Personality Identification Through Facial Features by Using Neural Networks for Pakistani People

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Declaration

I certify that this research work titled "*Personality Identification Through Facial Features by Using Neural Networks for Pakistani People*" is my own work. The work has not been presented elsewhere for assessment. The material that has been used from other sources it has been properly acknowledged / referred.

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Language Correctness Certificate

This thesis has been read by an English expert and is free of typing, syntax, semantic, grammatical, and spelling mistakes. The thesis is also according to the format given by the university.

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Copyright Statement

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Abstract

Computational physiognomy, also known as digital face reading, is a concept that uses automatic computational methods to recognize a person's personality traits, psychological qualities, or mentality based on their outward appearance, including structural, texture, or color-based face features. It has been one of the most exciting research topics in the last decade, not only for computer scientists but also for psychologists. Previously, an expert physiognomist measured all face attributes manually. However, as computational technologies, image processing techniques, and machine learning algorithms have advanced over the last decade, the physiognomy approach has shifted toward automatic personality analysis systems that can generate an individual's entire personality report using a single face image as input.

Computational physiognomy solutions have already been proposed in China, Taiwan, Australia, Singapore, Korea, and Poland for a variety of applications; however, they only incorporate datasets for their people and are not publicly available. Furthermore, the measurement-based approach extracted a very limited number of features, whereas the neural network approach used a non-uniform distribution of feature classes, which does not match generic or modern physiognomy literature.

In this thesis, we intend to investigate modern physiognomy principles, create a local dataset, and develop a prototype of an automatic personality identification system. We studied modern physiognomic rules and labeled a dataset of about 240 images for 10 different features. In addition, we investigated the measurement-based approach and proposed and developed an improved methodology for extracting face features from nearly any type of image. We also increased the number of features from 3 to 7, modified the calculation method with a cutting-edge machine learning-based landmarks detection model, and achieved a classification accuracy of 70% to 80% for each feature. Finally, we generated the ultimate personality report by comparing classification results to the personality trait knowledge library.

Keywords: *Physiognomy, Face reading, Personality, Automatic personality identification system, Facial attribute estimation*

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CHAPTER 1: INTRODUCTION

1.1 What is Personality?

When we see people around us, one of the very first things that grab us is how diverse they are from each other. Some people are extremely talkative, while others are quite silent. Some people are active, while others prefer to sit on the couch. Some people worry a lot, while others appear to be unconcerned practically all of the time. When we use adjectives like "talkative," "quiet," "active," or "anxious" to characterize everyone around us, we are referring to a person's personality—the distinct ways in which people vary from one another.

Multiple evaluation approaches are used to evaluate a person's personality traits. They include but are not limited to, questionnaires, word association tests, picture association tests, graphology, body language, audio voice, and physiognomy.

1.2 What is Physiognomy?

Physiognomy ('physis', meaning "nature," and 'gnomon', meaning "judge" or "interpreter"), also known as Face Reading, is the process of measuring a person's personality or character based on their external appearance, specifically one's face. Face reading is a regular component of human nature. Groups of early people had to rely on non-verbal cues before there was even a spoken language. Survival relies on prehistoric man's ability to understand the message in his fellow man's faces, gestures, and body language. We still read faces now, even if it's merely to identify one another, and most of us have an instant impression of everyone we encounter.

Everything matters in face reading. We know that every feature on our face serves a functional purpose: eyes for sight, noses for breathing, and ears for listening. However, we may not notice that each feature offers information about a person's personality. From a physiognomy perspective, eyes show wariness, noses imply support, and ears indicate independence. Every feature and line on a face is a tangible manifestation of the owner's mental, emotional, and spiritual patterns and behaviors. Our face is a visible representation of our life. Physiognomy denotes the relatively unchanging facial features that can be used to interpret a person's inner or hidden attributes. Details of the forehead, brows, eyes, nose, and mouth, etc. are all included in the facial features.

1.3 History and Types of Physiognomy

The practice of physiognomy or face reading is an ancient art known around the world. Some texts on this fascinating subject have been preserved through the ages, and it has been a part of Chinese medicine for centuries. It has been a facet of Western civilization starting with the Greeks, who studied and wrote about the relationship between facial structure and character. Hippocrates, the Father of Medicine, was familiar with physiognomy. Aristotle, in his addendum to History of Animals, discussed how to read a person's character from his face. He also wrote a treatise devoted entirely to the study of face reading.

Face reading is an old art form that is practiced throughout the world. Some literature on this fascinating subject has survived the years, and it has long been used in Chinese medicine and jury selection. It’s been a part of Western civilization since the Greeks investigated and wrote about the relationship between facial form and character. The reason that these works have survived illustrates how highly esteemed they were over a substantial span of Western history.

Many notable Western scholars have studied and respected physiognomy over the years. The very first significant development in physiognomy in the West occurred in 1775, with the publishing of Essays on Physiognomy by Johann Kasper Lavater, a Zurich pastor and poet. His work was the first Western attempt to treat physiognomy as a scientific subject, with scores of magnificent pictures and a thorough effort to develop a classification system.

1.4 Validation of Physiognomy

Identification of a person's personality using facial images has been one of the most fascinating research areas in the recent decade, not just for computer scientists but also for psychologists. A few people assume that it is impossible to determine a person's qualities from facial traits [1], though other studies have shown that it is feasible to deduce a person's characteristics from facial photos [2], [3], and [4]. Psychologists have identified and examined psychological qualities such as emotional stability, dominance, sensitivity, intelligence, confidence, trustworthiness, and responsibility.

1.5 Digital Physiognomy

Previously, all facial attributes like the shape of the face, the size of the forehead, the length of the eyes and nose, the density of the eyebrows, and so on, were humanly assessed by an expert face reader for various applications all over the world. Due to advances in computational technologies, image processing techniques, and machine learning algorithms over the last decade, the physiognomy approach has shifted toward digital personality systems, which can generate an individual's entire personality report from a single face image as input.

Computational personality analysis is becoming a popular field of research in a variety of applications, including job applicant recruitment from video CVs [5], recognition of convictable faces for prospective criminal record [6], organizational sustainability via teamwork [7], and personality identification on social media platforms Like Twitter [8].

1.6 Scientific Motivation

The ChaLearn Looking at People: First Impressions Apparent Personality Analysis Challenge was organized in 2016 by the European Conference on Computer Vision (ECCV). The competition's purpose was to automatically evaluate visible personality qualities in a video of persons speaking in front of a camera. Their goal was to generate a personality report from a one-minute video CV utilizing body language and audio voice to extract personality attributes. As a result, we'd like to build something similar but with simply a frontal facial photograph only.

1.7 Problem Statement

Physiognomy-based computational personality analysis solutions based on frontal faces have already been proposed and developed for a range of applications in China, Australia, Singapore, Taiwan, Korea, and Poland, but they are non-generic and not fully accessible or re-usable. Similarly, they are restricted from using the annotated dataset they created to train the algorithms elsewhere due to organizational constraints. As a result, we're interested in combining the many types of solutions currently available and proposing our automatic personality recognition method for local Pakistani people, based on state-of-the-art physiognomic principles. The objectives of the thesis are following.

A. Dataset Preparation

1. To study the Eastern and Western Physiognomy rules of face reading
2. To prepare a sample dataset of local people

B. Implementation

3. To study all the available computational physiognomy techniques
4. To study the required image processing techniques and ML algorithms
5. To implement & compare available methods (Calculation & Neural Network)
6. To modify the available techniques with additional features
7. To compare our model with existing Techniques

1.8 Research Significance and Applications

The thesis has multiple research implications in the research community, as well as being used in a variety of applications. Only a few of them are following.

1. To the best of our knowledge, this is the first-ever Automatic Personality Recognition System offered in Pakistan that uses physiognomy and powerful computer vision and machine learning algorithms.
2. This is a completely non-invasive method in which a system takes an input face image and generates a personality traits report in a matter of seconds, all without the need for a face reader expert.

3. The computational approach we presented can assist us and physiognomy professionals in annotating and validating a huge dataset, respectively.
4. This platform can also be utilized as a standard foundation for some highly specific applications, such as tracking students' progress, organizational team building, patient health monitoring, and security, forensic, and criminology research reasons.

1.9 Thesis Outline

The thesis other chapters’ contribution is as follow.

