International Journal of Science and Research (IJSR)
ISSN: 2319-7064
ResearchGate Impact Factor (2018): 0.28 | SJIF (2018): 7.426

Feature Extraction Techniques for Efficient Analysis and Classification of Biomedical Images

Dr Ibrahim M. Adekunle

Department of Information and Communication Technology, Osun State University, Osogbo, Nigeria

Abstract: ***This paper develops and evaluates different techniques for detection, classification and analysis of pattern in medical images. The research work studies the structure of fractal and multi-fractal images; and extracts the statistical self-similarity features characterized by the Holder exponent for pattern classification. The effectiveness of local and global features has recently attracted growing attention in the field of texture image classification and retrieval. Global features from multi-fractal descriptors are extracted and combined with local features from fractal descriptors to generate new descriptors for efficient discrimination of images. The experimental approaches are validated for different scales of images during the classification process in order to determine the appropriate image size that could yield the maximum classification accuracy. The experimental results show that the descriptors extracted from the combined features considerably improve the performance of the classifiers. The results achieved in this paper have greatly demonstrated the effectiveness of local and global features in the analysis and classification of biomedical images.***

Keywords: Global features, feature extraction, biomedical images, Local Features, Machine Learning and Multi-fractal Analysis

1. Introduction

1.1 Local and Global Features

This section introduces the reader to different learning techniques in the extractions of features in digital images. It explains how useful features can be obtained and combined to generate powerful features for accurate discrimination or detection of patterns. The theory and applications of machine learning are discussed in this section; different algorithmic steps that are involved in machine learning for analyzing images are thoroughly explained. The fundamental principles or general approach of image analysis that have been discussed in this section have been implemented and applied in the remaining sections of for identification and analysis of emphysema patterns.

1.2 What are features?

Features are the general information extracted from images or objects, which can be difficult to identify by human. When you consider image or object as data with certain dimension, features extraction would be of course smaller than the original image. This is simply because after preprocessing of images with image processing algorithms, some unwanted materials must have been eliminated while only useful information would be extracted as features and used for further experiments. This process would help us to focus on the important features in order to achieve accurate results since the inclusion of unwanted materials could make our experimental results to be erroneous. Additionally, processing of images or objects without feature extraction could increase the time and space complexity since the original image would occupy more memory and eventually consume more time than reduced features with smaller dimensions. This is why dimensional reduction is another stage in image processing, although, one must be very careful at this stage to ensure the important information are not being removed during this process. Some factors must be taken into consideration before you remove regions or parts of image. In computing, we can develop an algorithm or construct a model to achieve favourable results in this process.

There are two major types of features that can be extracted from images; local and global features. Global features are those features extracted from a complete image but when the same image is subdivided into various parts or sections or regions, the features extracted are called local features. Take for instance, image patches are smaller portions or fractional parts of the original image; that is they are smaller in sizes and dimensions compared to the original size; features extracted in these patches can be referred to as local features. In other words, several smaller images can be obtained from one image, which means you can extract local features from global features during the classification process.

Global descriptors describe the general properties of the entire image but not to focus on a particular section or region. A very good example is the multi-fractal descriptors that was previously implemented and used in the analysis and classification of biomedical images by [7-12]. It is a global representation of shapes, objects or images while local descriptors describe the image patches by focusing on certain regions within the images or shapes. Example of local descriptors can be found in local binary patterns (LBP) [3] and natural fractal objects. In this text, both descriptors would be used extensively in future extractions for efficient analysis and classification of image patterns. The remaining part of this paper can be described as follows: section 2 describes various techniques for feature extractions in biomedical images; section 3 explains the theory of machine learning approach in image classification. Implementations and computational aspect of local and global features for image analysis are contained in section 4. Section 5 discusses and analyzes some of the results generated in the analysis and classification of images. This paper also combines the features from local descriptors with that of global descriptors to generate new descriptors for further analysis and classification of biomedical images. Hopefully, hybrid concatenation of features from local and global descriptors could yield powerful features for efficient classification and analysis of images.

