ANALYSIS OF IMAGE CLASSIFICATION METHODS BASED ON PERFORMANCE AFFECTING PARAMETERS

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Abstract: Soft computing techniques for image classification have been used to address various issues and challenges which persisting in applying these techniques in image classification due to their basic property of images. This paper represents the role of soft computing techniques for image classification and analysis of various methods based on performance affecting parameters for image classification.

Index Terms - SCT, HoG, LRCNN, W-SVM, NNO.

I. INTRODUCTION

In nature, the human mind tries to solve the problem as per their need uses the problem-solving processes may be repeated several times to obtain the desired result, but as a human being, such a problem-solving process cannot repeat the same as the previous one. There may be a chance of error due to any environments or current situations of mind at the time of problem-solving. Therefore, the human mind invented fixed problem-solving techniques. Later on, these techniques are known as Hard computing. The researcher always tries to develop efficient computational problem-solving techniques, Up to some levels they achieved. But they unable to fulfil the gap between the capability of the human mind and machine.

Therefore, ‘Soft computing’ term is first coined by LA Zadeh in early 1990s, which is emerging family of problem-solving techniques which are tolerant of imprecision, approximation, tractability, robustness, and low-cost solution. These techniques mimic the ability of the human mind to reason and learn in an environment of imprecision, approximation, and uncertainty. The human mind can categorize the object into different classes based on their visual features. Classification problems also can solve by using computers (machines). Problem-solving techniques must be tolerant of the variations of input images and output class. For this, several researchers and scientists have developed various soft computing techniques for image classification.

This paper talk about many issues persisting due to their limitations for image classification. These persisting issues motivate us to take as a challenge to analyse and high lightened the problems for the interest of researchers to handle the Image classification problem.

Some important abbreviations that have used in this paper and their descriptions are listed in Table 1.

Table. 1. Abbreviations and their descriptions

Abbreviations	Descriptions
SCT	Soft Computing Techniques
SIFT	Scale Invariant Feature Transform
SURF	Speeded Up Robust Feature
LBP	Local Binary Pattern
HoG	Histogram of Gradient
LRCNN	Low Resolution Convolutional Neural network
FG-LRCNN	Fine Grain Low Resolution Convolutional Neural network
SRCNN	Super Resolution Convolutional Neural Network
SIT	Sparse Image Transformation
HR	High Resolution
LR	Low Resolution
W-SVM	Weilbull Support Vector Machine
Pi-SVM	Pi - Support Vector Machine
NNO	Nearest Non-Outlier
OSGOPF	Open Set Graph based Optimum Path Forest

This paper consists of four sections: review work of soft Methods for image classification has discussed in Section 2. Analysis of methods and their role for image classification based on performance affecting parameters have given in Section 3. After that, Issues and challenges in soft computing techniques for image classification have given in Section 4. Finally, Section 5 concludes the paper.

II. REVIEW WORK

With the emergence of soft computing techniques [1], it became the subject of interest of the researcher. To solve the image classifications problem, which mainly focused on extracting the feature and descriptions of elements of images, like corner, line, edge, shape, and texture using soft computing techniques such as fuzzy logic, probabilistic reasoning, genetic algorithm, and neural network. These techniques comprise two categories; category first is approximate reasoning: is a process by which a possibly imprecise conclusion has deduced from a set of imprecise premises, whereas category second: is functional approximation and optimization that approximate and optimize the function among the defined class of knowledge. Fuzzy logic and probabilistic reasoning belong to the Approximate reasoning category, while genetic algorithm and neural network belong to the functional approximation and optimization category [3].

