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# Analytical Study of Medical Image Combination Techniques

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**Abstract**

Image combination is a technique that fuses two or more medical images taken with different conditions or imaging devices into a single image contain complete information. In this study relied on mathematical, statistical and spatial techniques, to fuse MRI images that captured horizontal and vertical times (T1, T2), and applied a method of supervised classification based on the minimum distance before and after combination process, then examine the quality of the resulting image based on the statistical standards resulting from the analysis of edge analysis, showing the results to identify the best techniques adopted in combination process, determine the exact details in each class and between classes.

**Keywords**: combination, MRI, contrast

# الدراسة التحليلية لتقنيات صهر الصور الطبية

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**الخلاصة**

صهر الصور هي تقنية صهر المعلومات بين صورتين طبيتين أو أكثر التقطتا بظروف او اجهزة تصوير مختلفة ودمجها في صورة واحدة تحتوي على معلومات كاملة. اعتمد في هذه الدراسة على التقنيات الحسابية ، الإحصائية ، والمكانية ، لصهر الصور الطبية(MRI) الملتقطة بتوقيتات مختلفة افقي وعمودي (T1,T2)، وطبقت طريقة التصنيف الموجهه بالاعتماد على تقنية المسافة الدنيا على الصور قبل وبعد عملية الصهر، ثم فحص جودة الصورة الناتجة اعتمادا على التحليلات المعتمده على المعايير الاحصائية الكفوءة. بينت النتائج اي التقنيات المعتمدة هي الافضل في عملية الصهر ، وتحديد التفاصيل الدقيقة جدا في كل صنف وبين الاصناف .

## 1.1 Introduction

The advances in technology, different information can be obtained from images of different medical sources to produce a new high quality image containing functional and anatomical information which can be described as improving the quality of information from a variety of images, give more convenient for the purpose of human visual perception and data processor. Therefore, the task of image combination is to make a lot of the outstanding features in the new image, such as regions and borders as well as can be used in many fields such as medical, microscopic image, remote sensing, robotic and etc. [1, 2].

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Image combination can be categorized into three categories: pixel level, feature level and decision level where pixel level means combination at the lowest processing level referring to the combining of measured physical parameters, while Feature level combination requires first extraction of the features; those features can be determined by characteristics such as contrast, size, shape ,and texture, as for the decision level combination allows the information to be effectively combined at the highest level of abstraction. The choice of the convenient level depends on many factors such as data sources, application and available tools [3].

Medical imaging systems play a vital role in human health care and it provides complete information about the human body for better treatment. Medical image classification can play an important method in diagnosing and teaching purposes in medicine [4]. Combination techniques have many applications and there is no strict creation for testing the quality of the resulting image. Many works provided in the field of medical image fusion between the published works, it has been selected the following as a selective, due to their proximity to the field of research work we have: Deron Rodrigues et al. (2014) [4], presented image combination methods based on wavelet transform. Fusion of CT scanned images and MRI images using multi resolution wavelet transform with necessary preprocessing of it is proposed. Patil, P. et al. (2015) [5], used a multimodal image combination algorithm based on Dual tree discrete wavelet transform and particle swarm optimization (PSO) is proposed. Mr Ling N. et al. (2016) [6], in this research used Fusion for Medical Images based on Shearlet Transform and Compressive Sensing Model. Yin Fei et al. (2017) [7] a new combination mechanism for multimodal medical images based on sparse representation and decision map is proposed to deal with these problems simultaneously. Three decision maps are designed to include structure information map (SIM) and energy information map (EIM) as well as structure and energy map (SEM) to make the results reserve more energy and edge information. Proposed approach also improves the quality of the fused results by enhancing the contrast and reserving more structure and energy information from the source images.

In this study, supervised classification method was used that based on the idea that a user can select sample pixels in an image that are representative of specific classes and then direct the image processing software to use these training sites as references for the classification of all other pixels in the image , and applied to the adopted images before and after the combination process to identify the best techniques based on the extract of the statistical standers of each class and between classes.