The second chapter presents a literature review and our benchmark. It discusses all of the computation physiognomy techniques that are currently known, as well as their distinct approaches, datasets used, and contributions made. It had included a limitation in each research project. Finally, it provided a summary table of the total techniques available, while highlighting the most significant parameters.

The third chapter is about dataset collection. It went over the entire process of creating our local dataset from scratch. It discussed the selection of physiognomy literature and books, the creation of face charts, the collection of images, and the labeling of data.

The fourth chapter focuses on methodology. It goes over the available measurement-based computational approach in-depth, as well as the step-by-step modification process. The chapter presents the rule formulation, threshold settings, and implementation with a visual representation of images very effectively.

The fifth chapter is about evaluating the results and creating a personality assessment report. It reflects the accuracy of each feature classification using a measurement-based approach, as well as the subject's final personality report.

The sixth chapter discusses the overall thesis conclusion as well as some future recommendations.

CHAPTER 2: LITERATURE REVIEW

Automating the principle of personality identification using advanced computational approaches is a new area of research in the fields of computer science and psychology. From 2006 to 2017, four different types of techniques were used including Neural Networks [9], [10], Size Measuring [11], [12], [13], Personality Questionnaire (16PF) [14], [15], and a Fuzzy Logic [16] based techniques are among the ways used. Each approach is explained in detail in the sections below, and all approaches are summarized in chronological order in Table 2.1. The author gives an overview of the work that will be covered in the methodology chapter at the end of the chapter.

2.1 Neural Network-Based Approach

The Neural Network-based approach developed in 2016 [9], [10], annotated dataset of 5562 Chinese people and celebrities photos for 19 facial features of 5 different face components (each feature has 3 classes) and correlate with around 58 personality traits. They proposed an FRP (Facial Region Pooling Layer) based deep convolutional neural network model called FRP-net for features extraction and facial attribute estimation to generate the final result. Also, in the neural network model, they focused on the fine-grained facial attributes (length of nose, single/double-fold eyelid, the density of eyebrows, etc.). The model is trained on 66744 augmented images of the dataset. The challenging point is that the dataset is not publicly available because of their Institutional restrictions), so we cannot reuse the built-in dataset nor will be able to exactly compare the result because of the difference in dataset sizes and our and their annotation styles.

2.2 Size Measurement-Based Approach

In a size measurement-based approach [13] developed in 2006, they retrieved facial features of 11 attributes of 5 different face components using AAM (Active Appearance Model) and classified them into several classes using multi-class SVM. The Classification findings show that the proposed approach and people's perspectives are similar when it comes to classifying face traits into different groups. The proposed technique was tested on 200 samples of people and achieved a classification rate of 85.5% for all facial component features. They merely mentioned that the proposed method is an effective solution for analyzing face features and providing physiognomic information from a facial image. The same type of approach presented in 2016 [11] and 2017 [12], created a measuring method to search for the facial feature points for physiognomy and compared with another k-means clustering method which gives the same result. They measured each feature of the face using image binarization (Histogram and Otsu method), then identify the connected component and then find the features' points which can be used for features distance measurements for personality identification. They used the ORL face database for testing. They extract 22 facial features of 5 different components and relate them with the multiple personality traits.

2.3 Personality Questionnaire Based Approach

In a Personality Questionnaire-based Approach in 2013 [14] & 2017 [15], first created a Facial Elements and Personality database of volunteers by filling out a well-developed Cattel's sixteen personality factor (16PF) questionnaire. Then, a Personality Analysis System was created, which can learn traits (relationships) between five face components (no significant information about the sorts of features was provided) and a professional personality test (16 Personality Traits). Based on the premise that people with similar facial features have the same personality. So, given an input image, the suggested system will generate the related personality report by combining the personality scores from persons in the created database who have similar facial traits. Furthermore, they simply proposed a technique to automate the idea of physiognomy and did not present any desktop application. The fundamental difficulty with questionnaire-based techniques is that large databases cannot be prepared for feature correlation.

2.4 Fuzzy Logic Based Approach

The combined approach of Fuzzy and Neural Network in 2010 [16], proposed a hybrid expert system that can recognize some personality characteristics, based on human face pictures. They used a neural network and fuzzy system for pattern recognition and classification. The inference engine, employing the knowledge base, generates short personal characteristics articulated in natural language, which are delivered as the expert system's output. The knowledge base contains fuzzy IF-ELSE rules, and the inference engine generates the output choice using fuzzy logic. The rule basis and fuzzy logic inference are applied separately from the neural network. The network can learn from instances of face photos and the personality types that have been assigned to the presented faces. The knowledge is concealed in the link weights of the neural network. Following the learning process, the neural network may be used to identify and classify people using its knowledge. However, except for a mention of some of its applications, no detailed information regarding the face features they employed, the personality traits they correlated, the dataset, the implementation, or any comparable results are provided.

There are some other related approaches [3], [2] which they applied and used for validation purposes, means to verify the correlation between concepts of personality recognition from facial features using advanced computational methods and the actual personality of an individual recognized by self-reported personality tests, in addition to the above techniques available in literature so far. They investigated the relationship between facial features, personality traits, and intellect in [2], using the 16PF self-reported personality exam of 168 persons. Their findings suggest that certain personality traits may be successfully detected from face photos, but that predicting IQ from face photographs is difficult.

2.5 Summary

In this chapter, we reviewed the existing computational physiognomy literature and discovered that neither a direct built-in solution nor a labelled dataset exists for assessing personality from facial features. To classify features, we'll need both a dataset and a set of rules. As a result, we investigate physiognomy background knowledge, develop rules, and label the 240-image dataset. Then we consider using a measurement-based approach to create an automatic personality identification system that takes an input image of a person, extracts seven different facial features, classifies them into multiple classes, and generates a personality traits report. Our solution will be used as a prototype for future research into facial feature estimation and real-world applications based on physiognomy.

Table 2.1. Summary table of literature review

#	General Info	Title	Features	Methodology	Dataset
1	2006, IEEE, Conference, China	**Measurement Based Approach** Automatic Physiognomic Analysis by Classifying Facial Component Features [13]	11	1. Extract Features through Active Appearance Model (AAM) 2. Classified through SVM	200 Images (online)
2	2013, ACM, Conference, Taiwan	**Questionnaire Based Approach** Physiognomy Master: A Novel Personality Analysis System Based on Facial Features [14]	5	1. Construct a questionnaires database of volunteers by using 16PF 2. Then compare the features of Input Face with the features of a person already available in the database	-
3	2016, IEEE Conference, China/Australia	**Measurement-Based Approach** Facial Feature Extraction and Recognition for Traditional Chinese Physiognomy [11]	5	1. Image Binarization through histogram and Otsu method 2. Identify connected components using the two-pass method 3. Locate the features' points	ORL Face Database (29 Images)
4	2016, Springer Conference, China	**Neural Network-Based Approach** Computational Face Reader [9]	19	1. It used 2 pre-trained models including; 2. Alex Net model [10], 3. VGG16 model [19]	5,562 Images (online)
5	2016, Elsevier, Journal, China	**Neural Network Based Approach** Computational Face Reader Based on Facial Attribute Estimation [10]	19	1. Trained FRP based DCNN model 2. It also addressed few fine-grained face features like eyelid folding and eyebrows density	5,562 Images (online)
6	2017, Elsevier, Journal, China	**Measurement-Based Approach** A Physiognomy-Based Method for Facial Feature Extraction and Recognition [12]	5	1. Add a k-means classification factor after extracting features points 2. At the end the results of k-means and shape-based physiognomy classification are compared, which gives the same result	ORL Face Database (29 Images)

CHAPTER 3: DATASET COLLECTION

3.1 Physiognomy Rules

There are numerous features with distinct personality traits that are mentioned in books written by various authors. The majority of the features are similar, but a few stand out. We researched multiple books by various writers in-depth for this project and extracted all unique features, which we then transformed into face charts for easier data labeling.

3.1.1 Books Selection

We studied and gathered a set of books from the most relevant modern physiognomy literature that is most referenced by computational physiognomy scholars and is available online in English. **Fig.** ***3.1*** depicts the most frequently mentioned physiognomy books. We carefully analyzed and retrieved all unique features from the top two books, including Book-1 (The Ancient Science of Face Reading: How To Know Anyone At A Glance [17]) and Book-2 (Amazing Face Reading [18]). We extracted 25 features from Book 1 and a total of 43 features from Book 2. Table 3.1 includes a few examples of facial features.

