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A Survey on Classification and Clustering Of Images Using Evolutionary Techniques

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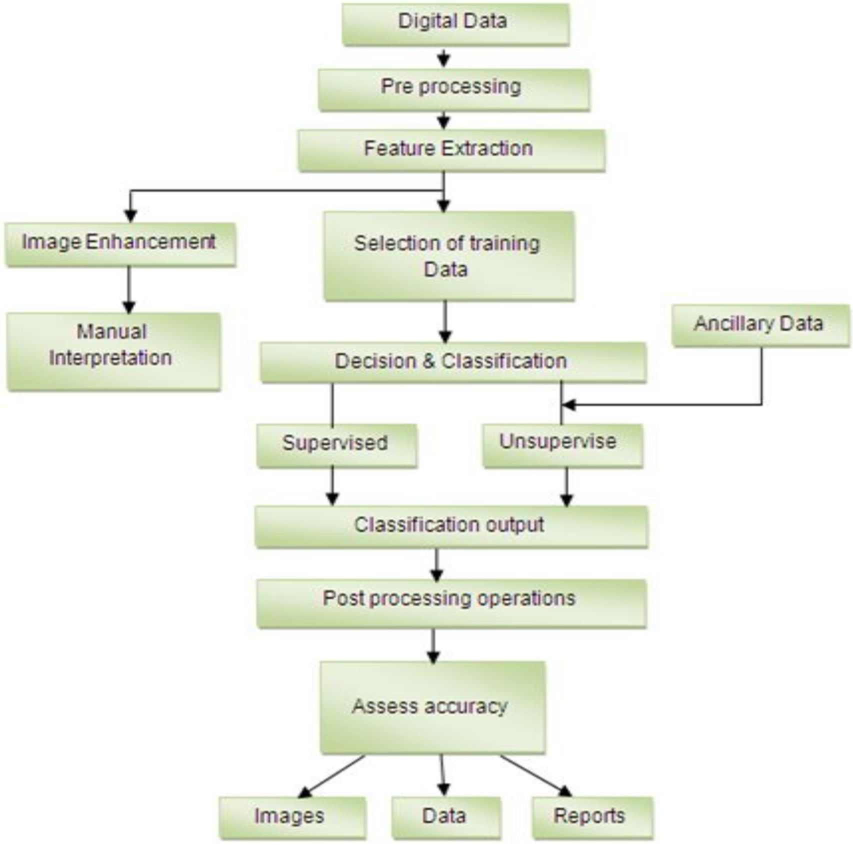
Abstract
Image processing has provided ample area of scope of research in the medical diagnostics of CT images of Brain, liver and chest etc. A thorough survey and comparative analysis of the classifiers or classification techniques implemented by investigators illustrated the dependency of the classification methods on the types of data sets being selected, types of features extracted and the features selected for the purpose of classification. The need of standardized classifier or classification technique for different types of data sets, to achieve required results, has been highlighted. Also the survey depicts that the results of different classifiers are different for the same dataset. Analysis shows the use of hybridized techniques to improve the performance of system classification accuracy based on classifiers like KNN, SVM, SOM and ABC etc but this can be further optimized using evolutionary techniques.

Keywords: Image, classification, features, texture, spectral, contextual, Ant Bee Colony, ABC, GLCM, Entropy, contrast.

1. Introduction

With the advancement in technology digital images can be processed using various algorithms. An image can be a line art (called Vector graphics) or pixel based (called bitmaps) that may be used to provide a visual illustration of something which can be stored electronically. An image is represented as a function (f) of two variables (x, y) i.e. as a two dimensional array or matrix of pixels or picture elements i.e. f(x, y) wherein 'f' representing amplitude is finite for digital image & (x, y) are spatial or plane coordinates representing intensity of image at a level. Value of pixel at any region in an image can be derived from the value denoted by f(x, y) at any point. The dimensions of pixel array (a matrix of pixels that contains 'a' number of columns representing image width and 'b' number of rows representing image height) can be used to calculate image size or number of pixels in an image. An analog image can be converted into digital image containing finite number of pixels with fixed location using Image processing (which is of two types: Analog & Digital). The following figure provides an overview of classification process.



While a grayscale image is of 8-bits or 16 bit but a true color image is of 24 bits contains approximately 16 million colors. Various types of image file formats are:.jpeg,.gif,.png,.tiff,.svg etc. An image can be of additive RGB (Red, green, blue) color model, being used for electronic media or subtractive CMYK (cyan, magenta, yellow, black) color model, being used for print media. Important phases involved in the digital processing technique are: pre-processing & post-processing operations. Some areas in which image processing find applications are: Transportation systems to recognize number plate, Remote Sensing systems to observe flooded areas, area under forest or agriculture for object recognition, Defense surveillance and most important in Biomedical Imaging techniques for medical diagnostics of diseases by using imaging tools like computer aided tomography (CT) for Brain, liver, chest, lung etc.

