Forensic Age Estimation Model Using Left Hand Bones Based On GA-ANN Hybrid Approach For Hispanic Population

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ABSTRAK

Model anggaran umur ialah bantuan berfungsi untuk membezakan identiti si mati atau individu hidup dari segi antropologi forensik. Model anggaran umur konservatif hanya terhad untuk penduduk spesifik serta variabiliti tinggi. Kajian ini memberi tumpuan dalam membina model anggaran umur menggunakan pendekatan hybrid GA-ANN (Genetic Algorithm-Artificial Neural Network) bergantung pada 19 panjang tulang tangan kiri individu yang berumur dari 0 hingga 18 tahun. Gambar X-ray tangan kiri dikumpul dari dataset penduduk Hispanik. 19 panjang tulang diukur menggunakan Photo Pos Pro dan pendekatan hybrid dilaksanakan mengguna Python skrip Python dan Matlab. GA adalah untuk memilih tulang paling sesuai manakala ANN menganggarkan usia. Kajian ini dikira berjaya sekira keputusan pendekatan hybrid dicadang dapat mengatasi penanda aras.

ABSTRACT

Age estimation model serves as an aid to distinguish the identities of deceased or alive individuals in term of forensic anthropology. The existing age estimation models are population specific and high variability. This research focuses on using Genetic Algorithm-Artificial Neural Network (GA-ANN) hybrid approach on age estimation models depend on the lengths of 19 left hand bones of alive individuals who ages from 0 to 18 years old. X-ray images of left hands are collected from Image Processing and Informatics Lab of University of Southern California. The lengths of the 19 bones are assessed using Photo Pos Pro while the hybrid approach is implemented using Python scripts and Matlab. GA approach is applied to select the appropriate bones while ANN approach is used to estimate age. It is believed that the research is successful as the results of GA-ANN hybrid approach outperform the ANN approach.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

LIST OF EQUATIONS

CHAPTER 1

INTRODUCTION

1.1 INTRODUCTION

There are many unidentified decedent cases in world and we may need some models or approaches to predict features or physical characteristics of unknown corpses. Lynnerup & Villa (2014) stated that evaluation of age at death is involved in the identification of human remains.

Age estimation is essential since it is possible that the examiner or investigator is requested to make an educated guess and hypothesize the age of an individual as a part of the investigation. Stavrianos, Mastagas, Stavrianou, & Karaiskou (2008) stated that age is the significant component in clinical practice, research, and court of law.

Age estimation serves in minimizing the scope of the probe feasibility for unknown deceased or living individuals for constitutional reasons. For people who thought to be guilty of crime with unrevealed chronological age, who are committed to a grave crime, the precisions of age estimation models are required for absolute justice (Duangto, Janhom, Prasitwattanaseree, Mahakkanukrauh, & Iamaroon, 2017). An entry of large number of asylum seekers, unlawful immigrants, and also more young perpetrators being subjected to trials in court have caused the grow desire for age estimation (Sykes, Bhayat, & Bernitz, 2017).

Age estimation in forensic medicine has progressively obtained significance since there are inevitable situations like individuals do not have or having falsified identification documents (Auf der Mauer et al., 2019). There is some current published literature with a particular attention allocate to age estimation to be used for refugees and individuals involved in human trafficking (Franklin, Flavel, Noble, Swift, & Karkhanis, 2015).

There is a lack of studies on age estimation model for Hispanic population. It is believed the field of forensic science prefers more age estimation models for different ethnic groups. Therefore, this research focuses on Hispanic population.

1.2 PROBLEM STATEMENT

The problems that this paper aims to tackle are as follows:

i. There are only few age estimation models for Hispanic population.
ii. There are difficulties in getting research studies that applying GA-ANN hybrid approach on age estimation model.
iii. The field of forensic science demands more age estimation models for different ethnic groups.

1.3 OBJECTIVES

The goal of this project is to apply GA-ANN hybrid approach on age estimation model using left hand bones for Hispanic population with the following objectives:

i. To investigate the adoption of GA approach for bone selection
ii. To hybridize the GA approach with ANN approach for age estimation
iii. To evaluate the GA-ANN hybrid approach with ANN approach

1.4 SCOPE

This research focuses on using GA-ANN hybrid approach on age estimation models depend on the lengths of 19 left hand bones of Hispanic population who ages from 0 to 18 years old. The lengths of the 19 bones are assessed using Photo Pos Pro while the hybrid approach is implemented using Python scripts and Matlab.

1.5 REPORT ORGANISATION

This thesis consists of five chapters. Chapter 1 will discuss on introduction of this thesis while chapter 2 will discuss on the literature review for this research paper. Chapter 3 is about methodology while chapter 4 is the implementation and discussion. Chapter 5 is the conclusion of this research.

CHAPTER 2

LITERATURE REVIEW

2.1 INTRODUCTION

Age estimation is pivotal in law enforcement and legal justice systems all over the world (Asif et al., 2019). Other than that, to be able to precisely determine the age of children and young adults has always been a problem in forensics since there are cases where youths without proper identification documents are requested to be assessed for their criminal responsibility, commonly regarding the range of their possible age, and also to determine if a residency permit can be given, and refugees that may look too old for their claimed age. (Bartolini et al., 2018).

Stern & Ursekter (2016) stated that it is critical to the fields of clinics and forensics that the evaluation of the age of individuals is accurate and precise, as medicine released from clinics places emphasis on the predicting the age to determine endocrinological diseases in children or in pediatric surgery while medicine in forensics emphasizes on age estimation under the condition where no distinct clues can be found to help in estimating the age, such as the age of minor refugees that has lost their identification documents.

In forensics, the search for victims can be simplified by creating a range for age through age prediction. The search for possible contributors of crime scene traces can also be made simpler by predicting the age range for possible suspects. Prediction intervals are always preferred when approximating age in a police investigation. (Smeers, Decorte, Van de Voorde, & Bekaert, 2018).

Other than that, it is essential to have age estimation of unspecified human bodies at the crime scene since the mortality age, birth date and other details allow investigators to get the true identity of a human body by providing potential counterparts. The determination of human bodies is always a difficulty to investigators when there is no sign about the identity from particular data (Alkass et al., 2009). The age of an individual is always an elemental piece of data relating to forensic identification of unknown human bodies (Lynnerup & Villa, 2014).

2.2 THE IMPORTANCE OF AGE ESTIMATION

There are several factors that make age estimation an important technique.

2.2.1 CRIMINAL RESPONSIBILITY

In much of the first-world nations, in example New Zealand and Australia, 10 years old is the standard age of criminal responsibility. Meanwhile it is 7 to 8 years old in India, Indonesia and Jordan. A formal statement made by the United Nations (UN) that children under the legal age of criminal responsibility must not be subjected to criminal accusations and nations should start to revise themselves if they have set criminal responsibilities for children under the age of 12 years and below. Doli incapax assumes that a child could not hope to commit a crime under common law. This is a presumption that is employed to children between the age of 13 or 14 years, depending on jurisdiction, and is a more controversial concept (Franklin et al., 2015).

17 to 21 years would be the standard range of age for young people which age between doli incapax and adulthood, depending on jurisdiction are ideally subjected to rehabilitation than punishment, as the full criminal liability of an adult is not carried by them. However, they must still face the consequence of their actions, albeit the consequences are lighter. (Franklin et al., 2015).

2.2.2 CHILD PORNOGRAPHY

Any activities relating to child pornographic files, especially having ownership to such files is a crime in several countries. Therefore, there are frequent requests for forensics analysis in computer storage devices to verify the presence of child pornography (Polastro & Eleuterio, 2012).

Macedo, Costa, & A. dos Santos (2019) proposed a combined method to detect child pornography using a child face detection module and a pornography detector. The results showed the viability of the strategy of combining different detectors and classifiers to perform detection of child pornography, but it requires much more improvement, especially in age estimation and pornography classification.

2.2.3 FALSIFICATION OF AGE

Falsification of age or also known as age cheating is a common practice in domain of sports and public service, and some members of society may have a different moral perspective and find this completely acceptable as they view it a vital underhandedness, or a means of survival in a situation of destitution (Jerome Tosam, 2015). It is important to have age estimation in the sports academics and military services at the entry and also retirement (Bakthula & Agarwal, 2014).

It is possible for some children in certain countries, while being born to this world, do not have their births registered and therefore a birth record is not made. There happened the alterations of births on official documents of players in hopes to obtain the right to compete with other countries in sports industry. International Olympic Committee has come out with a consensus statement since the matter of age verification in youth sports is a great concern (Malina, 2011).

To prevent issues of falsification of age and to protect children from recruitment in hostilities, General Assembly launched the Optional Protocol to the Convention on the Right of the Child on the involvement of children in armed conflict (OPAC). Office of the Special Representative of the Secretary-General for Children and Armed Conflict adopted the campaign Zero under 18 in order to support OPAC (UN, n.d.).

2.2.4 HUMAN TRAFFICKING

Kiss, Yun, Pocock, & Zimmerman (2015) stated that every year, many children fall victim to the grave crime of human trafficking. 5.7 million boys and girls have been estimated to work without their, 1.2 million are sold illegally, and about 1.8 million have been forced to sexual slavery.

Child labour robs children away from their childhood, potential and dignity, and can also cause harm to mental and physical development. Worst forms of child labour are trafficking, forced labour, sexual exploitation and use of underage children for security and military purposes (UNICEF, The Global Compact, & Save the Children, 2012).

Children with low socioeconomic contexts are unprotected to human trafficking and once trafficked, these children are frequently involved in criminal acts and therefore being inspected by local legal system with no or falsified identity documents (Franklin et al., 2015).

2.2.5 REFUGEE AND ASYLUM SEEKERS

According to United Nations High Commissioner for Refugees (UNHCR), almost half of victims of natural disasters, internal conflict, and war are vulnerable children and are now seeking international protection. The majority of UN members supports and signed The Convention on the Rights of the Child, which declares without discrimination, the rights of every child, defined as individuals under 18 years old, within any States Parties' jurisdiction will be respected and ensured (OHCHR, n.d.).

Sykes, Bhayat, & Bernitz (2017) states the asylum seeker crisis has contributed to the necessity of having age prediction, causing an increase in such cases, which is most likely caused by a sudden increase in trials involving refugees, illegal immigrants and juvenile offenders. This makes the legal authorities the main users who need age estimation tests in support of their investigation.

2.2.6 UNKNOWN DECEASED CHILDREN AND MISSING CHILDREN

Age estimation is the most precise biological identifier that a forensic anthropologist can give in the case of an unknown deceased child (Lewis & Flavel, n.d.). Lacking of documents, clothing or other personal belongings are often main issues of identification in historical grave findings. Thus, the focus will be on age estimation, so as sex and stature determination. Generally, the principal criteria to estimate age of deceased children and teenagers are the appearance of ossification centre, epiphyseal union, the development of teeth, and also bones lengths. Age estimation is more reliable to children and teenagers than adults as children and teenagers are based on skeletal and dental maturation while adults focus on degenerative changes (Huumonen et al., 2016).

Nowadays, missing children becomes a common phenomenon in world. Society today has becoming progressively worse for citizens especially children. Missing children is complicated occurrence and having many dimensions for it to deal with. There is two possible ways that a child can go missing, which are either the child has been kidnapped by someone against the assent of the child and also law, or, the child leaves the domination and protection of guardians without acknowledgment (Vij, 2016).

A crucial process that can bring closure in a tragic case is the cross-matching reports of missing people with unknown bodies. A successful matching helps criminal investigations and completes the civil procedures, and thus those who left behind can mourn their beloved one (People & Paper, 2011). Alkass et al. (2009) stated that age estimation is offering significant potentiality to police authorities and forensics pathologist in determining the time of death as well as the identity of unknown bodies or individuals.

2.3 THE HUMAN PARTS USED FOR AGE ESTIMATION

Hand bone, dental, knee, facial, and pelvis are several parts of human body that have mostly been used for age estimation. Details of each part will be explained in following sections.

2.3.1 HAND BONES

Radiography analysis of the staging of skeletal development has been a common method to estimate the timing of pubertal growth, so as to know the growth velocity and the proportion of growth remaining. In most cases, ossification of bones of the hand and wrist has been used in determining skeletal development since each type of bones can have a varying availability in the areas. The pattern of skeletal growth is almost the same in every individual, just the initiation, duration, and also amount of growth varies greatly due to the sudden, mandatory growth in puberty, and therefore, it becomes a significant consideration. Genetic and environment factors has impacted the skeletal development in every individual while the timing and ossification sequence of skeletal maturity within the hand-wrist area have shown polymorphism and sexual dimorphism that restricts clinical predictive use. Generally, there are two common methods to assess hand-wrist radiograph. The first method are the comparison approaches of Greulich and Pyle and Tanner et al. Geulich and Pyle adopt an atlas as the standard of comparison while Tanner et al. approach compares individual to the radiographic standards of skeletal development of common children in the same group of gender and age. The second approach to access hand-wrist radiograph is using particular indicators to associate skeletal development to growth curve of puberty. This method is focused on the skeletal development evaluation of an individual than the mean values (Flores-mir, Orth, Nebbe, & Ortho, n.d.).

Many researchers have proposed divergent approaches to estimate age using various parts of bones like knees, spinal cord, femur, foot bones, skull, rib, pelvis, Carpals and Epiphyses of the Ulna and Radius, and left hand bones. Normally, measurements of bone lengths, angles and shape variations are the main focuses of many forensic studies. All measurements are vary from observation to observation and scientist to scientist. Forensic research has driven into various domain of interests such as studies of dead skeleton bones, half decomposed corpses in crime investigation or skeleton development and medical diagnosis (Bakthula & Agarwal, 2014).

An accepted sequence of ossification for the carpal, metacarpal, and phalangeal bones that is extraordinarily constant and similar for both sexes of healthy children. Capitate is the first ossification center that comes in hand and wrist radiographs while sesamoid of adductor pollicis of thumb is usually the last one. The epiphyseal center of the distal radius is the first comes into existence, then following by those of the proximal phalanges, the metacarpals, the middle phalanges, the distal phalanges, and the ulna. Despite that, two main bones are to be exempted from the sequence, which are the epiphysis of the distal phalanx of thumb and of the metacarpals usually come into existence at the same time, and the epiphysis of middle phalanx of fifth finger is often the last to ossify (Gilsanz & Raitb, 2005).

2.3.2 DENTAL

The tooth, another part which can be used for age estimation is also the most rigid tissue that can be found in the physiology of humans. Physical and chemical stresses along with nutritional deficiencies can be resisted by teeth for a long time. Other than DNA profiling and fingerprint comparison, dental evaluation is vital in forensic identification of an unknown deceased individual. Therefore, it is important to have a valid and reliable approach of dental age estimation (Asif et al., 2019).

Asif et al. (2019) investigated the relationship between chronological age and pulp/tooth volume ratio in maxillary right central incisors and maxillary canines in order to derive a regression equation for dental age estimation for Malaysian population. The study sample of 300 cone-beam computed tomography (CBCT) scanned data belonging to 179 Malays and 121 Chinese, which stored in the Oral and Maxillofacial Imaging Division, Faculty of Dentistry, which were selected based on the image acquiring parameters, age of patients and the quality. The subjects were divided into 5 age groups, ranging from 16 to 65 years old, where each age group of 10 years range in order to ensure balanced sample distribution across the 5 groups. 300 intact teeth, which are 100 maxillary left canines, 100 maxillary right canines and 100 maxillary right central incisors, all with no caries and fully developed roots were eventually identified from database. Only one tooth per subject was selected in order to avoid bias in data acquired from the same patient.

By using i-CAT Cone Beam 3D Dental Imaging System, CBCT data was acquired and were then imported to the Mimics software for the analysis of pulp-tooth volume ratio. Images were first oriented in axial, coronal and sagittal planes. After setting different grayscale threshold values for each of the investigated teeth, new masks were created for the pulp cavity and tooth. Masks were cropped in 3 planes in order to separate the tooth from surrounding structures. There were slice by slice of manual checking of masks for segmentation and separation from surrounding structures. The pulp cavity and tooth were grown in the 'Region growing phase' of the software after editing mask in multiple slice editing phase. Three dimensional models of pulp tissue and tooth were created and the software calculated the volume of the pulp cavity and tooth. A strong inverse relationship between chronological age and pulp/tooth volume ratio has been indicated by the results and showed that this method of dental age estimation is indeed gender independent (Asif et al., 2019).

2.3.3 FACIAL

Important information related to identity, gender, age and ethnicity can be conveyed by human face. These attributes are used in facial image analysis applications and age estimation from facial image has become the active research area in computer vision community. It is because of its real world applications in multimedia communication, Human Computer Interaction (HCI), security and law enforcement (Sawant & Bhurchandi, 2019). Existing facial age estimation systems are roughly divided into two key components, which are face representation and age estimator learning (Liu, Lu, Feng, & Zhou, 2017).

Ouloul, Moutakki, Afdel, & Amghar (2019) proposed a new descriptor called Local Matched Filter Binary Pattern (LMFBP) which is designed specifically for the detection and extraction of skin wrinkles and is based on exploiting both the Matched Filter and the texture operator Local Binary Pattern (LBP). The Matched Filter will handle the detection of wrinkles using template matching between approximate shape of wrinkles using template matching between the approximate shape of wrinkles and the face image patches while LBP will encode the response of the Matched Filter into pattern codes to build the histogram of skin aging feature. Hierarchical approach has adopted in the learning phase in order to consider varying aging process from one age stage to another. It has been tested on both FGnetAD, HQfaces and PAL datasets, and the results proved the efficiency of the proposed approach when compared to the state-of-the-art age estimation methods.

2.3.4 KNEE

The distal end of femur, the proximal ends of tibia and fibula, and the patella are the four bony structures of human knee. All of those bones are present from birth, excluded patella. Patella is develop with the tendons and ligaments of knee from a cartilage precursor that only begins to ossify into bone around 3 years old while other bones are developed by epiphyses where the ends of bones from cartilage growth plates during skeletal development. Many studies have examined the age estimation of knee and or elements that make up the knee joint such as radiography (X-ray) studies and magnetic resonance imaging (MRI) studies (Maggio, 2017).

Maggio (2017) had conducted studies that showed the varying age estimation potential of the knee joint, and the elements that contained therein. Since there is no overlapping bony structures, it is easier to image the knee. The knee can be imaged at low doses of radiation for MRI, X-ray and ultrasonography. The potential of MRI for determining of legal majority has been demonstrated by many studies while there is still lack of information about the potential of ultrasonography of the knee for age determination.

Age and sex of a person might be estimated by the shape of knee in forensic medicine. Huang et al. (2018) had using geometric morphometric analysis of ten osteometric landmarks on three-dimensional reconstructions of 259 knees in Chinese population to study the differences of distal femur in term of sexual dimorphic and age. In order to identify the differences, General Procrustes analysis, principal component analysis (PCA), and other discriminant analysis had been conducted. PCA distinguished a significant difference of the distal femur between male and female while osteometric analysis showed the differences between the three age-related subgroup which are below 40 years, in between 40 to 60 years, and above 60 years.

2.3.5 CHARACTERISTICS OF SECONDARY SEXUAL

There are issues of secondary sexual characteristics associated with assessment such as privacy and cultural matters even though self-assessments have been implemented. The secondary sexual characteristics are pubic hair and genitalia in males while pubic hair and menarche in females (Malina, 2011).

Normal (2007) studied the yearly assessments of breast, genital, and pubic hair growth and those assessments had aided in analyzing the ages of individuals in each sexual maturity stage and the time it needed to go from one stage to the next. The findings from this study are essential in helping researchers to know the normative variation in the timing and also change in secondary sexual characteristics during puberty.

The timing of sexual maturity of a large group of healthy Danish children had been studied by TEILMANN et al. (2005) in order to assess the dissimilarities between USA and Denmark, and also to study the possible secular trends in sexual maturity development. The study showed that prepubescent child is easily affected by surrounding elements that may affect the endogenous hormonal milieu, and eventually impact the pubertal maturation.

2.3.6 THE SELECTED HUMAN PART TO DETERMINE AGE IN THIS RESEARCH

The most frequently traits that forensic anthropologists are going to assess in the identification of deceased bodies will be the age and the gender. This study focuses on the hand bones since other parts of the body have larger possibility to be missing before the criminal investigation is conducted. There are 19 bones in left hand and therefore it is harder to have no any hand bone remains at all. The widely used models to estimate age is based on the conservative method of observation of hand bones morphology which are Greulich and Pyle (GP) model and Tanner and Whitehouse (TW) model. The restrictions of these models are the estimated age generated is rely on the specialists or anthropologists and also the adopted subjects from certain population cannot ensure for other populations to implement these models in estimating age. (Cantekin, Celikoglu, Miloglu, Dane, & Erdem, 2012; Gungor, Sari, Gungor, Kale, & Celikoglu, 2015; Koc, Karaoglanoglu, Erdogan, Kosecik, & Cesur, 2001) have conducted studies of age estimation using these models for other populations and deduced that some factors like different surroundings circumstances and various ethnic background have made these models not sufficiently great. Furthermore, genetic, growth, health and lifestyle, nutrient, and so on are factors that may impact the performance of the models to other populations (Malina, 1994).

There are few studies (Cameriere & Ferrante, 2008; Cameriere, Ferrante, Mirtella, & Cingolani, 2006) conducted the multiple linear regressions model for age estimation using the bone measurement. A new age indicator which is based on quantitative dataset of bone measurement that is going to be a substitution input in order to reduce the dependency of the specialists in estimating age.

2.4 GENERAL APPROACHES IN AGE ESTIMATION USING HAND BONES

There are several general approaches in age estimation using hand bones discussed in the following sections.

2.4.1 GREULICH AND PYLE (GP)

GP method, also known as the atlas method, is an improvement of the protocol chronicled by Todd in 1930s. GP method had thriven on the American White Children from the area of Cleveland, OH, USA, who were born between 1917 and 1942. This method used plates as standards, which represents the birth to maturity of 31 boys and 29 girls. It allocated the skeletal age (SA) to each bone of the hand-wrist, which in total is 29 bones. Pragmatically, GP SAs are in general, while unseemly, it excluding variation among bones since it constructed from the SA of the standard plate to the youth closest matches. There is no allocation of SA to each of the 29 bones once a person has attained skeletal maturity. This method has been adopted in the survey of players in Asian Youth under 16 championships (Malina, 2011).

2.4.2 TANNER AND WHITEHOUSE (TW)

The output shown by earlier researches about the adoption of TW in forensic field and Pinchi et al. (2014) analysed and demonstrated that the TW2 method is the worst among the methods of GP, TW2, and TW3 as it has a tendency to be biased, causing it to evaluate the age with a dissatisfactory precision. The study stated the TW2 method is not fitting to forensic age estimation since there is very high risk caused by large overestimation. The higher overestimations and lower accuracy value of TW2 implicit higher risks than GP and TW3 methods of false positives.

Pinchi et al. (2014) took 266 out of the sample of 307 X-rays of left wrist-hand bones in order to analyse the bone maturation of children for orthodontic initiatives while 41 taken for auxological initiatives, which collected from private dental practices and paediatric hospital respectively. There were 145 females and 162 males in the sample. The birthdates and radiological examinations were all accessible. The chronological age of subjects fluctuated from 6 to 20 years. There are three methods using in the study to estimate bone age and found out TW2 is not valid for age estimation as it given the highest overestimation in both genders while GP and TW3 are fit to estimate age with similar values of accuracy. GP and TW3 are more reliable for males than females and TW3 is a way more dependable than GP particularly in criminal cases because of the extraordinary overestimation trend of GP.

2.4.3 MULTIPLE LINEAR REGRESSIONS

Darmawan et al.(2015) had carried out a study that involved 333 X-ray images of left hand bones from 166 males and 167 females of Asian population. These X-ray images were gathered from Children's Hospital Los Angeles where been grouped in nineteen age groups for female and male.

The left hand bones are split into four groups which are distal phalax, middle phalax, proximal phalax and metacarpal. The middle phalanx group consists of four bones while another three groups consist of five bones respectively. The total left hand bones is 19. The data set ranged from newborn to 18 years old with no records of any bone illnesses.

Analysis of variance of intra-observer and inter-observer for repeated measures had performed to prove the measured data are reproducible and no significant statistical difference between those measurements. Each measurement in each image was repeated thrice and regression models are designed using the mean of that three measurements. There were two observers for inter-observer trial and 50 X-ray images were randomly chosen and measured by these observers ten times. It shows that no significant difference between two observers by generating another analysis of variance for measures.

