CHAPTER 1

INTRODUCTION

1.1 General Introduction

Recent decades have witnessed speedy developments in the field of digital photography. Digital images have been employed in a broad variety of applications, ranging from military and reconnaissance to medical diagnosis and consumer photography. Booming with such a great popularity, the emergence of low-cost and complicated image editing software, the reliability of image content can no longer be lacking authenticity and several forensic-related questions rise in the midst of such an extensive usage. Most of these forensic questions correspond to the tracing of the origin of the digital image along with its creation process. Evidence got from such forensic studies would yield useful forensic information for the purpose of law enforcement, security, and intelligence agencies. Information about image-acquisition techniques can also be helpful in answering more forensic questions conforming to the nature of the additional processing the image would have experienced after capture. Swaminathan et al. (2008) have proposed a new methodology for the case of digital image forensics of color images techniques to identify the intrinsic traces which remain in a digital image as it goes through different processing blocks in the information processing chain.

Post camera processing operations include such manipulations like tampering and steganographic embedding. Currently, there has been an increase in the number of software tools developed for the manipulation of multimedia data. While these programs help facilitating the quality improvement, they also help in enabling easier editing and tampering of data. Hence, instituting the integrity of digital content has become specifically important while images are utilized as critical evidence in the fields of journalism and surveillance.
applications. Data authentication methods, including semi-fragile watermarking (Wu and Liu, 2002 & Fridrich, 1998) and robust hashing (Swaminathan et al., 2006), need the watermark/signature or more commonly extrinsic fingerprints, to be integrated at the moment of creation of multimedia data. The presence or absence of the watermark in interpolated images that are captured by the camera can be used for establishing the authenticity of digital color images (Giannoula et al., 2006). Nonetheless, these techniques enforce multiple restrictions on its virtues of applicability as several digital cameras and video recorders in the market still do not possess the capabilities to append a watermark or a hash during the instant of image creation. Therefore, there is a strong influence on the part of the rising field of image forensics to be able to devise nonintrusive techniques for distinguishing authentic images from the ones that are manipulated.

Image forgery, just like any other illegal and dangerous activity, could result in posing the critical threat to society. Therefore, verification of the authenticity of digital images is observed to be a very critical issue. Digital watermarks and signatures have been introduced as potential solutions to digital image authentication (Hartung and Kutter, 1999). Still, both of these techniques require some proactive processing like the insertion of an unrecognizable watermark or inclusion of a signature at the time of the data’s creation in order to facilitate tampering detection at a time later. This way, they are considered as active techniques. In the recent times, a passive technique has developed rapidly (Farid, 2009 & Luo et al., 2007). The technique assumes that the original multimedia has some inherent features that are proposed by different imaging devices and/or processing. By the analysis of how the multimedia data is captured and processed, we can answer some forensic questions, such as where is the data originating from, if it is a real one or not, and what tampering operations had been done previously. Compared with previous active techniques, the method introduced does not depend on any extra information such as a
watermark or a signature. Hence, it is passive and entirely blind. It is widely known that Joint Photographic Experts Group (JPEG) is a generally employed compression standard and has found its usage in many applications.

For example, many of the digital cameras in the market utilize this JPEG file format, and several image editing software like Adobe Photoshop, GIMP, support the operation of JPEG compression. Therefore, analyzing this type of image may play a useful role in image forensics. However, JPEG images are sometimes processed or stored as bitmaps. In that case, we will have no knowledge about whether the bitmap originates from a JPEG image, a raw bitmap image, or some other format. Identification of whether a bitmap has earlier been JPEG compressed and if it is so what kind of quantization table has been utilized is a crucial first step for many image forensic algorithms. So JPEG image compression becomes very important in digital image processing.

1.2 Digital Image Compression Techniques

Digital Image Compression, does the compression and reduction of the size of images by using different algorithms and standards. Two of the most common Digital Image Compression Techniques are lossless compression and lossy compression.

The basic objective of image compression (Wei, 2008) is to find an image representation in which pixels are less correlated. The two fundamental principles used in image compression are redundancy and irrelevancy. Redundancy removes redundancy from the signal source and irrelevancy technique omits pixel values which are not noticeable by the human eye. JPEG and JPEG 2000 are two important techniques used for image compression. Figure 1.1 shows the block diagram of the general image storage system. The main goal of such a system is to reduce the storage requirement as much as possible, and the decoded image displayed on the monitor can be similar to the
original image as much as can be. The essence of each block will be introduced in the following sections.

**Figure 1.1 General Image Storage System**

### 1.2.1. Lossy Compression Methods

The lossy compression technique is one which renders a minute reduction of quality in the output image. This minor loss is almost inconspicuous and difficult to identify. This technique finds its use where the smaller variation or loss of quality results in no problem like that in photographs. There are diverse methods and algorithms used in lossless and lossy compression.

