GENDER CLASSIFICATION FROM MYANMAR NATIONAL REGISTRATION CARD

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STATEMENT ORIGINALITY

I hereby certify that the work embodied in this thesis is the result of original research and has not been submitted for a higher degree to any other University or Institution.

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ABSTRACT

Gender classification is a basic function of determining gender by facial features which determine gender based on face images. Visual information from faces provides one of the more important sources of information for gender classification. This system proposes a gender classification system by faces from Myanmar National Registration Cards. In this system, Principal Component Analysis (PCA) and Support Vector Machines (SVM) are used to classify gender from the facial image. PCA is a dimensionality-reduction method that is used to reduce the dimensionality of large data sets, by transforming a large set of variables into a smaller one. SVM is a binary classification that incorporates PCA in the form of features, which can be predicted from two possible classes. The face regions were initially detected using the viola jones method, and then the faces were extracted. Then PCA is performed on the face region for feature extraction to encode the second-order statistics of the data. These principal components are fed as input to the SVM for classification. The proposed method is implemented by using the collected dataset file. The classification rate of the proposed system is described by three datasets; they are only female images, only male images, and combined male and female datasets for gender classification. It achieved better performance on all three types of experimentation in this system. The performance of the system is tested using the own data file with 180 images (80 males and 100 females) captured from the side of frontal views. SVM classifier achieves as high as 92.4% gender classification accuracy for 180 input images.

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CHAPTER 1

INTRODUCTION

Image processing is a field that processes biological features such as face, voice, and lips. Movement, hand geometry, smell, gait, iris, retina, fingerprints, etc. are important for recognition. Because the face is an accessible biometric characteristic, it does not need to attract human attention for face recognition. Recent areas of gender classification include human-computer interaction systems and other applications. One of the most significant biometric characteristics is face. It learns a lot about a person's identity, expression, age, gender, and ethnicity by evaluating their face. A gender classification system employs face of a person from a given image to tell the gender (male/female) of the supplied individual. Numerous other applications, such as facial recognition and intelligent human-computer interfaces, can perform better thanks to a good gender categorization approach.

1.1 Gender Classification

Gender classification is a basic task of face recognition, which determines gender based on face images. It is well known that many social interactions and services rely heavily on the correct gender perceptions of the parties involved. Considering the large population, the verification process for individuals is often time-consuming. The population could be divided in half according to gender as one solution. As a result, a large amount of time will be saved and the authentication search space will be reduced to almost half of the current data. Computer vision systems for gender classification, as used in many applications, will play an important role in our lives.

The process of gender discrimination in facial images has become an important issue today. In addition, the demand for face detection, gesture detection, person recognition, motion capture and detection are increasing dramatically due to the reliability of the security and authentication process. Gender classification can be done by using different methods such as gait, eye iris and hand shape.

Gender classification using facial images remains a challenging task. The main stages of gender segregation are pre-planning, features extraction and classification. A human can easily tell a man from a woman by the expression on his face, but a computer cannot directly determine. The machines require some significant information to perform the classification. When machines are used to determine face features based on gender, there are specific characteristics that set men and women apart.

The machine needs the proper input (feature) and a classification for gender classification because determining gender is a dual classification problem. Based on feature extraction, there are two groups of gender classification techniques. They are the fundamental characteristics of geometry, also known as local features, and the fundamental characteristics of appearance, also known as global features. Basic facial characteristics like the nose and eyes are developed from these features in geometry. Typically, distances, angles, and connections between facial points—geometric properties that are independent of scale, tilt, and rotation—are retrieved.

These characteristics represent faces and offer input to a trained classifier that conducts the classification. Geometric features are susceptible to changes in lighting conditions and face emotions, and lose information around ears and hair, which constitute significant information for gender recognition.

1.2 Motivation

This thesis specifically addresses the problem of building a method that can help us build efficient operating facial data extraction and gender classification techniques. This system proposes a Principal Component Analysis (PCA)-based gender classification scheme. The face image data is first split into a training set and a testing set according to gender. The topic of developing a methodology that can aid in the development of effective functioning face data extraction and gender categorization algorithms is the focus of this thesis. In this system, gender classification system using support vector machine (SVM) and principal component analysis (PCA) is proposed. First, the face dataset file is divided by gender into a training set and a testing set. PCA is then applied to the training set to extract facial features. Finally, the SVM classification method use to classify the input sets into their respective categories. PCA-based face recognition cannot only identify specific people from its training database, it can also be used to identify expressions, gender, and age. The traditional gender classification method in face recognition, namely the k-nearest neighbor algorithm, has some shortcomings. By using classification techniques that do not inherit the k-NN problem, the misclassification rate of face recognition systems can be reduced. The Support Vector Machine (SVM) classification algorithm can replace the k-NN algorithm.

1.3 Objectives

The main purpose of this thesis is to accurately detect male/female from an image of a person's face.

- To develop a method for classifying gender based on PCA characteristics and facial photos.
- To recommend suitable classification methods for gender classification applications.
- To learn face detection and recognition technology.
- To study the advantages of PCA algorithm and SVM algorithm in application

1.4 Thesis Organization

The selection of principle components as characteristics for face-based gender classification is examined in this thesis. This is how the thesis is structured:

Chapter 2 explains the underlying idea behind the work that needs to be done on gender classification, including geometric and appearance-based criteria.

Chapter 3 explains the proposed system, noise is removed by morphological procedures, and the viola jones approach is used for face detection. On its own database, these processes are carried out. The PCA method is applied to the face area that was extracted.

Chapter 4 explains the experimental setup using the PCA and SVM algorithms. Each image is represented to a lower dimension using PCA as an extract feature. SVM is utilized for classification, while Radial Basis Function (RBF) is the chosen kernel function. The biometric system's precision was attempted to be improved.

Chapter 5 concludes the whole system and proposes directions for future extension.

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CHAPTER 2

BACKGROUND THEORY

Face is the most obvious for human body parts. Classifying the use of facial images by gender is an interesting area of research today. Because of a person's face, it provides important information about gender, age, race, identity, and more. Classification is part of face recognition. Facial recognition is a biometric technology, checks and recognizes faces. Gender classification is still a difficult task. The main stages of gender classification are preprocessing, feature extraction, and classification. Visual tasks important to humans, many social interactions depend heavily on correct gender classification. As many applications are used, computer vision systems for gender classification will play the most important role in our lives.

2.1 Face Detection Algorithms

Gender classification is part of face recognition. Facial recognition is a biometric technology used to verify and recognize faces. Through the face detection algorithm, the computer recognizes the position of the face in the image, and then extracts the face features from a part of the image, and finally compares the extracted face feature data with the features stored in the face database to find the most suitable detection method. There are some distinguishable facial features between males and females, such as eyes, nose, mouth, etc., which are used to classify gender.

Feature invariant approaches, template matching methods, knowledge-based methods, and appearance-based methods are basically the four groups into which face detection techniques fall. Face features that are independent of facial angle, position, pose, and lighting conditions can be located using feature-invariant approaches. Template matching algorithms compare input photos to pre-selected faces as templates. To model facial features, such as a face with a symmetrical pair of eyes, a nose below the eyes, and a mouth at the bottom, knowledge-based methods use rules and data about the human face. In that they use a set of pre-labeled images to train or create a database of patterns that can be compared with input photos, appearance-based approaches are comparable to template matching techniques. The most common features are knowledge-based methods and appearance-based methods. Knowledge-based features have explicit physical meaning, such as the size of nose, mouth, and eyes; while appearance-based features have no physical meaning and are extracted from whole face segments. Several studies have proposed hybrid gender classification methods that combine appearance features and knowledge-based features.

2.1.1 Knowledge-based Features

The relative positions and sizes of significant components, such as the eyes, nose, and mouth, are employed in knowledge-based approaches to extract features. There are approximately two places where this group is concentrated. Create feature vectors from the regions where essential components are present in the image, important component directions, or edge detection results.

In [23], the *knowledge-based feature* methods, the main step is to locate and track a dense set of facial points. Most geometric feature-based methods use an Active Appearance Model (AAM) or its variants to track a dense set of facial points. As expressions evolve, the positions of these facial landmarks are then used in different ways to extract the shape of facial features and the motion of facial features.

Active Appearance Model (AAM) with second-order minimization and use of multilayer perceptron's to recognize facial expressions. Here different AAM fitting algorithms are compared and evaluated. Another example of a system that uses knowledge-based features to detect facial expressions is in [53]. The geometric displacements of some selected candid nodes, defined as the difference in node coordinates between the first and maximum facial expression intensity frames, are used as input to a novel multi-class SVM classifier.

In [14], knowledge-based features is used to detect sentiment. In this method, facial landmarks are manually located and those manually placed facial landmarks are tracked using piecewise Bezier volume deformation tracking. They tried a number of machine learning techniques and achieved the best results with a simple k-nearest neighbor technique.

In [11], a knowledge-based feature method is proposed for modeling, tracking and recognizing facial expressions on low-dimensional expression manifolds. Extract the start and offset segment features of the expression by using feature selection methods. These features are then used to train a AdaBoost classifier and build a Hidden Markov Model (HMM) to model the full temporal dynamics of an expression.

2.1.2 Appearance Based Feature

Using linear transformations and statistical techniques, this series of algorithms seeks to identify basis vectors that represent faces. In the literature, techniques like PCA and ICA have been suggested for this use. In order to minimize information loss, the PCA approach aims to reduce the dimensionality of the feature space while maintaining the key features. A second-order statistic from the data called the covariance matrix is used in the PCA approach. Local Binary Pattern (LBP) operator, Histogram of Oriented Gradients (HOG), Local Gabor Binary Pattern (LGBP), Local Orientation Pattern (LDP), Non-negative Matrix Factorization (NMF) based on texture features, texture information based on Gabor filter, Principal Component Analysis (PCA), Linear Discriminant Analysis (LDA), etc. are examples of appearance features that have been successfully used for emotion recognition.

In [38], the gender recognition problem is experimented on a heterogeneous database of images using discriminative functions including PCA, LDA, and SDA, which include variations in lighting, expressions, small poses, and ethnicity. Results indicate that PCA performs better than the combination of others. The outcomes demonstrate the linear discriminant function's strong generalizability even with a small number of training samples.

In [41], Discrete Cosine Transform (DCT) technique is used for feature extraction and high variance feature ranking. The k-Nearest Neighbor (k-NN) classifier uses Euclidean distance to find nearest neighbors. Different preprocessing techniques are use; such as face detection. For face detection, the Viola and Jones method was used. Histogram equalization techniques are used to stretch the contrast of an image and also to overcome lighting changes in the image. These sorted coefficients are arranged in a vector and passed to the k-NN classifier. The ratio of training and test images for the k-NN classifier is 50 % to 50%. Then the achievable accuracy is 99.3 %.