SPSS statistical tool version 16.0 had been utilized for age estimation based on the analysis of bone lengths. The single bone method is age estimation using 11 regression models on each left hand bone, which are Linear, Logarithmic, Inverse, Quadratic, Cubic, Compound, Power, S-curve, Growth, Exponential, and Logistic. Multiple linear regressions had been applied on the 19 left hand bones for all bone method to develop the regression model. MSE value, R-square value and parameter will be generated by each regression model. MSE value is the average of the squares of the difference between the actual age and estimated age. The correlation between age and all bone lengths are represented by R-square value which will generate an equation for age estimation. There were 11 equations for each bone since the total number of bones for both genders is 19. For all bone method, there are only two generated equations while 209 equations for single bone method. Regression model with highest R-square value of female and male was selected as the best correlation with age while the equation with lowest MSE value was chosen for age estimation.

The best regression model based on highest R-square value of 0.960 for male and 0.900 for female is the S-curve regression while the best regression model based on MSE value is multiple linear regressions applied to all bones, which its MSE values are 1.654 years for male and 3.006 years for female. The best method shown in the study is the equation from multiple linear regression, where the left hand bones are complete. Single bone method will be implemented using the equation from regression models with the lowest MSE value based on the availability of left hand bones.

2.4.4 GENETIC ALGORITHM (GA)

GA is a tool for optimizing purposes that developed by Holland and was influenced significantly by the mechanism of natural selection and also the continual growth of all life forms across eons. GA method is not using any specific data to do searching since it is a probabilistic approach while objective function evaluation is needed in every decision in order to do proceeding. In accordance with what is generally done in GA, individual in populations, namely candidate solutions, steadily meet the most favorable solutions over time. 0 and 1 s are chromosomes which forms one linear string that proposes solution of each candidate. Every iteration has its optimizing procedure that initiated generations, which are population sizes. In GA, reproduction, crossover, and mutation are three basic genetic operators that generate following generation. A reproduction operator is the method or selecting the ideal chromosomes following their scaled values taking into account of the given standard of fitness. The selected chromosomes will be sent immediately to the next generation. Crossover operator is particular parts of parents or individuals merging each other and produce new individuals while mutation operator is having an uncertain substitution in elements of chromosomes (Khandelwal et al., 2018).

There are mainly six phases in genetic algorithm, which are initial population, fitness function, selection, crossover, mutation, and termination (Jain, 2019). The process of initial population phase starts with all the dataset as population, where each record is characterized by a set of features known as genes. Genes will join to form chromosomes.

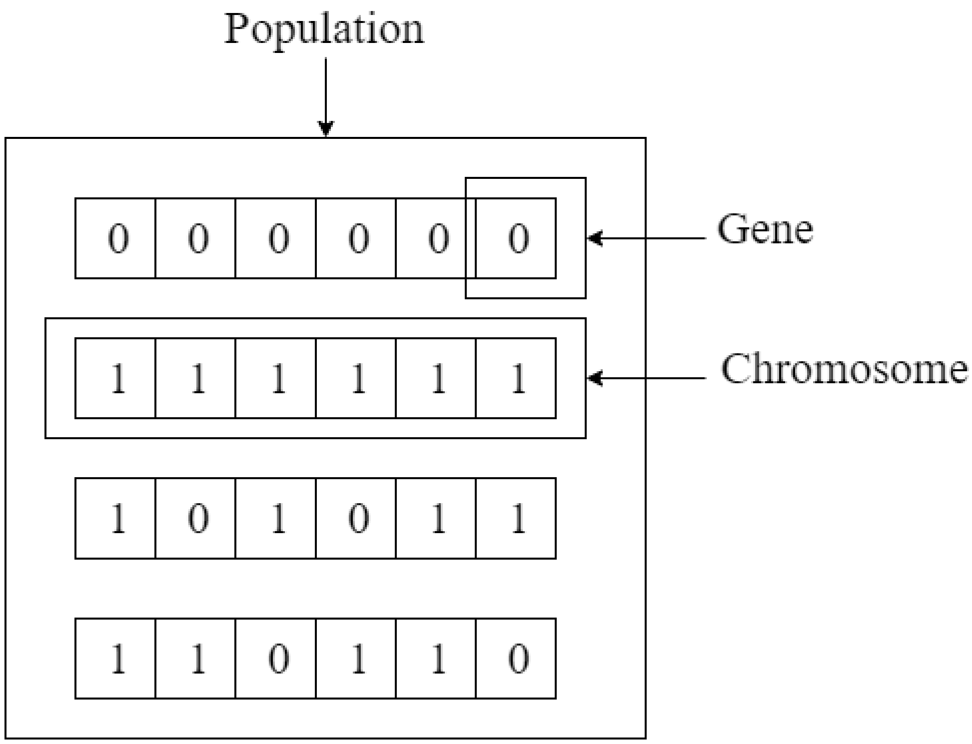

Figure 2.1: Gene, chromosome, and population of initial population phase

The fitness function phase is to measure the fitness of an individual where each of the individual is made up of some genes but not all of them. Features which having a major impact will be determined by finding the fitness of individual. In the selection phase, the two fittest individuals will be chosen for reproduction. The individuals chosen in selection phase will be used to form new individuals by changing some genes in individuals in crossover phase.

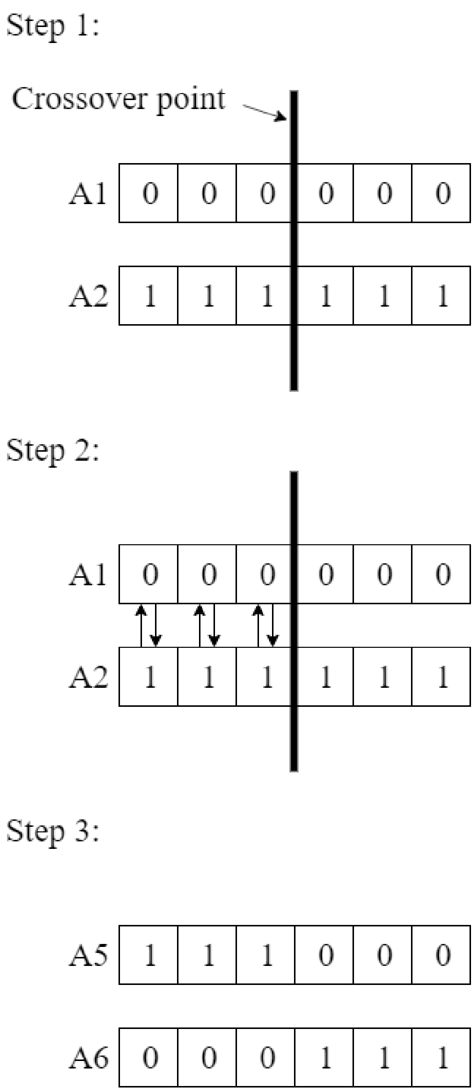

Figure 2.2: Three steps in crossover phase

In mutation phase, some genes are changed by adding some randomness. In termination phase, the genetic algorithm will terminated when population no longer generate any individuals.

2.4.5 ARTIFICIAL NEURAL NETWORKS (ANN)

ANN is functions of estimation that simulated from the way of sending information of the human brain. ANN is capable to be adopted even in extremely complex and non-linear contact circumstances (Khandelwal et al., 2018). Feed-

Forward Neural Network (FF-NN) is the extensively applied network to date. It is because of its simplicity and intelligibility compared to other networks and so as its potentiality to learn the implied governing relationship among the inputs and outputs when there is sufficient training data. A network structure like FF-NN will only propagate the signal or information in single direction (Sciences, 2015).

Typically, input, hidden and output layers are the three layers in FF-NN. It can possess hidden layers that make up more than one, yet a single layer is plenty to approach any function to a desired degree of accuracy. The number of neurons of input and output layers depend on the specific problem. In most cases, systemic trial and error is the finest procedure to find out the optimal number of neurons in hidden layer. Inputs will be fed through the input layer, then being multiplied by synaptic weights and are sent to the hidden layer. Normally, the selected logistic or the hyperbolic tangent is the nonlinear activation function that transforms the weighted sum of inputs in the hidden neurons. The same way goes through each hidden layers until the result attain the output neuron. On the other hand, the linear activation function is regularly implemented to the output layer. The most well received training algorithms that are extensively implemented for training FF-NN are back-propagation (BP) algorithms since it is easy to understand and applicable (Sciences, 2015).

The ANN compose a group of processing elements known as perceptrons which can be used to build a network structure via distinct arrangements. The network's layers are the location where these perceptrons reside. The releasing output, the managing input, and the input itself are obtained by every of the perceptron. They assimilate the releasing output, the managing input and the input itself, which makes these perceptrons the core components. There are two forms of input obtained by a perceptron, either an original input data is fed into the network, or the output data computed by another perceptron. Similarly, the output of a perceptron can be the final output of the network layer or to serve as an input into another perceptron. A single layer network must consists of at least one input layer and one output layer to establish a working network structure.

To construct the ANN, weights are utilized to link visible and hidden units with at least one other perceptron to the perceptrons in other layers. A hidden layer in a neural network is visualized with Figure 2.3 below.

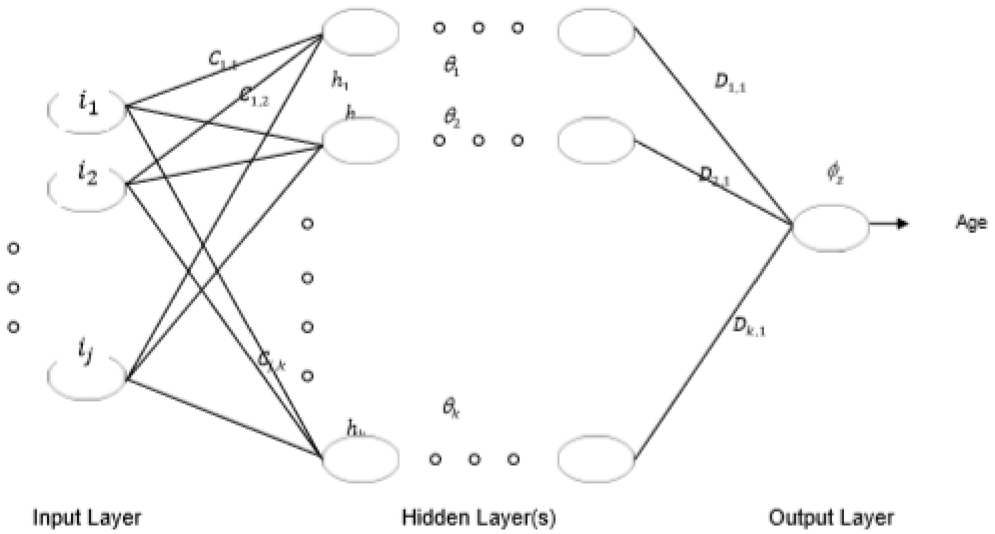

Figure 2.3: A conceptual design of a multiplayer neural network. Each layer are interlinked and the weights (c) indicates the links between the perceptron nodes.

The net input to unit k in the hidden layer is computed by implementing Equation 2.1 under the condition that a hidden layer network is utilized as in Figure 2.3.

$$net\_hidden = \sum_{j=1}^{J} C_{j,k}\, i_j + \theta_k$$

Where J is nodes number of the input layer, θ_k is the biases of the hidden nodes, i_j is the input variables (the nineteen bones) and $C_{j,k}$ is the weights between the input nodes and hidden nodes.

Equation 2.1 Formula to compute the net input in hidden layer

Therefore, the net output from unit z in the output layer can be computed with Equation 2.2.

$$net\_output = \sum_{k=1}^{K} D_{k,z} h_k + \emptyset_z$$

Where K is number of node in hidden layer, $\emptyset_z$ is the biases on the outputs nodes, h_k is the value of the output for hidden nodes and $D_{k,z}$ is the weight between hidden and output nodes.

Equation 2.2 Formula to compute the net output in output layer

Consequently, Equation 2.3 represents the result of hidden nodes and Equation 2.4 represents the result of output nodes which can be done with Equations 2.1 and 2.2. *f* is the transfer function to estimate the age.

$$h_k = f(net\_hidden)$$

Equation 2.3 Formula to compute result of all hidden nodes

$$o_z = f(net\_output) = age$$

Equation 2.4 Formula to compute result of all output nodes

To successfully construct an ANN, some variables are taken into consideration (Mohd, Haron, & Sharif, 2010) and the process trial and error is undergone. Researchers commonly implement the ANN in diverse, distinct areas, including forensics. However, an absence of detailed, recognized practices and procedures that could act as a standard guideline to establish the ideal approach. As a result, the effectiveness is ultimately reliant upon the operation of attempting different combinations for each variables and obtaining the best result. As a consequence, the procedure of trial and error will determine the effectiveness and capability of ANN. Therefore, the capability of the ANN could be impacted and affected by eight elements. These elements are the structure of the network, ratio of training and testing data, normalization of data, network algorithm, transfer function, performance function, training function, and learning function. With trial and error, the eight elements can decide the perfect and faultless ANN.

2.4.5.1 STRUCTURE OF THE NETWORK

Nodes (neurons) and layers are the basic components of the ANN. The input layer, hidden layer and the output layer is comprised of the underlying structure of the ANN. On a small note, the hidden layer is an optional layer while the input layer and output layer are mandatory in the ANN structure. Figure 2.4 visualizes an ANN with $(i - j - k \ldots - l - 1)$ structure. In the figure, the *i* nodes represent the nodes in the input layer, the *j* nodes in the first hidden layer, the *k* nodes in the second hidden layer, the *l* nodes in the m^{th} hidden layer and at least one node in the output layer.

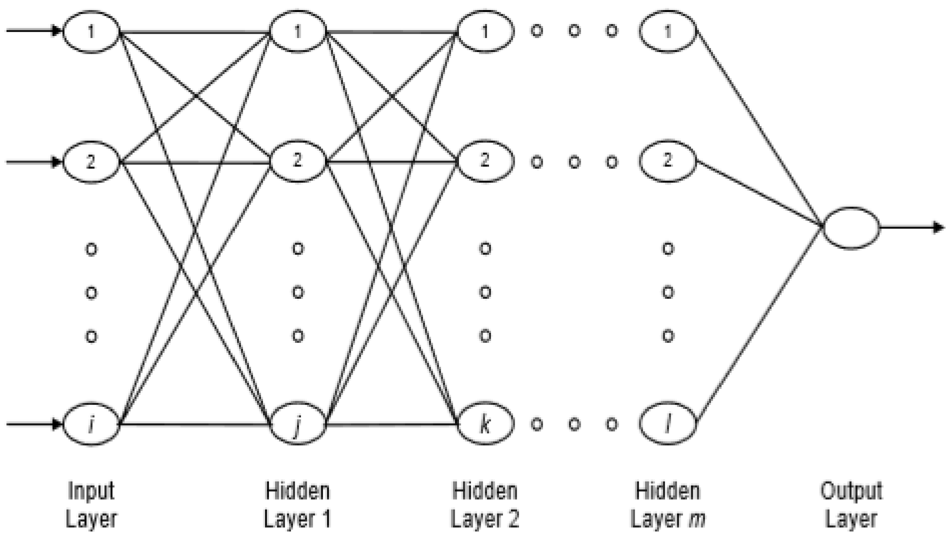

Figure 2.4: The ANN with $(i - j - k \ldots - l - 1)$ structure is visualized

Author	(Kohail, 2012)	(Kumar, P, Sriram, & Vijay, 2013)	(Sharma & Venugopalan, 2014)
Network Structure	95-50-50-50-1, 50-25-25-25-1	68-29-4-4	136-68-36-4, 136-68-36-2

Normalization Data	-	-	-
Performance Function	Accuracy, R value	MSE, Accuracy	MSE
Training Function	-	*trainscg*	Various training function
Network Algorithm	Feed-forward BP	Feed-forward BP	Feed-forward BP
Learning Function	-	-	-
Transfer Function	Sigmoid	-	Sigmoid
Ratio of Training, Validation, and Testing Data	-	60 : 20 : 20	-

Table 2.1: Significant elements of the construction of ANN taken from an earlier study on age estimation

The network structure are dissimilar according to earlier research in Table 2.1. This is a result of the randomness of the trial and error process while constructing the ANN for the prime results where the layer's number and node's number of all hidden layers are modified. With this, it is established that any value to the number of hidden layers and the number of nodes in every hidden layer can be attempted. Be that as it may, the possibility that the number of hidden layer and the number of nodes in every hidden layer is affected by the desired data control effect, the computation time, computer memory and the complexity of the mapping cannot be denied. It is stated by Al-Ahmari (2007) that the expected data control effect may not be obtained with a small number of nodes, while an excess of computation time and computer memory can be a result of excess nodes. The number of nodes in the hidden layer which is "$2n$ + 1", "$2n$", "$1n$", and "$n/2$", where the n is the number of input nodes can be computed with a formula suggested by (Zhang, Patuwo, & Hu, 1998) and (Mohd et al., 2010).

2.4.5.2 RATIO OF TRAINING AND TESTING DATA

Another factor to be attended to when constructing the ANN is the ratio of training and testing data. A fundamental principle of the ANN is that the accuracy of the ANN is linear to the amount of the training data, where the accuracy of the ANN increases when the amount of the training data increases. A portion from a normalized set of data of the nineteen bones and age of each subject is selected as training data for estimating age.

No rules are needed in selecting the ratio of training and testing data. From Table 2.1, the ratio of training and testing dataset differs from each other while some of the ratios are not mentioned, and thus the researchers have full authority over the selection of ratio for training and testing dataset, under the condition where the training data must be more than the testing data, based on statement by Mohd et al. (2010). On the other hand, a solution to this problem proposed by Zhang, Patuwo, & Hu (1998) suggests that the ratio of training and testing data is replaced with percentages that equals to 100%, such as 80%:20%, 85%:15%, or 90%:10%.

2.4.5.3 DATA NORMALIZATION

Before training and testing ANN, data normalization is generally carried out. A standard range, such as 0 to 1 or -1 to 1, is generally used when normalizing the data. It is a mandatory rule that if the output nodes employs nonlinear transfer functions such as the logistic sigmoid, the format of the expected output values must be converted to the same format of the range of the expected outputs of the network structure. Although a linear output is implemented, normalizing the outputs and the inputs to avoid problems from the computational process can be advantageous. When the issue regarding the data input/output normalization is taken into consideration, another issue that deserves attention is the method of deciding the normalization of the input/output data with the acquired size data. Suggested by (C. Sanjay; & C. Jyothi, 2006) and

(Mohd et al., 2010), a normalization equation for the input and output data is shown in Equation 2.5.

$$x_i = \frac{0.8}{d_{max} - d_{min}}(d_i - d_{min}) + 0.1$$

Where d_i is the input and output data at $_i$th, d_{min} is the minimum value of input and output data, and d_{max} is the maximum value of the input and output data.

Equation 2.5 Normalization equation for the input and output data

2.4.5.4 NETWORK ALGORITHM

Different algorithms aimed at modelling the ANN such as Self-Organizing Map, Radial Basis, Perceptron, Time-delay BP, Elman BP, Cascadeforward BP and so on, have been developed by previous researches. The most common algorithm would be the feed-forward backpropagation algorithm, where it is implemented by earlier studies in age approximation according to Table 2.1. However, the questions remains as to which algorithm is best suited to construct the ANN to produce the finest estimation results. With several choices considered, however, the feed-forward backpropagation is still the most generally used for countless problems compared to other network algorithms, according to a statement made by Mohd et al. (2010).

2.4.5.5 TRANSFER FUNCTION

Different transfer functions for age approximation are implemented, which can be hypothesized by observing Table 2.1. Applicable transfer functions are the linear transfer function (purelin), log-sigmoid transfer function (logsig), hard limit transfer function (hardlim), hyperbolic tangent transfer function (tansig) and so on. Given the many choices of transfer functions, one of them must be selected to produce the finest approximation result. Several options can be adopted, but no precise statements have been made that any notable effects are observed when different transfer functions are implemented.

According to the User's Guide of Neural Network Toolbox 6 written by (Demuth & Hagan, 2009), there are three transfer functions generally implemented together with the feed-forward backpropagation algorithm which are the tansig, logsig, and linear transfer function. The essence of the issue must align with the aim of the transfer function (Nalbant, Gökkaya, Toktaş, & Sur, 2009). As such, the nonlinear transfer function such as sigmoid and tansig is a fitting option when a non-linear relationship between input and output is applied for training the approximation model. The two key components, the simple derivative and self-limiting are the reason the sigmoid function has gained popularity. The end result is not able to develop infinitely large or small. The logsig and tansig are two transfer functions that have been applied by (Kohli & Dixit, 2005), and it is found that both results produced by the transfer functions are almost the same with each other. The sigmoid transfer function is widely implemented by researchers for age estimation, in which can be deduced from Table 2.1. Equation 2.6 is applied to compute the sigmoid transfer function while Equation 2.7 is employed to compute the tansig transfer function.

$$f = \frac{1}{(1+e^{-net})}$$

Equation 2.6 Formula to compute the sigmoid transfer function

$$f = \frac{2}{(1+e^{-2(net)})} - 1$$

Equation 2.7 Formula to compute the tansig transfer function

Using Equation 2.8, the hidden node's output is computed with the sigmoid function. Additionally the output for hidden nodes with the hyperbolic tangent transfer function is computed by implementing Equation 2.9. Equation 2.10 calculates the output nodes employing the sigmoid function and the output nodes using the hyperbolic tangent function can be computed as clarified in Equation 2.11.

$$h_k\textit{(sigmoid)} = f(net\_input) = \frac{1}{1+e^{-\sum_{j=1}^{J} c_{j,k} i_j + \theta_k}}$$

Equation 2.8 The hidden nodes' output with sigmoid transfer function is computed with the formula

$$h_k\textit{(hyperbolic tangent)} = f(net\_input) = \frac{2}{1+e^{-2(\sum_{j=1}^{J} c_{j,k} i_j + \theta_k}} - 1$$

Equation 2.9 The hidden nodes' output with hyperbolic tangent transfer function with the formula

$$o_z(sigmoid) = f(net\_output) = \frac{1}{1+e^{-\sum_{k=i}^{K} D_{k,z} h_k + \emptyset_z}}$$

Equation 2.10 Formula to compute the output nodes' output with sigmoid transfer function

$$o_z(hyperbolic\ tangent) = f\left(net_{output}\right) = \frac{2}{1+e^{-2\sum_{k=1}^{K} D_{k,z} h_k + \emptyset_z}} - 1$$

Equation 2.11 Formula to compute the output nodes' output with hyperbolic tangent transfer function

2.4.5.6 PERFORMANCE FUNCTION

According to Table 2.1, there is a widespread use of MSE value performance function among researchers for age estimation. To determine the MSE value, the basic equation is shown in Equation 2.12.

$$MSE = \frac{1}{n}\sum_{n=1}^{n}(actual\ output_n - predicted\ output_n)^2$$

Equation 2.12 Formula to compute the MSE value

A suitable performance function can be the performance measurement for the ANN, in which several options can be considered such as MSE value for age estimation in Table 2.1.

2.4.5.7 TRAINING FUNCTION

The error value must be minimized in the backpropagation approach. To do so, two main components should be assessed, the learning function and training function. To construct the greatest model, the mathematical specification software known as Matlab contains a toolbox of the ANN model that can facilitate the computation of the momentum (α) and learning rate (ŋ) value, where the range of 0 to 1 will be used as a benchmark for the values of these parameters. Some training functions such as trainscg (Scaled Conjugate Gradient algorithm), traingd (gradient descent backpropagation), trainlm (LevenbergMarquardt backpropagation), trainbr (Bayesian regularization backpropagation) and others have been applied by earlier researchers, and among these training functions, one must be selected as the top. Unfortunately, the absence of a precise statement where different training functions could bring forth different performances of the model implies that no guidelines are available to select the best training function, based on the earlier case study.

2.4.5.8 LEARNING FUNCTIONS

Once again, same as the selection of training functions, a definite statement is not given if different network performance are yielded from different learning functions, and various learning functions that are commonly seen would be learngd (gradient descent weight/bias), and learngdm (gradient descent with momentum weight/bias). Researchers have not stated the learning function they have chosen in Table 2.1.

2.4.6 HYBRID GENETIC ALGORITHM-ARTIFICIAL NEURAL NETWORKS (GA-ANN)

Although ANN has a lot of favorable features, there are problems like slow convergence and fail to progress at local minimum. In order to solve these issues, researchers proposed a hybrid approach of GA-ANN to improve the performance of ANN to attain the global minimum. GA-ANN contemplating a suitable fitness function and therefore, significant parameters of ANN will be deduced and modified. The intention of adopting hybrid GA-ANN model is to alter a set of weights and biases to lessen objective function (Armaghani, Mohamad, Monjezi, Faradonbeh, & Majid, 2016).