In this paper, the focus is on the classification based on set of features and then categorizing the data using pattern recognition techniques. Classification plays an important role in our daily life. Classification means systematic arrangement of different types of items on the basis of their uniqueness in to groups or categories. Arrangement of things into different groups helps in recover the required data within the required time frame. In image classification features of an image are classified into groups with similar features. Thus interpretation of the available of the calculated data can be done using the process of classification. The process of classification is a tiresome process, as it is influenced by various factors**.** Selection of suitable variables plays an important in the way of extraction and selection of features. Selection of classification system or a classifier is also crucial in process of classification i.e. the selection of the classification system or classifier for a specific or particular domain still remains an important area of research, as different output(s) are obtained based on the used approach for classification or type of classifier used. Thus performance of a classification system can be estimated qualitatively based on the expert knowledge and qualitatively based on the sampling methodology (**D. Luand and Q. Weng).** Investigators in their research have given various methods like accuracy, reproducibility, robustness, utilization of available data, uniform applicability and objectiveness to assess classification system performance. (**Cihlar et.al. (1998)**)which also includes means for estimating algorithm's aptness such as accuracy of classification system, resources calculation, algorithm stability **(DeFries and Chan, 2000)**.The process of classification can be categorized into two types viz. Supervised classification and unsupervised classification. In supervised classification, samples are selected to act as representatives. These samples are then used as reference or training sites on the input image and then the classes are formed or grouped based on the similarity of the pixels or other feature characteristics like density, texture etc. In brief stored knowledge or available information is used to group dissimilar items into groups of similar items. Whereas in unsupervised classification the representative samples are not required but the available data is group into clusters and then can be rearranged based on the required specifications. Thus it can be said that in supervised classification, first available knowledge is applied then classification process is done, thus classification algorithms play an important role whereas in unsupervised classification, first classification is done and then knowledge is applied, and thus clustering algorithms play an important role in such classifications.

Features are the quantifiable entities that define characteristics of the image. Feature extraction is a technique to produce features in classification methods. The basic features using for study the details of an image are categorized as: Spectral, textural and contextual Robert M. Haralick et.al. (1973). The spectral features provide information about the tonal variations in selected Electromagnetic (EM) bands i.e. visible or infrared. Textural features explain the spatial distribution of tonal variations in a band. Contextual features provide information obtained from the sections of regions adjoining the region of interest. Following textural features provide detailed analysis about texture features where p(i,j) means (i,j)th entry in GLCM, px(i)is the ith entry in GLCM, Ng is the number of distinct gray levels in quantized image

a. **Angular Second Moment (ASM)**

Provides a measure of similarity. High similarity in neighboring pixel leads to large ASM value. ASM can be calculated using:

$$f_1 = \sum_i \sum_j \{p(i,j)\}^2$$

b. Contrast

Contrast is used to measure intensity or grey-level variations between the reference pixel and its neighbor. With increase in contrast, the quality and clarity of picture increases and vice-versa. Contrast can be calculated using:

$$f_2 = \sum_{n=0}^{N_{g-1}} n^2 \{_{|i-j|=n} \sum_{i=1}^{N_g} \sum_{j=1}^{N_g} p(i,j)\}$$

c. Correlation

Correlation is a measure of linear dependency of grey levels on neighboring pixels. Correlation can be calculated as:

$$f_3 = \frac{\sum_i \sum_j (ij)p(i,j) - \mu_x \mu_y}{\sigma_x \sigma_y}$$

Where $\mu_x, \mu_y, \sigma_x, \sigma_y$ are means and standard deviations of P_x and P_y.

d. Sum of squares: Variance

Variance is a measure of dissimilarity, referring to variation in gray-level of pixel pairs. It can be calculated as:

$$f_4 = \sum_i \sum_j (i-\mu)^2 p(i,j)$$

e. Inverse Difference Moment (IDM)

f.

$$f_5 = \sum_i \sum_j \frac{1}{1+(i-j)^{2p}} \, p(i,j)$$

g. **Sum Average**

$$f_6 = \sum_{i=2}^{2N_g} i p_{x+y}(i)$$

h. Sum Variance

$$f_7 = \sum_{i=2}^{2N_g} (i - f_8)^2 P_{x+y}(i)$$

i. Sum Entropy

$$f_8 = -\sum_{i=2}^{2N_g} P_{x+y}(i) \log\{P_{x+y}(i)\}$$

j. Entropy:

