CHAPTER 1

Introduction

1.1 Prologue

Automatic recognition of handwritten characters has long been a goal of many research efforts in the pattern recognition field [41]. The sub problem of digit recognition is also seen as important, not only because advances in it are expected to lead to advances in the general case, but also because of its immediate applicability to a number of fields, the most frequently cited of which is the reading of postal ZIP codes from mail pieces [10]. The challenges in handwritten digit recognition arise not only from the different ways in which a single digit can be written, but also from the varying requirements imposed by the specific applications. The primary performance measures are classification accuracy and recognition speed.

Handwriting recognition is divided into on-line and off-line categories. Since the late 1960s, research on recognition of unconstrained handwritten characters has made impressive progress and many systems [21, 30, 50, 92, 121] have been developed, particularly in machine-printed and on-line character recognition. However, there is still a significant performance gap between human and machine in the recognition of off-line totally unconstrained handwritten character recognition.

The on-line recognition has the advantages of capturing dynamic information. This information consists of the number of strokes, their order, direction, and the speed of writing within each stroke. As contrasted with on-line recognition, the off-line case is much more difficult because it lacks the above knowledge [165]. Thus the off-line recognition of isolated handprinted characters is a necessary and often critical part in most real-world applications [45]. Off-line recognition has attracted enormous attention, including a competition sponsored by the National Institute of Standards and Technology (NIST) and there is still no solution that matches human performance [163]. Many
approaches today are based on nonparametric statistical methods such as neural networks, discriminant analysis, nearest neighbor rules with different metrics, and classification trees. Hybrid and multiple classifiers are also effective. Broadly, an off-line handwritten character recognition system includes three parts: document image preprocessor, feature extractor, and classifier. Preprocessing is primarily used to reduce variations of handwritten characters. Feature extractor is essential for efficient data representation and extracting meaningful features for later processing. Feature extraction refers to the process of finding a mapping that reduces the dimensionality of patterns. As a major factor influencing recognition performance, features play a very important role in handwriting recognition. This has led to the development of a variety of features for handwriting recognition and their recognition performances have been reported on standard databases [107, 155]. Some recent papers include those proposing directional distance features [107], gradient-based features [139], wavelet-based features [93], pixel distance features [141], and concavity features [39]. The features do not necessarily convey any intuitive meaning to a human and the dimensionality of the feature vectors is very high, in the hundreds, so it is difficult to understand their discriminative characteristics. A systematic evaluation of features in a specific feature vector is very important for designing a new feature vector by combining different feature vectors.

A special case of feature extraction is feature selection. Feature selection is a very important aspect in solving the problem of pattern classification. Many collected databases contain attributes that are redundant or irrelevant. The advantages of using only the relevant features of the data for classification are many; First, by reducing data-overfitting, a classifier with better generalization capability can be obtained. Second, by identifying the relevant features, the cost of future data collection can be reduced. Third, by excluding the irrelevant attributes, a simple classifier can be obtained and the time required to classify new patterns can be reduced [6].

Classification is the process of assigning the given input pattern to one of a finite number of classes or categories. Various classification methods used for character recognition include nearest neighbor classifiers, and multilayer perceptron networks.
There has also been a recent trend to combine the outputs of multiple classifiers. Although classification rates for handwritten digit recognition are inching up, it is somewhat difficult to assess the state-of-the-art. One reason is that many different "test sets" have been proposed and some are widely considered to be more difficult than others. At the National Institute of Standards and Technology competition, the best recognition rate at zero percent rejection was 98.44% and only about half the systems had error rates of less than 5% [163]. It has been found that the error rate is cut by more than half for every ten fold increase in the size of the training set from 10 to 100,000 samples [136].

Artificial Neural Networks are massively parallel computing models that rely on dense arrangement of interconnections and simple processors. They have evolved from our understanding of brain model and they take their name from the network of nerve cells in the brain called "Neurons". They have exhibited excellent behaviour in the resolution of complex artificial intelligence problems. These neural network models use the organizational principles such as learning, generalization, parallel processing, adaptivity, fault tolerance, distributed storage and computation in a network of weighted directed graphs in which the nodes are artificial neurons and weighted directed edges are connections between neuron outputs and inputs. One of the most interesting properties of neural networks is that they are universal approximators. They have the ability to learn complex non-linear input-output relationships, use sequential training procedures, and adapt themselves to the data.

