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A Statistical and Machine Learning Based Face Identification System with Enhanced Multiple Weighted Facial Attribute Sets

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Abstract: Academic and business institutions alike have been more interested in facial recognition studies in recent years. The idea of face recognition has grown in significance in several applications due to its openness and the myriad of security characteristics it encompasses. Face recognition solves several issues with alignment, age, lighting, emotion, and lighting. The aforementioned challenge arose while trying to differentiate one face from another in a facial recognition system. This study proposes a novel method for improving face recognition performance using Multiple Weighted Facial Attribute Sets in conjunction with the Principal Component Analysis (PCA) methodology. The results of this study demonstrate that the recognition system's overall performance was affected by the weights assigned to the various qualities. During the matching process, the user-defined input component of the proposed approach will prioritise a collection of picture characteristics.

Keywords: *Face Recognition, Multiple Weighted Facial Attribute, Principal Component Analysis*

Introduction

This study delves further into Face Recognition, which is defined as the capacity to identify a human face based on its unique features. Face recognition software that helps businesses and governments with tasks including border security, physical access management, and preventing identity theft. Academics and businesses alike have been more interested in facial recognition studies in recent years. Criminal identification may be greatly enhanced, for instance, if it were feasible to model a face application and distinguish it from stored face models[1][2]. The capacity to recognise faces isn't always necessary; sometimes, the ability to detect them is enough. The effectiveness of various enhancement and noise reduction methods is content dependent, however facial image detection from colour film processing may be quite beneficial. Humans have little trouble recognising faces based on their features; the process is almost instinctive and requires minimal cognitive processing power. It is not hard for people to identify faces, even when the corresponding picture is distorted—for example, when a person is wearing spectacles[3]. Meanwhile, computers need to be taught an algorithm to recognise faces and facial traits; it's not something they're born with. Modern algorithms, even the most advanced ones, depend heavily on statistical probability and are far from ideal. The system can quickly scan any face picture, determine a set of characteristics, and compare them to all of the previously trained images to determine which one is the guaranteed face. After that, it will compare the testing picture to the collection of trained face images and determine the likelihood of a match based on those probabilities. No match will be returned if none of the faces are matched[4].

Pose, lighting, emotion, backdrop imaged head size, and head orientation are just a few of the challenging issues that face recognition must solve. One source of this problem is the need to display faces in a manner that makes it easy to identify individual faces[5]. A number of recently developed algorithms have succeeded in creating a three-dimensional representation of a human face. The machine can accurately search face databases and verify one-to-one or one-to-many relationships. Even when a person's hairstyle, skin tone, or

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eyeglasses are all different, the system can still identify them[6].

Face Representation: The Face Representation Task Determines the Best Approach. Many different methods exist for representing faces, however they may be mainly grouped into three types: appearance-based, template-based, and feature-based. The template-based approach makes full use of the template[7]. This method takes an edge map of the initial face picture and utilises it as a single template for the whole face. A reduced collection of face feature templates that maps to the eyes, nose, and mouth for a single perspective is another key alternative. Facial, iris, and mouth feature extraction is an important approach. In order to gather information about the face, we employ skin colour data, iris intensity values, and the mouth colour space approach to assign the area of the lips[8]. The face photos are classified using template matching once all characteristics have been collected. Both the memory demand and the matching efficiency of this approach are low. Finding the optimal placement for the template inside the source picture is the main goal of the Feature-Based Approach, which relies on the template image's properties such edges and corners as measurements. This model represents a face by extracting geometric information such as its shape, measurements, eye breadth and placement, nose and mouth shape, distance between the eyes and nose, and eyebrow thickness. This method requires the employment of many sets of scales for various face characteristics, including those of the head and torso. The recognition speed is greater, and it takes very less memory. Images used in feature based techniques are susceptible to feature corruption due to lighting and noise[9].

Images of faces are projected onto a low-dimensional linear subspace via the Appearance Based Model. Principal Component Analysis is used to build such a subspace first, using a collection of training pictures as its eigenvectors and eigenfaces as its eigenvalues. Eigenfeatures, such eigeneyes, eigenmouth, etc., were later added to the ideas of eigenfaces to improve face feature recognition. To address identification in different lighting conditions, Fisherface Space and Illumination Subspace were suggested more recently. This is the model that the suggested method was tested on in the study[10].