GA is implemented to enhance the accomplishment of artificial intelligence (AI) techniques. GA is extensively applied to choose neural network topology like improving relevant feature subset, deducing the most favorable number of hidden layers and elements in process. Architectural factors of ANN such as feature subset, number of hidden layers, number of elements in process of hidden layers, activation functions, and so as the connection weights among layers are going to be deduced in advance. Nearly all of existing studies were emphasized on the enhancement of the learning algorithms itself (Kim & Han, 2000).

2.5 COMPARISON AND JUSTIFICATION

Source	**Approach**	**Advantages**	**Disadvantages**
(Pinchi et al., 2014) (Cantekin et al., 2012)	GP	Simple and effective Contains reliable references for different ages	Tend to overestimate Require professional anthropologists to execute

(Koc et al., 2001)			Accuracy is dependent on proficiency of the anthropologist
(Spampinato, Palazzo, Giordano, Aldinucci, & Leonardi, 2017) (Benjavongkulchai & Pittayapat, 2018) (Pinchi et al., 2014)	TW	More effective than GP for some ages Contains reliable references for different ages	Require professional anthropologists to execute More complex and time-consuming Accuracy is dependent on proficiency of the anthropologist
(Susan L. King, 1999) (Darmawan et al., 2015)	MLR	Understands the relationship between the variables	Dependent on the dataset as some data can be irrelevant to the prediction Require a predefined relationship between the variables Works only if the relationship between variables are linear
(Susan L. King, 1999) (Rucci, Coppini, Nicoletti, Cheli, & Valli, 1995) (Bocchi, Ferrara, Nicoletti, & Valli, 2003)	ANN	Require no relationships between the data to predict Find both linear and non-linear relationships between variables	Highly dependent on the dataset to make an estimation Require the data to be completely numerical Does not filter the input features as some input features may be irrelevant and negligible to the estimation

Table 2.2: Sources, advantages and disadvantages of approaches in age estimation using hand bones

The source column in Table 2.2 records the documents used as references in reaching these comparisons. The approach column states the names of the approaches. The advantage and disadvantage columns states the strong and weak points for each approach. As a conclusion, the ANN approach is the best approach in terms of estimating the age of the Hispanic population. One of the disadvantage of ANN approach is that input features are not filtered, which may cause waste of data and inaccurate estimations. The problem can be overcome by introducing a GA approach to select the best features among the input features to reduce the load and increase the accuracy of the estimation of the ANN approach. As such, a GA-ANN hybrid approach has been proposed, where the GA approach will be implemented first to select the best features and the ANN approach will estimate the age of the Hispanic population based on the best features.

2.6 SUMMARY

The conservative model for age estimation is reliant upon the examination results of bone morphology from the X-ray images of the left hand bones by forensic anthropologists. The main problem is that this model requires the professionalism of forensic anthropologists in estimating the age, and the variability may vary from one to another. In other words, different levels of experiences of forensic anthropologists in age estimation will result the high variable between the actual age and the estimated age. The next problem is the models of this study are population specific. This means that the models used for age estimation is not applicable for various populations. The third issue is only a few studies using soft computing model for age estimation. The target of the current research is to construct an age estimation model for Hispanic population.

There are advantages and disadvantages of different approaches on age estimation using hand bones. Through the comparison and justification, a conclusion is made and ANN approach has been known as the best approach to estimation the age. In the meantime, there is a biggest disadvantage of ANN approach, where there is no filter applied on input features, which may lead to waste of data and inaccurate estimation. Therefore, a GA-ANN hybrid approach is proposed, where GA approach is implemented to select features before the ANN approach.

CHAPTER 3

METHODOLOGY

3.1 INTRODUCTION

This chapter reviews the methodology that will be applied during data collection, data normalization, age estimation model using ANN approach, age estimation using GA-ANN approach, data denormalization, and validation and evaluation of results.

3.2 RESEARCH FLOW

The research flow of this study involves seven phases which are the problem definition, data collection, data normalization, age estimation model using ANN approach, age estimation using GA-ANN approach, data denormalization, and validation and evaluation of results.

3.3 PROBLEM DEFINITION

Problem definition is the first phase in this study as stated in Section 3.2. Problem definition requires a direct, specific, and incisive statement of issues to be explored and probed with the objective of getting a solution. In this study, problem definition has been stated in Section 1.2.

3.4 DATA COLLECTION

The original dataset is constructed from an online dataset taken from http://ipilabmysql.usc.edu/newindex.php. There are subjects of Caucasian, African American, Hispanic, and Asian in the online dataset. Only Hispanic subjects are adopted in this study as described in the Section 1.2.

There are 365 X-ray images of left hand bones of Hispanics, in which out of total, 182 are males while 183 are females. This dataset varied from age of 0 to 18 years without any problem or disease of bone like fractures, genetic bone problems and so on. Bones with those issues will be excluded since they are regarded as likely to be weak and easy to break which may influence the assessments or measurements. All the X-ray images were collected from Children's Hospital Los Angeles together with demographic data of patients as well as the reading of radiologists, dispersed into nineteen groups which are 0 to 18 years old, for both genders. The details of each subjects are the respective image name, race, gender, chronological age, date of birth, exam date, tanner, height (cm), weight (kg), trunk HT (cm), reading 1, and reading 2. Reading 1 and reading 2 are the estimated age evaluated by experienced radiologist using GP model (Gertych, Zhang, Sayre, Pospiech-Kurkowska, & Huang, 2007). In the end of this study, these estimated age generated using GP model will be adopted as the first benchmark for this study in order to validate and evaluate the proposed model.

The National Institute of Health has funded this X-ray images collection that gathered from the Image Processing and Informatics Lab of University of Southern California and is confined to only purposes of open research and education. Institutional review board has agreed with inspecting candidates for clinical investigations to be inspected for studies. The radiographs were digitalized to 2k x 2k images by applying a laser film scanner (Array, Tokyo, Japan) while patients' demographic data had manually inserted using the scanner GUI (graphical user interface) and saved as DICOM file (Gertych et al., 2007).

The 19 left hand bones are grouped into four main groups which are distal phalanx, middle phalanx, proximal phalanx, and metacarpal. There are four bones in the middle phalanx while five bones respectively in the other three groups. There are 19 bones in hand and Figure 3.1 shows the label of each bone in left hand. Epiphyses and diaphysis are two major parts of long bone during childhood. The former is at the tail of a long bone that has started to disengage from the main bone by a layer of cartilage and is joint to main bone through ossification during adulthood while the central shaft that having mostly of compact bones neighbouring a cavity. Table 3.1 shows the six key phases during childhood and adolescence (Gilsanz & Raitb, 2005).

Phase	**Male (age)**	**Female (age)**
Infancy	Newborn to 14 months	Newborn to 10 months
Toddlers	14 months to 3 years	10 months to 2 years
Pre-puberty	3 years to 9 years	2 years to 7 years
Early and Mid-puberty	9 years to 14 years	7 years to 13 years
Late Puberty	14 years to 16 years	13 years to 15 years
Post-puberty	16 years to 19 years	15 years to 17 years

Table 3.1: The six key phases during childhood and adolescence for both gender

Left hand bones lengths in normalization form is the input that adopted in this study. A free photo editor, Photo Pos Pro, Power of Software Company Ltd. is utilized in order to assess the nineteen bones lengths in each X-ray image by constructing a line on each bone, starting from base-middle point to end-middle point of the bone on each X-ray image. These lines are constructed by disregarding the epiphyseal in bone even if it exists for infant phage while lines will be constructed by involving the epiphyseal for other phases even if it is only a small epiphyseal occurred in the X-ray image.

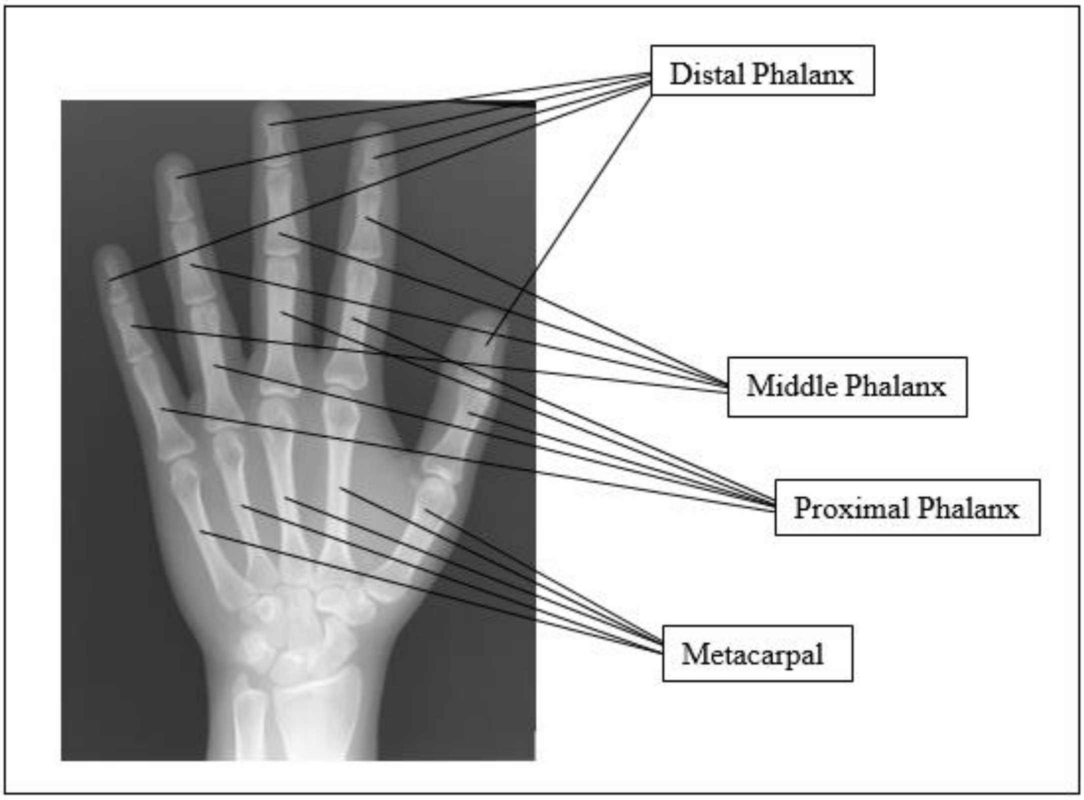

Figure 3.1: Left hand bone with labels

3.5 DATA NORMALIZATION

The proposed approach will adopt the normalized dataset in order to estimate the age. The dataset will normalized based on Equation 2.5, which contains the dataset in the range of 0.1 to 0.9. The normalization aims to remove any computing errors during the training of the ANN, since the ANN uses mathematical equations to estimate the age. Dataset which are not normalized may produce errors in estimating.

3.6 AGE ESTIMATION MODELS USING ANN APPROACH

The dataset will be distributed into two groups: training dataset and testing dataset. In order to train the age estimation models using ANN approach, we need to have training dataset while in order to validate and evaluate the models, we require testing dataset. Samui & Dixon (2012) have adopted different data division between training dataset and testing dataset and stated that there is no a strictly accurate principle. In this study, 70% of total dataset will be used as training dataset while another 30% will be adopted as testing dataset. The selected subjects for the training dataset and testing dataset are going to be determined chaotically by implementing the function *dividerand* in Matlab.

An estimated age in the conservative way of age estimation is determined based on qualitative data such as observation of bone morphology which requiring the inspection of forensic anthropologists. Bone length will be used as the quantitative age indicator in this study in order to reduce the dependency towards forensic anthropologists in estimating age while ANN approach has been proven in many research studies since it showing strong pattern classification, pattern recognition and estimation capabilities when quantitative data being used. Therefore, the adoption of bone length as quantitative age indicator to ANN approach is able to be trusted.

There are eight factors that discussed in Section 2.6.2 in creating age estimation models using ANN approach in order to let the models produce the finest result on the estimation. Test regression value and test set MSE value will be compared in order to choose the finest network structure for age estimation in ANN model for both genders.

3.7 AGE ESTIMATION MODELS USING GA-ANN APPROACH

GA approach is an algorithm to solve restricted and unconstrained optimization problems that rely on natural selection or biological evolution. A population of individual solutions will be altered time after time in this algorithm. The GA approach will generate a population at the beginning, which is completely randomized and then the next generation will be produced. The approach will use the individuals in the current generation in order to generate next population at each step. In order to generate the new population, GA approach will achieve each member of the current population by calculating its fitness value and these values are known as the raw fitness scores. A more utilizable range of values called expectation values is transformed by scaling the raw fitness scores and parents or the members are selected based on the expectation values. Individuals that having lower fitness in current population will be selected as elite and will be inherited to next generation. Two methods are used to generate children from parents: mutation which randomly modifies one parent and crossover which combines vector entries between two parents. The next generation is then comprised of all children of the parents in the earlier generation. The model will terminate when one of the stopping criteria is fulfilled. The approach will ultimately generate the best input features to be inserted into an ANN for training.

The age estimation model using GA-ANN hybrid approach is the combination of GA approach and ANN approach, where the purpose of GA approach is to select the most appropriate bones of left hand to be used as input in ANN approach while ANN approach is to estimate the age. This is because ANN approach is a black box learning approach that cannot perform the correlation between input and output. Figure 3.2 illustrates the flow of the implementation of the GA-ANN approach.

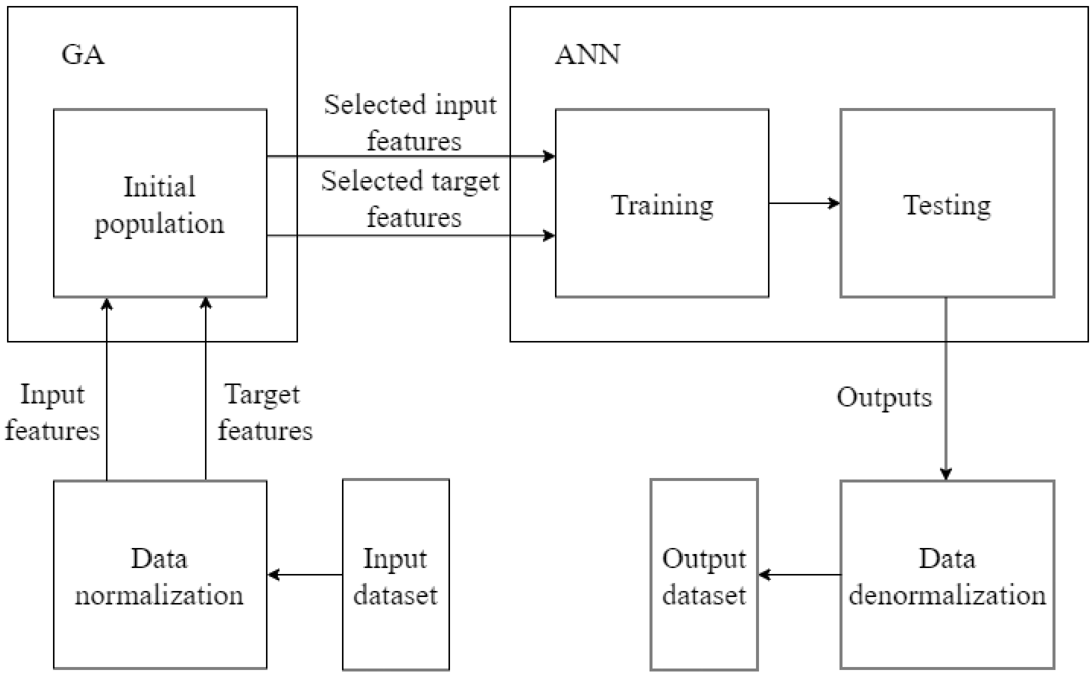

Figure 3.2: The flow of the implementation of the GA-ANN approach

The dataset is first normalized to avoid computation errors and fed into the GA approach. Through crossover and mutation, a new population containing the best input features will be generated. The best input features and target features will then be fed into the ANN for training and testing. The outputs will be denormalized to obtain the real estimated age and the errors will then be calculated. The process of denormalization and evaluation of results will be discussed later.

3.8 DATA DENORMALIZATION

The test set data consists of the input data, targeted output data, the estimated output data and the errors. The input data will not be taken as it is part of the normalized dataset and does not contribute in evaluating the results. The errors are generated from the ANN, in which the errors are generated based on the normalized inputs. These errors will not be used as a metric to evaluate the results, but instead it is used to validate the targeted output data and the estimated output data. This is done by subtracting the targeted output data with the estimated output data and the difference is matched with the errors.

The targeted output data and the estimated output data will be denormalized to obtain the actual age. The denormaliztion formula will be the inverse of the formula mentioned in the previous section, Section 3.5. The denormalization will convert the data into the range of 0 to 18. Once the data is denormalized, the targeted output data and the estimated output data will be used for the evaluation of results.

3.9 VALIDATION AND EVALUATION OF RESULTS

The test regression value, *r* and the test set MSE value will be used as the evaluation metric for the results for both approaches. These two evaluation metric are used for the majority of neural networks. The test regression value is a coefficient of correlation, where the closer the value of *r* is to 1, the better the correlation (Creative

Research Systems, 2016). The higher the test regression value, the better the performance for that approach. The test regression value is the accuracy of the approach, which reflects how well the test data was able to map to the ANN. On the other hand, the lower the test set MSE value, the better the performance for that approach. The test set MSE value is the average of all the test errors by subtracting the denormalized targeted output data with the denormalized estimated output data. The less errors predicted by the ANN, the lesser the test set MSE value, which increases the accuracy of the ANN. Below is a figure of the research flow.

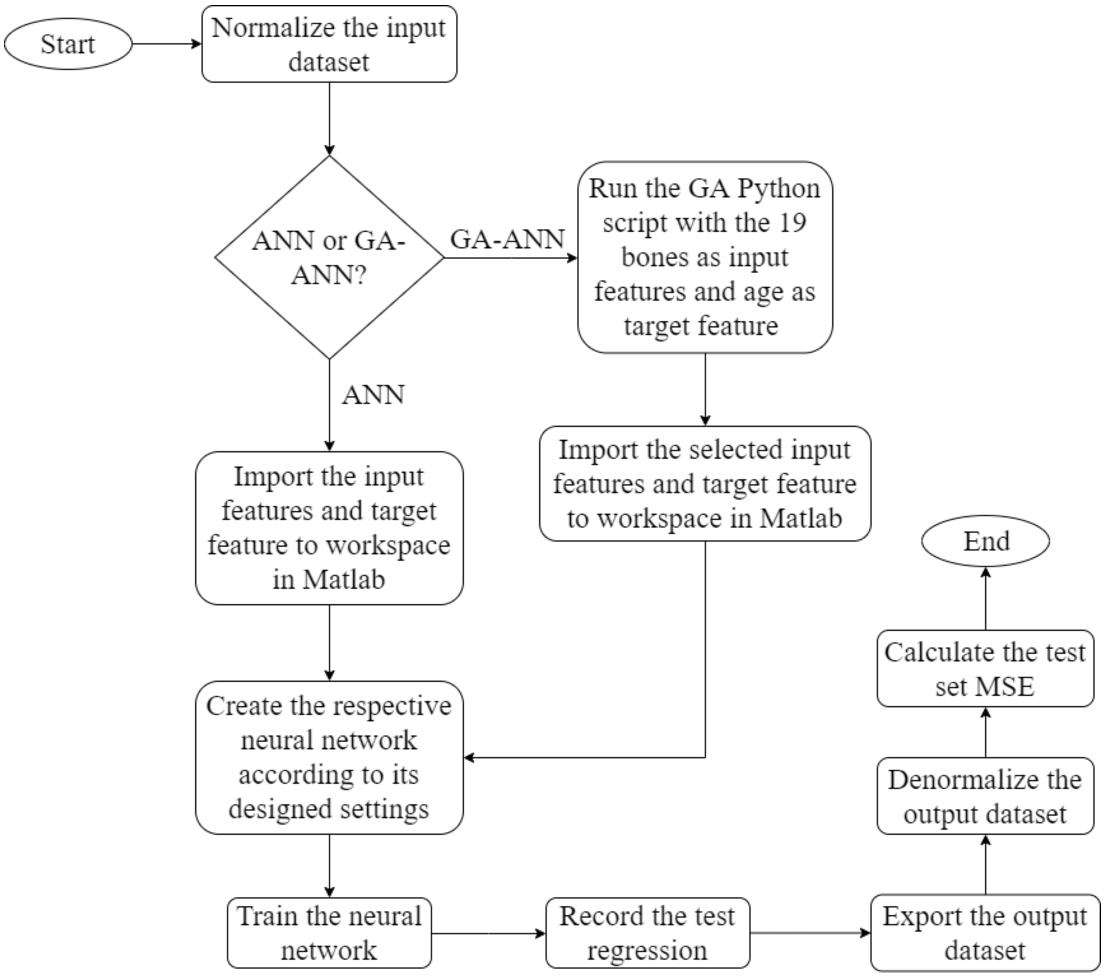

Figure 3.3: Flowchart of this research flow

In the flowchart above, the input is normalized first. For the ANN approach, the ANN will directly receive the normalized input, create and train the ANN based on the normalized input. The test regression and the test set MSE value is calculated to validate the performance of the ANN approach. For the GA-ANN hybrid approach, the normalized inputs will be reduced to the best input features through feature selection in the GA approach. The same steps with the ANN approach are repeated, where the difference is that the input will be the best inputs. The test regression value and the test set MSE value will be calculated for the GA-ANN hybrid approach. The test regression values and the test set MSE value will be compared from both approaches.

3.10 HARDWARE AND SOFTWARE

Tools in the configuration of hardware and software are compulsory to have in order to aid this research carry out in a smooth way. The hardware tool that adopted to perform the implementation is particularly efficacious and well-organized. The computer that operated for implementation of this research performs on Microsoft Windows 10 Pro with the specifications of Intel Core i5-6200U, 2.6GHz, 64-bit operating system, x64-based processor, and 8GB of random-access memory (RAM).

The software tools that are going to be utilized are a free photo editor, Photo Pos Pro, Power of Software Company Ltd. in order to assess the bones lengths, Microsoft Excel 2013 for data collection, Microsoft Word 2013 for documentation, and Matlab R2012a for constructing the approaches. Python scripts and the Miniconda tool are used to develop the GA approach.

3.11 GANTT CHART

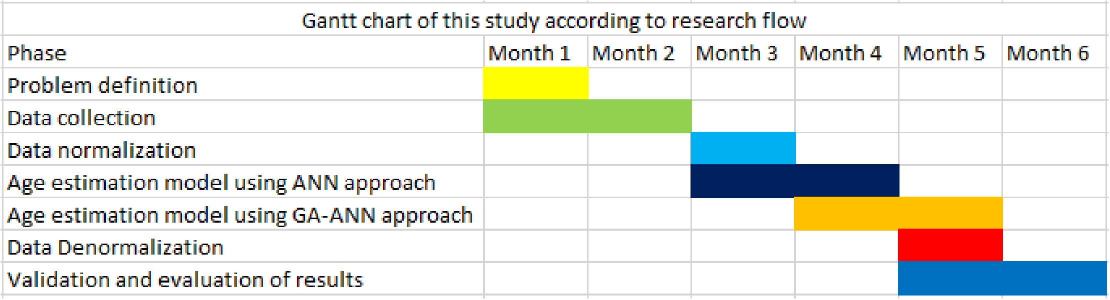

Figure 3.4 Gantt chart of project

3.12 SUMMARY

This chapter explored about the methodology used in age estimation models using GA approach, ANN approach, and hybrid GA-ANN approach. The flows and steps to implement approaches are discussed and the methods to validate and evaluate results have also been indicated.

CHAPTER 4

ARTIFICIAL NEURAL NETWORK MODELS AND HYBRID GENETIC ALGORITHM-ARTIFICIAL NEURAL NETWORK MODELS

4.1 INTRODUCTION

This chapter discusses the implementation of applying ANN approach and GA-ANN hybrid approach on age estimation models for both female and male population of Hispanic population, the results of the models, the discussion, and the justification of the mentioned results.

4.2 IMPLEMENTATION

The original data is constructed from an online dataset taken from http://ipilabmysql.usc.edu/newindex.php and only Hispanic subjects are adopted in this study. Photo Pos Pro, a free photo editor, Power of Software Company Ltd. is used in order to assess the nineteen bones lengths in each radiograph, by constructing a line on each bone, starting from base-middle point to end-middle point of the bone of each radiograph. The lines are constructed by disregarding the epiphyseal in bone even if it exists for infant phage while for other phases, lines are constructed by involving the epiphyseal even if it is only a small epiphyseal occurred in the radiograph. Below are the nineteen bones and its particular ages used as input features and target feature respectively during the implementation of ANN approach and the part of GA approach of the GA-ANN hybrid approach. For the input features, which are bones, each of them will be represented by an integer number, starting from 1 to 19, or feature name, starting from Bone 1 to Bone 19, while target feature, age, will labelled as 1 or Age.