Viola-Jones' appearance-based face detection approach, which was utilized in this study, does not distinguish between human and non-human faces based on skin tone; instead, it normalizes both training examples and input samples to grayscale, hiding the issue. In order to enable accurate feature selection and real-time detection, Viola and Jones (2001) suggested a face detection system. A knowledge base is formed by calculating the difference in pixel intensities between features. For example, in a human face, the lip area is darker than the bridge of the nose. The data is then used to train a classifier that classifies faces and non-faces.

2.2 Feature Extraction Methods

A dimensionality reduction technique called Principal Component Analysis (PCA) can be used to condense a large number of variables into a smaller set while retaining the majority of their information. To put it another way, PCA identifies the information on the best captures the variation in facial features. In this work, features are extracted from training data using PCA. Principal Component Analysis (PCA) and Independent Component Analysis are the two most often utilized feature extraction techniques (ICA).

A small subset of the FERET dataset (500 pictures) was utilized for Independent Component Analysis (ICA) in [40], which used SVM to achieve 96 percent accuracy. Genetic algorithms have been used in conjunction with ICA to remove possibly unneeded characteristics. The remaining features were then used to train a feedforward neural network, which on three datasets had an overall accuracy of 85%.

An approach utilizing ICA and SVM was proposed by Jain et al. in 2005 [3]. Different classifiers are tested, including the cosine classifier, which calculates the distance between two features located on a hypersphere, and the linear discriminant classifier, which determines the input image's projection while optimizing intra- and inter-class scatter. The proportion of, and SVM, which identifies the hyperplane with the greatest gap between traits of men and women. A 96 percent accuracy in ICA space was reached during the experiment, which used 500 photos from the FERET face database, including 250 photographs of women and 250 images of men.

In [55] proposed a hybrid method that fuses global and local features. Adaboost algorithm is used to extract global features and AAM is used for local features. The results show that the hybrid method provides higher accuracy. PCA efficiently encodes face image attributes such as gender, ethnicity, age, and identity—all with fairly high classification performance, well above chance level. Different components of PCA encode different attributes of the face. Few components are required to encode attributes such as gender, race, and age, and these are mainly the first few components, which capture most of the variance in the data.

HOG (Histogram of Oriented Gradients) is often used as a global feature extraction technique to express information about the direction of image curvature. HOG features can capture information about local edge and gradient structure while maintaining a certain degree of invariance to moderate changes in lighting, shadows, object positions, and 2D rotations. The HOG descriptor combined with the SVM classifier can be used as a global feature extraction mechanism.

HOG descriptors can be used in areas such as facial expression classification where landmark finding software indicates locations. A useful application of HOG descriptor variation is the automatic detection of pedestrians, which is made easier in part by the fact that pedestrians' poses are mostly upright. Furthermore, when using HOG descriptors to extract features from faces isolated by face-finding software, near-perfect results were obtained in facial expression classification.

2.2.1 Principal Component Analysis (PCA)

Principal Component Analysis (PCA) [20,49 and 39] is a mathematical procedure that converts observations of a set of possibly correlated variables into the values of a set of linearly uncorrelated variables called principal components by using an orthogonal transformation. The first principal component explains as much of the variability in the data as possible, and each subsequent component explains as much of the remaining variability as possible. Principal component analysis is similar to another multivariate process called factor analysis. Traditionally, PCA is performed on square symmetric matrices. It can be a covariance matrix (scaled sum of squares and cross product) and a correlation matrix (sum of squares and cross product of normalized data). PCA is mainly used to identify patterns in high-dimensional images. PCA can be applied to frequency and time domains, real and complex data, and spectral analysis quantified data. This is widely used in the areas of pattern recognition and computer vision problems (feature selection, object recognition, and gait recognition). Principal Component Analysis (PCA) is used for two objectives:

- Reduce the number of variables that make up the dataset while preserving the variability of the data.
- Identify hidden patterns in data and classify them based on the amount of information stored in the data.

One of the main disadvantages of PCA is that the factors are linear combinations of all the original variables, and most factor coefficients are not zero. This means that while PCA facilitates model interpretation (ensuring only a few axes are involved) and visualization by focusing information on a few factors. The factors themselves are still constructed using all variables, so are often difficult to interpret. The importance of PCA depends on several factors. First, by capturing the direction of the greatest variance in the data, principal components provide a way to compress data with minimal loss of information. Second, the principal components are uncorrelated, which aids interpretation or subsequent statistical analysis. Principal component analysis is also an important and essential technique for data reduction, image compression and feature extraction. It can be performed by Singular Value Decomposition (SVD) [9] of the data matrix A, or by eigenvalue decomposition if A is a covariance matrix. Since the PCA algorithm has to process information from the real world, it should have the ability to cope with noise or outliers.

It has been widely used in many fields including data communication, data compression, image processing, visualization, exploratory data analysis, pattern recognition, and time series prediction. PCA's popularity stems from three important attributes.

1. An optimal (in terms of mean squared error) linear method for compressing a high-dimensional vector set into a low-dimensional vector set and then reconstructing it.
2. Model parameters can be calculated directly from the data (e.g. by diagonal zing the sample covariance).
3. Compression and decompression are easy tasks to perform on given model parameters. Only matrix multiplication is required.

PCA is applied to human gait patterns to investigate the role and relative importance of temporal versus spatial features [1]. The data set consisted of various limb and body angles sampled over increasingly longer time intervals. Spatial and temporal cues can be useful for various aspects of cognition. Time signals contain information that can differentiate the phases of the gait cycle. Spatial cues are useful for distinguishing between running and walking. PCA and related technologies can be useful in identifying features used by the visual system to recognize biological movements. It presented a view-invariant approach for human identification using gait patterns. A PCA-based eigenspace transformation is applied to the binary silhouette of a moving object, which is a basic image feature. We can show that the algorithm is an effective and efficient gait representation.

A gait recognition algorithm based on Fuzzy Principal Component Analysis (FPCA) for Gait Energy Image (GEI) was proposed in [24]. First, the original gait sequence is preprocessed to obtain gait energy images. Second, eigenvalues and eigenvectors are extracted through fuzzy principal component analysis called fuzzy components. The eigenvectors are then projected into a low-dimensional space. Finally, Nearest Neighbor (NN) classifiers are utilized for feature classification. This method is tested on the CASIA database. Experimental results show that this algorithm achieves higher recognition performance. The two-component model, FPCA, explains 91.7% of the overall variance, and PCA explains only 39.8%. The success of PCA is due to two important optimal properties: First, it sequentially captures the maximum variability of the principal component among the columns of X, ensuring minimal loss of information. Second, the major components are uncorrelated.

In the work of [21], a technique for gait recognition of motion capture data based on two successive steps of PCA (Principal Component Analysis) was proposed. The first step in PCA provides a low-dimensional representation of gait. The components of this representation are closely consistent with specific spatiotemporal features of gait that have been shown to be important for visual perception of gait in separate psychophysical studies. The second stage of PCA captures the shape of a trajectory within a low-dimensional space during a given gait cycle across different individuals or gait. A view-invariant approach for identifying people from a distance using gait recognition is well represented. A simple and efficient gait recognition method based on PCA was described. And it showed that the gait recognition system using PCA (Principle Component Analysis) and random transformation is well proposed. A good recognition rate and classification accuracy were achieved. Images of slow walking, fast walking, and walking with a ball were used for recognition, achieving a recognition rate of over 95%.

PCA has been used successfully in the field of gait and behavioral recognition. In [30], PCA is used to compress features for gait recognition. Their features consisted of regions of self-similarity plots constructed by comparing every pair of frames of behavior. Features are extracted based on tracking of 5 body parts using PCA. Each part tracked provided eight time measurements. Therefore, a total of 40-time curves are used to represent the behavior. The training data consists of these curves for all example tasks. Each training sample is constructed by connecting all 40 curves. The training data is then compressed using PCA techniques. Behavior can now be expressed as a coefficient of several basis vectors. Given a new motion, recognition is performed by a retrieval process that involves calculating the distance between the coefficients for this motion and the coefficients of all example motions and choosing the minimum distance. PCA is based on linear mapping. Motion measurements are non-linear in nature and this non-linearity increases as these measurements are aggregated over the entire motion. Therefore, PCA can provide better identification when an operation is considered to be a sequence of entities rather than a single entity.

Dimension reduction is typically used to transform a high-dimensional data set into a low-dimensional subspace while maintaining most of the underlying structure of the data. PCA (Principal Component Analysis) is a classic linear technique for dimensionality reduction, but direct application to gait sequences requires reconstructing (vectorising) these tensor objects into vectors in a very high-dimensional space, resulting in high computational and memory requirements. Therefore, a dimensionality reduction algorithm that operates directly on the walking sequence of a tensor representation rather than a vectorized version is preferable. As a further development of PCA, Multi-Linear Principal Component Analysis (MPCA) formulas have been proposed for dimensionality reduction and feature extraction from gait sequences of natural tensor representations [20]. The MPCA algorithm obtained the number of each mode capable of gait recognition and performed dimension reduction in all modes. Also, in the work [26], a combination of PCA and DTW (Dynamic Time Warping) was presented to extract and recognize features from human gait. PCA is applied to remove correlations between features and to reduce the dimension of data features. These extracted feature vectors are used to recognize individuals. DTW is used to recognize individuals. Detect a binary silhouette of a walking person at each frame of a monocular image sequence. Experimental results performed on the CASIA gait database are encouraging to obtain accurate recognition rates.

Principal Component Analysis (PCA) is a classic data analysis technique that finds a linear transformation of data that maintains a maximum amount of variance. In work [31], the authors studied gait classification in which some and most of the high-dimensional data were missing values, showing that this problem has many features commonly associated with nonlinear models, such as overfitting. and bad topical optimal solutions. PCA with missing values can relate to many data sets that appear in practical applications. Principal Component Analysis (PCA) is also a widely adopted multivariate data analysis technique, in which the interpretation is established based on classical linear projections and probabilistic models such as probabilistic PCA (PPCA). The probabilistic formula of PCA (PPCA). [15] provides a good basis for handling missing values in gait recognition. Therefore, with the advancement of PCA in various applications in recent years, PPCA models have been proposed in gait recognition technology.

As a further extension of PCA, a Fuzzy Principal Component Analysis (FPCA) based gait recognition algorithm for Gait Energy Image (GEI) was also proposed in [33]. First, preprocess the original gait sequence to obtain gait energy images. Second, eigenvalues and eigenvectors are extracted through a fuzzy principal component analysis called a fuzzy component. Finally, a Nearest Neighbor (NN) classifier is utilized for feature classification. This algorithm is an experiment on the CASIA database. The detected results in the simulation show that the FPCA algorithm has higher recognition performance than the conventional PCA.