Analysis of Faces: Face localization is all that face detection is. The objective of face localization is to determine the positions and dimensions of a set of known faces. Frontal face identification is the primary focus of early algorithms[11]. The strategy relies on more recent algorithms that put more emphasis on the challenging issue of multiview of face. More recent algorithms adjust for differences based on aspects including lighting, stance, and look. Some digital cameras, human-computer interfaces, and video surveillance systems rely on face detection. As an additional method, it alters the pictures in "face space" to aid in face identification. The output of computing the distance from face space at each place in the picture is a "face map," which is a metric for "faceness" based on this distance. Having low values, or relatively close distances from face space, on the face map indicates the existence of a face. Performing face identification is confirming or identifying a person from a single frame of a video or still picture[12]. This is the part where a new face is compared to models already saved in a database; if a match is discovered, the new face will be assigned to a known person. A person's face might seem quite different in many photos taken from different angles and positions, making facial identification a challenging process. Using a face database in conjunction with picture comparisons of certain facial traits is one approach. It operates on each individual's database as a cluster. By dividing a person's information into clusters, binary trees may be constructed using two types of picture classification: similar and dissimilar[13]. The cluster has been taught to recognise human faces by learning their unique characteristics. In order to train a Support Vector Machine (SVM) to differentiate between each individual in the database, each cluster is employed. Another issue is disguising one's identity by alterations to one's facial features, such as a new hairdo, cosmetics, or eyewear. The majority of studies focus on the issue of eyeglasses[14].

Modern, cutting-edge electronics relies heavily on face recognition. Security and surveillance are only a few of their numerous practical uses; other examples include video indexing, credit card verification, and ID verification at ATMs. Nevertheless, studies in this area are ongoing and evolving. The classifier's feature selection is crucial to face image recognition; given a set of features, it should try to derive the optimal subset of features that lead to good classification performance, with the hope that future trials using unseen test data will also display similar performance[15]. Despite altered matching images (such a person wearing spectacles), people are still able to easily recognise faces. It is currently not feasible to model a human recognition system in its entirety and achieve its performance and accuracy with current technology. But there are limited capabilities of the human brain. Computer systems are advantageous because they can process massive amounts of data and carry out tasks in a predetermined, repeatable manner. Automatic face attribute analysis may benefit from the insights gained from studying human face recognition systems[16].

Research Objective

With the ability to use emotion data to pinpoint potential face locations, the face identification issue in still photos is more complex and harder to solve. The purpose of this study is to detail an innovative method for face recognition that may be used in picture database applications for image querying. A collection of potential candidates may be identified given an input picture of a face and a database of suspects. As a condition, it must be able to match faces in the supplied picture[17]. The suggested face recognition system's design makes use of the best method after an exhaustive analysis of current face recognition methods, including feature extraction and dimensionality reduction approaches, has been conducted. The method incorporates a novel approach, combining the PCA algorithm with Multiple Weighted Facial Attribute Sets[18]. Applying the "wavelet based image decomposition technique" considerably enhances the system's performance. The goal of this approach is to improve FR's performance over the current system by a significant margin.

Face recognition is still a challenging area. The challenge of facial recognition has been the subject of several research proposals. Recent research has divided face identification methods into two broad categories: feature-based and image-based. Snakes, deformable templates, edge data, skin tone, symmetry and motion metrics, feature analysis, and point distribution are all components of the feature based approaches. Neural networks and linear subspace methods (such as Eigen and Fisher faces) are examples of image-based algorithms[7].

Proposed Methods

A set of face photos with Multiple Weighted Facial Attribute Sets will be used by the suggested system to improve performance. By using a wavelet-based image decomposition approach, the system's performance will be significantly enhanced. We will use a Support Vector Machine for both the training and testing processes[8]. A user-defined input component will prioritise a collection of picture attributes throughout the matching process in the proposed approach. Because of this, the suggested approach is different and improves performance. In order to test and refine the suggested multi-attribute based facial recognition system, we will use MATLAB on a Windows machine. The system's performance will be evaluated using appropriate metrics[9].

The researchers in this study relied on trial and error to determine the feature sets' weights. This is going to work for systems that have their data sets determined in advance. However, this approach is not going to work for databases that are subject to constant modification. Picture lighting and backdrop have a significant impact on the Histogram Feature Set and the Intensity Feature Set. Both the Eigen Feature Set and the DCT Feature Set will take the picture's uniqueness into account[10]. In this way, the weights are selected via an iterative process depending on the available information. That being said, approaches to automatically estimating the feature sets' weights may be considered in further publications. Due to the manipulation of the feature extraction techniques and the training/testing set in this work, this approach may be a suitable engineering method. Research in the future could lead to a paradigm shift towards facial recognition algorithms that are more analogous to human performance[11]. While developing and executing the concept, the scalability considerations were disregarded. This face recognition algorithm may get some attention in the future.

