Accuracy Evaluation of Brain Tumor Detection using Entropy-based Image Thresholding

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دقة النهج القائم على الانتروبيا من خلال العتبة للكشف عن الورم الدماغي

</div>

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تفويـــض

أنا أمل قاسم اليحيى أفوض جامعة الشرق الاوسط بتزويد نسخ من رسالتي ورقياً والكترونيا للمكتبات، أو المنظمات، أو الهيئات والمؤسسات المعنية بالابحاث والدراسات العلمية عند طلبها.

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Dedication

(وقل رب زدني علمًا) طه الاية (111)

I dedicate this thesis to my Family who standing beside me and my Mother God's mercy. I hope to reach my research into the world to benefit from it and be ongoing charity to dear my father

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Accuracy Evaluation of Brain Tumor Detection using Entropy-based Image Thresholding

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Abstract

Image thresholding is one of the techniques that are used for image segmentation. Threshold techniques divide the image into two main regions, these are: Foreground and Background. The output of the thresholding process is a binary image with only two regions that are formed by the highest possible contrast that could be found in the image. Entropies are information gain approaches that have been used for image thresholding with various application and image modalities. However, the accuracy of the existing entropies for image thresholding has been studied in general domain (e.g.: natural images)that teams from the regular medical images and images that form in the ordinary image is a reflection of light objects, While medical images. Taken by magnetic resonance imaging, for example, A strong magnetic field is used with radio frequencies and computer to produce automatic selection of the best result. It produces the results with the highest accuracy. detailed images of organs and soft tissues, bones and other internal parts of the body. and were not compared thoroughly. In this work, the accuracy of the entropy-based thresholding approaches and their combination in brain tumor detection framework is investigated. For this purpose, a framework for brain tumor segmentation

is developed. The developed framework is made simple and has the core process of the image thresholding, in order to evaluate the accuracy of the entropies. Five entropies, namely, Reniyh, Maximum, Minimum, Tsallis and Kapur are evaluated. The aggregation of entropies was implemented and evaluated. The results show that the maximum entropy is the best for brain tumor detection. Moreover, it was shown that aggregation of entropies output does not enhance the result, however, it works as

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الملخص

ان صورة العتبة هي واحدة من التقنيات التي تستخدم لتجزئة الصورة. تقنيات العتبة هي عبارة عن تقسيم الصورة إلى منطقتين رئيسيتين ،هي: المقدمة والخلفية والناتج من هذه العملية عباره عن صورة ثنائية .الانتروبيا هي طريقة لتوزيع المعلومات بشكل متساوي في الصورة التي استخدمت فيها العتبة .ومع ذلك، فقد تمت دراسة دقة الانتروبيا القائمة لعتبة صورة في نطاق عام (مثلا: صور الطبيعية)وذلك لفرق الصور الطبيه عن الصور العاديه والتي تتشكل في ان الصور العادية هي عبارة عن انعكاس الضوء الاجسام   بينما الصور الطبيه على سبيل المثال التي تؤخذ بالرنين المغناطيسي, يستخدم حقل مغناطيسي قوي مع ترددات راديوية والكمبيوتر لإنتاج صور مفصلة من الأعضاء والأنسجة الرخوة والعظام وغيرها من أجزاء الجسم الداخلية .ولم تتم المقارنة بدقة بين الانتروبيا . في هذا العمل، الذي قام على التحقق من دقةالنهج القائم على الانتروبيا من خلال العتبة والجمع بينهما للكشف عن الورم الدماغي . لهذا الغرض ،وضع إطار لتجزئة الورم في المخ يحتوي هذا

الاطار على الانواع الخمسة الشائعة من الانتروبيا ،من أجل تقييم مدى دقة الانتروبيا.

الانواع الخمسة هي رينية ,كابور، ساليز، الحد الأقصى والحد الأدنى. تم تنفيذ جميع الانتروبيا

وتقييمها. وأظهرت النتائج أن نوع الحد الاقصى هو أفضل للكشف عن الورم في المخ. وعلاوة على

ذلك، فقد تبين أن دمج اكثر من نوع من الانتروبيا لايطور من النتيجة ، ومع ذلك ،فإنه يقوم بالاختيار

التلقائي لأفضل نتيجة..

الكلمات المفتاحية: دقة النهج القائم ، الانتروبيا ، الكشف عن الورم الدماغي.

CHAPTER ONE

INTRODUCTION

Captured images, over decades, have helped in solving many of the problems that were difficult to resolve using the traditional ways in many fields, such as: earth science, astronomy, biology, industry, etc. Images have also contributed to the development of the most important field, the medical, which helps in the survival of the human being .With the ever increase in the value of images; there is a demand for automatic analysis, processing and recognition of these images. The processing demand is emerged by the fact that it might be difficult to re-capture the images as the phenomena cannot be brought back to an earlier time or it is too expensive to capture the same image again and again. The solution to such atomization is the digital image processing.

Digital image processing is a branch of computer science that concerns about the automatic handling of the images in term of saving, improving, analysis and information extraction. Image segmentation is an important phase in digital image processing. Image segmentation divides the image into coherent and homogeneous regions according to specific criteria, such as: region color, region shape, or region boundary. The union of the segmented regions should result in reconfiguring the original image. Image segmentation allows the extraction of valuable information from the image as it provides a high-level description of each region individually, and allows for the linkage of neighboring regions in the image. An example of a segmented image is illustrated in Figure1.1 (Gonzales& Woods, 2002).
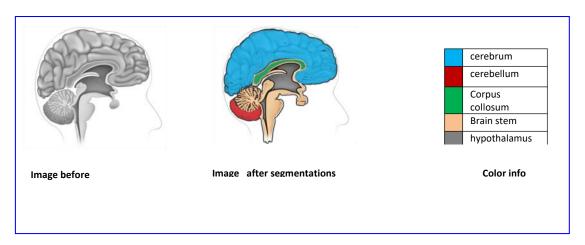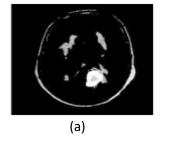
Figure 1.1: Segmentation of brain image (Myron et al., 1970)

1.1 Tumor Detection

Tumor is the abnormal growth of cells to form abnormal fraction that has different characteristics from the normal cells. Tumor is classified into a benign tumor, pre-malignant tumor and malignant. Benign tumor is the one that does not grow suddenly and has no effect on tissue, example of this class of tumor is moles. Pre-malignant is the class that if it is not treated quickly, it becomes a malignant tumor.Malignant tumor grows rapidly and affects the neighboring tissue and, with time, it affects human life and leads to the death. Tumor detection is an important part in the treatment process. Thus, tumor detection techniques have concerned researchers in computer fields, especially, image processing (Wu, & Chang, 2007).

(a) (b)

Figure 1.2:Brain tumor detection (a) input image and (b) detected tumorregion (Wu& Chang, 2007)

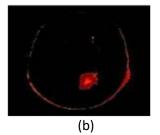Automatic tumor detection in early stage is critical task that were addressed by many existing approaches. One of the most important stage in tumor detection is image segmentation, in which tumor is being isolated from other healthy tissues. By isolating the tumor then determines its stage, the treatment becomes easier(Marcel ,2004).

1.2   Entropy-based Image Thresholding

Image thresholding is one of the techniques that are used for image segmentation. Threshold techniques divide the image into two main regions, these are: Foreground and Background. The output of the thresholding process is a binary image with only two regions that formed by the highest possible contrast that could be found in the image (Abu-Shareha et. al., 2008). This type of thresholding, which produce two regions, is called global thresholding. The other type of thresholding is called multi-thresholding. Multi-thresholding, in general, is implemented by segmenting an image into multiple objects and background, as illustrated in Figure 1.2.

What's happening, during the application of the thresholding? First, the value of the threshold is determined. Then, all pixels with values that are greater than the threshold considered in one object and all the pixels with values that are less than the threshold value is considered as a background and vice versa (Prasanna&Arora, 2006).
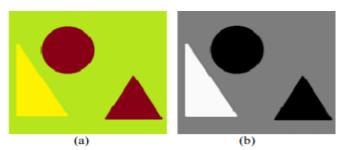

(a)   (b)

Figure 1.3: Example segmented image (a) an image of three objects and (b) the result of image segmentation.

The main assumption of global thresholding is that the object and background can be distinguished by searching the gray-level value that divides the image into two distinguished parts. Threshold mathematically easy and required less time compared to the other approaches of image segmentations (El-Sayed et al., 2014).

In order to determine the value of the threshold, several approaches have been developed and used. Entropy is one of these approaches that aim sat finding a threshold value that facilitates maximum information extraction from the image. Entropy has been emerged in Information Theory to extract the amount of information expressed by a piece of data (El-Sayed, 2014).

Entropy is a Greece word, which means "if any system has many point of information's, the entropy is incense until arrive to equal distribution for this information". This technique helps to get a good threshold for the regions in the image. Entropies not only used in computer sciences; it is used in many different fields, such as: physics, biology, astronomy, etc. Entropy in image processing measures the amount of information that can be obtained from the image, either in its original form or after some processing. There are several ways to use entropy, as well as several equations to be used as the entropy basis(Abu-Shareha et al., 2008).

The entropies that are used for thresholding, are many, each of them has different aim, such as: reducing error, increase efficiency and remove noise. Some kinds of entropy are: Renyih, maximum, Tsallis and minimum cross.

In this work, the accuracy of image thresholding, as the most important factor in tumor detection, is evaluated.

1.3   Problem Statement

The accuracy of the existing entropies for image thresholding has been studied in general domain (e.g.: natural images). However, natural image are different from medical images by all means (e.g.: the contrast, colors, etc.). Moreover, medical images differ from each other by the means of organ, modality and equitation parameters such as chosen thresholding value ,priorities value and possibilities value. Subsequently, there is a need to evaluate the existing entropies for medical image segmentation.

This problem can be further divided into the following sub-problems:

1. How to develop a tumor detection framework that depends on image thresholding.

2. How to use entropy based thresholding in the developed tumor detection framework.

3. How to combine more than single entropy to produce a single segmented image by merging and selection.

4. How to compare between different entropy-based thresholding in the developed tumor detection framework and different combinations.

1.4 Goal and Objectives

The goal of this work is to evaluate the accuracy of the entropy-based thresholding approaches and their combination in brain tumor detection framework. The objectives of this research are as follows:

1. To develop a tumor detection framework that takes a brain image and produces a segmented image with a detected tumor if the tumor is present.

2. To use different entropy based thresholding in the developed tumor detection framework.

3. To combine multiple thresholding approaches by applying logical operators (AND and OR) on the thresholding output and acquires an automatic selection of their outputs to get the best result.

4. To evaluate and compare the entropies results and their different combinations in the developed tumor detection framework.

1.5 Motivation

A human life is the most important thing in the globe; medical researcher tries to make human life comfortable by defeating and curing diseases that may decimate health. This work is motivated by both the crucial need for technology-based applications in the field of tumor detection, and also the significant amount of time and effort to be saved by involving machine learning techniques in this field. More specifically, this work is devoted to brain tumors that are not easy to be understood as it comes in images with different shapes and intensities. Currently, as the detection process is still immature, it is not really used for treatment and diagnosis, it is used for indexing and retrieval of images in teaching of medicine by example.

1.6   Research Methodology

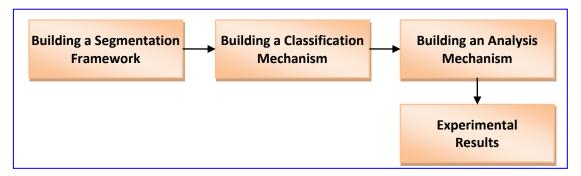The proposed work is implemented in various phases as given in Figure 1.4, these are:

Figure 1.4: Research Methodology

Building a Segmentation Framework

First, a segmentation framework, in which the entropies will be employed, is constructed. Simply, this framework reads the input image, applies the thresholding and report the results.

The proposed framework deals with medical image; subject matter is gray-level images. The difference between the gray-level images and color images is that each pixel in gray-level images is represented by a single value, usually 0-255, while each pixel in color images represented by more than one value (e.g.: 3 values for RGB images) (Mohamed and Clausi, 2001).

Building a Classification Mechanism

The images, before they undergo to image segmentation for the purpose of tumor detection, theyundergo classification process, which classifies the images based on the

presence and absence of tumor. The classification is implemented based on the images as a whole.

Building an Analysis Mechanism

The outputs of different entropies are collected and analyzed and combined using different logical operators.

Evaluation

The evaluation of the proposed framework is carried on based on a set of syntactic data.

1.7 Scope

The research conducted in this thesis evaluates the accuracy of the entropy-based image thresholding in tumor detection framework, the following summarizes the scope of the conducted research:

- Images used in this research are synthetic images provided by a well-known trusted provider. Obtaining Images of real tumor patients is not easy as this would involve privacy and data protection issues. However, what is applied on synthetic images can be applied on real images as they are identical by all the means.

- The processing framework deals with individuals 2D images. 3D volume processing is outside the scope of this research.

- This thesis focus on the original and mostly-utilized entropies. Other entropies that were developed by extended original one is outside the scope of this thesis.

1.8 Thesis Outlines

In this chapter, **Chapter One**, a brief introduction to the problem that will be investigates in this thesis is given. Moreover, the problem statement, goal and objectives and the proposed framework is given. **Chapter Two**, discusses the related work in the field of entropy-based image thresholding and tumor detection. **Chapter Three**, presents and discusses the proposed work for evaluating the existing entropy-based image thresholding in tumor detection framework. **Chapter Four**, present the experimental results and discusses he findings. **Chapter Five** presents a brief summary of the thesis findings and the future direction.