The most popularly used family of neural networks for pattern classification is the Self-Organising Map (SOM) or Kohonen Neural Network. It is based on the unsupervised competitive learning and neighbourhood concept. The learning process involves updation of interconnection weights so that the network can efficiently perform a pattern classification/clustering task. The increasing popularity of neural network models to solve pattern recognition problems has been primarily due to their seemingly low dependence on domain specific knowledge (relative to model-based) and rule-based approaches and due to the availability of efficient learning algorithms for practitioners to
use. Neural networks provide a new suite of non-linear algorithms and unified approaches for feature extraction and classification and flexible procedures for finding good, and moderately non-linear solutions [5].

Learning vector quantization (LVQ) is a supervised learning technique that uses class information for the final fine-tuning of a feature map and hence improves the classifier decision regions. LVQ is derived from the concept of vector quantization. Vector quantization (VQ) is a well known and efficient encoding/quantization method for speech and image signals [66, 98]. As being a pattern classifier, it has the potential of offering good performance in many recognition/classification tasks. [17, 66]. In various applications, there are variant schemes related to VQ such as matrix quantization (MQ), segment quantization, finite state vector quantization, and pruned trellis vector quantization. Some of them attained very good performance in coding and recognition tasks [17, 66, 98]. The adaptive vector quantization using neural network structures was proposed by Krishnamurthy et al. This method takes advantage of embeddings in the neural networks and vector quantizers. Kohonen et al. [76] developed a LVQ classifier that is similar in structure to the feature map classifier developed by Huang and Lippman. This classifier requires a final stage of supervised training that comes after the training used in the feature map classifier. The LVQ classifier provides reduced error rates as compared to the feature map classifiers, especially when the number of exemplar nodes is small. When compared to back-propagation classifiers using both artificial problems and speech problems, these classifiers typically have similar error rates but often train faster and require more memory and computation time during classification. Chen M.S. and H.C. Wang [18] have developed a decision enhanced neural network model that uses LVQ to improve the classifier performance. Kageyasu Miyahar and Fumio Yoda have used a multiple modified LVQ neural network model to recognize Japanese characters. T. Kohonen [78] has discussed three variants of the LVQ algorithm and is of the opinion that if the self-organizing maps are used for pattern recognition, their classification accuracy can be multiplied if the cells are fine-tuned using supervised learning principles. The three variants are called type one learning vector quantization (LVQ1), type two learning vector quantization (LVQ2) and type three learning vector quantization (LVQ3).
Practical applications of LVQ1 are discussed in [38, 108]. A rigorous mathematical discussion of the LVQ1, and suggestions to improve its stability have been represented in [85].

A Fuzzy System consists of a bunch of fuzzy if-then rules. The notion central to fuzzy systems is that truth values (in fuzzy logic) or membership values (in fuzzy sets) are indicated by a value in the range [0.0, 1.0], with 0.0 representing absolute Falseness and 1.0 representing absolute Truth. Fuzzy logic provides a natural tool to model and process uncertainty. Hence fuzzy rules have the advantage over classical production rules of allowing a suitable management of vague and uncertain knowledge. They represent knowledge using linguistic labels instead of numeric values, thus they are more understandable for humans and may be easily interpreted. These fuzzy rules describe the extent to which a pattern belongs or does not belong to one of the classes in terms of antecedent and consequent clauses provided in natural form [151]. Fuzzy rule based systems developed using fuzzy logic have become a field of active research during the last few years. These algorithms have proved their strengths in tasks such as the control of complex systems which are very hard to model using classical mathematics. The most important property of fuzzy-rule based systems is that they are universal approximators.

Thus fuzzy systems, including fuzzy logic and fuzzy set theory, provide a rich and meaningful addition to standard logic. The mathematics generated by these theories is consistent, and fuzzy logic may be a generalization of classical logic. The applications which may be generated from or adapted to fuzzy logic are wide-ranging, and provide the opportunity for modeling of conditions which are inherently imprecisely defined. Many systems may be modeled, simulated, and even replicated with the help of fuzzy systems, not the least of which is human reasoning itself.

The key advantage of neuro-fuzzy approach over traditional ones lies in that the former doesn't require a mathematical description of the system while modeling any system. Moreover in contrast to pure neural or pure fuzzy methods, the neuro- fuzzy method possesses both of their advantages. It brings the low-level learning and
computational power of neural networks into fuzzy systems and provides the high-level human like thinking and reasoning of fuzzy systems into neural networks.[80, 94, 95].

Thus the merits of neural – fuzzy computing are parallelism, fault tolerance, adaptivity and uncertainty management.