Face Recognition System

Figure 1 shows the general layout of a face recognition system. A face is characterised as "known" or "unknown" in the outline depending on whether it matches one of the recorded instances of known persons. An ideal system would be one that can learn to identify faces it has never seen before. In order to identify the person in an input picture, face recognition software compares it to a database of previously recorded faces.

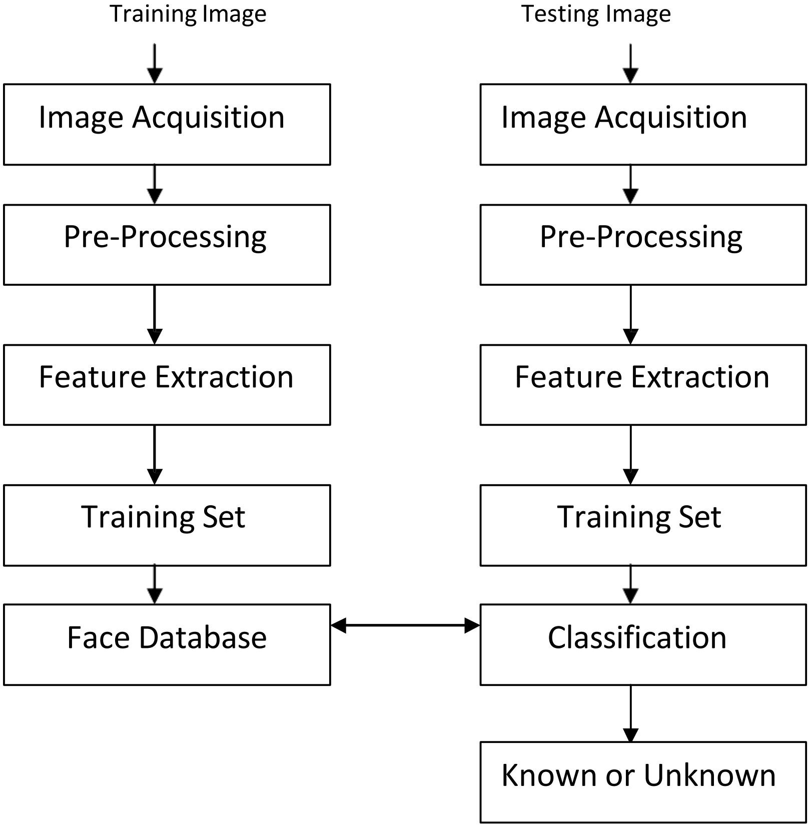

Fig 1. Face Recognition System

As shown in the above figure, there are six main functional blocks, whose responsibilities are given below:

Image Acquisition Module: By digitally scanning an existing image or using a camera to capture an image, an image acquisition module may request a facial image from many locations.

Pre-processing Module: Image normalisation for faces is done in this module. This will make the system's recognition performance better. A facial recognition system could use some of these pre-processing steps: Image processing tasks include resizing, balancing histograms, applying median and high pass filters, removing backgrounds, and standardising translation, rotation, and lighting.

Feature Extraction Module: Representing the facial picture, this module is in charge of extracting the feature vectors that will be valuable for classification. When it comes to facial picture classification, feature vectors will be invaluable.

Classification Module: Here, we use a pattern classifier to compare the face image's retrieved characteristics to those in the ORL DATABASE. The comparison is based on the values that are closer. By comparing the two, we can determine whether the facial picture is recognised or unknown. In the "knowledge phase" of facial recognition, a training set is used. Classification modules optimise their parameters to achieve optimal recognition performance by utilising training sets, and features extracted from faces are trained to make the computer system better understand them automatically, all without human knowledge of the data set.

Face Library or Face Database: Once a face image's classification is "Unknown," its feature vectors are saved to the face library. It may be used for comparative purposes in the future after the updated data has been entered into the Face Database. Using the face library directly, the categorization module.

Scale invariance: A face can be interpreted at different scale in a system depending on the focal distance between the face and the camera. The face image gets bigger, as the distance between the face and camera gets closer.

Shift invariance A Face can be displayed in a system at different perceptive and orientations. More overhead orientation may be changed due to translation and rotations. For example, it is possible to take frontal and profile views of face images of the same person.