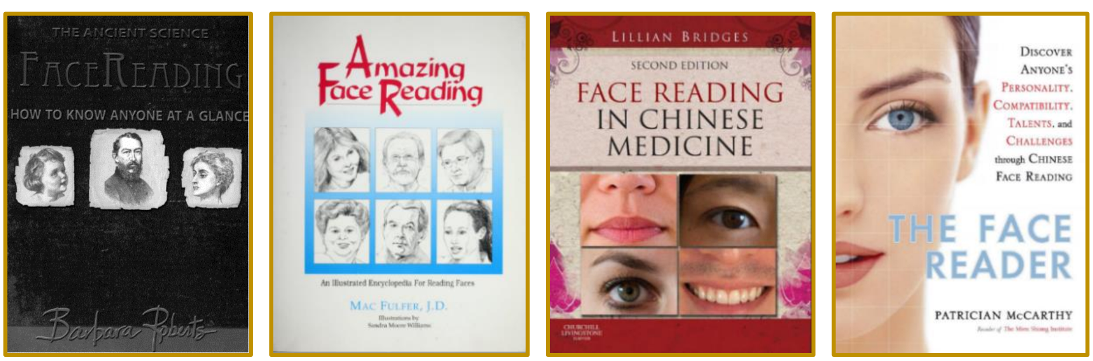


Fig. 3.1. Set of most cited physiognomy books [17], [18]

3.1.2 Face Charts Creation

We identified about 40 face traits in total from both books. As shown in Fig. 3.2, all features have multiple classes, and each class has its identification criteria, which are visually represented and explained in descriptive form. While turning pages and tallying the class description with the real image, it is difficult to recognize and apply the exact class label to each subject image feature. So, to conveniently label the dataset, we developed a one-pager face chart with the total number of classes per feature. Fig. 3.4 depicts a sample face chart for one feature.

Table 3.1: List of Sample Face Features Extracted from Book-1 and Book-2

Few Examples of *Face Features* Mentioned in Physiognomy Literature	
1. Hair Textures	11. Eyebrows Height
2. Hair Colors	12. Eyebrows Density
3. Forehead Shapes	13. Eyebrows Shapes
4. Forehead Lines	14. Cheeks
5. Forehead Height	15. Noses
6. Eyes Colors	16. Lips
7. Eyes Sizes	17. Teeth
8. Eyes Shapes	18. Ears Height
9. Eyelids	19. Ears Shapes
10. Lower Eye Area	20. Ears Sizes

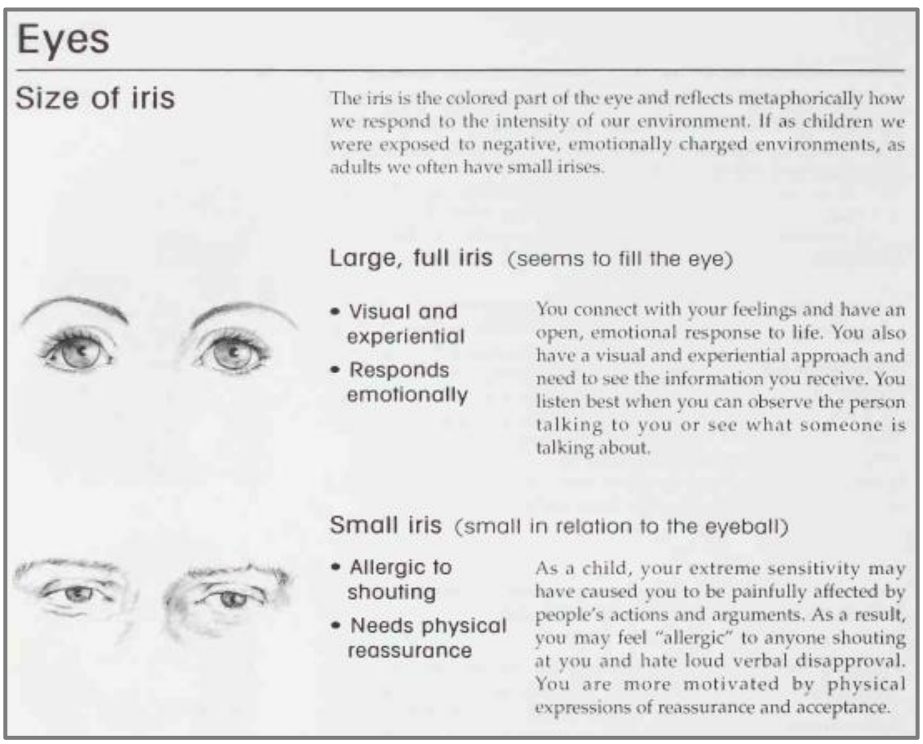


Fig. 3.2. Descriptive explanation of identification criteria for eye size [18]

3.1.3 Feature Selection for Labelling

In this phase, we selected 10 features from a total of more than 40 accessible features that may be directly quantified using the Dlib library [19]. As demonstrated in Fig. 3.3, Dlib is an open-source package available in both C++ and Python that returns 68 landmark points from any input face image. The following are the features that we chose for labeling our dataset;

1. Eyes Size
2. Eyes Shape
3. Eyes Angle
4. Eyebrows Height
5. Eyebrows Shape
6. Mouth Size
7. Mouth Angle
8. Lips Size
9. Chine
10. Jaw

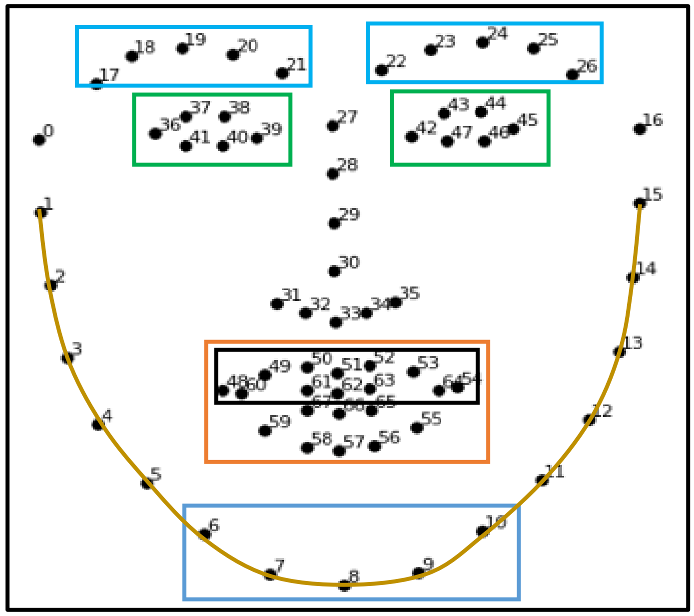


Fig. 3.3. Dlib's extracted 68-landmarks points

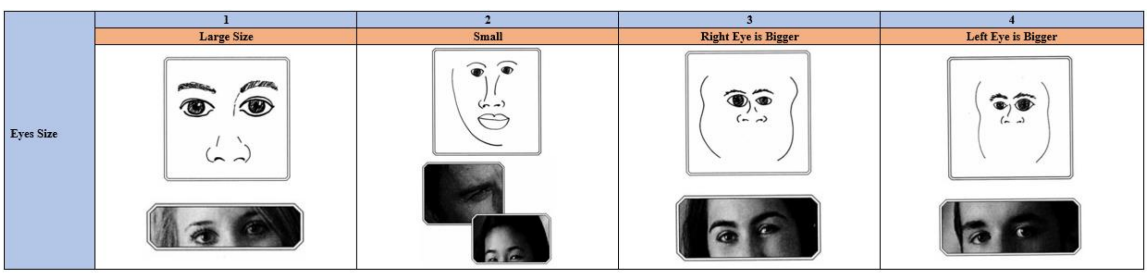


Fig. 3.4. Face chart for eye sizes with total number of classes and visualization [17], [18]

3.2 Images Collection

This is one of the most important phases of the project. Our key element is a collection of photographs that are needed for both training and testing algorithms and neural models. Because there was no single dataset available online, we will use these photos as a baseline for future personality trait identification and feature extraction problems. We gathered non-Chinese photographs from a variety of sources to make them as generic as possible.