2.2.2 Linear Discriminative Analysis (LDA)

Linear Discriminant Analysis (LDA) [52,1 and 24] is a widely used method of map Dimension Reduction (DR). Find the optimal set of linear projections by simultaneously maximizing inter-class dissimilarity and minimizing intra-class dissimilarity. LDA achieves maximum class discrimination by calculating the optimal transform by maximizing the inter-class distance while minimizing the intra-class distance. The optimal transform of LDA can be easily calculated by applying the Eigen decomposition to the scatterplot matrix. LDA has been widely used in many fields of computer vision research, such as machine learning, data mining, information retrieval, and pattern recognition. Because LDA assumes multiple Gaussians with the same covariance, the success of LDA depends primarily on accurate estimates of the model parameters (mean and common covariance). Therefore, LDA is a simple and effective method for many practical applications such as gait recognition.

LDA is also closely related to Principal Component Analysis (PCA) and factor analysis (FA). PCA is an unsupervised linear dimensionality reduction method. Find low-dimensional subspaces and preserve as much data variance as possible. LDA, on the other hand, is a supervised Linear Dimensionality Reduction method, which finds a low-dimensional subspace that keeps data points of different classes as far apart as possible and data points of the same class as close as possible. The purpose of LDA is to perform dimensionality reduction while preserving as much class identification as possible. In the study of [37], gait recognition based on PCA and LDA was also proposed. PCA is mainly used for dimensionality reduction techniques, and LDA is performed to optimize the pattern class. We used our own database for experiments and achieved better recognition rates in PCA compared to (LDA).

Gait representation and recognition using a unique feature extraction method utilizing LDA was proposed in [50]. The approach is based on haphazard binary silhouette transformations. The deformed silhouette is utilized to calculate the template for each gait sequence. Then, Liner Discriminant Analysis and subspace projection are applied to all template sets. A low-dimensional feature vector made up of chosen random template coefficients is used to describe each gait sequence. By appropriately comparing a test feature vector with feature vectors from a reference gait database, gait recognition and validation are accomplished. The recognition performance is significantly better when compared to the most recent gait recognition approach employing the gait challenge database.

Because gait is useful for walker identification, it has received a lot of attention from researchers in the field of vision. One of the main challenges in gait recognition is how to extract distinct shape features from 2D human silhouette images. The problem of gait-based walker recognition using statistical morphological features is dealt with in [13]. First, we normalize the silhouette of the pedestrian (to facilitate comparison of gait characteristics) to a square shape and draw the individual signatures included in the gait pattern using orthogonal projections in positive and negative diagonal directions. Then, Principal Component Analysis (PCA) and Linear Discriminant Analysis (LDA) are applied to reduce the dimensionality of the original gait feature and improve the topological structure of the feature space. Finally, we perform the recognition of unknown gait features according to the nearest-neighbor rule, with a discussion of the effect of distance metrics and scales on identification performance.

Another study of LDA on gait perception is proposed in [45]. To enhance gait identification performance, Enhanced Linear Discriminant Analysis (LDA) is used to feature extraction by PCA (Principal Component Analysis). To determine the low-dimensional tensile characteristics, a three-dimensional walking object is first projected into PCA space. The selection of discriminant characteristics is then used to produce low-dimensional vector features. Then, using a new feature weighting and sampling procedure, these feature vectors are fed into an LDA-style booster, where numerous regularizing and weakening LDA learners cooperate to produce robust learners. LDA students classify data using a straightforward nearest-neighbor classifier with weighted angular distance values. The proposed solution successfully enhanced gait recognition performance and outperformed a number of contemporary gait recognition algorithms, according to experimental results on the NIST/USF "gait challenge" dataset.

However, the current gait recognition may be difficult due to the change of the viewing angle. This is because the viewing angle generated by the gait signature database may not be the same as the viewing angle when acquiring the probe data. In the study [56] proposed a novel multi-view gait recognition approach to solve the above-mentioned problems. Unlike other approaches in the same category, this new method employs Singular Value Decomposition (SVD) technology and is called VTM (View Transformation Model) based on spatial domain GEI (walking energy image). To further improve the performance of the VTM, we optimize the GEI feature vectors obtained using Linear Discriminant Analysis (LDA). This method was validated with a large multiview gait database. You can reduce the dimensions of the gait feature and the size of the view transformation model.

With the increasing demand for visual surveillance systems, a simple and effective method to automatically recognize people based on their body silhouettes and gait has been demonstrated in [34]. A combination of a background subtraction generator and a simple correspondence method is used to segment and track the spatial silhouette of a walking figure. Two classification methods are used for recognition: Multi Discriminant Analysis (MDA) with Back Propagation Neural Network (BPNN) and LDA with BPNN. In the work in [48], the authors described a comparison of two subspace projection methods for automatic gait recognition. Two methods are presented for gait recognition based on subspatial analysis of kernel-guided high-dimensional space using PCA and Fisher's LDA. Kernel LDA uses polynomial kernels to produce the best results, while LDA provides a relatively inexpensive alternative with competitive performance. The results showed a view-invariant representation of a spatiotemporal surface associated with a person's gait used to perceive certain human activities.

In general, the performance of a gait recognition system strongly correlates with the classification accuracy of features, so features must have the ability to discriminate between different classes. Recognition of massive multi-view gait features is one of the challenges for which dimensionality reduction is a standard technique. Although many variants have been proposed, Linear Discriminant Analysis (LDA) is still widely used to gait features from a high-dimensional space to a smaller-dimensional space [28]. LDA handles the case of feature reduction easily. Experimental results showed that the proposed method is effective in gait recognition.

In [8] presented a study on the statistical integration of a bank of temporal filters for robust gait recognition using LDA. The temporal properties of the fixed function are first captured and expressed using a well-defined bank of time filters. These derived temporal functions can then be incorporated into fixed functions and compressed using LDA techniques. The LDA technique is used to reduce the dimension of the resulting feature vector and improve the discriminant ability in a maximal class recovery manner.

Experimental results show that recognition performance can be significantly improved in both clean and noisy environments.

LDA has two shortcomings that prevent it from being widely used in high-dimensional data analysis, where the dimensions of the data space are frequently thousands. One drawback is that traditional LDA cannot be directly applied to under sampled problems where the dimension of the data space is greater than the number of data samples due to the singularity of the scatter matrix. And the other is the lack of scarcity in LDA solutions. Numerous additions to the current LDA have been suggested in order to address the first issue. Uncorrelated LDA (ULDA), Regularized LDA, and Least Squares LDA are some of these extensions. Numerous attempts have been made to add rarely into LDA transforms in order to solve the second issue.

For high-dimensional data analysis in LDA solutions, sparsely is typically preferred because it makes it much simpler to analyze the retrieved features. Each feature in the case of LDA is a linear combination of every feature in the original data, and the coefficients of these linear combinations are frequently non-zero, making it challenging to interpret the extracted features. Robustness to noise or the prediction's computational effectiveness may serve as the driving forces behind a sparse LDA. [25] lists a few significant sparse LDA applications. In the work of [28], they studied sparse LDA extracting uncorrelated features and calculating sparse LDA transformations in gait perception. A sparse solution is computed as the least l1-norm solution in all solutions of the smallest dimension.

2.3 Gender Classification Methods

LDA and Fisher's algorithm are just two of the methods that can be used to classify gender. But we continue to use the Support Vector Machine (SVM) is used. By examining a few algorithms, the cause can be revealed:

2.3.1 k-Nearest Neighbor Classification (k-NN)

The purpose of the k-Nearest Neighbors (k-NN) algorithm [29,2 and 57] is to use a database in which data points are separated into several distinct classes to predict the classification of new sample points. The idea of the k-nearest neighbor algorithm is very simple. To classify the new test sample, the system finds the k nearest neighbors among the training samples and uses the k nearest neighbor categories to weight the category candidates. It also determines the class of test features based on the number of k closet training examples.

Therefore, the performance of a k-NN classifier is mainly determined by the choice of k and the distance metric applied. And the distance is calculated using one of the distance measurement methods: Euclidean Distance, Minkowski Distance, or Mahalanobis Distance method. The classifier's job is to predict the class label of x0 from a specified P class given a query vector x0 and a collection of N labeled instances Nxi, yi. Even though this algorithm is straightforward and simple to use, it yet produces results that are competitive with those of the most advanced machine learning techniques.

In the classification process, the k documents closest to the test documents in the training set are determined first. Then, prediction can be made according to the category distribution among this k nearest neighbors. Classification used the majority vote as the predicted value for new query instances. Classify new instances based only on the given training sample, without using any model to fit the data. Many researchers have found that the k-NN algorithm achieves very good performance in experiments on various data sets. One of the drawbacks of the k-NN algorithm is its efficiency because it requires comparing the test sample to every sample in the training set. Also, the performance of this algorithm is highly dependent on two factors: an appropriate similarity function and an appropriate value for the parameter k.

A gait-based gender identification system with a k-NN classifier is presented in [57]. By limiting the subsequent searching space into either a male database or a female database, it can help a human identification system focus only on the identified gender-related features and increase search speed and efficiency of the retrieval system. After preprocessing, the human silhouette has four binary moment characteristics and two spatial features retrieved. Then, two separate pattern classifiers, k-Nearest Neighbor (k-NN) and Support Vector Machine, are trained and tested using the retrieved features (SVM). The effectiveness of the gender classifiers that are now in use was demonstrated by experimental results. In this algorithm, the classifier classifies the data according to the information in the sample tests. There is absolutely no need to split the data group into two parts. You can classify the group into "n" parts, but it also increases the chances of errors.

So when you need to classify your data into two groups (male and female). Here, the algorithm does not classify the data according to facial features, but according to the data in the sample space.

The main advantage of the algorithm is that the final result does not produce a result. Minimize global assumptions about data distribution and classification errors in data generation training datasets. The purpose of the analysis is to find the features that best differentiate between different classes. The main advantage that feature-based technology provides is that when extracting feature points, no memory is required to store them.

2.3.2 Fisher' Algorithm

In Fisher's Algorithm, data are grouped according to the following properties of data. This grouping is done based on the difference between two consecutive data injected into the sample set. This gives better results than nearest neighbor classification. Data available in the algorithm sample set because it groups data according to attributes. However, a problem arises when calculating Eigen. Vectors and eigenvalues are generated to extract features. Used to group data into two parts. In particular, the training sample are less. Eigenvectors are best for feature.

2.3.3 Hidden Markov Model (HMM)

The Hidden Markov Model (HMM) [36,5 and 4] is a ubiquitous tool for modeling time series data. It is currently used in almost all speech recognition systems, computational molecular biology in data compression, artificial intelligence, and numerous other applications in pattern recognition. Recently, HMMs have been used in computer vision applications such as image sequence modeling, object detection and tracking. It is also a popular method in machine learning and statistics for modeling generative sequences, which can characterize the underlying processes that generate observable sequences. A probabilistic finite state machine in which the transitions between states are governed by a probability function. At each transition, the new state emits a value with a given probability. Emissions can be symbols of a finite alphabet and successive multidimensional values. Assuming that the transition probability in a Markovian process depends only on a finite number of previous transitions, it can be modeled as a Markov chain in Figure 2.1.