The input image is varied due to various image quality factors such as resolution, shape, scaling, rotation (viewpoint variation), illumination variation (brightness, contrast), and noise. Hence, the performance of soft computing-based image classification techniques is affected by these image quality factors. In literature, most of the quality factors experimentally visualized that how they affect the image classification performance. The modified MNIST dataset using motion blur, noise, resolution variation and successfully handled these image distortions by probabilistic quadtree DBN framework presented by Basu et al. [2]. Chevalier et al. [4] analyzed the effect of various resolutions on fine-grained classification. Various researchers attempted to handle these issues in the image classification problem. Lowe et al. [5] proposed local scale-invariant features called SIFT (Scale-invariant feature transform). This feature transforms input images into a large collection of local feature vectors that, invariant to image translation, scaling, rotation, and partially invariant to illumination changes, affine, and 3D projection. In 2006, Bay et al. [6] proposed a speed-up version of SIFT which is called SURF (Speeded Up Robust Features). Ojala et al.[7] proposed an excellent feature extraction method named local binary patterns (LBPs) and applied it to the multi-resolution gray-scale and rotation invariant texture images classification system in 2002. Dalal et al. [8] proposed an HoG (histogram of gradient) Feature descriptor for counting the occurrence of gradient orientation in the local part of the image.

In literature to handle the classification of low-resolution images, various models have been available such as LRCNN, SRCNN, sparse image transformation, the LRCNN, which leverages the benefit of a super-resolution layer to improve fine grain classification. Further, they improve low-resolution classification by integrating privileged information of CNN to fine grain classification. D. Cai et al. [9] proposed a super-resolution CNN model to handle the image classification of the low-resolution image. Wei et al. [10] presented an algorithm that learned a sparse image transformation by coupling, Sparse structures of image pairs from both HR and LR spaces, and successfully achieve competitive classification accuracy.

To improve the performance of the classifier several fusion methods have been developed by combining different feature extraction and classification methods. In literature, for image-level fusion, Rokni et al. [11] explore the various pixel-level image fusion techniques in the application of surface water change detection. Xiao et al. provided integration of object-level and part-level attention of images[12]. Gunes et al. [13] investigate the effect of recognition using early fusion and late fusion approaches. For mid-level feature fusion, Amarsaikhan et al. [14] explore the different data and feature level fusion for image classification, and Fernando et al. [15] present a logistic-based fusion method that adaptively selects a set of diverse and complementary visual features. But integration or fusion of classifiers for the distributed dataset is not considered by researchers.

To make image classification models robust to adverse, input various soft computing-based models are available to handle unknown classes for open set classification. In literature, Scheirer et al. formalized the Open set recognition problem, Open space risk, and openness of classifier and proposed a 1-vs-set machine[16]. Afterward, Scheirer et al. Proposed a novel Weibull-calibrated SVM (W-SVM) based on compact abating probability and binary SVM[17]. Jain et al. [18] proposed Pi-SVM, introduced for estimating the un-normalized posterior probability of class inclusion. Bendale et al. [19,20] proposed the nearest non-outlier algorithm and OpenMax layer. Zhang et al. [21] simplified the open set recognition problem into a set of hypothesis testing problems and proposed a sparse representation-based model using extreme value theory. A newly designed Open Set Graph-Based Optimum Path Forest classifier using genetic programming and majority voting fusion techniques.

The Next section provides the analysis of soft computing methods for image classification.

III. ANALYSIS OF SOFT COMPUTING METHODS FOR IMAGE CLASSIFICATION

Based on the systematic literature review, we have found that soft computing-based image classification methods are uses to solve the complete or part of an image classification problem. The evolution timeline of the image classification methods may categorize into three phases:

- Beginning phase (the 1970s to 1990s): The image classification techniques perform by matching the basic feature descriptions such as a corner, line, edge, and shape
- image. These techniques are only suitable for the ideal cases of images.
- In the mid-phase (the 1990s to 2010s), image classification techniques are mainly based on hand-crafted/ mathematically computed feature extraction and learning the classification task on these extracted features. Feature extraction techniques are specific, not generalized to handle the variations of input images.
- In the present phase (2010's to present), image classification is focused on deep learning-based models to automate feature learning and classification. The deep learning method provides the automated feature learning process.