Illumination invariance: A Person face image could be taken under different illumination condition and more over the position and the strength of the light source could also be modified Emotional expression and detail invariance

A Persons face image may differ due to variety of expressions while smiling and laughing. At same time details like dark glasses, beards or moustaches can be present.

Noise invariance : A strong face recognition system that is designed to be unaffected by camera or frame grabber noise. On top of that, it has to function correctly even when visuals are partly obscured. Assuming it has added the photos to its face database, it should still be able to identify familiar faces even in the aforementioned scenarios.

Expertise in the design framework of human face recognition systems is essential for researchers aiming to create non-natural face recognition systems. Perhaps the basics of the human system can be better understood with this kind of emphasis on the approach of a face recognition system for humans. In a two-dimensional format, human face recognition systems often make more extensive use of the data than machine recognition systems. These facial recognition systems rely on information gathered from many senses, including sight, sound, touch, and smell. The information gathered is used for storing and identifying faces, either alone or in groups[5]. However, machine recognition systems struggle with combinations of this sort of large data. In a similar vein, storage problems may make it difficult for humans to recognise a large number of faces. A machine system's storage capacity is its potential advantage, whereas a human face recognition system's characteristic is its parallel processing capability. Identifying a face as being neither "attractive" nor "unattractive" is a challenging task for humans. There has been research and debate on the use of both global and local characteristics in human face recognition systems[6].

Low spatial frequency features, such as the individual's global description and the ability to detect previously utilised high frequency components, are used for sex information classification. Human face recognition systems rely heavily on both holistic and feature-based data.

It is possible to identify a face using global descriptions, however the holistic approach may not work for traits that stand out, such as large ears, a tiny nose, etc. New research shows that inverted faces are far more difficult to identify than regular ones. The nose is less important for recognising a face than the hair, eyes, lips, and margins of the face[7]. Recognition using the top half of the face is more effective than using the bottom half, according to the study.

When it comes to remembering faces, qualities like attractiveness, pleasantness, and beauty have a significant effect. Facial recognition using photographic negatives is a challenging task for humans[8].

Using negative images of human faces to identify them is an area where the research is lacking. Another reason to look at lighting as a concern is that differing lights may make a huge difference to how a person's face looks in a photograph. Humans have an advantage when faced with faces that are lit vertically rather than horizontally[9].

Evaluation Of Feature Extraction And Dimensionality Reduction Algorithms

In order to mitigate the performance drop caused by changes in face features, the assessment research focused on several dimensionality reduction strategies. We devised an experiment to study the improvement in resistance to light and changes in expression. The basic premise behind dimensionality reduction methods was to generate facial feature vectors and then identify the parts that were less affected by inherent deformations caused by things like expression or external influences like lighting. Images of faces from ORL's facial image databases were used to evaluate the suggested approaches, which account for variations in lighting and expression. Further comparative and statistically meaningful findings were obtained[10].

"Dimensionality reduction" was the statistical term for lowering the amount of potential variables.Feature selection and feature extraction are the two main categories. The first kind uncovered some of the initial factors. For data analysis tasks like classification or regression, there are instances when a more precise reduction of the original space is required[11]. Data transformation from a multidimensional space into a space with fewer dimensions was used in the second kind. This indicates that a linear transformation was applied to the original feature space.

There had been a lot of progress in dimensional reduction thanks to the statistics and machine learning groups. A plethora of linear and novel (nonlinear) dimensionality reduction methods have been put forward within the last ten years[12].

These methods derive From the realm of global nonlinear techniques, we have selected Principal Component Analysis (KPCA) and Linear Discriminant Analysis (LDA) as two dimensionality reduction methods. From the realm of extensions and variants of local nonlinear techniques, we have selected Locality Preserving Projections (LPP) and Neighbourhood Preserving Embedding (NPE). In this study, the accuracy of the face recognition application was tested using these methods. Results that are comparable have been obtained[13].

When it came to reducing dimensionality, Principal Components Analysis (PCA) was the method of choice. Finding a linear subspace of dimension d less than n where the data points mostly reside is the goal of principal component analysis (PCA) given a collection of data on n dimensions. Rather, they sought to discover a subspace that would preserve the majority of the data's variability. The 'principal components,' a set of two orthogonal vectors that provide a new system of coordinates, may be used to describe the linear subspace. The original data points were transformed into main components that were orthogonal and linear, hence the number of them cannot exceed n. Nevertheless, the expectation was that the region covered by the n original axes could be approximated using just $d < n$ primary components.