**Figure 1.2 Lossy image compressions**

Generally, most lossy compressors (Figure 1.2) are three-step algorithms, each of which is in accordance with three kinds of redundancy. The first stage is
a transform to eliminate the inter-pixel redundancy to pack information efficiently. Then a quantizer is applied to remove psycho-visual redundancy to represent the packed information with as few bits as possible. The quantized bits are then efficiently encoded to get more compression from the coding redundancy.

(i) **Quantization**

Quantization is a many-to-one mapping that replaces a set of values with only one representative value. Scalar and vector quantization are two basic types of quantization. Scalar Quantization (SQ) performs many-to-one mapping on each value. Vector Quantization (VQ) replaces each block of input pixels with the index of a vector in the codebook, which is close to the input vector by using some closeness measurements. The decoder simply receives each index and looks up the corresponding vector in the codebook.

(ii) **Transform Coding**

Transform coding is a general scheme for lossy image compression. It uses a reversible and linear transform to decorrelate the original image into a set of coefficients in the transform domain. The coefficients are then quantized and coded sequentially in the transform domain. The transform methods of discrete Karhunen-Loeve Transform (KLT), Discrete Fourier Transform (DFT) and Discrete Cosine Transform (DCT) are used.

(iii) **Block Transform Coding**

In order to simplify the computations, block transform coding exploits correlation of the pixels within a number of small blocks that divide the original image. As a result, each block is transformed, quantized and coded separately. This technique, using square $8 \times 8$ pixel blocks and the DCT followed by Huffman or Arithmetic coding, is utilized in the ISO JPEG draft international standard for image compression. The disadvantage of this scheme is that
blocking (or tiling) artifacts appear at high compression ratios. The new JPEG-2000 standard is based upon wavelet decompositions combined with more powerful quantization and encoding strategies such as embedded quantization and context-based arithmetic. It provides the potential for numerous advantages over the existing JPEG standard. Performance gains include improved compression efficiency at low bit rates for large images, while new functionalities include multi-resolution representation, scalability and embedded bit stream architecture, lossy to lossless progression, ROI (region of interest) coding.

(iv) Full-Frame Transform Coding

To avoid the artifacts generated by block transforms, full-frame methods, in which the transform is applied to the whole image as a single block, have been investigated in medical imaging research. The tradeoff is the increased computational requirements and the appearance of ringing artifacts (a periodic pattern due to the quantization of high frequencies).

(v) Dequantization

The JPEG image compression standard is employed in a large number of image-intensive applications. In some of these applications, dequantization is required when the amount of compression needed is unknown in advance. Ideally, one would like to always work from the original image when dequantizing since JPEG compression is lossy. However, the original image is not always available: it may no longer exist, or it may be too difficult to retrieve in real time. Dequantizing an already quantized image can lead to seemingly unpredictable behavior and unwanted artifacts.

(vi) Lossy Compression Disadvantages

- It works towards the identification of unrelated or irrelevant information (not only redundant data) and removal of the bits.
• By this way, data compression gains improvement, though at the cost of yielding lossy compression a nonreversible process - as it results in the loss of part of the information.

• Lossy compression is therefore not desirable for general purpose file archiving (for example, losing a single byte in an executable file might cause it not to work), but it works sufficiently well, whilst the loss of information with less relevance is acceptable, as in the case of multimedia files compression.

1.2.2. Lossless Compression Methods

Lossless compressors (Sahni et al., 1998) have shown in Figure 1.3 use two-step algorithms. The first step transforms the original image to some other format in which the inter-pixel redundancy is reduced. The second step uses an entropy encoder to remove the coding redundancy. The lossless decompressor is a perfect inverse process of the lossless compressor.

Typically, medical images can be compressed losslessly to about 50% of their original size. Charles et al. (1988) investigated the use of three entropy coding methods for lossless compression with an application to digitized radiographs and found that a bit rate of about 4 to 5 bpp was best. Tavakoli (1991, 1992) applied various lossless coding techniques to MR images and reported a compression down to about 5 to 6 bpp, with LZ (Lempel-Ziv) coding achieving the best results. Lossless compression works best with decorrelated data.

Roos.P and Viergever.M.A (1991) investigated prediction, linear transformation, and multiresolution methods for decorrelating medical image data before coding them. The compression ratio was 3:1 and less than 2:1 for angiograms and MRI respectively. Gopinath et al. (1992) studied similar techniques and found linear prediction and interpolation techniques gave the best
results with similar compression ratios. Here, the lossless compression methods are summarized into four categories.