Inspired by the above, in the present research work we have developed various techniques for feature extraction, feature selection, and classification. We have designed a modified feature extractor, neural network based feature selector, and classifier models based on Kohonen Neural Network, Learning Vector Quantization, and Fuzzy System. We have made a comparative study of the following systems that we have developed with regard to the recognition of off-line totally unconstrained handwritten numerals:

1. Modified feature extractor.
2. Neural network based feature selector.
3. A single layer Kohonen Neural Network models with and without feature selector.
4. Combined Kohonen Neural Network and Learning Vector Quantization models.
5. Multi-Layer Neural Network models.

1.2 State of the Art

The origin of character recognition can be found in 1870 when Carey invented the retina scanner, an image-transmission system using a mosaic of photocells. The history of the optical character reader (OCR) got its start with the memorable patent on machine reading of printed numerals by Gustav Tauschek in 1928. The first prototypes of printed numeral OCRs were developed in the 1950s in America. Then, as early as 1960s, OCRs for printed alpha-numerals and symbols came into practical use and research on automatic recognition of handwritten alpha-numerals began, with the aim of recognizing free-formatted handwriting.
Research in Chinese character recognition has matured significantly since Casey opened up the field in 1966 [15]. Recently, pattern matching has become the main topic of Chinese character and Japanese character recognition study.

In Japan, from 1965 to 1968 research on developing the automatic postal code reading and sorting machines that recognize the three digit handwritten numerals was carried out under the direction of the Ministry of Posts and Telecommunications. This was followed by a national program to research and develop a "Pattern Information Processing System", which was implemented under the direction of the Ministry of International Trade and Industry in 1971.

Research in handwritten Kanji and Kana recognition using the ETL9B database has made tremendous progress [159, 156, 152, 69, 10, 127, 132, 149, 150].

In the early 1980s many research results were reported on handwritten Kanji recognition algorithms that assumed each Kanji character to be accurately written in block style in the boxes. In latter half of the 1980s, several manufacturers developed the prototypes and commercial OCR systems for handwritten Kanji, Kana and other alphanumeric that took full advantage of the contextual post processing techniques. Tsukumo has developed a non-linear pattern matching method called Direction Pattern Matching [155]. This is a method that uses shading and shifting of a character pattern based on the direction of the pattern. More recently, using the compression of higher dimensional features, Wakabayashi et al. report a recognition rate of 99.05% [31]. They use the Modified Quadratic Discriminant Function to avoid errors caused by a finite number of samples. N. Kato et al, have developed a handwritten Chinese and Japanese character recognition system with a recognition rate of 99.08% [68].

While any OCR would need some mechanical transport system which can be rather elaborate, the OCR literature clearly suggests that the key to high performance is the ability to detect and utilize the distinctive features of the characters [145]. But they
are extremely difficult to define. Measurable and visible features such as the density of points, moments, crossing counts, mathematical transforms, loops, end-points, junctions, arcs, concavities and convexities, strokes etc., can lead to a good classification of the characters. But the underlying factors which determine the true identity of handwritten characters remain to be unbeatable and it is probably safe to say that no simple scheme is likely to achieve high recognition and reliability rates, not to mention human performance.

The above situation has led to a number of recent efforts directed towards more sophisticated systems for pre-processing, feature extraction and classification stages. Approaches based on neural networks, fuzzy systems and mathematical morphology have also been studied.

Several high accuracy algorithms have recently been proposed for the recognition of handwritten numerals [44, 52, 103, 133, 134, 72, 74, 86, 144, 138, 53]. In an interesting paper [86], Lam and Suen describe a recognition system that consists of a sequential combination of a fast structural classifier and a robust relaxation algorithm. The classification is based on the configuration of a set of primitives derived from the image of the numeral. Although very low error rates are realized, the method is relatively slow, owing to an extensive preprocessing of the numeral image prior to feature extraction and the complexity of the relaxation algorithm. Srihari et al. proposed a recognition system [138] that utilizes three algorithms: (1) a template matching algorithm, (2) a mixed statistical and structural classifier utilizing features derived from the contours, and (3) a structural classifier utilizing features such as size and stroke placement etc. The accuracies obtained were reported to be significantly higher than those achieved with the individual algorithms. Kimura and his co-workers developed a statistical classification technique [72, 75] that utilized the histogram of the direction vector derived from the contours of the character. This technique was developed for the recognition of Chinese characters. Sridhar et al. reported a high speed accuracy structural recognition algorithm that utilized features derived primarily from the left and right profiles of the numeral images [133, 134]. However it did not provide for the rejection of
bad samples. F. Kimura et al. have combined two algorithms for the recognition of unconstrained isolated handwritten numerals [73] which has resulted in very low error rates of 0.2% or less and rejection rates below 4%.

