Optimization of image processing techniques using Neural Networks –A Review

BHARATHI P. T *
Research Scholar

Dr. P. SUBASHINI*
Associate Professor

*Department of Computer Science, Avinashilingam Institute for Home Science and Higher Education for Women, Coimbatore, INDIA
email_id: bharathi2028@gmail.com, mail.p.subashini@gmail.com

Abstract: - This paper reviews the application of artificial neural networks in image preprocessing. Neural networks, especially uses feed-forward neural networks, Kohonen feature maps, back-propagation neural networks, multi-layer perception neural networks and Hopfield neural networks. The various applications are categorized into a novel two-dimensional taxonomy. One dimension specifies the type of task performed by the algorithm, preprocessing, data reduction or feature extraction, segmentation, object recognition, image understanding and optimization. The other dimension captures the abstraction level of the input data processed by the algorithm that is pixel-level, local feature-level, structure-level, object-level, object-set-level and scene characterization. Each of the six types of tasks poses specific constraints to a neural-based approach. A synthesis is made of unresolved problems related to the application of pattern recognition techniques in image processing and specifically to the application of neural networks. By this survey, the paper try to answer what the major strengths and weakness of applying neural networks for image processing would be.

Keywords: - Image preprocessing, Data reduction, Image Segmentation, Object recognition, Image understanding, optimization and Neural Networks.

1. Introduction

In the past years, artificial neural networks (ANNs) have seen an increasingly lots of interests in image processing. The intention of this article is to cover those approaches introduced and to make a map for ANN techniques used in image processing. Initially, pattern recognition problems were often solved by linear and quadratic discriminates or non-parametric k-nearest neighbor classifier. Since then, neural networks with one or more hidden layers can, in theory, be trained to perform virtually any regression or discrimination task. Since from 1990’s neural networks have increasingly been used as an alternative to classic pattern classifiers and clustering techniques. Non-parametric feed-forward neural networks quickly turned out to be attractive trainable machines for feature-based segmentation and object recognition. When no good standard is available, the self-organizing map (SOM) feature is an interesting alternative for supervised techniques. The current use of neural networks in image processing exceeds the aforementioned traditional applications. The role of feed-forward neural networks and SOMs has been extended to encompass also low-level image processing tasks such as noise suppression and image enhancement. Hopfield neural networks were introduced as a tool for finding satisfactory solutions to complex optimization problems. This makes them an interesting alternative to traditional optimization algorithms for image processing tasks that can be formulated as optimization problems.

This study paper discusses different types of Neural Networks methods used in image processing from 1990 to 2011. The review article on image processing using neural networks is prepared to solve different problems in image processing. There are two central questions which we will try to answer in this study paper, what are major applications of neural networks in image processing now and in the nearby future and which are the major strengths and weaknesses of neural networks for solving image processing tasks.

From the reviewed literatures, it is found that neural network model employed for image processing when compared with conventional image processing methods, the time for applying a trained neural network to solve a image processing problem was negligibly small, though the training of a neural network is a time cost work and also image processing tasks often require quite complex computation. We think that this may be the major contribution of using neural network for solving image processing tasks.

Despite their success story in image processing, artificial neural networks have several disadvantages compared to other techniques. The first one is that a neural network is hard to express human expert's knowledge and experience, and the construction of its topological structure lacks of theoretical methods. A solution to these problems may be to combines fuzzy technique with neural networks together by using neural networks to process fuzzy information. It provides neural networks ability to express qualitative knowledge and network topological structure and joint weight have clear physical meaning. Also, it can make the initialization of network easier, avoid the local optimization of network training and ensure the stability of networks. The second problem relates to the amount of input data. For achieving a high and reliable performance for non-training cases, a large number of training cases are commonly required. If an ANN is trained with only a small number of cases, the generalization ability (performance for non-training cases) will be lower.

This review paper provides the information about how different types of neural networks can be used in various steps of image processing. For each step in image processing which are the neural network methods gives the good results and also the advantages and disadvantages of using neural network. Section 2 discusses the Steps involved in Image processing, section 3 discusses some real-world applications and issues of neural networks in image processing and section 4 gives the conclusion and followed by references used to complete this article.

2. Steps involved in Image processing

2.1 Preprocessing

The first step in image processing consists of preprocessing. Preprocessing means any operation of which the input consists of sensor image and the output will be a full image. Preprocessing operations generally fall into one of three categories: image reconstruction (to reconstruct an image from a number of sensor measurements), image restoration (to remove any aberrations introduced by the sensor, including noise) and image enhancement (accentuation of certain desired features, which may facilitate later processing steps such as segmentation or object recognition). Applications of ANN in these three preprocessing categories will be discussed separately below. The majority of the ANN was applied directly to pixel level data and feature level data [1]. The following flow chart shows the preprocessing steps.

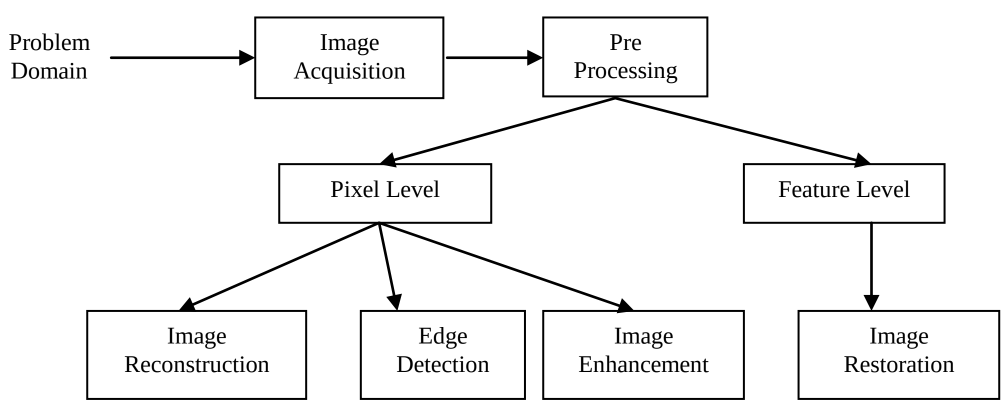

Fig.1: Block diagram of Preprocessing.

2.1.1 Image Restoration

Digital image restoration is a field of engineering that studies methods used to recover an original scene from degraded observations. It is an area that has been explored extensively in the signal processing, astronomical, and optics communities for some time. Many of the algorithms used in this area have their roots in well-developed areas of mathematics, such as estimation theory, the solution of ill-posed inverse problems, linear algebra and numerical analysis. Techniques used for image restoration are oriented toward modeling the degradations, usually blur and noise, and applying an inverse procedure to obtain an approximation of the original scene.

Neural networks are well-suited to the image restoration task because they are effectively adapted to the local nature of the problem. They may also be used to realize well-known algorithms without the need for extensive underlying assumptions about the distribution of the parameters being estimated. They may also be used to estimate the regularization parameter in the CLS approach, and can be developed to alternate between learning and restoration cycles. Finally, neural network processing techniques have recently led to efficient VLSI architectures for image restoration due to their highly parallel processing nature.

In 1993, Henry Hanek, Nirwan Ansari and Zeeman Z. Zhang [2], have done a comparative study on the generalized adaptive neural filter, stack filters, GANF structure, a single neuron, a 2 layer 3-neuron and a three layer neuron. Back-propagation was used to train the 2 layer and 3 layer neuron networks. They have concluded that a single neuron cannot implement all possible boolean function for all given input vector, a 2 layer can implement any boolean function consisting of 2 variables and a 3 layer neuron can implement any function defined on $[0, 1]^N$. The 3 layer neuron used in GANF structures uses both 3x3 and 5x5 window sizes. However, it was also shown that the structure of the neural operators need not be overly complex to achieve good results.

In 1996, Armando J. Pinho [3], have developed a tuned neural network filter for noise reduction in gray level images and compared with median filters. First they have degraded the images with Gaussian noise and then filtered with three neural network filters. The noisy test image was processed by a 3 x 3 and a 5 x 5 median filter. Neural network filter provides always a higher reduction in noise variance when compared to the median filters.

In 2002, Dianhui Wang, Tharam Dillon and Elizabeth Chang [8], in their work on pattern learning based on image restoration scheme for degraded digital images. The key points addressed in their work 1) The use of edge information extracted from source images as *a priori* knowledge in the regularization function to recover the details and reduce the ringing artifact of the coded images, 2) The theoretic basis of the pattern learning-based approach using implicit function theorem, 3) Subjective quality enhancement with the use of an image similarity for training neural networks and 4) Empirical studies with comparisons to the set partitioning in hierarchical tree (SPIHT) method. The main motivation of this paper is to establish a mathematical foundation for the use of the neural networks. Image quality is improved by reducing the ringing artifact and preserving more edge information.

In 2009, Deng Zhang and Toshi Hiro Nishimura [4], in their PCNN based anisotropic diffusion method eliminated the appearance of the pulse noise like spots on three grayscale images polluted by l/f noise: a 400 x l00 abrupt edge image, a 400 x l00 gradual edge image, and a 512 x 512 Lena image and along with the proposed method they have compared with traditional de-noising methods like median filter, Wiener filter, Lee filter and the traditional anisotropic diffusion filter. They have used PSNR, S/MSE, SSIM, and β as the performance matrix. The results obtained by PSNR, S/MSE, SSIM, and β are 29.83, 19.38, 0.02 and 0.93 respectively for an abrupt edge image. The proposed method produced good results in noise suppression and edge detail preservation.

In 2009, Chen Junhong and Zhang Qinyu [5], have performed de-noising in the image based on combined Neural Networks filter modeled by using BPNN filter and self-organizing mapping neural networks (SOMNN). SOMNN is a kind of unsupervised neural networks. The corrupted image contains white Gaussian noise which can itself be considered as training data. First they mapped the tow-dimensional corrupted image into one-dimensional sequence by 4 ways and got 4 semi-recovered images. Then the fusion system is used to reduce the remaining noise. The PSNR value obtained by average 3 X 3 windows and the proposed method are 22.12dB and 27.74dB respectively.