(i) Run Length Coding

Run length coding replaces data by a (length, value) pair, where “value” is the repeated value and “length” is the number of repetitions. This technique is especially successful in compressing bi-level images since the occurrence of long run of a value is rare in ordinary gray-scale images. A solution to this is to decompose the gray-scale image into bit planes and compress every bit-plane separately. Efficient run-length coding method (Sarika and Srilali, 2013) is one of the variations of run length coding.

(ii) Lossless Predictive Coding

Lossless predictive coding predicts the value of each pixel by using the values of its neighboring pixels. Therefore, every pixel is encoded with a prediction error rather than its original value. Typically, the errors are much smaller compared to the original value so that fewer bits are required to store them. Differential Pulse Code Modulation (DPCM) is a predictive coding based on lossless image compression method. It is also the base for lossless JPEG compression. A variation of the lossless predictive coding is the adaptive
prediction that splits the image into blocks and computes the prediction coefficients independently for each block to achieve high prediction performance. It can also be combined with other methods to get a hybrid coding algorithm with a still higher performance.

(iii) **Entropy Coding**

Entropy represents the minimum size of dataset necessary to convey a particular amount of information. Huffman Coding, LZ (Lempel-Ziv) Coding and Arithmetic coding are the commonly used entropy coding schemes. Huffman coding utilizes a variable length code in which short code words are assigned to more common values or symbols in the data, and longer code words are assigned to less frequently occurring values. Modified Huffman Coding (HC) and Dynamic Huffman Coding (DHC) are two examples among many variations of Huffman’s technique.

(iv) **Multi-resolution Coding**

HINT-Hierarchical INTerpolation (Gopinath et al., 1992) is a multiresolution coding scheme based on sub-samplings. It starts with a low-resolution version of the original image and interpolates the pixel values to successively generate higher resolutions. The errors between the interpolation values and the real values are stored, along with the initial low-resolution image. Compression is achieved since both the low-resolution image and the error values can be stored in fewer bits than the original image.

Lossless compression makes use of statistical models for mapping the input for a smaller output thus helping in the elimination of the redundancy in the data. By this means, the output carries precisely all the information that is featured by the input in reduced number of bytes, and can be expanded when needed for a 1:1 copy of the actual data, which is a basic property for saving few kinds of data - i.e. software, a database.
(v) **Applications of Digital Image Compression**

Digital Image Compression has various applications ranging from image compression for personal use to the compression of more significant images such as medical images. Digital Image Compression helps to save a large amount of memory space and therefore widely used for compressing photographs, technical drawings, medical imaging, artworks, maps etc. Images that are reduced in size by Digital Image Compression can be sent, uploaded or downloaded in a shorter time and this way it makes it lot easier to share images. Numerous transforms are used in a variety of applications.

(vi) **Need for JPEG compression**

Joint Photographic Experts Group (JPEG), Graphics Interchange Format (GIF), Tagged Image File Format (TIFF), Portable Network Graphics (PNG), BitMaP (BMP) and several other file types are employed for encoding the digital images. One bit of reason for the plethora of file types is the necessity for compression. Image files can be quite huge, and larger file types indicate more disk usage and also slower download. Compression is a term that is used to explain means for cutting down the size of the file. Another reason for having so many file types is that the images have a difference in the number of colors they have. If an image has less number of colors, a file type can be designed to just to exploit this as a means to reduce the file size.

In comparison with other image file types, the JPEG format is highly unique in the concept that images are compressed in accordance with the human eye. Since the human eye is not very good at picking up subtle color differentiations and high-frequency brightness variations, data can be eliminated without entirely modifying the image. But, as this data is being removed, the quality of the image sees a decrease. This is the cause why JPEG compression is regarded as lossy and lossless. It has some advantages such as:

- Large compression ratios = shorter file transfer time
- Full-color information
- Good for photographs, graphic artwork, banner ads, etc.
(vii) **JPEG Compression**

JPEG is a lossy compression algorithm (Marcus, 2014) for images. A lossy compression scheme is a way to inexacty represent the data in the image, such that less memory is used and yet the data appears to be very similar. This is why JPEG images will look almost the same as the original images they were derived from most of the time, unless the quality is reduced significantly, in which case there will be visible differences. The JPEG algorithm takes advantage of the fact that humans cannot see colors at high frequencies. These high frequencies are the data points in the image that are eliminated during the compression. JPEG compression also works best on images with smooth color transitions and image compression methods are discussed in what follows.

### 1.2.3 Discrete Cosine Transform

The Discrete Cosine Transform (DCT) (Andrew, 1994) is a technique used for the conversion of a signal into its elementary frequency components. It finds its application largely in image compression. Here some simple functions are developed in order to compute the DCT and hence compress the images. These functions demonstrate the power of Mathematics in creating the prototype of image processing algorithms.