### 1.2 Combination Techniques

A medical combination technique is important for the purpose of enhancing information, thus simplifying the understanding of image data sets in the clinical diagnostic process. Therefore, in this study the process of fusion in the medical image was carried out using a mathematical technique is a collection of mathematical processes such as the combination, subtraction, division and standard deviation used to fuse the medical images bands and combine in several ways to get the best effect for these models give us a great bonding for bands such as Brovey transformation (BO) and Multiplicative method (MLT) [8, 9]. While spatial technique based on spatial frequency transforms that use high and low pass filters based on Fourier Transforms or wavelet transform. These techniques make on fused the different information between different medical images. Which includes is the High Frequency Intensity Modulation Technique (HIFM) [10, 11].

As for the statistical techniques , which are performs by on statistical standards such as Statistical mean, standard deviation, variance and covariance of the local correlation used to solve the two main problems in image fusion chromatic deformation and the displacement dependency through fit of gray values for image being fused and to distortion of gray band to the fusion result to limit the chromatic deformation, also include to evaluation the gray value relationship between gray band for input image to remove problem displacement dependency (limit the effect of dataset different) and automation the fusion process, which include Local Mean Matching(LMM) and [12,13].

### 1.3 Magnetic Resonance Imaging

Medical imaging technique used in radiology to form autopsy images and physiological processes of the body in both health and disease. MRI scanners use strong magnetic fields, radio waves, and field gradients generate images of the inside of the body. MRI is a safe technique which requires a magnetic field which is both strong and uniform [14, 15].

A Contrast in MRI can be weighted to show different anatomical structures or diseases. All tissues return to balance after excitation through the independent processes of T1 (spin-lattice) and T2 (spin-

spin) relaxation. To create a weighted T1 image, the magnetization is allowed to recover before measuring the MRI signal by changing the time of repetition (TR) as shown in Fig. This image weighting a useful to evaluate cerebral cortex, identification of fatty tissue, distinguishes the focal liver lesions and in general to obtain morphological information, as well as for post contrast imaging. To create a weighted T2 image, the magnetization is allowed to decay before measuring the MRI signal by changing the echo time (TE). This image weighting is useful for detecting edema, inflammation, detection white matter lesions and evaluate of anatomy of the prostate and uterus region [16, 17]. The MRI interests: noninvasive and painless, without ionizing radiation, high spatial resolution operator independent and etc. While the MRI risks: long scan and post processing time, a large amount of the probe may be needed, no real time information and etc. [18, 19, 20]

## 1.4 Practical Part and Algorithms

The analytical study of the MRI-T1 and MRI-T2 images adopted before and after the combination process was to study the (statistical) measures based on the quality measures test that highly efficient, to purpose of identifying the best image after the fusion process and determining its preference for the images before the fusion process, and any adopted techniques are best, through the following algorithm:

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**Algorithm:** to study the quantitative statistical characteristics between the classified image and to study them also in edges region

**Input**

- Load classified image (cimg).

**Output**

- Calculate edge analysis for source and merge images

***Start algorithm***

- *Make edge for the classified image (cimg) using Soble operator and calculate statistical measures in the edge region using steps following:*
- ***Step1**: calculate statistical mean ($\mu_c$) for each class by:*

*(cimg) = μ(c)*

- ***Step2:** calculate the number (L) of edge points for each class in image (cimg) by:*

*L(c) = L(c) +1*

- ***Step 3:** To Calculate total contrast in each edge point for classified the image (cimg) using steps following:*
- ***Step I:** the open loop and test point (i, j) by putting a condition*

*If egde point (i, j) =1*

*Then calculate the sum of edges point*

- ***Step II**: open window (3×3) to calculate maximum and minimum intensity.*

*wnd1=max (max (e-img (i-1: i+1, j-1: j+1)))*

*wnd2=min (min (e-img (i-1: i+1, j-1: j+1)))*

- ***Step III:** to calculate the intensity contract for each edge point calculates using the following relationships:*