In 2011, MingYong Jiang, XiangNing Chen, and XiaQiong Yu [54], have used an adaptive Sub-Optimization Hopfield Neural Network for regularized image restoration based on edge detection. The procedure of the algorithm is choose the i-th pixel of image, suppose the image has periodic boundaries and form the sub image on its neighborhood next restore the sub-image using modified continuous HNN image restoration then take the corresponding value of result as the restored result. The parameters considered are ISNR, iteration and time. Adaptive regularization is implemented by using the edge information detected by the Sobel Detector, which can preserve the details and improve the performance of the algorithm. The result shows 5.6305dB improvement in SNR

Table 1: Comparison of various image restoration methods

Author	**Year**	**Method**	**Performance Criteria**	**Result**
Henry Hanek, Nirwan Ansari and ***Zeeman*** *Z. Zhang*	1993	Generalized Adaptive Neural Filter for Digital Images	MAE, MSE and SNR	The results obtained by MAE, MSE and SNR are 15.74, 602.51 and 10.23 respectively
Armando J. Pinho	1996	BPNN, FFNN for Gray Level Images	Noise variance of σ^2 (400, 900 and 1600) and iteration.	Neural network filter provided a higher reduction in noise variance when compared to the median filters
Dianhui Wang, Tharam Dillon and Elizabeth Chang	2002	Feed-Forward NN for Degraded Digital Images	mean square error (MSE), peak signal-to-noise ratio (PSNR), set partitioning in hierarchical tree (SPMT)	The experimental results demonstrate promising performance on both objective and subjective quality for lower compression ratio sub band images
Deng Zhang & Toshi Hiro Nishimura	2009	PCNN for CMOS of Gray scale Images	PSNR, S/MSE, SSIM, and β (linking strength factor between synapses)	The results obtained by PSNR, S/MSE, SSIM, and β are 29.83, 19.38, 0.02 and 0.93 respectively for an abrupt edge image
Chen Junhong, Zhang Qinyu	2009	BPNN and SOMNN for 8-bit Grayscale Images	PSNR	The PSNR = 27.74dB value obtained by the proposed method is high compared to other methods.
MingYong Jiang, XiangNing Chen, and XiaQiong Yu	2011	Sub-Optimization Hopfield Neural Network for Digital Images	ISNR, Iteration and time	The result showed us that we got 5.6305dB improvement in SNR

2.1.2 De-blurring

Image deblurring is the process of obtaining the original image by using the knowledge of the degrading factors. Degradation comes in many forms such as blur, noise, and camera misfocus. A major drawback of existing restoration methods for images is that they suffer from poor convergence properties, the algorithms converge to local minima and they are impractical for real imaging applications. Added to its disadvantage, some methods make restrictive assumptions on the PSF or the true image that limits the algorithm's portability to different applications. In conventional approach, deblurring filters are applied on the degraded images without the knowledge of blur and its effectiveness. The key issue is that some information on the lost details is indeed present in the blurred image—but this information is “hidden” and can only be recovered if we know the details of the blurring process. BPNN, MLMVN and CNN are used for image restoration to get a high quality restored image and attain fast neural computation, less computational complexity due to the less number of neurons used and quick convergence without lengthy training algorithm. Deblurring of a high quality image from a degraded recording is a good application area of neural networks.

In 1994, John P. Miller, Tamas Roska, Tamas Sziranyi, Kenneth R. Crounse, Leon O. Chua and Laszlo Nemes [6], in their work on image de-blurring by using Cellular neural network solved the problem of 3-D cofocal image reconstruction of microscopy in real-time. The blurring is caused by motion, light scattering within the optics, diffraction of the light due to the finite aperture of the device, and resolution. They have used 3-D PSF by inverse Fourier transformation as a de-blurring function. The proposed method is to solve the basic 3-D cofocal image reconstruction task of microscopy in real-time application.

In 2008, Igor Aizenberg, Dmitriy V. Paliy, Jacek M. Zurada and Jaakko T. Astola [7], have used error back-propagation algorithm and training algorithms for the continuous multi level multi valued neural (MLMVN) network. The performance is evaluated in terms of blur identification, speed of convergence and classification rate (CR). The methods used for blurring are Gaussian blur with PSF $\tau = 2$, rectangular blur of the size 9 X 9 and boxcar blur of the size 9 X 9. For blur identification the proposed method is compared with discrete valued MLMVN, SVM based classification and the results obtained are 98.0%, 97.9% and 96.4% respectively. The SVM-based method provides CR = 97.5% but the proposed method results CR = 99.14%. The proposed method yields 92.4% for speed of convergence. This identification procedure is computationally fast and cheap and the proposed network can be used as an efficient estimator of PSF, whose precise identification is of crucial importance for image de-blurring.

In 2011, Dr.P.Subashini, M.Krishnaveni and Vijay Singh [51], have used BPNN for blur parameter identification. The parameters extracted from blur type are trained using BPN and network is simulated to restore the image. Deblurring with convolution Lucy Richardson algorithm and Deblurring with convolution Wiener algorithm are the two methods considered in this paper to evaluate the performance of BPN. In the Lucy-Richardson algorithm, no specific statistical noise model is assumed. This function can be effective when the PSF is known but less performance when there is additive noise in the image. It only works when the noise is not too strong and works well for Gaussian blur. Wiener filter tries to minimize the mean square error between the image acquired and its restored estimate. In the absence of noise, the Wiener filter reduces to the ideal inverse filter. Time performance and mean square error (MSE) are the evaluation parameters used between conventional methods and BPN. Back propagation neural network model have great potential in areas where high computation rates are required and the current best systems are far from equaling human performance. Deblurring of a high quality image from a degraded recording is a good application area of neural nets.

Table 2: Comparison of various Deblurring methods

Author	Year	Method	Performance Criteria	Result
John P. Miller, Tamas Roska, Tamas Sziranyi, Kenneth R. Crounse, Leon O. Chua and Laszlo Nemes	1994	Cellular Neural Network by using Point Spread Function (PSF) for Digital Images	Blur H window	This can be applied to the real-time image processing task of performing efficient and robust de-convolution
Igor Aizenberg, Dmitriy V. Paliy, Jacek M. Zurada and Jaakko T. Astola	2008	multilayer neural network based on multi-valued neurons (MLMVN)for Grayscale Images	Blur identification, Speed of convergence and Classification Rate (CR)	The proposed method results CR = 99.14%, speed of convergence = 92.4% and blur identification = 98.0%
P.Subashini, M.Krishnaveni and Vijay Singh	2011	Back Propagation Neural Network for digital images	Time and MSE	The proposed method proves the efficient and effective restoration technique

2.1.3 Image Enhancement

Image enhancement refers to emphasis or sharpening of image features such as edges, boundaries or contrast to make a graphic display more useful for display and analysis. Image enhancement features are that correct color hue and brightness imbalances as well as other image editing features, such as red eye removal, sharpness adjustments, automatic cropping etc. The enhancement process does not increase the inherent information content in the data. But it does increase the dynamic range of the chosen features so that they can be detected easily. Objectives in image enhancement are noise reduction, feature enhancement, the removal of inhomogeneous background etc. Cellular neural networks (CNN) are parallel-computing, analog arrays, which are suitable for most of the computation needed. Adaptive sensing is one of the ideal applications for CNN-type sensor machines.

In 2004, Moustafa Abdel Aziem Moustaf & Hanafy M Ismaiel [9], have done a comparative study on traditional techniques both in spatial and frequency domains with self-organizing artificial neural networks techniques for recovering images corrupted with different percentages of impulse noise 10%-90% of the photographic image. The performance evaluation methods used are Normalized Mean Square Error (NMSE), Projection Mean Square Error (PMSE), and Quantitative evaluation method. Artificial Neural Networks (ANN) technique is better than the traditional techniques both in spatial and frequency domain when dealing with noise ratios 30%- 40%.

In 2007, Chin-Teng Lin, Kang-Wei Fan, Her-Chang Pu, Shih-Mao Lu, and Sheng-Fu Liang [10], have proposed a novel HVS-directed adaptive interpolation scheme to combine the bilinear interpolation and ANN for image interpolation to balance the tradeoff of speed and quality. The performance evaluation methods used are MSE and PSNR. They have compared their results with bilinear interpolation, bi-cubic interpolation, linear associative memories (LAM) interpolation, edge-directed interpolation & aqua interpolation. The result shows that the proposed method produces a higher visual quality for the interpolated image than the conventional interpolation methods.

In 2008, S. Battiato, E. U. Giuffrida and F. Rundo [11], have used a Cellular Neural Network for zooming digital color images. An adaptive gradient driven enhancement process is used to improve the quality of the enlarged image. They have compared their result with Replication, Bi-cubic & ALZ algorithms. The result shows that the proposed method is more effective than other methods.

In 2010, Seyed Mohammad Entezarmahdi and Mehran Yazdi [55], have developed two transform based super resolution methods for enhancing the resolution of a stationary image. In the first method, neural network is trained by wavelet transform coefficients of lower resolution of a given image, and then this neural network are used to estimate wavelet details subbands of that given image. In the second method, the wavelet transform is replaced by contourlet transform. These two methods have been compared with each other and with the bicubic method on different types of images. PSNR is used for evaluating the two methods. The experimental results demonstrate the superiority performance of the proposed methods compared with regular stationary image resolution enhancing methods.

Table 3: Comparison of various image enhancement methods

Author	Year	Method	Performance Criteria	Result
Moustafa Abdel Aziem Moustaf & Hanafy M Ismaiel	2004	Artificial NN for Digital Images	Normalized Mean Square Error (NMSE), Projection Mean Square Error (PMSE), and Quantitative evaluation method.	NEMM filter has the best performance when the images corrupted with 10% impulse noise with mask size 3x3, where its NMSE = 0.0004 is the lowest value compared with other filters
Chin-Teng Lin, Kang-Wei Fan, Her-Chang Pu,	2007	HVS-Directed NN for natural	MSE and PSNR	The proposed method results a low MSE = 19.99 and high PSNR =

Shih-Mao Lu, and Sheng-Fu Liang		photographic Images		35.12 for Lena image
S. Battiato, E. U. Giuffrida and F. Rundo	2008	Cellular NN for Digital Color Images	PSNR	Improve the quality of the enlarged image generated by the CNN processing
Seyed Mohammad Entezarmahdi, and Mehran Yazd	2010	Contourlet and Wavelet Transforms by means of the Artificial Neural Network for digital images	PSNR	The experimental results demonstrate the superiority performance of the proposed methods compared with regular stationary image resolution enhancing methods

2.1.4 Edge Detection

In image processing and computer vision, edge detection is a process which attempts to capture the significant properties of objects in the image, particularly in the areas of feature detection and feature extraction, which aim at identifying points in a digital image at which the image brightness changes sharply or more formally has discontinuities. These properties include discontinuities in the photometrical, geometrical and physical characteristics of objects. Such information gives rise to variations in the grey level image. There are many more methods for edge detection, but most of them can be grouped into these three categories search-based, zero-crossing based and threshold based. Artificial neural network optimizes and solves the problem of unstable detection precision for tile dimension detection. The parallel model was applied to dimension and defect detection of tile, precision and speed can meet the requirement of edge detection.