CHAPTER TWO

BACKGROUND AND LITRATURE REVIEW
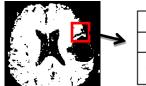
This chapter is devoted for clarifying the concept of image thresholding based on entropy and automatic tumor detection. A brief background is given in section 2.1. Section 2.2 reviews the related work on segmentations. Section 2.3presents the related work on brain tumor detection. Section 2.4 gives a summary of this chapter

2.1 Background

As mentioned before, global image thresholding divides the image into two main regions, that are: Foreground and Background. The output of the thresholding process is a binary image with only two regions that represents the highest possible contrast that could be found in the image. This process is illustrated in Figure 2.1. The image is first read as a matrix of numbers, each value in the matrix represents the intensity at each pixel. Then, the threshold is determined. Shown in Figure 2.1, as the value of 1,0. Finally, a binary matrix is generated based on the threshold value and the output image from the binary matrix. While, there are many thresholding techniques presented such as :histogram shape-based methods, global and local, entropies are one of the most utilized technique for it is reliability(Beck&Teboulle, 2009). Image thresholding is simply finding the optimal value to be used to transform an image into a Black/White image based on the optimal thresholding value. Pixels of the original image is to be scanned against the optimal threshold, where the value of the pixel is to be set to 0, Black, if the value of the pixel is less than the thresholding value. Otherwise, the pixel is transformed to 255, White, as shown in figure 2.1.

Figure 2.1: Image Thresholding

Table2.1: List ofEntropies used in Image Thresholding

Name	Aim	Usability
Renyi	Reduce error Reduce noise	Works on the distribution of gray level priorities that are represented by the density scale.
Maximum	Reduce the time and Increase equality	Generate a strong correlation between data partitions .
Tsallis	Reduce the time	Determine the value of the gray-level and mid-level gray in order to choose the optimal data distribution.
Minimum	Noise resistant	Increases the contrast at the edges in the image.
Kapur	Reduce error Reduce noise	Expresses quantifiable information that gives the best state of distribution.

Renyih Entropy was established in 1961, by Renyih, with the aims to divide a given set of data into two main parts that maximizes the information gain. Later on, Renyih entropy were used in many fields, including image thresholding. Renyih entropy is based on mathematical equation, as given in Equation 2.1, Equation 2.2 and Equation 2.3.

$$H1(t) = \frac{1}{1-a} \ln \sum_{i=1}^{t} p_i^a \qquad (2.1)$$

$$H2(t) = \frac{1}{1-a} \ln \sum_{j=t}^{n} p_j^a \qquad (2.2)$$

$$T = MAX\ (H_1 + H_2) \qquad (2.3)$$

where, H1 and H2 are the generated parts using the threshold value, t. a is a small selected value in the range (0-1), pi and pj are the probability of data pieces in H1 and H2 regions, respectively (Abu-Shareha et al., 2008).

Tsallis entropy deals with bilateral level or multi-level data (e.g.: images). Compare to Renyih, this type is much easier to be implemented takes less time and the value that produced by Tsallisis moreflexible. Unlike Renyih, which focus on the within homogeneity, Tsallisfocuses on the among heterogeneity, which form more clear edges in the image, and thus a better segmentation for the image.Tsallisentropy is based on mathematical equation, as given in Equation 2.4, Equation 2.5 and Equation 2.6 (Sahoo, 2006).

$$H1_n^x(t) = \frac{1}{x-1} \; 1 - \sum_{i=1}^{t} p_i^x \text{where } x \neq 0 \quad (2.4)$$

$$H2_n^x(t) = 1 - \sum_{j=t}^{n} p_i^x \quad (2.5)$$

$$t = MAX \, (H_1 + H_2) \quad (2.6)$$

where, H1 and H2 are the generated parts using the threshold value, t. t is a selected value, pi and pj are the probability of data pieces in H1 and H2 regions, respectively In the maximum and minimum entropy, the assumption is that, there is a strong correlation between data elements . The aim is to find the best distributionthat maximize the information gain. Maximum entropy is calculated based on mathematical equation, as given in Equation 2.7, Equation 2.8 and Equation 2.9 (Sahoo, 2006).

$$H1(t) = - \sum_{i=1}^{t} P_i \log P_i \qquad (2.7)$$

$$H1(t) = - \sum_{j=t}^{n} P_j \log P_j \qquad (2.8)$$

$$t = MAX (H_1 + H_2) \qquad (2.9)$$

Minimum entropy is seen as an extension of the maximum entropy, noted that in the absence of advanced sufficient information, both maximum and minimum produced preliminary equal information (Phillips et al., 2006).

Kapurentropy is very similar to Tsallisentropy. However,Sarkar, (2013) results proved that Kapur Entropy gives more effective results than Tsallis in terms of noise removal, although most researchers confirm that the entropy, in general, is similar, they produced different results based on the underlying application. Kapurentropy is calculated based on mathematical equation, as given in Equation 2.10, Equation 2.11 and Equation 2.12(Bhandari et al., 2014).

$$H1(t) = \frac{1-(\sum_{i=1}^{t} p_i^{1/a})^a}{1-a} \qquad\qquad (2.10)$$

$$H1(t) = \frac{1-(\sum_{j=t}^{n} p_j^{1/a})^a}{1-a} \qquad\qquad (2.11)$$

$$T = \text{MAX } (H_1 + H_2) \qquad\qquad (2.12)$$

2.2   Related Work

There are many approaches and techniques that are used for entropy-based image thresholding. The original entropies, as have been discussed earlier, and enhanced by many techniques proposed in the literature, by modifying the underlying calculations, adding pre-processing or post-processing steps. In the following, a summary of these techniques are given.

Chang et al., (1994) used entropy-based thresholding with hash-based distance metrics in order to enhance the accuracy in images with a very limited gray-level range. The experimental result shows that while the original entropy focused on the homogeneity within region parts, the developed approaches gain both the within region and among region homogeneity and heterogeneity criteria.

Sahoo, (2006) proposed an image thresholding technique using Tsallis entropy. The proposed approach extends the original entropy by proposing a two dimensional histogram that capture the differences in neighborhood pixels. Then, the proposed technique calculates the entropy based on the constructed histogram and using a various, alpha values. The value of alpha, has been proved to change the results significantly. Thus, the value of alpha was chosen automatically by analyzing the output of several alpha's and select the optimal one.

Yin, (2007)proposed multi-level image thresholding based on Minimum entropy. In-order to ease the process of calculating the distribution for all possible threshold values, the proposed approach uses an optimization approach. The experimental showed that using swarm optimization increases the efficiency of the minimum entropy.

Abu-Shareha et al., (2008) proposed an image thresholding using Renyih entropy by calculating distribution of information between two regions. The final threshold value is the maximum value for the distribution of information components, which showed high efficiency and more accurate results. The developed technique uses the advantage of texture and image intensityin order to increase the homogeneity within the regions and heterogeneity among regions.

Zhang and Wu, (2011) proposed a multi-level image thresholding based on Tsallis. In-order to ease the process of calculating the distribution for all possible threshold values, the proposed approach uses an optimization approach. The experimental results showed that using Bee colony algorithm increases the efficiency of the Tsallis entropy. It was clear that Bee colony is much faster than Genetic Algorithm in this context. Moreover, compared with other entropies, Tsallis is shown to give superior results.

El-Sayed et al., (2014) proposed a new thresholding approach based on Tsallis entropy. The proposed approach constructs a two-dimensional histogram by the gray value of all pixels compares with the average gray value of all pixels.AmodifiedTsallis entropy was then applied on the generated histogram. The experimental result which was implemented on real and synthetic images showed that the proposed approach outperformed many of the thresholding techniques using the original entropies.

El-Sayed, (2015) used Shannon entropies, which is identical to Renyi, to segment the image and highlight the edges. The proposed approach uses the entropy as it is follow the thresholding process with edge detection on the generated thresholded image. The results show that the proposed approach outperforms the well-known edge detection techniques.

Overall, different approaches were proposed for image processing based on using entropies for information extraction. The reviewed papers, above, shows that different entropies have shown to give different results in different domains and applications. Thus, there is no best entropy for all applications. The reviewed Literationis summarized in Table 2.2.

Table 2.2: Summery of the Related Works in Entropy-based Thresholding

Author(Year)	Entropy	applications	Feature Threshold	Binraization	Reduce Error	Enhance Quality	Reduce Time	Noise Removal
Chang et al., (1994)	Tsallis	Mammography image		√	√	√		
Sahoo (2006)	Tsallis	Segmentation image		√		√		
Yin (2007)	Minimum	The temperature distribution				√	√	
Abu-Shareha et al., (2008)	Renyi	a novel combination mechanism	√	√				
Bhandari et al., (2014)	Kapur	segmentation purposes		√		√	√	√
El-Sayed et al., (2014)	Tsallis	Canny method Sobel method LOG method		√		√	√	
Phillips et al., (2006)	Maximum	wildlife			√	√		√
El-Sayed (2015)	Haverd tasllis	Brain image		√	√	√	√	

The differences of entropy based thresholding results are caused by many factors, as shown on 2.2. For example, the type of used entropy is indeed affecting the results. Also different images give different results, based on level of details and noise in the image. Maximum Entropy, for instance works based on the distribution of information on image borders. So better results are expected of Maximum entropy when distribution of information in the image is better.

2.3 Brain Tumor Detection

Statistics say that the low survival rate of patients with brain tumor is due to the lack of disease understanding. The most effective way for more success in dealing with the disease is the advances in medical image processing. However, brain images are complex and require careful processing stage in-order to reveal the underlying information. Subsequently, several approaches, techniques and approaches for brain tumor detection were proposed (Prastawa et al., 2004).

Prastawa et al., (2004) proposed an approach for brain tumor detection using image thresholding. As illustrated in Figure 2.2, after the threshold is applied, a graph structure of the brain regions in the image is generated. Based on the edge weights which reflects the region connectivity, the best option for tumor treatment is determined. These options are: surgery, radiation therapy and chemotherapy. The choice of therapy, for example depends on the size and type of tumor grade and location, which all revealed in the constructed graph.
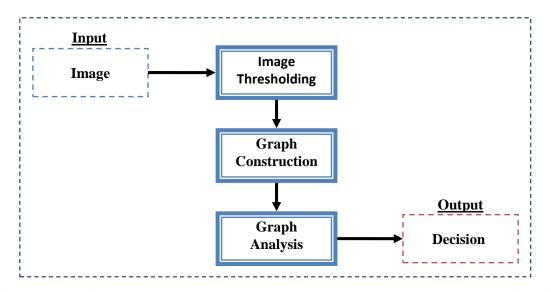
Figure 2.2 Brain Tumor Detection Framework Proposed by Prastawa et al., (2004)

Ahmed& Mohammad (2008)Proposed a brain tumor extraction and segmentation from the MR images. First, the image is enhanced. Then, k-means clustering is implemented over a group of different modality images that represent the same brain view, namely. The proposed framework is illustrated in Figure 2.3.
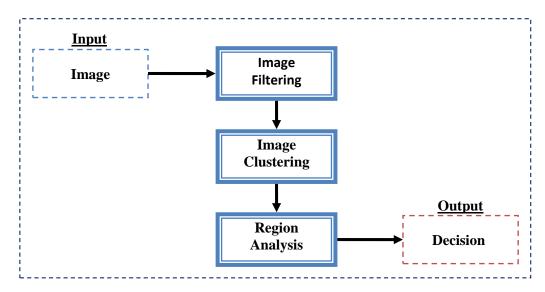
Figure 2.3: Brain Tumor Detection Framework Proposed by Ahmed & Mohammad (2008)

Mustaqeem, (2012) implements an image segmentation for the brain images and tumor identification. The detected tumor is classified into benign tumor, pre-malignant tumor and malignant tumor. This approach as claimed to help in the diagnose is of brain tumor in early stage, which in turn prevent the disease to develop from benign into malignant. The framework, as illustrated in Figure 2.4, is simple in the manner that is depends on two stages, image segmentation and region classification.
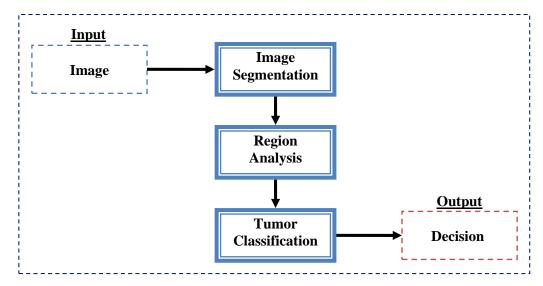
Figure 2.4: Brain Tumor Detection Framework Proposed Mustaqeem, (2012)

Roy &Bandyopadhyay (2012)proposedafully an automatic tumor detection and quantifying framework using image thresholding .The framework consists of four main stages, these are: filtering, segmentation, tumor recognition and tumor analysis. The results show that the proposed framework has achieved a full result for the detection and analysis of tumor in MRI images, which is confirmed by a medical expert. The proposed framework is illustrated in Figure 2.5.
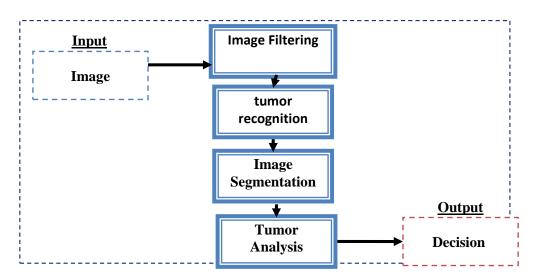
Figure 2.5: Brain Tumor Detection Framework Proposed by Roy et al., (2012)

Several other have proposed automatic detection of brain tumor based on using segmentation with other filtering process. Some of these techniques, are: Karayiannis, (2000), Akram&Usman (2011), Arockiaraj et al. (2012), Cobzas et al. (2007), Menzeet al. (2015), Kharrat et al (2009), Bauer et al. (2013) and Xavierarockiaraj et al (2012). A summary of these approaches is given in Table 2.3.

Table 2.3: Summery of the Related Works of Brain Tumor Detection

Author (Year)	Techniques	Results
Akram&Usman (2011),	The global threshold in addition to noise removal	MRI is better than CT, improving accuracy
Ahmed & Mohammad (2008)	Alberona principle filtering and K-means clustering	High efficient detection
Bauer et al. (2013)	Fragmentation for the tumor and the surrounding tissues	
Bhandari et al. (2014)	Wigheted aggregation and classification	Effective results in terms of the size of the tumor
Cobzas et al. (2007)	Used of priors, logistical system with the three-dimensional images.	Less noise
Kharrat et al. (2009)	K-means, Morphology – threshold	High quality segmentation
Roy &Bandyopadhyay (2012)	Segmentation and region analysis	Effective results in tumor detection
Prastawa et al., (2004)	Thresholding and Graph-based Decision Making	Good results for tumor detection
Mustaqeem et al., (2012)	Threshold and watershed segmentation	Effective results for the heterogeneous images

Menze et al. (2015)	Merge several algorithms into the hierarchy approach and study the neighborhoods relationships	Remove noise and provide primary estimates of the tumor
Xavierarockiaraj et al (2012)	Threshold in addition to Canny filter	Optimal and clear results

2.4 Summary

In summary, brain tumor detection is implemented basically by segmenting the image into regions and recognize the tumor region, if present, in the image. One of the segmentation aapproach is the thresholding, for image thresholding, different entropies were used. The entropies are either run directly on the image histogram or over features extracted from the image.