The immensely popular technique for image compression, over the past several decades, was Discrete Cosine Transform (DCT). Its choice as the standard for JPEG is one of the big reasons for its gaining popularity. DCT finds its usage in many non-analytical applications like image processing and signal-processing DSP applications including video conferencing. The DCT is utilized in transformation for data compression. DCT is an orthogonal transform, having a specified set of basis functions. DCT is useful for mapping an image space into a frequency. DCT has several advantages: (1) It has the capability for packing energy in the lower frequencies for the cause of image data. (2) It has the ability to eliminate the blocking artifact effect and this impact results from the boundaries between sub-images, thus going visible.
The statistics of DCT coefficients in double-compressed JPEG images may hugely differ from those statistics in single-compressed images. These differences adversely impact the accuracy of few steganalyzers evolved under the assumption that the stego image has been compressed only one time. This is particularly true for steganalysis methods that are based on calibration, which is a process that is applied for the estimation of macroscopic properties of the cover image from the stego image.

(i) **Double compression**

Double-compression in JPEG images (Pevny and Fridrich, 2008) occurs while a JPEG image is decompressed to the spatial domain and then again resaved with another different (secondary) quantization matrix. The first quantization matrix is called the primary quantization matrix. There are various reasons for the interest shown in the detection of double-compressed JPEG images and the related issue of estimation of the primary quantization matrix. First and foremost, detection of double compression is a forensic tool that is helpful in the recovery for the processing history.

Double-compressed images are also often generated during image manipulation. By the detection of the traces of recompression in the individual image segments, the forged region may be identified since the non-tampered part of the image will show the traces of double compression. Till now, all the methods introduced for detection of double compression and for estimating the primary quantization matrix were developed assuming that the image under investigation is an original image. As the act of embedding alters the statistics of DCT coefficients further, there is a requirement for techniques which can accurately detect double compression in compressed images and do the estimation of the primary quantization matrix.

(ii) **Quantization**

Quantization is achieved by compressing a range of values to a single quantum value (Bhawna, 2010). When the number of discrete symbols in a given
stream is reduced, the stream becomes more compressible. A quantization matrix is used in combination with a DCT coefficient matrix to carry out the transformation. Quantization is the step where most of the compression takes place. DCT really does not compress the image because it is almost lossless. Quantization makes use of the fact that the higher frequency components are less important than low-frequency components. It allows varying levels of image compression and quality through selection of specific quantization matrices. Thus, quality levels ranging from 1 to 100 can be selected, where 1 gives the poor image quality and highest compression, while 100 gives the best quality and lowest compression. As a result, quality to compression ratio can be selected to meet different needs. The JPEG committee suggests a matrix with quality level 50 as a standard matrix. For obtaining quantization matrices with other quality levels, scalar multiplications of the standard quantization matrix are used. Quantization is achieved by dividing each element in the transformed image matrix by the corresponding element in the quantization matrix used, and then rounding to the nearest value. In the resultant matrix, coefficients situated near the upper left corner have lower frequencies. The human eye is more sensitive to lower frequencies. Higher frequencies are discarded. Lower frequencies are utilized for reconstructing the image. The quantization method is using the Neural Networks (NN) learning algorithms.

1.3 Quantization Matrix Estimation Using Neural Networks (NN)

1.3.1 Neural Networks

Neural Networks (NN) are generally grouped in layers. Layers are created by a number of interconnected 'nodes' containing an 'activation function'. Patterns are given to the network through the 'input layer', which, in turn, communicates to one or more 'hidden layers' where the real processing is done through a system of weighted 'connections'. The hidden layers thereafter connect to an 'output layer' where the answer is taken as the output.
There are two types of networks:

- Fuzzy Neural Network (FNN)
- Adaptive Neuro-Fuzzy Inference System (ANFIS)

### 1.3.2 Fuzzy Neural Networks (FNN)

The general architecture of a Fuzzy Neural Network (FNN) (Abdul and Abdul, 2010) satisfying this need is illustrated in Figure 1.4. But, just to the explanation of its working, the simplified case of only two classes is indicated in Figure 1.5. Every class grouping of the FNN operates in the same way. More classes give fuzzy memberships in some more classes from which a maximum value winner is selected at the last output node.

In Figure 1.4, there are N features seen in the input exemplar feature vectors. Here there are two classes observed in the training exemplar data, \{(x(q), t(q)): q = 1, \ldots, Q\}, i.e., the t(q) has two unique labels, so K = 2 class groups of hidden nodes I used where every such node denotes a Gaussian function that is centered on an exemplar feature vector having a corresponding label. Every Gaussian in a class group has a different center though with the same label. Let us consider the first group of hidden nodes for Class 1 in Figure 1.5.

