



# Satellite Image Processing Using SVM Classifier and ELBP-ML Features: A Review

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**Abstract:** Satellite images in course of capturing and transmitting are frequently degraded due to image effects or uncertain conditions. These effects introduce different noise patterns such as, Additive White Gaussian Noise, Salt & Pepper Noise and Mixed Noise. Therefore, retrieved images are highly noise corrupted because the image contents are more attenuated or amplified. The selection of optimum Image Processing and filtering technique depends to have knowledge about the characteristics of degrading system and noise pattern in an image. In this paper, Machine learning model used with components Support vector machine (SVM) Classifier and Extended Local Binary Patterns (ELBP) is used for Image Processing from highly noise corrupted images. The implementation of proposed methodology is being carried out by estimating the noise patterns of wireless image through configuring System Identification with SVM Classifier. Then, these estimated noise patterns are eliminated by configuring Signal Processing with SVM algorithm. The Processing of satellite images are done on basis new proposed ELBP Processing techniques.

**Keywords:** ELBP-Extended Local Binary Patterns, Artificial Neural Network, Support vector machine.

## I. INTRODUCTION

Recently, image Processing is growing and becoming a trend among technology developers especially with the growth of data in different parts of industry such as e-commerce, automotive, healthcare, and gaming. The most obvious example of this technology is applied to Facebook. Facebook now can detect up to 98% accuracy in order to identify your face with only a few tagged images and classified it into your Facebook's album. The technology itself almost beats the ability of human in image Processing or recognition (What is the Working of Image Recognition and How it is Used, [21]). One of the dominant approaches for this technology is deep learning. Deep learning falls under the category of Artificial Intelligence where it can act or think like a human. Normally, the system itself will be set with hundreds or maybe thousands of input data in order to make the 'training' session to be more efficient and fast. It starts by giving some sort of 'training' with all the input data [22] Machine learning is also the frequent systems that has been applied towards image Processing. However, there are still parts that can be improved within machine learning. Therefore, image Processing is going to be occupied with deep learning system. Machine Vision has its own context when it comes with Image Processing. The ability of this technology is to recognize people, objects, places, action and writing in images. The combination of artificial intelligence software and machine vision technologies can achieve the outstanding result of image Processing[23].

Image Processing has become a major challenge in machine vision and has a long history with it. The challenge includes a broad intra-class range of images caused by colour, size, environmental conditions and shape. It is required big data of labelled training images and to prepare this big data, it consumes a lot of time and cost as for the training purpose only [24] The characteristics of the satellite image, or of the unwanted satellite image, or of a systems influence on the satellite image that we like to compensate. Classifiers can adjust to unknown environment, and even track satellite image or system characteristics varying over time. LDA & PCA are the popular Classifiers methods for linear systems. Local Binary Patterns is a good choice when we needed Classifier in non linear Systems.

**1.1 Local Binary Patterns:** The original LBP operator labels the pixels of an image with decimal numbers, called Local Binary Patterns or LBP codes, which encode the local structure around each pixel. It proceeds thus, as illustrated in Fig.1: Each pixel is compared with its eight neighbours in a 3x3 neighbourhood by subtracting the centre pixel value; The resulting strictly negative values are encoded with 0 and the others with 1; A binary number is obtained by concatenating all these binary codes in a clockwise direction starting from the top-left one and its corresponding decimal value is used for labelling. The derived binary numbers are referred to as Local Binary Patterns or LBP codes.

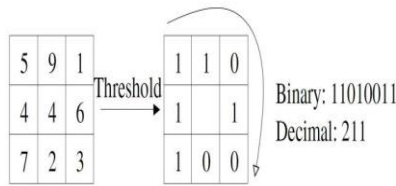


Fig. 1 An example of the basic LBP operator

One limitation of the basic LBP operator is that its small 3x3 neighbourhood clubfoot capture dominant features with large scale structures. To deal with the texture at different scales, the operator was later generalized to use neighbourhoods of different sizes [1]. LBP methodology has been developed recently with plenty of variations for improved performance in different applications. These variations focus on different aspects of the original LBP operator: (1) improvement of its discriminative capability; (2) enhancement of its robustness; (3) selection of its neighbourhood; (4) extension to 3D data; (5) combination with other approaches. In this section, we review recent variations of LBP.