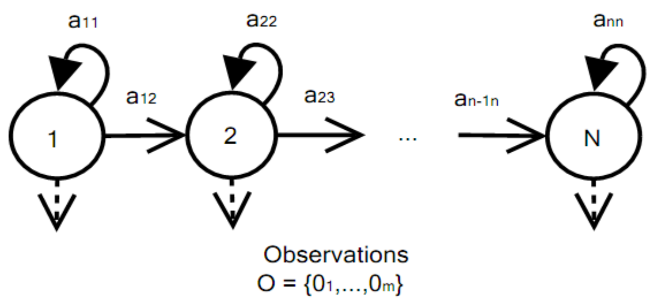


Figure 2.1 Markovian process in HMM

There are also two main categories of HMM-based gender classification. The first one is from feature to model, which classifies the testing data by selecting the model with maximum likelihood. For example, in [46] Gaussian Process Latent Variable Model (GPLVM) is utilized to transform the gait silhouette into low dimensional embedding, and learned the temporal dynamics via HMM in the corresponding embedding space. The second category is from model to feature, and these works are aim to extract the templates and stances without traditional period detection based on similarity. HMMs depict various facial phases as hidden states. The underlying premise is that the history state is irrelevant and that the current state is only influenced by the prior state. Through the use of training input data, observation probabilities and transition probabilities are computed. The recognized outcome is the subject that has the highest posterior probability. Because they leverage both the similarity of forms between test and reference sequences and the probability of shapes emerging and succeeding in a walking period, HMM-based techniques are often preferred over alternative procedures.

In gender recognition, rapid change in clothing had a negative effect on recognition performance. The recognition method is sensitive to changes in viewing angles of more than 10 degrees, but is fairly robust to changes in speed. This is because it is natural for a person's walking speed to change with time. HMM allows us to handle this variability without explicit time normalization. In the case of human gait recognition [54], the recognition performance slightly deteriorated due to the large change in stride length according to the gait speed. And the recognition method is not resistant to sudden changes in the silhouette that can be caused by changes in clothing or lighting. A methodology was adopted to derive low-dimensional observation sequences from the silhouette of the body during the gait cycle. Learning is achieved by training the HMM for each person over multiple gait cycles. Gait recognition is performed by evaluating the log probability that a given sequence of observations will be generated by the HMM model presented in the database.

HMM (Hidden Markov Model)-based gait recognition software was proposed in [42]. To fill in the gaps and eliminate noisy regions, morphological techniques are used to preprocess the input binary silhouette image. The image feature is the outer contour's width vector. Following iterative training with the Viterbi and Baum-Welch algorithms, HMM is employed for recognition. Due to its statistical properties and ability to capture the gait's temporal state transition features, HMM is a good choice for gait detection. We have demonstrated the general HMM-based framework's suitability for recognizing unique gaits. The HMM parameters are trained using binary silhouette feature vectors, and the subject's posture is thought of as the HMM's state.

We normalized gait function, suggesting a specific insensitivity to changes in gait speed. Gabor filters and Maximization of Mutual Information (MMI) methods were used to extract low-dimensional features, and Hidden Markov Models (HMM)-based Bayes rules were applied to gender classification. The HMM-based hierarchical framework accurately models the granularity of perspective and gender. High classification performance was achieved with bayes decision.

A two-step model-based approach has been proposed [8]. To avoid shape information, we fit a 5-link biped locomotion model for each image and then extract reliable gait features by recognizing it using Hidden Markov Models (HMM) based on the following. The frequency component of the trajectory of the relative joint position. It is a method to automatically detect abnormal human gait on stairs presented from image data. The system identifies potential sequences containing anomalies and reduces the amount of data that humans have to search. Optical flow is calculated for the silhouette minus the background to capture the overall movement of the person going down the stairs. Then, a Hidden Markov Model (HMM) is used to generate a statistical model of the temporal progression of functions derived from the tracked foot position and optical flow for normal stair descent.

One of the most well-liked and difficult fields of computer vision research is the analysis of human activities and the detection of anomalies in video sequences. The study in [27] describes how to classify gait types and addresses the classification of human gait types based on the concept that gait types can be analyzed as a series of successive postural types. For classification, HMM is proposed to recognize the gait classification of human motions. For effective gait rehabilitation treatment, it is necessary to accurately analyze the patient's gait condition. Gait motions can be analyzed as gait phases because gait motions cycle through multiple gait phases. Therefore, it can be said that the gait phase is analyzed in the gait motion by applying the HMM (Hidden Markov Model).

Because HMMs have several advantages for modeling temporal sequence data, they have had considerable success in handwritten character recognition, gesture recognition, part-of-speech tagging, machine translation, and other pattern recognition fields such as bioinformatics. Support Vector Machines (SVMs) and Hidden Markov Models (HMMs) have been used for numerous classification tasks in pattern recognition. In the case of biometrics, this method also showed good classification results in the work of [56]. Analyze the effect of time on recognition rate and present results for normal and fast walking. It also compares the results obtained when using different amounts of training data. It can be seen that the SVM is slightly better than the HMM, producing an Equal Error Rate (EER) of about 10%.

2.3.4 Support Vector Machines

This algorithm uses a support vector to partition the data into two groups. The most significant factor separating the two groups is a support vector. With less chance of error and no eigenvector and eigenvalue calculations, it produces results that are nearly identical to those of Fisher's Algorithm.

Due to their computational effectiveness and strong generalization capabilities, Support Vector Machines (SVMs) [6, 35 and 10] have been widely used for pattern identification and regression. SVM has emerged as a crucial learning method for dealing with classification and regression problems in a number of areas, including text classification, handwritten digit recognition, tone recognition, picture classification, and object detection. A Support Vector Machine (SVM) is one approach to supervised learning that takes an annotated training dataset as input and outputs a generalizable model, which can then be used to accurately predict the outcome of future events. It uses mathematical optimization techniques to train relatively quickly on large data sets. It can provide higher performance in terms of classification accuracy than other data classification algorithms.

The Support Vector Machine performs classification by constructing an N-dimensional hyperplane that optimally separates the data into two categories. Intuitively, good separation is achieved by the hyperplane with the greatest distance to the nearest training data point of any class. In general, the larger the margin, the lower the generalization error of the classifier. However, it is important to note that SVMs are basically second-class classifiers. This is because the SVM first maps the training sample to a high-dimensional space and then finds the separating hyperplane that maximizes the margin between the two classes in this high-dimensional space. If the data are not linearly separable, a set of slack variables is introduced that indicates how much the linear constraint is violated by each data point. Without any knowledge of the mapping, the SVM can find the optimal hyperplane using the dot product function of the original space called the kernel. SVM theory is based on the idea of structural risk minimization. In addition, the characteristics of the SVM minimize the empirical classification error and maximize the geometrical margin.

In a study [6], the authors investigated the potential benefits of using Support Vector Machine (SVM) learning to classify genders in video sequences. Statistical methods and signal analysis techniques are used to extract gait features from the input video signal. SVM classifiers compare favorably with other neural network-based classification approaches by performing leave-one-out cross-validation. The performance of SVM over other state-of-the-art classifiers is also confirmed in the classification of human gait features. Finally, we also examine the effect of the number of features on the classification ratio for two real data sets.

Another work of the SVM-based classification approach is presented in [33] for gender prediction of Indian names. The purpose of the approach is to explore the applicability of the SVM classifier on text data and analyze its performance. This is because not much work has been done to use the SVM classifier for gender identification of names displayed in text. They first identified and evaluated various features based on morphological analyzes that could be useful for this classification. We then describe an approach that uses the n-gram suffix, along with these features that provide significant advantages over the baseline approach. Major contributions have been in extensive analysis of the various word-level features of Indian names that differentiate between the two genders and identifying the features that are most helpful for classifying and displaying state-of-the-art methods for gender identification using SVM.

In [10], an improved SVM algorithm was proposed for the analysis of children's abnormal gait. The algorithm combines SVM with fuzzy clustering to improve the accuracy of SVM. Only samples with weak relationships with all clusters are chosen to be trained on the SVM. A simulation experiment was performed to show that the improved SVM-based algorithm can obtain better effects than the general SVM when applied to the analysis of abnormal gait in children. [44] proposed an automatic gender classification system in human gait using a Support Vector Machine (SVM). It collects large amounts of gait data from DV cameras and extracts human bodies and contours from image sequences. A 2D bar shape is used to represent the structure of the human body, and points on the body are determined and extracted from the body outline. To extract the body points, the joint angles of each segment are extracted through linear regression analysis from the gait skeleton data, and the movement points of the movements are tracked to describe the gait motion between key frames. Body segments and movement points are basically guided by topological analysis with anatomical knowledge. In addition, we compute the characteristics based on motion parameters from the rod-shaped sequences and then use the SVM classifier to classify the genders in the gait patterns.

Using complete spatial and temporal information of segment movements defined by markers, a study in [32] describes a strategy to classify group differences in gait patterns. A classification rate of 95.8% can be attained using a Support Vector Machine with a linear kernel. We were able to see how various indicators contributed to group distinction of location and time thanks to our categorization methodology. This method did not rely on any particular presumptions or pre knowledge of particular gait cycle points. Any study including marker measurement can immediately apply it to the group classification problem. To investigate the relative impact on classification, we apply SVM for automated recognition of young or old gait patterns using temporal and distance measurements, kinetic and kinematic variables in gait model development.

To classify gait conditions, the machine learning technique SVM was applied in [12]. Additionally, SVMs are contrasted with other machine learning techniques like Bayesian Belief Networks, Radial Basis Function Networks, and Artificial Neural Networks (ANNs) (BBNs). It was discovered that the SVM technique performed better for classification than the other three techniques. The SVM results demonstrated that stairs uphill and downwards can be discriminated from one another and from other walking circumstances with 100% accuracy utilizing a single sensor unit mounted to the shank segment. To undertake a quantitative analysis of activity patterns, the SVM technique can automatically detect the gait state utilizing a portable kinematic sensor unit.

In [18] proposed a gait recognition method based on a human silhouette. The classification process is performed through two different methods: Nearest Neighbor (NN) and Support Vector Machine (SVM). The results of SVM with polynomial kernels produced good classification rates of 96% for an average of 100 subjects. Another work of SVM was investigated in [48] in recognizing gait patterns in young and old using spatiotemporal, kinematic and motor data. Support Vector Machines (SVMs) are also widely applied in pattern recognition due to their excellent learning ability. [19] applied SVM to the running kinematics data of 17 young and 17 elderly male runners for gait classification in children and the elderly. The linear kernel SVM achieved 100% classification performance.

