New Algorithm Techniques for Efficient Analysis of Tissue Images

Adekunle M. Ibrahim, Adepeju A. Adigun
Department of ICT, Osun State University, Nigeria
*Corresponding Authors Email: ibrahima@uniosun.edu.ng, fempeg2013@gmail.com

Article Info

Abstract

The importance of global features in the analysis of tissue images cannot be overemphasized especially in texture image classification and retrieval. This paper presents different techniques for detection, classification and analysis of diseases pattern in medical images. The research work studies the structure of tissue images; and extracts the similarity features characterized by the Holder exponent for pattern classification. Features from multi-fractal descriptors have been extracted and combined with features from fractal descriptors to generate new descriptors for efficient analysis of images. The experimental procedures have been tested with different extracted features during the classification process to determine the appropriate image features that could yield maximum detection accuracy. The results showed that the descriptors extracted from different features could improve the performance of the models. Our findings in this paper have greatly demonstrated the importance of global features in the analysis of tissue pattern.

1. Introduction

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 for identification and analysis of tissue patterns.

1.1. 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, feature 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 case.

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 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 [1-6] involve complete representation of shapes, objects or images while local descriptors describe image patches by focusing on certain regions within the images or shapes. Example of local descriptors can be found in local binary patterns (LBP) Dan et al. (2014) and natural fractal objects. In this text, both descriptors would be used extensively in feature 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. Results generated in the analysis and classification of images are also presented in section 4.

2.Methods 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 [7-8], the algorithm is concern with the relationship between the center 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 in developing image processing algorithms is very important. 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 it is 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. 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.
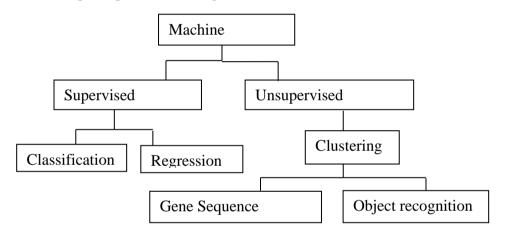

Figure 1: Overview of machine learning techniques

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

This approach generates model to predict discrete responses for a particular event. 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 [9] is the best linear classifier while regression logistics is the best in nonlinear; 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 Figure 2.
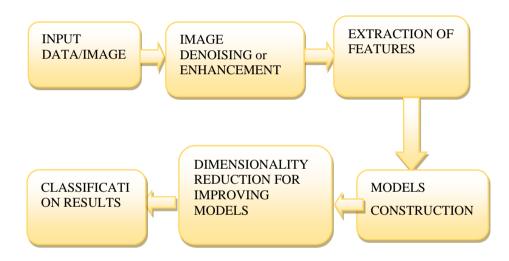

Figure 2: Illustrating different algorithmic steps in supervised learning

As presented in Figure 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 image. 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 involves converting images to digital form before performing some operations on it. This process would help to extract some useful information from the image. 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 development of classification models, before the selection of 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. For instance, 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 [10], 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) [9], [11]. The computation of confusion matrix would help us to determine the performance of the models or algorithms [12] 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) [11,13,14] or linear discriminant Analysis (LDA) [15] 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 our previous paper on feature selection [3], 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. 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

Feature 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. In this paper, features obtained from fractal decompositions of images could be used as input to the classification algorithms, which are then validated with the ground truth patches to identify the region of interest (Figure 3). On the other hand, the fractal dimension calculated by box-counting and Higuchi 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 that can be used for the classification task. The details of computing the fractal dimension using the box-counting and Higuchi's dimension are discussed in the following sections.
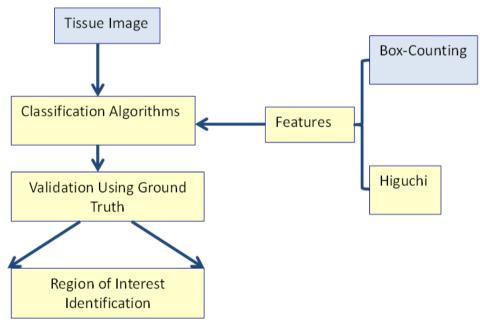
Figure 3: General overview of feature computation

This paper also investigates the feature characteristics of the multi-fractal parameters in the analysis and classification of tissue images. Several types and combinations of fractal features have been studied in detail, and extensive experimental analyses were carried out to analyze their effectiveness in algorithms for identifying regions with medical issues. The fractal system described in the previous paper [6] falls 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). 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 [14], [15],[18] for image analysis applications.