	ANN	GA
Features	**Integer number**	**Feature name**
First Metacarpal	1	Bone 1
Second Metacarpal	2	Bone 2
Third Metacarpal	3	Bone 3
Fourth Metacarpal	4	Bone 4
Fifth Metacarpal	5	Bone 5
First Proximal Phalanx	6	Bone 6
Second Proximal Phalanx	7	Bone 7
Third Proximal Phalanx	8	Bone 8
Fourth Proximal Phalanx	9	Bone 9
Fifth Proximal Phalanx	10	Bone 10
Second Middle Phalanx	11	Bone 11
Third Middle Phalanx	12	Bone 12
Fourth Middle Phalanx	13	Bone 13
Fifth Middle Phalanx	14	Bone 14
First Distal Phalanx	15	Bone 15
Second Distal Phalanx	16	Bone 16
Third Distal Phalanx	17	Bone 17
Fourth Distal Phalanx	18	Bone 18
Fifth Distal Phalanx	19	Bone 19
Age	1	Age

Table 4.1: The features and its represented integer number and feature name in ANN approach and part of the GA approach of GA-ANN hybrid approach respectively

In the implementation of ANN approach, the nineteen bones are used as input features and each of the bones is represented by an integer number, starting from 1 to 19. During the implementation of the part of GA approach of GA-ANN hybrid approach, the nineteen bones are used as input features and each of them is represented by its respective feature name. For example, first metacarpal is represented by integer number 1 in the implementation of ANN approach, and Bone 1 in the implementation of the part of GA approach of GA-ANN hybrid approach. The feature, age has been represented by integer number 1 in the implementation of ANN approach while it remains the same in the implementation of the part of GA approach of GA-ANN hybrid approach. First metacarpal and age, both features can be represented by the same integer number 1 since the feature of age is imported as another variable in the workspace in Matlab.

Before all the models are trained, the data is normalised to prevent any technical errors during the training of the models. The normalization formula is Equation 2.9 in Chapter 2.6.2. The normalised data can be found in the appendix.

4.2.1 ARTIFICIAL NEURAL NETWORK

The input data and target data for all models are imported to the workspace in Matlab.

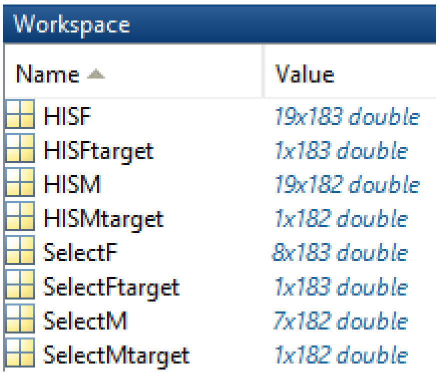

Figure 4.1: The imported input data and target data for all models in the workspace of Matlab

HISF and HISFtarget are the input features and target feature of age estimation model using ANN approach for female Hispanic population while HISM and HISMtarget are for the male Hispanic population. SelectF and SelectFtarget are the input features and target feature of age estimation model using the GA-ANN approach for female Hispanic population while SelectM and SelectMtarget are for the male Hispanic population. All of these input features and target features are imported as variables in the workspace in Matlab. The data or the input features, and the target feature of SelectF, SelectM, SelectFtarget and SelectMtarget have gone through the process of feature selection using GA approach.

Below is the command in Matlab to open the Network/Data Manager window which can import, create, use, and export neural networks and data.

```
>> nntool
```

Figure 4.2: The command to open Network/Data Manager window in Matlab

The command in Figure 4.2 is entered in the command window in Matlab in order to open the Network/Data Manager window which has been shown in Figure 4.5.

A network can be created by giving a name to the network, select the network type, input data, target data, training function, adaption learning function and performance function, customize the number of layers and also the number of neurons for Layer 1, and transfer function for Layer 1 and Layer 2. Below is the table of the settings for each neural network to be created.

		Female		**Male**	
Name		HISFnet	SelectFnet	HISMnet	SelectMnet
Network type		Feed-forward backprop	Feed-forward backprop	Feed-forward backprop	Feed-forward backprop
Input data		HISF	SelectF	HISM	SelectM
Target data		HISFtarget	SelectFtarget	HISMtarget	SelectMtarget
Training function		TRAINLM	TRAINLM	TRAINLM	TRAINLM
Adaption learning function		LEARNGDM	LEARNGDM	LEARNGDM	LEARNGDM
Performance function		MSE	MSE	MSE	MSE
Number of layers		2	2	2	2
Properties for Layer 1	Number of neurons	13	6	13	6
	Transfer function	PURELIN	PURELIN	PURELIN	PURELIN
Properties for Layer 2	Transfer function	TANSIG	TANSIG	TANSIG	TANSIG

Table 4.2: The settings of each neural network in this paper

HISFnet and HISMnet are the neural networks where only ANN approach has been applied while SelectFnet and SelectMnet are the neural networks where their respective input data and target data have gone through the process of feature selection using GA approach.

HISFnet is the feed-forward backpropagation neural network with the input data, HISF and target data, HISFtarget. The training function, adaption learning function, and performance function of HISFnet are TRAINLM, LEARNGDM and MSE respectively. The number of layers of HISFnet is two while the number of neurons in Layer 1 is 13. The transfer function for Layer 1 and Layer 2 are PURELIN and TANSIG respectively.

SelectFnet is the feed-forward backpropagation neural network with the input data, SelectF and target data, SelectFtarget. The training function, adaption learning function, and performance function of SelectFnet are TRAINLM, LEARNGDM and MSE respectively. The number of layers of SelectFnet is two while the number of neurons in Layer 1 is 6. The transfer function for Layer 1 and Layer 2 are PURELIN and TANSIG respectively.

HISMnet is the feed-forward backpropagation neural network with the input data, HISM and target data, HISMtarget. The training function, adaption learning function, and performance function of HISMnet are TRAINLM, LEARNGDM and MSE respectively. The number of layers of HISMnet is two while the number of neurons in Layer 1 is 13. The transfer function for Layer 1 and Layer 2 are PURELIN and TANSIG respectively.

SelectMnet is the feed-forward backpropagation neural network with the input data, SelectM and target data, SelectMtarget. The training function, adaption learning function, and performance function of SelectMnet are TRAINLM, LEARNGDM and MSE respectively. The number of layers of SelectMnet is two while the number of neurons in Layer 1 is 6. The transfer function for Layer 1 and Layer 2 are PURELIN and TANSIG respectively.

Below are the Network/Data Manager windows to create neural network, and also to import, export, and use the neural networks and data.

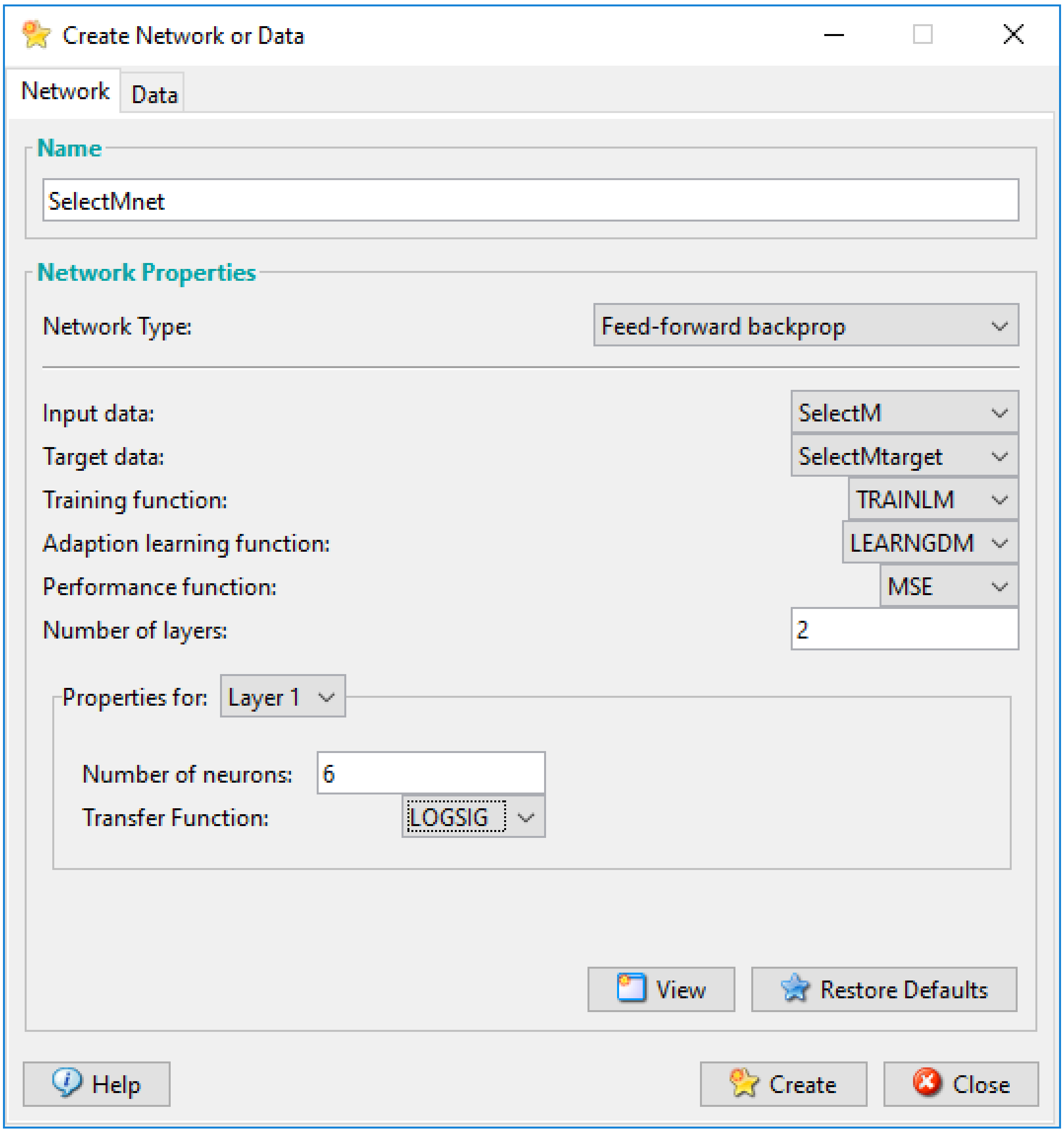

Figure 4.3: Example of the Network/Data Manager window to create one of the neural networks

Figure 4.3 is the example of Network/Data Manager window where a neural network can be created by selecting its network type, input data, target data, training function, adaption learning function and performance function, and customizing the number of layers, the number of neurons of Layer 1 and also the transfer function for Layer 1 and Layer 2. All networks, which are HISFnet, HISMnet, SelectFnet and

SelectMnet will be created with this window. Figure 4.4 has shown the example of customizing the transfer function for Layer 2 of one of the neural networks.

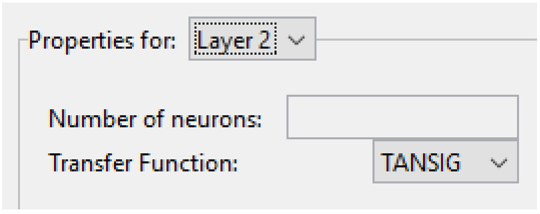

Figure 4.4: Example of customizing the transfer function for Layer 2 of one of the neural networks

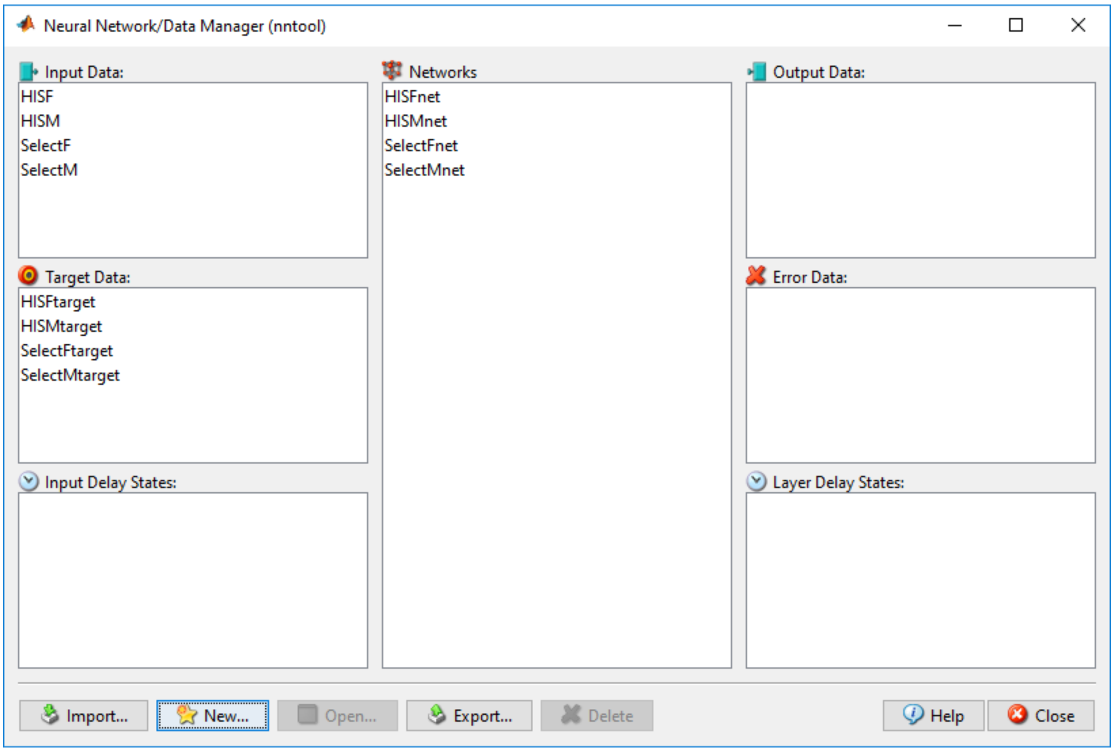

Figure 4.5: The Network/Data Manager which creates neural network, imports, exports, and uses the neural networks and data

All the created networks are exported to the workspace in Matlab.

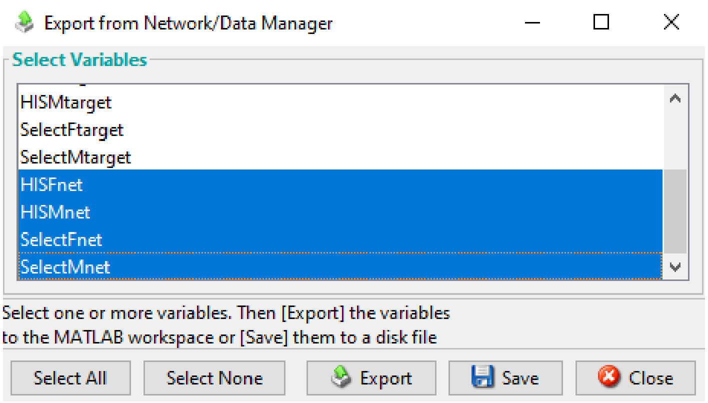

Figure 4.6: Example of exporting the neural networks to workspace of Matlab

Figure 4.6 shows that HISFnet, HISMnet, SelectFnet and SelectMnet are going to be exported to workspace in Matlab.

Below is the command to randomly generate column indices to be used to divide the data into 70% training data and 30% testing data respectively.

```
>> [trainInd, testInd, valInd] = dividerand(183, 0.7, 0.3, 0);
```

Figure 4.7: The command to randomly generate column indices for the division of the data into 70% training data and 30% testing data respectively

The command in Figure 4.7 is entered in the command window in Matlab to randomly generate column indices for the division of the data into 70% training data and 30% testing data respectively. The number of data, which is the number of individuals will be specified first before the percentages of the divided data. For the female and male networks, the number will be 183 and 182 respectively. The generated column indices will be applied on those variables which are formed by the data of input features and target features. Since one column represents one individual in the variable, column indices are used in the division of the data.

Below is the command to change the divide function in order to enable dividing data with indices.

```
>> HISFnet.dividefcn = 'divideind';
```

Figure 4.8: The command to change the divide function in order to enable dividing data with indices

The command in Figure 4.8 is entered in the command window in Matlab to change the divide function in order to enable dividing data with indices.

Below are the commands to set the generated indices to a particular neural network.

```
>> HISFnet.divideParam.trainInd = trainInd;
>> HISFnet.divideParam.testInd = testInd;
>> HISFnet.divideParam.valInd = valInd;
```

Figure 4.9: The commands to set the generated indices to a particular neural network

The command in Figure 4.9 is entered in the command window in Matlab to set the generated indices to a particular neural network. All networks will have their respective input data divided in this method.

Below is the neural network design for HISFnet and HISMnet.

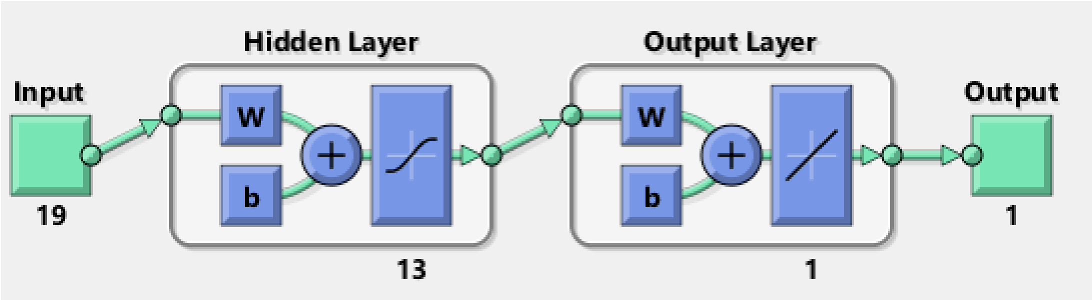

Figure 4.10: The neural network design for HISFnet and HISMnet

Figure 4.10 shows the neural network design for HISFnet and HISMnet. There are 19 input features, which are the 19 bones while the hidden layer consists of the weights and biases and also 13 neurons. There are weights and biases and also one neuron for the output layer and one output feature will be produced.

Below is the neural network design for SelectFnet.

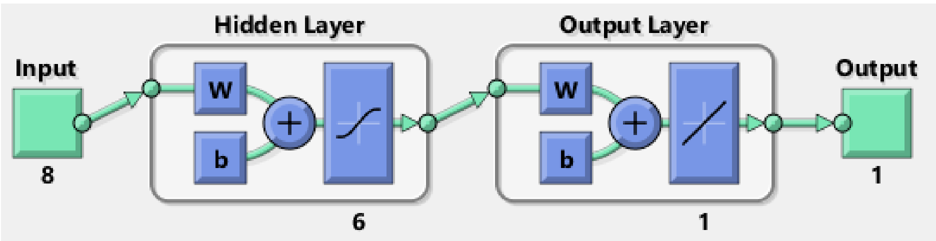

Figure 4.11: The neural network design for SelectFnet

Figure 4.11 shows the neural network design for SelectFnet. There are eight input features, which are the eight selected bones using GA approach while the hidden layer consists of the weights and biases and also six neurons. There are weights and biases and also one neuron for the output layer and one output feature will be produced.

Below is the neural network design for SelectMnet.

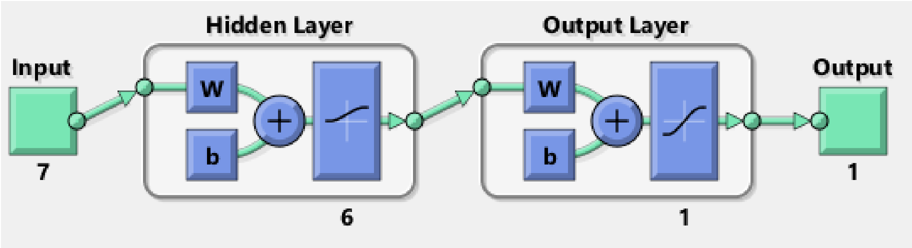

Figure 4.12: The neural network design for SelectMnet

Figure 4.12 shows the neural network design for SelectMnet. There are seven input features, which are the seven selected bones using GA approach while the hidden layer consists of the weights and biases and also six neurons. There are weights and biases and also one neuron for the output layer and one output feature will be produced.

After training all of the networks, the outputs and errors for each network are exported to the workspace in Matlab.

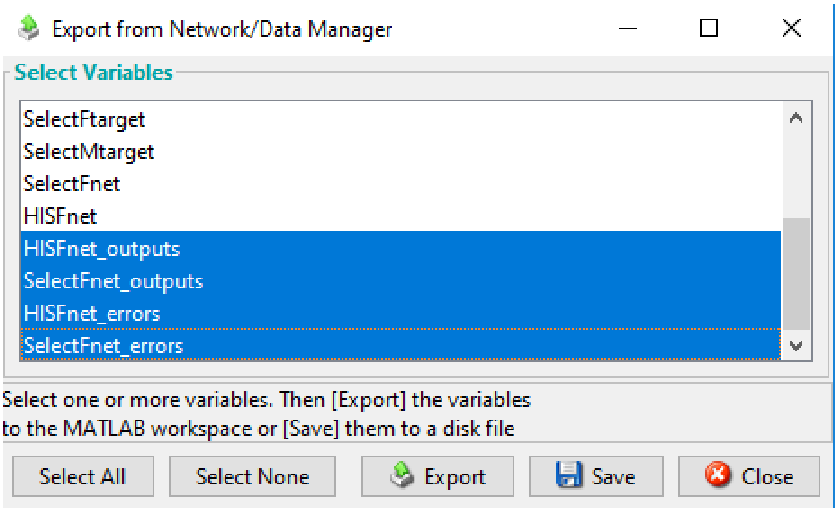

Figure 4.13: Example of exporting the outputs and errors of one of the neural networks

Figure 4.13 shows that HISFnet_outputs, SelectFnet_outputs, HISFnet_errors and SelectFnet_errors are going to be exported to workspace in Matlab. The errors and outputs of the training for all networks will be exported to the workspace in Matlab as it contains the results of the training.

Below are the commands to extract the data based on the generated indices.

```
>> i = 1
```

Figure 4.14: The command to initialize the variable of a for-loop in order to extract the data based on generated indices

The command in Figure 4.14 is entered in the command window in Matlab to initialize the variable of a for-loop in order to extract the data based on generated indices.

```
>> for i = 1:19
HISFtrain(i,:) = HISF(i, [trainInd]);
end
```

Figure 4.15: The for-loop command and also command to extract the data based on generated indices from a specific data

The commands in Figure 4.15 are entered in the command window in Matlab to execute the for-loop and to extract the data based on generated indices from a specific data.

4.2.2 HYBRID GENETIC ALGORITHM-ARTIFICIAL NEURAL NETWORK

Below is the command to activate the Miniconda environment to enable the use of Python.

```
>conda activate yeemayfypenv
```

Figure 4.16: Example of command to activate Miniconda environment

The command in Figure 4.16 is entered in the Command Prompt to activate Miniconda environment named ‘yeemayfypenv’.

Below is the command to run the Python script to select features for female Hispanic population.

```
>python GAfemale.py
```

Figure 4.17: Example of command to run Python script

The command in Figure 4.17 is entered in the Command Prompt to run the Python script named ‘GAfemale.py’ in order to carry out the process of feature selection on the data of input features and target feature of female Hispanic population using GA approach. Another Python script named ‘GAmale.py’ is run to select features for male Hispanic population.

The script will generate a graph showing the best scores and the average scores throughout 200 generations.

Below is the graph for the results of GA approach for 200 generations.