CHAPTER THREE
PROPOSED WORK

3.1 Introduction

This chapter presents the proposed comparison of using entropies and their aggregation in the segmentation of the brain tumor images .Subsequently ,detection of tumor if presented in brain section.

In order to evaluate the accuracy of the entropies in brain tumor. A framework for brain tumor detection is built. Thresholding based on the entropy is implemented as the main step in this framework. An enhancement is proposed by combining entropies that results in an automatic selection of the optimal entropies result.

3.2. Proposed Framework

The proposed framework is made as simple as possible in-order to give a major rule for the thresholding process, subject matter of this research. The proposed work consists of several processing stages, as illustrated in Figure 3.1.
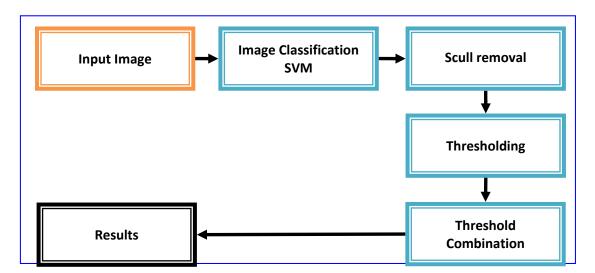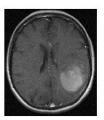
Figure 3.1: The Proposed Work

3.2 Scull Removal

The Scull removal is the process for excluding the outer structure of the brain, which helps in concentration on the interior region of the brain. Technically, the scull is identified and removed as the complete circle with distinguish color in the brain images. To get rid of this structure the white matter, gray and cerebrospinal fluid are isolated in the brain images using the level set approaches.

MATLAB function called, Remove Scull, is used in this step. This function uses few processing steps to remove the scull as illustrated . Example of the input/output of the scull removal is given in Figure 3.2.
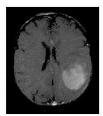
Figure 3.2: Scull Removal Example

3.3 Image Thresholding

The main component of the proposed work is the image thresholding. Thresholding takes as input the image of the brain and produce a thresholded, or so called segmented image.

Five types of entropies, which are discussed in Chapter Two, are used. The differences between the entropy was the calculations, which are implemented according to the equation discussed earlier.

3.4 Threshold Aggregation

The results of several thresholding, using different entropies, are combined. This work propose a combination process based logical operators. Figure 3.3, illustrates an example of such combination.
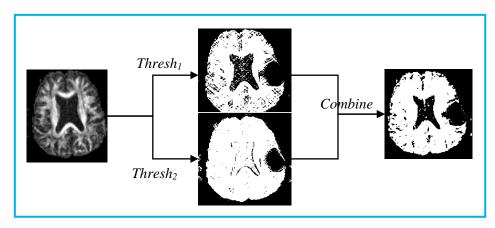
Figure3.3: Threshold Combination

Thelogic operators that are used, AND and OR, which are implemented as follows: The AND takes two inputs, which represents a corresponding pixel in the resulted segmented images from two entropies and produce one output .

Examples of applying AND and OR on input segmented images are given in Figure 3.4 and Figure 3.5, respectively.

0	0	1
1	1	1
0	1	0
1	0	0

1	1	1
0	1	1
1	0	1
0	1	1

0	0	1
0	1	1
0	0	0
0	0	0

=
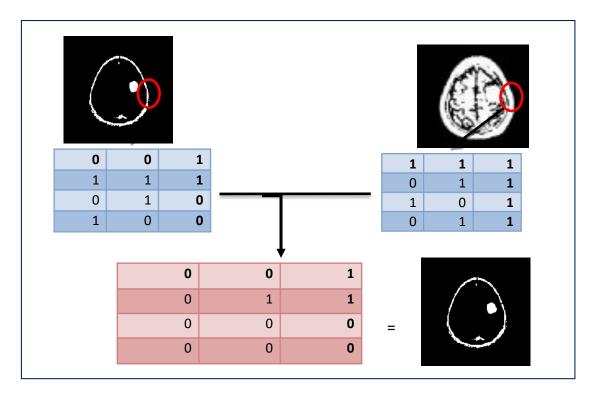
Figure 3.4: Example of Applying AND Operation

0	0	1
1	1	1
0	1	0
1	0	0

1	1	1
0	1	1
1	0	1
0	1	1

1	0	1
1	1	1
1	1	1
1	1	1

=
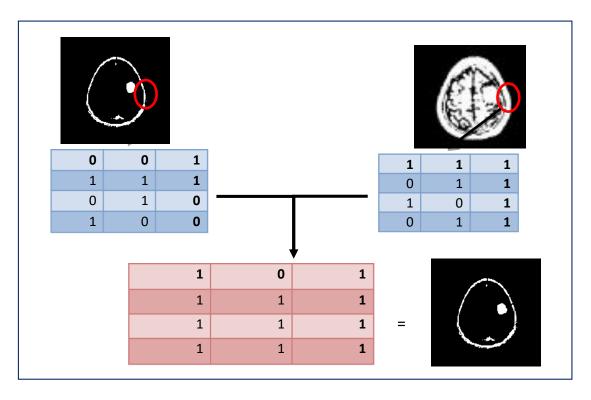
Figure 3.5: Example of Applying OR Operation

3.3 Summary

In summary, brain tumor detection is implemented in the proposed work by, extracting features from the image, segmenting the image, using several thresholding and combined threshold process. The idea of entropy reflects the separation of objects from the background, which contributes significantly to the separation of tumor part from the rest of the brain discussed.

CHAPTER FOUR

EXPERIMENTAL RESULTS

4.1 Introduction

This chapter presents the experiments conducted for entropies comparison and aggregation on brain images. The results are presented and discussed accordingly in this chapter.

In order to experiment the proposed frame work a set of brain images are collected. The underlying images are tested using implemented framework with tools and programming as will be discussed accordingly.

4.2 Dataset
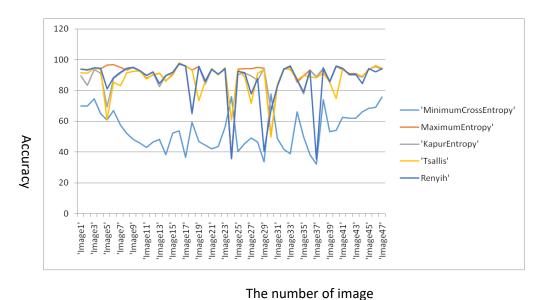
The dataset that is used in the thesis are synthetic images mimics the natural brain images captured using the magnetic resonance images (MRI). Besides the images, the ground truth segmentation is provided for these images (Prastawa et al., 2009). 300 images were used, 150 of these images are with tumor and 150 without. The resolutions of these images are 189x 188 and sizes ranging from 17 KB to 30 KB. The type of images is PNG.

4.3 Software used

The software used in the proposed application is MATLAB program .A pilot program of mathematic programming and engineering calculations (Program version is R-2016).

4.4 Results of Individual Entropies

In this thesis, 5 entropy-based thresholding techniques have been applied on 150

different images of brain tumor. Figure 4.1 illustrates the accuracy rate of all the used

techniques across all the images. It can be clearly seen that minimum cross entropy has

the lowest average accuracy, where at its best value the accuracy never reached 80%,

while all other methods have better accuracy rate.
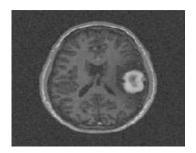
Figure 4.1: Entropies Comparison for Tumor Detection

The average accuracy for these entropies are given in Table 4.1. Example results of

applying the proposed framework with Renyih , Tsallis, maximum, minimum and Kapur

entropies, are illustrated in Figure 4.2, Figure 4.3, Figure 4.4, Figure 4.5 and Figure 4.6,

respectively.

Table 4.1: Average Accuracy of the Entropies

'Renyie'	'Tsallis'	'Kapur'	'Maximim'	'MinCross'
86.35738753	87.71731117	88.24548896	90.36235245	54.2981202
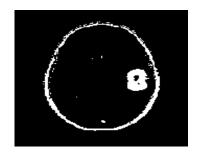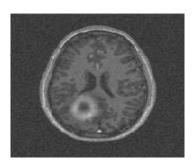
Figure 4.2: Example of Renyi Entropy Output
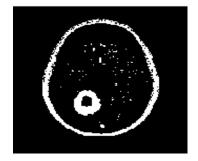
Figure 4.3: Example of Tsallis Entropy Output
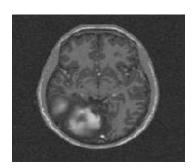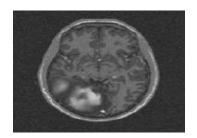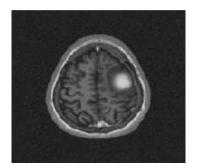
Figure 4.4: Example of Minimum Entropy Output

Figure 4.5: Example of Maximum Entropy Output
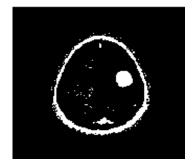
Figure 4.6: Example of Kapur Entropy Output

4.5 Results of Entropies Aggregation

The goal of applying AND and OR logical functions on the threshold images to get the optimal threshold value which will help in detecting the tumor in better way. The use of these functions showed different output rather than the original goal, as it does not enhance the results, however it always produces identical result with the entropy that have the best accuracy. On the other hand, OR-gate produced unstable results .The gate OR always choose worst one .it works unlike AND gate and including the AND choose the best offer and choose the worst between the two sets of entropy, according to the truth table and apply it to the pixels in each image applied by the entropy values.

The results of the aggregations are given in Figure 4.7. Example of the produced aggregation results are given in Figures 4.8 to 4.17
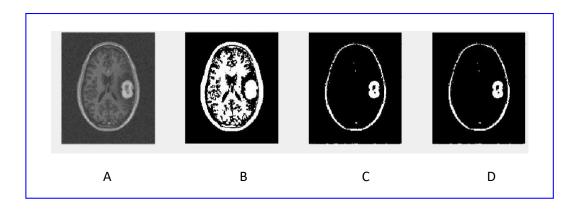
Figure 4.7: Entropies Aggregation Comparison for Tumor Detection