In 1996, Si Wei Lu and Jun Shen [12], have used Artificial Neural Network for boundary extraction. Boundary extraction it performed by back propagation neural network and boundary enhancement by a modified Hopfield neural network. The back propagation neural network is trained by a set of typical boundary samples with a *5* x *5* window. The boundary enhancement is performed on the eight boundary orientations separately. They have compared the boundary detection with DRF, SDEF & GEF methods. The proposed method removed more noise and detected more boundary points.

In 2008, Weiqing Li, Chengbiao Wang, Qun Wang and Guangshe Chen [13], have used back propagation neural network for edge detection. First they have converted the image into binary image and applied Sobel edge detection method. The hidden layer consists of 8 neurons and one output layer with the threshold value of 0.90. They have compared the results with Sobel, Sobel with sub-pixel and parallel back propagation neural network with sub-pixel method (the proposed method) are 99.58%, 99.75% and 99.97% respectively.

In 2008, Alima Damak, Mohamed Krid and Dorra Sellami Masmoudi [14], in their work on edge detection with pulse mode operations and floating point format precision. Floating point operation is used as its activation function. Canny operator was used as learning neuron for a multilayer neural network. A series of image data base was used for validation and testing. Each set is subdivided into two classes, one is for the network learning and the other is used for testing the network generalization. Experimental result shows that the proposed method has good learning performances.

In 2009, Hamed Mehrara, Mohammad Zahedinejad & Ali Pourmohammad [15], in their work on edge detection by using BP Neural Network based on threshold binarization. Firstly they have converted the gray image to binary image by Otsu's method threshold value. Next they have used 2x2 windows because all other windows reduce the details and include more training set, but this is efficiently simple and accurate. They have compared the experimental results with Canny, Roberts, Prewitt and Sobel methods. The results demonstrated that the proposed technique provides the better results compared with traditional edge detection techniques while improved in the computations complexity. The proposed method solved the problem of difficulty in convergence, if the back propagation neural network was used directly for edge detection of gray image because a too huge training sample set was needed.

In 2010, Dawei Qi, Peng Zhang, Xuejing Jin and Xuefei Zhang [16], in their work on edge detection initially they have used traditional edge algorithm then a single layer Hopfield neural network which maps the two-dimensional network to an initial binary image. They have compared the proposed method with Sobel edge operator, Roberts's edge operator, Prewitt edge operator, Laplacian operator and canny operator. The experimental result shows that the proposed method provides more noiseless and more vivid edge points than the traditional methods for edge detection.

Table 4: Comparison of various Edge detection methods

Author	Year	Method	Performance Criteria	Result
Si Wei Lu and Jun Shen	1996	BPNN and boundary enhancement by a modified Hopfield neural network for Digital Images	Boundary patterns	The proposed method is proved to be good in extracting the boundaries, eliminating the noise and boundary elements which are missed in other methods
Weiqing Li, Chengbiao Wang, Qun Wang and Guangshe Chen	2008	BPNN for Binary Image as well as Gray level Image	Detected dimension (mm) and accurate rate (%)	The experiment results show the accurate rate of tile dimension detection can reach to 99.97%
Alima Damak, Mohamed Krid and Dorra Sellami Masmoudi	2008	Multilayer NN for Digital Images	Training error and Generalization error	Each image in the data base has a training error doesn't exceed 5.34% and a generalization error reach a maximum with 6.79%
Hamed Mehrara , Mohammad Zahedinejad and Ali Pourmohammad	2009	BPNN Threshold Binarization for Gray level Image	Edge patterns	The proposed method has better visual performance in maintaining the edge characteristics, when compared Canny, Roberts, Prewitt and Sobel edge detection methods. It also improves the computations complexity
Dawei Qi, Peng Zhang, Xuejing Jin and Xuefei Zhang	2010	Hopfield NN for X-Ray Images	α , β , γ and edge initiation	The proposed method provides a good result in detecting edges of wood defect images, the noises were effectively removed

2.1.5 Applicability of neural networks in preprocessing

There appears to be three types of problems in preprocessing to which ANNs can be applied:

1. Optimization of an objective function defined by a traditional preprocessing problem.
2. Approximation of a mathematical transformation used for image reconstruction, e.g., by regression.
3. Mapping by an ANN trained to perform a certain task, usually based directly on pixel data.

To solve the first type of problems, traditional methods for optimization of some objective function may be replaced by a Hopfield network. For the approximation task, regression (feed-forward) ANNs could be applied. Although some applications such ANNs were indeed successful, it would seem that these applications call for more traditional mathematical techniques, because a guaranteed (worst-case) performance is crucial in preprocessing.

In several other applications, regression or classification (mapping) networks were trained to perform image restoration or enhancement directly from pixel data. A remarkable finding was that non-adaptive ANNs were often used for preprocessing. Secondly, when networks were adaptive, their architectures usually differed much from those of the standard ANNs: prior knowledge about the problem was used to design the networks that were applied for image restoration or enhancement. The interest in non-adaptive ANNs indicates that the fast, parallel operation and the ease with which ANNs can be embedded in hardware may be important criteria when choosing for a neural implementation of a specific preprocessing operation. However, the ability to learn from data is apparently of less importance in preprocessing. While it is relatively easy to construct a linear filter with a certain, desired behavior, e.g., by specifying its frequency profile, it is much harder to obtain a large enough data set to learn the optimal function as a high-dimensional regression problem. This holds especially when the desired network behavior is only critical for a small subset of all possible input patterns. Moreover, it is not at all trivial to choose a suitable error measure for supervised training, as simply minimising the mean squared error might give undesirable results in an image processing setting.

2.2 Data reduction

Two of the most important applications of data reduction are image compression and feature extraction. In general an image compression algorithm is used for storing and transmitting images, it involves two steps: encoding and decoding. For these two steps ANN can be used. Feature extraction is used for subsequent segmentation or object recognition. The kind of features one wants to extract often corresponds to particular geometric or perceptual characteristics in an image or application dependent [1]. The following flow chart shows the Data Reduction steps.

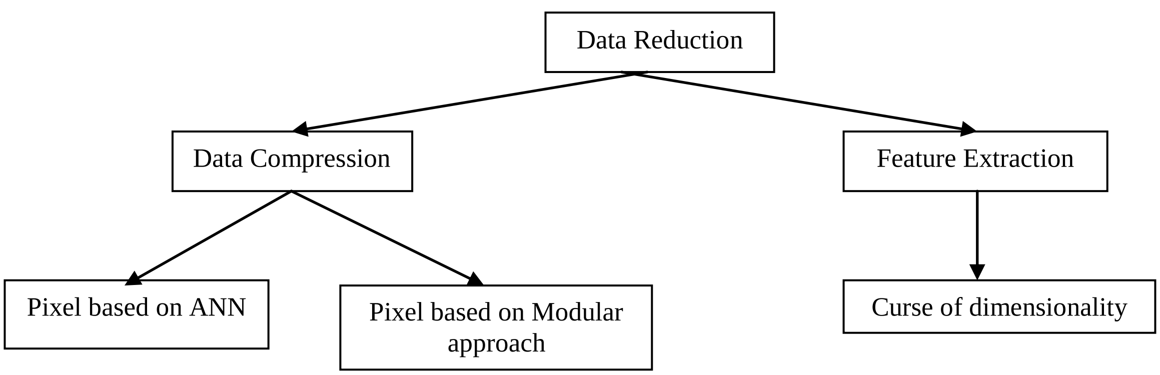

Fig.2: Block diagram of Data Reduction

2.2.1 Image compression

Computer images consist of large data and hence require more space to store in the memory. The compressed image requires less storing space of memory and less time to transmit. Two different types of image compression approaches can be identified, direct pixel-based encoding/decoding by ANN and pixel-based encoding/decoding based on a modular approach. Different types of ANNs have been trained to perform image compression: feed-forward networks, SOMs, adaptive fuzzy clustering. ANN approaches have to compete with well-established compression techniques such as JPEG. The major advantage of ANN is that their parameters are adaptable which may give better compression rates when trained on specific image material. However, such a specialization becomes a drawback when novel types of images have to be compressed.

In 1993, Tracy Denk, Keshab K. Parhi and Wadimir Cherkassky [17], have used wavelet transform and neural networks for image compression. Image compression technique is performed in three steps. First, the image is decomposed at different scales using the wavelet transform to obtain an orthogonal wavelet representation of the image. Second, the wavelet coefficients are divided into vectors which are projected onto a subspace using a neural network. Finally, the coefficients which project the vectors of wavelet coefficients onto the subspace are quantized and entropy coded. The results shown by the proposed method are as follows, compressed image with bit rate 0.25 bits/pixel, MSE = 79.6 and PSNR = 29.1Db for the Lena image. The vector quantization *to* quantize the values at the hidden layers of the neural networks provides better performance than using scalar quantization on the hidden layer values.

In 1998, Christophe Amerijckx, Michel Verleysen, Philippe Thissen and Jean-Didier Legat [18], have performed image compression by using self-organized Kohonen's algorithm. They have used the compression scheme based on discrete cosine transform (DCT) of the original image, vector quantization by Kohonen's map, differential coding by first-order predictor, and entropic coding of the differences. The compression scheme consists of a cut of frequency (six or eight DCT coefficients). The proposed method is compared with JPEG compression algorithm. The results are as follows for the proposed method compression rate = 38, PSNR = 24dB and compression rate = 38.55, PSNR = 22.46dB by the JPEG algorithm. By using Kohonen's self-organization method the compression rate is increased by about 80%. It is an important result showing the effectiveness of the proposed compression scheme.

In 2010, Vilas Gaidhane, Vijander Singh and Mahendra Kumar [19], have used feed forward back propagation neural network method for image compression. The performance criteria used are MSE, PSNR and CR. The results obtained are PSNR = -30.3078, MSE = 30.9772 and epoch = 300 for PCA method and PSNR = 85.0179, MSE = 5.1149E-06 and epoch = 300 for the proposed method. From their work it is understood that as the number of hidden neuron increases we get the effective results. PCA method is not satisfactory when compared with feed forward BPNN for image compression.

In 2010, Jin Wang, Xiaomei Lin and Kebing Wu [20], have used wavelet neural network algorithm for ECG data compression. In the proposed method, by continuously adjusting the initial weights the convergence speed is accelerated. This method is compared with Wavelet compression algorithm and the average result obtained was compression rate (CR) = 7.6%, Percent Root-mean square Difference (PRD) = 2.74% and ECG signal after restoration keeps the original ECG waveform features.