*c1= (wnd1-wnd2)*

*c2= (wnd1+wnd2)*

- ***Step IV**: put a condition:*

*If c1=0 and c2=0 then contrast vector (ct) =0*

- *Else calculate (ct) in each edge point of:*

*ct = c1/c2*

- *End condition.*
- *End loop.*
- ***Step V:** Calculate total contrast vector (cont) by relationship:*

*cont= mean (ct)*

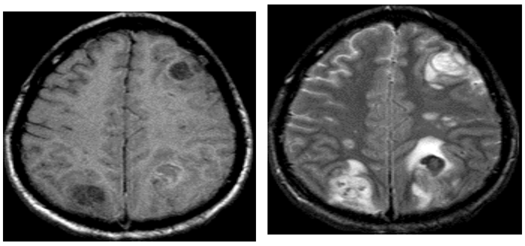
- ***Step4:** calculate the strongest statistical scale (MD) between classes through the following:*

- *Find value points between classes (Z)*

*Z= find (Q)*
*MD= mode (Z)*
***End algorithm***

## 1.4 Results and Discussions
The results in this work included several parts:

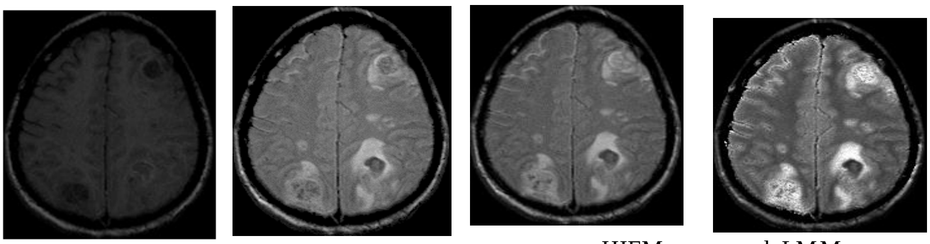
### 1.4.1 Adopted Images
Include two types adopted medical image, Magnetic Resonance Imaging type (MRI-T1) has a size (169×204) pixels and bit depth (8bits), shown as in Figure-1(A) and Magnetic Resonance Imaging (MRI-T2) has a size (166×201) pixels and bit depth (8bits), as shown in Figure-1(B)[21,22].



. MRI-T1 B. MRI-T2

**Figure 1 (A, B)-**Adopted medical images [21, 22].

### 1.4.2 Combination Process Results
The images resulting from the combined of the images of the medical as shown in Figure-2



a. BO b. MLT c. HIFM d. LMM

**Figure 2-**The medical images resulting combination process.

### 4.3 Classification Image Results
The Supervised classification method by minimum distances applied to images before and after the combination process by choosing different blocks of numbers (7 blocks) and the size of each block (3×3) depending on the most visible image, the results of the classification shown in Figure-3. Then calculation of the contrast (cont.C) between the classes to distinguish the classes from each other, results shown in Table-1.

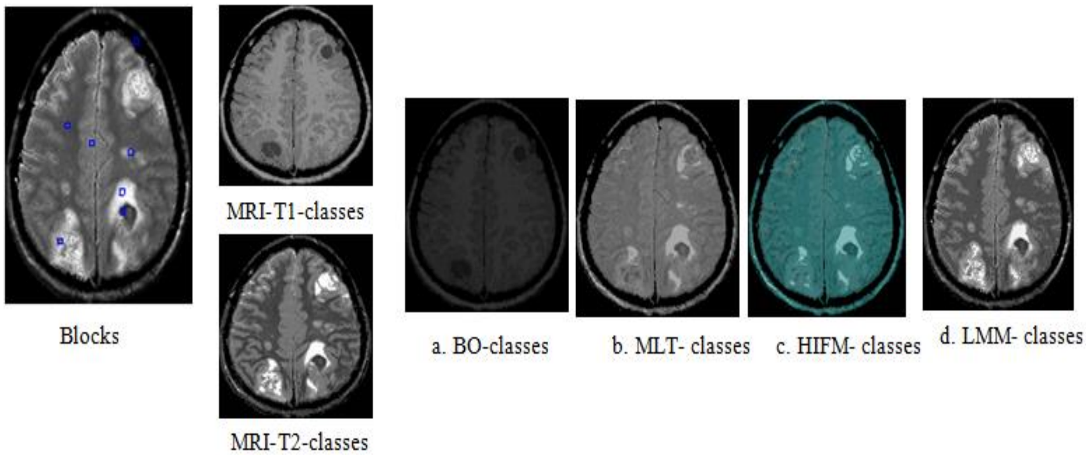



**Figure 3-**The results of the classification for the medical images before and after combination process

**Table 1-**The statistical scale (cont.C) between the classes for medical image before and after the combination process