To improve the classification rate, information fusion provides a promising solution for the development of high-performance classification systems. In the study of [22], multiple gait components such as spatial, temporal, and wavelet were fused to increase the gait classification rate. Initially, background modeling is performed on the video sequence, and foreground moving objects in individual frames are segmented using a background subtraction algorithm. Featured gaits are then extracted to train and test multi-class k-Nearest Neighbor models (k-NN) and multi-class Support Vector Machine models (SVMs). The goal was successfully achieved with two gait cycles, and the experimental results show that the classification ability of SVM is superior to that of k-NN.

In [43] classifies five gait conditions: uphill, downhill, flat, uphill, and downhill using kinematic data obtained from the pre-swing phase. The kinematic data consisted of anteroposterior accelerations and angular velocities collected at the shank and foot locations. To categorize gait conditions, machine learning technique SVM is utilized. SVM was also contrasted with other machine learning methods such as Artificial Neural Network (ANN), Radial Basis Function Network (RBF), and Bayesian Belief Network (BBN) (BBN). The SVM algorithm was found to perform better in gait classification than the other three methods.

Support Vector Machine (SVM) based classification approaches [47] are used by many machine learning applications. They are generally easier to implement and perform better than other classification approaches SVM, on the other hand, is a novel class of learner that, by maximizing the width of the classification margin, may automatically modify the capacity according to the size of a particular problem. Depending on the length of training, support vector machines are effective tools for binary classification and can produce very quick classifier functions. By applying nonlinear functions to translate the original features to a high-dimensional space, one advantage is that you may examine more information in a given set of data.

Support Vector Machine, [16] is a supervised learning technique in the field of machine learning that can be applied to both classification and regression. The basic training principle of SVM is to find the optimal separation hyperplane that separates positive and negative samples with maximum margin. Following this principle, linear SVM uses a systematic approach to find the linear function with the lowest Vapnik Chervonenkis (VC) dimension. For data that is not linearly separable in order to locate a linear hyperplane, the SVM can map its input into a high-dimensional feature space. Age estimation and gender classification have both been accomplished with SVM [51].

In [17] Support Vector Machine (SVM)-based proposed gender categorization classifies all training vectors by creating a hyperplane that divides classes into two or more. In a Support Vector Machine (SVM), samples are efficiently segregated in a non-linear way utilizing kernel in a high-dimensional feature space. Accuracy of 88% is achieved using a Support Vector Machine (SVM) in this system was compared to other systems using a Support Vector Machine (SVM) classification technique.

CHAPTER 3

THE PROPOSED SYSTEM

Face detection and gender classification play an essential role in video investigation for monitoring area and face image database management system. In this system, Gender classification by face from Myanmar National Registration Card is implemented by using its own datasets. This process involves three stages. Firstly, Viola-Jones algorithm is used for face detection. Then, Principal Component Analysis (PCA) is applied from the face images to extract facial features. Finally, Support Vector Machine (SVM) classification techniques will be evaluated for gender classification. The proposed system is implemented by using MATLAB software.

3.1 Gender Classification

Humans often recognize each other by unique facial characteristics. Gender classification using faces is important because it considers different parts of the facial structure. The face is one of the most important biometric features of humans and is commonly used as a means of identification. Everyone has a natural face, and most have different faces. This system proposes gender classification by face of Myanmar National Registration Card. This process includes three steps: face detection, feature extraction, and classification. The input and training photos were utilized to recognize and locate faces using the Viola-Jones face detection algorithm. After that, PCA is used to extract face features from the facial image. The data that best captures the variation in facial traits between faces is found using PCA. The evaluation of Support Vector Machine (SVM) classification methods for gender classification is the final step. Many other applications, such as person recognition and intelligent human-computer interactions, can perform better when using a gender categorization approach that is successful.

The process of human gender recognition involves first detecting the face and then observing the detailed features of the face. The flow chart of the proposed system is as shown in Figure 3.1.

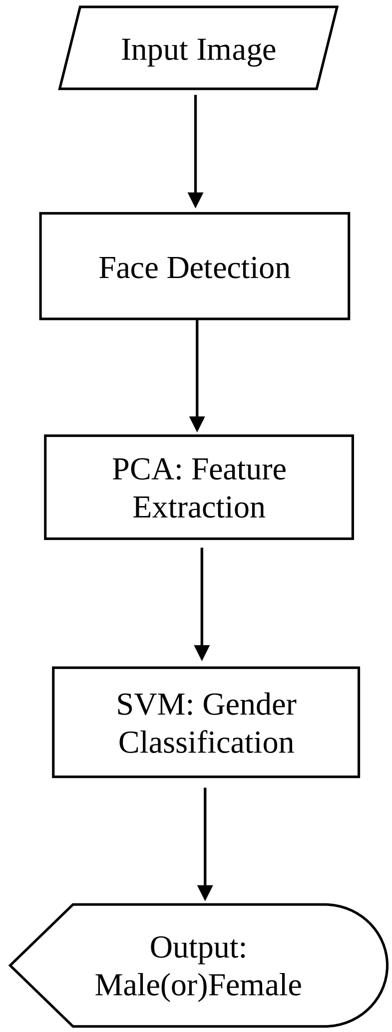


Figure 3.1 Flow chart of the system

3.2 Face detection

Face detection in the input scene is a key process in this study. For the detection part, the Viola-Jones method was used. The training of cascading functions requires a combination of positive and negative images. All highlighted features have been extracted from the image to match a specific pattern, and all features represent a single value: the sum of pixels in the black rectangle minus the sum of pixels below the white rectangle.

To avoid counting all more than 160,000 features in a single window, the integral values of the image are used so that only the values of the four corners can be considered and only the sum of the pixels of a given rectangle can be calculated. It reduces the number of features and enables real-time detection One illustration of appearance-based face detection is Viola-Jones face recognition. Automatic face detection technique that, thanks to quick feature calculation, offers accurate feature selection and real-time detection. The suggested system finds and locates faces in the input and training photos using the Viola-Jones face detection method.

3.2.1 Viola-Jones Face Detection

Face detection is an easy and simple task for humans. Face detection is the process of identifying one or more human faces in an image or video. It plays an important role in many biometric, security and surveillance systems, as well as image and video indexing systems. The Viola-Jones detector was chosen as the detection algorithm because of its high detection rate and real-time execution capability. Training is slow, but detection is very fast.

Because Viola-Jones is made for front-facing faces, it can detect front-facing faces better than faces that are looking up, down, or to the side. Before face detection, the image is transformed to grayscale. because there is less info to process and it is easier to work with. The Viola-Jones algorithm locates faces in color photos after first detecting them in grayscale images. The algorithm has 4 steps.

- Select Haar Features
- Create a unified/ Integral image
- Adaboost training
- Cascading classifier

3.2.1.1 Haar like features

The Haar-like feature is used to detect changes in the black and light parts of an image. This calculation forms a single rectangle around the detected face. Haar features are computed across the image, which will result in nearly 160000 features per image.

Commonly used Haar functions include 2, 3, or 4 rectangular functions as shown in Figure 3.2.

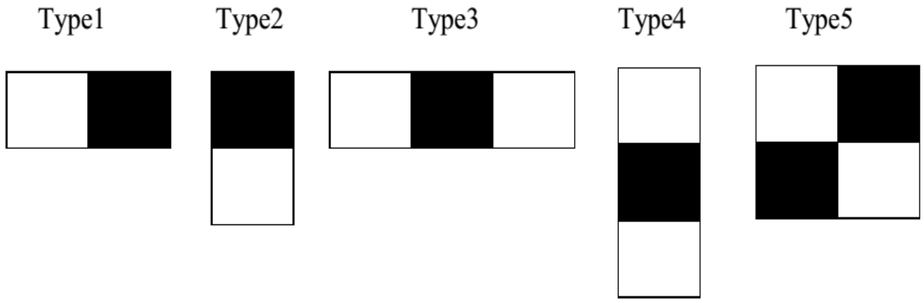


Figure 3.2 Haar features using Viola-Jones Algorithm

The horizontal and vertical functions for face detection define how the system sees the nose, eyes, mouth and eyebrows, respectively. These functions for face detection stage is as shown in Figure 3.3.

Figure 3.3 Horizontal and Vertical functions for face detection stage

The feature's level of darkness is indicated by the number of pixel in the box. The difference of the sum of pixels of areas inside the rectangle within the original image is feature value. The value of a certain feature indicates certain characteristics of a particular area of the image such as eyes, eyebrows, nose, mouth. The particular area of the image can be detected by adjusting the threshold values as shown in Table 3.1.

Table 3.1 Threshold values for the particular area

‘FrontalFaceCART/	20
‘UpperBody’	[18 - 22]
‘EyePairBig’ ‘EyePairSmall’	[11- 45] [5 - 22]
‘LeftEye’ ‘RightEye’	[12 -18]
‘LeftEyeCART’ ‘RightEyeCART’	20
‘Mouth’	[15- 25]
‘Nose’	[15 -18]

3.2.1.2 Creating Integral Images

A cost-effective method for calculating the pixel intensities of a certain rectangle in a picture is to create an integral image. Used for quick calculations of Haar-like functions. The meaning of the integral image is the outline of the pixel values of the original image. Also called a summing area table. Integral images are used to facilitate fast feature detection. As the number of pixels is substantially higher within features with a big number of pixels, these calculations can really be highly time-consuming. These laborious calculations are carried very rapidly using integral pictures so that we may determine whether the functions of various characteristics meet the requirements.

Integral images are used because features like Haar are actually rectangles, and the integral image process makes it very easy to find features within an image and find the difference between two rectangles as if you already know the value of the sum of a particular square. In a normal image, just subtract two squares from the integral image. Therefore, the unified image method makes the computation much less intensive and can save a lot of time for all face detection models.

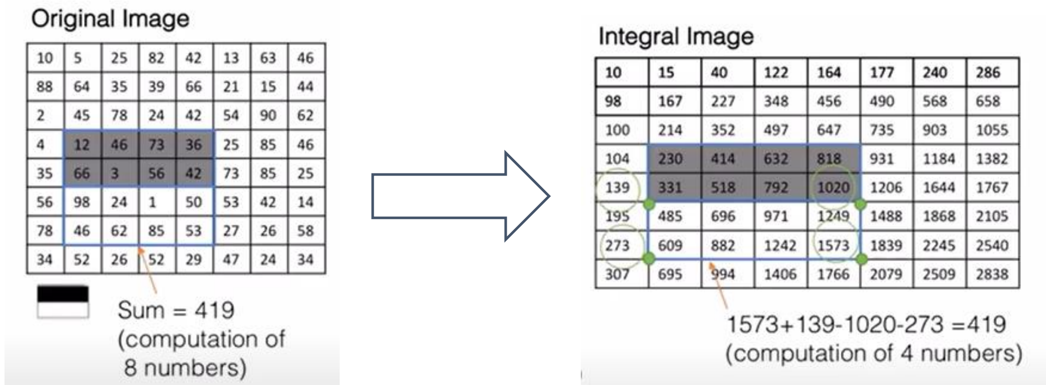


Figure 3.4 Original image to Integral image for face detection stage

The integral image is a solution Viola and Jones come up with to fasten the processing. The feature in an image can be calculated. The sum of the black side and white side is calculated and then they will be subtracted from each other. In this example, each side adds eight numbers. A better way is to create an integral image by adding the intensities of the rows and columns before each and every pixel. Hence the first pixel is 10 the second is 10 plus 5 and so on for the first row. The first pixel in the second row is 88 plus 10, the second pixel is 64 plus 5 plus 88 plus 10 and so on. This implementation is as shown in Figure 3.4.