The entropies comparison for tumor detection is given in Figure 4.7. Figure 4.7 (A) illustrates a brain with tumor as captured by Magnetic Resonance. Figure 4.7 (B) is the image after applying minimum cross entropy thresholding. Figure 4.7 (C) gives the result of applying maximum entropy thresholding and Figure 4.7 (D) is the result of merging two entropies by applying the logic gates over the results of these entropies.
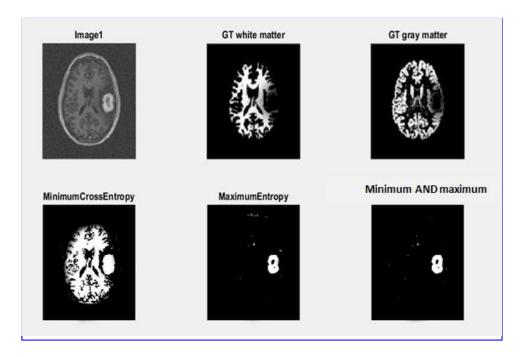
Figure 4.8: Example of Minimum AND Maximum Entropy Output
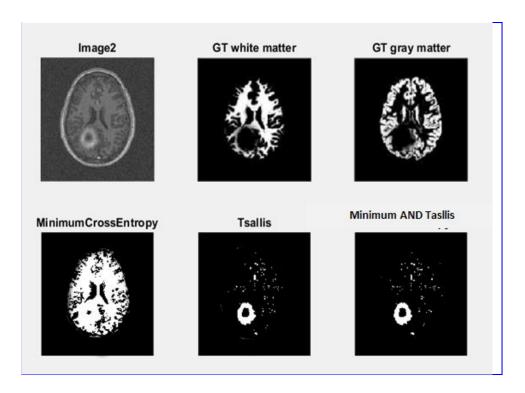
Figure 4.9: Example of Minimum AND Tsallis Entropy Output
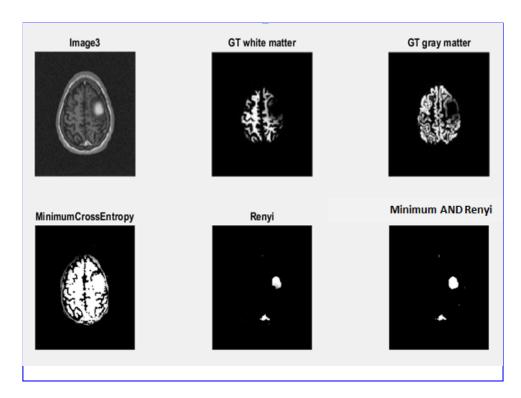
Figure 4.10: Example of Minimum AND Renyih Entropy Output
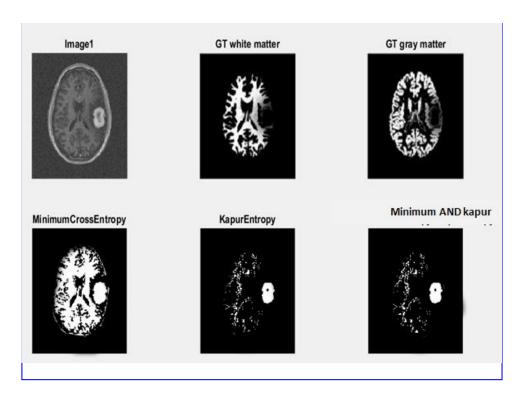
Figure 4.11: Example of Minimum AND Kapur Entropy Output
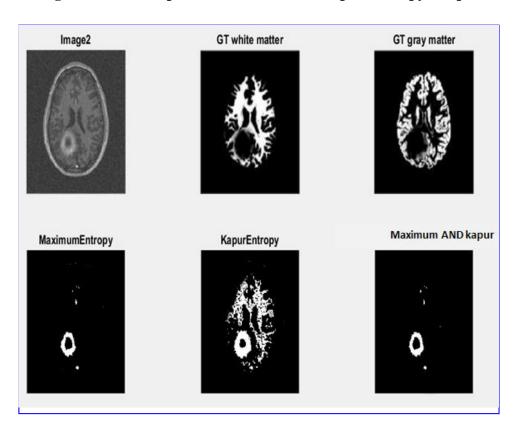
Figure 4.12: Example of Maximum AND Kapur Entropy Output
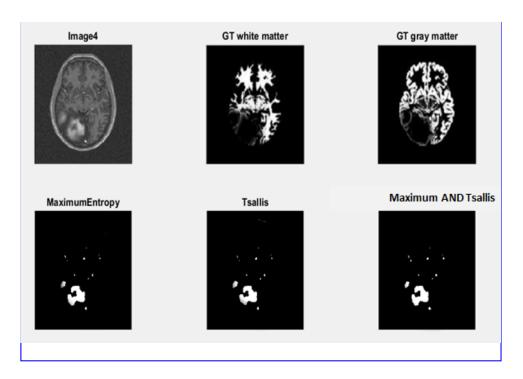
Figure 4.13: Example of Maximum AND Tsallis Entropy Output
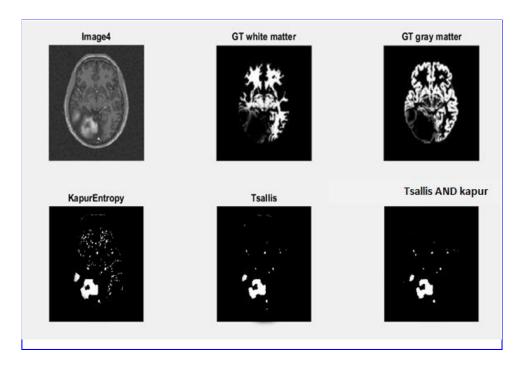
Figure 4.14: Example of Kapur AND Tsallis Entropy Output
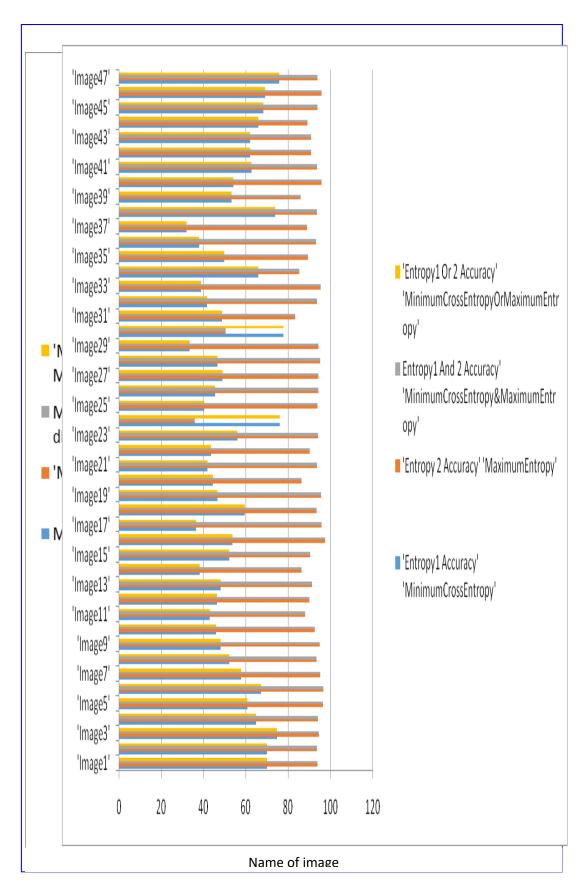
Figure 4.15: Maximum(AND –OR)   Minimum Entropy Scatter
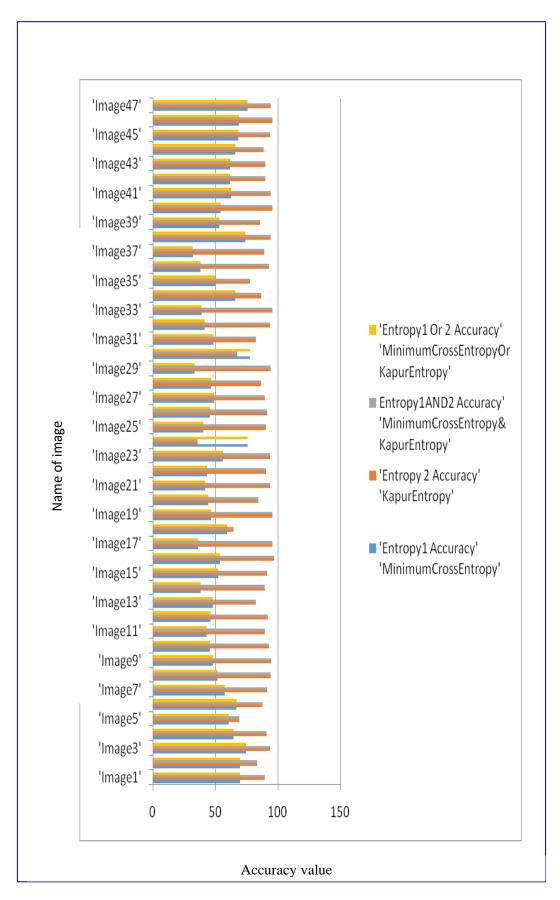
Figure 4.16: Kapur (AND –OR) Minimum Entropy Scatter
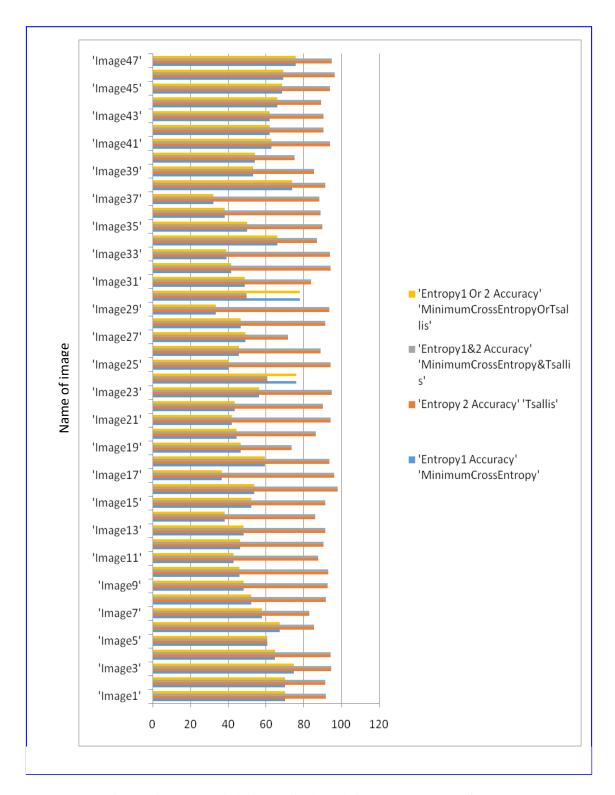
Figure 4.17: Tsallis(AND –OR) Minimum Entropy Scatter
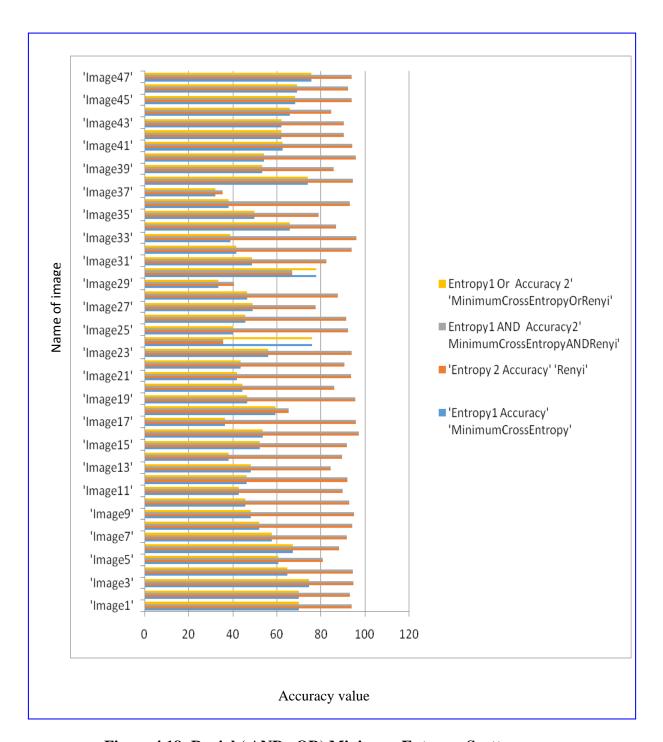
Figure 4.18: Reniyh(AND –OR) Minimum Entropy Scatter
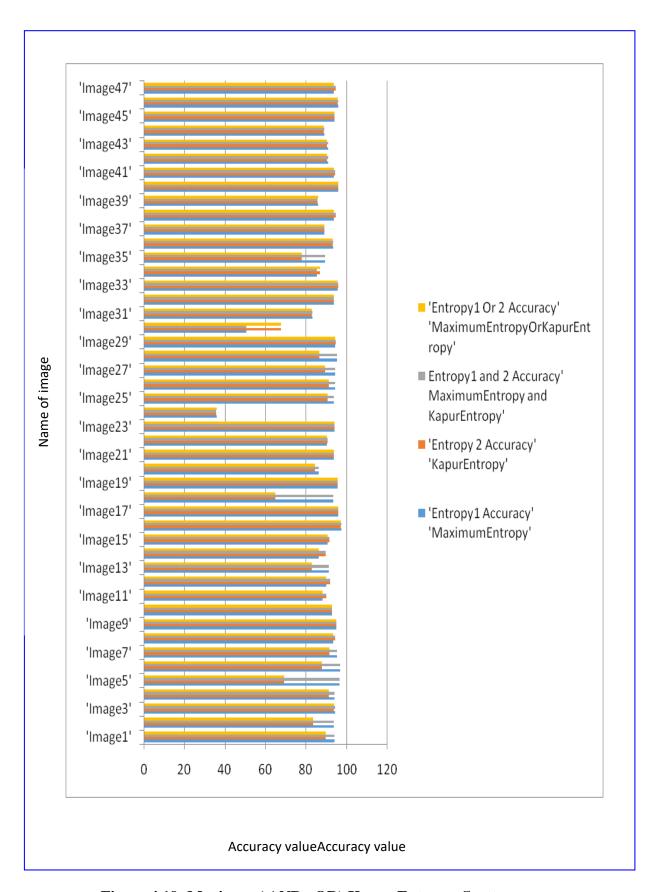
Figure 4.19: Maximum(AND –OR) Kapur Entropy Scatter
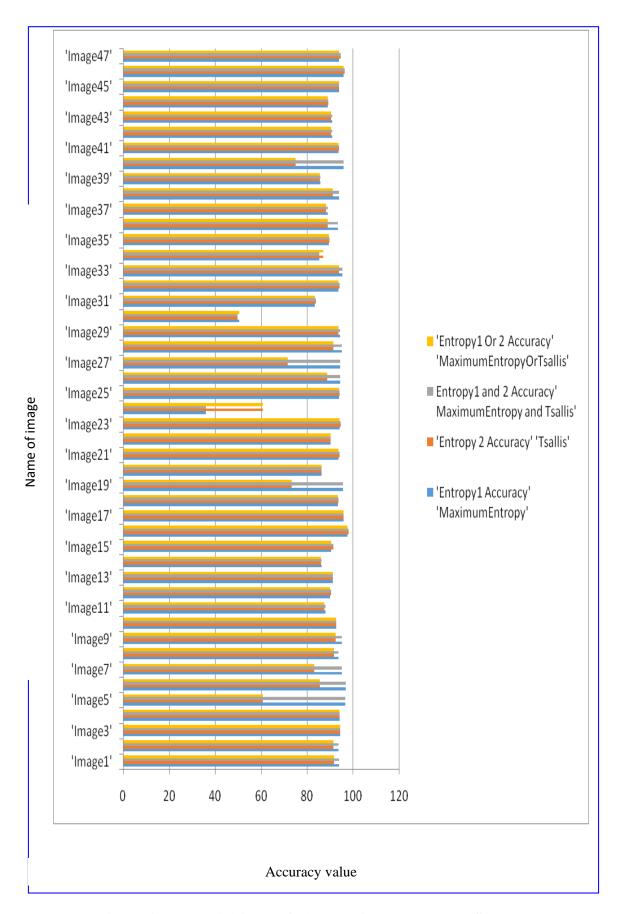
Figure 4.20: Tsallis(AND –OR)   Maximum Entropy Scatter
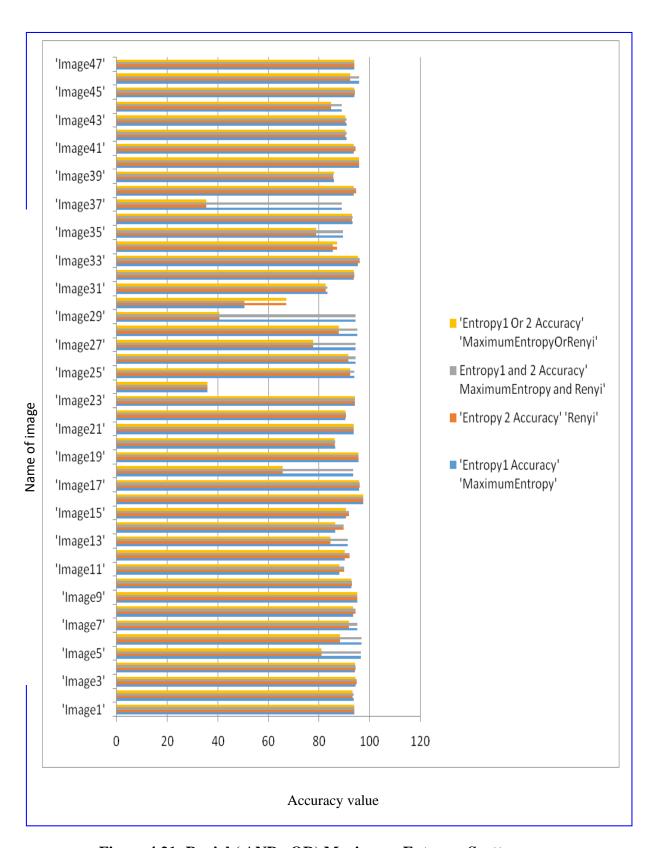
Figure 4.21: Reniyh(AND –OR) Maximum Entropy Scatter
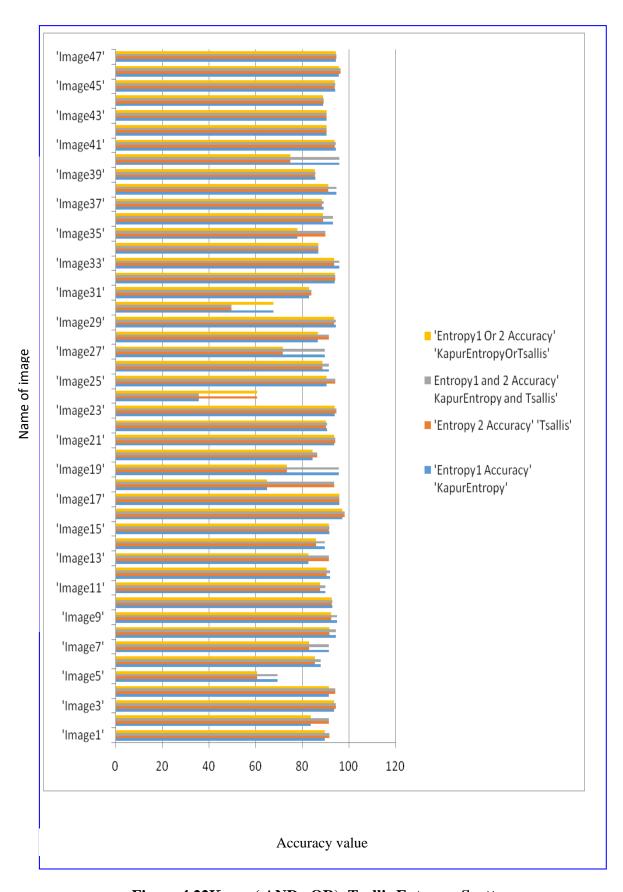
Figure 4.22Kapur(AND –OR) Tsallis Entropy Scatter
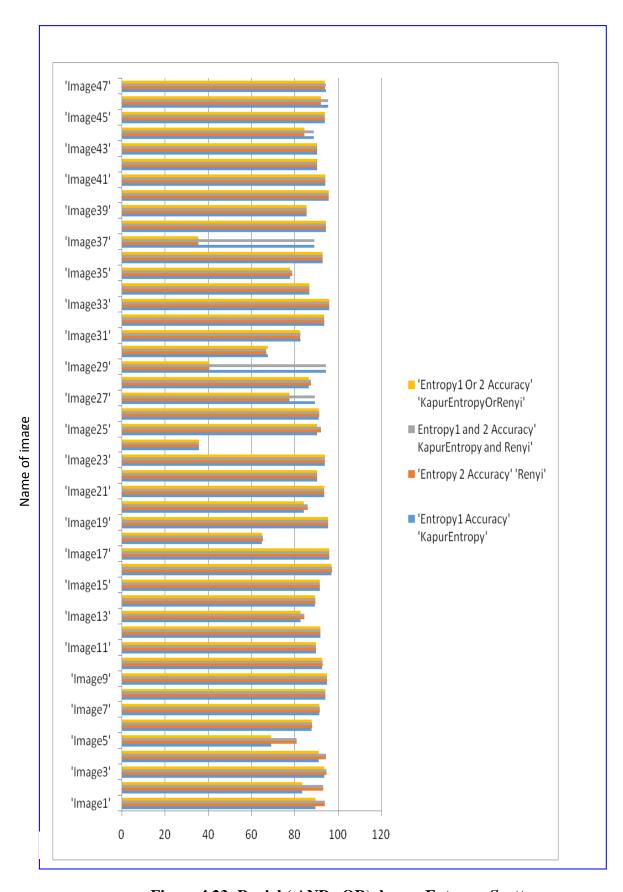
Figure 4.23: Reniyh(AND –OR) kapur Entropy Scatter
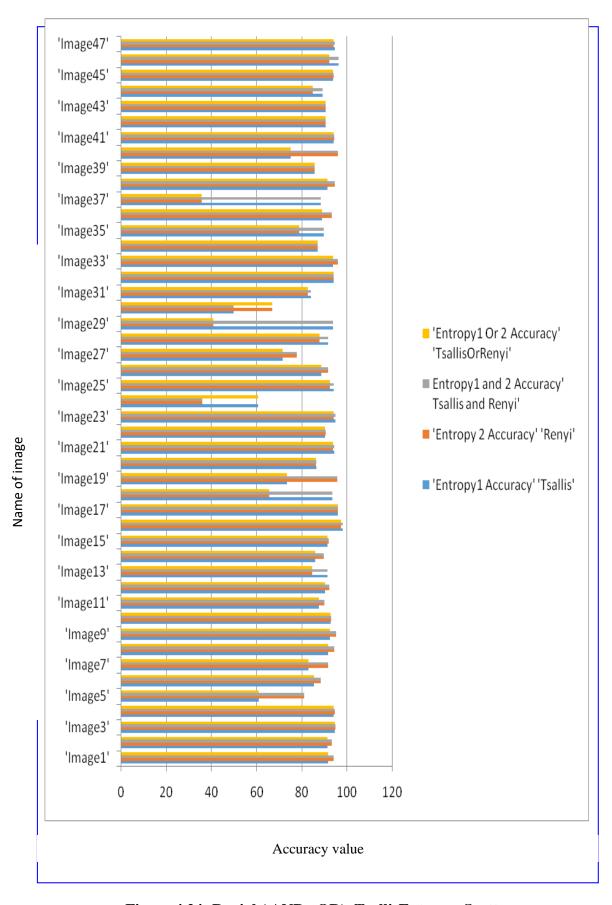
Figure 4.24: Reniyh(AND –OR) TsallisEntropy Scatter