3.2.1 Pakistanis Images

We collected 100 passport-size photographs from Google (sample images shown in **Fig.** ***3.6***) and 40 images of CEME and NCRA's students, staff, and faculty (as shown in **Fig.** ***3.5***). In this Google's based dataset, we faced several major challenges. First, it is difficult to tell the difference between Pakistanis, Indians, and Bangladeshis. Second, the majority of passport-size photos on the internet are manipulated and not authentic. This means that these photos lack moles and other real corners. Third, as the size of the dataset grows, the repetition of labels for each individual grows. Fourth, the majority of the photographs we gathered are of varying sizes and resolutions. As a result, using such a dataset for texture-based feature extraction in the future will be problematic.

Fig. 3.6. Set of Pakistani peoples' images collected from Google

Fig. 3.5. Set of images of CEME and NCRA (students, staff, and faculty)

3.2.2 Non-Pakistanis and Non-Chinese Images

We identified around 20 unpaid datasets online with frontal and neutral face photographs while focused on overcoming the aforementioned obstacles and locating high-quality images. Then, as shown in Table 3.2, we filtered and selected the top 5 high-quality, non-Chinese datasets, resulting in around 1100 total photographs.

Table 3.2: list of open-source datasets (neutral images) used in our dataset construction

#	Dataset	License	Region	# of Images
1	SiblingsDB [20]	Politecnico di Torino University	Italy	180
2	FEI Face Database [21]	AI Lab of FEI in São Bernardo do Campo, São Paulo	Brazil	200
3	The Chicago Face Database [22]	University of Chicago, US	Diff. Ethnicity	597
4	The Tufts Face Database [23]	Tufts University, US	USA	112
5	MIT-CBCL-Facerec-Database [24]	MIT University, US	USA	10

Fig. 3.7 displays a sample image from each dataset. The light intensity, image resolution, and background are all consistent across all photographs in these datasets.

Fig. 3.7. Set of non-Pakistani & non-Chinese images collected for dataset construction [20], [21], [22], [23], [24]

3.3 Labeling Based on Number of Classes

As no clear direction has been stated in any computational physiognomy literature, data labeling was the next most essential part of the project. As a result, we labeled our dataset depending on the number of classes distribution for each feature.

3.3.1 Uniform Distribution of Classes

There are three classes for each feature in [10]. We labeled our Pakistanis (130x Images) and Non-Pakistanis (100x Images) datasets for the seven different features listed in Table 3.3 based on this consistent distribution.

Table 3.3: Features' uniform distribution of classes

1	2	3	4	5	6	7	8	9	10
Area of Eyes	**Distance of Eyes**	**Eye Corners**	**Eyebrows Height**	**Shape of Eyebrows**	**Area of Mouth**	**Mouth Corner**	**Shape of Lips**	**Chin**	**Jaw**
1 Large	1 Large	1 Bullish	-	1 Eight	1 Large	1 Bullish	1 Thick	-	-
2 Medium	2 Medium	2 Horizontal	-	2 One	2 Medium	2 Horizontal	2 Medium	-	-
3 Small	3 Small	3 Dropping	-	3 Inverted-Eight	3 Small	3 Dropping	3 Thin	-	-

3.3.2 Non-Uniform Distribution of Classes

Uneven distribution of classes for individual traits was indicated in the physiognomy texts that we researched and pulled information from when creating face charts. As a result, we labeled our Pakistanis (130x Images) and Non-Pakistanis (100x Images) datasets for the 10 different features listed in Table 3.3.

Table 3.4: Features' non-uniform distribution of classes

1	2	3	4	5	6	7	8	9	10
Eyes Size	**Eyes Shape**	**Eyes Angle**	**Eyebrows Height**	**Eyebrows Shape**	**Mouth Size**	**Mouth Angle**	**Lips Size**	**Chin**	**Jaw**
0 N/A	0 N/A	0 N/A	0 N/A	0 N/A	0 N/A	0 N/A	0 N/A	0 N/A	0 N/A
1 Large	1 Wide	1 Up	1 Low	1 Arched	1 Large	1 Turns Up	1 Full	1 Broad	1 Broad
2 Small	2 Close	2 Down	2 High	2 Rounded	2 Small	2 Straight	2 FL Lip	2 Very Broad	2 Narrow
3 Right Eye Bigger	-	3 No Angle	3 Uneven	3 Flat	-	3 Turns Down	3 FU Lip	3 Long	3 Left Side Bigger
4 Left Eye Bigger	-	-	-	4 Unibrow	-	-	4 Thin	4 Small	-
-	-	-	-	-	-	-	5 Bow	5 Round	-
-	-	-	-	-	-	-	-	6 Straight	-
-	-	-	-	-	-	-	-	7 Pointed	-

3.4 Summary

In this chapter, we covered how to build a dataset from the scratch. Initially, we studied the top 2 physiognomy books, comprising Books 1 and 2, and extracted over 40 distinct features. Face Chart was constructed based on those features to aid in the data labeling process. In addition, we chose 10 features that may be measured and retrieved using Dlib 68-landmarks points. Then we gathered 100 passport-size Pakistani pictures from Google, 30 from EMEnents, and 1100 from built-in online open-source datasets. Finally, we labeled these datasets based on their Uniform and Non-Uniform Distribution of Classes.

CHAPTER 4: METHODOLOGY

4.1 Available Approach

In 2016 and 2017, [11] and [12] made significant contributions to the measurement-based method. They employed a calculation-based method to measure and classify face features for personality trait recognition. The thresholding of the histogram values for an input image yields the binary image. They then use a two-pass connected component approach to determine the feature's region. The contour is then classified using the k-means approach and the calculation method. The block diagram of the measurement-based feature extraction approach is shown in Fig. 4.1.

They discussed and developed classification rules for five different features during their research. However, they conducted experiments on 29 different topic photographs and only displayed the results of three features: eye shape, mouth shape, and face shape. According to physiognomy literature, each feature is classified into many classes. Eyebrow shape is split into four classes, eye shape is divided into two classes, eye shape is divided into four classes, eye shape is divided into two classes, nose shape is separated into seven classes, and mouth shape is divided into two classes.

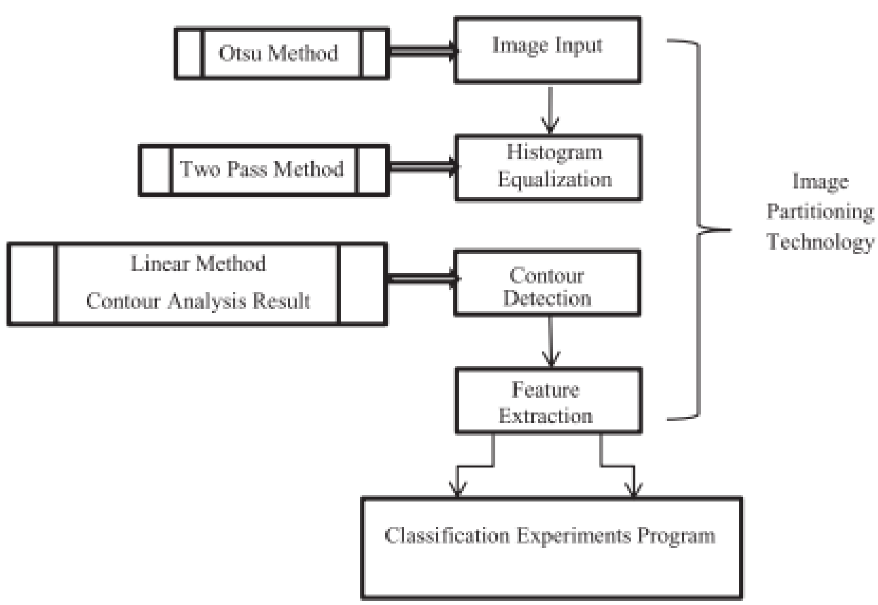


Fig. 4.1. The block diagram of facial feature extraction [12]

4.1.1 Procedure

The system takes an image as input and converts it to binary using the histogram, adaptive threshold value, and Otsu method, as shown in Fig. 4.3. The two-pass method is used to identify the connected areas of the binary image shown in Fig. 4.2. The internal and external contours of the component are divided into two parts: contour and hole. As shown in Fig. 4.4, exterior lines (face outline and hair) are represented by green lines, while interior lines (eye, nose, and mouth) are represented by yellow lines. The physiognomy approach and the k-means method are used to classify each facial feature in Fig. 4.5, and the results are nearly identical.