Actually many systems have been developed [129] but more work is still required before human performance can be matched in a meaningful way. In the past four decades, a wide variety of approaches have been proposed to capture the distinctive features of handwritten characters [148]. These approaches generally fall into two categories: global analysis and structural analysis. In the first category, we find techniques such as template matching, measurements of density of points, moments, characteristic loci, and mathematical transforms. Features of this type are often used in conjunction with the statistical classification methods [133, 146]. In the second category, efforts are aimed at capturing the essential shape features of characters, generally from their skeletons or contours. Most often a syntactical classification approach is used with the structural features [52, 2, 8, 10].

Lee et al. [90] used artificial neural networks to approximate the Bayesian decision. According to Barron et al [9] back propagation training provides estimates of the Bayes probability functions. These will be good estimates only when the network has enough flexibility to closely approximate the Bayes functions and there is sufficient training data. D.S. Lee et al. [90] used artificial neural networks to approximate the Bayesian decision. Le cun et al [88] and Jiri Sima [62] have described a neural network OCR that performs particularly well on noisy, handwritten characters. Rumelhart and Mc Lelland [125] used neural networks as an alternative to the careful design of structural or statistical methods in pattern recognition. Solla [137] mentions that learning and generalization from training sets are two attractive features of the neural networks.

1.2.1 Feature Extraction Methods

Feature extraction has been one of the most important topics in pattern recognition and has been studied by many authors [37,28].
Venu Govindaraju and S.N. Srihari [157] have developed a dynamic character recognizer which uses a hierarchical feature space to achieve multiresolution. Chulhee Lee et al., [23] have developed a Decision Boundary Feature Extraction method for feed forward neural networks. Pattrick proposed a nonparametric feature extraction process where a non-quadratic distance function, defined between classes, is used to define the best linear subspace. Fukunaga proposed a nonparametric discriminant analysis method which is based on a nonparametric extension of commonly used scatter matrices. Short and Fukunaga proposed a feature extraction algorithm using problem localization [23].

Jun Cao et al., have developed a modified directional histogram feature extraction method. Rolf Ingold et al., [122] have developed a new statistical approach in which global typographical features are extracted from the text image and used by a multivariate Bayesian classifier. Some recent papers include those proposing directional distance features [143], gradient – based features [139], wavelet – based features [91], pixel-distance features [42], and concavity features [31]. A systematic evaluation of features in a specific feature vector is very important for designing a new feature vector by combining different feature vectors. Likewise, combination of multiple types of features has been attempted. In [31], several combinations of features are tested. Using three types of features representing local, intermediate, and global shapes, they have reached the conclusion that the combination of three feature types improved the recognition performance. A feature selection-based approach has also been tested, [19] in which it is said that the approach of multiple feature combination improves the recognition. II – Seok Oh et al, [55] have proposed a new approach to combine multiple features in handwriting recognition based on the two ideas; feature selection-based combination and class-dependent features.

1.2.2 Feature Selection Techniques

The research on feature selection dates back to the early sixties [27]. The most recent advances in this area are attributed to Narendra and Fukunaga [106] who
introduced and tested the use of branch and bound, and Foroutan et al. [35] who introduced the concept of approximate monotonicity and studied the use of branch and bound for selecting features for piecewise linear classifiers. In both cases the branch and bound method was used to minimize the number of features provided that a certain additional constraint was satisfied. The constraint induces back tracking in the branch and bound algorithm and consequently limits the size of the search space to a feasible region.

The process of feature selection is often incorporated into the classification process. Classification algorithms that build decision tree such as ID3 [111] and CART [12] select the most suitable feature at each branching node to grow the decision trees. R. Setiono et al. [131] have developed a neural network feature selector that uses a Quasi-Newton network pruning algorithm. A simple criterion to remove each feature based on the accuracy rate of the network is developed. B.A. Blesser et al. [11] performed empirical tests for feature selection based on a psychological theory of character recognition. A number of feature selection methods have been proposed in the literature [165]. Some of them are exhaustive search, branch-and-bound search, sequential forward selection, sequential backward selection, sequential forward floating search and sequential backward floating search methods. Of all these methods, only the first two guarantee an optimal subset. All other strategies are sub optimal due to the fact that the best pair of features need not contain the best single feature [25]. Ferri et al. [33] and Jain and Zongleer [167] have compared several of the feature selection algorithms in terms of classification error and run time. The general conclusion is that the sequential forward floating search method performs almost as well as the branch-and-bound algorithm and demands lower computational resources.