4.6 Discuss the results

After the apply the proposed work on the dataset of approximately 300 different picture of brain tumors 150 image of brain tumor and 150 for normal brain, the results obtained were as follows: The aggregation of the five common types of entropies, Maximum, Minimum, kapur , Tasills and Renyih, helps to get a good value for the threshold, which means a good segmentation output that accurately isolates the brain tumor .The use of the aggregation process based on the logical operators, gives the best results among the aggregated entropies. Aggregation using OR-AND did not improve the result of entropies, however, it works as an automatic selection for the best entropy, as for the AND gate. In general the AND gate give better results for Entropy as shown in Figures 4.15 to Figure 4.23. On the other hand, the OR-gate results for the entropy was give less efficiency.

4.7 Summary

In summary, Maximum entropy was shown to give the best results in brain tumor segmentation. The use of aggregation showed different output rather than the original goal, as it does not enhance the results, however it always produces identical result with the entropy that have the best accuracy. On the other hand, OR-gate produced unstable results.

CHAPTER FIVE

CONCLUSION AND FUTURE WORKS

5.1 Summary

In this thesis, evaluation of the entropies accuracy and their combination in brain tumor detection has been implemented. The findings of this research are as follows:

1. Developed a tumor detection framework that takes as input brain image and produces a segmented image with a detected tumor if tumor is present.

2. Used different entropy based thresholding in the developed tumor detection framework.

3. Compared between different entropies based thresholding and it was found that maximum entropy achieved the best result in the tumor detection framework.

4. The aggregation of the entropies using AND operations has play the roles of automatic selection of the best threshold.

5.3 Conclusion

This thesis has discussed how to detect brain tumor using image processing techniques. More specifically, Entropy-based image thresholding techniques have been used in this thesis to find the optimal thresholding value, in order to be used to segment brain mages into background and objects. The use of these techniques would indeed improve the quality and accuracy of tumor detection on brain images. Applying many

different entropy-based thresholding approaches has resulted in different results, and hence, has made the process of choosing the best thresholding technique even easier.

On the other side, no significant results has been gained by merging entropies using logical gates, AND/OR, for the purpose of improving the accuracy of the tumour detection. However, the merging process has been considered as the automatic selection technique of the best entropy-based thresholding method, where Maximum Entropy gave the best accuracy average rate

5.4 Future Work

The future directions include the following:

1. Evaluates more thresholding techniques in the developed framework.

2. Evaluate the thresholding within the framework with different image modalities and corresponding to different organs.

3. Apply this evaluation technique on real brain images rather than synthetic ones.

4. Experiment on the degree of maligning if possible .

5. Comparison of the five types and choose the best among them and apply it

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http://www.nitrc.org/projects/tumorsim/

APPENDIX A

ACCURACY TABLES

'Image'	'Entropy1 Accuracy'	'Entropy 2 Accuracy'	'Entropy1&2 Accuracy'	'Entropy1 Or 2 Accuracy'	'time'
'-----'	MinimumCrossEntropy	'MaximumEntropy'	'MinimumCrossEntropy&MaximumEntropy'	'MinimumCrossEntropyOrMaximumEntropy'	'time'
'Image 1'	69.9213355	93.84795532	93.84795532	69.9213355	0.155948437
'Image 2'	70.02642167	93.58373867	93.58373867	70.02642167	0.128005074
'Image 3'	74.67723533	94.35236894	94.35236894	74.67723533	0.110635892
'Image 4'	64.84116976	94.06713505	94.06713505	64.84116976	0.11449419
'Image 5'	60.69176725	96.41506035	96.41506035	60.69176725	0.142726647
'Image 6'	67.0990212	96.69729178	96.69729178	67.0990212	0.163034242
'Image 7'	57.68029784	95.09397706	95.09397706	57.68029784	0.163765103
'Image 8'	52.07169879	93.43962049	93.43962049	52.07169879	0.130590672
'Image 9'	48.17450309	94.91082688	94.91082688	48.17450309	0.118095895
'Image 10'	45.83858764	92.57791389	92.57791389	45.83858764	0.117844434
'Image 11'	42.83912809	87.97513961	87.97513961	42.83912809	0.121100594
'Image 12'	46.39404312	89.98078424	89.98078424	46.39404312	0.112627478
'Image 13'	48.11145139	91.20578875	91.20578875	48.11145139	0.115423055
'Image 14'	38.10424548	86.20368702	86.20368702	38.10424548	0.117940228
'Image 15'	52.24283913	90.44616586	90.44616586	52.24283913	0.127172858
'Image 16'	53.70203567	97.39386297	97.39386297	53.70203567	0.117019916
'Image 17'	36.44688645	95.82657779	95.82657779	36.44688645	0.120968877
'Image 18'	59.44574551	93.33453432	93.33453432	59.44574551	0.124077496
'Image 19'	46.640245	95.56236114	95.56236114	46.640245	0.100307184
'Image 20'	44.46045758	86.25172642	86.25172642	44.46045758	0.204605239

'Image 21'	41.92637963	93.52969435	93.52969435	41.92637963	0.118430748
'Image 22'	43.49966973	90.23899598	90.23899598	43.49966973	0.153831548
'Image 23'	56.11301267	94.09115475	94.09115475	56.11301267	0.16932632
'Image 24'	76.01933586	35.93046298	35.93046298	76.01933586	0.166981919
'Image 25'	40.34408215	93.76989131	93.76989131	40.34408215	0.21028791
'Image 26'	45.61340299	94.20224584	94.20224584	45.61340299	0.174470575
'Image 27'	48.95214076	94.27130247	94.27130247	48.95214076	0.24443055
'Image 28'	46.57419084	95.10598691	95.10598691	46.57419084	0.119406228
'Image 29'	33.42640966	94.34336156	94.34336156	33.42640966	0.163791618
'Image 30'	77.80580076	50.4984087	50.4984087	77.80580076	0.135767428
'Image 31'	48.7509758	83.24025701	83.24025701	48.7509758	0.151870753
'Image 32'	41.68318021	93.62577313	93.62577313	41.68318021	0.108436038
'Image 33'	38.94193238	95.35519126	95.35519126	38.94193238	0.128881765
'Image 34'	65.97910286	85.26091395	85.26091395	65.97910286	0.15437082
'Image 35'	49.8738966	89.37728938	89.37728938	49.8738966	0.141763142
'Image 36'	38.10124302	93.18441122	93.18441122	38.10124302	0.130529517
'Image 37'	32.06929682	88.96595208	88.96595208	32.06929682	0.137097433
'Image 38'	73.89959767	93.6918273	93.6918273	73.89959767	0.1905337
'Image 39'	53.21563682	85.78033988	85.78033988	53.21563682	0.184837344
'Image 40'	54.18843452	95.75151624	95.75151624	54.18843452	0.151463626
'Image 41'	62.66138233	93.63778298	93.63778298	62.66138233	0.215573718
'Image 42'	61.96781361	90.80946376	90.80946376	61.96781361	0.162016852
'Image 43'	61.96781361	90.80946376	90.80946376	61.96781361	0.162078007
'Image 44'	65.95208071	88.9959767	88.9959767	65.95208071	0.192083519
'Image 45'	68.33603555	93.88398487	93.88398487	68.33603555	0.155861195
'Image 46'	69.02059689	95.74851378	95.74851378	69.02059689	0.195499195

