produces a final decision. We have noticed an outperformance of system at different clusters of image datasets with system performance factors. We intend to further enhance the collaborative framework in future to address neural network logic with genetic algorithm for medical diagnostics.

5. References

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