Entropy measures the randomness of intensity distribution in an image.

$$f_9 = -\sum_i \sum_j p(i,j) \log(p(i,j))$$

k. Difference Variance

$$f_{10} = variance\ of\ p_{x-y}$$

l. Difference Entropy

$$f_{11} = -\sum_{i=10}^{N_{g-1}} P_{x-y}(i) \log\{ P_{x-y}(i)\}$$

m. Maximal Correlation Coefficient

$$f_{14} = (Second\ largest\ eigen\ value\ of\ Q)^{1/2}$$

Where

$$Q(i,j) = \sum_k \frac{p(i,k)p(j,k)}{P_x(i)P_y(k)}$$

n. Homogeneity

.

$$f_{15} = \sum_{i=0}^{N_g-1} \sum_{j=0}^{N_g-1} \frac{1}{1+(i+j)^2} Pd, \theta(i,j)$$

o. Energy

Energy detects different textures in an image.

$$Energy = \sqrt{(ASM)}$$

p. Dissimilarity

$$f_{16} = \sum_{j=0}^{N_g-1} Pd, \theta(i-j)^2$$

In this paper Section 1provides the introduction to the basics of image, image processing, need of classification and various textural features of an image, Section 2 provides the literature survey of the research done by various investigators in the field of image classification, Section 3. Provides an elaborated comparative analysis of the techniques used for classification and also the performance comparison of the outputs obtained, Section 4 concludes the survey and at last Section 5 provides a window for further scope of research in the area of classification

2. Literature Survey

Veronika Cheplygina et.al. (2017) proposed meta-learning as important means in investigating and predicting the technique to be used for unknown classification problem on basis of initial knowledge gained from existing classification problems related to analysis of medical images. The technique involved uses embedding of meta datasets using MDS (multi dimensional scaling and t-stochastic nearest neighbor (t-SNE). While MDS focuses on long distance and could be used to compute outliers but t-SNE focuses on small distances for better visualizations. The results concluded that t-SNE is better for clustering of datasets for classification. Further the authors proposed methods including preprocessing and feature extraction based on ideas like meta learning are beneficial in medical imaging.

Bahriye Akay and Dervis Karaboga (2015) presented a review on the use of Artificial bee colony in Images. A survey of various techniques for image classification was elaborated viz. fusion of ABC and artificial neural network wherein the weight values are computed on the basis of local and global search operators and the error is measured using the following equation: E(t)=$\frac{1}{n}\sum_{j=1}^{n}\sum_{k=1}^{k}(d_k - o_k)^2$ where d_k is the desired output node k, O_k is the actual output value of the node k, K is the number of output nodes and n is the number of patterns. In second technique in which ABC and Support Vector machine were mixed for classification purpose with ABC being used for segmentation and SVM classifier to classify the segmented image. An extensive review concluded that using ABC algorithm different optimization problems can be conveniently resolved with efficiency.

Vartika Agrawal and Satish Chandra (2015) use Artificial Bee Colony (ABC) to select features in Computed Tomography (CT Scan) images. The purpose was to detect whether the given input is cancerous. Beginning with segmentation of images, ACM (Active Contour Segmentation) algorithm was implemented. To carry out the classification combination of Algorithm like ABC and SVM was compared combination of ABC with K-NN. The analysis concluded that ABC with SVM (Gaussian Kernel) performed better than the ABC with SVM (Linear Kernel) and ABC with K-NN classifier providing an accuracy of 97%.

D. Chandrakala and S. Sumathi et.al. (2014) proposed an image classification system for reduction in the computation time in retrieving the images from a dataset based on features like colour and texture. A fusion of colour and texture features are used as input in proposed FRBFN network for classification of dataset and ABC algorithm is used to optimize initial network weights in the Hidden layer. The authors used color histogram in HSV to derive color features whereas the texture features can be calculated using Co-occurrence matrix. Statistical properties like contrast, energy, entropy, correlation and local stationary can be used for calculating texture features. The proposed ABC based FRBFN classifier produced better classification results by 44.28% and reduced the computational time by 38.2%. Also the precision rate is much better in comparison to FRBFN method. Low level features like shape and spatial location features, location of image can be the basis of future research in classification methods.

D. Janaki Sathyaa and K. Geethab (2013) implemented an Artificial Bee Colony (ABC) algorithm for training the artificial neural network in the proposed computer assisted mass classification system, as ABC avoids convergence to local minima. The system was used to classify the mass based on certain features like entropy, standard deviation, mean, skewness, kurtosis, variance, energy; that were extracted from ROI in breast (Dynamic Contrast Enhanced MRI Images) DCE-MRI images, providing better accuracy in diagnosis by classification of mass abnormalities. Further the work could be extended on much larger database to check whether the use of proposed classification system can be generalized.