'Image'	'Entropy1 Accuracy'	'Entropy2 Accuracy'	'Entropy1&2 Accuracy'	'Entropy1 Or 2 Accuracy'	'time'
'Image 47'	75.71908965	93.76388639	93.76388639	75.71908965	0.213663813
'=========='	'==========='	'==========='	'==========='	'==========='	'=========='
'Image'	'Entropy1 Accuracy'	'Entropy2 Accuracy'	'Entropy1&2 Accuracy'	'Entropy1 Or 2 Accuracy'	'time'
'-----'	'MinimumCrossEntropy'	'KapurEntropy'	'MinimumCrossEntropy&KapurEntropy'	'MinimumCrossEntropyOrKapurEntropy'	'time'
'Image 1'	69.92133355	89.60847895	89.60847895	69.9213355	0.96762559
'Image 2'	70.02642167	83.51648352	83.51648352	70.02642167	0.92361451 7
'Image 3'	74.67723533	93.64679037	93.64679037	74.67723533	0.92172343
'Image 4'	64.84116976	91.1937789	91.1937789	64.84116976	0.95055174
'Image 5'	60.69176725	69.2728037	69.2728037	60.69176725	0.94971925
'Image 6'	67.0990212	87.7709722	87.7709722	67.0990212	0.96719805 6
'Image 7'	57.68029784	91.33789708	91.33789708	57.68029784	0.96025423 2
'Image 8'	52.07169879	94.21125323	94.21125323	52.07169879	0.93319525 8
'Image 9'	48.17450309	94.8777998	94.8777998	48.17450309	0.94013608 8
'Image 10'	45.83858764	92.79409115	92.79409115	45.83858764	0.91119244 1
'Image 11'	42.83912809	89.78562421	89.78562421	42.83912809	0.94551384 2
'Image 12'	46.39404312	91.91737225	91.91737225	46.39404312	0.92758272 2
'Image 13'	48.11145139	82.64576953	82.64576953	48.11145139	0.95935615 8
'Image 14'	38.10424548	89.46736324	89.46736324	38.10424548	0.94737242 7
'Image 15'	52.24283913	91.54806942	91.54806942	52.24283913	0.94349018 1
'Image 16'	53.70203567	97.14766108	97.14766108	53.70203567	0.91909292 8
'Image 17'	36.44688645	95.89863688	95.89863688	36.44688645	0.93160951 6
'Image 18'	59.44574551	64.80814268	64.80814268	59.44574551	1.10638586 3
'Image 19'	46.640245	95.56836606	95.56836606	46.640245	0.95251240 5
'Image 20'	44.46045758	84.31513841	84.31513841	44.46045758	1.01518344

'Image 21'	41.92637963	93.63478052	93.63478052	41.92637963	0.939883772
'Image 22'	43.49966973	90.46117817	90.46117817	43.49966973	0.94981861
'Image 23'	56.11301267	93.88398487	93.88398487	56.11301267	0.967953721
'Image 24'	76.01933586	35.75031526	35.75031526	76.01933586	0.99447214
'Image 25'	40.34408215	90.4191437	90.4191437	40.34408215	1.035204079
'Image 26'	45.61340299	91.27484537	91.27484537	45.61340299	0.982176649
'Image 27'	48.95214076	89.45235093	89.45235093	48.95214076	1.060071324
'Image 28'	46.57419084	86.64204648	86.64204648	46.57419084	0.923437896
'Image 29'	33.42640966	94.42442803	94.42442803	33.42640966	0.957496289
'Image 30'	77.80580076	67.59442743	67.59442743	77.80580076	0.954629722
'Image 31'	48.7509758	82.73284093	82.73284093	48.7509758	0.972662195
'Image 32'	41.68318021	93.79090855	93.79090855	41.68318021	0.919890076
'Image 33'	38.94193238	95.92265658	95.92265658	38.94193238	0.942793532
'Image 34'	65.97910286	86.88824836	86.88824836	65.97910286	0.96716812
'Image 35'	49.8738966	77.84783522	77.84783522	49.8738966	0.941600377
'Image 36'	38.10124302	92.93820933	92.93820933	38.10124302	0.929015364
'Image 37'	32.06929682	89.08605056	89.08605056	32.06929682	0.927562195
'Image 38'	73.89959767	94.55053144	94.55053144	73.89959767	1.013165767
'Image 39'	53.21563682	85.63021678	85.63021678	53.21563682	1.016261984
'Image 40'	54.18843452	95.79355071	95.79355071	54.18843452	0.98797436
'Image 41'	62.66138233	94.21425569	94.21425569	62.66138233	0.982053485
'Image 42'	61.96781361	90.26601813	90.26601813	61.96781361	0.986708075
'Image 43'	61.96781361	90.26601813	90.26601813	61.96781361	0.977680719
'Image 44'	65.95208071	88.73776497	88.73776497	65.95208071	1.018071818
'Image 45'	68.33603555	93.98907104	93.98907104	68.33603555	0.97282
'Image 46'	69.02059689	95.58938329	95.58938329	69.02059689	1.037366727

'Image 47'	75.71908965	94.42442803	94.42442803	75.71908965	1.045673485
'=========='	'==========='	'=========='	'==========='	'==========='	'=========='
'Image'	'Entropy1 Accuracy'	'Entropy2 Accuracy'	'Entropy1&2 Accuracy'	'Entropy1 Or 2 Accuracy'	'time'
'-----'	'MinimumCrossEntropy'	'Tsallis'	'MinimumCrossEntropy&Tsallis'	'MinimumCrossEntropyOrTsallis'	'time'
'Image 1'	69.92133555	91.50903741	91.50903741	69.9213355	0.205761616
'Image 2'	70.02642167	91.28985768	91.28985768	70.02642167	0.201161766
'Image 3'	74.67723533	94.35236894	94.35236894	74.67723533	0.175285684
'Image 4'	64.84116976	93.95604396	93.95604396	64.84116976	0.185267564
'Image 5'	60.69176725	60.69176725	60.69176725	60.69176725	0.207163467
'Image 6'	67.0990212	85.36299766	85.36299766	67.0990212	0.242718222
'Image 7'	57.68029784	82.90698373	82.90698373	57.68029784	0.228841266
'Image 8'	52.07169879	91.59310635	91.59310635	52.07169879	0.192714309
'Image 9'	48.17450309	92.34972678	92.34972678	48.17450309	0.179854315
'Image 10'	45.83858764	92.6799976	92.6799976	45.83858764	0.19065216
'Image 11'	42.83912809	87.46472107	87.46472107	42.83912809	0.187190726
'Image 12'	46.39404312	90.25100582	90.25100582	46.39404312	0.20369348
'Image 13'	48.11145139	91.20578875	91.20578875	48.11145139	0.19717731
'Image 14'	38.10424548	85.8974359	85.8974359	38.10424548	0.1875491
'Image 15'	52.24283913	91.2328109	91.2328109	52.24283913	0.188935128
'Image 16'	53.70203567	97.96733321	97.96733321	53.70203567	0.181365218
'Image 17'	36.44688645	95.85359995	95.85359995	36.44688645	0.191329565
'Image 18'	59.44574551	93.50867712	93.50867712	59.44574551	0.216006504
'Image 19'	46.640245	73.32912989	73.32912989	46.640245	0.170470723
'Image 20'	44.46045758	86.23371164	86.23371164	44.46045758	0.26891419

'Image 21'	41.92637963	94.10016213	94.10016213	41.92637963	0.175588035
'Image 22'	43.49966973	90.12790488	90.12790488	43.49966973	0.237067625
'Image 23'	56.11301267	94.64961268	94.64961268	56.11301267	0.238602905
'Image 24'	76.01933586	60.6167057	60.6167057	76.01933586	0.232409187
'Image 25'	40.34408215	94.00108089	94.00108089	40.34408215	0.287511167
'Image 26'	45.61340299	88.62667387	88.62667387	45.61340299	0.238945883
'Image 27'	48.95214076	71.51864529	71.51864529	48.95214076	0.309110278
'Image 28'	46.57419084	91.36491923	91.36491923	46.57419084	0.193009391
'Image 29'	33.42640966	93.53569927	93.53569927	33.42640966	0.221956031
'Image 30'	77.80580076	49.60967994	49.60967994	77.80580076	0.221323103
'Image 31'	48.7509758	83.86777157	83.86777157	48.7509758	0.236590791
'Image 32'	41.68318021	94.04611782	94.04611782	41.68318021	0.196058139
'Image 33'	38.94193238	93.67681499	93.67681499	38.94193238	0.199331405
'Image 34'	65.97910286	86.88824836	86.88824836	65.97910286	0.243263909
'Image 35'	49.8738966	89.70155528	89.70155528	49.8738966	0.224444552
'Image 36'	38.10124302	88.81582898	88.81582898	38.10124302	0.192381167
'Image 37'	32.06929682	88.23935627	88.23935627	32.06929682	0.197367616
'Image 38'	73.89959767	91.15174443	91.15174443	73.89959767	0.26263879
'Image 39'	53.21563682	85.44106167	85.44106167	53.21563682	0.272679259
'Image 40'	54.18843452	74.94145199	74.94145199	54.18843452	0.227195225
'Image 41'	62.66138233	93.85696271	93.85696271	62.66138233	0.273690661
'Image 42'	61.96781361	90.37410677	90.37410677	61.96781361	0.239682304
'Image 43'	61.96781361	90.37410677	90.37410677	61.96781361	0.249042375
'Image 44'	65.95208071	89.04701856	89.04701856	65.95208071	0.277016102
'Image 45'	68.33603555	93.71584699	93.71584699	68.33603555	0.222916115
'Image 46'	69.02059689	96.22290278	96.22290278	69.02059689	0.283829918

'Image 47'	75.71908965	94.56554375	94.56554375	75.71908965	0.274577189
'================'	'==========='	'==========='	'==========='	'==========='	'=========='
'Image'	'Entropy1 Accuracy'	'Entropy2 Accuracy'	'Entropy1&2 Accuracy'	'Entropy1 Or 2 Accuracy'	'time'
'-----'	'MinimumCrossEntropy'	'Renyi'	'MinimumCrossEntropy&Renyi'	'MinimumCrossEntropyOrRenyi'	'time'
'Image 1'	69.92133555	93.84795532	93.84795532	69.9213355	0.13960306
'Image 2'	70.02642167	93.12436198	93.12436198	70.02642167	0.136075339
'Image 3'	74.67723533	94.72467423	94.72467423	74.67723533	0.110521708
'Image 4'	64.84116976	94.38539602	94.38539602	64.84116976	0.124705293
'Image 5'	60.69176725	80.84429232	80.84429232	60.69176725	0.145712958
'Image 6'	67.0990212	88.18831442	88.18831442	67.0990212	0.173432657
'Image 7'	57.68029784	91.6051162	91.6051162	57.68029784	0.165729747
'Image 8'	52.07169879	94.23827539	94.23827539	52.07169879	0.127662523
'Image 9'	48.17450309	94.91082688	94.91082688	48.17450309	0.123329101
'Image 10'	45.83858764	92.88116255	92.88116255	45.83858764	0.116286917
'Image 11'	42.83912809	89.76160452	89.76160452	42.83912809	0.121525683
'Image 12'	46.39404312	91.95039933	91.95039933	46.39404312	0.124987972
'Image 13'	48.11145139	84.44424428	84.44424428	48.11145139	0.13711625
'Image 14'	38.10424548	89.55143217	89.55143217	38.10424548	0.11928178
'Image 15'	52.24283913	91.62913589	91.62913589	52.24283913	0.129334651
'Image 16'	53.70203567	97.27076202	97.27076202	53.70203567	0.109221639
'Image 17'	36.44688645	95.90764427	95.90764427	36.44688645	0.127040285
'Image 18'	59.44574551	65.43265478	65.43265478	59.44574551	0.124848985
'Image 19'	46.640245	95.56836606	95.56836606	46.640245	0.106559491
'Image 20'	44.46045758	86.02053684	86.02053684	44.46045758	0.222108276

'Image 21'	41.92637963	93.6678076	93.6678076	41.92637963	0.116159476
'Image 22'	43.49966973	90.50021017	90.50021017	43.49966973	0.153063053
'Image 23'	56.11301267	93.98907104	93.98907104	56.11301267	0.169693248
'Image 24'	76.01933586	35.75632018	35.75632018	76.01933586	0.171454328
'Image 25'	40.34408215	92.27466523	92.27466523	40.34408215	0.2107656
'Image 26'	45.61340299	91.45199063	91.45199063	45.61340299	0.186244327
'Image 27'	48.95214076	77.58662103	77.58662103	48.95214076	0.245991061
'Image 28'	46.57419084	87.59983186	87.59983186	46.57419084	0.115367032
'Image 29'	33.42640966	40.66234312	40.66234312	33.42640966	0.155266756
'Image 30'	77.80580076	66.91887348	66.91887348	77.80580076	0.13458197
'Image 31'	48.7509758	82.55569567	82.55569567	48.7509758	0.159220848
'Image 32'	41.68318021	93.8179307	93.8179307	41.68318021	0.120662676
'Image 33'	38.94193238	95.9286615	95.9286615	38.94193238	0.132664368
'Image 34'	65.97910286	86.93028283	86.93028283	65.97910286	0.156966254
'Image 35'	49.8738966	78.82964031	78.82964031	49.8738966	0.145450805
'Image 36'	38.10124302	93.0042635	93.0042635	38.10124302	0.129384687
'Image 37'	32.06929682	35.44706659	35.44706659	32.06929682	0.138557017
'Image 38'	73.89959767	94.55653636	94.55653636	73.89959767	0.183402563
'Image 39'	53.21563682	85.59418723	85.59418723	53.21563682	0.195683514
'Image 40'	54.18843452	95.79355071	95.79355071	54.18843452	0.159255488
'Image 41'	62.66138233	94.23227046	94.23227046	62.66138233	0.207566745
'Image 42'	61.96781361	90.37410677	90.37410677	61.96781361	0.160544011
'Image 43'	61.96781361	90.37410677	90.37410677	61.96781361	0.164391617
'Image 44'	65.95208071	84.57635261	84.57635261	65.95208071	0.211233454
'Image 45'	68.33603555	94.00108089	94.00108089	68.33603555	0.169200162
'Image 46'	69.02059689	92.15156428	92.15156428	69.02059689	0.204613364