3.2.1.3 Adaboost Training

The AdaBoost algorithm helps to select small features from faces that facilitate quick and easy calculations. The AdaBoost algorithm discards unnecessary background and gives the desired area of the object. Decide which features are relevant and which are not. A strong classifier is a linear combination of weak classifiers. The algorithm is more accurate as it learns from the provided images and can determine false positives and true negatives from the data. After looking at all possible locations and combinations of their features, you get a very accurate model.

As a sample, f1, f2 and f3 are the features and a1, a2, a3 are the respective weights of the features. Each of the features is known as a weak classifier. The left side of the equation F(x) is called a strong classifier. Although one weak classifier may not be as good, a strong classifier can be achieved by the combination of two or more weak classifiers. As a result, it is considerably more efficient and cuts down on calculation time because all the features cannot necessarily pass through. Combination of Weak Classifiers to form Strong Classifier is as shown in Figure 3.5.

$$F(x) = \alpha_1 f_1(x) + \alpha_2 f_2(x) + \alpha_3 f_3(x) + \ldots$$

Figure 3.5 Combination of Weak Classifiers to form Strong Classifier

3.2.1.4 Cascade classifier

The cascade eliminates candidates by creating more stringent requirements at each stage, with later stages much more difficult for the candidate to pass through. Candidates end the cascade if they pass all stages or fail in one stage. If a candidate passes all the steps, only faces are detected. This process steps are as shown in the Figure 3.6.

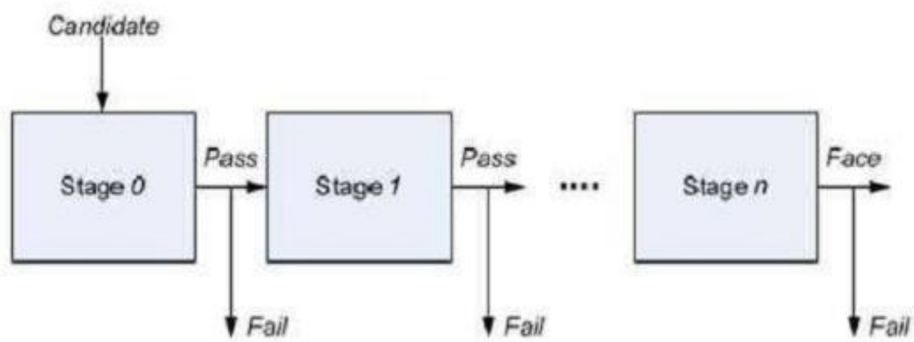


Figure 3.6 Cascade classifier Step in Viola-Jones Algorithm

In this system, faces are detected from NRC cards by Viola-Jones because of their high detection rate and real-time execution capability. Human face-like properties include: (i)The corners of the eyes are darker than the cheeks. (ii) The bridge of the nose is brighter than the eyes.

Useful domain knowledge is Location – Size: Eye & Nose Area and Value: Darker/Lighter Face detection sample using Viola-Jones Algorithm is as shown in Figure 3.7.

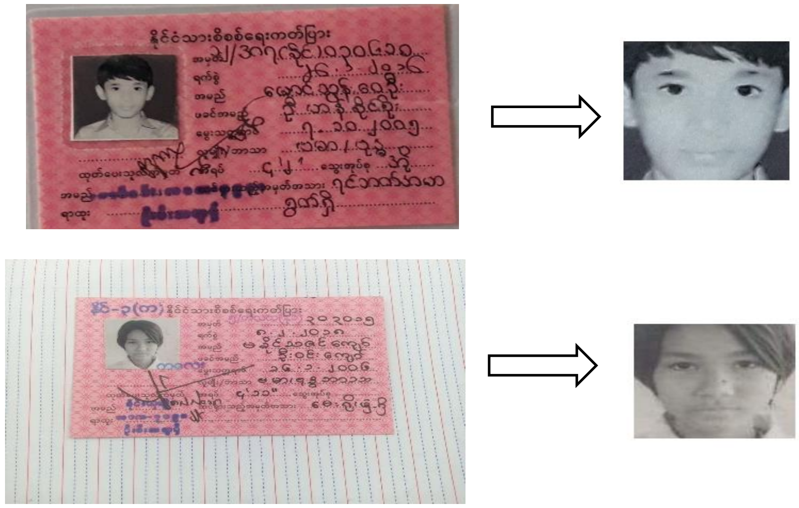


Figure 3.7 Face detection results using Viola-Jones Algorithm

3.3 Features Extraction by PCA

An important aspect to realize is that every image has a repeating pattern in the face area. There are always certain features like eyes, nose, mouth and relative distance to help classify faces. These features are called principal components or eigenfaces. It can be extracted from the raw image data using a mathematical tool called Principal Component Analysis (PCA). PCA allows you to transform each original image in the training set into its own unique face.

An important feature of PCA is that it can reconstruct the original image from the training set by combining Eigen faces. When all unique faces (features) are added in the correct proportions, the original face image can be reconstructed from the unique faces. Each unique face represents only certain features of the face, which may or may not be present in the original image. The PCA space consists of a number of major components (PCs). Each principal component has a different robustness depending on the degree of dispersion in the direction.

In this system, for feature extraction and classification, PCA is employed. It is an unsupervised technique for dimensionality reduction and is used to reduce a high-dimensional space to a low-dimensional feature vector space. PCA is an unsupervised technique for dimensionality reduction. It is also used for data compression, deduplication for feature extraction. Unique faces are important for face recognition and classification. PCA is used to extract features from human facial images. The process of the PCA algorithm is as shown in Figure 3.8.

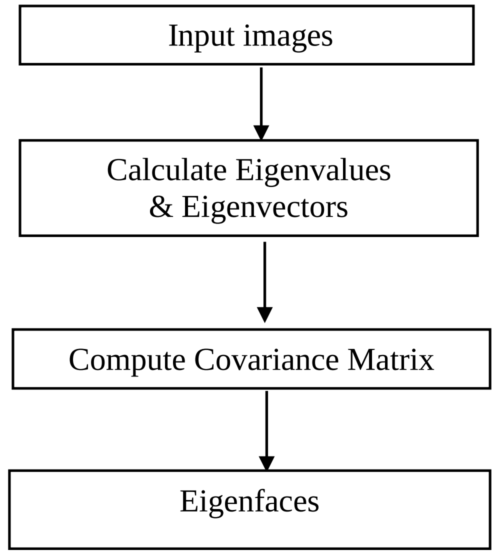


Figure 3.8 The process of PCA Algorithm

3.3.1 Eigenfaces

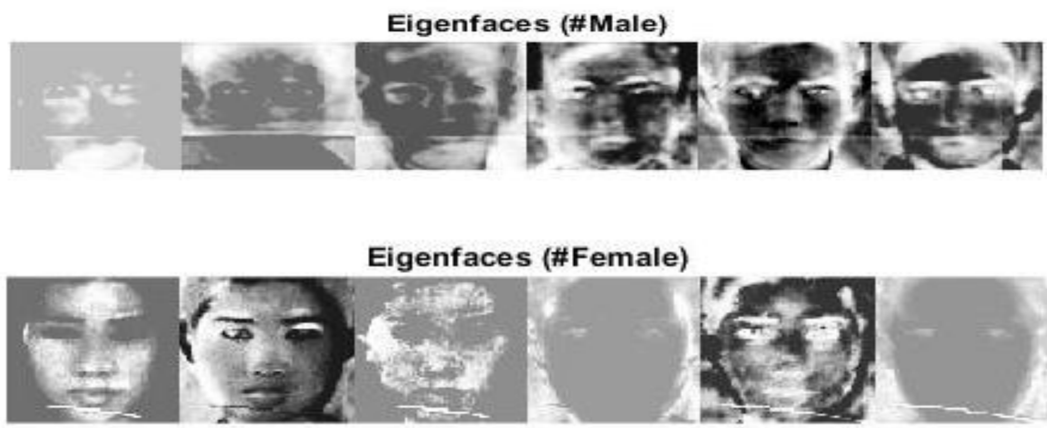


Figure 3.9 Eigenfaces by PCA

While PCA decreases the dimensionality of the original data, the data that most accurately captures the variance of the data can be maintained. Despite its lengthy history, PCA is still a suitable and often employed face recognition approach. PCA is a conventional method of portraying faces. In this step, the facial features of the face are extracted from the face image using Principal Component Analysis (PCA). The detailed steps to compute the low-dimensional space of the PCA technique using the covariance matrix are summarized in Algorithm (1). Eigenfaces calculated by PCA is as shown in Figure 3.9.

Algorithm 1: Calculating PCs using Covariance Matrix Method

1. Assuming there are N training samples, after face detection, image pixels in matrix form are transformed into vectors for every samples. Given data matrix X = [x1,x2, … , xN], where N represents the total number of samples and x_i represents the ith sample. Each row is transposed and concatenated with the top and bottom rows as in the equation below.

$$X = \begin{pmatrix} a_{1,1} & a_{1,2} & \dots & a_{1,N} \\ a_{2,1} & a_{2,2} & \dots & a_{2,N} \\ \cdot & \cdot & & \cdot \\ \cdot & \cdot & & \cdot \\ \cdot & \cdot & & \cdot \\ a_{N.1} & aN.2 & & aN.N \end{pmatrix}_{N*N} \xrightarrow{\textbf{Concatenation}} \begin{pmatrix} a_{1,1} \\ \vdots \\ a_{1,N} \\ \vdots \\ a_{2,N} \\ \vdots \\ \end{pmatrix}_{N^2*1} \qquad \textbf{(3.1)}$$

2. The mean face is computed in the second stage of feature extraction. Average face identifies facial characteristics that are common to all training samples. Divide the total count by each sample vector row. The outcome in the sample ought to be a vector of mean faces. Calculate the average of all samples as follows:

$$\mu = \frac{1}{N}\sum_{i=1}^{N} x_i \qquad \textbf{(3.2)}$$

3. To identify the distinct facial characteristics shared by all samples, remove average side of all sample vectors. At this stage, all the common features and keeps them distinct from all samples. From each samples, deduct the mean as follows:

$$D = \{d_1,\ d_2,\ \dots,\ d_N\} = \sum_{i=1}^{N} x_i - \mu \qquad \textbf{(3.3)}$$

4. The vectors from the previous step are joined in this phase so that each vector forms the columns of the matrix D, the covariance matrix C, which is created by only multiplying D by the transpose. Compute the covariance matrix as follows:

$$C = \frac{1}{N-1} D \times D^T \quad \textbf{(3.4)}$$

5. The equation below represents the covariance matrix C, eigenvalues λ_i and eigenvector V.

$$CV = \lambda_i V \quad \textbf{(3.5)}$$

Not all eigenvectors V contain useful variances, so only some an eigenvector V with high variance is used to train the classification.