Table 5: Comparison of various image compression methods

Author	**Year**	**Method**	**Performance Criteria**	**Result**
Tracy Denk, Keshab K. Parhi, and Wadimir Cherkassky	1993	wavelet transform and NN for Digital Images	Peak Signal to Noise Ratio(PSNR), Mean-Squared-Error (MSE)	The compressed image with bit rate 0.25 bits/pixel, MSE = 79.6 and PSNR = 29.1dB
Christophe Amerijckx, Michel Verleysen, Philippe Thissen and Jean-Didier Legat	1998	Kohonen's NN for Digital STILL Image	DCT transform of the original image, vector quantization by Kohonen's map, peak signal to noise ratio (PSNR)	The proposed method allows an increase of about 80% for the compression rate compared to the JPEG standard and also shows better performances (in terms of PSNR) for compression rates higher than 30
Vilas Gaidhane , Vijander Singh, Mahendra Kumar	2010	FF, BPNN for 32 X 32 and 256 X 256 images Digital Images	PCA Algorithm, MSE, PSNR and CR	The results of proposed method are as follows PSNR = 85.0179, MSE = 5.1149E-06 and epoch = 300
Jin Wang, Xiaomei Lin and Kebing Wu	2010	Neural Networks for ECG Data	Compress Ratio (CR), Percent Root-mean square Difference (PRD)	The proposed method provides CR = 7.6%, PRD = 2.74%, and ECG signal after restoration keeps the original ECG waveform features

2.2.2 Feature extraction

Feature extraction can be seen as a special kind of data reduction of which the goal is to find a subset of informative variables based on image data. Since image data are by nature very high dimensional, feature extraction is often a necessary step for segmentation or object recognition to be successful. The extracted features were used for segmentation image matching or object recognition. It is important to make a distinction between application of supervised and unsupervised ANN for feature extraction. Both supervised and unsupervised ANN feature extraction methods have advantages compared to traditional techniques such as PCA, Feed-forward ANN with several hidden layers which can be trained to perform non-linear feature extraction.

In 1996, C. H. Chen and G. G. Lee [21], have proposed a novel statistical feature extraction method using Gaussian Markov random field (GMRF) under a multi-resolution wavelet decomposition scheme. The task of automated recognition of ANN can be achieved in two steps. The first step involves a careful selection of features that best characterize the class membership of the patterns. In the second step a good ANN is designed to differentiate the given or measured patterns based on the information provided by the selected features with minimum error. Feature extraction is efficient for real world digital mammograms and natural textural images.

In 1999, S. J. Perantonis and V. Virvilis [22], have developed a novel neural network based method for feature extraction. They have used synthetic and real world examples to evaluate the proposed method and the examples considered are rotated XOR (R-XOR) problem, machine learning repository, namely the BUPA a Liver Disorders set and the Ionosphere set. In their proposed method once features are extracted, each problem is solved using two different learning paradigms namely, MFNNs and nearest neighbor classifiers. The results are compared to those obtained by other feature selection extraction methods namely Ruck's method, PCA and t-test method. The method achieves dimensionality reduction of input vectors used for supervised learning problems.

In 2002, C. Neubauer and M. Fang [23], have used multi layer perceptron as a statistical classifier for recognition of objects in gray scale images. Edge filters, local features and distance transformation are used as image preprocessing techniques in order to improve the recognition accuracy in combination with neural network classifier. The performance criteria considered are the mean recognition error, the best recognition error and the standard deviation. The best result obtained by the proposed method is 19.40% for 10 classes and 6.32% for 6 classes both without rejection.

In 2008, Dr. Amitabh Wahi, F. Mohamed Athiq and C. Palanisamy [24], have proposed a hybrid feature extraction method for rotated objects. The proposed method consists of two part, the first part is to extract required information from the rotated edge images, in the second part training of multilayer neural network with error back propagation algorithm is used for feature extraction.. Initially the color image is converted into gray-scale image which is then converted into binary image using a suitable threshold value. The resulting image may contain noise and it can be removed using a suitable noise removing filter such as median filter. Then only the Region of Interest (ROI) is selected and cropped and then the position invariant is achieved. To calculate the features the proposed technique uses two methods of transformations namely, the 2-D DFT and 2-D DWT. The percentage of classification is found to be 95.5% and 98.33% respectively on feature extraction.

In 2011, Wu Jiang, Huang Rule, Xu Ziyue and Han Ning [56], have developed a novel algorithm for image-based forest fire smog feature extraction based on Pulse-Coupled neural network (PCNN). Fixed size, unfixed size and execution time are the parameters used to evaluate the results of PCNN and GLCM.

The experimental results show that the algorithm accurately distinguishes smog and non-smog images which outperform both the traditional Euclidean distance algorithms and the algorithms based on grey level co-occurrence matrix (GLCM). The recognition accuracy is 98% with robustness on our smog image database.

Table 6: Comparison of various feature extraction methods

Author	Year	Method	Performance Criteria	Result
C. H. Chen and G. G. Lee	1996	FCM clustering for Texture Images and real world digital mammogram images	Variance and Mean features	A novel feature extraction scheme based on Multi resolution wavelet, MRF modeling provides an excellent preprocessing approach for *ANN* classification and also simplify the task of the neural networks in the process of stochastic relaxation
S. J. Perantonis and V. Virvilis	1999	Principal Component Analysis (PCA) with neural network for Digital Images	R-XOR, BUPA and IONO	The proposed method is resulting in the accuracy rate up to 91.3%
C. Neubauer and M. Fang	2002	Multi layer perception, Sub sampling, Convolution filters, Canny edge detector, Distance transformation for Gray Scale Images	Recognition rate as best, mean and standard deviation	The proposed method provides good results when compared with other methods. The best result obtained by the proposed method is 19.40% for 10 classes and 6.32% for 6 classes both without rejection
Dr. Amitabh Wahi, , F. Mohamed Athiq and C. Palanisamy	2008	Discrete Fourier Transformation (DFT) & Discrete Wavelet Transformation (DWT) for color image	Feature vector and Recognition rate	The proposed method provides the best results for classification are 95.5% and 98.33% respectively from the two methods
Wu Jiang, Huang Rule, Xu Ziyue and Han Ning	2011	Pulse- Coupled Neural Network for smog images	Fixed size, unfixed size and execution time	The recognition accuracy is 98% with robustness for smog image database

2.3 Image Segmentation

The goal of image segmentation is to cluster pixels into salient image regions, i.e., regions corresponding to individual surfaces, objects, or natural parts of objects. Segmentation could be used for object recognition, occlusion boundary estimation within motion or stereo systems, image compression. When considered as a classification task, the purpose of segmentation is to assign labels to individual pixels. Some neural-based approaches perform segmentation directly on the pixel data, obtained either from a convolution window or the information is provided to a neural classifier in the form of local features. The following flow chart shows the Segmentation steps. Segmentation task that is most frequently performed by feature based ANNs is texture segregation.

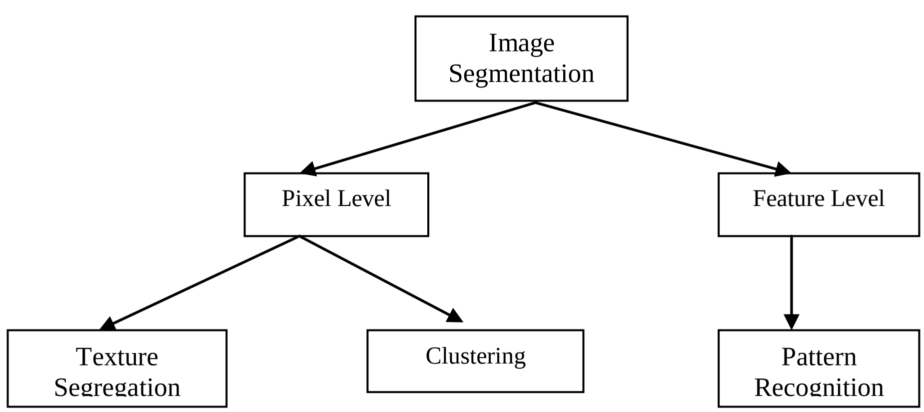

Fig.3: Block diagram of Segmentation

2.3.1 Texture segregation

Texture refers to properties that represent the surface or structure of an object and is defined as something consisting of mutually related elements. Texture is an important characteristic for the analysis of many types of images including natural scenes, remotely sensed data and biomedical modalities. The perception of texture is believed to play an important role in the human visual system for recognition and interpretation. Classification of textured images in an unsupervised manner is useful to delineate different regions present in many natural images.

In 1992, M.M. Van Hulle and T. Tollenaere [25], have developed an entropy driven artificial neural network (EDANN) model for texture segregation and line- and edge detection. The EDANN model consists of five processing stages for performing two tasks: line- and edge detection and texture segregation. Initially it starts with a filtering stage and continues with four instantiations of the same core EDANN module arranged into two pathways, the EDANN1, 2 and 3 modules comprise the texture segregation pathway and the EDANNl and EDANN4 modules comprise the line- and edge detection pathway. The proposed method provides good result for identifying lines- and edges and textures from images.

In 1993, Andrew Laine and Jian Fan [26], in their work for texture classification have used wavelet packet signatures. The performances of wavelet packet spaces are measured in terms of sensitivity and selectivity for the classification of twenty-five natural texture images. Each texture was computed with 128 x 128 sub-samples, represented by a vector of 341 features. For Discrimination it uses a Simple Minimum-Distance Classifier and a Neural Network Classifier. Texture signatures based on multi-resolution wavelet packet analysis holds a great potential for accomplishing robust classification and subtle discrimination. In the proposed method even the simple minimum-distance classifier using wavelet packet signatures from level 3 alone was able to discriminate 550 sample patterns (22 samples/texture x 25 textures) with 96%.

In 1993, Giacomo M. Bisio, Daniele D. Caviglia, Giacomo Indiveri, Luigi Raffo, Silvio P. Sabatini [27], have developed a three layer hierarchical neural network architecture for early vision processing tasks, the first layer of the network extracts oriented textured elements, the second layer increases the sensitivity to texture differences and the last layer improves the selectivity of textural elements on the basis of their size. For each layer, taking the output cells with the same orientation, one generates four output images that encode the textural information extracted by this method. The proposed method uses pre-processing of images which are to be analyzed in order to reduce the dimensionality of the input space and computational cost to accomplish a high speed and efficiency.

In 1997, P. P. Raghu, R. Poongodi, and B. Yegnanarayana [28], in their work on texture classification have used unsupervised neural network architecture. The texture features are extracted by using two-dimensional (2-D) Gabor filters. The classification model comprises of feature quantization, partition and competition processes. The feature quantization process uses a vector quantization to quantize the features into code-vectors where the probability of grouping the vectors is modeled as Gibbs distribution. An energy function corresponding to the *a posteriori* probability is derived from these processes and a neural network is used to represent this energy function. The proposed method provides efficient result for classification of the textured image in the final equilibrium state of the vector quantization.