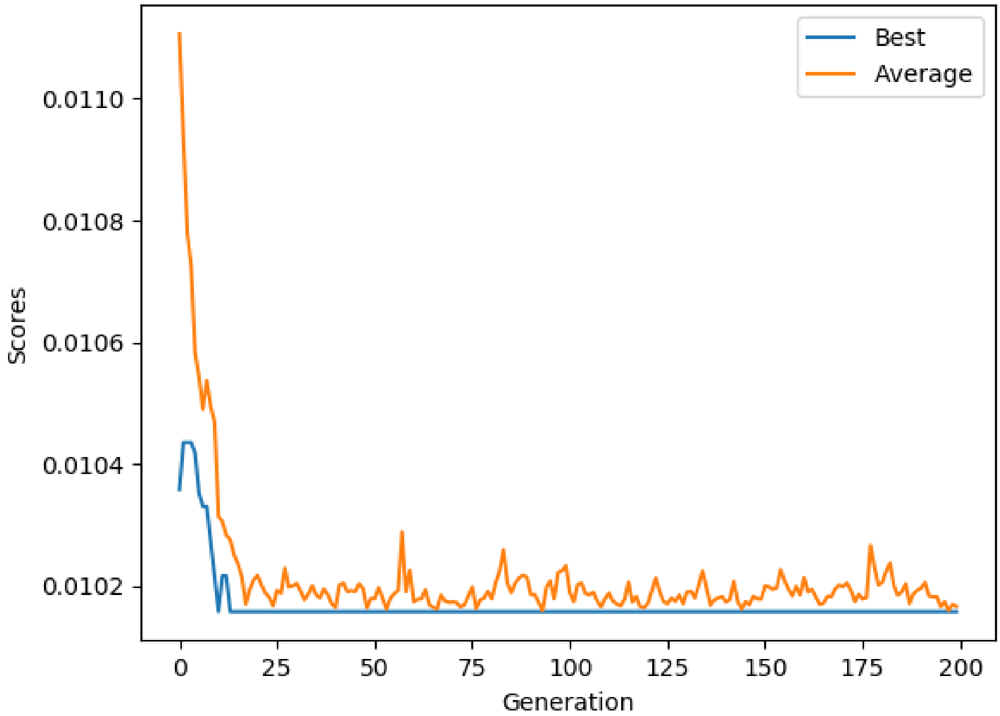

Figure 4.18: A generated graph of the best scores and the average scores throughout 200 generations

The x-axis represents the generation during the training of the GA approach while the y-axis represents the cross-validation MSE score. The blue line represents the best cross-validation MSE score that was obtained in that particular generation while the orange line represents the mean cross-validation MSE score among 200 chromosomes in that generation. As observed, the cross-validation MSE scores are decreasing with each generation, with implies an increase in performance for the GA. The 200th generation, which is the last generation, has displayed similar scores between the best and mean scores. This means that the majority of the chromosomes in the 200th generation have high fitness scores.

The script will generate the cross-validation MSE values before feature selection and after feature selection.

```
(yeemayfypenv) C:\Users\MS\Documents\FYP_YM\GA dataset>python GAfemale.py
CV MSE before feature selection: 0.01111391
CV MSE after feature selection: 0.01015822
```

Figure 4.19: The generated cross-validation MSE values before and after the feature selection throughout 200 generations

Figure 4.19 shows that the generated cross-validation MSE values before and after the feature selection throughout 200 generations for female Hispanic population.

A CSV file of the data of latest population will be generated by running the script.

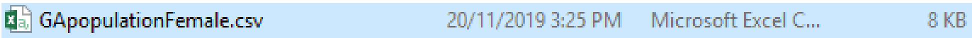

Figure 4.20: A generated CSV file of the data of latest population

The CSV file contains 200 chromosomes in the last generation, which are the fittest individuals in the GA approach. Each chromosome will have value of 0 or 1 for each bone, where 1 represents the bone has been selected after the process of feature selection while 0 represents the bone is not being selected. This CSV file is used to analyse which features are selected during the execution of the GA approach.

The implementation of part of the ANN approach of GA-ANN hybrid approach is the same as the ANN approach discussed in Section 4.2.1.

4.3 RESULTS

Below are the cross-validation (CV) MSE results of female and male Hispanic population before feature selection and after feature selection for 200 generations.

	Female		Male	
	Before feature selection	After feature selection	Before feature selection	After feature selection
CV MSE	0.01111391	0.01015822	0.00896640	0.00836916

Table 4.3: The CV MSE results of female and male Hispanic population before and after feature selection for 200 generations

Before the feature selection, the CV MSE value of female Hispanic population is 0.01111391 and after using the GA approach for feature selection, the CV MSE value has dropped to 0.01015822. For male Hispanic population, the CV MSE value before feature selection is 0.00896640 while after the feature selection using GA approach, the CV MSE value is dropped to 0.00836916. The smaller the MSE, the more preferable or desirable selection it is as it shows the data values are dispersed closely to its central moment. Therefore, GA approach has improved the performance of the CV MSE of both genders of Hispanic population.

There are 200 individuals for both female and male Hispanic population after feature selection. Each individual will have a chromosome consisting of 0 and 1. The 0 implies the feature is not selected while the 1 implies the feature is selected. Below is the total number of 1 (s) for each bone across 200 individuals for female and male Hispanic population.

Female		Male	
Bone1	0	Bone1	**200**
Bone2	0	Bone2	0
Bone3	0	Bone3	0
Bone4	**190**	Bone4	0
Bone5	**200**	Bone5	0
Bone6	**200**	Bone6	0
Bone7	0	Bone7	**190**
Bone8	0	Bone8	0
Bone9	0	Bone9	0
Bone10	0	Bone10	0
Bone11	**200**	Bone11	0
Bone12	0	Bone12	0
Bone13	0	Bone13	**200**
Bone14	0	Bone14	**200**
Bone15	**180**	Bone15	**200**
Bone16	**200**	Bone16	**200**
Bone17	0	Bone17	0

Bone18	**200**	Bone18	0
Bone19	**195**	Bone19	**175**

Table 4.4: The sum of 1 (s) for each bone across 200 individuals for female and male Hispanic population

The features which consists more than 85% of the sum of 1 (s) after will be selected. Therefore, Bone 4, Bone 5, Bone 6, Bone 11, Bone 15, Bone 16, Bone 18, and Bone 19 are the selected features across 200 individuals for female Hispanic population. Bone 1, Bone 7, Bone 13, Bone 14, Bone 15, Bone 16, and Bone 19 are the selected features across 200 individuals for male Hispanic population.

After exporting the outputs of the all networks, the errors are used to confirm the validity of the testing target data and the testing output data. When both data are correct, the testing target data and the testing output data are denormalized using the age range of zero to 18. The denormalization formula is the inverse of the normalization formula. The test errors are calculated for each individual by subtracting the testing target data with the testing output data. Table 4.5 records the testing target data, testing output data and the test set MSE for all four networks.

Female						Male					
ANN			GA-ANN			ANN			GA-ANN		
Target	**Output**	**Error**	**Target**	**Output**	**Error**	**Target**	**Output**	**Error**	**Target**	**Output**	**Error**
1	1.35528	-0.35528	1	1.602258	-0.60226	0	2.279791	-2.27979	0	1.880664	-1.88066
1	1.93271	-0.93271	1	2.00224	-1.00224	2	2.187777	-0.18778	2	2.587926	-0.58793
2	2.651318	-0.65132	2	3.131187	-1.13119	2	3.003875	-1.00387	2	2.576813	-0.57681
2	2.450083	-0.45008	2	2.376769	-0.37677	3	4.046295	-1.04629	3	4.491861	-1.49186
2	2.032009	-0.03201	2	1.650577	0.349423	3	2.507708	0.492292	3	2.696342	0.303658
5	4.825922	0.174078	5	4.905369	0.094631	4	5.990798	-1.9908	4	4.981924	-0.98192
6	5.177644	0.822356	6	5.339039	0.660961	4	2.276225	1.723775	4	2.432137	1.567863
6	4.960624	1.039376	6	4.966668	1.033332	5	5.596441	-0.59644	5	6.465045	-1.46505
6	5.264418	0.735582	6	5.669032	0.330968	5	7.464246	-2.46425	5	5.459937	-0.45994
6	5.869192	0.130808	6	5.740944	0.259056	5	5.223394	-0.22339	5	6.074604	-1.0746
7	5.891033	1.108967	7	5.283911	1.716089	5	5.56253	-0.56253	5	6.148144	-1.14814
7	8.978694	-1.97869	7	7.027829	-0.02783	6	5.728094	0.271906	6	6.050651	-0.05065
7	6.808137	0.191862	7	7.618726	-0.61873	6	5.842269	0.157731	6	6.625014	-0.62501
7	5.812521	1.187479	7	6.843336	0.156664	7	8.583953	-1.58395	7	7.879906	-0.87991
7	8.446568	-1.44657	7	8.578115	-1.57811	7	7.168705	-0.16871	7	6.36083	0.63917
8	7.162575	0.837425	8	6.572998	1.427002	7	8.315154	-1.31515	7	7.965232	-0.96523
8	7.815088	0.184912	8	8.388447	-0.38845	7	7.174108	-0.17411	7	7.029521	-0.02952
9	9.86298	-0.86298	9	9.440739	-0.44074	8	8.313136	-0.31314	8	9.095267	-1.09527
9	12.58331	-3.58331	9	11.50172	-2.50172	8	6.807768	1.192232	8	8.806426	-0.80643
9	11.63552	-2.63552	9	11.55004	-2.55004	8	5.420717	2.579283	8	7.087681	0.912319
9	12.23898	-3.23898	9	12.28615	-3.28615	8	9.409963	-1.40996	8	8.851337	-0.85134
9	7.797965	1.202035	9	9.090821	-0.09082	9	9.895757	-0.89576	9	9.615734	-0.61573
10	10.26316	-0.26316	10	10.80231	-0.80231	9	12.21161	-3.21161	9	10.72366	-1.72366
10	12.17328	-2.17328	10	13.02223	-3.02223	9	11.80746	-2.80746	9	11.43072	-2.43072
10	9.582207	0.417793	10	9.864999	0.135001	10	8.486977	1.513023	10	8.458489	1.541511
11	9.241172	1.758828	11	9.40432	1.59568	10	10.39876	-0.39876	10	10.69318	-0.69318
11	12.98901	-1.98901	11	12.20051	-1.20051	10	11.58187	-1.58187	10	11.03624	-1.03624
11	12.97893	-1.97893	11	13.41669	-2.41669	11	9.799663	1.200337	11	10.67472	0.325278
11	13.73625	-2.73625	11	13.32999	-2.32999	11	11.36402	-0.36402	11	11.90709	-0.90709
11	12.65805	-1.65805	11	12.87533	-1.87533	12	14.71938	-2.71938	12	14.66741	-2.66741
11	11.94189	-0.94189	11	12.37348	-1.37348	12	12.37906	-0.37906	12	11.87477	0.12523

11	12.25132	-1.25132	11	12.49909	-1.49909	12	13.07592	-1.07592	12	12.85053	-0.85053
12	14.92424	-2.92424	12	15.19039	-3.19039	12	12.56777	-0.56777	12	13.00823	-1.00823
12	11.99764	0.002363	12	10.99238	1.007624	12	11.74689	0.253114	12	11.80488	0.195123
13	13.74639	-0.74639	13	12.98272	0.017276	12	13.51462	-1.51462	12	13.68316	-1.68316
13	13.99543	-0.99543	13	13.50413	-0.50413	13	12.88582	0.114182	13	12.79072	0.209278
13	13.33478	-0.33478	13	13.19567	-0.19567	13	14.9704	-1.9704	13	15.13407	-2.13407
13	14.15341	-1.15341	13	14.43896	-1.43896	13	12.01156	0.988439	13	13.97713	-0.97713
13	14.30844	-1.30844	13	14.5066	-1.5066	13	14.08809	-1.08809	13	14.01194	-1.01194
14	14.56199	-0.56199	14	14.57401	-0.57401	13	13.42562	-0.42562	13	12.08177	0.918231
14	15.04137	-1.04137	14	14.66595	-0.66595	13	15.50421	-2.50421	13	14.16714	-1.16714
15	12.80126	2.198745	15	12.34801	2.651988	13	14.07654	-1.07654	13	13.41905	-0.41905
15	15.24468	-0.24468	15	15.21399	-0.21399	14	15.93439	-1.93439	14	15.26242	-1.26242
15	14.48925	0.51075	15	13.73032	1.269677	14	14.01759	-0.01759	14	14.37134	-0.37134
16	14.72155	1.278452	16	14.18035	1.819646	14	13.30549	0.694506	14	13.44556	0.554436
17	13.68745	3.312554	17	13.41085	3.589153	15	15.21143	-0.21143	15	14.95085	0.049152
17	14.49464	2.505358	17	14.78106	2.218936	15	15.54973	-0.54973	15	15.39551	-0.39551
17	12.86728	4.132715	17	12.58131	4.418687	16	14.93511	1.064889	16	14.93419	1.065813
17	14.60787	2.392127	17	14.31431	2.685692	16	14.5612	1.4388	16	14.40863	1.591374
18	14.61873	3.381266	18	14.70434	3.295661	17	16.32826	0.671738	17	15.4769	1.523102
18	15.29742	2.70258	18	15.24403	2.755965	17	15.10961	1.89039	17	15.07638	1.923624
18	13.63488	4.365124	18	14.26258	3.737422	17	14.92314	2.076855	17	15.29023	1.709767
18	15.1634	2.836596	18	15.45068	2.549322	17	15.26041	1.739593	17	15.30366	1.696342
18	13.89982	4.100182	18	14.28753	3.712467	18	14.75171	3.248289	18	14.36874	3.631262
18	12.83249	5.16751	18	12.67444	5.325557	18	13.81731	4.182687	18	15.30516	2.694836

Table 4.5: The testing target data, testing output data and the test set MSE for all four ANNs

The test set MSE value, which is the mean of the test errors for that particular network, is then calculated for all four networks. The formula for the calculation of the test set MSE can be found in Equation 2.12 in chapter 2.

Below are the results of age estimation models using ANN approach and GA-ANN hybrid approach for both female and male Hispanic population.

	Female		**Male**	
	ANN	GA-ANN	ANN	GA-ANN
Test Regression (r value)	0.90686	0.9086	0.9426	0.96226
Test set MSE	4.096813	4.060201	2.429385	1.702814

Table 4.6: The results of age estimation models using ANN approach and GA-ANN hybrid approach for both female and male Hispanic population

The test regression value and the test set MSE are used as metrics for evaluation. The training regression value will always improve as the number of the data used for training increases, which makes the training regression value not a reliable metric. The overall regression value is also not selected as it is calculated to be the mean between the training and test regression values. The test set MSE is the MSE calculated on the test data only, without regard to the training data.

In the results shown in Table 4.6, the performance of the hybrid GA-ANN approach is better than the ANN approach. For the female networks, the test regression value for hybrid GA-ANN approach, 0.9086 is slightly higher than the test regression value for ANN approach, 0.90686. For the male networks, the test regression value for hybrid GA-ANN approach, 0.96226 is higher than the test regression value for ANN approach, 0.9426. The lower the test set MSE value, the less errors, which implies a better performance of the network. For the female networks, the test set MSE for hybrid GA-ANN approach, 4.060201 years is slightly lower than the ANN approach, 4.096813 years. For the male networks, the test set MSE for hybrid GA-ANN approach, 1.702814 years is significantly lower than the ANN approach, 2.429385 years. Overall, there is a better performance in the hybrid GA-ANN approach compared to the ANN approach for networks of both gender, which produces a higher test regression value and a lower test set MSE.

4.4 DISCUSSION AND JUSTIFICATION

Adaption learning function, transfer function, cross-validation, and test set MSE are discussed in the following sections.

4.4.1 ADAPTION LEARNING FUNCTION

			Female		**Male**	
Learning function	Layer 1	Layer 2	Test regression (R)	MSE	Test regression (R)	MSE
learnGD	purelin	tansig	0.94419	0.00595	0.91708	0.00514
learnGDM	purelin	tansig	0.94419	0.00595	0.91708	0.00514

Table 4.7: The comparison results of using different learning functions for neural networks

The learning function will compute the learning rate for different parameters, calculate the weight change during training, ultimately improving the ANN. The comparison above is done after dividing the dataset into 70% training data and 30% testing data, in which the female neural networks use the same training and testing data and the male neural networks use the same training and testing data. The performance of the female neural networks are the same whereas the performance of the male neural networks are the same too, despite the differences of the adaption learning function. Since most researches uses learnGDM, the learnGDM learning function is chosen for this paper.

4.4.2 TRANSFER FUNCTION

		Female		Male	
Layer 1	Layer 2	Test regression (R)	MSE	Test regression (R)	MSE
tansig	logsig	0.5005	0.0143	0.64528	0.0146
tansig	tansig	0.38641	1.21e-10	0.69575	1.61e-10
tansig	purelin	0.56364	1.11e-23	0.78547	2.49e-22
logsig	logsig	0.42071	0.0143	0.58935	0.0146
logsig	tansig	0.16697	2.87e-11	0.476	6.05e-11
logsig	purelin	0.67053	7.79e-17	0.81512	9.96e-16
purelin	logsig	0.72728	0.0183	0.75804	0.0162
purelin	**tansig**	**0.9152**	**0.00549**	**0.91076**	**0.00490**
purelin	purelin	0.91394	0.00534	0.90863	0.00431

Table 4.8: The comparison results of different combinations of transfer functions for Layer 1 and Layer 2 for several tests of neural networks

Transfer function, also known as activation functions help neural networks to learn non-linear relationships by applying the transfer function to produce the final output. In Table 4.8, the combination of purelin and tansig of transfer functions has the highest performance with the highest test regression values, which are 0.9152 for female and 0.91076 for male. Since any MSE value is considered to be valid when it is less than 2, the MSE value of 0.00549 years for female and 0.00490 years for male are acceptable. Even though there are MSE values that are even lower than the purelin and tansig combination, the difference between the test regression values can be quite large, which becomes the reason for elimination.

4.4.3 CROSS-VALIDATION

Cross-validation aims to test the ability of the result to generalize to an independent dataset. With cross-validation, a validation data set can be used to test the model during training. Problems such as underfitting and overfitting can be limited through cross-validation (scikit-learn developers, 2014). In the GA approach, cross-validation is used when selecting the input features to generate the best features. Five-fold cross validation has been used in the GA approach, where the training dataset is divided into groups of five chromosomes. The first four chromosomes are used for training, while the fifth chromosome will be used for validation. This process repeats for all chromosome groups of five.

4.4.4 TEST SET MEAN SQUARED ERROR (MSE)

Errors are the difference between the expected output and the actual output, which have been one of the metrics to evaluate the accuracy of the data. The theory is that the less errors are generated, the more accurate the model is. The test set MSE is the average of the test errors for that particular network (Rowe, 2015). It is calculated after denormalization of the test target data and test output data, where the actual age predicted by the ANN can be obtained. The test set errors is then calculated by using the denormalized test target data and denormalized test output data. The average of the sum of test errors will then be calculated, obtaining the test set MSE. Microsoft Excel has been used for the denormalization until the calculation of the test set MSE.

4.5 SUMMARY

In this Chapter 4, the overall performance of the GA-ANN hybrid approach is better comparative to the ANN approach, with the GA-ANN hybrid approach producing a higher test regression value and a lower test set MSE value. The feature selection introduced in the GA-ANN hybrid approach will have two main advantages, which are a better performance and the results is obtained and less data is required. An increase in performance will enable the neural network to produce more accurate results. The feature selection for this GA-ANN hybrid approach has reduced the input features required from 19 bones to seven or eight, which is more than 50% of the data, resulting in an optimization of the effort in procuring training data.

CHAPTER 5

CONCLUSION AND RECOMMENDATION

5.1 INTRODUCTION

This chapter concludes the paper, where the project constraints and the future work of this research is discussed.

5.2 PROJECT CONSTRAINT

Below are the project constraints faced during this research:

- Lack of readily available data

The training dataset used for the training of both ANN approach and GA-ANN hybrid approach originated from X-ray images that does not have any measurements of the 19 bones. The measurements were obtained manually by using Photo Pos Pro, which is a tiring process. Too much time was used to acquire the measurements.

- Lack of good hardware

The research was carried out on a laptop with 8 GB of RAM. However, the laptop does not have the suitable technical specifications to support Photo Pos Pro, and the application would have latency during use. There are times when the laptop has shut down on its own, causing loss of measurement data during the procurement of measurements of the 19 bones.

5.3 RECOMMENDATION AND FUTURE WORK

For this research, more training data can be used to produce more accurate results, as the data will not too biased since there are more variety of data. The increase in the amount of training data can also evaluate the performance of the feature selection.

Other bones, such as dental and right hand bones can be used as a combination with the left hand bones for the Hispanic population to produce even more accurate age estimations. This can also increase the robustness of the GA-ANN hybrid approach as it receives more bones to estimate the age.

Other ethnicity should also be used, such as Caucasian or Native Americans. The results of the feature selection for the 19 bones should be different due to biological factors, which means that it is possible that the weightage for the 19 bones may be different compared to another ethnic group during age estimation.

More neural networks can be integrated with the approach. For example, two GA approaches can be integrated with the ANN approach to possibly improve the feature selection. The possibility of an approach with a comparatively more robust feature selection should be tested.

Another approach for the feature selection other than the GA approach can be tested to see if it performs well. There is a possibility where another approach can produce better results during feature selection.

5.4 CLOSING NOTE

In this paper, the measurements of the 19 bones for the Hispanic population have been made to form the general dataset. The dataset is then normalized to avoid computing errors when fed into the ANN.

The ANN approach involves using all 19 bones as input features to estimate the age of the Hispanic population. Since the age estimation will be different based on the gender of the individual, two ANN approaches are created for male and female.

The GA-ANN hybrid approach will use the GA approach to perform feature selection, which reduces the number of input features. The selected input features will then be fed into the ANN approach to produce the expected output data and actual output data.

The expected output data and the actual output data are denormalized to obtain the estimated age and the actual age. The difference between the two ages, which are known as errors are then computed to evaluate the performances of both approaches.

The future work and recommendations are then proposed at the end of this paper.

REFERENCES

Al-Ahmari, A. M. A. (2007). Predictive machinability models for a selected hard material in turning operations. *Journal of Materials Processing Technology*, *190*(1–3), 305–311. https://doi.org/10.1016/j.jmatprotec.2007.02.031

Alkass, K., Buchholz, B. A., Ohtani, S., Yamamoto, T., Druid, H., & Spalding, K. L. (2009). Age Estimation in Forensic Sciences. *Molecular & Cellular Proteomics*, *9*(5), 1022–1030. https://doi.org/10.1074/mcp.m900525-mcp200

Armaghani, D. J., Mohamad, E. T., Monjezi, M., Faradonbeh, R. S., & Majid, M. Z. A. (2016). An optimized ANN model based on genetic algorithm for predicting ripping production. *Neural Computing and Applications*, *28*(S1), 393–406. https://doi.org/10.1007/s00521-016-2359-8

Asif, M. K., Nambiar, P., Mani, S. A., Ibrahim, N. B., Khan, I. M., & Lokman, N. B. (2019). Dental age estimation in Malaysian adults based on volumetric analysis of pulp/tooth ratio using CBCT data. *Legal Medicine*, *36*(October 2018), 50–58. https://doi.org/10.1016/j.legalmed.2018.10.005

Auf der Mauer, M., Säring, D., Stanczus, B., Herrmann, J., Groth, M., & Jopp-van Well, E. (2019). A 2-year follow-up MRI study for the evaluation of an age estimation method based on knee bone development. *International Journal of Legal Medicine*, *133*(1), 205–215. https://doi.org/10.1007/s00414-018-1826-4

Bakthula, R., & Agarwal, S. (2014). Automated Human Bone Age Assessment using Image Processing Methods - Survey. *International Journal of Computer Applications*, *104*(13), 33–42. https://doi.org/10.5120/18265-9259

Bartolini, V., Pinchi, V., Gualco, B., Vanin, S., Chiaracane, G., D’Elia, G., … Focardi, M. (2018). The iliac crest in forensic age estimation: evaluation of three methods in pelvis X-rays. *International Journal of Legal Medicine*, *132*(1), 279–288. https://doi.org/10.1007/s00414-017-1629-z

Benjavongkulchai, S., & Pittayapat, P. (2018). Age estimation methods using hand

and wrist radiographs in a group of contemporary Thais. *Forensic Science International*, *287*, 218.e1-218.e8. https://doi.org/10.1016/j.forsciint.2018.03.045

Bocchi, L., Ferrara, F., Nicoletti, I., & Valli, G. (2003). An artificial neural network architecture for skeletal age assessment. *IEEE International Conference on Image Processing*, *1*, 1077–1080. https://doi.org/10.1109/icip.2003.1247153

C. Sanjay;, & C. Jyothi. (2006). A study of surface roughness in drilling using mathematical analysis and neural, 846–852. https://doi.org/10.1007/s00170-005-2538-8

Cameriere, R., & Ferrante, L. (2008). Age estimation in children by measurement of carpals and epiphyses of radius and ulna and open apices in teeth: A pilot study. *Forensic Science International*, *174*(1), 60–63. https://doi.org/10.1016/j.forsciint.2007.03.013

Cameriere, R., Ferrante, L., Mirtella, D., & Cingolani, M. (2006). Carpals and epiphyses of radius and ulna as age indicators. *International Journal of Legal Medicine*, *120*(3), 143–146. https://doi.org/10.1007/s00414-005-0040-3

Cantekin, K., Celikoglu, M., Miloglu, O., Dane, A., & Erdem, A. (2012). Bone Age Assessment: The Applicability of the Greulich-Pyle Method in Eastern Turkish Children. *Journal of Forensic Sciences*, *57*(3), 679–682. https://doi.org/10.1111/j.1556-4029.2011.02035.x

Creative Research Systems. (2016). Correlation. Retrieved from https://www.surveysystem.com/correlation.htm

Darmawan, M. F., Yusuf, S. M., Abdul Kadir, M. R., & Haron, H. (2015). Age estimation based on bone length using 12 regression models of left hand X-ray images for Asian children below 19 years old. *Legal Medicine*, *17*(2), 71–78. https://doi.org/10.1016/j.legalmed.2014.09.006

Demuth, H., & Hagan, M. B. M. (2009). *Neural Network Toolbox TM 6 User' s Guide*.

du Jardin, P., Ponsaillé, J., Alunni-Perret, V., & Quatrehomme, G. (2009). A comparison between neural network and other metric methods to determine sex from the upper femur in a modern French population. *Forensic Science International*, *192*(1–3), 127.e1-127.e6. https://doi.org/10.1016/j.forsciint.2009.07.014

Duangto, P., Janhom, A., Prasitwattanaseree, S., Mahakkanukrauh, P., & Iamaroon, A. (2017). Age Estimation Methods in Forensic Odontology. *Journal of Dentistry Indonesia*, *23*(3), 74–80. https://doi.org/10.14693/jdi.v23i3.1023

Flores-mir, C., Orth, C., Nebbe, B., & Ortho, F. F. D. S. A. (n.d.). Flores-Mir C, Nebbe B, Major PW. Use of skeletal maturation based on hand-wrist radiographic analysis as a predictor of facial growth- a systematic review. Angle Orthod. 2004;74-118–124..pdf, (c), 15–20.