6. Algorithm Sorts the eigenvectors according to their eigenvalues. Only a part of the eigenvectors V with high variance will be used to train classification algorithms because not all eigenvectors V have useful variance.
7. Eigenvectors are sorted by their associated eigenvalues.
8. The weights for each sample element are calculated as the eighth and last stage of feature extraction. According to the categorization approach, all samples' weights are used. To multiply the eigenvectors' transposition and the weights of all samples calculated in step three with adjusted face D. Select the largest eigenvalue $W = \{\lambda_1, \ldots, \lambda_k\}$. The selection of eigenvectors (W) represents the projection space of PCA.

3.4 Gender Classification

The eigenvector W computed from feature extraction is then used in the classification step. The weights from the recognition phase serve as input to the classification algorithm during the training phase and the weights from feature extraction are utilized to train the algorithm. The facial features in the feature extraction stage are input into a Support Vector Machine (SVM) classifier and classified as male or female.

After performing PCA on the data set, the results for gender classification are displayed. First, it computed the correlation matrix of the input data and found the eigenvectors. We then projected the training data onto these base vectors and estimated the projection coefficients. These coefficients were used for classification. This system uses the Support Vector Machine (SVM) as its classification method.

3.4.1 Support Vector Machine (SVM)

After feature extraction, classification is performed to classify the stairs as male or female. The eigenvector W computed from feature extraction is then used in the classification step. In the training phase, the weights from feature extraction are used to train the classification algorithm, and the weights from the recognition phase are used as input to the algorithm. This system uses the Support Vector Machine (SVM) as the classification method. The facial features in the feature extraction stage are input into a Support Vector Machine (SVM) classifier and classified as male or female.

Support Vector Machine is a learning algorithm for pattern classification and regression [11, 53]. The basic training principle of SVM is to find the optimal linear hyperplane for an unseen test sample with minimal expected classification error and good generalization performance. According to the principle of structural risk minimization induction [11], functions that correctly classify the training data and belong to the set of functions with the lowest Vapnik Chervonenkis (VC) dimension [53] generalize best regardless of the dimensions of the input space. Following this principle, linear SVM uses a systematic approach to find the linear function with the lowest Vapnik Chervonenkis (VC) dimension. For data that is not linearly separable, the SVM can (non-linearly) map the input to a higher-dimensional feature space where a linear hyperplane can be found. There is no guarantee that a linear solution will always exist in high-dimensional space, but in practice it is quite possible to construct a working solution.

Given a labeled set of M training samples (x_i, y_i), where $x_i \in R^N$ and y_i is the associated label ($y_i \in \{-1,1\}$ the SVM classifier correctly separates (classifies) the optimal hyperplane look for the largest part of the data point while maximizing the distance of the two classes in the hyperplane (margin). When creating an ideal hyperplane, Vapnik Chervonenkis (VC) [11] demonstrates that increasing the margin distance is equivalent to decreasing the (VC) dimension. Quadratic programming methods are used to tackle the constrained optimization problem of determining the optimal hyperplane. The level set of defines the discriminant hyperplane as

$$f(x) = \sum_{i=1}^{M} y_i \propto_i . k(x, x_i) + b \qquad \textbf{(3.6)}$$

where the members of x are determined by the sign of f(x), and k (x, x i) is a kernel function. Finding all non-zero I am comparable to creating an ideal hyperplane. The Support Vector (SV) of the ideal hyperplane is the vector xi corresponding to a nonzero value. A desirable feature of SVMs is that the number of training points maintained as support vectors is usually very small, providing a compact classifier.

CHAPTER 4

THE EXPERIMENTAL SETUP

In this system, the gender classification of face from Myanmar National Registration Card is implemented by MATLAB software. 180 images of jpg file (80 males and 100 females) is used in this experiment. The percentage accuracies rate for male and female classification of the system is 92%.

4.1 The Experimental Study

The simulation results for the support vector machine-based gender classification will be reported in this section. In this system properly, it is desired to train and test the system using the face from Myanmar National Registration Card (NRC). Testing and training image is captured the NRC card from the fontal view using a camera. All of the input images are converted sizes to 100×100 pixels to analyses the system performance. A database of 180 images (80 males and 100 females) is used to analyze the system performance. The images of face are under 30 years old and the images sized are 100 × 100 pixels. The proposed system is implemented in MATLAB software. In proposed system, SVM classification method is applied to classify the gender.

The variation of facial feature among faces can be found the best by using the Principal Component Analysis (PCA). A set of basis images is derived from the dataset file supplied to the system through eigenvalue-eigenvector decomposition. Any face in the feature space is then given a weight vector that describes it after being projected onto the collection of basis pictures. The weight vector of a new face is determined when it is submitted to the system, and an SVM-based classifier is then used to categorize it.

4.2 Gender Classification System

The gender classification of the proposed system is presented by three experiments. The first experiment is tested on only female images and the second is tested on only male images. The third experiment is gender classification on mixed (female and male) dataset. For this experiment, each facial data file is split into two sets: a training set and a testing set. The first testing set 30% was utilized as test samples and the remaining 70% was used as training samples. Frequently, they will be provided with experimental results in detail in the next subsection.

In the first experiment, the dataset of 80 female facial images is used to evaluate the gender classification rate of the system. It has two images for each woman. Figure 4.1 shows sample dataset of female face images from Myanmar NRC card. The entire database's sample photos were used. Use the following formula to determine the accuracy:

$$\frac{Number\ of\ correct\ classification}{Number\ of\ Testing\ samples} \times 100 = Accuracy\ \%$$

Figure 4.1 Sample female image dataset

In the second experiment, a dataset of 80 male’s facial images are used to evaluate the gender classification. It has two images per person. Sample dataset for male images is shown in Figure 4.2.

Figure 4.2 Sample male image dataset

The third experiment is gender classification on mixed (female and male) dataset. A dataset of 160 images (80 males and 80 females) is used in this experiment. There are 180 images which are 100 of female images and the remaining 80 are males. Sample dataset of mix (female and male) images are shown in Figure 4.3.

Figure 4.3 Sample Dataset of the proposed system

In every example, the proportion of male faces that are labeled as female and vice versa is documented. Table 4.1 displays the percentage accuracy for male and female face classification. These findings once more show that categorizing female faces involves significantly more inaccuracy. Approximately 4.4% of males are mistakenly assigned to the female gender. A bigger inaccuracy was seen when it came to female photos, and almost 15,000 percent of the female faces were mistaken for men.

Table 4.1 Results of Gender Classification by SVM

Dataset	Accuracy	Error Rate(%)
Male (80 images for 40 people)	95.6%	4.4 %
Female (80 images for 40 people)	85.0%	15.0%
Female (100 images for 60 people)	93.6%	6.4%
Combined (male and female) (180 images for 100 people)	92.4%	7.6%

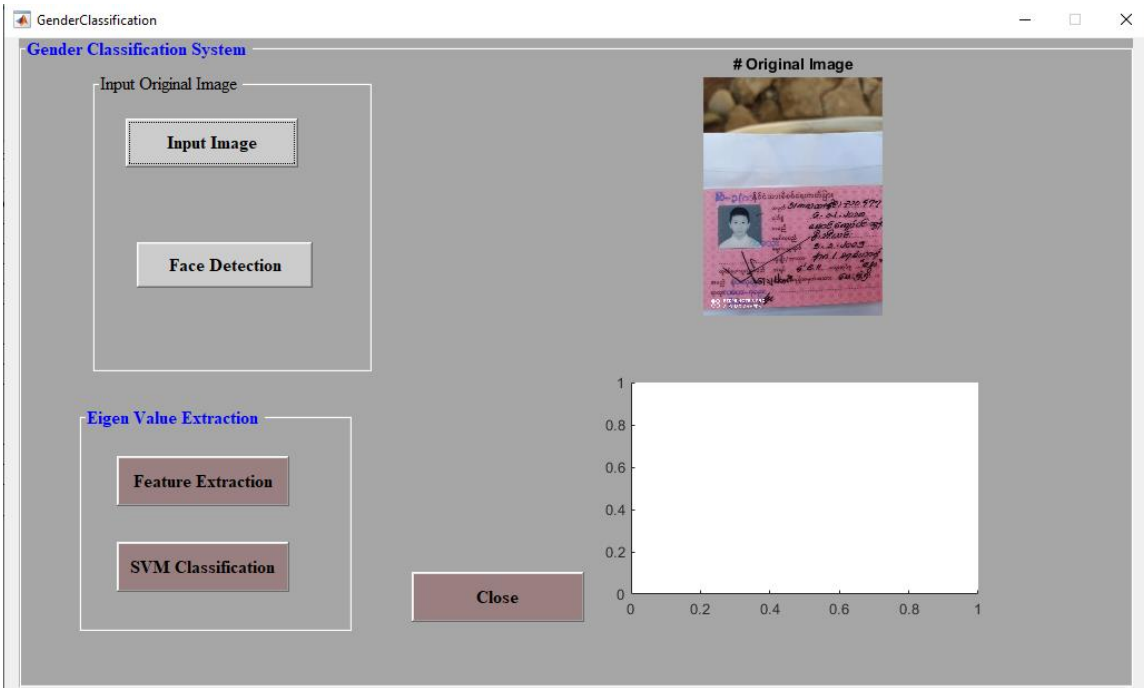
The experiment was also repeated on female images dataset by increasing the number of objects. It is really difficult to classify women whose hair is relatively short. Thus, the images where women have relatively short hair take many images for each collectively. Therefore, the number of objects with short hair faces is increased that contained 100 female images for 60 people in this experiment. In this case, the percentage accuracy for female was around 94%. As a result, it is clear that increasing the size of the training set significantly improves performance.