In the paper, we have taken four soft computing techniques for analysis purposes, proposed by various researchers, and analysed them based on subjective evaluating parameters (roles/tasks) such as classification, clustering, segmentation, feature extraction, feature learning, and optimization, which shown in Fig. 1.

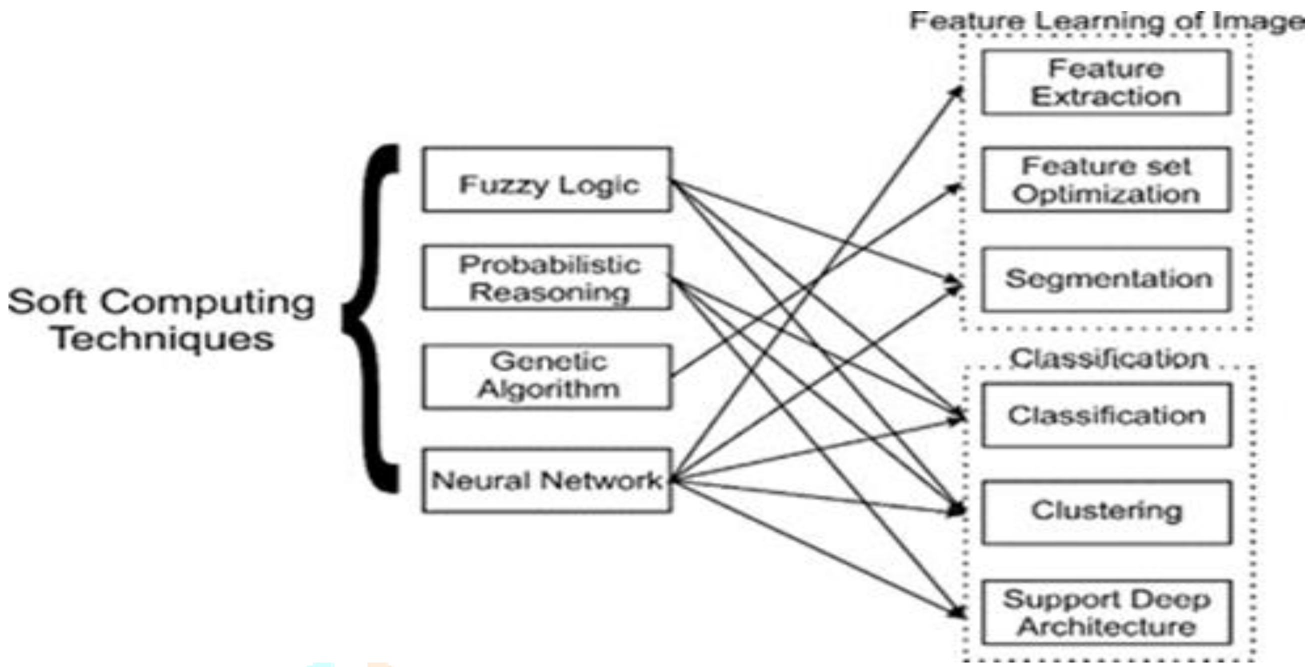

Fig. 1. Roles of soft computing techniques in image classification

Here, based on Fig. 1. it is clear that

- Fuzzy logic-based methods perform the segmentation, clustering, and classification task. The main work of these methods is to generate the fuzzy relation rules for input features of the image and output class of the image,
- the probabilistic reasoning-based methods based on probabilistic theory and belief theory perform the task of classification in image classification, in both supervised and unsupervised manners.
- Genetic algorithm-based methods perform the task of optimization of features (feature selection, feature optimization).
- Neural network-based methods perform the feature learning (automated feature extraction) and classification task. It learns from the examples of images (training dataset). The main work of these methods is to learn a mapping between the input images and their out classes.

The soft computing techniques play a major role in image classification.