| Image | Contrast between classes | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| MRI-T1 | Class | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| | 1 | **0.000** | 1.000 | 1.000 | 0.996 | 0.000 | 0.989 | 0.971 |
| | 2 | 0.739 | **0.000** | 0.264 | 0.163 | 0.000 | 0.155 | 0.199 |
| | 3 | 0.566 | 0.219 | **0.000** | 0.200 | 0.000 | 0.215 | 0.334 |
| | 4 | 0.729 | 0.350 | 0.337 | **0.000** | 0.000 | 0.298 | 0.464 |
| | 5 | 0.000 | 0.000 | 0.000 | 0.000 | **0.000** | 0.000 | 0.000 |
| | 6 | 0.788 | 0.822 | 0.758 | 0.750 | 0.000 | **0.000** | 0.809 |
| | 7 | 0.571 | 0.151 | 0.142 | 0.214 | 0.000 | 0.486 | **0.000** |
| MRI-T2 | Class | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| | 1 | **0.000** | 0.977 | 0.983 | 0.954 | 0.346 | 1.000 | 0.907 |
| | 2 | 0.784 | **0.000** | 0.232 | 0.258 | 0.231 | 0.222 | 0.241 |
| | 3 | 0.477 | 0.263 | **0.000** | 0.194 | 0.183 | 0.268 | 0.301 |
| | 4 | 0.583 | 0.410 | 0.485 | **0.000** | 0.824 | 0.679 | 0.696 |
| | 5 | 0.200 | 0.202 | 0.174 | 0.285 | **0.000** | 0.194 | 0.122 |
| | 6 | 0.656 | 0.271 | 0.322 | 0.373 | 0.252 | **0.000** | 0.254 |
| | 7 | 0.609 | 0.217 | 0.206 | 0.253 | 0.266 | 0.334 | **0.000** |
| BO | Class | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| | 1 | **0.000** | 1.000 | 1.000 | 0.993 | 0.000 | 0.992 | 0.991 |
| | 2 | 0.797 | **0.000** | 0.237 | 0.161 | 0.000 | 0.156 | 0.205 |
| | 3 | 0.602 | 0.200 | **0.000** | 0.239 | 0.000 | 0.236 | 0.374 |
| | 4 | 0.707 | 0.349 | 0.306 | **0.000** | 0.000 | 0.299 | 0.496 |
| | 5 | 0.000 | 0.000 | 0.000 | 0.000 | **0.000** | 0.000 | 0.000 |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | 6 | 0.765 | 0.813 | 0.770 | 0.759 | 0.000 | **0.000** | 0.886 |
| | 7 | 0.698 | 0.147 | 0.142 | 0.227 | 0.000 | 0.514 | 0.000 |
| MLT | Class | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| | 1 | **0.000** | 0.946 | 0.930 | 0.907 | 0.885 | 0.885 | 0.845 |
| | 2 | 0.588 | **0.000** | 0.243 | 0.206 | 0.206 | 0.204 | 0.259 |
| | 3 | 0.532 | 0.228 | **0.000** | 0.159 | 0.137 | 0.198 | 0.272 |
| | 4 | 0.513 | 0.366 | 0.322 | **0.000** | 0.349 | 0.357 | 0.509 |
| | 5 | 0.435 | 0.246 | 0.190 | 0.321 | **0.000** | 0.321 | 0.327 |
| | 6 | 0.540 | 0.261 | 0.197 | 0.240 | 0.286 | **0.000** | 0.312 |
| | 7 | 0.630 | 0.202 | 0.171 | 0.185 | 0.237 | 0.254 | 0.000 |
| HFIM | Class | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| | 1 | **0.000** | 0.995 | 1.000 | 0.974 | 1.000 | 0.948 | 0.927 |
| | 2 | 0.460 | **0.000** | 0.222 | 0.209 | 0.185 | 0.180 | 0.180 |
| | 3 | 0.424 | 0.188 | **0.000** | 0.141 | 0.146 | 0.271 | 0.212 |
| | 4 | 0.545 | 0.322 | 0.446 | **0.000** | 0.888 | 0.669 | 0.710 |
| | 5 | 0.188 | 0.157 | 0.405 | 0.218 | **0.000** | 0.138 | 0.081 |
| | 6 | 0.506 | 0.216 | 0.231 | 0.261 | 0.167 | **0.000** | 0.201 |
| | 7 | 0.559 | 0.164 | 0.158 | 0.188 | 0.312 | 0.297 | **0.000** |
| LMM | Class | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| | 1 | **0.000** | 0.986 | 0.996 | 0.968 | 0.907 | 0.914 | 0.850 |
| | 2 | 0.550 | **0.000** | 0.282 | 0.335 | 0.248 | 0.223 | 0.283 |
| | 3 | 0.577 | 0.307 | **0.000** | 0.252 | 0.182 | 0.221 | 0.323 |
| | 4 | 0.769 | 0.668 | 0.700 | **0.000** | 0.617 | 0.742 | 0.660 |
| | 5 | 0.690 | 0.412 | 0.293 | 0.350 | **0.000** | 0.291 | 0.266 |
| | 6 | 0.608 | 0.334 | 0.318 | 0.278 | 0.319 | **0.000** | 0.276 |
| | 7 | 0.671 | 0.232 | 0.206 | 0.225 | 0.255 | 0.310 | **0.000** |