2. Techniques in Feature Extraction

Feature extraction technique involves processing of pixels or developing algorithms to manipulate pixels within images in order to detect or identify certain region. Basically in all digital images, arrangement of pixel gives useful information that could be used to process such image. For instance, in order to classify images, models could be developed to further refine or process the pixels for easy classification. In local binary patterns for instance [13-14], the algorithm is concern with the relationship between the centre pixel and its neighborhood. Various features can be derived or obtained from images but this depends on the model definition and how the pixel is processed. Most digital images have discrete pixels and this makes it easy for processing and manipulation to obtain discriminating features that can be used for classification, detection or identification. Pixel manipulation, arrangement or computation requires that one must be very good in Mathematics. The knowledge of mathematics cannot be overemphasized in developing image processing algorithms. Features extracted within certain region of an image can be used to detect the characteristics that the entire image possesses and this could be used in matching technique during recognition process. This technique would help the programmer or analyst to easily differentiate between closely related objects. Since you are not generally looking at the overview of images or objects, selecting small patches in an image would go a long way in helping us to identify the similarities and differences in images.

Transformation of pixels to another meaningful information using mathematical models that would allow further techniques such as machine learning, deep learning or even reinforcement learning involves feature extraction techniques. What you are trying to achieve would determine the methods or techniques you use for gathering information during this process. It is very important to study the data very well and probably visualize the contents of the object to understand how the data are arranged.

3. Efficient methods in Machine learning for image classification

In machine learning, the use of correlation or regression and other plots could be used to visualize the data. Combination of pixels in an image is like a very large matrix; features are attributes extracted from this matrix by using various mathematical techniques or operations for further processing, analysis or recognition. Various methods or techniques could be used to extract these features, which can also be grouped under local and global features as previously discussed. Computer vision is all about features since pixels are what the intelligent system or model uses to differentiate images. Feature extraction helps us to understand the underlining structure of the objects or images and uses these features or properties to identify the similarities and differences between the images. In order to find the characteristic properties of a line, circle, edges etc, the image pixels must be involved and used for the computation by extracting the useful features and the relationships between the pixels and its neighboring elements.

Machine learning technique is a very wide area that can be applied on different kind of features such as images, natural languages, metadata or patterns. Machine learning normally applies two types of techniques: supervised learning that trains models on input and output data to make future predictions, and unsupervised learning, which finds hidden patterns within input data. Example to illustrate this technique is presented in Figure 1-1.

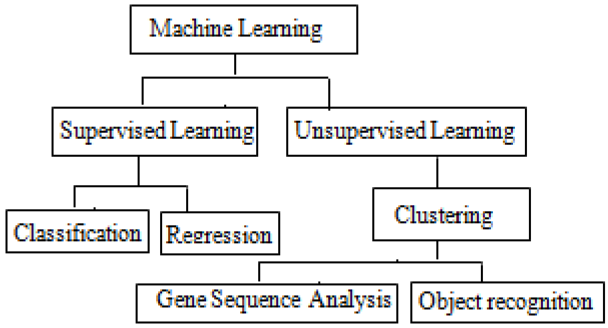

Figure 1.1: Overview of Machine Learning Techniques

Supervised learning builds predictive model, it uses the information from the input and output data to generate models through the use of classification and regression techniques. Unsupervised learning uses the information from the hidden patterns to draw inferences in the analysis of data. The most common languages used in Machine learning are Python and R but machine learning can also be done using java, in these languages, special libraries have been created for the development and use of scientific technologies. Most of the in-built libraries in these languages are free, Scikit-learn and PyTorch are popular tools for machine learning and both support Python programming language.