4.1 Computation of Tissue Image and Results

In this section, the subdivision of the α-range of the tissue image gives a decomposition of the image to generate a set of α-slices. We can calculate the fractal dimension of each α-slice to obtain another feature descriptor known as multifractal spectrum for the tissue images. This powerful approach gives the variation of the fractal dimension with intensity component of α-values for a given intensity measure. Figure 4 demonstrates how powerful the feature extracted could be in analyzing the components of biomedical images.
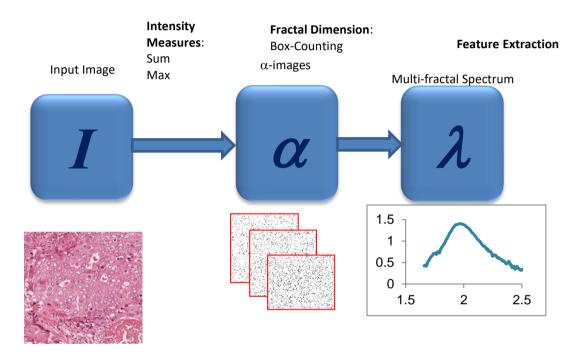

Figure 4: Tissue image and its multi-fractal spectrum

In the computation of this spectrum (Figure 4), the α values are subdivided into 120 subintervals, with each of the α-slices generating a fractal dimension. Fractal dimensions with a magnitude less than 0.5 are generally considered insignificant and not used as part of any feature vector. Similarly, values within the range of [α_{min}, α_{max}] have been selected to eliminate the points at both ends of the fractal spectrum where high-frequency oscillations could be detected. The multi-fractal spectra computed for different parts of the tissue image in Figure 4 using the summation intensity measures are given in Figure 5.
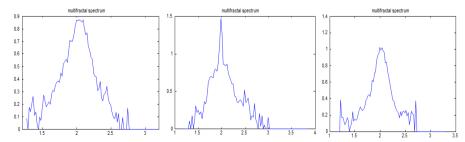

Figure 5: Spectra for different regions of tissue image using summation intensity measures

4.2 Algorithm Applications and Results

In this Section, Higuchi's method for computing the fractal dimension of an image has been presented. 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 computational time complexity of the algorithm. The three fundamental fractal shapes (Cauliflower, Romanesco, and trees) selected for experimental analyses using the Higuchi's approach are presented in Figure 6.
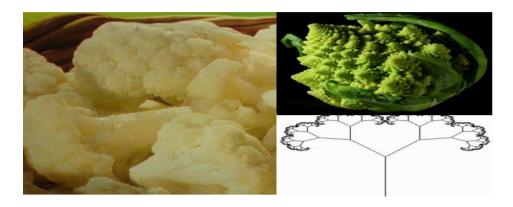

Figure 6: Fractal images for computation of Higuchi's dimension [20]

The slope of the linear regression of the log-log plots in Figure 7 gives the estimated fractal dimension of the trees using the box-counting method and the Higuchi's method. As can be seen in Table 1, the estimated fractal dimension using Higuchi's method results deviates more from the theoretical FD with a p-value of 0.7975 compared to the box counting method with a p-value of 0.1867. This difference is attributed to the horizontal and vertical projections of image values used in 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.

Table 1: Estimation of fractal dimensions of fractal images

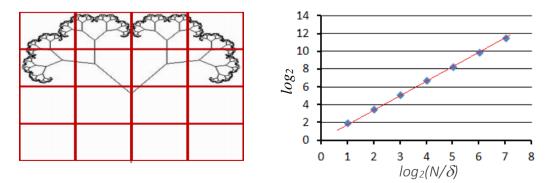|	Box counting	Higuchi 's Method	Theoretical FD
Cauliflower	2.9067	2.9384	2.8738
Romanesco	2.8873	2.8529	2.7057

Figure 7: Double logarithm plots generated using the box counting method for the trees

5. Conclusion

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 useful tool in the analysis of image patterns.

References

[1] Ibrahim, M., & Mukundan, R. (2014). Multifractal 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

[2] 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

[3] 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.

[4] 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

[5] 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), 4(1),16-24, 2018.

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

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

[8] Ojala, T., Pietikäinen, M., & Mäenpää, T. (2002). Multiresolution gray- scale and rotation invariant texture classification with local binary patterns. *PAMI*, *24*(7), 971–987.

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

[10] 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

[11] 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.*

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

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

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

[15] 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.

[16] 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.

[17] 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

[18] 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

[19] 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.

[20] 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