Franklin, D., Flavel, A., Noble, J., Swift, L., & Karkhanis, S. (2015). Forensic age estimation in living individuals: methodological considerations in the context of medico-legal practice. *Research and Reports in Forensic Medical Science*, 53. https://doi.org/10.2147/rrfms.s75140

Gertych, A., Zhang, A., Sayre, J., Pospiech-Kurkowska, S., & Huang, H. K. (2007). Bone age assessment of children using a digital hand atlas. *Computerized Medical Imaging and Graphics*, *31*(4–5), 322–331. https://doi.org/10.1016/j.compmedimag.2007.02.012

Gilsanz, V., & Raitb, O. (2005). *Had Bone Age*. *Springer*. Retrieved from http://www.chospab.es/biblioteca/DOCUMENTOS/Atlas_of_Hand_Bone_Age.pdf

Gungor, A., Sari, Z., Gungor, Oe., Kale, B., & Celikoglu, M. (2015). Validity of the Demirjian method for dental age estimation for Southern Turkish children. *Nigerian Journal of Clinical Practice*, *18*(5), 616. https://doi.org/10.4103/1119-3077.154216

Huang, W., Xu, W., Telmon, N., Cheng, Q., Li, K., & Cavaignac, E. (2018). Morphometric evaluation of the knee in Chinese population reveals sexual dimorphism and age-related differences. *International Orthopaedics*, *42*(10), 2349–2356. https://doi.org/10.1007/s00264-018-3826-x

Huumonen, S., Särkioja, T., Salo, S., Niskanen, M., Maijanen, H., & Hirvonen, J.

(2016). Twelve unidentified skeletons as remains of an epidemic or famine in Northern Finland. *Scandinavian Journal of Forensic Science*, *22*(2), 33–40. https://doi.org/10.1515/sjfs-2016-0006

Jain, V. (2019). Beginners guide to Feature selection techniques using python: Retrieved May 2, 1BC, from https://medium.com/@vijain2010/beginners-guide-to-feature-selection-techniques-using-python-4d23fcb8951a

Jerome Tosam, M. (2015). The Ethical and Social Implications of Age-Cheating in Africa. *International Journal of Philosophy*, *3*(1), 1. https://doi.org/10.11648/j.ijp.20150301.11

Khandelwal, M., Marto, A., Fatemi, S. A., Ghoroqi, M., Armaghani, D. J., Singh, T. N., & Tabrizi, O. (2018). Implementing an ANN model optimized by genetic algorithm for estimating cohesion of limestone samples. *Engineering with Computers*, *34*(2), 307–317. https://doi.org/10.1007/s00366-017-0541-y

Kim, K., & Han, I. (2000). <1-s2.0-S0957417400000270-main_2.pdf>, *19*, 125–132. Retrieved from www.elsevier.com/locate/eswa

Kiss, L., Yun, K., Pocock, N., & Zimmerman, C. (2015). Exploitation, violence, and suicide risk among child and adolescent survivors of human trafficking in the greater mekong subregion. *JAMA Pediatrics*, *169*(9), 15–17. https://doi.org/10.1001/jamapediatrics.2015.2278

Koc, A., Karaoglanoglu, M., Erdogan, M., Kosecik, M., & Cesur, Y. (2001). Assessment of bone ages: Is the Greulich-Pyle method sufficient for Turkish boys? *Pediatrics International*, *43*(6), 662–665. https://doi.org/10.1046/j.1442-200X.2001.01470.x

Kohail, S. N. (2012). Using artificial neural network for human age estimation based on facial images. *2012 International Conference on Innovations in Information Technology, IIT 2012*, 215–219. https://doi.org/10.1109/INNOVATIONS.2012.6207735

Kohli, A., & Dixit, U. S. (2005). A neural-network-based methodology for the prediction of surface roughness in a turning process. *International Journal of Advanced Manufacturing Technology*, *25*(1–2), 118–129.

https://doi.org/10.1007/s00170-003-1810-z

Kumar, H. S., P, S. P., Sriram, N. S., & Vijay, G. S. (2013). International Conference On DESIGN AND MANUFACTURING , IConDM 2013 ANN based evaluation of performance of wavelet transform for condition monitoring of rolling element bearing. *Procedia Engineering*, *64*, 805–814. https://doi.org/10.1016/j.proeng.2013.09.156

Lewis, M. E., & Flavel, A. (n.d.). CAPITULO_age assessment of child skeletal remains in forensic contexts_Lewis, Flavel.pdf, 243–257.

Liu, H., Lu, J., Feng, J., & Zhou, J. (2017). Ordinal Deep Learning for Facial Age Estimation. *IEEE Transactions on Circuits and Systems for Video Technology*, *29*(2), 486–501. https://doi.org/10.1109/TCSVT.2017.2782709

Lynnerup, N., & Villa, C. (2014). Age estimation of skeletal remains: principal methods. *Research and Reports in Forensic Medical Science*, 3. https://doi.org/10.2147/rrfms.s35660

Macedo, J., Costa, F., & A. dos Santos, J. (2019). A Benchmark Methodology for Child Pornography Detection, (1), 455–462. https://doi.org/10.1109/sibgrapi.2018.00065

Maggio, A. (2017). The skeletal age estimation potential of the knee: Current scholarship and future directions for research. *Journal of Forensic Radiology and Imaging*, *9*(May), 13–15. https://doi.org/10.1016/j.jofri.2017.05.002

Mahfouz, M., Badawi, A., Merkl, B., Abdel, E. E., Pritchard, E., Kesler, K., … Jantz, L. (2007). Patella sex determination by 3D statistical shape models and nonlinear classifiers, *173*, 161–170. https://doi.org/10.1016/j.forsciint.2007.02.024

Malina, R. M. (1994). Physical Growth and Biological Maturation of Young Athletes.

Malina, R. M. (2011). Skeletal age and age verification in youthsport. *Sports Medicine*, *41*(11), 925–947. https://doi.org/10.2165/11590300-000000000-00000

Mohd, A., Haron, H., & Sharif, S. (2010). Expert Systems with Applications Prediction of surface roughness in the end milling machining using Artificial Neural Network. *Expert Systems With Applications*, *37*(2), 1755–1768. https://doi.org/10.1016/j.eswa.2009.07.033

Nalbant, M., Gökkaya, H., Toktaş, I., & Sur, G. (2009). The experimental investigation of the effects of uncoated, PVD- and CVD-coated cemented carbide inserts and cutting parameters on surface roughness in CNC turning and its prediction using artificial neural networks. *Robotics and Computer-Integrated Manufacturing*, *25*(1), 211–223. https://doi.org/10.1016/j.rcim.2007.11.004

Nogueira, L. (2015). Comparing discriminant analysis and neural network for the determination of sex using femur head measurements, *253*, 81–87. https://doi.org/10.1016/j.forsciint.2015.05.023

Normal, S. (2007). X 2 (1), *2007*(2), 2012.

OHCHR. (n.d.). Convention on the Rights of the Child. Retrieved from https://www.ohchr.org/en/professionalinterest/pages/crc.aspx

Ouloul, I. M., Moutakki, Z., Afdel, K., & Amghar, A. (2019). Improvement of age estimation using an efficient wrinkles descriptor. *Multimedia Tools and Applications*, *78*(2), 1913–1947. https://doi.org/10.1007/s11042-018-6275-z

People, M., & Paper, B. (2011). Cross-matching unidentified bodies and missing person reports, 1–7.

Pinchi, V., De Luca, F., Ricciardi, F., Focardi, M., Piredda, V., Mazzeo, E., & Norelli, G. A. (2014). Skeletal age estimation for forensic purposes: A comparison of GP, TW2 and TW3 methods on an Italian sample. *Forensic Science International*, *238*, 83–90. https://doi.org/10.1016/j.forsciint.2014.02.030

Polastro, M. D. C., & Eleuterio, P. M. D. S. (2012). A statistical approach for identifying videos of child pornography at crime scenes. *Proceedings - 2012 7th International Conference on Availability, Reliability and Security, ARES 2012*, 604–612. https://doi.org/10.1109/ARES.2012.71

Rowe, W. (2015). Mean Squared Error, R2, and Variance in Regression Analysis. Retrieved from https://www.bmc.com/blogs/mean-squared-error-r2-and-variance-in-regression-analysis/

Rucci, M., Coppini, G., Nicoletti, I., Cheli, D., & Valli, G. (1995). Automatic analysis of hand radiographs for the assessment of skeletal age: A subsymbolic approach. *Computers and Biomedical Research*. https://doi.org/10.1006/cbmr.1995.1016

Samui, P., & Dixon, B. (2012). Application of support vector machine and relevance vector machine to determine evaporative losses in reservoirs. *Hydrological Processes*, *26*(9), 1361–1369. https://doi.org/10.1002/hyp.8278

Sawant, M. M., & Bhurchandi, K. (2019). Hierarchical facial age estimation using Gaussian process regression. *IEEE Access*, *7*, 9142–9152. https://doi.org/10.1109/ACCESS.2018.2889873

Sciences, N. (2015). Estimation of groundwater level using a hybrid genetic algorithm- neural network. *Pollution*, *1*(1), 9–21. Retrieved from http://journals.ut.ac.ir/article_52176_1.html

scikit-learn developers. (2014). sklearn.cross_validation.cross_val_score. Retrieved from https://scikit-learn.org/0.16/modules/generated/sklearn.cross_validation.cross_val_score.html

Sharma, B., & Venugopalan, P. K. (2014). Comparison of Neural Network Training Functions for Hematoma Classification in Brain CT Images, *16*(1), 31–35.

Smeers, I., Decorte, R., Van de Voorde, W., & Bekaert, B. (2018). Evaluation of three statistical prediction models for forensic age prediction based on DNA methylation. *Forensic Science International: Genetics*, *34*(December 2017), 128–133. https://doi.org/10.1016/j.fsigen.2018.02.008

Spampinato, C., Palazzo, S., Giordano, D., Aldinucci, M., & Leonardi, R. (2017). Deep learning for automated skeletal bone age assessment in X-ray images. *Medical Image Analysis*, *36*(February), 41–51. https://doi.org/10.1016/j.media.2016.10.010

Stavrianos, C., Mastagas, D., Stavrianou, I., & Karaiskou, O. (2008). Dental age estimation of adults: A review. *Research Journal of Medical Sciences*, *2*(5), 258–268. https://doi.org/10.1016/B978-0-12-275950-5.50016-X

Stern, D., & Ursekter, M. (2016). From individual hand bone age estimates to fully automated age estimation via learning-based information fusion. *Proceedings - International Symposium on Biomedical Imaging*, *2016-June*, 150–154. https://doi.org/10.1109/ISBI.2016.7493232

Susan L. King. (1999). Neural Networks Vs. Multiple Linear Regression For Estimating Previous Diameter.

Sykes, L., Bhayat, A., & Bernitz, H. (2017). The effects of the refugee crisis on age estimation analysis over the past 10 years: A 16-country survey. *International Journal of Environmental Research and Public Health*, *14*(6). https://doi.org/10.3390/ijerph14060630

TEILMANN, G., LAURSEN, E. M., HOLM, K., MAIN, K. M., SCHEIKE, T., JUUL, A., … SKAKKEBAEK, N. E. (2005). Pubertal development in Danish children: comparison of recent European and US data. *International Journal of Andrology*, *29*(1), 247–255. https://doi.org/10.1111/j.1365-2605.2005.00556.x

UN. (n.d.). Optional Protocol on the Involvement of Children in Armed Conflict - United Nations Office of the Special Representative of the Secretary-General for Children and Armed Conflict | To promote and protect the rights of all children affected by armed conflic. Retrieved from https://childrenandarmedconflict.un.org/tools-for-action/opac/

UNICEF, The Global Compact, & Save the Children. (2012). Children's Rights and Business Principles. Retrieved from https://www.unglobalcompact.org/docs/issues_doc/human_rights/CRBP/Childrens_Rights_and_Business_Principles.pdf

Vij, N. (2016). Dentistry to the rescue of missing children : A review, *8*(1). https://doi.org/10.4103/0975-1475.176947

Zhang, G., Patuwo, B. E., & Hu, M. Y. (1998). Forecasting with artificial neural networks : The state of the art, *14*, 35–62.

APPENDIX A

ORIGINAL DATASET OF FEMALE HISPANIC POPULATION

Image ID	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	Age
5584	1.46	2.48	2.33	1.98	1.83	1.13	1.56	1.73	1.61	1.29	0.81	1.15	1.03	0.64	0.76	0.5	0.59	0.67	0.57	0
5068	1.69	3.16	2.93	2.49	2.13	1.3	1.75	1.96	1.88	1.49	1.07	1.23	1.2	0.92	1.05	0.62	0.7	0.77	0.57	1
5070	1.48	2.35	2.28	2	1.74	1.11	1.51	1.82	1.76	1.29	0.87	1.18	1.23	0.76	0.81	0.64	0.68	0.73	0.57	1
5102	1.67	2.59	2.35	2.47	2.08	1.09	1.75	1.9	1.76	1.5	0.78	1.19	1.01	0.67	0.87	0.52	0.67	0.68	0.55	1
5111	1.39	2.2	2.1	1.86	1.62	1.09	1.51	1.68	1.65	1.23	0.85	1.07	1.03	0.63	0.81	0.63	0.67	0.67	0.57	1
5585	1.65	2.97	2.78	2.48	2.2	1.21	1.88	1.99	1.98	1.58	0.84	1.12	1.17	0.65	1.01	0.58	0.65	0.74	0.49	1
5017	1.93	3.45	3.3	2.92	2.72	1.44	2.04	2.28	2.38	1.6	1.29	1.55	1.48	0.89	1.2	0.9	1.01	0.99	0.72	2
5036	1.68	3.08	2.84	2.59	2.27	1.22	1.68	1.94	1.83	1.35	0.99	1.11	1.13	0.6	0.86	0.66	0.7	0.74	0.57	2
5107	1.56	2.99	2.88	2.35	2.11	1.18	1.83	2.09	2	1.29	0.89	1.19	1.23	0.65	1	0.57	0.61	0.57	0.56	2
5117	1.88	3.08	3	2.74	2.29	1.29	1.81	2.07	1.96	1.48	1.15	1.42	1.41	0.79	0.93	0.73	0.77	0.87	0.7	2
5588	1.68	3.14	3.02	2.61	2.34	1.32	2	2.26	1.96	1.51	1.18	1.49	1.37	0.85	0.97	0.65	0.94	0.8	0.63	2
5061	2.19	3.65	3.47	3.04	2.68	1.6	1.94	2.26	2.33	1.63	1.3	1.6	1.53	0.97	1.15	0.62	0.89	0.72	0.64	3
5065	2.67	3.81	3.64	3.36	3.07	1.55	2.19	2.5	2.34	1.69	1.24	1.52	1.49	0.85	1.29	0.78	0.83	0.87	0.8	3
5067	2.59	3.9	3.67	3.3	3.05	1.73	2.18	2.47	2.57	1.74	1.3	1.64	1.55	0.86	1.46	0.98	1.13	1.14	0.78	3
5090	2.06	3.96	3.82	3.38	3	1.41	2.01	2.31	2.18	1.56	1.36	1.65	1.53	1.04	1.28	0.66	0.84	0.84	0.66	3
6137	2.15	3.84	3.74	3.39	3.21	1.59	2.27	2.55	2.39	1.84	1.23	1.68	1.55	0.91	1.22	0.59	0.77	0.8	0.71	3
5109	2.33	4.04	3.92	3.56	3.09	1.66	2.27	2.88	2.72	2.11	1.33	1.71	1.56	1.25	1.3	0.76	0.79	1.07	0.69	4
5120	2.35	3.91	3.92	3.45	3.2	1.63	2.24	2.58	2.36	1.75	1.22	1.57	1.49	0.82	1.43	0.91	0.98	1.04	0.85	4
5140	2.54	3.83	3.6	3.09	2.96	1.44	2.02	2.34	2.21	1.63	1.3	1.46	1.57	0.99	1.21	0.79	0.78	1.02	0.71	4
5269	2.14	3.84	3.7	3.33	3.02	1.6	2.16	2.46	2.56	1.95	1.42	1.66	1.44	1.01	1.32	1.01	1.13	1.16	0.81	4
6130	2.32	4.06	3.88	3.51	3.16	1.66	2.28	2.61	2.78	2.16	1.33	1.71	1.68	1.18	1.32	0.72	0.85	0.88	0.73	4
5050	2.59	4.21	4.16	3.8	3.45	1.68	2.4	2.87	2.61	1.94	1.3	1.74	1.61	0.98	1.23	0.96	1.06	1.12	0.96	5
5133	3.08	4.43	4.43	3.87	3.59	2.05	2.57	2.88	2.74	2.15	1.37	1.72	1.68	1.25	1.51	0.85	0.97	1.01	0.85	5
5141	2.48	4.49	4.24	3.81	3.57	1.64	2.42	2.71	2.56	1.86	1.18	1.57	1.45	0.84	1.08	0.81	0.87	0.94	0.81	5
5143	2.94	4.41	4.36	3.95	3.54	1.64	2.29	2.97	2.81	2.17	1.47	1.82	1.75	1.11	1.18	0.88	1	0.99	0.81	5
5156	2.2	3.92	3.86	3.38	3	1.93	2.18	2.45	2.59	1.78	1.47	1.56	1.46	1.15	1.45	0.84	0.89	0.9	0.8	5

7038	2.16	4.17	4.08	3.54	3.15	1.36	2.46	2.7	2.5	1.75	1.38	1.57	1.57	1.01	1.43	0.8	0.85	0.9	0.76	5
7039	2.87	4.32	4.38	3.88	3.5	1.79	2.59	3.05	2.9	2.13	1.29	1.76	1.89	1.28	1.59	0.87	0.94	0.96	0.88	5
7040	2.76	4.29	4.23	3.71	3.19	1.57	2.53	2.87	2.71	2.01	1.41	1.74	1.64	1.02	1.4	0.88	1.08	0.97	0.77	5
7121	2.66	4.01	3.93	3.51	3.17	1.54	2.26	2.58	2.44	1.82	1.25	1.53	1.54	1.03	1.22	0.78	1	1.06	0.81	5
7244	2.2	4.08	4.01	3.51	3.23	1.56	2.23	2.63	2.72	2.1	1.4	1.71	1.64	1.03	1.3	0.79	0.8	1.01	0.69	5
5056	2.51	4.39	4.33	3.82	3.41	1.77	2.59	2.9	2.8	1.92	1.61	1.94	1.81	1.15	1.49	1.07	1.11	1.16	0.85	6
5057	3.21	4.84	4.75	4.15	3.75	1.93	2.79	3.57	3.29	2.49	1.66	1.94	2.07	1.32	1.57	0.87	1.01	1.23	0.72	6
5079	3.04	4.54	4.5	3.85	3.55	1.87	2.71	3.09	2.86	1.95	1.47	1.67	1.56	1.14	1.47	0.87	1.16	1.05	0.86	6
5142	3.05	4.37	4.24	3.85	3.56	1.89	2.54	2.84	2.74	2.07	1.55	1.71	1.75	1.18	1.2	0.93	1.2	1.23	1.06	6
5343	3.13	4.44	4.26	3.81	3.47	1.83	2.51	3.11	2.94	2.19	1.47	1.9	1.81	1.16	1.56	0.9	1.05	1.06	0.89	6
7041	2.97	4.42	4.13	3.8	3.55	1.64	2.56	2.94	2.79	1.95	1.46	1.77	1.67	1.15	1.41	0.92	0.98	1.23	0.9	6
7042	2.54	4.5	4.3	4.01	3.65	1.75	2.62	3.24	2.97	2.31	1.55	1.97	1.84	1.11	1.57	0.94	1.05	1.09	0.91	6
7043	2.97	4.15	3.93	3.57	3.25	1.99	2.65	2.98	2.86	2.17	1.31	1.69	1.65	1.25	1.48	0.91	1.05	1.06	0.92	6
7254	3.03	4.4	4.26	3.81	3.6	1.82	2.5	3.16	3.02	2.25	1.53	1.93	1.87	1.16	1.48	0.98	1.1	1.11	1.07	6
7278	2.97	4.5	4.34	3.83	3.56	1.99	2.76	3.15	2.98	2.1	1.46	1.86	1.91	1.29	1.64	0.96	1.09	1.2	0.91	6
5136	3.49	5.06	5.04	4.41	3.93	1.87	2.67	3.5	3.15	2.31	1.63	2.02	1.59	0.98	1.28	0.91	0.99	1.27	0.87	7
5137	3.37	5.33	5.22	4.69	4.18	2.2	2.92	3.24	3	2.35	1.86	1.99	2.18	1.47	1.76	1.03	1.11	1.19	0.87	7
5145	3.48	4.91	4.76	4.33	3.92	1.92	2.97	3.4	3.13	2.38	1.79	2.08	1.93	1.32	1.66	0.93	1.02	1	1.07	7
5153	3.51	4.79	4.6	4.06	3.81	2.44	2.98	3.45	3.31	2.35	1.94	2.2	2.2	1.54	1.82	1.35	1.19	1.5	1.31	7
5926	2.89	5	4.89	4.03	3.96	2.21	2.9	3.28	2.81	2.12	1.69	2.06	1.91	1.29	1.62	0.99	1.31	1.33	1.16	7
7044	3.37	5.05	4.83	4.3	3.94	2.22	3.04	3.22	3.14	2.12	1.79	2.22	1.98	1.32	1.74	1.15	1.31	1.33	0.94	7
7082	3.26	4.98	4.79	4.34	4.02	2.19	3.02	3.39	3.16	2.41	1.78	2.14	2.02	1.41	1.63	0.91	1.02	1.03	0.87	7
7139	3.01	4.63	4.52	4.04	3.66	2.14	2.58	3.09	2.96	2.09	1.62	2.01	1.89	1.42	1.61	1.03	1.2	1.25	0.87	7
7207	3.14	4.85	4.7	4.11	3.84	1.81	2.96	3.29	3.09	2.05	1.76	2.1	1.93	1.25	1.66	1.24	1.23	1.28	0.88	7
7285	3.47	4.95	4.86	4.25	3.8	2.14	2.85	3.19	2.99	2.33	1.43	2.02	1.95	1.23	1.63	1.04	1.27	1.29	1.17	7
5054	3.77	5.59	5.28	4.64	4.08	2.32	3.23	3.51	3.23	2.34	1.79	2.18	2.12	1.45	1.75	1.2	1.3	1.13	1.01	8
5062	3.53	5.02	4.92	4.44	4.08	2.09	3.19	3.47	3.35	2.62	1.87	2.31	2.26	1.44	1.82	1.34	1.24	1.52	1.32	8
5761	3.3	4.96	4.92	4.31	3.82	2.24	2.98	3.41	3.19	2.41	1.77	2.09	2.09	1.38	1.77	1.09	1.17	1.43	1.25	8
5762	3.5	5.08	4.97	4.39	3.87	2.28	3.06	3.45	3.28	2.46	1.89	2.23	2.12	1.44	1.74	1.18	1.24	1.5	1.05	8
5776	2.82	4.83	4.56	4.08	3.8	2.14	3.03	3.29	3.15	2.49	1.79	2.12	1.98	1.35	1.63	0.95	1.26	1.32	1.18	8
7112	3.31	4.59	4.56	4.07	3.81	2.19	2.77	3.14	2.95	2.3	1.59	1.9	1.8	1.27	1.66	1.2	1.27	1.29	1.22	8
7115	3.39	5.1	5.04	4.53	4.2	2.46	3.26	3.52	3.36	2.65	1.93	2.34	2.19	1.56	1.76	1.13	1.2	1.46	1.1	8
7226	3.48	5.36	5.34	4.66	4.19	2.24	3.07	3.51	3.3	2.41	1.85	2.29	2.17	1.39	1.76	1.04	1.16	1.17	0.98	8
7249	3.6	5.5	5.36	4.82	4.38	2.34	3.09	3.32	3.25	2.59	1.76	2.14	2.1	1.6	1.78	1.07	1.39	1.45	1.2	8