Fig. 4.3. Binary images [12]

Fig. 4.2. Connected images [12]

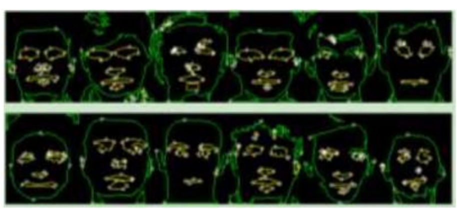


Fig. 4.4. Endpoints of each facial features [12]

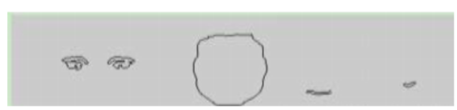


Fig. 4.5. Features contour [12]

4.1.2 Major Issues

This is the only technique in the literature that mentions the construction of rules for feature classification based on physiognomy and is a measurement-based strategy for feature extraction for face reading. However, the approach has some very common shortcomings. First, due to varying light intensity and shade levels, exact feature contour extraction (endpoints) is not achievable for all binary images. Second, only three of the five features were specified in the research effort, and the results were only shown for three of them. There are more than 40 features that can be extracted for each subject. The idea behind physiognomy is that the more features you extract, the clearer the genuine personality qualities become. Third, similarly, there is no mention in this study of a final personality report or a knowledge library concerning matching features.

4.2 Our Modified Approach

To solve the three research gaps described above in measurement-based computational physiognomy, we created, implemented, and tested our model with a new approach, as shown in Fig. 4.7's block diagram. The following is a detailed description of the step-by-step approach shown in **Fig. *4.6***:

First, we take a JPG input-colored image (recommended size 300x400). The image is then pre-processed by cropping the frontal face and aligning it. We use the Dlib library's shape predictor function to identify the 68-landmarks points. Using landmarks, we precisely find our desired features. Dlib allows us to recognize landmarks and extract features from nearly all images. Previously, extracting feature lines from face and hairlines for all images was difficult. Then, we develop rules for seven different features, including Eyes Size, Eyes Shape, Eyes Angle, Mouth Size, Mouth Angle, Lips Size, and Jaw Size Classification. All of these criteria are written generically concerning image size. We also attempted to develop methods for binarization-based features like eyebrow size classification, however, the results were not very significant based on our dataset. The mechanics of rule formation and associated pseudocode are covered in length in the parts that follow. Finally, we generated a personality report using the physiognomy knowledge library.

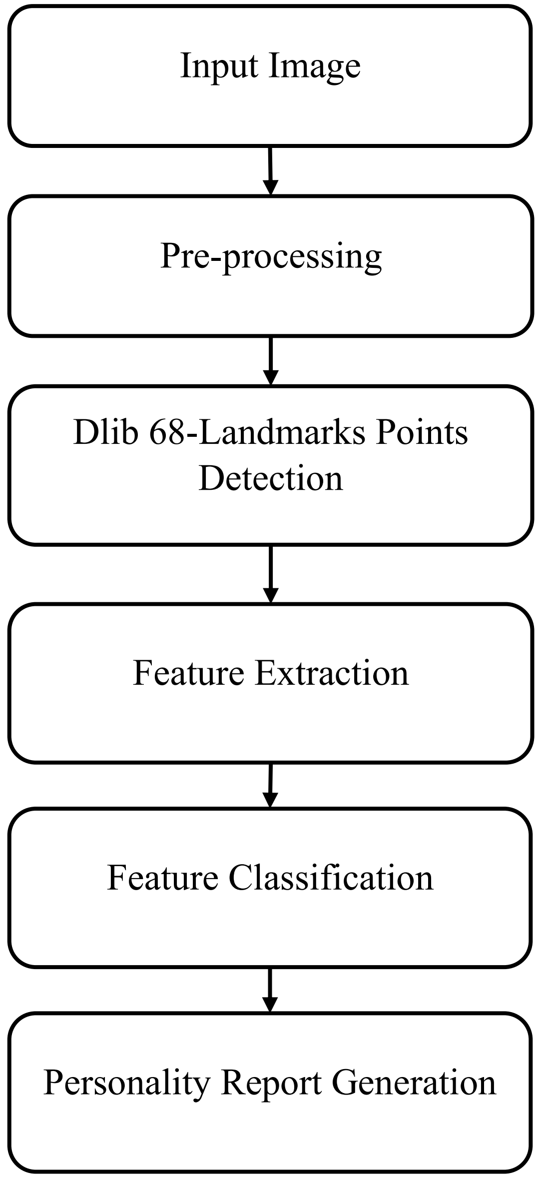


Fig. 4.7. Block diagram for our measurement-based modified approach

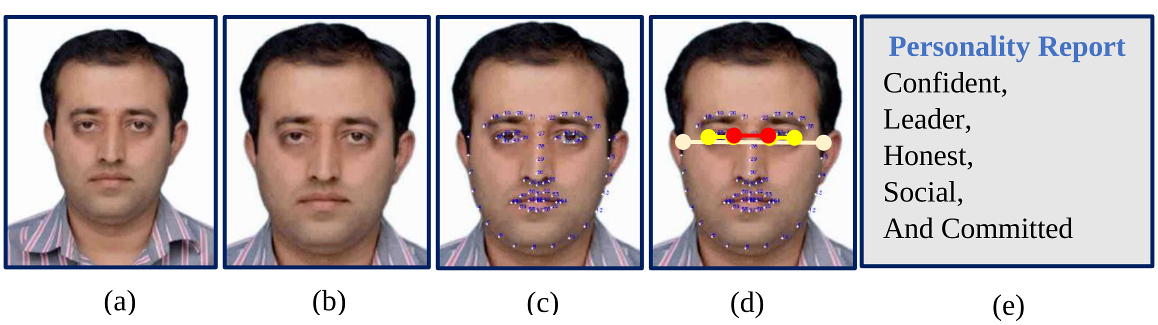


Fig. 4.6. Step-by-step process of our measurement based modified approach (a) Input image (b) Pre-processing (c) Landmarks detection (d) Features extraction & classification (e) Personality report

4.3 Rules Formulation

4.3.1 Rule # 1. Eyes Size Classification

The size of the eye refers to the size of the iris. The iris is the colorful component of the eye that figuratively represents how we respond to the intensity of our environment. There are two types of eyes: large eyes and small eyes. Large eyes indicate a large iris (one that appears to fill the entire eye), whereas small eyes indicate a small iris (small to the eyeball).

We identify the landmark points using Dlib and generate a generic classification rule based on the ratio of the average enclosed area of eyes to the total enclosed area of the face. We estimated the eye size values for our training dataset images and compared the results to our labeled data to determine the threshold value of 0.9 percent at which classification accuracy stays more than 70%. According to our testing results, the formulation's ultimate accuracy is 77%.

Rules Formulation:

$$Avg\ Eye\ Area\ = \frac{Left\ Eye\ Area + Right\ Eye\ Area}{2}$$

$$\%\ Eye\ Area\ = \frac{Avg\ Eye\ Area}{Total\ Face\ Area} *\ 100$$

And the Individual Eyes Area and Total Face Area are calculated in Python from the enclosed surface shown in **Fig. 4.8**

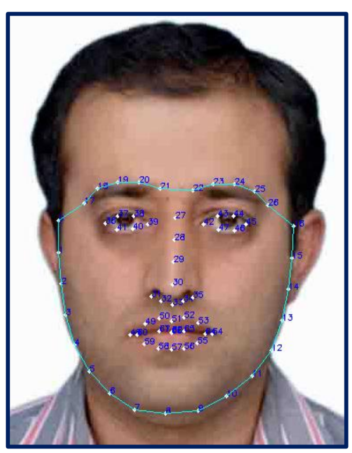


Fig. 4.8. Enclosed area used for eye size classification **(Small Eyes)**

4.3.2 Rule # 2. Eyes Shape Classification

It's no surprise that eyes have been called "the windows of the soul" because they are the primary sensory organ for light. Our eyes are a reflection of our outlook, attitudes, and openness. It's all about perspective when it comes to the shape or spacing of the eyes. Our eyes are around one eye's width apart on average as shown in **Fig. *4.9***. Wide-set and narrow-set eye shapes are the two basic types of eye shapes. If the distance between the two eyes is greater than the length of one eye, it is regarded as a wide set of eyes; otherwise, it is considered a close set of eyes. The eye shape is calculated as follows.