![Figure 1.4 The Fuzzy Neural Network](image-url)
In the common case, there might be a big number $K_p$ of feature vectors in class $p$ ($p = 1, 2$ here), so those feature vectors that are near to another feature vector with the same label are eliminated. This decreases the number of centers, and therefore Gaussians (nodes) too, which represent every Class $p$. The fuzzy truth related to input vector $x$ being in the same class as $x(q)$ is given by the Gaussian Fuzzy Set Membership Function FSMF centered on $x(q)$. The qth Gaussian FSMF is the function where $F$ can be measured to be one-half of the average distance existing between all ideal pairs.

![Figure 1.5 FNN for only two classes](image)

All the fuzzy truths corresponding to the centers of Gaussians in Class 1 are now input from their Gaussian nodes into the maximizer node of the Class 1 fuzzy truths, which behaves as a fuzzy OR node in choosing the representative center and fuzzy truth which is, that $x$ belongs to some $x(k)$ for Class 1. This maximum fuzzy truth for $x$ to be in Class 1 is now transmitted to the final output maximizer node as the Class 1 representative. The final output maximizer node also obtains the Class 2 representative (maximum fuzzy truth) that $x$ belongs to Class 2 and decides the maximum of these fuzzy truths, such the class that sent it is pronounced the winner. This way, the input $x$ belongs to the winning class as fixed by the label of the winning Gaussian center vector.
1.3.3 Adaptive Neuro-Fuzzy Inference System (ANFIS)

An Adaptive Neuro-Fuzzy Inference System (ANFIS) is a type of Artificial Neural Network (ANN) which is based on Takagi–Sugeno fuzzy inference systems. The technique was evolved in the early 1990s. (Jang, 1991, 1993) As it incorporates both neural networks and fuzzy logic principles, it has the capability to acquire the advantages of both in a single framework. Its inference system relates to a set of fuzzy IF–THEN rules which possess learning capability for approximating nonlinear functions. (Abraham, 2005) Therefore, ANFIS is regarded as a universal estimator. (Jang et al., 1997) For employing the ANFIS in a more effective and optimal way, one can make the use of the best parameters that are rendered by genetic algorithm (Tahmasebi, 2012).

![Figure 1.6 Overall descriptions of ANFIS](image)

The fuzzy inference system that is being considered is a model which maps:

- Input characteristics to input membership functions,
- Input membership functions in rules,
- Rules to a set of output characteristics,
- Output characteristics of output membership functions, and
- The output membership function to a single-valued output, or
- A decision associated with the output.

In ANFIS, we only considered membership functions which have been predetermined, and in some way or the other chosen arbitrarily. Also, fuzzy inference is only applied to modelling systems whose rule structure is typically fixed by the user’s cognition of the features of the variables in the model. Generally, the shape of the membership functions is dependent on parameters
whose adjustment can be made in order to alter the shape of the membership
function. The parameters can be adjusted automatically based on the data on
which it is tried to be modelled.

(i) Model Learning and Inference through ANFIS

- Suppose we already have a repository of input/output data and would want
to develop a fuzzy inference model/system which approximates the data.
- Such kind of a model would comprise of a number of membership
functions and rules with parameters that are adjustable similar to that of
neural networks.
- Instead of selecting the parameters that are associated with a given
membership function randomly, these parameters could be selected in
order to tailor cut the membership functions according to the input/output
data for the purpose of accounting for these kinds of variations in the data
values.
- The neuro-adaptive learning techniques suggest a method for the fuzzy
modelling procedure for learning information about a data set, so as to
compute the membership function parameters which best allows the
associated fuzzy inference system in tracking the input/output data given.
- Utilizing a given input/output data set, the toolbox function ANFIS builds
a Fuzzy Inference System (FIS) whose membership function parameters
are tuned (adjusted) making use of either a back-propagation algorithm
only or in combination with the least squares kind of method.
- This lets the fuzzy systems to be able to learn from the data that they are
modelling.

(ii) FIS Structure and Parameter Adjustment

- A network-type structure just as similar to that of a neural network, which
does the mapping of the inputs via input membership functions and
associated parameters, and then again by means of output membership
functions and associated parameters to outputs, can be useful in interpreting the input/output map.

- The parameters related to the membership functions will undergo change through the learning process.

- The computation of these parameters (or their adjustment) is enabled by a gradient vector that yields a measure of the efficiency with which the fuzzy inference system is providing the model of the input/output data for a given set of parameters.

- As soon the gradient vector is received, any one of the many optimization routines could be applied for adjusting the parameters so that some error measure is reduced (generally defined by the sum of the squared difference between the original and required outputs).

- ANFIS makes use of either Back Propagation (BP) or a combination of least squares estimation and back propagation for the purpose of membership function parameter estimation.