5045	3.69	5.43	5.2	4.54	4.13	2.41	3.28	3.7	3.53	2.77	1.88	2.35	2.26	1.62	1.77	1.07	1.42	1.5	1.11	9
6022	3.93	5.83	5.66	5.05	4.67	2.53	3.4	3.89	3.7	2.77	2.07	2.64	2.48	1.78	1.87	1.37	1.61	1.64	1.41	9
6023	3.7	5.28	5.36	4.9	4.34	2.34	3.15	3.67	3.42	2.69	1.83	2.21	2.12	1.4	1.89	1.42	1.49	1.26	1.36	9
6024	3.4	5.21	5.3	4.69	4.35	2.12	3.37	3.81	3.53	2.77	1.97	2.41	2.23	1.56	1.83	1.4	1.51	1.49	1.34	9
6025	3.95	6	5.82	5	4.59	2.68	3.59	4.13	3.78	2.87	2	2.48	2.38	1.65	1.71	1.3	1.42	1.2	1.27	9
7075	3.35	5	4.74	4.05	3.74	2.1	2.88	3.18	2.92	2.26	1.63	1.98	1.86	1.16	1.54	1.19	1.24	1.23	1.14	9
7081	3.66	5.24	5.32	4.58	4.3	2.37	3.13	3.6	3.31	2.43	1.82	2.27	2.13	1.33	1.82	1.5	1.57	1.61	1.41	9
7100	3.82	5.46	5.56	4.94	4.48	2.01	3.2	3.71	3.64	2.73	1.72	2.34	2.25	1.57	1.97	1.41	1.28	1.4	1.42	9
7224	3.9	5.92	5.7	5.01	4.69	2.65	3.54	3.93	3.74	2.72	2.01	2.47	2.32	1.7	1.94	1.49	1.59	1.53	1.35	9
7284	3.33	4.92	4.95	4.58	4.28	2.22	3.01	3.42	3.26	2.52	1.77	2.2	2.1	1.37	1.73	1.23	1.3	1.36	1.15	9
5702	3.61	5.52	5.61	4.89	4.54	2.48	3.49	3.95	3.67	2.92	2.12	2.51	2.35	1.62	1.99	1.5	1.53	1.51	1.38	10
5707	3.79	5.47	5.36	4.72	4.33	2.48	3.32	3.77	3.55	2.74	1.92	2.34	2.21	1.39	1.94	1.28	1.12	1.51	1.3	10
5717	3.54	5.51	5.4	4.87	4.49	2.37	3.26	3.71	3.52	2.78	1.82	2.15	2.08	1.59	1.78	1.19	0.97	1.37	1.23	10
5725	4.12	5.83	5.55	4.88	4.47	2.79	3.62	4.05	3.83	2.98	2.15	2.68	2.57	1.74	2.08	1.47	1.56	1.62	1.42	10
5726	3.75	5.38	5.35	4.73	4.42	2.47	3.06	3.51	3.23	2.53	1.86	2.27	2.14	1.43	1.82	1.33	1.44	1.43	1.3	10
5728	3.82	5.65	5.5	4.95	4.66	2.58	3.43	3.91	3.72	2.88	1.92	2.43	2.3	1.55	1.84	1.44	1.56	1.56	1.38	10
5754	3.66	5.32	5.12	4.59	4.18	2.21	3.17	3.61	3.45	2.7	1.86	2.37	2.2	1.53	1.83	1.08	1.48	1.5	1.14	10
5763	3.39	5.06	4.95	4.38	3.89	2.14	2.86	3.39	3.19	2.37	1.64	2.09	2.01	1.37	1.77	1.06	1.44	1.45	1.04	10
5773	4.1	5.75	5.63	5.03	4.58	2.65	3.44	3.94	3.78	2.89	2.03	2.53	2.51	1.8	2.01	1.58	1.6	1.66	1.48	10
5777	3.66	5.27	5.04	4.54	4.15	2.36	3.28	3.71	3.48	2.71	1.97	2.39	2.3	1.57	1.77	1.32	1.44	1.5	1.24	10
7134	3.94	5.66	5.71	5.02	4.72	2.58	3.52	3.77	3.66	2.78	2.03	2.45	2.39	1.58	2.13	1.41	1.51	1.62	1.53	10
7189	3.88	5.6	5.45	4.72	4.33	2.59	3.58	3.96	3.66	2.94	2.15	2.55	2.3	1.71	2.07	1.4	1.51	1.53	1.34	10
7237	3.71	5.47	5.33	4.73	4.24	2.48	3.29	3.81	3.44	2.64	1.79	2.3	2.08	1.47	1.88	1.34	1.5	1.55	1.37	10
7283	3.69	5.77	5.61	4.93	4.5	2.49	3.31	3.82	3.56	2.66	1.85	2.36	2.29	1.48	1.9	1.41	1.47	1.43	1.27	10
5703	3.6	5.13	5.04	4.44	4.02	2.36	3.41	3.75	3.56	2.61	1.99	2.43	2.3	1.63	1.89	1.35	1.45	1.53	1.23	11
5708	3.88	5.75	5.38	4.91	4.52	2.57	3.49	3.96	3.75	2.87	1.95	2.43	2.3	1.51	1.7	1.39	1.49	1.59	1.35	11
5709	4	5.9	5.72	4.96	4.61	2.72	3.63	4.15	3.91	2.93	1.94	2.46	2.36	1.48	2.05	1.36	1.49	1.63	1.45	11
5718	4.41	6.08	6	5.45	5.02	3.01	3.94	4.26	4.01	3.15	2.27	2.73	2.73	1.77	1.99	1.4	1.59	1.54	1.43	11
5719	4.22	6.07	5.85	4.94	4.63	2.73	3.59	4.06	3.87	3.1	1.99	2.43	2.39	1.58	1.76	1.46	1.55	1.73	1.37	11
5729	3.97	5.9	5.71	5.11	4.86	2.67	3.55	4.07	3.83	3.01	2.05	2.53	2.38	1.63	1.87	1.49	1.57	1.6	1.45	11
5733	3.94	5.61	5.46	4.75	4.46	2.55	3.52	4	3.79	2.94	1.94	2.49	2.25	1.22	1.99	1.47	1.58	1.71	1.38	11
5741	3.88	5.97	5.77	5.33	4.84	2.54	3.45	3.9	3.76	2.96	1.98	2.39	2.28	1.66	1.94	1.4	1.54	1.51	1.37	11
5745	4.13	5.86	5.62	4.77	4.64	2.84	3.58	3.95	3.69	3.06	1.99	2.49	2.44	1.68	1.88	1.45	1.46	1.55	1.26	11
5747	4.26	6.02	6.05	5.26	4.92	2.87	3.7	4.2	3.88	3.04	2.1	2.57	2.45	1.69	2.11	1.49	1.61	1.64	1.57	11

5908	3.98	5.76	5.62	5.05	4.78	2.61	3.5	4.01	3.8	2.96	2	2.52	2.39	1.61	1.82	1.47	1.54	1.61	1.4	11
7068	4.09	5.87	5.71	5.07	4.63	2.89	3.71	4.14	3.88	3.02	2.14	2.65	2.45	1.81	1.92	1.33	1.49	1.51	1.41	11
7072	3.95	6.18	5.99	5.31	5.01	2.92	3.95	4.4	4.14	3.35	2.21	2.8	2.76	1.87	2.02	1.62	1.74	1.68	1.55	11
7073	4.2	5.81	5.7	5.15	4.76	2.55	3.46	3.86	3.66	2.9	2.15	2.61	2.42	1.73	2.08	1.52	1.68	1.69	1.47	11
7227	3.87	5.62	5.43	4.89	4.44	2.61	3.32	3.74	3.49	2.81	1.97	2.31	2.18	1.63	1.82	1.36	1.52	1.53	1.37	11
5710	4.18	6.05	5.84	5	4.71	2.76	3.7	4.15	3.98	3.02	2.01	2.55	2.38	1.54	1.85	1.42	1.51	1.66	1.39	12
5716	4.09	5.97	5.65	4.94	4.5	2.88	3.73	4.29	3.97	3.09	2.04	2.68	2.47	1.67	1.83	1.4	1.47	1.39	1.38	12
5723	4.21	6.31	6.13	5.61	5.1	2.99	3.98	4.43	4.16	3.21	2.33	2.85	2.68	1.76	2.21	1.6	1.77	1.82	1.28	12
5727	3.77	5.83	5.89	5.11	4.56	2.75	3.59	4.1	3.89	2.98	2.15	2.63	2.59	1.68	1.97	1.43	1.63	1.72	1.45	12
5734	4.02	5.7	5.62	4.65	4.51	2.62	3.54	4.02	3.8	2.96	1.94	2.48	2.35	1.27	2.07	1.45	1.6	1.65	1.38	12
5744	4.15	6.06	5.91	5.37	4.86	2.89	3.71	4.1	3.75	3	2.09	2.64	2.46	1.76	2.11	1.58	1.74	1.74	1.57	12
5746	4.27	6.04	5.78	4.99	4.71	2.86	3.67	4.06	3.78	3.21	2.11	2.6	2.51	1.74	2.09	1.52	1.61	1.62	1.35	12
5758	4.24	6.26	6.16	5.57	4.93	2.98	3.76	4.23	4.09	3.23	2.16	2.76	2.71	1.94	1.99	1.52	1.64	1.62	1.54	12
5765	4.01	6.07	5.83	5.2	4.56	2.76	3.61	4.08	3.82	2.99	1.93	2.48	2.32	1.5	1.77	1.4	1.64	1.53	1.45	12
5769	4.13	6.36	6.24	5.45	5	2.83	3.87	4.35	4.13	3.16	2.12	2.57	2.38	1.75	1.89	1.45	1.57	1.71	1.39	12
5774	4.32	6.56	6.21	5.75	5.24	3.03	3.82	4.25	4.09	3.17	2.1	2.56	2.48	1.69	2.07	1.57	1.74	1.79	1.53	12
7107	4.65	7.15	6.85	6.28	5.77	3.38	4.29	4.68	4.47	3.53	2.59	3.01	2.93	1.95	2.36	1.63	1.83	1.89	1.49	12
7200	3.8	5.56	5.3	4.44	4.08	2.54	3.32	3.94	3.64	2.82	1.92	2.44	2.27	1.35	1.89	1.44	1.5	1.52	1.4	12
7210	3.91	5.98	5.84	5.29	4.66	2.8	3.65	4.17	3.91	3.05	1.96	2.53	2.28	1.6	2.11	1.47	1.61	1.6	1.42	12
7218	4.17	5.87	5.81	5.07	4.8	2.82	3.56	3.96	3.73	2.93	2.09	2.44	2.34	1.69	2.1	1.47	1.6	1.54	1.52	12
5701	3.88	6.05	5.92	5.13	4.58	2.82	3.76	4.24	3.92	3.05	2.33	2.68	2.53	1.78	1.88	1.49	1.63	1.63	1.43	13
5705	4.18	5.94	5.64	5.05	4.36	2.68	3.59	3.94	3.72	2.83	2.09	2.44	2.33	1.47	2.07	1.62	1.71	1.72	1.61	13
5706	4.28	6.13	5.96	5.18	4.91	2.97	3.96	4.45	4.14	3.26	2.36	2.78	2.67	1.97	2.12	1.63	1.79	1.77	1.61	13
5714	3.99	5.85	5.74	5.1	4.7	2.82	3.55	4.14	3.76	2.88	1.89	2.46	2.32	1.51	1.74	1.35	1.44	1.43	1.31	13
5721	4.2	6.01	5.7	4.99	4.65	2.85	3.76	4.11	3.88	3	2.14	2.55	2.42	1.62	2.03	1.7	1.87	1.78	1.6	13
5735	4.02	5.55	5.58	4.77	4.49	2.73	3.56	4.07	3.79	3.05	2.01	2.48	2.33	1.24	2.02	1.52	1.65	1.71	1.42	13
5748	4.28	6.17	6.04	5.19	5.04	2.91	3.84	4.29	3.95	3.08	2.23	2.7	2.52	1.76	2.06	1.61	1.68	1.72	1.51	13
5756	4.24	6.37	5.99	5.35	4.85	2.78	3.81	4.3	4.05	3.2	2.06	2.43	2.4	1.67	2.12	1.63	1.69	1.75	1.51	13
5759	4.2	6.34	6.13	5.43	4.86	3.02	3.81	4.29	4.08	3.25	2.17	2.76	2.71	1.88	1.91	1.49	1.64	1.63	1.46	13
5770	4.16	6.46	6.26	5.51	5.06	2.94	3.81	4.36	4.14	3.17	2.13	2.65	2.49	1.71	1.97	1.49	1.62	1.7	1.39	13
5902	4.11	6.36	6.22	5.66	5.1	2.9	3.8	4.18	3.99	3.07	2.22	2.62	2.51	1.71	2.06	1.6	1.66	1.7	1.51	13
7071	4.23	6.11	5.97	5.25	4.62	2.71	3.58	4.12	3.66	2.82	2.2	2.62	2.39	1.72	2.04	1.48	1.58	1.59	1.39	13
7077	4.05	5.84	5.5	4.81	4.51	2.67	3.72	4.14	3.84	2.9	2	2.46	2.3	1.02	1.85	1.49	1.54	1.6	1.42	13
7247	4.42	6.28	6.08	5.39	4.9	2.86	3.74	4.17	3.89	2.95	2.16	2.55	2.5	1.67	2.06	1.56	1.67	1.67	1.52	13

7252	4.06	6.24	5.95	5.09	4.8	2.93	3.81	4.26	3.96	3.14	2.15	2.66	2.48	1.73	2.11	1.73	1.82	1.85	1.55	13
5715	4	5.84	5.66	5.14	4.69	2.87	3.55	4.17	3.8	2.89	1.95	2.47	2.38	1.51	1.73	1.36	1.4	1.47	1.3	14
5737	4.71	6.59	6.27	5.51	5.22	3.02	3.93	4.28	4.01	3.24	2.3	2.77	2.68	1.78	2.17	1.68	1.77	1.77	1.69	14
5743	4.2	6.18	6.16	5.71	5.14	2.82	3.68	4.13	3.95	3.17	2.15	2.57	2.34	1.8	1.98	1.53	1.62	1.63	1.53	14
5755	3.94	5.92	5.88	5.28	4.78	2.82	3.53	3.96	3.72	2.95	2.04	2.47	2.37	1.75	1.4	1.53	1.7	1.73	1.52	14
5760	4.31	6.37	6.24	5.63	5.09	3.05	3.72	4.2	4.07	3.28	2.2	2.82	2.72	1.86	1.96	1.49	1.61	1.62	1.5	14
5900	4.18	6.08	5.94	5.2	4.77	2.72	3.78	4.25	4.04	3.11	2.08	2.57	2.44	1.65	2.02	1.44	1.58	1.67	1.44	14
5901	4.01	5.76	5.6	5.07	4.54	2.69	3.49	3.91	3.68	2.95	1.89	2.44	2.47	1.7	1.78	1.38	1.37	1.51	1.38	14
5910	4.36	6.4	6.2	5.57	5.13	3	3.92	4.39	4.05	3.17	2.31	2.81	2.63	1.87	2.06	1.68	1.84	1.84	1.62	14
5914	4.58	6.42	6.13	5.36	5.08	3.19	4.11	4.55	4.2	3.31	2.32	2.68	2.56	1.79	2.09	1.66	1.73	1.76	1.51	14
5917	4.44	6.17	6.14	5.45	5.08	2.94	3.87	4.27	3.97	3.12	2.23	2.7	2.51	1.71	2.09	1.61	1.68	1.74	1.52	14
5925	4.74	6.65	6.16	5.32	5.12	3.25	4.24	4.75	4.39	3.37	2.51	3.05	2.9	1.98	1.86	1.56	1.72	1.75	1.43	14
7209	4.22	6.38	6.36	5.66	5.29	2.87	3.71	4.14	3.89	3.04	2.1	2.64	2.45	1.66	2.17	1.55	1.76	1.71	1.57	14
7216	3.86	5.99	5.92	5.41	5	2.8	3.75	4.13	3.8	3.02	2.19	2.61	2.48	1.66	2.01	1.49	1.72	1.62	1.52	14
7264	4.39	6.65	6.44	5.79	5.42	3.15	4.03	4.54	4.29	3.23	2.31	2.78	2.51	1.68	2.24	1.68	1.85	1.93	1.66	14
5039	4.6	6.42	6.49	5.66	5.15	3.01	3.84	4.32	4.06	3.19	2.3	2.66	2.56	1.95	2.07	1.77	1.79	1.82	1.64	15
5905	4.5	6.44	6.47	5.78	5.32	2.92	3.95	4.49	4.09	3.26	2.2	2.67	2.5	1.85	2.04	1.62	1.69	1.75	1.58	15
5909	4.14	6.1	5.89	5.22	5.03	2.74	3.67	4.18	3.94	3.09	2.06	2.59	2.46	1.67	1.83	1.58	1.61	1.66	1.45	15
5911	4.03	5.75	5.54	4.85	4.5	2.67	3.56	4.1	3.85	3.04	2.01	2.5	2.36	1.28	2.04	1.5	1.65	1.72	1.41	15
5913	4.74	6.65	6.41	5.65	5.28	3.06	4.01	4.31	4.02	3.28	2.16	2.7	2.64	1.77	2.14	1.68	1.81	1.76	1.7	15
5915	4.3	6.39	6.2	5.71	5.19	2.82	3.7	4.16	3.98	3.21	2.09	2.57	2.37	1.78	1.95	1.59	1.7	1.69	1.54	15
5919	4.08	5.81	5.27	4.49	4.23	2.73	3.49	3.94	3.59	2.7	2.01	2.39	2.13	1.18	1.76	1.45	1.49	1.57	1.4	15
5922	4.54	6.47	6.33	5.7	5.29	2.99	3.98	4.45	4.18	3.24	2.34	2.83	2.66	1.68	2.02	1.69	1.79	1.86	1.57	15
5923	4.2	6.52	6.35	5.54	5.07	2.85	3.84	4.42	4.17	3.25	2.2	2.58	2.48	1.7	2.04	1.5	1.62	1.68	1.41	15
6026	3.92	5.87	5.63	5.12	4.72	2.98	3.59	4.18	3.96	3.15	2.08	2.58	2.47	1.74	1.97	1.57	1.69	1.69	1.54	15
5030	3.79	5.72	5.57	4.93	4.56	2.84	3.65	4.1	3.8	2.9	2.1	2.59	2.39	1.61	2.05	1.57	1.6	1.57	1.5	16
5058	4.71	6.82	6.68	5.9	5.46	3.15	4.07	4.52	4.19	3.25	2.32	2.78	2.59	1.67	2.23	1.69	1.84	1.78	1.62	16
5103	4.27	6.12	5.98	5.38	4.9	2.81	3.84	4.19	3.93	3.05	2.21	2.62	2.4	1.59	2.07	1.54	1.73	1.73	1.42	16
5139	4.31	6.48	6.42	5.82	5.42	3.02	3.88	4.31	4.12	3.21	2.05	2.62	2.49	1.74	2.06	1.63	1.8	1.84	1.55	16
5906	4.55	6.48	6.5	5.77	5.39	2.92	4.01	4.54	4.1	3.24	2.2	2.73	2.52	1.9	2.08	1.63	1.66	1.81	1.59	16
5916	4.01	6.11	6.07	5.39	4.95	2.59	3.57	4.08	3.86	2.91	1.92	2.33	2.24	1.34	1.9	1.43	1.6	1.66	1.51	16
5918	4.18	6	6.05	5.29	4.95	2.84	3.71	4.3	3.96	2.98	2.07	2.5	2.42	1.51	2.05	1.67	1.73	1.72	1.63	16
5924	4.36	6.47	6.46	5.67	5.15	2.83	4.03	4.62	4.26	3.33	2.22	2.86	2.69	1.75	1.73	1.33	1.74	1.81	1.32	16
6027	4.26	6.17	5.87	5.28	4.73	2.87	3.79	4.19	3.92	3.05	2.15	2.58	2.46	1.66	2.02	1.71	1.84	1.82	1.69	16

6028	4.43	6.34	6.2	5.58	5.11	2.98	3.92	4.42	4.12	3.16	2.34	2.84	2.67	1.86	2.07	1.77	1.85	1.88	1.59	16
5055	4.09	5.68	5.58	4.77	4.67	2.79	3.67	4.2	3.84	3.14	2.02	2.44	2.38	1.84	1.91	1.45	1.65	1.71	1.57	17
5071	3.97	6.24	6.28	5.54	5.03	2.77	3.72	4.17	4	3.1	2.09	2.58	2.52	1.68	1.85	1.52	1.59	1.67	1.46	17
5081	4.23	6.15	6.01	5.38	4.85	2.85	3.72	4.07	3.84	2.99	2.21	2.59	2.54	1.73	1.89	1.49	1.58	1.59	1.46	17
5099	3.98	5.97	5.82	5.23	4.87	2.75	3.64	4.07	3.76	2.89	2.15	2.48	2.46	1.76	2.01	1.57	1.71	1.68	1.54	17
5100	4.27	6.3	5.95	5.39	5.01	3.08	3.89	4.34	3.99	3.25	2.2	2.75	2.59	1.89	1.95	1.58	1.7	1.73	1.55	17
5116	4.21	6.3	6.13	5.69	5.26	3.07	3.84	4.29	4.08	3.16	2.34	2.77	2.65	1.94	2.27	1.59	1.82	1.9	1.61	17
5118	4.08	6	5.66	4.91	4.44	2.7	3.47	4.02	3.63	2.8	1.87	2.43	2.25	1.4	1.87	1.49	1.61	1.62	1.45	17
5126	4.63	6.64	6.56	5.56	5.19	3.27	4.14	4.68	4.29	3.46	2.29	2.95	2.76	2.06	2.42	1.73	1.87	1.92	1.7	17
5268	3.84	5.69	5.61	4.91	4.55	2.76	3.59	4.1	3.82	2.97	2.14	2.54	2.4	1.6	2.04	1.58	1.62	1.56	1.53	17
5920	4.13	6.38	6.17	5.59	4.88	2.8	3.68	4.25	3.98	3.04	2.02	2.56	2.46	1.6	2.14	1.55	1.71	1.69	1.51	17
5086	4.28	6.34	6.31	5.72	5.13	2.82	3.81	4.4	4.11	3.25	2.3	2.69	2.63	1.95	2.31	1.78	1.84	1.91	1.63	18
5092	4.59	6.75	6.47	5.71	5.39	3.27	4.21	4.72	4.34	3.57	2.58	3.07	2.86	2.11	2.38	1.81	1.96	1.94	1.8	18
5104	4.01	5.88	5.83	5.19	4.66	2.78	3.79	4.11	3.88	2.98	2.09	2.62	2.57	1.73	1.98	1.51	1.51	1.61	1.44	18
5110	3.98	5.98	5.77	5.11	4.52	2.52	3.47	4.03	3.73	2.7	1.97	2.46	2.31	1.44	1.92	1.39	1.5	1.53	1.36	18
5112	4.09	5.87	5.86	5.32	4.79	2.93	3.65	4.14	3.85	3.04	2.12	2.63	2.49	1.79	2.26	1.63	1.8	1.86	1.56	18
5271	4.09	6.2	6.01	5.41	4.91	2.85	3.72	4.13	3.83	3.02	2.17	2.73	2.45	1.74	2.19	1.62	1.78	1.73	1.59	18
5273	4.32	6.04	5.79	4.98	4.78	2.92	3.72	4.11	3.86	3.19	2.09	2.59	2.51	1.76	1.81	1.55	1.61	1.65	1.35	18
5274	4.68	6.54	6.43	5.7	5.18	3.29	4.1	4.68	4.34	3.42	2.34	3	2.78	2.04	2.41	1.75	1.87	1.87	1.75	18
5294	4.14	6.18	6.02	5.36	5.08	2.8	3.7	4.22	3.99	3.06	2.02	2.62	2.42	1.74	1.88	1.58	1.63	1.68	1.49	18
5304	3.83	5.77	5.66	4.99	4.6	2.75	3.65	4.12	3.83	2.97	2.14	2.6	2.41	1.58	2.02	1.56	1.58	1.58	1.48	18