The goal of Fisher's (1936) Linear Discriminant Analysis (LDA) is to boost the linear separability between class-specific data points. Being a supervised methodology, LDA stands out from other dimensionality reduction methods. For a low-dimensional data representation, LDA finds a linear mapping M that maximises linear class separability.

Kernel Principal Component Analysis (KPCA)

Linear variables in high-dimensional data may be modelled using principal component analysis (PCA). Nonlinearity, however, is a common feature of many high-dimensional data sets. Since PCA is unable to accurately represent data variability when the high-dimensional data is located on or close to a nonlinear manifold rather than a linear subspace, PCA is not applicable in such instances. Kernel principal component analysis (PCA) is one approach that aims to remove nonlinear dimensions. In Kernel Principal Component Analysis (Kernel PCA), high-dimensional feature spaces that are linked to the input space by nonlinear mapping may have their principal components quickly calculated using kernels.

Neural Networks And Learning Paradigms

It is theoretically possible to train the widely used neural network to directly recognise face images. Using a Neural Network Approach, Rowley's research shown that the Face Detection Problem may be effectively solved. The complexity and difficulty of training even a seemingly simple network might be surprising. When it comes to abstract learning tasks, there are essentially three main paradigms to choose from. Supervised, unsupervised, and reinforcement learning are the three main types. In most cases, any of those tasks can make use of any given kind of network architecture. There are two main steps to neurocomputing, which is concerned with processing information. The first is learning, during which an artificial neural network adapts to new input by applying a learning rule. The second is deployment, during which the network is prepared to operate in its environment and carry out its intended task. Just Like Their Biological Ancestors, Their Adaptability Is What Makes Them Fascinating.

Since its inception in 1943 with Mcculloch and Pitts Neurons—simple logical units devoid of learning—neurocomputing has come a long way. Neural networks are now used effectively in a variety of domains, including pattern classification (i.e., speech and character recognition), clustering (i.e., function approximation), prediction and forecasting, optimisation, and many more. To accomplish more targeted goals, researchers use specialised neural network architectures that employ a variety of learning algorithms and rules. When building a neural network model, the goal is to train it to minimise a cost metric by picking a model from a pool of possible ones (or, in a Bayesian context, by calculating a distribution across those models). Training neural network models may be accomplished using any number of techniques, the majority of which are simple implementations of optimisation theory and statistical estimation. When it comes to training artificial neural networks, gradient descent is the method of choice. Doing so is as easy as determining the cost function's derivative with regard to the network parameters and adjusting them in a gradient-related way. The most common implementation of the multi-layer perceptron (MLP) architecture, which employs a single input layer, a single output layer, and an arbitrary number of hidden layers—neurons in these layers may be completely linked or sparse—and back propagation techniques for MLPs The three-layer architecture consists of an input, an output, and a hidden layer; the basis of rule-learning is the principle of error propagation, which entails minimising an error function by modifying the weights of neurons. There are a number of commercial programmes available for building and testing neural networks, such as Matlab and Simulink. Simulink has an intuitive interface for testing and visualising results, as well as a nice collection of tools and algorithms for processing images.

Support Vector Machines (SVMs)

In the mid-1990s, Vladimir Vapnik created a family of algorithms called Support Vector Machines (SVMs) for use in supervised learning tasks including regression and classification. Recent developments in statistical learning theory provide the basis of this new generation of learning algorithms. Its generalizability is limited to a small number of training samples. The SVM is chosen as the classification algorithm. Superior generalisation performance is one way in which support vector machines (SVMs) stand out from more conventional neural networks.An method for pattern classification, support vector machine Using the idea of structural risk reduction, this binary classification approach determines the best linear decision surface..

Evaluation Model

In a Support Vector Machine, given a collection of feature vectors from n classes, the goal is to maximise the distance between each class and the hyperplane that separates the most features from the same class on each corresponding space. In most cases, SVMs learn discrimination functions between each picture class after an appropriate transformation is applied to extract characteristics of facial images. In order to assess the efficacy of the dimensionality reduction methods that were used for our study, we drew up the following model of the total face recognition system.