3.1 Classification Technique

It generates model to predict discrete responses for a particular events. It could be used to determine whether the patient has a particular disease or not. For example, it could be used to determine if certain part of the body is healthy or unhealthy. The percentage of classification accuracy would help the researcher to take a decision on the experiment conducted and use for further analysis. Many factors could be responsible for improving the classification accuracy or the predictive models in research; some of these factors would be further discussed and analyzed in the following section. The structure of the datasets would determine how effective the classifier can be. Some are saying SVM [2] is the best linear classifier while regression logistics is the best in non linear; this is not true. It all depends on the data structure; the performance of the algorithm on a particular data cannot be generalized as this can be varied from one data to the other.

3.2 Regression Techniques

This is when a model is built to predict continuous responses for certain event or experiment in research. A very good example is the changes in temperatures or fluctuations in power supply. Regression gives the linear trend of the outcomes while residuals are the left-over points after fitting the regression models.

3.3 Methods in Supervised Learning

There are general methods for solving problems and analyze data in machine learning; a very good example to illustrate these techniques could be to train input data for building the classification models in solving problems in health related issues. In this case, supervised learning algorithms would be developed as shown in the Figure 1-2 below.

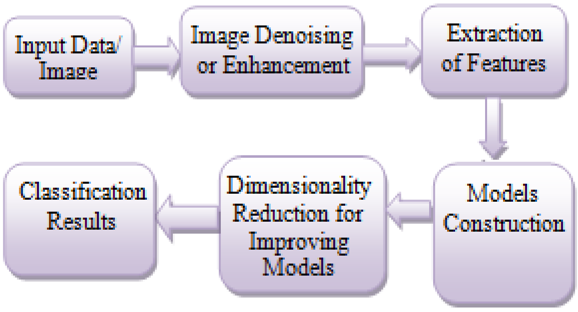

Figure 1-2: Illustrating Different algorithmic steps in Supervised Learning

As presented in Figure 1-2, the first step is to load the image or data into the algorithm, at this stage we look at the size and format of the image to check if all is fine with the system. It is always good to have a flexible algorithm that can take in any type of data or images. The problem with machine learning is that it could be very difficult to separate the noise from the useful information within the images. This issue would take us to preprocessing stage where a noise removal algorithm can be used to eliminate the unwanted materials that could introduce errors into our computation. An exploratory data analysis method can be adopted here for plotting of data to understand how the pixels are arranged. At this stage, any data point that does not fit in properly or outside the rest of the data should be eliminated in order to determine the useful information that the algorithm would be trained with. Processing of image also involves converting images to digital form before performing some operations on it. This process would help to extract some useful information from the images. The technique involves treating images as two dimensional array of element where each element can be referred to as a pixel. Image processing also involves image registration, enhancement, data compression, manipulation and some patterns that are not humanly visible. At this stage, data could be divided into two parts; one for testing (test dataset) and the other for training (train dataset) for classification process.

The step three stage is for feature extraction, as explained in the previous sections, extraction of feature is very important in machine learning. The feature extraction would help us to capture those important features that would increase the accuracy of machine learning algorithm, boost the model performance, reduce model complexity and prevent over fitting. For health related issues, a feature extraction technique to distinguish between healthy and unhealthy images would be implemented; overall the raw data or image collected must have been transformed into useful form to achieve desired results. Like we have previously explained, the kind of feature to be extracted would depend on what researchers are trying to achieve.

The next stage deals with training and building of classification models, before we select a classifier the structure of the data must be taken into consideration but it is always good to try with something very simple for easy interpretation. In this example, a very simple decision tree could be used to determine the healthy and unhealthy classes. A confusion matrix of the data would be calculated or plotted to compare true classes with those classes predicted by the algorithm or classifier. The performance of the algorithm can be improved with a KNN classifier [4], if the results generated with decision trees are not good enough. If the result with KNN classifier is not good enough, one can try support vector machine (SVM) [2], [16] and so on. The computation of confusion matrix would help us to determine the performance of the models or algorithms [20] used in the research. Some of the classifiers discussed here would be applied on clinical data in future chapters.