TABLE 1 DIFFERENT LBP METHODS

Subsection	Variations	Properties
Enhancing the discriminative ability[6-10]	Improved LBP (Mean LBP)	Consider the effects of central pixels; present complete structure patterns.
	Hamming LBP	Incorporate non-uniform patterns into uniform patterns
	Extended LBP	Discriminate the same local binary patterns; cause high dimensionality.
	Completed LBP	Include both the sign and the magnitude information of the given local region
Improving the robustness[11]	Local Ternary Patterns	Bring in new threshold; no longer strictly invariant to gray-level transformation.
	Soft LBP	Not invariant to monotonic greyscale changes; cause high computational complexity.
Choosing the neighbourhood[12]	Elongated LBP	Extract the anisotropic information and lose anisotropic information; not invariant to rotation.
	Multi-Block LBP	Capture micro- and macro- structure information
	Three/Four Patch LBP	Encode patch type of texture information
Extending to 3D[13]	3D LBP	Extend LBP to 3D volume data
	Volume LBP (LBP-TOP)	Describe dynamic texture; cause high dimensionality.
Combining with other features[14-17]	LBP and Gabor Wavelet	Combine advantages of Gabor and LBP; increase time cost and cause high dimensionality.
	LBP and SIFT	Bring in the advantages of SIFT; reduce feature vector length
	LBP Histogram Fourier	Obtain rotation invariance globally for the whole region

**1.2 Support Vector Machine:** SVM is a supervised machine learning model that uses Processing algorithms for two-group Processing problems. After giving an SVM model sets of labelled training data for each category, they're able to categorize new text. The basics of Support Vector Machines and how it works are best understood with a simple example. Let's imagine we have two tags: red and blue, and our data has two features: x and y. We want a classifier that, given a pair of (x,y) coordinates, outputs if it's either red or blue. We plot our already labelled training data on a plane shown in figure 2:

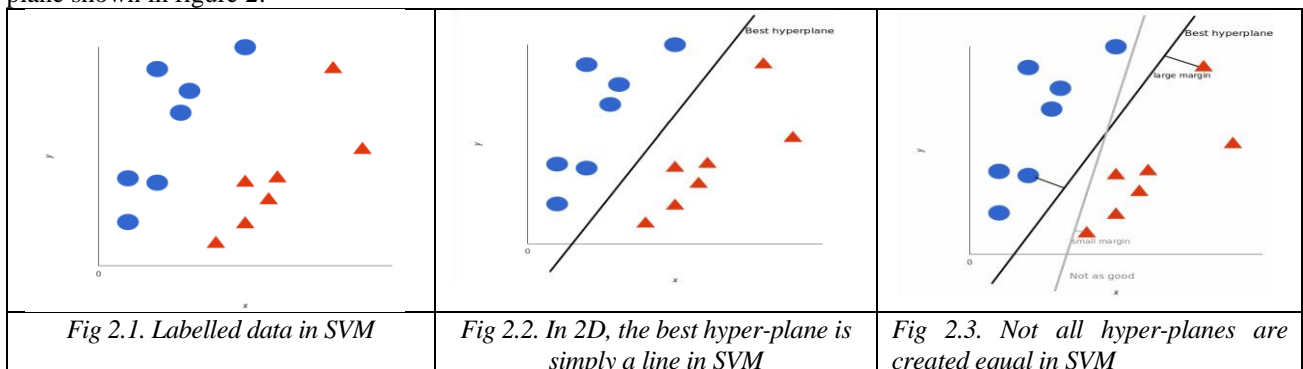


Fig 2.1. Labelled data in SVM

Fig 2.2. In 2D, the best hyper-plane is simply a line in SVM

Fig 2.3. Not all hyper-planes are created equal in SVM



A support vector machine takes these data points and outputs the hyperplane (which in two dimensions it's simply a line) that best separates the tags. This line is the decision boundary: anything that falls to one side of it we will classify as blue, and anything that falls to the other as red. But, what exactly is the best hyperplane. For SVM, it's the one that maximizes the margins from both tags. In other words: the hyperplane (remember it's a line in this case) whose distance to the nearest element of each tag is the largest.