Vishal S.Thakare et.al (2013) presented a survey of the techniques used for extraction of texture features viz. scalar number, discrete histograms, empirical distributions or texture analysis using two dimensional Gray level co-occurrence matrices (GLCM) or gray-level spatial dependence matrix to identify specific objects or region of Interest (ROI) from image and then implementing image classification using self organizing maps. The authors finally concluded that while a model of SOM can assemble identical image texture and also be used to mine model for such groups, the GLCM gather's vector information.

R. Suganya and S. Rajaram (2013) used haralick texture features for classification of ultrasound diseased liver into fatty, cyst and cirrhosis. The methodology used was preprocessing using Anisotropic Diffusion speckle reduction method in first phase, and then feature analysis or extraction i.e. feature selection and texture classification using GLCM and then implementing classification using SVM. Frequency of achievable pairs of nearby pixel values is shown by GLCM. The haralick features used for evaluation are Contrast, Correlation, Auto Correlation, Homogeneity, Dissimilarity, Energy, Entropy, angular second Momentum, Mean, Variance, cluster prominence and cluster shade. Hybridization of feature extraction with SVM provides classification accuracy rate of 81.7% for given dataset of liver disease ultrasound images.

C.D.Almeida et.al. (2010) implemented a hybridization of GLCM with SOM for texture based image classification. The standard dataset namely Brodatz texture image database was used for experimental analysis. The proposed approach used consists of four phases viz. Texture descriptor, then preprocessing, then clustering and finally classification. In brief the GLCM is applied on the images received from the database in first phase namely texture descriptor module. In the second phase the GLCM matrices are preprocessed in the preprocessing module. The output thus obtained is fed as input to the clustering module wherein the SOM is implemented. The phase from the input of image database from to the clustering module constitutes the learning stage. The last module compares the output of the pre-processing module i.e. preprocessed query image with the output of the clustering module i.e. prototypes, thus providing an output inform of retrieval list of images fitting in few clusters. This output is what is called user's query. The GLCM is defined by $P_{d,\theta}(i,j)$= = $P_r(I(p_1) = i \wedge I(p_2) = j \wedge \|p_1 - p_2\| = d)$ and correct classification rate (CCR) is given by : CCR = (Number of correctly classified samples / Number of classified samples) *100%. In the paper CCR was calculate in framework of Monte Carlo experience by comparing GLCM + SOM with single SVM, Fused SVM, Bayes classifier and LVQ classifier. The proposed GLCM + SOM provided an CCR of 97%, much better than other classifiers.

M.Seetha (2008) et.al. implemented the hybridization of genetic algorithm with conventional classifier system and fusion of fuzzy and SVM. The analysis provided a conclusion that the results obtained on comparison of SVM and FSVM showed that results were better with FSVM. Also the use of GA with conventional classifier yielded better results. In GA fusion with Neural Networks involved three phases viz. representation of training weights, then calculating fitness function and then finally applying selection, crossover and mutation operations using GA. The analysis showed that when evolution stops when fitness is more than the predefined value. In nutshell advanced classification techniques like ANN, SVM, fuzzy logic, GA and their fusion were compared on basis of parameters like type of approach, Non-linear decision boundaries, training speed, accuracy and general performance. Further scope was shown in the field of applying GA for neural network optimization.

Robert M. Haralick et.al. (1973) laid emphasis on the basic perspectives of generalizing the evaluation methods of maximum kind of images. Defining types of images features like Spectral, Textual and Contextual the authors explained in depth the methods of deriving features for image classification. Authors proposed a set of 28 textural features based on gray-tone-apatial dependencies that can be used as an input to the classifier viz. Angular Second Moment (ASM), Contrast, Correlation, Sum of squares, Inverse Difference Moment, Sum Average, Sum Variance, Sum Entropy, Entropy, Difference Variance, Difference Entropy, Information measure of correlation and Maximal Correlation coefficient. The analysis was done on three types of database like photomicrograph, aerial photograph, satellite image, to calculate region of interest (ROI) in an image or for identifying objects. After experimenting on dataset, divided into training set and test set, an accuracy of 89 % was achieved for test data set