Table 7: Comparison of various Texture segregation methods

Author	Year	Method	Performance Criteria	Result
M.M. Van Hulle and T. Tollenaere	1992	EDANN model, for Retinal Images	Energy maps and tuning curves	The proposed method provides good result for identifying lines- and edges and

				textures from images
Andrew Laine and Jian Fan	1993	Neural Networks with Wavelet Packet Networks for Textured images	Training epochs, training time and number of error	The proposed method provides good result for minimum-distance classifier using wavelet packet signatures from level 3 alone was able to discriminate 550 sample patterns with 96%
Giacomo M. Bisio, Daniele D. Caviglia, Giacomo Indiveri, Luigi Raffo and Silvio P. Sabatini	1993	Neural Networks for natural texture images		The proposed method could pre-process the images to be analyzed in order to reduce the dimensionality of the input space, the computational cost and accomplish a high speed and efficiency
P. P. Raghu, R. Poongodi, and B. Yegnanarayana	1997	Unsupervised Texture Classification using Neural Networks for Textured images	MH Index and energy function	The proposed method provides efficient result for classification of the textured image in the final equilibrium state of the vector quantization

2.3.2 Pattern recognition

Humans can easily recognize familiar patterns or objects regardless of their size or orientation differences. This is due to our intelligent system of perception which had been trained to recognize the objects over time. Pattern recognition is defined as "the act of taking in raw data and taking an action based on the category of the pattern identification ". Identification of objects in images by their shapes, forms, outlines, color, surface texture, temperature and other attributes. Feed forward ANN is the powerful tools for pattern recognition and classification.

In 1989, Y. Le Cun, L. D. Jackel, B. Boser, J. S. Denker, H. P. Graf, I. Guyon, D. Henderson and R. E. Howard [29], have described two methods for achieving handwritten digit recognition. The first method is based on a neural network chip that performs line-thinning and feature extraction using local template matching. The second method which is implemented on a digital signal processor makes extensive use of constrained automatic learning. The MSE is 2.5×10^{-3}n the training set and 1.8×10^{-2}on the test set. The percentage of misclassified patterns is 0.14% on the training set and 5.0% on the test set. The percentage of rejections would be 12.1% to achieve 1% error on what is left in the test set. The proposed method provides efficient results for throughput rates from camera to classified image of more than 10 digits per second were obtained.

In 1992, Minoru Fukumi, Sigeru Omatu, Fumiaki Takeda, and Toshihisa Kosaka [30], have developed a neural pattern recognition system which is insensitive to rotation of input pattern by any number of degrees. The system is designed to preprocess retinal patterns with a rotationally invariant fixed neural network (box of slabs) followed by a trainable multilayered network. In recognizing 500-yen and 500- won coins, they also distinguish between the obverse and reverse sides of each coin. Thus, as the number of patterns to be discriminated is 4, the number of output units in the multilayered network is 4. The proposed algorithm used for weight adaptation requires about 500 training cycles until the value of the total error function becomes 1, while the Back-Propagation method requires about 2000. The best recognition accuracy would require a total of *25* slabs and 72 neuron units in the slab. The results show that the proposed neural network approach works well for variable rotation pattern recognition problem.

In 2000, M. Egmont-Petersen, U. Schreiner, S. C. Tromp, T. M. Lehmann, D. W. Slaaf, and T. Arts [31], have developed an automatic detection and characterization of leukocytes in the video images. The neural network model was trained to detect leukocytes using a training set consisting of images of leukocytes and the background consisting of fast-moving erythrocytes in a venial. The method consists of two training sets, one consisted of a mixture of samples of background and leukocyte images, both extracted from different video images. In the second training set a synthetic leukocyte images were used, which were generated using a novel stochastic model of the intensity distribution of a leukocyte. The performance of the neural networks was compared by computing receiver operating characteristic (ROC) curves. The proposed method provides efficient results with 11 hidden nodes, among those trained with real leukocyte images, its average ROC area is 0.71.

In 2011, Sari Dewi Budiwati, Joko Haryatno and Eddy Muntina Dharma [57], have developed Back-Propagation Neural Network for Japanese character recognition. Japanese language has complex writing systems Kanji and Kana (Katakana and Hiragana). Each one has different style of writing. One simple way to differentiate is Kanji have more strokes than Kana. Meanwhile, it needs a lot of effort to remember characters of Katakana and Hiragana, thus it will be very difficult to distinguish handwritten Katakana and Hiragana, since there are a lot of similar characters. This is the reason why pattern recognition is needed. Pattern recognition on Kana is started based on Optical Character Recognition (OCR) consist of scan image, preprocessing, feature extraction and post-processing. Classification process is done in post-processing using neural network back propagation. The processing of input images, involves training and testing image. Training image uses 3.956 characters done in three phases of training. Testing image uses 552 characters of some images inputted in training phase. The test result achieves maximum accuracy of recognition system at 92.29% from train image and 31.03% from test image.

Table 8: Comparison of various Color recognition methods

Author	Year	Method	Performance Criteria	Result
Y. Le Cun, L. D. Jackel, B. Boser, J. S. Denke,r H. P. Graf, I. Guyon, D. Henderson and R. E. Howard	1989	BPNN for 16 x 16 gray-scale image	Mean Square Error (MSE)	The proposed method provides efficient results for throughput rates from camera to classified image of more than 10 digits per second were obtained
Minoru Fukumi, Sigeru Omatu, Fumiaki Takeda, and Toshihisa Kosaka	1992	Neural Network for Gray scale image	The operator *R(n)* represents a rotation by n degrees	The results show that the proposed neural network approach works well for variable rotation pattern recognition problem
M. Egmont-Petersen, U. Schreiner, S. C. Tromp, T. M. Lehmann, D. W. Slaaf, and T. Arts	2000	Neural Network for leukocyte image	Receiver Operating Characteristic (ROC) curves	The proposed method resulted in an 18% larger area under the ROC curve than the best performing neural network trained with manually detected leukocytes
Sari Dewi Budiwati, Joko Haryatno, Eddy Muntina Dharma	2011	Back-Propagation Neural Network for Japanese character recognition	MSE, Epoch, node, LR, recognition result	The accuracy from the Kana recognition system is 92.29% from 3.956 training image and 31.03 from 552 testing image

2.3.3 Clustering

Every image contains semantic information which is what we infer after seeing the image. This semantic information could be the presence/ absence of a certain set of objects or the attributes of these objects or their relative positions with respect to each other. Understanding the semantics in an image has great applications in areas ranging from face detection, medical imaging to image retrieval. In the self-organizing mode, the process of grouping feature vectors into classes is called clustering. Clustering can be considered the most important *unsupervised learning* problem. It deals with finding a *structure* in a collection of unlabeled data. A *cluster* is therefore a collection of objects which are “similar” between them and are “dissimilar” to the objects belonging to other clusters.

In 1999, Songyang Yu and Ling Guan [32], have used general regression neural networks (GRNN) for selecting the most discriminating features for the automatic detection of clustered micro-calcifications in digital mammograms. The proposed method uses wavelet coefficients and feed forward neural networks to identify possible micro-calcification pixels and a set of structure features to locate individual micro-calcifications. The training data set consists of 174 true individual micro-calcification objects and 164 false individual micro-calcification objects. All the 31 features of each true or false individual micro-calcification are first calculated. The performance of the proposed system is increased to 90% mean true positive detection rate at the cost of 0.5 false positive per image.

In 2002, Jonathan Randall, Ling Guan & Xing Zhang, WanQing Li [33], have used hierarchical cluster model (HCM) for region segmentation and recognition in digital images. In their paper they have considered three level networks. The first level is comprised of all neurons in the network, Clusters of first level neurons give rise to the second level in the network and if we then cluster these clusters we obtain a third level network. The image is firstly filtered using a Sobel filter, next all edges are checked against a pre-trained edge configuration set. The proposed method has achieved good results for image region segmentation and recognition, also provides the basis for hierarchical image processing.

In 2007, D. Ashutosh, N. Subhash Chandra Bose, Prabhanjan Kandula and Prem. K Kalra [34], have proposed three new algorithms using modified forward only counter propagation network (MFOCPN). These algorithms consists of sub-clustering in Kohonen's layer for enhancing the clustering process, a new entropy metric based initialization of the Kohonen's layer for efficient color-map design and faster convergence of network, further the two approaches are merged to yield third algorithm. The performance criteria used are RMSE and PSNR for 128 and 256 number of colors. The proposed method provides good results both in convergence and preciseness in clustering.

In 2008, Li Jing, Fenli Liu [35], have proposed a robust digital image watermarking method based on general regression neural network (GRNN) and fuzzy c-mean (FCM) clustering algorithm. Fuzzy C-Mean clustering algorithm is used to identify the watermark embedding location and embedding strength based on the human visual system (HVS) and General Regression Neural Network to embed and extract watermark at the identified locations. The performance evaluation methods are PSNR and BCR. The proposed method provides good results for the watermarked Lena image and Baboon image and their PSNR are 41.25 and 39.34 respectively and bit correct rate is 1 for both images.

In 2011, Tung Xuan Truong, Yongmin Kim and Jongmyon Kim [58], have proposed an effective four-stage approach that detects fire automatically. The proposed algorithm is composed of four stages. In the first stage, an approximate median method is used to detect moving regions. In the second stage, a fuzzy c-means (FCM) algorithm based on the color of fire is used to select candidate fire regions from these moving regions. In the third stage, a discrete wavelet transform (DWT) is used to derive the approximated and detailed wavelet coefficients of sub image. In the final stage, a generic-based back-propagation neural network (BPNN) is utilized to distinguish between fire and non-fire. Accuracy rate and error rate are performance criteria. Experimental results showed that the proposed approach outperforms other state-of-the-art fire detection algorithms in terms of fire detection accuracy, providing a low false alarm rate and high reliability in open and large spaces.