## II. LITERATURE SURVEY

After doing lots of literature works in related area for selection of proposed work. after going through literature from books, research papers and standard websites we come up with conclusion that available methods are good enough but with some limitation regarding the speed of complete Processing (Processing time). Available methods are quite good so we did not make any changes in the methods, we have improvised the Processing rate developing a unique combination of two Local Binary Pattern. The purpose of this paper work is to provide a practical introduction to the new affine combination of Local Binary Pattern. This introduction includes a description and some discussion of the basic Local Binary Pattern, a derivation, description and some discussion of the Local Binary Pattern, and a relatively simple (tangible) example with real numbers & results.

**2.1 LBP Background:** During the last few years, Local Binary Patterns (LBP) [5] has aroused increasing interest in image processing and computer vision. As a non-parametric method, LBP summarizes local structures of images efficiently by comparing each pixel with its neighbouring pixels. The most important properties of LBP are its tolerance regarding monotonic illumination changes and its computational simplicity. LBP was originally proposed for texture analysis [6], and has proved a simple yet powerful approach to describe local structures. It has been extensively exploited in many applications, for instance, face image analysis [7], image and video retrieval [8], environment modelling [9], visual inspection [9], motion analysis [10], biomedical and aerial image analysis [11], remote sensing [12], so forth (see a comprehensive bibliography of LBP methodology online [13]). LBP-based facial image analysis has been one of the most popular and successful applications in recent years. Facial image analysis is an active research topic in computer vision, with a wide range of important applications, e.g., human-computer interaction, biometric identification, surveillance and security, and computer animation etc. LBP has been exploited for facial representation in different tasks containing face detection [14], face recognition [15], facial expression analysis [16], demographic (gender, race, age, etc.) Processing [17], and other related applications [18]. The development of LBP methodology can be well illustrated in facial image analysis, and most of its recent variations are proposed in this area.

Some brief surveys on image analysis [19] or face analysis [20] using LBP were given, but all these works discussed limited papers of the literature, and many new related methods have appeared in more recent years. In this paper, we present a comprehensive survey of the LBP methodology, including its recent variations and LBP-based feature selection, as well as the application to facial image analysis. To the best of our knowledge, this paper is the first survey that extensively reviews LBP methodology and its application to facial image analysis, with more than 10 related literatures reviewed.

**2.2 SVM background:** Support Vector Machines (SVMs) are a relatively new supervised Processing technique to the land cover mapping community. They have their roots in Statistical Learning Theory and have gained prominence because they are robust, accurate and are effective even when using a small training sample. By their nature SVMs are essentially binary classifiers, however, they can be adopted to handle the multiple Processing tasks common in remote sensing studies. The two approaches commonly used are the One-Against-One (1A1) and One-Against-All (1AA) techniques. In this paper, these approaches are evaluated in as far as their impact and implication for land cover mapping. The main finding from this research is that whereas the 1AA technique is more predisposed to yielding unclassified and mixed pixels, the resulting Processing accuracy is not significantly different from 1A1 approach [24]. It is the authors conclusions that ultimately the choice of technique adopted boils down to personal preference and the uniqueness of the dataset at hand. Over the last three decades or so, remote sensing has increasingly become a prime source of land cover information [25] This has been made possible by advancements in satellite sensor technology thus enabling the acquisition of land cover information over large areas at various spatial, temporal spectral and radiometric resolutions. The process of relating pixels in a satellite image to known land cover is called image Processing and the algorithms used to effect the Processing process are called image classifiers [26]. The extraction of land cover information from satellite images using image classifiers has been the subject of intense interest and research in the remote sensing community [27]. Some of the traditional classifiers that have been in use in remote sensing studies include the maximum likelihood, minimum distance to means and the box classifier. As technology has advanced, new Processing algorithms have become part of the main stream image classifiers such as decision trees and Local binary patterns. Studies have been made to compare these new techniques with the traditional ones and they have been observed to post improved Processing accuracies [28]. In spite of this, there is still considerable scope for research for further increases in accuracy to be obtained and a strong desire to maximize the degree of land cover information



extraction from remotely sensed data [29]. Thus, research into new methods of Processing has continued, and support vector machines (SVMs) have recently attracted the attention of the remote sensing community [30]. Support Vector Machines (SVMs) have their roots in Statistical Learning Theory [31]. They have been widely applied to machine vision fields such as character, handwriting digit and text recognition [32], and more recently to satellite image Processing [32]. SVMs, like Local binary patterns and other nonparametric classifiers have a reputation for being robust [33]. SVMs function by nonlinearly projecting the training data in the input space to a feature space of higher (infinite) dimension by use of a kernel function. This results in a linearly separable dataset that can be separated by a linear classifier. This process enables the Processing of remote sensing datasets which are usually nonlinearly separable in the input space. In many instances, Processing in high dimension feature spaces results in over-fitting in the input space, however, in SVMs over-fitting is controlled through the principle of structural risk minimization[34].