From the results of the Table-1 noticed that each combination technique was able to distinguish the different classes in the image from each another according to method of fusion information for each technique, when calculating the statistical scale (Cont.c) between the classes noticed that the similar classes of spatial coordinates of each image (i, j) the statistical contrast shall be equal to zero [(cont.C) i=j=0], the value of which is different when spatial coordinates are different adopted in the combine of information. The results of the tables were observed efficiency of this measure in determining the sharpness of the common information between the different classes in the image.

**1.4.4 Edge Analysis of Classified Images Results**

The edge analysis applied on classified images before and after the fusion process based on important and efficient statistical measures to separate the very fine detail of each and between the classes in the image. Where is calculating the number of edge points (L(c)), the results shown in

Figure-4.Then calculate the strongest measures mode (MD) between classes for each classified images, the results shown in the Table-2.

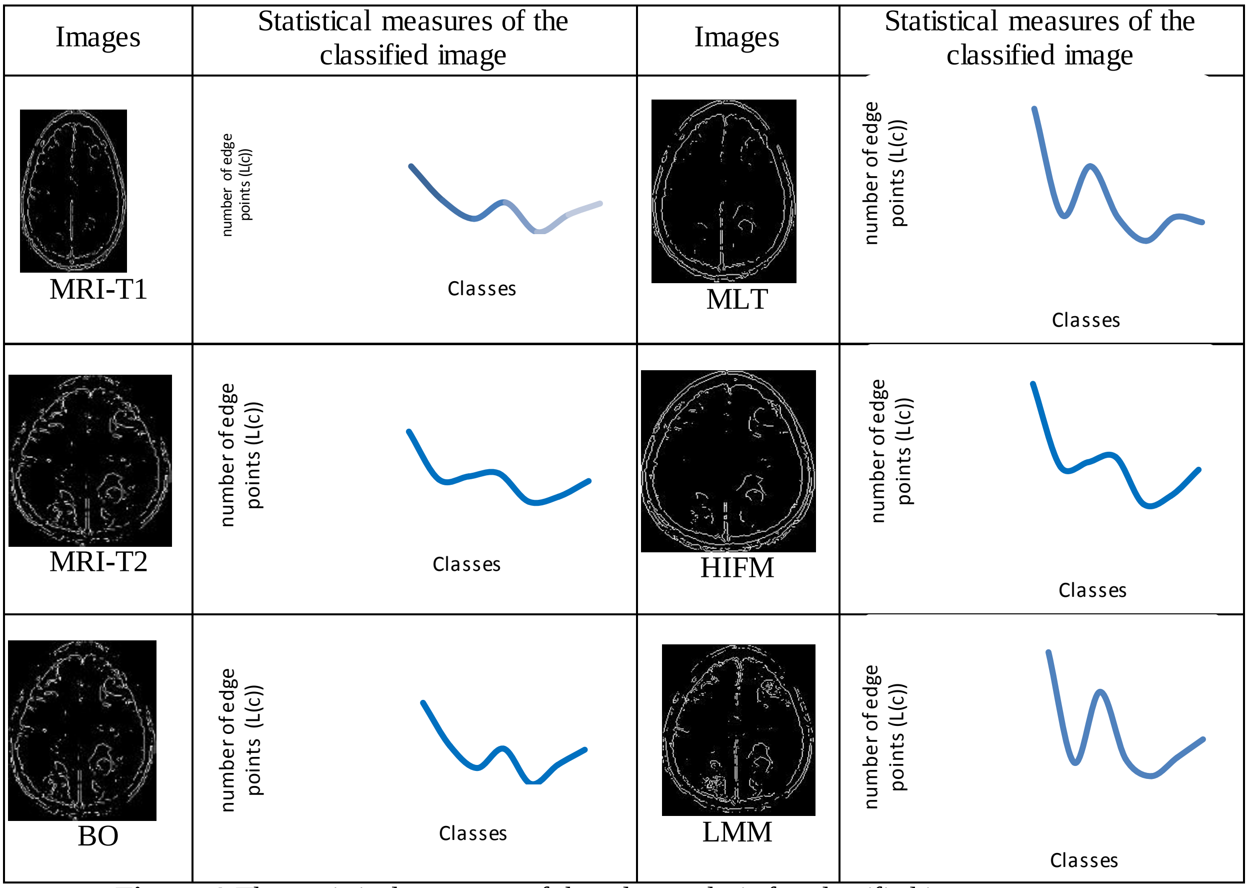



**Figure 4-**The statistical measures of the edge analysis for classified image

**Table 2-**The statistical measures of the classified image of medical images

| Image | Mode | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| MRI-T1 | Class | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| | 1 | **0** | 17 | 17 | 17 | 0 | 17 | 17 |
| | 2 | 118 | **0** | 118 | 118 | 0 | 118 | 118 |
| | 3 | 154 | 154 | **0** | 154 | 0 | 154 | 154 |
| | 4 | 86 | 104 | 104 | **0** | 0 | 86 | 104 |
| | 5 | 0 | 0 | 0 | 0 | **0** | 0 | 0 |
| | 6 | 35 | 68 | 68 | 68 | 0 | **0** | 68 |
| | 7 | 136 | 136 | 136 | 136 | 0 | 136 | **0** |
| MRI-T2 | Class | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| | 1 | **0** | 17 | 17 | 17 | 17 | 17 | 17 |
| | 2 | 118 | **0** | 118 | 118 | 136 | 136 | 118 |
| | 3 | 86 | 86 | **0** | 86 | 86 | 86 | 86 |
| | 4 | 35 | 68 | 68 | **0** | 50 | 68 | 68 |
| | 5 | 204 | 204 | 204 | 204 | **0** | 204 | 204 |
| | 6 | 154 | 154 | 154 | 154 | 186 | **0** | 154 |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | 7 | 100 | 100 | 100 | 100 | 100 | 100 | **0** |