Then, female and male (mix) dataset are used to study the performance. A dataset of 180 images (80 males and 100 females) is used in this experiment. There are 180 faces which are 60 of female images and the remaining 40 are male. The percentage accuracies rate for male and female classification of the system is 92%. The effectiveness of this system is assessed using its own dataset of 100 individuals (40 males and 60 females). The investigation found that SVM findings had good classification rates, with an average of 92 percent for 180 participants. Women supplementing the training set may improve accuracy. Many other applications, such as person recognition and intelligent human–computer interactions, can perform better with a proper gender classification approach.

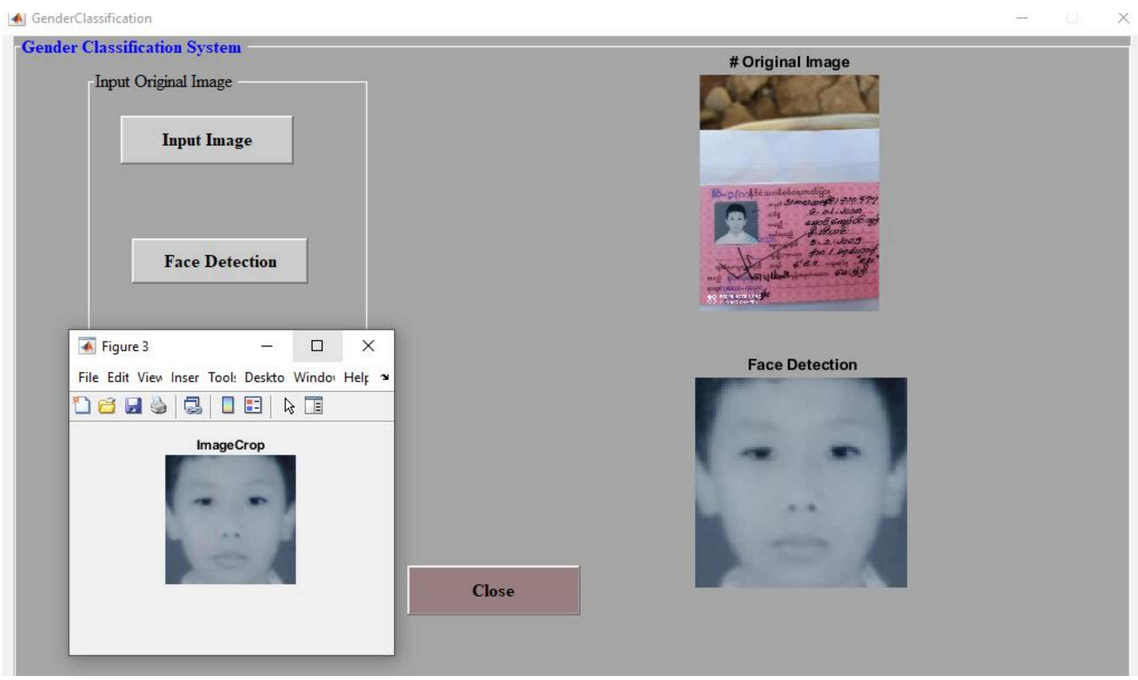
4.3 Gender Classification from Myanmar National Registration Card

In this section, gender classification by face from Myanmar National Registration Card is implemented. There are 180 images (males and females) in this experiment. This system determines whether the result is male or female by using Support Vector Machine (SVM).

In this system, the input image for NRC is first browsed by pressing “Input Image” button as shown in Figure 4.4 (a). By clicking “Face Detection” button, CascadeObjectDetector function detects the face first and the detected face is cropped as in Figure 4.4 (b).



(a) Browsing the testing image for NRC



(b) Image cropping and face detection

Figure 4.4 Face detection from Myanmar National Registration Card

The cropped image is inserted as an input in Feature Extraction step. By clicking "Feature Extraction" button, the cropped image is converted to the gray image. Then, the gray image is resized as in Figure 4.5 and features are calculated by using Principal Component Analysis (PCA).

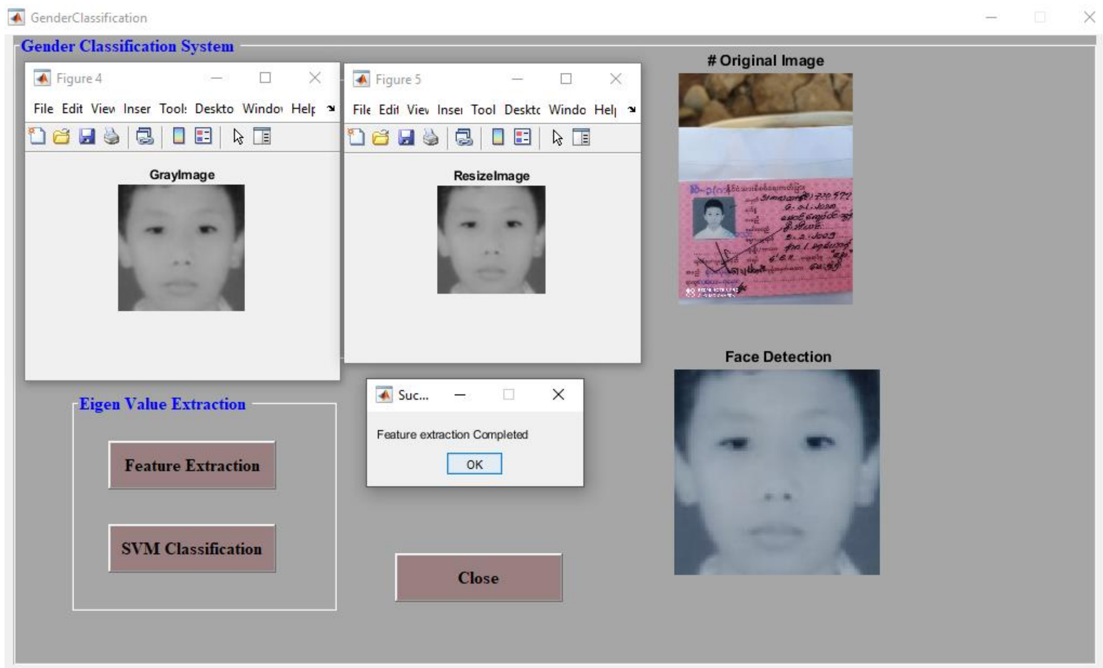
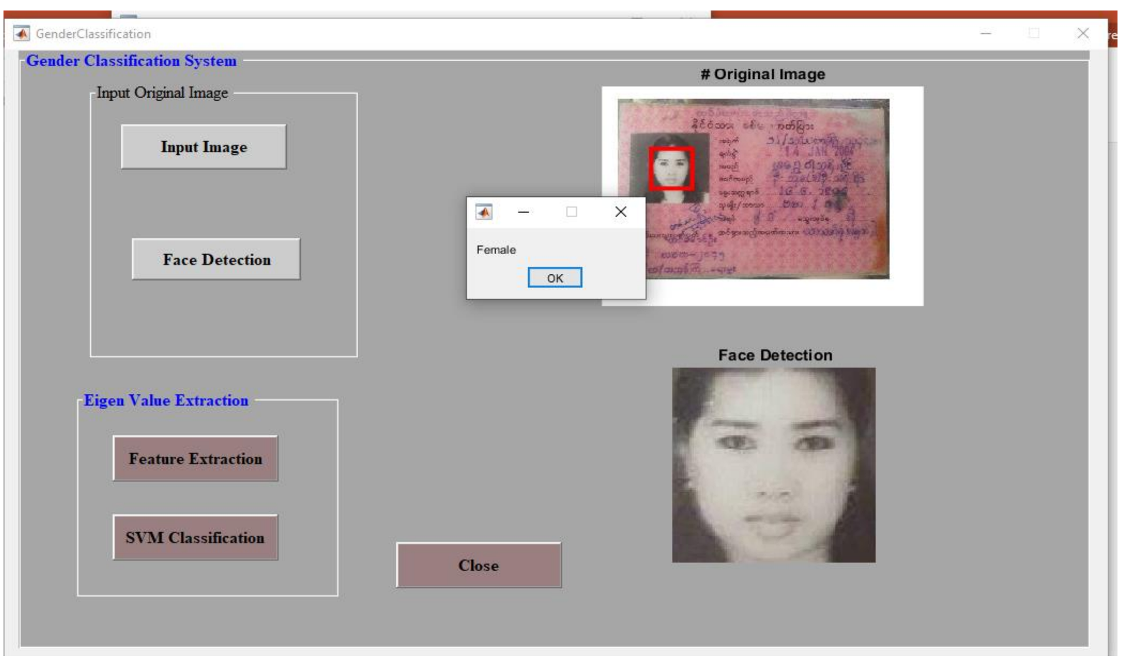


Figure 4.5 Feature Extraction

The next is classification step in that Support Vector Machine (SVM) is used to classify gender from the extracted features. As in Figure 4.6, by clicking "SVM Classification" button, the system shows male or female result for the input image.

(a) Male



(b) Female

Figure 4.6 Gender Classification System from Myanmar National Registration Card

CHAPTER 5

CONCLUSION AND FURTHER WORKS

This chapter discusses some facts on the proposed system architecture, concludes on the overall thesis and proposes directions for future extension. The proposed system simulated the features extraction by Principal Components Analysis (PCA) and used the Support Vector Machines (SVM) classifier for this study. The aim of this system is in order to identify and classify the gender from identity card which means that these images can be with different resolution and different lighting system. Support Vector Machine (SVM) is used to classify male or female. The experimental evaluation of proposed system confirms the good performance.

5.1 Conclusion

The classification rate of the proposed system is described by three datasets; they are only female images, only male images and combined male and female dataset for gender classification. SVM classifier is used on three types of experiments to determine the gender signatures. It achieved the better performance on the all three types of experimentation in this system. This system is tested using the own database with 100 people (40 males and 60 females) captured from the side of frontal views. SVM classifier achieves as high as 92.4% gender classification accuracy for 180 subjects.

Presenting to the experimental results, the accuracy of male type is higher than the accuracy of female type. The gender classification rate of SVM is the good results with 95.6% for male type and 85.0% for female type in same classification method. The gender classification rate of combined is lower than the others only female and male. The combined dataset has the good gender classification rate by the SVM classification method. According to the experiment, the accuracy of combined (male and female) dataset is lower than the others but it is still reasonable results.

5.1.1 System Limitations and Future Implementations

The proposed system has some limitations. The system performs well in the classification task of determination whether observed human face is female or male. But the system cannot identify the person and the images with very low sharpen and having complex background situation are not allowed.

As the first point for the future implementation, this system will continue to be developed to provide a more accurate classification result on the real-world facial data for online gender classification. For further experiments, the proposed system will be tested on the larger value of dataset and will be executed the other machine learning algorithm to compare with the proposed method. It would be the second point of further implementation for this system. In addition, the proposed system used only the face signatures to simulate the system performance. It may be more efficient to combine face recognition with other biometrics, such as fingerprint and voice recognition, than to use just one biometric.

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