If the developed model is too complex in terms of space or time, this can take us to stage five where we can implement dimensionality reduction to reduce the model complexity and possibly improve the classification accuracy. Principal of component analysis (PCA) [17], [19] or linear discriminant Analysis (LDA) can be used for this process. This process would further remove the redundancy and fine-tune the data to produce robust models that can yield better results. In my previous paper on feature selection [9], over fitting of data or data complexity could adversely affect the overall performance of algorithm. Additionally, the process of normalization and standardization of features can also take place at this stage to generate models to achieve the best results.

3.4 Unsupervised Learning Techniques

This section deals with some data exploration to get or extract useful information that you can build your data upon. It is very good especially when you do not have a clue of what the data contains. This technique can also be used to reduce the dimension of the data in order to reduce the model complexity of your system and for the algorithm to work with only useful information. It helps to understand the structure and arrangement of your data and how it can be treated. In this section, data are grouped using some measure of similarity or characteristics such that those with similar properties are grouped together as this would help to differentiate between the data with different characteristics. In this case, clustering approach could be used to check the similarities between pair of points to determine which part of the data is similar and which parts are different. You can explore this feature by visualizing the data to capture the useful area and unwanted features; and also to have an idea on how the data is grouped.

Vision and learning can be classified under machine intelligence, several properties that could be used to determine the level of intelligence in machine include perception, learning, language understanding, communication etc. vision that can be grouped under perception, computer vision has got numerous applications in Engineering and computer science for several years. It cannot be separated from machine learning; there are so many learning problems that require observation or visualization. Take for example, learning to predict the future of stock price demands that you visualize the existing stock in order to determine or calculate its future states. Computer vision helps to see or visualize the behavior of a scenario or experiments through the use of algorithms while the machine learning can be used as a tool for developing computer vision systems. Computer vision is determined by the interpretation of video and images; it takes in an image or series of images to generate new or non image information after applying several stages of operations. Examples can be found in the identification of different structures from building. Unlike the computer graphics that is mainly concerned with the tools to develop videos and images. Computer vision takes pictures of the world and turn them into abstract information that the computer can understand while computer graphics take an abstract world in the computer as inputs and convert it to images that human can see and understand.

4. Computation of Features

Multi-fractal analyses of images have recently found several applications in the field of biomedical image processing. This is because multi-fractal features could be employed as efficient texture features for the analysis, segmentation and classification of images. Some applications of the multi-fractal approach are the detection of micro-calcifications in mammograms, tissue classification, and nodule detection in lung CT images and identification of regions of interest in MRI images. Multi-fractal analysis allows an image to be decomposed into a mutually disjoint set of images where the intensity distribution in each image follows nearly the same power law according to a chosen measure. This type of fractal decomposition gives us a range of values of fractal parameters such as the fractal dimension and the Holder exponent (Figure 4-1). These parameters are then selected as texture features for the classification task. The Holder exponents (or singularity exponents) represent the level of irregularities in the intensity values. The fractal dimension, on the other hand, measures the self-similar characteristics in the distribution and the amount of space filled by pixels with the same Holder exponent. These parameters measured across the images in the fractal decomposition can be used to build important feature sets called multi-fractal spectrum and the α-histogram.