| BO | Class | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| | 1 | **0** | 6 | 6 | 6 | 0 | 6 | 6 |
| | 2 | 39 | **0** | 39 | 39 | 0 | 39 | 39 |
| | 3 | 51 | 51 | **0** | 51 | 0 | 51 | 51 |
| | 4 | 29 | 35 | 35 | **0** | 0 | 29 | 35 |
| | 5 | 0 | 0 | 0 | 0 | **0** | 0 | 0 |
| | 6 | 12 | 23 | 23 | 23 | 0 | **0** | 23 |
| | 7 | 45 | 45 | 45 | 45 | 0 | 45 | **0** |
| MLT | Class | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| | 1 | **0** | 24 | 29 | 24 | 34 | 29 | 34 |
| | 2 | 115 | **0** | 118 | 118 | 118 | 115 | 118 |
| | 3 | 101 | 108 | **0** | 101 | 108 | 108 | 108 |
| | 4 | 42 | 82 | 82 | **0** | 77 | 82 | 82 |
| | 5 | 148 | 148 | 148 | 148 | **0** | 148 | 148 |
| | 6 | 93 | 96 | 96 | 96 | 96 | **0** | 96 |
| | 7 | 123 | 127 | 127 | 127 | 127 | 127 | **0** |
| HIFM | Class | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| | 1 | **0** | 85 | 91 | 148 | 137 | 57 | 91 |
| | 2 | 255 | **0** | 255 | 255 | 255 | 255 | 255 |
| | 3 | 255 | 255 | **0** | 255 | 255 | 255 | 255 |
| | 4 | 255 | 255 | 255 | **0** | 255 | 255 | 255 |
| | 5 | 255 | 255 | 255 | 255 | **0** | 255 | 255 |
| | 6 | 255 | 255 | 255 | 255 | 255 | **0** | 255 |
| | 7 | 255 | 255 | 255 | 255 | 255 | 255 | **0** |
| LMM | Class | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| | 1 | **0** | 23 | 16 | 16 | 0 | 26 | 25 |
| | 2 | 122 | **0** | 118 | 118 | 130 | 118 | 118 |
| | 3 | 67 | 96 | **0** | 74 | 70 | 96 | 94 |
| | 4 | 30 | 66 | 66 | **0** | 45 | 66 | 58 |
| | 5 | 255 | 197 | 199 | 196 | **0** | 255 | 201 |
| | 6 | 146 | 134 | 136 | 137 | 192 | **0** | 134 |
| | 7 | 115 | 109 | 98 | 98 | 111 | 115 | **0** |

From results of the Figure-4: noticed that (L(c)) for each class in the techniques (BO and HFIM) show details of (the first, fourth and seventh) classes more than the other classes (i.e., separated the fine details in those classes) while in the techniques (MLT and LMM) show details of (the first and third) classes more than the other classes (i.e., separated the fine details in those classes) , when calculating the statistical measures included the most frequent number (MD) between the classes noticed that the similar classes of spatial coordinates of each image (i, j) the statistical (From the results of the tables (1-2) noticed that each combine technique was able to separate the different classes in the image from each another according to method of fusion information for each technique(MD) shall be equal to zero