The value for the threshold is set to 70%. Close-set of eyes are defined as those with a percent eye width less than or equal to the threshold value, while the wide set of eyes are defined as those with a percent eye width higher than or equal to the threshold value. On the testing dataset, total accuracy of 77% is reached.

Rules Formulation:

To begin, we normalized the individual widths of the Left Eye, Central Width, and Right Eye with Total Face Width. Then calculated the,

$$Avg\ Eye\ Width = \frac{Left\ Eye\ Width + Right\ Eye\ Width}{2}$$

$$\%\ Eye\ Width = \frac{Avg\ Eye\ Width}{Central\ Width} * 100$$

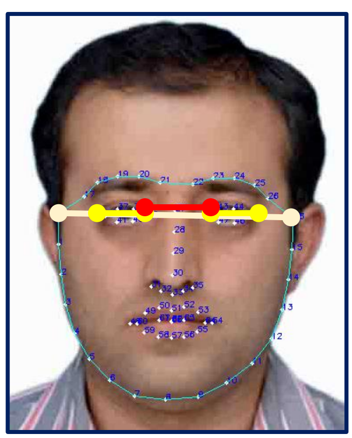


Fig. 4.9. Width representing eyes shape classification
(Close Set)

4.3.3 Rule # 3. Eyes Angle Classification

Our eye angle reflects our worldview and perspective. The angle of our eye will reveal if we are optimists, pessimists, or realists. The right eye reflects our professional or business attitude, whereas the left eye reflects our interpersonal and personal life. Angles of the eyes are classified into three types: no angle angles down and angles up as shown in **Fig.** ***4.10***. The basic technique for classifying any type of eye into these three classes is represented in the pseudocode below and shown in **Fig.** ***4.11***.

(a) (b) (c)

Fig. 4.10. (a) No Angles, (b) Angles Down, (c) Angles Up

Pseudocode:

If (LLP == LRP OR RLP == RRP)

Class = No Angle

Elseif (LLP > LRP AND RRP > RLP)

Class = Angle Down

Elseif (LLP < LRP AND RRP < RLP)

Class = Angle Up

Else

Difference_LE % = (Abc(LLP - LRP)) / Face_Height

Difference_RE % = (Abc(RLP - RRP)) / Face_Height

Class = Class of Less Difference_%'s Value

Whereas the Variables are:

LLP = Left Eye Left Point Height

LRP = Left Eye Right Point Height

RLP = Right Eye Left Point Height

RRP = Right Eye Right Point Height

Difference_LE = Height Difference btw Left Eye's Points

Difference_RE = Height Difference btw Right Eye's Points

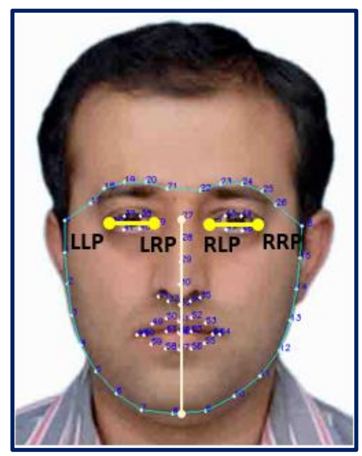


Fig. 4.11. Rules formulation for eyes angles classification **(Angles Up)**

4.3.4 Rule # 4. Mouth Size Classification

Our mouth, more than any other facial feature, brings us into direct and continual contact with our surroundings. This intriguing organ not only reflects our expressive style, but also our level of sensuality and even how we understand what people say to us. In proportion to the face, mouth size is grouped into two types: small mouth and large mouth as shown in **Fig.** ***4.13***.

The threshold value of 37% is obtained by calculating mouth size in proportion to face width as shown in **Fig.** ***4.12*** using the following rule. Mouth widths less than 37% are classified as small, and those more than that as large. On testing data, a final accuracy of 76% is achieved.

Rules Formulation:

$$\% \, Mouth\ Width \ = \frac{Mouth\ Width}{Total\ Face\ Width} * \ 100$$

(a) (b)

Fig. 4.13. (a) Small Size, (b) Large Size

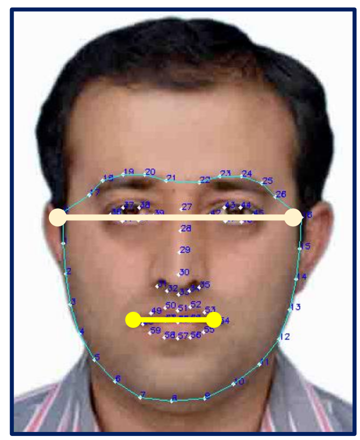
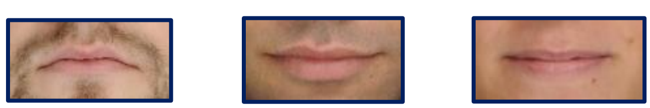


Fig. 4.12. Rules formulation for mouth size classification **(Small)**

4.3.5 Rule # 5. Mouth Angle Classification

The angle of the mouth shows how people listen. It is classified into three types: turns up, straight, and turns down as shown in **Fig.** ***4.14***. When the face is relaxed and not smiling, this feature may be computed accurately. To achieve the best throughput rate, all images in the dataset are extensively filtered to choose only neutral faces as shown in **Fig.** ***4.15*** and then aligned during the pre-processing stage. The pseudocode is provided below to help you fully grasp the measuring technique.



(a) (b) (c)

Fig. 4.14. (a) Angle Down, (b) Angle Up, (c) Straight

Pseudocode:

If (LP > CP && RP > CP)

Class = Turns Down

Elseif (LP < CP && RP < CP)

Class = Turns Up

Else

Class = Straight

Whereas the Variables are:

LP = Y-Coordinate of Left Point

RP = Y-Coordinate of Right Point

CP = Y-Coordinate of Central Point

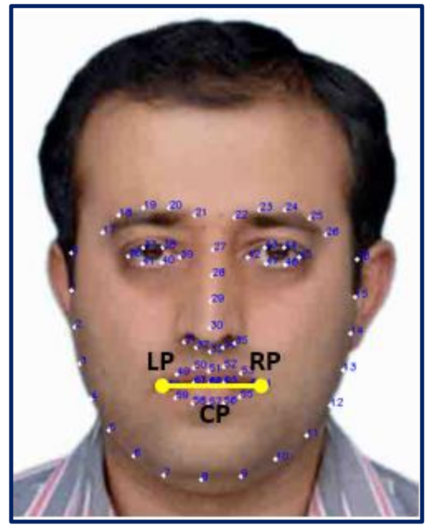
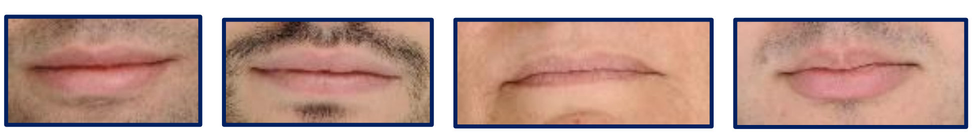


Fig. 4.15. Rules formulation for mouth angle classification **(Turns Down)**

4.3.6 Rule # 6. Lips Size Classification

The lips are the portions of our mouth. The upper lip signifies feminine energy and components of our inner life, especially our feelings. The bottom lip represents masculine energy, indicating how we react to the outside world and reflecting our concentration on the action. Lips are classified into four categories based on size. Full lips, full lower lips, full upper lips, and thin lips in our method as shown in **Fig. *4.16***, we ran the normalized values of the upper and lower lips relative to the face through a predefined threshold calculated for the training data. The pseudocode with threshold values is shown below with supportive **Fig. *4.17***.