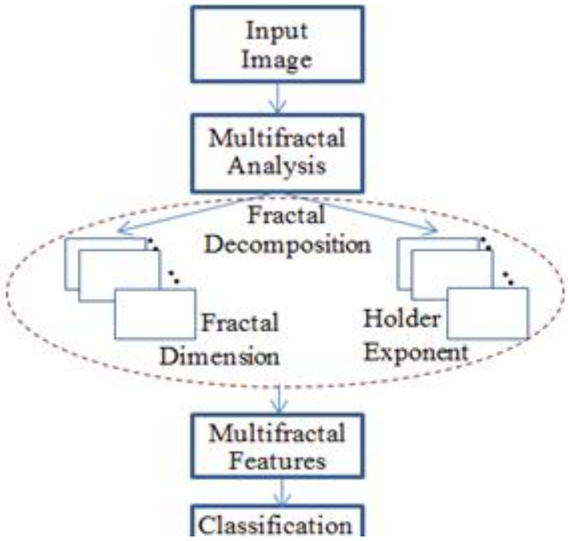

Figure 4-1: General overview of multi-fractal analysis

This paper investigates the feature characteristics of these multi-fractal parameters in the analysis and classification of emphysema patterns in HRCT images. Several types and combinations of fractal features have been studied in detail, and extensive experimental analysis carried out to analyze their effectiveness in algorithms for identifying regions of interest and classification. Novel algorithms for automatically classifying emphysema disease patterns have been proposed and their performance evaluated using images from an online emphysema image database.

The fractal systems described in the previous papers fall into the category of mono-fractals whose characteristics are represented by a single exponent called the fractal dimension. This concept can be generated into a wider and more complex multi-fractal system characterized by a continuous spectrum of exponents (called the singularity spectrum or multi-fractal spectrum). Thus, a multi-fractal system can be thought of as a combination of several fractal systems collectively exhibiting a variation of fractal dimensions at different scaling exponents. However, it should be noted here that we do not use multi-fractal analysis to characterize or identify multiple self-similar structures in an image. Since a fractal property can be considered as a statistical representation of roughness of the object, a more general multi-fractal descriptor encodes the statistical distribution of irregularities in an image; these irregularities have been applied as texture feature descriptors [5], [18] for image analysis applications.

5. Results and Discussion

As mentioned in the previous section, the subdivision of the α range of an input image gives a decomposition of the image in terms of a set of α- slices. If we compute the fractal dimension of each of the α-slices, we get another powerful feature descriptor called the multi-fractal spectrum. The multi-fractal spectrum gives the variation of the fractal dimension with the Holder exponent α for a given intensity measure. It has been used as robust feature descriptors in image analysis applications including tissue image classification. Figure 5-1 presents a multi-fractal spectrum computation of a tissue image; it demonstrates how powerful the feature extracted could be in analyzing the components of biomedical images.

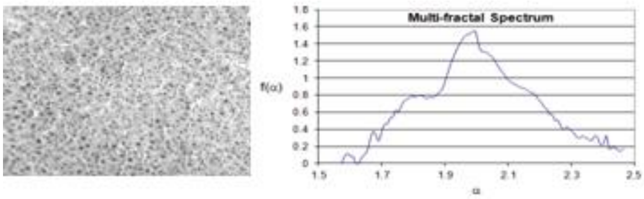

Figure 5-1: A tissue image and its multi-fractal spectrum

This spectrum was generated by subdividing the range of α values into 100 subintervals, with each of the 100 α-slices generating one fractal dimension. Fractal dimensions with magnitude less than 0.4 are generally considered insignificant and not used as part of any feature vector. Similarly, values of α_{min} and α_{max} are also chosen to eliminate the points at both ends of the fractal spectrum where high frequency oscillations are usually found.
The multi-fractal spectra computed for the tissue image in Figure 5-1 corresponding to the four intensity measures presented earlier in this section, are given below in Figure 5-2.

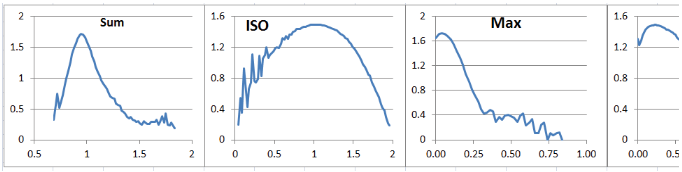

Figure 5-2: The multi-fractal spectra corresponding to four different intensity measures, computed for the input image in Figure 3-5

5.1 Applications and Algorithms

In this Section, we present the Higuchi's method for computing the fractal dimension of an image. This method has become very popular due to its simplicity and speed of computation. The decomposition of a two-dimensional image into one-dimensional signals greatly helps in reducing the complexity of the algorithm. Two fundamental fractal shapes were used, the Sierpinski triangle and the Sierpinski carpet (Figure 5-3) for our analysis of Higuchi's method.