**2.3 Base Literature:** Andreas Kolsch et al [4] This paper presents an approach for real-time training and testing for document image Processing. In production environments, it is crucial to perform accurate and time-efficient training. Existing deep learning approaches for classifying documents do not meet these requirements, as they require much time for training and fine-tuning the deep architectures. Motivated from Computer Vision, we propose a two-stage approach. The first stage trains a deep network that works as feature extractor and in the second stage, Extreme Learning Machines (ELMs) are used for Processing. The proposed approach outperforms all previously reported structural and deep learning based methods with a final accuracy of 83:24% on Tobacco-3482 dataset, leading to a relative error reduction of 25% when compared to a previous Convolutional Neural Network (CNN) based approach (DeepDocClassifier). More importantly, the training time of the ELM is only 1:176 seconds and the overall prediction time for 2; 482 images is 3:066 seconds. As such, this novel approach makes deep learning-based document Processing suitable for large-scale real-time applications.

Mohd Azlan Abu et al [3] This research study about image Processing by using the deep neural network (DNN) or also known as Deep Learning by using framework TensorFlow. Python is used as a programming language because it comes together with TensorFlow framework. The input data mainly focuses in flowers category which there are five (5) types of flowers that have been used in this paper. Deep neural network (DNN) has been choosing as the best option for the training process because it produced a high percentage of accuracy. Results are discussed in terms of the accuracy of the image Processing in percentage. Roses get 90.585% and same goes to another type of flowers where the average of the result is up to 90% and above.

Sehla Loussaief et al [2] Hereby in this paper, we are going to refer image Processing. The main issue in image Processing is features extraction and image vector representation. We expose the Bag of Features method used to find image representation. Class prediction accuracy of varying classifiers algorithms is measured on Caltech 101 images. For feature extraction functions we evaluate the use of the classical Speed Up Robust Features technique against global color feature extraction. The purpose of our work is to guess the best machine learning framework techniques to recognize the stop sign images. The trained model will be integrated into a robotic system in a future work. In this paper, we related the different techniques and algorithms used in our machine learning framework for image Processing. We presented machine learning state-of-the-art applied to image Processing. We introduced the Bag of Features paradigm used for input image encoding and highlighted the SURF as its technique for image features extraction. Through experimentations we proofed that using SURF local feature extractor method for image vector representation and SVM (cubic SVM) training classifier performs best prediction average accuracy. In test scenarios we focused on stop sign image as we project to apply the trained classifier in a robotic system.

Anju Asokan et al [1] This paper presents the detailed comparison of various image processing techniques for analyzing satellite images .The satellite images are large in size, acquired from long distances and are affected by noise and other environmental conditions .Hence it is necessary to process them so that they can be used by the researchers for analysis. Satellite images are widely used in many real time applications such as in agriculture land detection, navigation and in geographical information systems. In this paper, a review of some popular machine learning based image processing techniques is presented. Also a detailed comparison of various techniques is performed. Limitations in each image processing method are also described. In addition to reviewing of different methods, different metrics for performance evaluation in each of the image processing areas is studied. The frequent availability of satellite images has made the remote applications flourish. Some of the common challenges found in the literatures are the image complexity, large image sizes, presence of unwanted artifacts and background information in the satellite images. It is especially difficult in feature detection in panchromatic images due to the presence of cloud cover. Most image fusion techniques suffer from the drawback that it cannot capture the smoothness between the contours. On examining the literature it is seen that deep learning and hybrid machine learning based techniques are finding wide popularity recently. Also deep learning techniques can be used as part of supervised image Processing and would be helpful in minimizing the misProcessing errors and hence improving the overall Processing accuracy. In this paper, we have discussed various image processing techniques, existing algorithms and the improved algorithms which could overcome the limitations of the existing algorithm. Also the difference metrics for evaluating the overall performance of the image processing techniques are presented. Furthermore, new objective performance evaluation methods could



be developed to validate these techniques. At present, even though a wide range of techniques are available for image processing, it is extremely cumbersome to arrive at a technique which can be commonly applied to all types of satellite images owing to the different color and textural variations. Hence presently the researchers are trying to arrive at some solutions by combining various image processing techniques or introducing hybrid models based on spectral and spatial indices for the same to improve the outcome.