Table 9: Comparison of various Clustering methods

Author	Year	Method	Performance Criteria	Result
Songyang Yu and Ling Guan	1999	General Regression Neural Networks (GRNNs) for digital mammograms	Free response operating characteristics (FROC) curves.	The performance of the proposed system is increased to 90% mean true positive detection rate at the cost of 0.5 false positive per image
Jonathan Randall, Ling Guan & Xing Zhang, WanQing Li	2002	Neural Network for Digital Images	Hierarchical Cluster Model with iterations	The proposed method sets up a basis for hierarchical image processing and also has achieved good results for image region segmentation and recognition
D. Ashutosh, N. Subhash Chandra	2007	Modified Forward Only Counter-propagation	RMSE and PSNR	The proposed method results in RMSE = 0.056517016 and

Bose, Prabhanjan Kandula and Prem. K Kalra		Network (MFOCPN) for Color Images		PSNR = 74.12525537 for 256 colors
Li Jing, Fenli Liu	2008	General Regression Neural Network (GRNN) and Fuzzy C-Mean (FCM) for Digital Images	PSNR and bit correct rate (BCR)	The proposed method provides good results for the watermarked Lena image and Baboon image and their PSNR are 41.25 and 39.34 respectively
Tung Xuan Truong, Yongmin Kim and Jongmyon Kim	2011	Genetic-based Back-propagation Neural Networks for vides	Accuracy rate and error rate	Experimental results indicate that the proposed method outperforms other fire detection algorithms, providing high reliability and low false alarm rate

2.4 Object recognition

Object recognition consists of locating the positions and possibly orientations and scales of instances of objects in an image. The purpose may also be to assign a class label to a detected object. Objects can even be recognized when they are partially obstructed from view. This task is still a challenge for computer vision systems in general. Our survey of the literature on object recognition using ANNs indicates that in most applications, ANNs have been trained to locate individual objects based directly on pixel data. Another less frequently used approach is to map the contents of a window onto a feature space that is provided as input to a neural classi1er.The following flow chart shows the Object recognition steps.

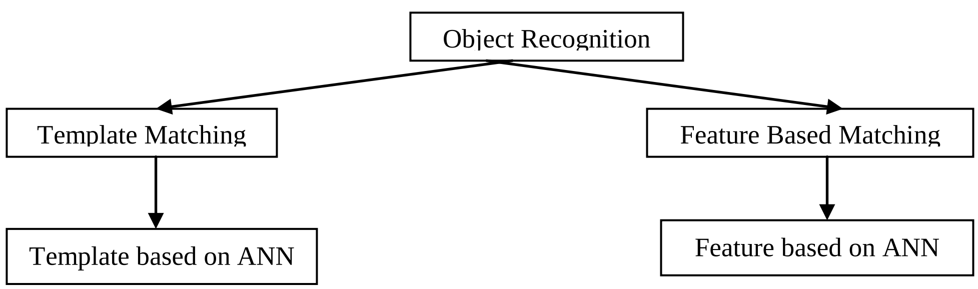

Fig.4: Block diagram of Object recognition

2.4.1 Template matching

Template matching is a technique for finding small parts of an image which match a template image. It can be used in a way to navigate a mobile robot or as a way to detect edges in images. Template matching can be subdivided in to two approaches, feature-based and template-based matching. The feature-based approach uses the features and the template based approach may potentially require sampling of a large number of points. Convolutional neural networks provide an efficient method to constrain the complexity of feedforward neural networks by weight sharing and restriction to local connections. This network topology has been applied in particular to image classification when sophisticated preprocessing is to be avoided and raw images are to be classified directly. CNN does not require normalization for an image and no complex feature extraction techniques were involved.

In 1996, Jyh-Shyan Lin, Shih-Chung B. Lo, Akira Hasegawa, Matthew T. Freedman, and Seong K. Mun [36], have developed a neural-digital computer-aided diagnosis system based on parameterized two-level convolution neural network (CNN) architecture and a special multi label output encoding procedure. The proposed method performs automatic suspect localization, feature extraction and diagnosis of a particular pattern-class aimed at a high degree of “true-positive fraction” detection and low “false-positive fraction” detection. Receiver Operating Characteristic curve (A_Z) is used as the performance index to evaluate all the simulation results. The proposed two-level CNN architecture is proven to be promising and to be extensible, problem-independent, and therefore, applicable to other medical or difficult diagnostic tasks in two-dimensional 2-D image environments.

In 1998, Claus Neubauer [37], have developed a convolution neural network for visual recognition. This network methodology has been applied in particular to image classification when sophisticated preprocessing is to be avoided and raw images are to be classified directly. In their work a modular procedure is applied whereby layers are trained sequentially from the input to the output layer in order to recognize features of increasing complexity. In the proposed method two variations of convolutional networks, neocognitron and a modified neocognitron (NEO) are compared with classifiers based on fully connected feed forward layers as multilayer perceptron (MLP), nearest neighbor classifier and auto-encoding network with respect to their visual recognition performance. The proposed method is compared with MLP and the results for scaling (MLP = 6.16% and NEO = 2.2%) and rotation (MLP = 5.70% and NEO 3.08%) respectively.

In 1998, Zhigang Zhu, Shiqiang Yang, Guangyou Xu, Xueyin Lin, and Dingji Shi [38], have proposed omni directional view image analysis by using back-propagation neural networks to understand the outdoor road scene by a mobile robot. The rotation-invariant image features are extracted by a series of image transformations which serve as the inputs of a road classification network (RCN). Each road category has its own road orientation network (RON) and the classification result activates the corresponding RON to estimate the road orientation of the input image. Classification is performed before orientation estimation so that the system can deal with road images with different types effectively and efficiently. Experimental results with real scene images show that the method is fast and robust.

In 2011, K. YILMAZ [59], have proposed a novel hybrid approach for license plate recognition system based on Neural Network and Image Correlation for classification of characters. This hybrid system is composed of transformation to gray level, histogram equalization, thresholding and some novel algorithms in finding the character of license plate number. MSE, Epochs and learning rate are the performance criteria used to evaluate the result of the proposed methods. LVQ NN is more successful for noisy images and it gives better result when image correlation is insufficient. This novel algorithm makes powerful increase on success rate of template matching. It extracts features (area, centroid i.e.) of object and then uses them to eliminate noise and extract characters. Experimental results show the hybrid system is quite successful of 96.64% for recognizing private Turkish license.

Table 10: Comparison of various Template matching methods

Author	**Year**	**Method**	**Performance Criteria**	**Result**
Jyh-Shyan Lin, Shih-Chung B. Lo, Akira Hasegawa, Matthew T. Freedman, and Seong K. Mun	1996	Convolution Neural Network (CNN) for 2-D radiograph images	Receiver Operating Characteristics (ROC)	The proposed method provides efficient performance (A_Z = 0.93) in two-level CNN compared to the single-level CNN (A_Z = 0.85)
Claus Neubauer	1998	Feed-forward NN for Digital Images	validation error	The validation error of the proposed method is 14.20% compared with MLP is 33.74%
Zhigang Zhu, Shiqiang Yang, Guangyou Xu, Xueyin Lin, and Dingji Shi	1998	road understanding neural networks (RUNN) for omni-view image	RMSE , road classification network (RCN) and road orientation network (RON)	The training rate of RCN is 96.3%, 98.5% for 4 and 12 hidden nodes respectively and the RMSE is 1%
K. YILMAZ	2011	Neural network with Learning Vector Quantization for character recognition	MSE, Epochs and learning rate	The percentage of successful character recognition is 96.64%

2.4.2 Feature-based recognition

In computer vision, the task of finding a given object in an image or video sequence is difficult, but humans recognize a multitude of objects in images with little effort, despite the fact that the image of the objects may vary somewhat in different viewpoints, in many different sizes / scale or even when they are translated or rotated. Objects can even be recognized when they are partially obstructed from view. This task is still a challenge for computer vision systems in general. Several neural-network approaches have been developed for feature-based object recognition including: feed-forward ANNs, Hopfield ANNs, and fuzzy ANN.

In 1994, Jin-Yinn Wang and Femand S. Cohen [39], have proposed a 3-D object recognition and shape estimation system that identifies particular objects by recognizing the special markings like text, symbols, drawings, etc on their surfaces. The shape of the object is identified from the image curves using B-spline curve modeling. This is achieved by first estimating the 3-D control points from the corresponding curves in each image in the stereo imaging system. A Bayesian framework is used for classifying the image into one of the possible surfaces based on the extracted 3-D object curves. Neural network can differentiate the bottles surface as a particular object by reading the text markings on the surface. For rotated, translated and scaled version of the template the object curves are "unwrapped" into planar curves before the matching process, this eliminates the need for templates that are surface shape dependent and results into a planar curve. For the matching process of rotation, translation and scaling transformations, Fourier descriptors (FD) measure which is derived from the control points associated with the unwrapped parent curves is used. The proposed system has been tried on a variety of real objects and provides good results.

In 2000, Syed Afaq Husain and Eiho Shigeru [40], have proposed a back-propagation neural network that serves as the classifier for feature based recognition of liver region on CT image of the abdomen. The proposed method consists of three layers, first the input layer containing 5 neurons corresponding to the number of input features, second the hidden layer is designed to have 8 neurons which is also a compromise between efficiency and accuracy and third the output layer comprises of l neuron, representing the single liver region. The weights are updated by back propagation of error if the net-error exceeds the set criteria of 5%, the training weight adjustment is stopped when the net error criteria is satisfied. As the preprocessing step the image is smoothed and then the gradient operator is applied to enhance its edges, the liver region is visible as a dark gray textured region containing a darker patch of tumor. For an input region belonging to the liver class, the output neuron is designed to give a unity output whereas for all other inputs the output is designed to be zero.

In 2002, S.K.Singh, Mayank Vaisa, Richa Singh and D.S.Chauban [41], have made a comparison study on neural network based and line based approaches for face recognition. In Neural Network approach automatic detection of eyes and mouth is followed by a spatial normalization of the images. The classification of the normalized images is carried out by hybrid Neural Network that combines unsupervised and supervised methods for finding structures and reducing classification error respectively. In line based approach it does not use any detailed biometric knowledge of the human face, it rather use either the pixel-based bi-dimensional array representation of the entire face image or a set of transformed images or template sub-images of facial features as the image representation. The compared results shows that neural network approach provides efficient result then line based approach.

In 2010, Jong-Min Kim and Myung-A Kang [42], have developed a face recognition method combined with principal component analysis (PCA) and the multi-layer neural network (MLNN) which is one of the intelligent classifications. As a preprocessing step of input face image, the method computes the Eigen face through PCA and expresses the training images with it as a fundamental vector. Each image takes the set of weights for the fundamental vector as a feature vector and it reduces the dimension of image at the same time and then the face recognition is performed by inputting the multi-layer neural network. The proposed method is compared with Euclidean and Mahananobis method. The proposed method suggested by comparing with the existing method showed the improvement in the recognition rate as 95.3%.