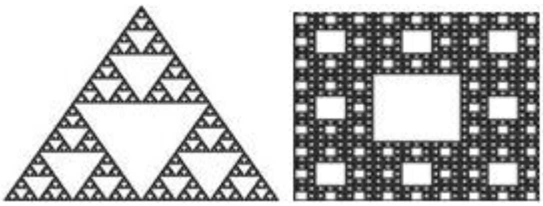

Figure 5-3: Images of the Sierpinski triangle and Sierpinski carpet used for the computation of Higuchi's dimension

The slopes of the linear regression of the log-log plots in Figure 5-4 gives the estimated fractal dimension of the Sierpinski carpet using the box counting method and the Higuchi's method. As can be seen in Table 2-2, the estimated fractal dimension using Higuchi's method results deviates more from the theoretical FD with a p- value of 0.7995 compared to the box counting method with a p-value of 0.1857. This difference is attributed to the horizontal and vertical projections of image values used in the Higuchi's method. However, the two algorithms seem to perform well in general, and can be used for efficient computation of digital images since the estimated FD values are sufficiently close to the theoretical values.

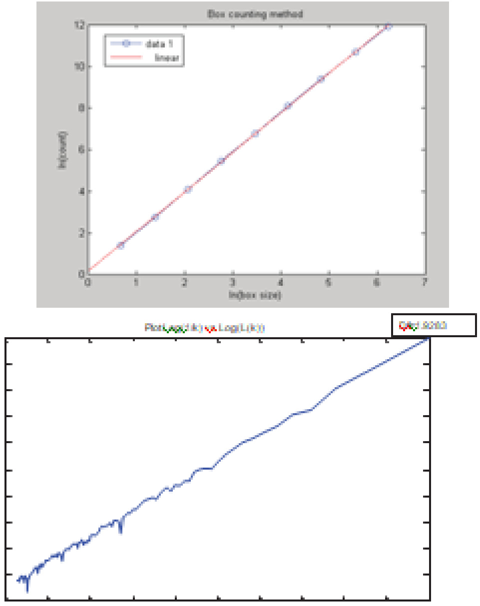

Figure 5-4: Double logarithm plots generated using the box counting method and Higuchi's method for the Sierpinski carpet image

Table 2.2: Estimation of fractal dimensions of fractal images

	Box counting	Higuchi 's Method	Theoretical FD
Sierpinski Carpet	1.9013	1.9283	1.8928
Sierpinski Triangle	1.5673	1.6519	1.5850

5.2 Parameter Selection for Higuchi's Algorithm

In Higuchi's algorithm, selection of k_{max} is very important in the estimation of fractal dimension as this parameter determines the performance of the algorithm. Few studies in the past have attempted to address the issue of k_{max} selection: the authors in [1] selected $k_{max} = 6$ as the optimum value. Other studies have suggested that the selection of k_{max} range should probably be subjected to further consideration if a large N is to be used, that is, the authors suggested increasing k_{max} for increasing N. In another study [15], the authors provided an algorithmic estimation of k_{max}, inspired by a divider method for *FD* estimation. In their approach, k_{max} of Higuchi's method was re-calculated for every *FD* estimation.