### III. PROBLEM STATEMENTS

The satellite images differ widely in terms of the textural contrasts, colour variations and also are quite complex due to the presence of these variations. Hence applying processing techniques on the satellite data is quite difficult. Also the satellite data is captures from long distances and is affected by the presence of unwanted interferences which affects the quality of the image. This poses a serious difficulty in the succeeding processing stages and reduces the overall quality of the final image. The final image is very much essential for future analysis and for decision making purposes. Hence the noise distorted satellite images should be pre-processed before further processing techniques on the image is carried out. There are few specific problems

**3.1 Understanding Which Processes Need Automation:** It's becoming increasingly difficult to separate fact from fiction in terms of Machine Learning today. Before you decide on which AI platform to use, you need to evaluate which problems you're seeking to solve. The easiest processes to automate are the ones that are done manually every day with no variable output. Complicated processes require further inspection before automation. While Machine Learning can definitely help automate some processes, not all automation problems need Machine Learning.

**3.2 Lack of Quality Data:** The number one problem facing Machine Learning is the lack of good data. While enhancing algorithms often consumes most of the time of developers in AI, data quality is essential for the algorithms to function as intended. Noisy data, dirty data, and incomplete data are the quintessential enemies of ideal Machine Learning. The solution to this conundrum is to take the time to evaluate and scope data with meticulous data governance, data integration, and data exploration until you get clear data. You should do this before you start.

**3.3 Inadequate Infrastructure:** Machine Learning requires vast amounts of data churning capabilities. Legacy systems often can't handle the workload and buckle under pressure. You should check if your infrastructure can handle Machine Learning. If it can't, you should look to upgrade, complete with hardware acceleration and flexible storage

**3.4 Implementation:** Organizations often have analytics engines working with them by the time they choose to upgrade to Machine Learning. Integrating newer Machine Learning methodologies into existing methodologies is a complicated task. Maintaining proper interpretation and documentation goes a long way to easing implementation. Partnering with an implementation partner can make the implementation of services like anomaly detection, predictive analysis, and ensemble modelling much easier.

**3.5 Lack of Skilled Resources:** Deep analytics and Machine Learning in their current forms are still new technologies. Thus, there is a shortage of skilled employees available to manage and develop analytical content for Machine Learning. Data scientists often need a combination of domain experience as well as in-depth knowledge of science, technology, and mathematics. Recruitment will require you to pay large salaries as these employees are often in high-demand and know their worth. You can also approach your vendor for staffing help as many managed service providers keep a list of skilled data scientists to deploy anytime.

### IV. CONCLUSION

At present, even though a wide range of techniques are available for image processing, it is extremely cumbersome to arrive at a technique which can be commonly applied to all types of satellite images owing to the different color and textural variations. Hence presently the researchers are trying to arrive at some solutions by combining various image processing techniques or introducing hybrid models based on spectral and spatial indices for the same to improve the outcome. In near future this type of combination can be implemented for better accuracy. The frequent availability of satellite images has made the remote applications flourish. Some of the common challenges found in the literatures are the image complexity, large image sizes, presence of unwanted artefacts and background information in the satellite images. It is especially difficult in feature detection in panchromatic images due to the presence of cloud cover. Most image fusion techniques suffer from the drawback that it cannot capture the smoothness between the contours. On examining the literature it is seen that deep learning and hybrid machine learning based techniques are finding wide popularity recently.

In this paper work it relate the different techniques and algorithms used in proposed machine learning framework for satellite image Processing. paper presented machine learning state-of-the-art applied to image Processing. This work introduced the Bag of Features paradigm used for input image encoding and highlighted the Extended Local Binary Pattern as its technique for image features extraction. Through experimentations this work proofed that using ELBP local feature extractor method for image vector representation and LKSVM and RKLBP training classifier performs



best prediction average accuracy. In test scenarios this focused on satellite image as we project to apply the trained classifier in a general system.

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