Table 11: Comparison of various Feature-based recognition methods

Author	Year	Method	Performance Criteria	Result
Jin-Yinn Wang and Femand S. Cohen	1994	Neural Network for frontal view images	Minimum Mean-Squared Error,	MMSE = 0.00065672 is the result obtained from the proposed method
Syed Afaq Husain and Eiho Shigeru	2000	BPNN for X-ray and CT images of the abdomen region	Mean gray level, Standard deviation, Skewness, Entropy and Homogeneity	The proposed method detects the liver region accurately and clearly identifies all the features of the image
S.K.Singh, Mayank Vaisa, Richa Singh and D.S.Chauban	2002	Neural Network for Digital Images	Wrap, gradient, Eigen vectors	The neural network approach provides 95% and 80% result for brightness and contrast of the image
Jong-Min Kim and Myung-A Kang	2010	PCA, Multi-Layer Neural Networks for Digital Images	Matching Failure, Incorrect Matching and Matching Success	The proposed method provides the results as Matching failure = 1.7%, Incorrect Matching = 3% and Matching Success = 95.3% for face recognition

2.5 Image understanding

Image understanding is a complicated area in image processing. It couples techniques from segmentation or object recognition with knowledge of the expected image content. A major problem when applying ANNs for high level image understanding is their black-box character. It is virtually impossible to explain why a particular image interpretation is the most likely one. Another problem in image understanding relates to the level of the input data. We feel that image understanding is the most dubious application of ANNs in the image processing chain. The following flow chart shows the Image understanding steps.

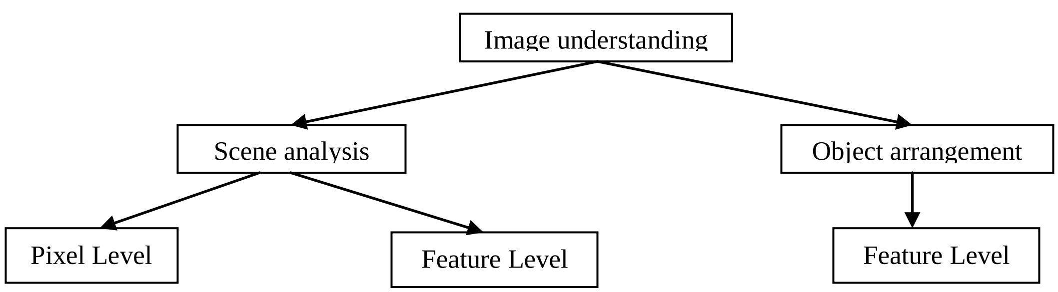

Fig.5: Block diagram of Image understanding

2.5.1 Scene analysis

The scene analysis of texture in natural objects is a challenging task considering the variability due to noise, changes in illumination, inherent variation between samples of the same class, etc. The problem of scene analysis is different to the recognition of well-defined objects. Natural objects do not have well defined shapes and boundaries and as such texture and color are the two main clues to their recognition. Neural networks have played the role of classifiers for feature selection to find which color and which grey-scale features together give the best results by evaluating the strength of weights on various connections.

In 2002, M. Markou, M. Singh and *S.* Singh [43], have investigated how much of an advantage color analysis offers using a neural network classifier. For the analysis of the natural scenes they have used the publicly available MINERVA benchmark. The benchmark consists of 448 still images of natural objects like trees, grass, sky, clouds, bricks, pebbles, road, water, leaves etc. All of the images collected are stored in bitmap (.bmp) format with 16-bit color depth and a resolution of 720 x 576 pixels. The images have been reduced to a size of 512 x 512 pixel resolution. The neural networks classifier consists of three separate sets of classifiers. In the first set, they have used one network per grey-scale feature extraction method to demonstrate its relative ability in object recognition. In the second set, they have developed two neural networks, one for color moments and one for correlogram features. Finally, they generate two combined feature data sets, one for grey-scale and one for color features. Principal components analysis is used to reduce the number of dimensionality and we use only those components that have eigen value greater than 1. They have tested the results with vegetation analysis and other natural object analysis, the combined method results in better performance up to 88.25% for vegetation analysis and 76.10% for other natural object analysis.

In 2003, Seiji Ita, Yasue Mitsukura, Minom Fukumi, Norio Akamatsu and Sigern Omatu [44], have used the factor analysis and the sandglass-type neural network (SNN) for image searching. As image preprocessing, objective images are segmented by using maximin-distance algorithm (MDA). Small regions are integrated into a near region. Thus, objective images are segmented into some region. After images preprocessing, keywords in images are analyzed by using factor analysis and a sandglass-type neural network (SNN) for image searching. Image searching systems are divided into 3 methods, they are keyword search, Similarity-based image retrieval and browsing search. They have compared these three methods and concluded that keyword searching method is better. Keywords can be added automatically in the recognized images. Images data are compressed to a 2-dimensional space by using factor analysis and the sandglass-type neural network methods, thus, keywords are analyzed in detail. They have used 40 images as learning data, in 40 images 140 regions are obtained by using image preprocessing. By using factor analysis and SNN, the proposed method works well.

Table 12: Comparison of various Scene Analysis methods

Author	Year	Method	Performance Criteria	Result
M. Markou, M. Singh and *S.* Singh	2002	MLP with BPNN for Color Images	Auto correlation function (ACF), edge frequency (EF), Law's masks (LM) and run length (RL)	The combined method results in better performance up to 88.25% for vegetation analysis and 76.10% for other natural object analysis
Seiji Ita Yasue Mitsukura Minom Fukumi, Norio Akamatsu and Sigern Omatu	2003	Sandglass-Type Neural Network (SNN) for Digital Images	Average and variance of RGB and HSI	It was found that the proposed method works well by using factor analysis and SNN

2.5.2 Object arrangement

An object in image processing is an identifiable portion of an image that can be interpreted as a single unit. Object tracking has been regarded as one of the most important problem, that could not be solved completely and researches are being continued in this field. A desirable tracking method should be able not only to diagnose and track referred object in consequent frame, but also should include considerable reliability and power along with implantable capability in real time practices [51]. Neural networks have been widely used for object arrangement and classification purposes due its adaptive learning, and complex nonlinear mapping capability.

In 2010, P.S. Hiremath and Parashuram Bannigidad [45], have used active contours in image processing applications, particularly to locate object boundaries.

The Geometric features are used to identify the arrangement of cocci bacterial cells, namely, cocci, diplococci, streptococci, tetrad, sarcinae and staphylococci using 3σ, K-NN and neural network classifiers. Some bacterial contains different shapes which are more complex, so the automated digital image analysis is used to identify their geometric shape features. First color cocci bacterial cell image is converted into gray scale image and adjusts the image intensity values, then perform active contour without edges up to 1350 iterations to obtain segmented image, which yields binary image. The performance criteria mean square error and standard deviation are used in the sampling distribution of these features are obtained from the training images which are stored in the knowledge base of the cells. In the testing phase, the feature extraction algorithm is applied and the test feature values $x_i^{(test)}$ for each segmented region are used for classification. The results obtained for testing images, the 3σ classifier has yielded an accuracy in the range of 84% to 94%, K-NN classifier has yielded 75% to 100% for K=1(i.e. minimum distance classifier) and 96% to 100% for K=3. The neural network classifier has yielded 98% to 100% accuracy.

Table 13: Comparison of various Object arrangement methods

Author	Year	Method	Performance Criteria	Result
P.S. Hiremath and Parashuram Bannigidad	2010	3σ, K-NN and Neural Network classifiers for digital microscopic cell images	mean square error (MSE) and standard deviation (SD)	The neural network classifier has yielded 98% to 100% accuracy for different cocci cell types

2.6 Optimization
Optimization refers to the selection of a best element from some set of available alternatives. More generally, it means finding "best available" values of some objective function given a defined domain, including a variety of different types of objective functions and different types of domains. Some image processing (sub) tasks such as graph and stereo-matching can best be formulated as optimization problems, which may be solved by Hopfield ANNs. The following flow chart shows the Optimization steps.

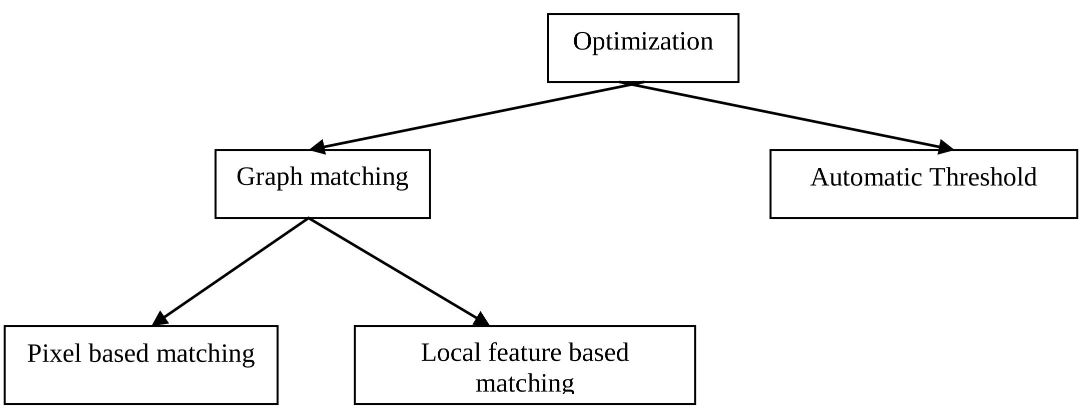

Fig.6: Block diagram of Optimization

2.6.1 Graph matching
Image interpretation is the process of understanding and giving meaning to an image by identifying and labeling significant objects in the image. Graphs have been proved as an effective way of representing objects. In graph matching the image is modeled as a weighted, undirected graph. Usually a pixel or a group of pixels are associated with nodes and edge weights define by similarity or dissimilarity between the neighborhoods pixel. The graph (image) is then partitioned according to a criterion designed to model "good" clusters. Neural networks have also extensively been applied to many graph matching problems. Very different types of neural networks

have been tested trying to find the most suitable for each particular graph matching problem.

In 1994, Tsu-Wang Chen and Wei-Chung Lin [46], have developed a Neural Network recognition subsystem for computer vision based on Constructive Solid Geometry (CSG) for 3-D Objects. The proposed system uses an equivalent representation scheme as precedence graphs for object representation. Each node in the graph represents a primitive volume and each arc between two nodes represents the relation between them. CSG is effective in representing unsculptured, man-made objects such as industrial parts. The energy function associated with the network is used to enforce the matching constraints including match validity, primitive similarity, precedence graph preservation, and geometric structure preservation. The energy level is at its minimum only when the optimal match is reached. The proposed method for object matching can be used for any kind of object descriptions as long as object features can be reliably extracted.