(a) (b) (c) (d)

Fig. 4.16. (a) Full Lips, (b) Full Upper Lips, (c) Full Lower Lips, (d) Thin Lips

Pseudocode:

If (UL_Ratio > 1)

Class = Full Upper Lip

Elseif (UL_Ratio > 0.6 && LTA > 0.04)

Class = Full Lips

Elseif (UL_Ratio > 0.6 && LTA < 0.03)

Class = Thin Lips

Else

Class = Full Lower Lip

Whereas the Variables are:

FTA = Face Total Area

LTA = Lips Total Area

ULA = Upper Lip Area

LLA = Lower Lip Area

UL_Ratio = Upper / Lower Lip

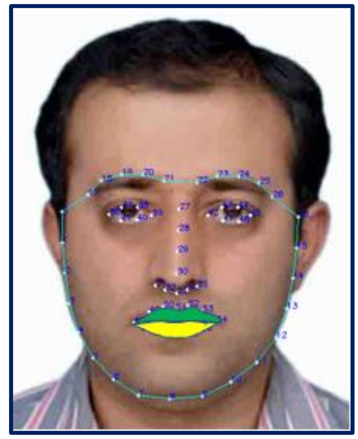
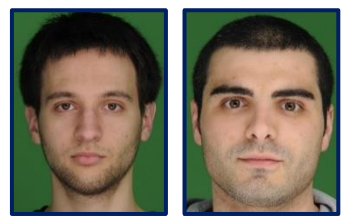


Fig. 4.17. Rules formulation for lips size classification **(Full Lips)**

4.3.7 Rule # 7. Jaw Size Classification

Jaws represent physical power, determination, and strength. The stronger the physical stamina, the larger the jaws. Based on the size, the jaw is split into two classes: big jaws and narrow jaws as shown in **Fig. *4.18***. We calculated jaw size as a percentage of face width as shown in **Fig. *4.19*** and used 79.3% as the cutoff. Jaw widths more than the criterion are characterized as broad jaws, while those smaller than the threshold are categorized as narrow jaws.



(a) (b)

Fig. 4.18. (a) Narrow Size, (b) Broad Size

Rules Formulation:

$$\% \, Jaw\ Width \; = \frac{Jaw\ Width}{Face\ Width} * \ 100$$

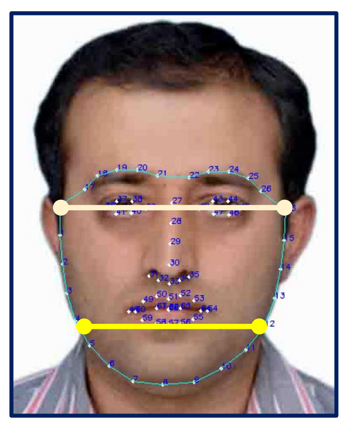


Fig. 4.19. Rules formulation for jaw size classification **(Broad)**

4.3.8 Rule # 8. Eyebrows Density Classification

The density of the eyebrows is split into two categories: thick or bushy eyebrows and thin eyebrows. We attempted to extract the density of eyebrows using image binarization and contour, but the results were unsatisfactory, thus we did not include it in the system at this time.

4.4 Summary

In this chapter, we went through the available measurement-based technique for facial feature extraction in-depth, as well as our modified approach with step-by-step instructions. In the prior technique, picture binarization was utilized to extract contours and features, and rules were developed to classify three specific features. There were several significant drawbacks, such as the image binarization approach not being applicable for all sorts of images due to differences in light intensity and shadows, and there are other features that may be extracted and can offer value to actual personality trait assessment. As a result, in our suggested approach, we used a Dlib pre-trained model to find landmarks points for individual features, and the results are almost universally applicable to all types of images. We enhanced the number of retrieved features from three to seven, and we developed proportion-based general rules for each face to classify. In addition, we created a knowledge library for each of the 7 feature classes and generated a final personality report for the input image.

CHAPTER 5: EXPERIMENTATION AND RESULTS

5.1 Rules Formulation's Accuracy

We trained an individual feature on 70% of the dataset to identify the threshold value that offers the highest possible accuracy and then tested that threshold value on the remaining 30% of the dataset to acquire the accuracy displayed in Table 5.1. At this point, the results we obtained and the approach we took seem fairly reasonable. Our extracted features are either proportional to the enclosed area or distance-based to the face and are entirely reliant on the location of the landmark points obtained by Dlib. Although we acquire landmark points for practically all sorts of images, the location of these points isn't as precise as we need to be to determine the genuine corners and borders of facial components. Using a deep learning technique or re-training the Dlib custom shape predictor to obtain more landmark points for each face component can assist us in precisely identifying the real size of these structural shapes and increasing classification accuracy. The details of our accuracy comparison to the benchmark are detailed in the appendix section and shown in Table A.**1**.

Table 5.1. Face features' classification accuracy of our personality identification system

#	Face Feature	Classification Accuracy (%)
1	Eyes Size	77
2	Eyes Shape	77
3	Eyes Angle	77
4	Mouth Size	76
5	Mouth Angle	77
6	Lips Size	65
7	Jaw Size	78

5.2 Face Reading Library

We employed the face reading knowledge library as shown in **Table *5.2*** (derived from physiognomy books [17] and [18]) after classifying individual facial features to associates personality traits to those classes.

Table 5.2. Face reading library

#	Feature	Classes	Personality Traits
1	Eyes Size	Large	Soft Hearted, Generous, Sentimental
		Small	Picks up minute details in other's behavior or environment
2	Eyes Shape	Wide Set	Kind-hearted, Sees Big Picture, Humanitarian
		Close Set	Detail-oriented, Precision driven, Perfectionist
3	Eyes Angles	Angles Up	Optimistic, Inspired imagination
		Angles Down	Expects problems, is Compassionate, Admits mistakes
		No Angle	Pragmatic and objective, Balanced view, Resilient under stress
4	Mouth Size	Large/Wide	Generous, Affectionate, Warm
		Small	Self-absorbed, Rich fantasy life, Makes great actor
5	Mouth Angle	Turns Up	Optimistic
		Straight	Objective, Reflective listener
		Turns Down	Mistrust what you are told, prepared to hear the worst
6	Lips Size	Full Lips	Emotionally expressive, Sense of humor
		Full Lower Lip	Can be persuasive, Focused on outcome
		Full Upper Lip	Outspoken, Expresses feelings verbally, Perceptive
		Thin Lips	Cool reserved, Mistrust flattery
7	Jaw Size	Broad	Incredible resilience, physically demonstrative
		Narrow	Sensitive to criticism, Non-competitive

5.3 Generated Personality Report

The final personality traits report is generated by integrating an input image, features identified in *Table 5.1*, and knowledge library in *Table 5.2*. The report depicted in **Fig.** ***5.2*** and **Fig.** ***5.1*** are of the subjects being used as an example throughout the formulation of the rule in the methodology section of the thesis.

Personality Identification System

Name: _EME00001
Gender: Male

#	Feature	Class Identified	Personality Traits
1	Eyes Size	Small	Picks up minute details in other's behavior
2	Eyes Shape	Close Set	Detail-oriented, Precision driven, Perfectionist
3	Eyes Angle	Angles Up	Optimistic, Inspired imagination
4	Mouth Size	Small	Self-absorbed, Rich fantasy life
5	Mouth Angle	Turn Down	Prepared to hear the worst
6	Lips Size	Full Lips	Emotionally expressive, Sense of humor
7	Jaw Size	Broad	Incredible resilience, physically demonstrative

Fig. 5.1. Sample personality identification system report # 1

Personality Identification System

Name: _DSC0019
Gender: Male

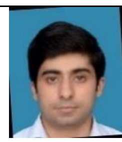
#	Feature	Class Identified	Personality Traits
1	Eyes Size	Large	Soft hearted, Generous, Sentimental
2	Eyes Shape	Close Set	Detail oriented, Precision driven, Perfectionist
3	Eyes Angle	Angles Up	Optimistic, Inspired imagination
4	Mouth Size	Small	Self-absorbed, Rich fantasy life, Makes great actor
5	Mouth Angle	Turn Up	Optimistic
6	Lips Size	Full Lower Lip	Can be persuasive, Focused on outcome
7	Jaw Size	Broad	Incredible resilience, Physically demonstrative

Fig. 5.2. Sample personality identification system report # 2

Disclaimer: *The personality report generated in* **Fig. 5.1** *and* **Fig. 5.2** *does not represent the author's point of view and is purely based on physiognomy literature. It's also at a very basic and testing level, so it can't establish the subject's actual personality at this point.*

5.3.1 Feature # 1. Results of Eyes Size Classification

#	Class	Personality Traits
1	Large Eyes	Soft Hearted, Generous, Sentimental
2	Small Eyes	Picks up minute details in other's behavior or environment