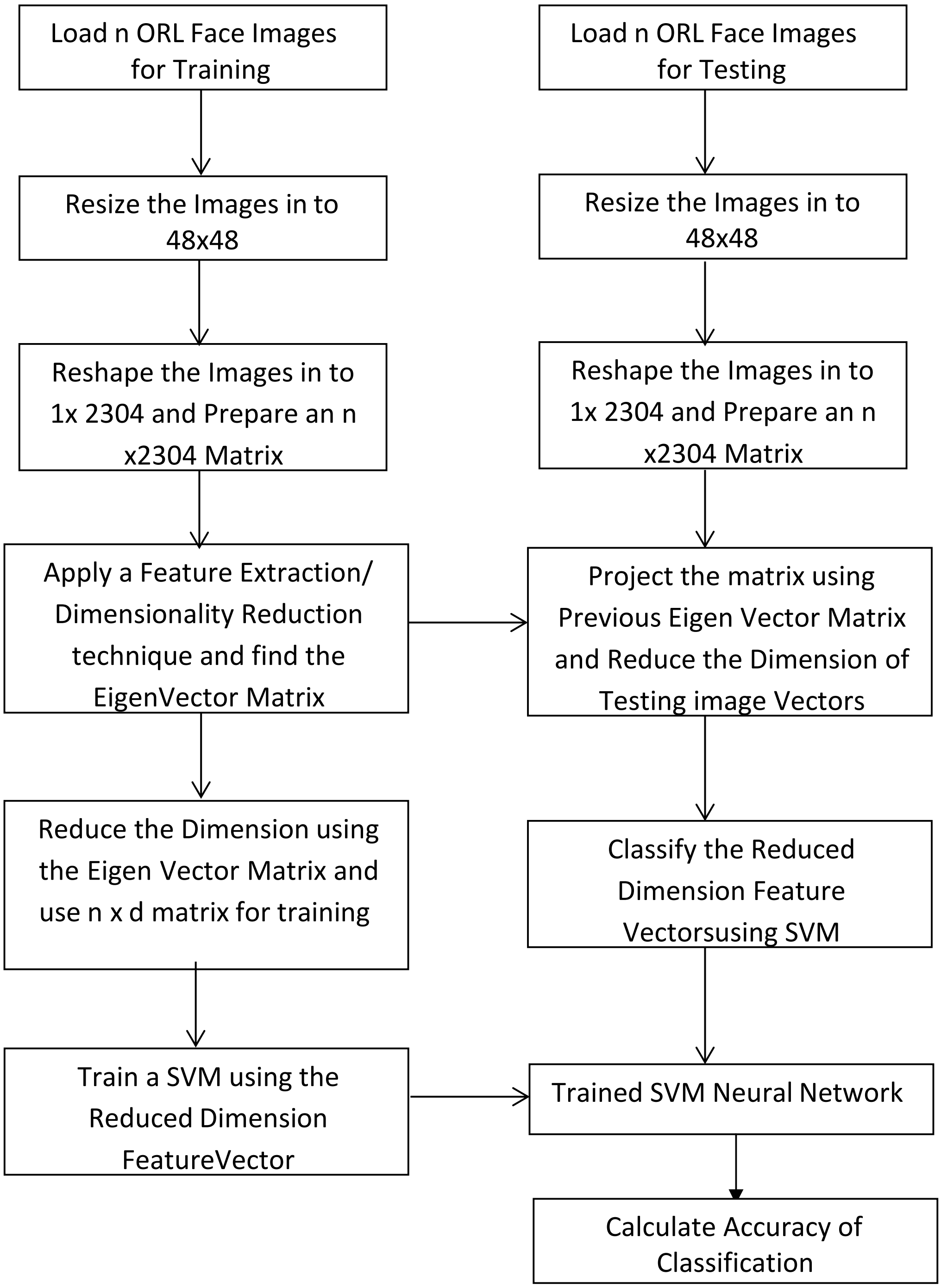

Fig 2. The Model of the FR System

Figure 2 shows the FR system model with several techniques substituted for the dimensionality reduction part. This will allow us to compare the model's performance with a typical face data set. It goes without saying that we need some faces to test the system. A face detection algorithm may be tested and rated using any number of standard face datasets. In order to provide algorithm developers with standard imagery and to provide enough photos to test these algorithms, a standard collection of face imagery was necessary. It will be impossible to compare and assess face recognition algorithms without these kinds of datasets and standards.

Conclusion

When comparing the effectiveness of various feature extraction and dimensionality reduction algorithms in the proposed study, PCA and KPCA achieved comparatively high correct recognition rates compared to other algorithms; consequently, these two dimensionality reduction algorithms significantly enhance recognition performance overall. In this study, we used the industry-standard ORL Database to assess the outcomes for a large number of photos. This study accomplished its goal by providing training for a face recognition system that is based on Multiple Weighted Feature Attribute Sets, which significantly improves the system's performance accuracy.

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