In this study, a wide range of k_{max} values was considered in the range 17-25. The image size $N=512$ was used. Using each of those values, the *FDs* using Higuchi's algorithm were calculated for different Weierstrass sequences. In order to generate Weierstrass sequences; a deterministic Weierstrass cosine function, sampled at N equidistant points was used:

$$W_H(x) = \lambda^{iH} \cos(2\Pi\lambda^{i} x) < H < 1 \qquad (5\text{-}1)$$

Where t> *l* and, following, and x ‹ $[0, l]$, $N = 512$ was used. The above defined function is Weierstrass's example of a continuous function that is nowhere differentiable and has a known theoretical *FD*. More specifically, parameter *H* is connected to the theoretical *FD* (FD_{th}) of the Weierstrass function by $FD_{th} = 2\text{-}H$. Using (5-1), Weierstrass sequences, each having a different theoretical *FD* value (i.e. *1.1*, *1.2*, *1.3*,..., *1.9*), were generated. In order to evaluate the performance of the algorithm for different k_{max} values, a mean square error (*MSE*) was estimated according to (5-2).

$$\text{MSE}= \frac{1}{n}\sum_{i=1}^{n} FD_{th}(i) - FD_e(i))^2 \qquad (5\text{-}2)$$

Where FD_{th} is the theoretical *FD* value for the images, FD_e is the estimated fractal dimension and n is the number of weierstrass sequences (of different theoretical *FD* values) used for the *MSE* estimation. Figure 5-5 shows the *MSE* against k_{max} (Higuchi steps); it reflects the performance of the algorithm with respect to *k*-values. As can be seen in the figure, when *k* ranges from 17 to 25, the *MSE* value is almost zero and this means the expected fractal dimension and the estimated fractal dimension at these points are almost the same. These values of k_{max} were considered in *FD* estimation using Higuchi's algorithm when applied to fractal images.

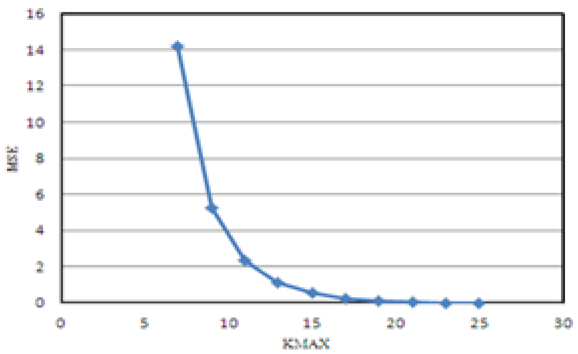

Figure 5.5: MSE for Higuchi's FD estimations for increasing KMAX values.

The values of *k* less than *7* led to a poor performance, which resulted in very High *MSE* values. However, as the value of *k* increases from 7, the value of *MSE* decreases.

6. Conclusions

The algorithms presented in this paper rely on several concepts from the theory of feature extractions. This paper has outlined some of the important properties of fractals such as self-similarity and measures associated with them. The most widely used measure is the fractal dimension. This paper has discussed various techniques for feature extraction in digital images and the differences between local and global features have been outlined. In this paper, the linear regression of digital images has been calculated to demonstrate the capability of features derived from fractal objects and how this can be used for analyzing biomedical images. This process has led to the computation of global features from tissue images, which eventually demonstrated the effectiveness of multi-fractal spectrum as a powerful tool in the analysis of patterns. Some of the factors or parameters have been selected to determine the range of values at which the computational errors tend towards zero in order to improve the overall efficiency of the algorithms.

References

[1] Accardo, A., Affinito, M., Carrozzi, M., & Bouquet, F. (1997). Use of the fractal dimension for the analysis of electroencephalographic time series. *Biological Cybernetics*, *35O*, 339–350.

[2] Chang, C. C., & Lin, C. J. (2016). LIBSVM - A Library for Support Vector Machines. Retrieved from https://www.csie.ntu.edu.tw/~cjlin/libsvm/.

[3] Dan, Z., Chen, Y., Yang, Z., & Wu, G. (2014). An improved local binary pattern for texture classification. *Optik - International Journal for Light and Electron Optics*, *l25*(20), 6320–6324. doi:10.1016/j.ijleo.2014.08.003

[4] Demšar, J., & Demšar, J. (2006). Statistical Comparisons of Classifiers over Multiple Data Sets. *The Journal of Machine Learning Research*, *7*, 1–30. doi:10.1016/j.jecp.2010.03.005

[5] Dubey, S.R., Singh, S.K., & Singh, R.K. (2016). Local bit-plane decoded pattern: A novel feature descriptor for biomedical image retrieval, *IEEE Jrnl. of Biomedical and Health Informatics*, 20(4), 1139-1147.