ID	Subject	Class Identified	Label	Accuracy
_EME00002		Small Eyes	Small Eyes	✓
_EME00003		Large Eyes	Large Eyes	✓
_EME00005		Large Eyes	Large Eyes	✓
_EME00006		Large Eyes	Large Eyes	✓
_EME00007		Small Eyes	Small Eyes	✓
_EME00008		Large Eyes	Small Eyes	✗
_EME00009		Small Eyes	Small Eyes	✓
_EME00010		Small Eyes	Small Eyes	✓

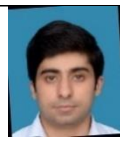
5.3.2 Feature # 2. Results of Eyes Shape Classification

#	Class	Personality Traits
1	Wide Set	Kind-hearted, Sees Big Picture, Humanitarian
2	Close Set	Detail-oriented, Precision driven, Perfectionist

ID	Subject	Class Identified	Label	Accuracy
_EME00002		Close Set	Close Set	✓
_EME00003		Wide Set	Wide Set	✓
_EME00005		Close Set	Close Set	✓
_EME00006		Close Set	Close Set	✓
_EME00007		Wide Set	Wide Set	✓
_EME00008		Wide Set	Wide Set	✓
_EME00009		Wide Set	Close Set	✗
_EME00010		Wide Set	Wide Set	✓

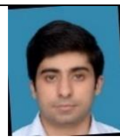
5.3.3 Feature # 3. Results of Eyes Angle Classification

#	Class	Personality Traits
1	Angles Up	Optimistic, Inspired imagination
2	Angles Down	Expects problems, is Compassionate, Admits mistakes
3	No Angle	Pragmatic and objective, Balanced view, Resilient under stress

ID	Subject	Class Identified	Label	Accuracy
_EME00002		No Angle	No Angle	✓
_EME00003		No Angle	Angle Up	✗
_EME00005		No Angle	No Angle	✓
_EME00006		Angle Down	Angle Down	✓
_EME00007		Angle Up	Angle Up	✓
_EME00008		Angle Up	Angle Up	✓
_EME00009		Angle Down	Angle Down	✓
_EME00010		Angle Down	Angle Up	✗

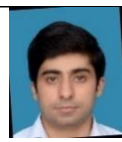
5.3.4 Feature # 4. Results of Mouth Size Classification

#	Class	Personality Traits
1	Large/Wide	Generous, Affectionate, Warm
2	Small	Self-absorbed, Rich fantasy life, Makes great actor

ID	Subject	Class Identified	Label	Accuracy
_EME00002		Large Size	Large Size	✓
_EME00003		Large Size	Small Size	✗
_EME00005		Small Size	Small Size	✓
_EME00006		Large Size	Large Size	✓
_EME00007		Small Size	Small Size	✓
_EME00008		Large Size	Large Size	✓
_EME00009		Large Size	Large Size	✓
_EME00010		Large Size	Large Size	✓

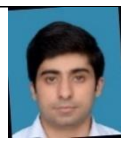
5.3.5 Feature # 5. Results of Mouth Angle Classification

#	Class	Personality Traits
1	Turns Up	Optimistic
2	Straight	Objective, Reflective listener
3	Turns Down	Mistrust what you are told, prepared to hear the worst

ID	Subject	Class Identified	Label	Accuracy
_EME00002		Angle Down	Angle Down	✓
_EME00003		Straight	Angle Up	✗
_EME00005		Straight	Straight	✓
_EME00006		Angle Down	Straight	✗
_EME00007		Straight	Straight	✓
_EME00008		Angle Up	Angle Up	✓
_EME00009		Angle Up	Angle Up	✓
_EME00010		Angle Up	Angle Up	✓

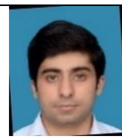
5.3.6 Feature # 6. Results of Lips Size Classification

#	Class	Personality Traits
1	Full Lips	Emotionally expressive, Sense of humor
2	Full Lower Lip	Can be persuasive, Focused on outcome
3	Full Upper Lip	Outspoken, Expresses feelings verbally, Perceptive
4	Thin Lips	Cool reserved, Mistrust flattery

ID	Subject	Class Identified	Label	Accuracy
_EME00002		Full Lips	Full Lower Lip	✗
_EME00003		Full Lower Lip	Full Lower Lip	✓
_EME00005		Full Lower Lip	Full Lips	✗
_EME00006		Full Lips	Full Lips	✓
_EME00007		Thin Lips	Thin Lips	✓
_EME00008		Full Lower Lip	Full Lower Lip	✓
_EME00009		Full Lower Lip	Full Lower Lip	✓
_EME00010		Full Lower Lip	Full Lower Lip	✓

5.3.7 Feature # 7. Results of Jaw Size Classification

#	Class	Personality Traits
1	Broad	Incredible resilience, physically demonstrative
2	Narrow	Sensitive to criticism, Non-competitive

ID	Subject	Class Identified	Label	Accuracy
_EME00002		Broad	Broad	✓
_EME00003		Broad	Broad	✓
_EME00005		Narrow	Broad	✗
_EME00006		Broad	Broad	✓
_EME00007		Broad	Broad	✓
_EME00008		Broad	Broad	✓
_EME00009		Broad	Broad	✓
_EME00010		Broad	Broad	✓

CHAPTER 6: CONCLUSION AND FUTURE RECOMMENDATIONS

6.1 Conclusion

In this thesis, we investigated the automatic personality identification system. Physiognomy, also known as face reading, is a concept that recognizes personality traits based on structural and texture-based features on the face. Physiognomy was initially used in the east for medical diagnostics and jury selection, but it was later used in the west for a variety of applications such as recruitment, team building, career counseling, photo analysis in criminology, and forensic reports.

An expert face reader manually measured all of these face attributes. However, due to advancements in computational methods and computer vision algorithms, we can now apply physiognomy rules to face images and generate personality reports. Several computational physiognomy solutions, both manual measurement, and neural network-based have already been proposed in various countries; however, they only incorporate the dataset for their people and are not publicly available. Furthermore, the measurement-based approach extracted a very limited number of features, whereas the neural network approach used a non-uniform distribution of feature classes, which does not correspond to generic or modern physiognomy literature.

In this thesis, we intend to investigate modern physiognomy principles, build a local dataset, and create a prototype of an automatic personality identification system. We reviewed the top modern physiognomic rules, extracted over 40 features, created our face charts, prepared a dataset of approximately 1200 unique general images, and labeled approximately 240 images for 10 different features. We thoroughly investigated the measurement-based approach and proposed and developed our improved methodology for extracting face features from nearly any type of image. We also increased the number of features from 3 to 7, modified the calculation method with a cutting-edge machine learning-based trained model of Dlib, and generated the final personality report while comparing classification results with the knowledge library. With an accuracy of 70% to 80%, we can classify characteristics into the appropriate class.

6.2 Future Recommendations

There are still plenty of opportunities to work in this field, improve accuracy, and apply pseudoscience to real-life issues. By increasing the dataset size and using a deep neural network, the accuracy of feature estimation can be improved. More interesting features, such as texture-based features, can be extracted with the help of advanced algorithms. Face reading has a concept that the five most noticeable features of any face represent the actual personality traits, which could aid us in locating the most desired feature-based subject among a group of images. We only looked at positive personality traits that were available in the physiognomy literature for this project. In the future, we can conduct research and identify negative traits, or, because these traits are distributed continuously in each person, we can score and find the lowest and highest score-based feature. After implementing a few of the above recommendations, we can easily target some specific applications such as recruitment, security, and medical treatment.

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Appendix

Table A.1. Comparison of our face features' classification accuracy with benchmark [12]

#	Face Feature	Our Accuracy (%)	Benchmark's Accuracy (%)
1	Eye Size	77	-
2	Eye Shape	77	76
3	Eye Angle	77	-
4	Mouth Size	76	75.8
5	Mouth Angle	77	-
6	Lips Size	65	-
7	Jaw Size	78	-
8	Face Shape	-	79.3
9	Eyebrow Shape	-	-
10	Nose Shape	-	-

Completion Certificate

It is certified that the thesis titled **"Personality Identification Through Facial Features by Using Neural Networks for Pakistani People"** submitted by CMS ID. 00000203002, NS Rizwan Ullah Khan of MS-2017 Mechatronics Engineering is completed in all respects as per the requirements of MainOffice, NUST (Exam branch).

Supervisor: ___________________

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