![Figure 1.7: Adaptive Neuro-Fuzzy Inference System (ANFIS)](image)

The advantage of the Fuzzy Inference System (FIS) is that it can deal with linguistic expressions and the advantage of a neural network is that it can be trained and so can self-learn and self-improve. Jang, (1993) took both
advantages, combining the two techniques, and proposed the Adaptive Neuro-Fuzzy Inference System (ANFIS). The idea behind Neural Network (NN) and fuzzy inference combination is to design a system that uses a fuzzy system to represent knowledge in an interpretable manner and has the learning ability derived from a neural network that can adjust the membership functions parameters and linguistic rules directly from data in order to enhance the system performance (Wang et al., 2006). The ANFIS architecture contains a five-layer feed forward neural network as shown in Figure 1.7. It has some advantages such as

- **Interpretability** - The capability of the model to express the behaviour of the system in an understandable way. These aspects include the number of input variables, comprehensible linguistic terms, a small number of rules that can interpret the whole model, and the shape of fuzzy sets.
- **Accuracy** - The capability of the developed model to respond to the real system. The closer the model of the system, the higher its accuracy.

On a larger measure, fuzzy logic, neuro-computing, and probabilistic reasoning are complementary to each other, though not competitive. It is therefore becoming increasingly evident that in several cases it is advantageous to have them combined. A case in view is the rapidly growing number of “neuro-fuzzy” consumer products and systems which employ a combination of fuzzy logic and neural-network techniques.

Hybrid tools designed by the combinations of neural networks; evolutionary computation and fuzzy logic solve difficult issues, need relatively smaller development times, and are reliable.

### 1.3.4 *Mamdani model based Adaptive Neural Fuzzy Inference System (MANFIS)*

By means of an in-depth knowledge of FNN structure and a comparative analysis between merits and demerits in ANFIS model, a Mamdani model based
Adaptive Neural Fuzzy Inference System (MANFIS) is proposed, which is named as MANFIS.

It is a class of adaptive neural network that is equivalent to Mamdani fuzzy inference system in terms of its function, which is referred to as M-ANFIS. It abbreviates to an adaptive network based fuzzy inference system. The neural network has the significant function of managing with inaccurate data by training, while fuzzy logic can tackle the uncertainty of human interpretation. The nature of these two techniques is a universal approximator and they perform the function of non-linear modelling. Truly, neural networks and fuzzy logic have combined very well. Fuzzy neural networks realize the important steps of fuzzy inference in an ordered layer of a neural network with architecture in a way that the weights are to be adjusted in the network. This, in turn, results in the fuzzy inference closer to the real situation through the learning capability of NN. FNN are extensively employed in several areas.

Mamdani model based Adaptive Neural Fuzzy Inference System (MANFIS) (Chai et al., 2009) that is greatly superior to ANFIS in the expression of the resultant part and is intuitive of fuzzy reasoning. This model will be a reflection of popular Fuzzy rule-based Inference System are Mamdani fuzzy method and Tagaki-Sugeno (T-S) fuzzy method. Merits of the Mamdani fuzzy inference system:

- It is intuition based.
- It has widespread acceptance.
- It’s well suited to human cognition

Mamdani model can illustrate its legibility and comprehensibility to the layman. The Mamdani fuzzy inference system exhibits its advantage in output expression and is applied in this research. In order to wholly specify the operation of a Mamdani fuzzy inference system, a function needs to be assigned for each of the following operators:
• AND operator (generally T-norm) for the rule firing strength computation along with AND’ed antecedents.
• OR operator (usually T-conorm) for computing the firing strength of a rule with OR’ed antecedents.
• Implication operator (generally T-norm) for computing qualified consequent Member Functions (MF) on the basis of the given firing strength.
• Aggregate operator (usually T-conorm) for aggregation of the qualified consequent MFs for generating an overall output MF.
• Defuzzification operator for the transformation of an output MF to a short single output value.

1.4 Resizing Images

The most obvious and common way to change the size of an image is to resize or scale an image. The content of the image is then enlarged or more commonly shrunk to fit the desired size. However, while the actual image pixels and colors are modified, the content represented by the image is essentially left unchanged. However, resizing images can be a tricky matter. It can modify images in extremely detrimental ways, and there is no 'best way' as what is best is subjective as to what we actually want out of the resize process.

Resizing will cause drastic changes to an image, and avoiding or minimizing unwanted 'artifacts' is of greatest importance. Perhaps just a slight shave off the edges or a more general crop of the image will produce a better and more desirable outcome than a wholesale resize of the image. It generally will look better and the area left will be a perfect copy of the original. Resize is a term which is very vague and kind of ambiguous. It has no particular meaning till it is said what it means. There are three very diverse means to "resize" an image, and all three have extremely different meanings and also results.
**Crop it** - to just cut away some of the edges, in order to include less area in the final image, a little similar to zooming in a little tighter, but usually done afterwards. Cropping tighter can enhance the composition by eliminating uninteresting or empty or distracting side detail whose contribution is nothing, and thereby drags attention away from the subject. Cropping tighter thus increases the size of the subject in the frame, rendering it more dominant. With much less arbitration, cropping is frequently needed to make the image shape to fit the shape of the printer paper.