[6] Y. Hu, G. Li, H. Chen, H. Li, and J. Liu, "Sensitivity analysis for PCA-based chiller sensor fault detection, " *International Journal of Refrigeration*, vol. 63, pp. 133–143, 2016.

[7] Ibrahim, M., & Mukundan, R. (2014). Multifractral Techniques for Emphysema Classification in Lung Tissue Images. *International Proceedings of Chemical, Biological & Environmental Engineering*, *78*, 115–119.Retrieved from http://www.etlibrary.org/?m=fbook&a=details&aid=15734

[8] Ibrahim, M., & Mukundan, R. (2015). Cascaded techniques for improving emphysema classification in computed tomography images. *Artificial Intelligence Research*, *4*(2), 112–118. doi:10.5430/air.v4n2p112

[9] Ibrahim M.A., Ojo O.A., Oluwafisoye P.A. (2017). On Feature Selection Methods for Accurate Classification and Analysis of Emphysema CT Images. *International Journal of Medical Imaging*, *SciencePG* 5(6), 2017, 70-78.

[10] Ibrahim M.A., Ojo O.A., Oluwafisoye P.A.(2017). Analysis of Emphysema Patterns Computed Tomography Image, *International Journal of Scientific & Engineering Research*, 8(12), 2157-2168. https://www.ijser.org/research-paper-publishing-december- 2017_page6.aspx

[11] Ibrahim M.A., Ojo O.A, P.A. Oluwafisoye P.A. (2018). Identification of Emphysema Patterns in High Resolution Computed Tomography Images. *Journal of Biomedical Engineering and Informatics* (Canada, 2017), Sciedupress 4(1), 16-24, 2018.

[12] Ibrahim M.A., Ojo O.A. "New Multi-fractal Techniques for Pattern Analysis in Biomedical Images", *SIA OmniSciptum Publishing, Latvia(2018), European Union;LAMBERT Academic Publishing: ISBN:978613989296-9***.** https://www.omniscriptum.com

[13] Ojala, T., Pietikäinen, M., & Mäenpää, T. (2000). Gray Scale and Rotation Invariant Texture Classification with Local Binary Patterns. *In Practice*, *l842*, 404–420.

[14] Ojala, T., Pietikäinen, M., & Mäenpää, T. (2002). Multiresolution gray- scale and rotation invariant

texture classification with local binary patterns. *PAMI*, *24*(7), 971–987.

[15] Paramanathan, P., & Uthayakumar, R. (2008). An algorithm for computing the fractal dimension of waveforms. *Applied Mathematics and Computation*, *l95*(2), 598–603. doi:10.1016/j.amc.2007.05.011

[16] Raikwal, J., and Saxen, K. (2012). Performance Evaluation of SVM and K- Nearest Neighbor Algorithm over Medical Dataset, *International Journal of Computer Applications*, 50, 35-39.

[17] Wilmar, H. &Alfredo M. (2018). Application of Principal Component Analysis to Image Compression. *Statistics - Growing Data Sets and Growing Demand for Statistic*, *opentech*, *109-135*.

[18] Xu, J. W., & Suzuki, K. (2014). Max-AUC feature selection in computer- aided detection of polyps in CT colonography. *IEEE Journal of Biomedical and Health Informatics*, *l8*(2), 585–593. doi:10.1109/JBHI.2013.2278023

[19] Tsun-Kuo, L.(2018). PCA/SVM-Based Method for Pattern Detection in a Multisensor System, Hindawi Journals: 1-13.

[20] Zhang, H. (2009). A Novel Bayes Model: Hidden Naive Bayes. *IEEE Transactions on Knowledge and Data Engineering*, *2l*(10), 1361–1371.