'Image'	'Entropy1 Accuracy'	'Entropy2 Accuracy'	'Entropy1&2 Accuracy'	'Entropy1 Or 2 Accuracy'	'time'
'Image 47'	75.71908965	93.93502672	93.93502672	75.71908965	0.216851976
'==========='	'==========='	'==========='	'==========='	'==========='	'==========='
'Image'	'Entropy1 Accuracy'	'Entropy2 Accuracy'	'Entropy1&2 Accuracy'	'Entropy1 Or 2 Accuracy'	'time'
'-----'	'Maximum Entropy'	'KapurEntropy'	'MaximumEntropy& KapurEntropy'	'MaximumEntropyOrKapurEntropy'	'time'
'Image 1'	93.84795532	89.60847895	93.84795532	89.60847895	0.949670642
'Image 2'	93.58373867	83.51648352	93.58373867	83.51648352	0.940914847
'Image 3'	94.35236894	93.64679037	94.35236894	93.64679037	0.907398292
'Image 4'	94.06713505	91.1937789	94.06713505	91.1937789	0.94000266
'Image 5'	96.41506035	69.2728037	96.41506035	69.2728037	0.963750734
'Image 6'	96.69729178	87.7709722	96.69729178	87.7709722	0.987313206
'Image 7'	95.09397706	91.33789708	95.09397706	91.33789708	0.974252642
'Image 8'	93.43962049	94.21125323	94.21125323	93.43962049	0.94606295
'Image 9'	94.91082688	94.8777998	94.91082688	94.8777998	0.924517296
'Image 10'	92.57791389	92.79409115	92.79409115	92.57791389	0.933535671
'Image 11'	87.97513961	89.78562421	89.78562421	87.97513961	0.926164193
'Image 12'	89.98078424	91.91737225	91.91737225	89.98078424	0.907901641
'Image 13'	91.20578875	82.64576953	91.20578875	82.64576953	0.935368597
'Image 14'	86.20368702	89.46736324	89.46736324	86.20368702	0.905902357
'Image 15'	90.44616586	91.54806942	91.54806942	90.44616586	0.924201259
'Image 16'	97.39386297	97.14766108	97.39386297	97.14766108	0.925084366
'Image 17'	95.82657779	95.89863688	95.89863688	95.82657779	0.912749959
'Image 18'	93.33453432	64.80814268	93.33453432	64.80814268	0.939739653
'Image 19'	95.56236114	95.56836606	95.56836606	95.56236114	0.896240362
'Image 20'	86.25172642	84.31513841	86.25172642	84.31513841	1.017435896
'Image 21'	93.52969435	93.63478052	93.63478052	93.52969435	0.953540914

'Image 22'	90.23899598	90.46117817	90.46117817	90.23899598	0.95760363
'Image 23'	94.09115475	93.88398487	94.09115475	93.88398487	0.97494 0738
'Image 24'	35.93046298	35.75031526	35.75031526	35.93046298	0.96897 667
'Image 25'	93.76989131	90.4191437	93.76989131	90.4191437	1.00912 5289
'Image 26'	94.20224584	91.27484537	94.20224584	91.27484537	0.99232 9592
'Image 27'	94.27130247	89.45235093	94.27130247	89.45235093	1.05713 5905
'Image 28'	95.10598691	86.64204648	95.10598691	86.64204648	0.93719 9813
'Image 29'	94.34336156	94.42442803	94.42442803	94.34336156	0.97088 187
'Image 30'	50.4984087	67.59442743	50.4984087	67.59442743	0.94894 0636
'Image 31'	83.24025701	82.73284093	83.24025701	82.73284093	0.97340 8452
'Image 32'	93.62577313	93.79090855	93.79090855	93.62577313	0.92676 8896
'Image 33'	95.35519126	95.92265658	95.92265658	95.35519126	0.95689 7573
'Image 34'	85.26091395	86.88824836	85.26091395	86.88824836	0.96470 3548
'Image 35'	89.37728938	77.84783522	89.37728938	77.84783522	0.92865 1003
'Image 36'	93.18441122	92.93820933	93.18441122	92.93820933	0.93083 3323
'Image 37'	88.96595208	89.08605056	89.08605056	88.96595208	0.96785 5788
'Image 38'	93.6918273	94.55053144	94.55053144	93.6918273	0.99929 9502
'Image 39'	85.78033988	85.63021678	85.63021678	85.78033988	1.00375 7371
'Image 40'	95.75151624	95.79355071	95.79355071	95.75151624	0.96683 8398
'Image 41'	93.63778298	94.21425569	94.21425569	93.63778298	1.03062 8177
'Image 42'	90.80946376	90.26601813	90.80946376	90.26601813	0.97840 5593
'Image 43'	90.80946376	90.26601813	90.80946376	90.26601813	0.97726 119
'Image 44'	88.9959767	88.73776497	88.9959767	88.73776497	0.99827 0138
'Image 45'	93.88398487	93.98907104	93.98907104	93.88398487	0.97361 1588
'Image 46'	95.74851378	95.58938329	95.74851378	95.58938329	1.00896 8339
'Image 47'	93.76388639	94.42442803	94.42442803	93.76388639	1.01438 5437

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'Image'	'Entropy1 Accuracy'	'Entropy2 Accuracy'	'Entropy1&2 Accuracy'	'Entropy1 Or 2 Accuracy'	'time'
'-----'	'Maximum Entropy'	'Tsallis'	'MaximumEntropy&Tsallis'	'MaximumEntropyOrTsallis'	'time'
'Image 1'	93.84795532	91.50903741	93.84795532	91.50903741	0.205875372
'Image 2'	93.58373867	91.28985768	93.58373867	91.28985768	0.186016387
'Image 3'	94.35236894	94.35236894	94.35236894	94.35236894	0.176600721
'Image 4'	94.06713505	93.95604396	94.06713505	93.95604396	0.183028366
'Image 5'	96.41506035	60.69176725	96.41506035	60.69176725	0.205697896
'Image 6'	96.69729178	85.36299766	96.69729178	85.36299766	0.254987198
'Image 7'	95.09397706	82.90698373	95.09397706	82.90698373	0.223394233
'Image 8'	93.43962049	91.59310635	93.43962049	91.59310635	0.183341409
'Image 9'	94.91082688	92.34972678	94.91082688	92.34972678	0.182298788
'Image 10'	92.57791389	92.6799976	92.6799976	92.57791389	0.191001554
'Image 11'	87.97513961	87.46472107	87.97513961	87.46472107	0.186104056
'Image 12'	89.98078424	90.25100582	90.25100582	89.98078424	0.177721603
'Image 13'	91.20578875	91.20578875	91.20578875	91.20578875	0.193801834
'Image 14'	86.20368702	85.8974359	86.20368702	85.8974359	0.176868005
'Image 15'	90.44616586	91.2328109	91.2328109	90.44616586	0.187431067
'Image 16'	97.39386297	97.96733321	97.96733321	97.39386297	0.172758674
'Image 17'	95.82657779	95.85359995	95.85359995	95.82657779	0.188669127
'Image 18'	93.33453432	93.50867712	93.50867712	93.33453432	0.199650863
'Image 19'	95.56236114	73.32912989	95.56236114	73.32912989	0.157730045
'Image 20'	86.25172642	86.23371164	86.23371164	86.25172642	0.280391577
'Image 21'	93.52969435	94.10016213	94.10016213	93.52969435	0.186221233
'Image 22'	90.23899598	90.12790488	90.23899598	90.12790488	0.228236135

'Image 23'	94.09115475	94.64961268	94.64961268	94.09115475	0.231384954
'Image 24'	35.93046298	60.6167057	35.93046298	60.6167057	0.230181535
'Image 25'	93.76989131	94.00108089	94.00108089	93.76989131	0.308228455
'Image 26'	94.20224584	88.62667387	94.20224584	88.62667387	0.233558294
'Image 27'	94.27130247	71.51864529	94.27130247	71.51864529	0.305328103
'Image 28'	95.10598691	91.36491923	95.10598691	91.36491923	0.192429919
'Image 29'	94.34336156	93.53569927	94.34336156	93.53569927	0.226687171
'Image 30'	50.4984087	49.60967994	49.60967994	50.4984087	0.211928392
'Image 31'	83.24025701	83.86777157	83.86777157	83.24025701	0.237245102
'Image 32'	93.62577313	94.04611782	94.04611782	93.62577313	0.186585167
'Image 33'	95.35519126	93.67681499	95.35519126	93.67681499	0.19579898
'Image 34'	85.26091395	86.88824836	85.26091395	86.88824836	0.248635248
'Image 35'	89.37728938	89.70155528	89.70155528	89.37728938	0.220209491
'Image 36'	93.18441122	88.81582898	93.18441122	88.81582898	0.20014908
'Image 37'	88.96595208	88.23935627	88.96595208	88.23935627	0.203195262
'Image 38'	93.6918273	91.15174443	93.6918273	91.15174443	0.269077554
'Image 39'	85.78033988	85.44106167	85.78033988	85.44106167	0.250239807
'Image 40'	95.75151624	74.94145199	95.75151624	74.94145199	0.215719975
'Image 41'	93.63778298	93.85696271	93.85696271	93.63778298	0.277544255
'Image 42'	90.80946376	90.37410677	90.80946376	90.37410677	0.248527907
'Image 43'	90.80946376	90.37410677	90.80946376	90.37410677	0.242215729
'Image 44'	88.9959767	89.04701856	89.04701856	88.9959767	0.280102483
'Image 45'	93.88398487	93.71584699	93.88398487	93.71584699	0.215558322
'Image 46'	95.74851378	96.22290278	96.22290278	95.74851378	0.282730847
'Image 47'	93.76388639	94.56554375	94.56554375	93.76388639	0.27378389
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'Image'	'Entropy1 Accuracy'	'Entropy2 Accuracy'	'Entropy1&2 Accuracy'	'Entropy1 Or 2 Accuracy'	'time'
'-----'	'Maximum Entropy'	'Renyi'	'MaximumEntropy& Renyi'	'MaximumEntropyOrRenyi'	'time'
'Image 1'	93.84795532	93.84795532	93.84795532	93.84795532	0.135808483
'Image 2'	93.58373867	93.12436198	93.58373867	93.12436198	0.127077491
'Image 3'	94.35236894	94.72467423	94.72467423	94.35236894	0.114722985
'Image 4'	94.06713505	94.38539602	94.38539602	94.06713505	0.121718982
'Image 5'	96.41506035	80.84429232	96.41506035	80.84429232	0.152414301
'Image 6'	96.69729178	88.18831442	96.69729178	88.18831442	0.166659468
'Image 7'	95.09397706	91.6051162	95.09397706	91.6051162	0.15640731
'Image 8'	93.43962049	94.23827539	94.23827539	93.43962049	0.118149779
'Image 9'	94.91082688	94.91082688	94.91082688	94.91082688	0.114015217
'Image 10'	92.57791389	92.88116255	92.88116255	92.57791389	0.111775163
'Image 11'	87.97513961	89.76160452	89.76160452	87.97513961	0.116681642
'Image 12'	89.98078424	91.95039933	91.95039933	89.98078424	0.110507168
'Image 13'	91.20578875	84.44424428	91.20578875	84.44424428	0.12073666
'Image 14'	86.20368702	89.55143217	89.55143217	86.20368702	0.115868243
'Image 15'	90.44616586	91.62913589	91.62913589	90.44616586	0.123376571
'Image 16'	97.39386297	97.27076202	97.39386297	97.27076202	0.108740528
'Image 17'	95.82657779	95.90764427	95.90764427	95.82657779	0.120362463
'Image 18'	93.33453432	65.43265478	93.33453432	65.43265478	0.117748212
'Image 19'	95.56236114	95.56836606	95.56836606	95.56236114	0.093208122
'Image 20'	86.25172642	86.02053684	86.25172642	86.02053684	0.202789846
'Image 21'	93.52969435	93.6678076	93.6678076	93.52969435	0.119342935
'Image 22'	90.23899598	90.50021017	90.50021017	90.23899598	0.148034265
'Image 23'	94.09115475	93.98907104	94.09115475	93.98907104	0.161932177

'Image 24'	35.93046298	35.75632018	35.75632018	35.93046298	0.175529447
'Image 25'	93.76989131	92.27466523	93.76989131	92.27466523	0.208630321
'Image 26'	94.20224584	91.45199063	94.20224584	91.45199063	0.163609437
'Image 27'	94.27130247	77.58662103	94.27130247	77.58662103	0.250875302
'Image 28'	95.10598691	87.59983186	95.10598691	87.59983186	0.112561192
'Image 29'	94.34336156	40.66234312	94.34336156	40.66234312	0.15773646
'Image 30'	50.4984087	66.91887348	50.4984087	66.91887348	0.136165574
'Image 31'	83.24025701	82.55569567	83.24025701	82.55569567	0.157255349
'Image 32'	93.62577313	93.8179307	93.8179307	93.62577313	0.114935957
'Image 33'	95.35519126	95.9286615	95.9286615	95.35519126	0.153024564
'Image 34'	85.26091395	86.93028283	85.26091395	86.93028283	0.157957129
'Image 35'	89.37728938	78.82964031	89.37728938	78.82964031	0.140951026
'Image 36'	93.18441122	93.0042635	93.18441122	93.0042635	0.128167582
'Image 37'	88.96595208	35.44706659	88.96595208	35.44706659	0.144428712
'Image 38'	93.6918273	94.55653636	94.55653636	93.6918273	0.181365646
'Image 39'	85.78033988	85.59418723	85.59418723	85.78033988	0.193023931
'Image 40'	95.75151624	95.79355071	95.79355071	95.75151624	0.153623708
'Image 41'	93.63778298	94.23227046	94.23227046	93.63778298	0.19971159
'Image 42'	90.80946376	90.37410677	90.80946376	90.37410677	0.160371238
'Image 43'	90.80946376	90.37410677	90.80946376	90.37410677	0.166222405
'Image 44'	88.9959767	84.57635261	88.9959767	84.57635261	0.194519866
'Image 45'	93.88398487	94.00108089	94.00108089	93.88398487	0.166322049
'Image 46'	95.74851378	92.15156428	95.74851378	92.15156428	0.198793416
'Image 47'	93.76388639	93.93502672	93.93502672	93.76388639	0.205259122
'==========='	'==========='	'==========='	'==========='	'==========='	'==========='