**Resample it** - to create a new image with different image dimensions (in pixels). Resampling might for instance, substitute 4000 pixels across with only suppose 1000 new pixels across, however with the same scene view, but a much smaller image. The reasons behind would be to get a large size image smaller, just to show it way smaller on the video screen, or to send it as an email attachment, or to print only in 6x4 inch size. The idea is about making the image size more suitable so that it can be used. There is no way that it can be retrieved, so the original is not overwritten - this second one must be a copy, and with a different file name. Resampling is irreversible, resampling smaller removes pixels (detail) for them to be smaller. The smaller copy has sufficient pixels for the smaller size for sure, but less than earlier.

**Scale it** - The third way of resizing is to scale the image existing for printing on paper. Scaling does not alter the image pixels by any means. Its only action is to modify the single number for dpi (ppi) that is an arbitrary number which is simply saved in the image file separately. It is only utilized by the printer, and it only makes changes in the size of this image which will be printed on paper (at so many pixels per inch). The number has no impact on images when observed on the computer screen. The camera has no idea what size the image might be printed, and it just cooks up some number.
Disadvantage

When resizing an image, simple methods such as scaling and cropping have obvious limitations. Simple image scaling distorts the entire image if the input and output aspect ratios differ too much. Cropping simply discards some image parts and is inappropriate when multiple objects of interest are far away from each other.

1.4.1 Resizing seam carving method

Seam carving is an effective image processing operator for the purpose of content-aware image resizing. It generates an energy map of the gradient intensity of pixels and looks for seams that are vertical or horizontal contiguous paths of pixels running through local minimum energy areas. Removal or insertion of pixels along a seam helps users to either shrink or enlarge pictures by a broader range, when retaining all the other details of the image. The aim of this seam carving algorithm is the resizing of images. This permits the image to be resized without any loss of meaningful content due to cropping or scaling. The clue is locating the image's optimal seams, connected pixel paths passing from top to bottom or left to right, to eliminate or insert while maintaining the photorealism of the image. In addition, the gradient energy map which describes the optimality of a seam is allowed for functionality such as object removal is manipulated. The technique explained below refers to the implementation of the algorithm proposed in Avidan and Shamir (2007).

1.4.2 Growcut based seam carving

GrowCut is an interactive image cutout tool designed to extract solid or opaque objects. Provided a small number of user labelled pixels, the remaining of the image is segmented automatically by a Cellular Automaton. The process is iteration based, while the automaton is labelling the image, the user is able to
observe the segmentation evolution and provide guidance to the algorithm with human input at the point where the segmentation is hard for computing (Vezhnevets and Konouchine, 2005). GrowCut is a high degree of interactivity, which allows easy and intuitive correction, and controllable boundary smoothness can be obtained. Other valuable advantages of GrowCut are its simplicity, multi-label assignment, speed and easy extensibility. Therefore, GrowCut can meet the requirement of user control in image resizing so as to remove or protect an object in the image. It is motivating to use GrowCut in combination with seam carving. By combining Seam Carving and GrowCut, a user can select objects or region of interest by just drawing one line inside and one line outside the object, respectively. These two lines will automatically select or identify the object to be protected or removed by GrowCut.

1.4.3 Shape-preservation image resizing

To take into account image content, we propose the use of similarity constraints for resizing images, in order to preserve the shapes of important regions and image edges. Ideally, each image region should undergo a homogeneous scaling. This is clearly impossible if the new image size has a different aspect ratio. To achieve arbitrary image resizing, diffuse distortion throughout the image, allowing distortion to be greater in less important regions, while more important regions and image edges are less deformed.

1.5 Problem Specification

With the rapid development of image processing technology, it is becoming easier to corrupt digital images without letting any trace that is visual obviously. Nowadays, seeing does no longer equal to believing (Zhu et al., 2004). Image forgery, just like any other illegal and harmful activity, could pose a serious threat to society. Hence, authenticity verification of digital images has emerged a very significant issue. JPEG is one of the most widely used image
formats to verify the authenticity of digital images. Theoretical analysis of the impacts of these errors on single and double JPEG compression becomes very important. Some of the issues faced during the JPEG in the existing algorithms which are described as follows:

- Quantization matrix estimation is a very challenging task. Bigger image samples are difficult to quantize and decompress. It does not maintain information regarding all compression results such as single and double compression methods. This is due to decreased JPEG error compression results.

- Compression distortion is not a random noise, in the sense that the additive distortion induced by compression, conditioned on the original (input) image, is completely deterministic. Under certain conditions, however, compression noise is uncorrelated with the quantized (output) image.