[ (MD)i=j=0], the value of which is different when spatial coordinates are different adopted in the merge of information. The results of the tables were observed efficiency of these measures in determining separate force and extract fine details and determine the most frequent pattern between the different classes in the image

**1.5 Conclusions**

From the results, can be concluding the following points:

1. Found fusion presses are an important method of integrating different information, distinguishing classes, identifying common information and more frequent information, separating force and extracting the common characteristics between the classes and in each class and these are very useful in the definition of disease and diagnosis of the doctor to apply the best treatment.
2. Concluded that the edge analysis process which was conducted on the classified image it was a highly efficient process in distinguishing high-intensity (homogeneous) classes and information classes (edges) was observed from the results of the statistical measure (L(c)) according to a technique that integrates information which helps to detect the required medical information and facilitates clinical diagnosis
3. The classification process was very efficient in classifying the image regions and distinguishing the fine details between the classes based on the statistical scale (Cont.c) between the classes found that the similar classes of spatial coordinates of each image (i, j) the statistical contrast shall be equal to zero [(cont.C) i=j=0], the value of which is different when spatial coordinates are different adopted in the merge of information. This measure observed efficiency in determining the sharpness of the common information between the different classes in the image.
4. Concluded that statistical the statistical scale (mode (MD)) gives the best results in separating common information between classes and identifying the most frequent information between them.

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