1.2.3 Classification Methods

Huang et al. [51] developed a feature map classifier which is an exemplar classifier that uses combined supervised and unsupervised training and requires less memory than a k-nearest neighbour classifier. T. Kohonen et al. [76] developed a LVQ
classifier that is similar in structure to the feature map classifier developed by Huang and Lippman. This classifier requires a final stage of supervised training that comes after the training used in the feature map classifier. When compared to back propagation classifiers, LVQ classifiers have similar error rates but often train faster and require more memory and computation time during classification. Quinlan [112], Jain [59], Brieman et al. [12] have shown that decision tree classifiers require complex but efficient training procedures that are not biologically motivated and that require simultaneous access to all training examples. These classifiers have been successful for many pattern classification and artificial intelligence applications. According to Fisher et al. [33] binary decision tree classifiers which have small memory and computation requirements, often perform as well as more complex back-propagation classifiers, but are more complex to adapt. Stauffill et al. [140] and Wolpert [162] have demonstrated that the modified K-nearest neighbour classifiers train rapidly but require large amounts of memory, computation, and sometimes perform as well as back-propagation classifiers, which are more complex to train but require less memory.

Tenorio et al. [154] have proved that the Group Method of Data handling (GMDH) network provides lower mean square error and requires fewer internal connections than the back-propagation network for the chaotic-time series non linear mapping problem. These networks provide many of the capabilities of back-propagation classifiers but use complex and efficient training procedures that require simultaneous access to all the training examples. Reilly et al. [117, 118] have demonstrated that Restricted Coulomb Energy (RCE) classifiers require less memory than the K-nearest neighbour classifiers but adapt classifier structure over time using simple adaptation rules that recruit new nodes to match the complexity of the classifier to that of the training data.

1.2.4 Databases

Although classification rates for handwritten digit recognition are inching up, it is somewhat difficult to assess the state-of-the-art. One reason is that many different test
sets have been proposed and some are widely considered to be more difficult than others. At the National Institute of Standards and Technology competition the best recognition rate at zero percent rejection was 98.44% and only about half the systems had error rates of less than 5%. It has been found that the error rate is cut by more than half for every ten fold increase in the size of the training set from 10 to 100,000 samples. In the database used by Beun [10], automatic method of reading handwritten numerals was trained with data collected from Netherlands Post Office as well as from various colleagues and visitors. This was an unbalanced data set. The largest public database of handwritten characters in Japan is the ETL9B [13]. In the ETL9B, 2, 965 kinds of Chinese characters (Kanji), and 71 kinds of Japanese characters (Kana), called the first class of Japanese Industrial Standard are included. The characters have been written by about 4,000 people and scanned as bitmaps. There are 200 samples of each character, so that 607,200 total character samples are included in the ETL9B. Ahmed and Suen [1] have used a subset of CENPARMI database of unconstrained handwritten ZIP codes. In the database of Duerr et al. [29] the unconstrained data were collected from different writers. Half were used to train the algorithm and the other half to test it. Gader et al. [39] report on many combinations of classifiers for handwritten digit recognition. A total of 3 different databases are used for testing. The different classifiers were trained on various data sets. Cohen et al. [24] have presented a method involving the use of four digit recognition algorithms combined with a decision tree to improve performance. Their database contained handwritten addresses collected from the U.S. Postal Services. Krzyzak et al. [82] used the CENPARMI data sets to develop a recognition system. It used Fourier descriptors as dominant features and applied a modified back-propagation model for the classification of handwritten digits. Josef Kittler et al. [64] have used the CEDAR-CD ROM database produced by the Center of Excellence for Document Analysis and Recognition, at the State University of New York, Buffalo. Images are scanned from dead-letter envelopes provided by the U.S. Postal Service. The BR and BS sets of the database that consist of bitonal isolated images of numeric characters are used. BR set contains 18,468 samples and is used as a training set while the BS set containing 2,213 samples is used as a test set.
1.3 Organization of the Thesis

Chapter 1 introduces the importance of automatic handwritten character recognition. Off-line handwritten recognition is compared with the on-line handwritten recognition and its relevance in the real-world applications is stressed. The concept of neural networks, learning vector quantization and fuzzy systems is introduced. An extensive survey of various techniques related to feature extraction, feature selection, databases, and classifiers is presented. The relevance and applications of our work has also been mentioned.