- However, the existing methods in the literature can only reveal the compression history of a given image, and cannot detect the local duplicated tampered region in a given image.

Other forensics/stegoanalysis issues attempt to identify the double JPEG compressed images and/or further conduct the estimation of the primary quantization table. In such conditions, the input images of these algorithms are JPEG images instead of bitmap images, which mean that can receive all the parameters of the final JPEG compression from the file header, and as a result, their techniques will not be appropriate for the forensic situations proposed.

1.6 Objective of the Research

In this work, first we analyze the main sources of errors introduced through JPEG compression and their relationships with JPEG recompression, and then we propose three novel methods for the estimation of JPEG history. The main objectives of this research work are:
- The aim of digital image forensics is to cope with any kind of image modifications and to determine the authenticity of digital images. We reduce the size of the compressed image to solve storage complexity problem.

- An efficient feature can be got for quantization step estimation, quantization estimation error values found from classification methods to analyze compression results.

- Theoretically, analyze the effects of errors on single and double JPEG compression by classification methods. A simple though very efficient technique for extracting the quantization table from a JPEG decompressed image in order to enhance the compression results is obtained.

- We apply an image denoising method to eliminate the noises at the same time preserving the important resized JPEG image characteristics like edges, details as much as possible.

- The relationship between compression quality factor, image complexity, and the performance of the double compression detection algorithm is analyzed.

1.7 Research Contribution

The main aim of this research work is to present a well-organized double compression schema for JPEG images attained by modified DCT Methods. We reduce the size of the images after JPEG compression of images resized by using Seam carving, Growcut based seam carving and Shape-preserving image resizing. To remove noises from image samples, Non Local Means Filtering and its method noise Thresholding by means of wavelets (NLFMT), Hybrid Non-Local Means Filtering (HNLMF) have been formulated. For the purpose of assessing the influence of image compression on the performance of JPEG, a sample Discrete Cosine Transform-Singular Value Decomposition (DCT-SVD) is computed for single and double image compression, images were quantized by
means of numerous quantization matrices, and quantization matrix results are assessed using the classification methods.

- Initially, we proposed system presents a well-organized double compression schema for JPEG images attained by modified Discrete Cosine Transform (DCT) methods. After the images are resized from resizing method, then we apply quantization step from Fan and de Queiroz (2003) to analysis the error of compression methods by using Fuzzy Neural Network (FNN) (Ghosh et al., 2008). We accurately examine of error results from quantization matrix in both single and double compression methods.

- After this, double compression schema is formulated for JPEG images by improved DCT-SVD Methods. With the purpose of eliminating noise from the resized JPEG image sample, Non Local-Means Filter and its Method noise Thresholding by means of wavelets (NLFMT) (Kumar, 2013) is proposed. We executed quantization step to examine the error of compression techniques using Adaptive Neuro-Fuzzy Inference System (ANFIS).

- Then double compression schema is formulated for JPEG images by Multi-directional Curvelet Transform with Fourier Transform matching Invariant Rotation (MCFTIR) scheme. We eliminate noises from the duplicated region using HNLMF (Shamsi and Kim, 2013). MANFIS which is a grouping of the quantitative fuzzy logic approach and adaptive ANN. It builds the fuzzy inference process by means of known quantization matrix from DCT-SVD.

1.8 Organization of the Thesis

Chapter 1 provides an introduction to image compression, types of image compression, need and properties of image compression and an overview of various transformations.
Chapter 2, “Literature Survey” discusses the existing image compression techniques. This chapter analyses and examines the existing JPEG image compression techniques. The inference from the existing techniques and its limitations are also discussed in this chapter.

Chapter 3 deals with the detailed explanation of the first proposed methodology, namely, a novel algorithm for quantization matrix estimation for JPEG error analysis to digital image forensics which overcomes the drawbacks of the existing image compression techniques with more accuracy and significance. Modified Discrete Cosine Transform (DCT) method is used to attain double compression schema for JPEG images.

Chapter 4 discusses the second proposed approach for JPEG compressed image namely, a novel Non Local Linear Filtering for denoising and ANFIS algorithm for quantization matrix estimation for JPEG error analysis to digital image forensics. The proposed method has improved the results with a slight increase in performance in terms of Method noise, PSNR and Mean Square Error (MSE).

Chapter 5 discusses the third proposed methodology, namely, detection of the duplicate region and hybrid non-local means filtering for denoising with quantization matrix estimation for JPEG error analysis. This approach detects duplicate region and removes images through the theoretical analysis of the impacts of these errors on single and double JPEG compression. The simulation results indicate that the proposed technique gives better results.

Chapter 6 shows the comparison of the experimental results with the previous approaches. This chapter also concludes the thesis with the findings for image compression on various performance parametric standards.

Chapter 7 provides the conclusions and scope of the future work.