'Image'	'Entropy1 Accuracy'	'Entropy 2 Accuracy'	'Entropy1&2 Accuracy'	'Entropy1 Or 2 Accuracy'	'time'
'-----'	'KapurEntropy'	'Tsallis'	'KapurEntropy&Tsallis'	'KapurEntropyOrTsallis'	'time'
'Image1'	89.60847895	91.50903741	91.50903741	89.60847895	1.405840989
'Image2'	83.51648352	91.28985768	91.28985768	83.51648352	1.42441359
'Image3'	93.64679037	94.35236894	94.35236894	93.64679037	1.412863929
'Image4'	91.1937789	93.95604396	93.95604396	91.1937789	1.402831585
'Image5'	69.2728037	60.69176725	69.2728037	60.69176725	1.39091072
'Image6'	87.7709722	85.36299766	87.7709722	85.36299766	1.436451204
'Image7'	91.33789708	82.90698373	91.33789708	82.90698373	1.432355131
'Image8'	94.21125323	91.59310635	94.21125323	91.59310635	1.409460228
'Image9'	94.8777998	92.34972678	94.8777998	92.34972678	1.40367663
'Image10'	92.79409115	92.6799976	92.79409115	92.6799976	1.398957464
'Image11'	89.78562421	87.46472107	89.78562421	87.46472107	1.407512262
'Image12'	91.91737225	90.25100582	91.91737225	90.25100582	1.396549343
'Image13'	82.64576953	91.20578875	91.20578875	82.64576953	1.388765606
'Image14'	89.46736324	85.8974359	89.46736324	85.8974359	1.370952519
'Image15'	91.54806942	91.2328109	91.54806942	91.2328109	1.389168456
'Image16'	97.14766108	97.96733321	97.96733321	97.14766108	1.379311878
'Image17'	95.89863688	95.85359995	95.89863688	95.85359995	1.419057647
'Image18'	64.80814268	93.50867712	93.50867712	64.80814268	1.381164477
'Image19'	95.56836606	73.32912989	95.56836606	73.32912989	1.382807098
'Image20'	84.31513841	86.23371164	86.23371164	84.31513841	1.47231045
'Image21'	93.63478052	94.10016213	94.10016213	93.63478052	1.383316434
'Image22'	90.46117817	90.12790488	90.46117817	90.12790488	1.470914586
'Image23'	93.88398487	94.64961268	94.64961268	93.88398487	1.427838673
'Image24'	35.75031526	60.6167057	35.75031526	60.6167057	1.443599447

'Image25'	90.41914 37	94.00108 089	94.00108089	90.4191437	1.491756 321
'Image26'	91.27484 537	88.62667 387	91.27484537	88.62667387	1.445201 44
'Image27'	89.45235 093	71.51864 529	89.45235093	71.51864529	1.552835 626
'Image28'	86.64204 648	91.36491 923	91.36491923	86.64204648	1.416723 509
'Image29'	94.42442 803	93.53569 927	94.42442803	93.53569927	1.423611 738
'Image30'	67.59442 743	49.60967 994	49.60967994	67.59442743	1.446556 677
'Image31'	82.73284 093	83.86777 157	83.86777157	82.73284093	1.438922 619
'Image32'	93.79090 855	94.04611 782	94.04611782	93.79090855	1.386333 108
'Image33'	95.92265 658	93.67681 499	95.92265658	93.67681499	1.425380 516
'Image34'	86.88824 836	86.88824 836	86.88824836	86.88824836	1.433944 295
'Image35'	77.84783 522	89.70155 528	89.70155528	77.84783522	1.448164 657
'Image36'	92.93820 933	88.81582 898	92.93820933	88.81582898	1.378303 042
'Image37'	89.08605 056	88.23935 627	89.08605056	88.23935627	1.393861 963
'Image38'	94.55053 144	91.15174 443	94.55053144	91.15174443	1.521995 333
'Image39'	85.63021 678	85.44106 167	85.63021678	85.44106167	1.472030 764
'Image40'	95.79355 071	74.94145 199	95.79355071	74.94145199	1.450727 162
'Image41'	94.21425 569	93.85696 271	94.21425569	93.85696271	1.558432 767
'Image42'	90.26601 813	90.37410 677	90.37410677	90.26601813	1.586040 849
'Image43'	90.26601 813	90.37410 677	90.37410677	90.26601813	1.470924 422
'Image44'	88.73776 497	89.04701 856	89.04701856	88.73776497	1.505524 225
'Image45'	93.98907 104	93.71584 699	93.98907104	93.71584699	1.443672 576
'Image46'	95.58938 329	96.22290 278	96.22290278	95.58938329	1.482124 262
'Image47'	94.42442 803	94.56554 375	94.56554375	94.42442803	1.485495 889
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'Image'	'Entropy1 Accuracy'	'Entropy 2 Accuracy'	'Entropy1&2 Accuracy'	'Entropy1 Or 2 Accuracy'	'time'
'-----'	'KapurEntropy'	'Renyi'	'KapurEntropy&Renyi'	'KapurEntropyOrRenyi'	'time'
'Image1'	89.60847895	93.84795532	93.84795532	89.60847895	1.340952994
'Image2'	83.51648352	93.12436198	93.12436198	83.51648352	1.347713354
'Image3'	93.64679037	94.72467423	94.72467423	93.64679037	1.331234548
'Image4'	91.1937789	94.38539602	94.38539602	91.1937789	1.352936724
'Image5'	69.2728037	80.84429232	80.84429232	69.2728037	1.36490121
'Image6'	87.7709722	88.18831442	88.18831442	87.7709722	1.380392133
'Image7'	91.33789708	91.6051162	91.6051162	91.33789708	1.353628241
'Image8'	94.21125323	94.23827539	94.23827539	94.21125323	1.320296861
'Image9'	94.8777998	94.91082688	94.91082688	94.8777998	1.360062301
'Image10'	92.79409115	92.88116255	92.88116255	92.79409115	1.317507699
'Image11'	89.78562421	89.76160452	89.76160452	89.78562421	1.33772121
'Image12'	91.91737225	91.95039933	91.95039933	91.91737225	1.3311905
'Image13'	82.64576953	84.44424428	84.44424428	82.64576953	1.333752577
'Image14'	89.46736324	89.55143217	89.55143217	89.46736324	1.314288745
'Image15'	91.54806942	91.62913589	91.62913589	91.54806942	1.358207136
'Image16'	97.14766108	97.27076202	97.27076202	97.14766108	1.306642712
'Image17'	95.89863688	95.90764427	95.90764427	95.89863688	1.315338636
'Image18'	64.80814268	65.43265478	65.43265478	64.80814268	1.340583072
'Image19'	95.56836606	95.56836606	95.56836606	95.56836606	1.306231309
'Image20'	84.31513841	86.02053684	86.02053684	84.31513841	1.438918342
'Image21'	93.63478052	93.6678076	93.6678076	93.63478052	1.338797616
'Image22'	90.46117817	90.50021017	90.50021017	90.46117817	1.375150802
'Image23'	93.88398487	93.98907104	93.98907104	93.88398487	1.36980726
'Image24'	35.75031526	35.75632018	35.75632018	35.75031526	1.390235454

'Image25'	90.4191437	92.27466523	92.27466523	90.4191437	1.422784227
'Image26'	91.27484537	91.45199063	91.45199063	91.27484537	1.39196446
'Image27'	89.45235093	77.58662103	89.45235093	77.58662103	1.40661376
'Image28'	86.64204648	87.59983186	87.59983186	86.64204648	1.334483438
'Image29'	94.42442803	40.66234312	94.42442803	40.66234312	1.376674534
'Image30'	67.59442743	66.91887348	66.91887348	67.59442743	1.365363932
'Image31'	82.73284093	82.55569567	82.73284093	82.55569567	1.365147966
'Image32'	93.79090855	93.8179307	93.8179307	93.79090855	1.334940173
'Image33'	95.92265658	95.9286615	95.9286615	95.92265658	1.326652232
'Image34'	86.88824836	86.93028283	86.93028283	86.88824836	1.365269848
'Image35'	77.84783522	78.82964031	78.82964031	77.84783522	1.364817817
'Image36'	92.93820933	93.0042635	93.0042635	92.93820933	1.325473189
'Image37'	89.08605056	35.44706659	89.08605056	35.44706659	1.413085453
'Image38'	94.55053144	94.55653636	94.55653636	94.55053144	1.408870492
'Image39'	85.63021678	85.59418723	85.59418723	85.63021678	1.407134643
'Image40'	95.79355071	95.79355071	95.79355071	95.79355071	1.376700193
'Image41'	94.21425569	94.23227046	94.23227046	94.21425569	1.395121832
'Image42'	90.26601813	90.37410677	90.37410677	90.26601813	1.364900354
'Image43'	90.26601813	90.37410677	90.37410677	90.26601813	1.37279015
'Image44'	88.73776497	84.57635261	88.73776497	84.57635261	1.393048992
'Image45'	93.98907104	94.00108089	94.00108089	93.98907104	1.369304339
'Image46'	95.58938329	92.15156428	95.58938329	92.15156428	1.385920849
'Image47'	94.42442803	93.93502672	94.42442803	93.93502672	1.412570985
'==========='	'==========='	'==========='	'==========='	'==========='	'==========='

'Image'	'Entropy1 Accuracy'	'Entropy 2 Accuracy'	'Entropy1&2 Accuracy'	'Entropy1 Or 2 Accuracy'	'time'
'-----'	'Tsallis'	'Renyi'	'Tsallis&Renyi'	'TsallisOrRenyi'	'time'
'Image1'	91.50903741	93.84795532	93.84795532	91.50903741	0.251967531
'Image2'	91.28985768	93.12436198	93.12436198	91.28985768	0.228292158
'Image3'	94.35236894	94.72467423	94.72467423	94.35236894	0.216261813
'Image4'	93.95604396	94.38539602	94.38539602	93.95604396	0.225599219
'Image5'	60.69176725	80.84429232	80.84429232	60.69176725	0.262075997
'Image6'	85.36299766	88.18831442	88.18831442	85.36299766	0.280734556
'Image7'	82.90698373	91.6051162	91.6051162	82.90698373	0.260133591
'Image8'	91.59310635	94.23827539	94.23827539	91.59310635	0.221178983
'Image9'	92.34972678	94.91082688	94.91082688	92.34972678	0.223784254
'Image10'	92.6799976	92.88116255	92.88116255	92.6799976	0.230496289
'Image11'	87.46472107	89.76160452	89.76160452	87.46472107	0.219753184
'Image12'	90.25100582	91.95039933	91.95039933	90.25100582	0.211445142
'Image13'	91.20578875	84.44424428	91.20578875	84.44424428	0.242248658
'Image14'	85.8974359	89.55143217	89.55143217	85.8974359	0.218331233
'Image15'	91.2328109	91.62913589	91.62913589	91.2328109	0.22640663
'Image16'	97.96733321	97.27076202	97.96733321	97.27076202	0.204987562
'Image17'	95.85359995	95.90764427	95.90764427	95.85359995	0.220759027
'Image18'	93.50867712	65.43265478	93.50867712	65.43265478	0.267057315
'Image19'	73.32912989	95.56836606	95.56836606	73.32912989	0.200390277
'Image20'	86.23371164	86.02053684	86.23371164	86.02053684	0.312723957
'Image21'	94.10016213	93.6678076	94.10016213	93.6678076	0.210501737
'Image22'	90.12790488	90.50021017	90.50021017	90.12790488	0.281413244
'Image23'	94.64961268	93.98907104	94.64961268	93.98907104	0.274816675
'Image24'	60.6167057	35.75632018	35.75632018	60.6167057	0.274635777

'Image25'	94.00108089	92.27466523	94.00108089	92.27466523	0.334535185
'Image26'	88.62667387	91.45199063	91.45199063	88.62667387	0.259516913
'Image27'	71.51864529	77.58662103	77.58662103	71.51864529	0.328179813
'Image28'	91.36491923	87.59983186	91.36491923	87.59983186	0.225996509
'Image29'	93.53569927	40.66234312	93.53569927	40.66234312	0.267327165
'Image30'	49.60967994	66.91887348	49.60967994	66.91887348	0.254243935
'Image31'	83.86777157	82.55569567	83.86777157	82.55569567	0.276378041
'Image32'	94.04611782	93.8179307	94.04611782	93.8179307	0.235696138
'Image33'	93.67681499	95.9286615	95.9286615	93.67681499	0.242947017
'Image34'	86.88824836	86.93028283	86.93028283	86.88824836	0.277463428
'Image35'	89.70155528	78.82964031	89.70155528	78.82964031	0.259403585
'Image36'	88.81582898	93.0042635	93.0042635	88.81582898	0.226762438
'Image37'	88.23935627	35.44706659	88.23935627	35.44706659	0.24944437
'Image38'	91.15174443	94.55653636	94.55653636	91.15174443	0.300609792
'Image39'	85.44106167	85.59418723	85.59418723	85.44106167	0.299945645
'Image40'	74.94145199	95.79355071	95.79355071	74.94145199	0.272030507
'Image41'	93.85696271	94.23227046	94.23227046	93.85696271	0.321219311
'Image42'	90.37410677	90.37410677	90.37410677	90.37410677	0.287054005
'Image43'	90.37410677	90.37410677	90.37410677	90.37410677	0.28652072
'Image44'	89.04701856	84.57635261	89.04701856	84.57635261	0.326333629
'Image45'	93.71584699	94.00108089	94.00108089	93.71584699	0.253232532
'Image46'	96.22290278	92.15156428	96.22290278	92.15156428	0.322710542
'Image47'	94.56554375	93.93502672	94.56554375	93.93502672	0.318615751
'========'	'========'	'========'	'========'	'========'	'========'
'==========='	'==========='	'==========='	'==========='	'=========='	'==========='

'Image'	'Entropy1 Accuracy'	'Entropy 2 Accuracy'	'Entropy1&2 Accuracy'	'Entropy1 Or 2 Accuracy'	'time'
'----'	MinimumCrossEntropy	'MaximumEntropy'	'MinimumCrossEntropy&MaximumEntropy'	'MinimumCrossEntropyOrMaximumEntropy'	'time'
'Image 1'	69.9213355	93.84795532	93.84795532	69.9213355	0.15594843 7
'Image 2'	70.02642167	93.58373867	93.58373867	70.02642167	0.12800507 4
'Image 3'	74.67723533	94.35236894	94.35236894	74.67723533	0.11063589 2
'Image 4'	64.84116976	94.06713505	94.06713505	64.84116976	0.11449419
'Image 5'	60.69176725	96.41506035	96.41506035	60.69176725	0.14272664 7
'Image 6'	67.0990212	96.69729178	96.69729178	67.0990212	0.16303424 2

APPENDIX B

ENTROPY-BASED THRESHOLDING IMAGES

Image4   MinimumCrossEntropy   MaximumEntropy   MinimumCrossEntropy&MaximumEntropy

Image5   MinimumCrossEntropy   MaximumEntropy   MinimumCrossEntropy&MaximumEntropy

Image3   MinimumCrossEntropy   KapurEntropy   MinimumCrossEntropy&KapurEntropy

Image3   MinimumCrossEntropy   KapurEntropy   MinimumCrossEntropy&KapurEntropy

Image4   MinimumCrossEntropy   KapurEntropy   MinimumCrossEntropy&KapurEntropy

Image5   MinimumCrossEntropy   KapurEntropy   MinimumCrossEntropy&KapurEntropy