Chapter 2 explains the importance of features, their extraction, and the database creation. Need for real world data is mentioned, and several standard databases are introduced. The limitations of conventional feature extractor are highlighted, followed by the design of the modified feature extractor. Feature extraction algorithm is presented. The generation of 10,000 samples for our database has been discussed. Both the modified feature extractor and the sample database are an integral part of the subsequent chapters.

Chapter 3 deals with the design and development of a neural network based feature selector. The importance of feature subset selection in the context of classifier performance has been thoroughly discussed. The Quasi-Newton network pruning algorithm is presented along with the three layer fully connected feed forward neural network structure.

Chapter 4 is devoted to the development of the single layer Kohonen neural network models. The Kohonen algorithm based (KA) and modified Kohonen algorithm based (MKA) classifiers are developed with and without feature selectors. Also feature selector based MKA50, MKA75 classifiers are developed and evaluated. A decision rule is implemented to estimate the recognition rate, classification rate, rejection rate, and reliability of these techniques. The superior performance of the feature selector based MKA50 classifier is demonstrated.
Chapter 5 stresses the importance of fine-tuning the feature map by applying the supervised learning principle. The type two learning vector quantization (LVQ2) method is combined with the classification techniques developed in chapter 4. The classification performances of the various combined classifiers are investigated and the superior performance of the combined MKA50 and LVQ2 method is again justified.

Chapter 6 presents a multilayer neural network model and its advantages over the single layer neural network model discussed in chapter 4. The classification performance of the multi-layer model based on KA, MKA, MKA50, MKA75 methods and also their behaviour when combined with LVQ2 method is studied. The superior performance of the combined MKA50 and LVQ2 method is illustrated. Also the enhanced performance of all the eight techniques is demonstrated.

Chapter 7 explains a neuro-fuzzy handwritten character recognition system. The concept of fuzzy logic is introduced and the advantages of neuro-fuzzy approach are highlighted. The superior performance of the combined MKA, LVQ2 and fuzzy model is justified in terms of less training time and the computer memory that it requires.

Chapter 8 covers an application of the developed MKA50, and LVQ2 combined system for document processing. The efficacy of the developed system for the processing of the bank cheques or forms and resolving conflicts in the recognition of unconstrained handwritten characters in PIN or ZIP codes of mailing addresses is discussed. The suitability of the developed recognition systems for solving the dead letter problem of postal department is justified.

Chapter 9 presents the summary of our research work and also focuses on avenues for further research.

Appendix A describes learning in the context of neural networks. Types of learning and their relative merits and demerits are discussed.
Appendix B introduces the fuzzy system, fuzzy membership functions and a typical fuzzy algorithm.

Appendix C shows the representative set of samples used for testing and training.

1.4 Contributions

The main contributions of our research work presented in this thesis are listed below:

1. Design and implementation of the database generation algorithm which uses as seed values some of the samples of the CENPARMI database of Concordia University.

2. Development of a modified feature extractor so as to overcome the drawbacks of conventional bar-mask encoder.

3. Design and implementation of the neural network based feature selector so as to remove redundant features and enhance classification performance.

4. Design of a KA classifier based on Kohonen neural network for the recognition of unconstrained handwritten characters.

5. Modification of this classifier into the MKA classifier so as to reduce the training time and improve recognition rate. Comparative study of these two models both with and without feature selector. Study of classifier behavior based on the time of collection of centroids. Three models MKA, MKA50 and MKA75 were developed based on the time of collection of centroids.

6. Incorporation of learning vector quantization in the classification process so as to fine tune the feature vector map and hence multiply the classification accuracy. Study and evaluation of the performance of the combined MKA, MKA50, MKA75 and LVQ2 methods.

7. Development of a multi-layer neural network recognition system so as to avoid the intersection of classification regions, which was observed in the case of a single layer neural network model. Conduction of eight different experiments so as to study the efficacy of this model.
8. Development of the combined MKA, LVQ2 and Fuzzy model for the recognition of off-line totally unconstrained handwritten characters, and justifying its superior performance in terms of reduced training time and reduced memory requirement.

9. Analysis of the developed combined MKA50 and LVQ2 recognition system for document processing in the context of mail address interpretation and processing of forms and bank cheques.