3. Comparative Analysis

Year	Authors	Topic Name	Algorithm/ Technique used	Comparative Result
2017	Veronika Cheplygina et.al.	Exploring the similarity of Medical Imaging Classi-fication Problems	MDS (Multi Dimensional Scaling) Algorithm & t-SNE (stochastic nearest neighbor); 1- nearest neighbor classifier	Results with t-SNE were better. ; Detection of which dataset is to be used for which classifier
2015	Vartika Agrawal and Satish Chandra,	Feature Selection using Artificial Bee Colony Algo-rithm for Medical Image classification	ABC+ KNN ABC + SVM (linear kernel) ABC + SVM (Gaussian kernel)	Accuracy with ABC + SVM (Gaussian kernel)were better
2015	A. Veeramuthu et.al.	An efficient and fast brain CT image classification using hybrid technique	Hybrid classifier using SVM, Statistical classifier, Neural classifier	Classification Accuracy was 92% with Hybrid classifier
2014	D. Chandrakala and S. Sumathi	Image Classification based on Color and Texture features using FRBFN network with Artificial Bee Colony Optimization Algorithm	RBFN, FRBFN, FRBFN + ABC	Results of FRBFN + ABC are better for precision rate for color feature, texture feature and multi-features.
2013	D. Janaki Sathyaa and K. Geethab	Mass Classification in breast DCE-MR images using an artificial neural network trained via a bee colony optimization algorithm	ANN, SVM, ANN+ABC for testing accuracy, sensitivity, specificity	ABC + ANN are best performers
2013	Vishal S.Thakare et.al.	Survey on image texture classification techniques	GLCM + SOM	GLCM + SOM is used for classification
2013	R. Suganya and S. Rajaram	Feature extraction and classification of ultrasound liver images using haralick texture-primitive features: Application of SVM classifier	Support Vector Machine (SVM + RF) & SVM using GLCM	Accuracy of proposed SVM with GLCM is better
2012	Jinho Kim et.al.	Comparing Image Classification Methods:K-Nearest- Neighbor and Support-Vector-Machines	KNN SVM	Performance of SVM classifier was better by 4%
2011	Y. Zhang	Magnetic resonance brain image classification by an improved artificial bee colony algorithm	Scaled chaotic ABC (SCABC), GA, elite GA with migration, Simulated annealing (SA), ABC	Least Mean MSE and 100% classific-ation accuracy with DWT + PCA+SCABC –FNN
2010	Zhang, Y., S.Wang, and L.u,	A novel method for magnetic resonance brain image classification based on adaptive chaotic PSO	DWA+PCA+Adaptive Chaotic PSO (ACPSO) -FNN	Classification accuracy is 98.75% and computation time per image is 0.0452s
2010	C.D.Almeida et.al.	Texture classification based on co-occurrence matrix and self-organizing map	GLCM + SOM, SVM, fused SVM BAYES classifier LVQ classifier	Correct Classification Rate (CCR) is better with GLCM + SOM
2008	M.Seetha et.al.	Artificial neural networks and other methods of image classification	ANN, SVM, FUZZY LOGIC, GA	Performance of GA+SVM was better than GA or SVM
2008	D. Karaboga and B. Basturk	On the performance of artificial bee colony (ABC) algorithm	Differential Evolution (DE), Particle Swarm Optimization (PSO), Evolutionary Algorithms (EA), ABC	Performance of ABC for multi-dimensional numeric problems was better.
2007	J. Zhang et.al.	Local Features and Kernels for Classification of Texture and Object Categories: A Comprehensive Study	Proposed (HS+LS), (SIFT+SPIN) and compared with Berg et.al. (2005) & Grauman and Darewell (2005)	Classification accuracy on CalTech 101 dataset by proposed method is 53.9
2003	Chris A. Cocosco ET.AL.	A fully automatic and robust brain MRI tissue classification method	PRUNING + KNN	Performance was improved
1973	Robert M. Haralick et.al.	Textural Features of Image Classification	Haralick features to compute texture based characteristics were proposed for image classification applications	Result with computable textural features were better for image classification applications

Conclusion

In this paper, a survey of research done by investigators was thoroughly studied. A comparative analysis of the classifiers or classification techniques proposed and implemented by those investigators has been illustrated, which shows the dependency of the classification methods on the types of data sets being selected, types of features extracted and the features selected for the purpose of classification. A standardized classifier or classification technique is still required or needs consideration for implementation on different types of data sets, to achieve required results. Also the survey depicts that the results of different classifiers are different for the same dataset. The analysis also shows the use of hybridized techniques to improve the performance of classification system and also improve the classification accuracy based on classifiers like KNN, SVM, SOM and ABC etc.

Future work

Thus the survey focuses on the need of optimized system for classification to develop standardized classifier for required output using evolutionary techniques.

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