In 1996, V.P. Kumar and U.B. Desai [47], have proposed an Image Interpretation by using Bayesian Networks and Probabilistic inference. The proposed method requires the specification of the conditional probabilities features given by the interpretations. This was achieved by considering only the class of aerial images and the objects identifiable from the air. Hence, the conditional probabilities were determined heuristically by studying an aerial image for the following identifiable objects like *road, grassland, foliage, vehicle (car), building,* and *shadow. The* segmented image consists of several blocks of size 8 x 8 which were placed randomly all over the image such that each block would lie completely in one segment. For each identifiable object in the image, a histogram was prepared with the feature level on the horizontal axis and the frequency of occurrence of the feature level for that object on the vertical axis. Then the histogram was used as an approximation for the conditional distribution of features given the interpretations. Since several feature values gave the value of zero. The proposed method has deliberately segmented the image very coarsely to show that the technique can be used with segmentation schemes that are not very accurate.

In 2009, Zhi-Wei Gao, Wen-Kuo Lin, Yu-Shian Shen, Chia Yen Lin and Chih-Cheng Chang [48], have developed conventional correlation methods for Block based stereo matching. But this process is fallible in scenarios where a rotational offset is present between a stereo image pair. In this paper the author introduced a proposed rotation invariant correlation method for solving the above said problem. Two guidelines serve as the fundamental basis in solving the correspondence problem. They are the correlation based and feature-based methods. The primary step in this method is detection of interest points/regions by locating prominent features. Execution time, number of matches, number of ill matches is the evaluation metrics by which the performance of the proposed method is evaluated against the conventional correlation method. Stereo processing incorporating this proposed methodology produces substantial improvement in stereo perception quality.

In 2011, Nani Fadzlina Nairn, Ahmad Ihsan Mohd Yassin, Nurafizah Binti Zakaria and Norfishah Ab. Wahab [61], have developed Multi-Layer perceptron neural network for thumb print images. The classification of thumbprint is used in order to match the person's identification and train the data by using ANN. 30 thumb print images are used as input for artificial neural network for learning purposes. MSE and the number of iterations are used as the performance criteria for the network. The proposed method produces the lowest MSE value that is obtained is less than 0.1 and the iteration is around 30-40 at hidden unit 30.

Table 14: Comparison of various Graph matching methods

Author	Year	Method	Performance Criteria	Result
Tsu-Wang Chen and Wei-Chung Lin	1994	Annealed Neural Networks for Object	Error root, error trans and degree	The object recognition scheme proposed in this system can be

		Recognition in Digital Image		considered as an engineering implementation of the concept of recognition-by-component
V.P. Kumar and U.B. Desai	1996	Bayesian network, Markov Random Field (MRF) Neural Network for Satellite Image	Average gray level, average texture and contrast	In actual practice several more features and color information can be incorporated to make the technique powerful
Zhi-Wei Gao, Wen-Kuo Lin, Yu-Shian Shen, Chia Yen Lin, Chih-Cheng Chang	2009	warping matrix H, low-pass filter for Digital Image	Size, time, matched , ill matched and the hit percentage	Experimental analysis validated that the proposed method yields more precise stereo results in comparison to conventional correlation
Nani Fadzlina Nairn, Ahmad Ihsan Mohd Yassin, Nurafizah Binti Zakaria and Norfishah Ab. Wahab	2011	Multi-Layer perceptron neural network for thumb images	MSE and iteration	The lowest MSE value that is obtained is less than 0.1 and the iteration is around 30-40 at hidden unit 30

2.6.2 Automatic thresholding

Automatic thresholding means reduction of a gray image to binary image. The method assumes that the image to be threshold contains two classes of pixels then calculates the optimum threshold separating those two classes so that their combined spread is minimal. MLP based hierarchical classification strategies reduce the training period and improve classification beyond any known method.

In 1992, Nasser M. Nasrabadi and Chang *Y.* Choo [49], have developed a Hopfield neural network for stereo correspondence vision images as a minimization of a cost function. This cost function is at its minimum, when the system is at its equilibrium or stable state. The proposed stereo technique uses the salient feature points extracted by Moravec's interest operator as a base for matching stereo images. They have used Horizontal displacement, Vertical displacement and Diagonal displacement for matching both left and right images. The advantage of using a neural network is that a global match is automatically achieved because all the neurons (processors) are interconnected in a feedback loop and the output of one affects the input of all the others.

In 1998, Boaz Lerner [50], have developed an automatic neural network based human chromosome analysis by using segmentation, feature description, selection and extraction, and classification. First the image pixels are clustered to create a binary image without a need for threshold selection. These hypotheses are verified by a multilayer perceptron neural network that classifies the two segments created by each separating line. The classification-driven segmentation process gives very promising results without a need for shape modeling. For feature extraction, Sammon's mapping using principal component based initialization is applied, significantly it reduces the dimensionality of the feature space and allowing high classification capability. Finally, they have applied MLP based hierarchical classification strategies to a well-explored chromosome database. The proposed method achieves a classification performance of 83.6%. This is higher than ever published on this database and an improvement of more than 10% in the error rate.

In 2011, Jing Jiao and Yuanyuan Wang [60], have developed an improved pulse coupled neural network (PCNN) model to categorize the image into different classes from which the ROI is selected by using the background rules. The rough contour for the breast tumor is obtained at this stage. Then, the rough contour is used as the initial condition for the modified active contours without edges (ACWE) to get the final boundary of the breast tumor. Three error metrics, true-positive ratio (TP), false-negative ratio (FN) and false-positive ratio (FP) are used to measure the segmentation performance. The final results with TP= 96.7%, FN=3.12%, and FP=5.50% demonstrate that the proposed method can segment Breast ultrasound images efficiently and automatically.

Table 15: Comparison of various Automatic thresholding methods

Author	Year	Method	Performance Criteria	Result
Nasser M. Nasrabadi and Chang *Y.* Choo	1992	Hop-Field Neural Network for stereo images	Left feature points, right feature points and disparity	Although each individual neuron is very slow, the network as a whole will be very powerful, owing to the fact that the neurons in the network are operating simultaneously
Boaz Lerner	1998	MLP with NN for chromosome images	Line connecting points and classifier score	The proposed method achieves a classification performance of 83.6%. This is higher than ever published on this database and an improvement of more than 10% in the error rate
Jing Jiao and Yuanyuan Wang	2011	Improved Pulse Coupled Neural Network for Breast ultrasound (BUS) images	true-positive ratio (TP), false positive ratio (TP) and false-negative ratio (FN)	The proposed method can segment BUS images efficiently and automatically with TP= 96.7%, FN=3.12%, and FP=5.50%

3. Artificial Neural Networks

3.1 Real time applications

Two major advantages of ANNs are applicable to a wide variety of problems and are relatively easy to use. This review has concentrated on applications of ANNs to image processing problems, which were reported in the scientific literature. However, as the field matured, ANNs have gradually found their way into a large range of applications. The ANN-based application systems are

1. Industrial inspection: quality and process control, e.g., the detection of defect objects in the production of steel, textiles, fruit, vegetables, plants or other food products.
2. Document processing: computerized reading of machine-generated and hand-written text used for, e.g., automatic processing of forms and mail sorting.
3. *I*dentification and authentication: e.g., license plate recognition, fingerprint analysis and face identification and verification.
4. *M*edical diagnosis: e.g., screening for cervical cancer or breast tumor.
5. Defence: various navigation and guidance systems, target recognition systems, etc.

3.2 Neural network Issues

A number of unresolved problems exist in the field of ANNs. We will in turn consider the lack of a profound theoretical basis for ANNs, the problem of choosing the best architecture and the black-box problem. Several theoretical results regarding the approximation capabilities of ANNs have been proven. Although feed-forward ANNs with two hidden layers can approximate any (even discontinuous) function to an arbitrary precision, theoretical results on, e.g., the rate of convergence are lacking. For other (non) parametric classifiers, the relation between the size of the training set and the expected error rate has been studied theoretically. One obstacle in developing a more profound statistical foundation for trained ANNs is that convergence to the global minimum of the risk function (squared error) cannot be guaranteed. Furthermore, there is always a danger of overtraining an ANN as minimizing the error measure on a training set does not imply finding a well-generalizing ANN. Nevertheless, the large body of work on application of ANNs presented in the last decade provides (novice) users with many rules of thumb on how to set the various parameters. Also, methods such as regularisation, early stopping and ensemble training/bagging can help in avoiding the problem of overtraining.

Another problem is how to choose the best ANN architecture. No general guidelines exists that guarantee the best trade-off between bias and variance of the classifier for a particular size of the training set. Training unconstrained networks using standard performance measures such as the mean squared error might even give very unsatisfying results. Note that this does not automatically imply that unconstrained ANNs should not be applied to image processing. It does indicate that as much prior knowledge as possible should be used in both ANN design and training.

ANNs suffer from what is known as the black-box problem: given any input a corresponding output is produced, but it cannot be elucidated why this decision was reached, how reliable it is, etc. In image understanding, this is certainly problematic, so the use of ANNs in such applications will remain limited. Some fuzzy neural architecture facilitates extraction of fuzzy rules after training. We expect that fuzzy ANNs will be more applicable in image understanding.

4. Conclusion

We have designed our survey according to the six steps in the image processing chain. Neural networks have been trained to perform these six tasks with various degrees of success:

1. *Image preprocessing* is a popular application area. Several neural networks methods were developed for image reconstruction, image restoration and image enhancement. But these neural networks are not only partially adaptive. A general conclusion is that neural networks solutions are truly interesting when the existing algorithms fail or when neural networks may reduce the amount of computation considerably. The largest risk in preprocessing is that training the results in neural networks being tuned to specific image material.
2. *Data reduction* is an interesting application of neural networks. As there is no unique way of evaluating compression algorithms, approaches should be compared with competing compression algorithms on novel test images. Feature extraction is a useful application of SOM. Also, the possibility of non-linear feature extraction by feed-forward neural networks with several hidden layers offers additional functionality.
3. *Image segmentation* has largely been performed by pixel-based or feature-based approaches. Pixel-based approaches provide the classifier with all relevant information, but usually result in high-dimensional input spaces.
4. *Object recognition* is a feature-based approach, essentially compresses the information obtained from a local neighborhood into a vector of salient features. On the one hand, it cannot be guaranteed that the chosen features comprise most of the discriminative information. On the other hand, a feature-based approach may be the only way to guarantee rotation and scale invariance. A possible remedy is to develop novel pixel-based classification approaches in which neighboring pixels are no longer regarded as completely separate variables.
5. *Image understanding* is a doubtful application of neural networks because of their black-box character and the need for a large number of images as training and test sets. As long as there is no accepted facility for explaining why a particular class label has been assigned to a pattern, black-box classifiers will not be widely applied in image understanding.
6. *Image Optimization* problems have in most cases been approached by solutions based on Hopfield neural networks.

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