These soft computing-based image classification methods in terms of subjective performance affecting parameters (issues)

such as scaling, rotation (viewpoint), resolution, integration of classifier, and unknown images are tabulated in Table 2.

Table. 1. Analysis based on methods and performance affecting parameters

Methods	**Feature learning/ Feature representation**			**Classification**		**Reference**
	Scaling	**Rotation (View-point)**	**Resolution**	**Integration of classifier**	**Unknown image**	
SIFT	Yes	Yes	No	No	No	Lowe et al. [5]
SURF	Yes	Yes	No	No	No	Bay et al. [6]
LBP	Yes	Yes	No	No	No	Ojala et al. [7]
HOG	Yes	Yes	No	No	No	Dalal et al. [8]
Quadtree DBN	No	No	Yes	No	No	Basu et al. [2]
LRCNN	No	No	Yes	No	No	Chevalier et al. [4]
FG-LRCNN	No	No	Yes	No	No	
SRCNN	No	No	Yes	No	No	D. Cai et al. [9]
SparT	No	No	Yes	No	No	Wei et al. [10]
Pixel level fusion	No	No	No	Yes	No	Rokni et al. [11]
Object-level fusion	No	No	No	Yes	No	Xiao et al. [12]
Early late fusion	No	No	No	Yes	No	Gunes et al. [13]
Data feature fusion	No	No	No	Yes	No	Amarsaikhan et al. [14]
Logistic fusion	No	No	No	Yes	No	Fernando et al. [15]
1-vs-set	No	No	No	No	Yes	Scheirer et al. [16, 17]
W-SVM	No	No	No	No	Yes	
Pi-SVM	No	No	No	No	Yes	Jain et al. [18]
NNO algorithm	No	No	No	No	Yes	Bendale et al. [19] [20]
OpenMax	No	No	No	No	Yes	
Sparse representation	No	No	No	No	Yes	Zhang et al. [21]

Here, based on Table 2, it is clear that

- SIFT, SURF, LBP, HOG are hand-crafted feature extraction methods that successfully handle the scaling and rotation variation in input images. classification of these extracted features improves the performances of image classification methods.
- Resolution is an important quality factor of input images. the low resolution affects the performance of image classification methods. Quadtree DBN, LRCNN, FG-LRCNN, SRCNN, SparT methods handle the low-resolution image. But, cascading of these low and super-resolution of the image have not been explored.
- Integration of the classifier provides the low-cost solution of classification methods of a large dataset. Integrations based on the pixel level, object level, early-late level, data feature level. Logistic-based fusion methods, and suitable for the whole dataset. But, the integration of the classifier in the area of the distributed dataset, not explored.
- Image classification methods mostly perform well on known image classes. 1-vs-set machine, W-SVM, Pi-SVM, NNO algorithm.

IV. ISSUES AND CHALLENGES

After analysis of soft computing techniques presented in Fig.1 and various methods tabulated in Table 2, the issues such as scaling, rotation (viewpoint variation), resolution (high and low), blurriness (related to low resolution), illumination (contrast, brightness) related to the basic property of images. These are the main cause of variation (uncertainty) in images, which leads to an increase in the image classification complexity. Some image classification models based on the issue, such as integration of classifiers, unknown (adverse) images are taken into interest by various researchers. The model-based issue arises from various aspects of real-world image classification problems, which leads the specialized image classification domain to the general image classification domain. Therefore, it is not possible to incorporate and resolve all issues in a single soft computing technique. These are challenging tasks for researchers to develop a soft computing method for image classification which resolve the issues of low resolution, integration of classifiers for distributed image dataset and unknown (open set) image.

V. CONCLUSION

This paper presents comparative analysis of various methods-based on performance affecting parameters, issues and challenges that arise in applying soft computing techniques for image classification. Analysis shows that methods: 1-vs-set, W-SVM, Pi-SVM, NNO algorithm, Open Max, Sparse representation classify unknown (adverse) images clearly.

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