APPENDIX B

ORIGINAL DATASET OF MALE HISPANIC POPULATION

Image ID	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	Age
5589	1	1.59	1.52	1.33	1.22	0.79	1.1	1.24	1.19	0.9	0.63	0.82	0.81	0.48	0.57	0.42	0.51	0.47	0.39	0
5590	1.25	1.87	1.87	1.63	1.59	1.04	1.35	1.53	1.47	1.19	0.8	1.04	0.96	0.6	0.75	0.55	0.66	0.67	0.51	0
5591	1.26	2.13	2.01	1.86	1.57	1.01	1.4	1.59	1.5	1.13	0.81	1.01	0.97	0.65	0.77	0.56	0.6	0.68	0.55	0
5592	1.37	2.3	2.13	1.84	1.69	1.02	1.51	1.72	1.67	1.28	0.81	1.02	0.99	0.65	0.7	0.46	0.56	0.51	0.41	0
5272	2.05	3.49	3.27	2.89	2.74	1.51	2.15	2.6	2.44	1.97	1.29	1.62	1.57	1.07	1.04	0.72	0.85	0.85	0.72	1
5538	0.87	1.4	1.34	1.2	1.05	0.68	0.96	1.12	1.02	0.81	0.53	0.67	0.64	0.42	0.46	0.34	0.4	0.41	0.37	1
5540	1.58	2.78	2.47	2.25	1.98	1.2	1.81	2.05	1.81	1.43	0.9	1.12	1.09	0.8	1.06	0.63	0.7	0.72	0.63	1
5593	1.53	2.66	2.45	2.14	1.95	1.18	1.86	2.07	1.99	1.54	0.98	1.26	1.16	0.61	1.07	0.64	0.75	0.78	0.57	1
5594	1.57	2.55	2.45	2.26	1.96	1.28	1.78	1.95	1.86	1.49	0.95	1.19	1.18	0.78	0.91	0.68	0.73	0.76	0.56	1
5542	1.87	2.99	2.73	2.33	2.16	1.4	2.07	2.32	2.21	1.73	1.19	1.46	1.41	0.95	1.12	0.69	0.85	0.87	0.67	2
5543	1.89	3.18	3.04	2.72	2.51	1.49	2.17	2.47	2.36	1.77	1.3	1.61	1.57	1.02	1.16	0.82	0.9	0.96	0.76	2
5544	1.84	3.13	2.98	2.64	2.39	1.34	2.06	2.35	2.21	1.71	1.11	1.37	1.33	0.85	1.2	0.75	0.96	0.93	0.73	2
5596	2.07	3.4	3.31	2.87	2.69	1.41	2.16	2.43	2.33	1.8	1.26	1.54	1.51	0.95	1.12	0.73	0.91	0.93	0.69	2
5598	1.94	3.25	2.94	2.62	2.37	1.42	2.09	2.29	2.19	1.67	1.11	1.37	1.35	0.77	1.21	0.74	0.93	0.94	0.72	2
5270	2.21	3.48	3.24	2.97	2.63	1.49	2.09	2.4	2.29	1.71	1.26	1.47	1.43	0.89	1.17	0.9	0.78	0.94	0.68	3
5545	2.03	3.61	3.49	3.08	2.77	1.48	2.37	2.74	2.65	1.99	1.27	1.72	1.63	1.07	1.24	0.82	0.8	0.89	0.72	3
5546	0.97	1.76	1.68	1.47	1.31	0.83	1.15	1.28	1.21	0.91	0.61	0.81	0.78	0.5	0.62	0.41	0.49	0.5	0.41	3
6118	2.35	3.65	3.38	3.06	2.62	1.76	2.44	2.73	2.56	2	1.29	1.64	1.58	0.97	1.29	0.82	1	1.04	0.92	3
6148	1.99	3.62	3.44	3	2.58	1.79	2.41	2.62	2.43	1.87	1.42	1.66	1.59	0.91	1.33	0.91	1.02	1.03	0.87	3
5038	2.32	3.85	3.8	3.35	3.01	1.65	2.49	2.8	2.59	1.99	1.4	1.69	1.63	1.12	1.37	0.99	1.04	1.03	0.96	4
5105	2.1	3.71	3.55	3.23	2.85	1.58	2.43	2.81	2.66	2.01	1.48	1.86	1.75	1.1	1.35	1.08	1.11	1.19	1	4
5177	2.24	3.84	3.63	3.26	2.98	1.6	2.34	2.62	2.46	1.91	1.34	1.52	1.43	0.94	1.4	1.06	1.14	1.14	1.01	4
5316	2.73	4.63	4.61	4.13	3.73	2.12	2.71	3.17	3.03	2.26	1.48	1.86	1.8	1.17	1.53	1.01	1.21	1.2	0.93	4
6047	1.85	3.42	3.22	2.85	2.44	1.3	1.99	2.23	2.07	1.55	1.18	1.43	1.3	0.69	1.13	0.73	0.82	1	0.66	4
5053	2.77	4.43	4.17	3.73	3.29	1.76	2.54	2.82	2.62	2.03	1.48	1.76	1.7	1.14	1.43	1.06	1.14	1.21	1	5
5085	2.44	3.85	3.66	3.15	2.95	1.58	2.38	2.8	2.62	1.77	1.46	1.8	1.74	1.22	1.39	0.88	0.93	1.19	1.05	5
5106	2.8	4.3	4.08	3.66	3.24	1.83	2.79	3.14	3.01	2.25	1.69	2.09	1.97	1.32	1.63	1.22	1.25	1.3	1.1	5

5165	2.65	3.9	3.6	3.2	2.71	1.78	2.37	2.62	2.46	1.81	1.34	1.61	1.48	0.88	1.37	1.03	1.08	1.1	0.94	5
5166	2.91	4.36	4.27	3.73	3.45	1.83	2.74	3	2.8	2.15	1.58	1.94	1.88	1.34	1.53	1.07	1.21	1.25	1.03	5
7045	2.62	4.49	4.28	4	3.63	2.06	2.94	3.2	3.01	2.36	1.69	2.06	1.98	1.49	1.47	1.04	1.14	1.2	0.98	5
7104	2.82	4.37	4.17	3.67	3.46	1.94	2.71	2.98	2.8	2.24	1.49	1.76	1.73	1.15	1.43	1.07	1.14	1.16	0.96	5
7208	2.52	3.95	3.71	3.2	3.03	1.77	2.3	2.71	2.53	1.89	1.25	1.66	1.61	1.07	1.33	0.93	1.02	1.09	0.91	5
7215	2.38	4.21	3.96	3.47	3.12	1.66	2.58	2.84	2.71	1.99	1.35	1.68	1.61	0.9	1.37	0.94	1.11	1.13	0.95	5
5060	2.66	4.86	4.61	4.12	3.71	2.2	2.87	3.19	3.02	2.34	1.69	2.06	2.07	1.42	1.69	1.22	1.3	1.35	1.19	6
5063	3.31	4.86	4.66	4.12	3.85	2.14	3	3.34	3.19	2.5	1.69	2.04	1.96	1.37	1.7	1.26	1.35	1.37	1.12	6
5098	3.01	4.62	4.67	4.08	3.68	1.87	2.95	3.3	3.1	2.31	1.72	2.09	2	1.43	1.7	1.26	1.36	1.34	1.17	6
5134	2.79	4.52	4.5	3.99	3.54	1.86	2.75	3.09	3.03	2.25	1.56	1.9	1.89	1.29	1.46	1.07	1.16	1.14	1.12	6
5144	2.71	4.02	4	3.53	3.16	1.8	2.38	2.69	2.56	1.97	1.31	1.7	1.68	1.03	1.31	1	1.09	1.11	0.94	6
7046	2.92	4.43	4.35	3.84	3.45	2.03	2.75	3	2.82	2.14	1.5	1.78	1.71	1.16	1.49	1.06	1.22	1.28	1.07	6
7047	2.6	3.93	3.92	3.46	3.08	1.73	2.57	2.91	2.65	2.02	1.48	1.73	1.66	1.08	1.33	0.97	1.08	1.14	1.01	6
7048	2.92	4.63	4.38	3.82	3.46	1.97	2.6	2.93	2.76	2.17	1.54	1.97	1.86	1.29	1.51	1.07	1.18	1.23	1	6
7049	2.97	4.72	4.58	4.09	3.77	2.07	2.78	3.15	2.92	2.41	1.61	1.94	1.86	1.25	1.7	1.17	1.2	1.29	1.12	6
5029	3.31	5.15	5.02	4.44	4.11	2.32	3.04	3.42	3.19	2.48	1.9	2.28	2.08	1.4	1.71	1.23	1.36	1.38	1.1	7
5069	2.86	4.45	4.29	3.81	3.42	2.01	2.75	3.03	2.86	2.17	1.71	2.05	1.89	1.2	1.57	1.05	1.15	1.23	0.99	7
5091	3.1	4.68	4.45	4.05	3.65	2.06	2.75	3.16	2.96	2.2	1.54	1.88	1.85	1.2	1.5	1.04	1.16	1.17	1.07	7
5093	3.01	4.64	4.5	4.06	3.77	2.05	2.83	3.32	3.11	2.33	1.77	2.24	2.12	1.25	1.79	1.27	1.44	1.46	1.22	7
5108	3.03	4.65	4.5	3.89	3.59	2.16	2.84	3.07	2.83	2.29	1.76	2.15	1.96	1.36	1.65	1.18	1.26	1.36	1.19	7
7050	3.2	4.96	4.76	4.26	3.81	2.33	2.95	3.24	3.05	2.38	1.81	2.17	2.04	1.5	1.7	1.34	1.36	1.4	1.22	7
7051	3.21	4.63	4.41	3.92	3.56	2.21	2.66	3	2.89	2.23	1.63	1.94	1.91	1.39	1.64	1.21	1.26	1.3	1.15	7
7099	3.43	4.98	4.95	4.54	4	2.15	2.83	3.29	3.13	2.37	1.64	1.99	1.97	1.31	1.74	1.29	1.4	1.48	1.27	7
7133	3.16	4.75	4.61	3.94	3.66	2.26	3.02	3.32	3.12	2.33	1.74	2.14	2.04	1.46	1.73	1.22	1.35	1.41	1.2	7
7211	2.9	4.39	4.33	3.86	3.32	1.92	2.61	2.96	2.73	2.02	1.49	1.76	1.67	1.03	1.53	1.1	1.17	1.19	1.05	7
5035	3.05	4.73	4.5	4.03	3.68	2.02	2.7	2.99	2.88	2.16	1.59	1.87	1.73	1.18	1.59	1.11	1.24	1.27	1.02	8
5041	3.09	4.84	4.8	4.45	4.13	2.12	2.85	3.16	3.03	2.35	1.62	1.91	1.8	1.13	1.69	1.29	1.32	1.39	1.23	8
5064	3.46	4.9	4.88	4.43	4	2.16	3.12	3.47	3.37	2.53	1.72	2.23	2.1	1.41	1.78	1.23	1.35	1.39	1.23	8
5500	3.45	4.95	4.85	4.27	3.82	2.29	3.16	3.51	3.3	2.52	1.75	2.16	2.1	1.38	1.79	1.31	1.43	1.44	1.24	8
5547	3.15	4.63	4.67	4.17	3.9	2.04	2.99	3.3	3.21	2.5	1.74	2.08	1.99	1.41	1.63	1.25	1.3	1.32	1.16	8
5548	3.42	5.13	4.88	4.09	3.95	2.31	3.09	3.39	3.24	2.58	1.83	2.27	2.11	1.28	1.9	1.32	1.4	1.47	1.3	8
7052	3.09	4.52	4.52	4.04	3.65	2.18	2.88	3.21	3.04	2.35	1.69	2.2	2.06	1.39	1.66	1.23	1.31	1.34	1.17	8
7053	3.42	5.13	5.14	4.48	4.01	2.31	2.97	3.34	3.15	2.39	1.76	2.04	1.84	1.2	1.7	1.31	1.46	1.45	1.23	8
7097	3.12	4.72	4.6	3.96	3.57	2.27	2.89	3.14	3.09	2.39	1.81	2.09	2.02	1.4	1.83	1.26	1.37	1.37	1.15	8

7119	3.39	5	4.89	4.38	4.07	2.12	2.97	3.48	3.27	2.45	1.62	2.02	1.93	1.24	1.78	1.36	1.35	1.41	1.17	8
5023	3.39	5.01	4.99	4.42	3.93	2.21	2.99	3.34	3.17	2.4	1.83	2.1	1.95	1.49	1.77	1.3	1.33	1.38	1.19	9
5119	4.09	5.95	5.66	5.11	4.82	2.68	3.5	3.95	3.68	2.81	2.04	2.51	2.32	1.49	1.94	1.49	1.66	1.63	1.3	9
5135	3.27	4.67	4.54	3.96	3.74	2.06	2.83	3.24	3	2.26	1.55	1.94	1.82	1.07	1.64	1.2	1.3	1.35	1.17	9
5147	3.47	5	5.02	4.56	4.09	2.26	3.05	3.45	3.3	2.48	1.74	2.15	2.06	1.41	2.04	1.32	1.57	1.62	1.34	9
5549	3.84	5.71	5.61	5.06	4.49	2.4	3.08	3.73	3.41	2.42	1.5	2.04	1.89	0.9	1.78	1.27	1.48	1.57	1.18	9
7054	3.55	5.19	5.34	4.65	4.11	2.35	3.3	3.59	3.53	2.66	1.87	2.36	2.43	1.63	1.79	1.34	1.55	1.6	1.36	9
7055	3.25	4.98	4.88	4.2	3.8	2.27	3.05	3.42	3.15	2.42	1.63	2.11	1.92	1.24	1.75	1.2	1.34	1.3	1.16	9
7056	3.61	5.41	5.16	4.54	4.32	2.54	3.31	3.64	3.4	2.67	2.05	2.29	2.17	1.45	2.08	1.53	1.64	1.68	1.49	9
7070	3.66	5.28	5.19	4.48	4.04	2.57	3.18	3.6	3.3	2.63	1.82	2.25	2.16	1.68	1.86	1.34	1.44	1.49	1.35	9
7111	3.34	5.03	5.12	4.47	4.02	2.36	3.03	3.46	3.23	2.58	1.79	2.19	2.1	1.54	1.83	1.34	1.46	1.48	1.29	9
5043	3.15	4.75	4.68	4.19	3.77	2.2	2.86	3.26	3.07	2.38	1.59	1.92	1.87	1.25	1.83	1.38	1.37	1.43	1.26	10
5044	3.74	5.47	5.3	4.73	4.29	2.21	3.27	3.72	3.54	2.72	1.83	2.32	2.27	1.56	1.88	1.38	1.54	1.56	1.37	10
5089	3.7	5.5	5.44	4.78	4.27	2.36	3.29	3.64	3.39	2.59	1.89	2.35	2.21	1.44	1.75	1.21	1.38	1.46	0.98	10
5161	4.11	5.51	5.32	4.61	4.24	2.59	3.34	3.66	3.51	2.79	1.95	2.34	2.25	1.66	1.82	1.36	1.46	1.45	1.35	10
5164	3.43	4.9	4.84	4.41	3.75	2.22	3.09	3.46	3.26	2.32	1.77	2.15	2.09	1.35	1.78	1.36	1.53	1.57	1.3	10
5501	3.65	5.41	5.37	4.78	4.19	2.4	3.33	3.73	3.48	2.62	1.84	2.21	2.09	1.35	2.03	1.39	1.5	1.56	1.42	10
5502	3.14	4.93	4.78	4.26	3.8	2.14	3.04	3.49	3.25	2.48	1.6	2.05	1.92	1.23	1.77	1.21	1.36	1.39	1.17	10
5503	3.5	5.22	4.93	4.34	4	2.34	3.09	3.48	3.22	2.45	1.74	2.18	2.07	1.43	1.76	1.3	1.34	1.48	1.21	10
5504	3.72	5.11	4.87	4.28	4.09	2.62	3.16	3.37	3.22	2.48	1.95	2.27	2.19	1.42	1.71	1.38	1.48	1.57	1.39	10
5505	3.56	5.7	5.65	5	4.53	2.5	3.28	3.84	3.65	2.7	2.04	2.5	2.37	1.66	1.98	1.55	1.64	1.65	1.43	10
7057	3.53	5.44	5.33	4.71	4.37	2.53	3.06	3.56	3.36	2.7	1.81	2.28	2.19	1.64	1.83	1.39	1.5	1.58	1.46	10
7241	3.69	5.54	5.42	4.89	4.28	2.39	3.38	3.96	3.65	2.78	1.89	2.47	2.28	1.63	1.89	1.47	1.57	1.59	1.41	10
5082	3.58	5.07	4.96	4.41	3.97	2.32	3.03	3.42	3.16	2.35	1.82	2.26	2.08	1.4	1.88	1.41	1.55	1.62	1.35	11
5101	3.47	5.28	5.26	4.56	4.27	2.26	3.05	3.5	3.3	2.66	1.81	2.23	2.15	1.59	1.94	1.43	1.57	1.54	1.43	11
5211	3.59	5.47	5.45	4.8	4.46	2.56	3.33	3.78	3.58	2.78	1.96	2.47	2.38	1.66	2.06	1.6	1.59	1.63	1.53	11
5318	4.06	5.85	5.65	5.06	4.54	2.8	3.72	4.14	3.85	2.9	1.98	2.44	2.24	1.36	1.99	1.42	1.67	1.65	1.32	11
5320	3.89	5.6	5.46	4.84	4.4	2.42	3.29	3.6	3.46	2.82	2	2.46	2.3	1.72	1.96	1.5	1.61	1.6	1.36	11
5340	4.62	6.69	6.47	5.78	5.41	3.1	3.98	4.46	4.22	3.22	2.3	2.81	2.69	1.66	2.21	1.7	1.9	1.82	1.57	11
5506	3.54	5.34	5.26	4.72	4.15	2.42	3.2	3.61	3.37	2.63	1.91	2.24	2.17	1.58	1.85	1.47	1.64	1.67	1.52	11
5507	2.02	2.89	2.79	2.48	2.33	1.35	1.75	1.94	1.86	1.42	0.99	1.16	1.1	0.77	0.98	0.7	0.73	0.72	0.65	11
5508	2.09	3	2.87	2.47	2.32	1.41	1.81	2.06	1.93	1.5	1.1	1.37	1.35	0.88	1.11	0.81	0.9	0.96	0.8	11
5550	4.69	6.42	6.41	5.62	5.08	2.89	3.74	4.24	3.99	3.1	2.2	2.61	2.55	1.82	2.22	1.58	1.6	1.79	1.54	11
7058	3.71	5.59	5.28	4.65	4.43	2.33	3.2	3.68	3.48	2.63	1.8	2.2	2.12	1.5	1.93	1.44	1.5	1.52	1.43	11

7059	3.37	4.8	4.89	4.32	3.88	2.17	2.86	3.29	3.1	2.35	1.67	2.08	2.03	1.32	1.66	1.27	1.32	1.39	1.17	11
7106	3.89	5.63	5.45	4.79	4.35	2.34	3.09	3.47	3.29	2.53	1.83	2.28	2.24	1.61	1.88	1.4	1.55	1.57	1.44	11
7135	3.91	5.64	5.46	4.8	4.58	2.48	3.35	3.64	3.53	2.63	1.97	2.35	2.27	1.57	1.99	1.54	1.58	1.59	1.42	11
5509	3.79	6.03	5.91	5.35	4.77	2.75	3.4	3.94	3.78	2.9	2.13	2.65	2.51	1.84	2.12	1.63	1.72	1.78	1.59	12
5510	3.98	5.86	5.86	5.2	4.62	2.64	3.53	4.02	3.71	2.87	2.19	2.67	2.55	1.8	2.11	1.6	1.73	1.76	1.57	12
5511	4.53	6.59	6.12	5.51	5.04	3.18	3.88	4.26	4.1	3.19	2.29	2.78	2.53	1.59	2.05	1.66	1.75	1.73	1.6	12
5512	4.81	6.93	6.86	6.03	5.46	3.25	4.1	4.63	4.37	3.35	2.31	2.76	2.72	1.94	2.46	1.61	1.83	1.97	1.66	12
5513	3.85	6.16	6.06	5.44	4.78	2.86	3.47	4.04	3.8	2.96	2.2	2.65	2.6	1.87	2.15	1.64	1.76	1.82	1.64	12
5514	4.2	6.07	6.16	5.41	4.88	2.83	3.68	4.15	3.9	3	2.33	2.76	2.67	1.88	2.26	1.66	1.78	1.81	1.64	12
5516	4.5	6.69	6.22	5.37	5.15	3.23	3.92	4.32	4.15	3.19	2.28	2.78	2.62	1.64	2.08	1.71	1.81	1.78	1.59	12
5551	4.22	6.06	6.08	5.47	5	2.64	3.78	4.17	3.92	3.02	2.2	2.78	2.61	1.79	2.24	1.68	1.81	1.64	1.65	12
5552	4.39	6.68	6.53	5.83	5.43	3.05	4.05	4.6	4.22	3.4	1.97	2.71	2.52	1.63	2.27	1.46	1.47	1.63	1.45	12
6116	4.34	6.26	6.07	5.26	4.93	3.2	3.88	4.11	3.93	3.18	2.11	2.7	2.59	1.89	2.21	1.63	1.76	1.84	1.62	12
7060	3.77	5.72	5.47	4.72	4.34	2.5	3.24	3.73	3.4	2.65	1.82	2.23	2.14	1.31	1.95	1.54	1.72	1.75	1.47	12
7061	4.3	6.2	6.13	5.33	4.93	2.95	3.87	4.32	4.01	3.31	2.19	2.7	2.62	2.02	2.24	1.72	1.79	1.8	1.72	12
7223	3.67	5.34	5.2	4.65	4.3	2.45	3.29	3.63	3.38	2.72	1.85	2.26	2.02	1.44	1.98	1.56	1.6	1.66	1.46	12
7236	4.36	6.17	6.15	5.32	5.11	2.99	3.84	4.39	4.21	3.26	2.2	2.7	2.58	1.86	2.13	1.71	1.78	1.84	1.67	12
7277	4.29	6.07	5.99	5.27	4.78	2.9	3.72	4.13	3.89	3.07	2.11	2.5	2.38	1.76	2.15	1.53	1.61	1.69	1.53	12
5517	4.09	6.22	6.04	5.39	4.76	2.83	3.72	4.19	3.93	3.06	2.1	2.56	2.45	1.86	2.2	1.72	1.83	1.87	1.72	13
5518	4.19	6.24	6.09	5.34	4.92	2.81	3.54	3.98	3.69	2.86	2.07	2.47	2.43	1.72	2.15	1.53	1.64	1.68	1.48	13
5519	3.98	5.73	5.58	4.89	4.62	2.56	3.39	3.75	3.55	2.75	2.04	2.35	2.19	1.5	2.28	1.54	1.52	1.64	1.46	13
5520	4.36	5.92	5.56	4.93	4.7	2.86	3.65	4.15	3.93	3.02	2.16	2.62	2.49	1.67	2.04	1.46	1.67	1.69	1.54	13
5521	4.98	7.14	7.02	6.23	5.66	3.29	4.17	4.71	4.45	3.49	2.43	2.84	2.84	2.04	2.49	1.65	1.87	2.05	1.7	13
5522	4.11	5.77	5.74	5.06	4.57	2.76	3.57	4.07	3.74	2.89	2.13	2.61	2.38	1.59	2	1.45	1.49	1.54	1.43	13
5553	4.44	6.5	6.26	5.46	4.99	3.1	4.03	4.43	4.02	3.2	2.25	2.85	2.61	1.8	2.38	1.72	1.94	1.93	1.64	13
5554	4.39	6.6	6.53	5.81	5.15	3.09	3.88	4.18	4.14	3.3	2.37	2.72	2.65	1.95	2.31	1.72	1.8	1.84	1.7	13
5555	4.54	6.54	6.22	5.46	5.07	3.27	3.92	4.34	4.14	3.23	2.35	2.84	2.63	1.66	2.09	1.68	1.61	1.77	1.6	13
5556	4.16	6.64	6.45	5.7	5.25	2.88	3.72	4.26	4.03	3.13	1.88	2.47	2.47	1.55	1.98	1.63	1.94	1.9	1.71	13
7062	4.7	6.86	6.67	5.72	5.34	3.18	4.02	4.45	4.18	3.3	2.27	2.88	2.68	1.79	2.4	1.71	1.81	1.83	1.7	13
7063	3.92	5.54	5.53	4.94	4.7	2.81	3.54	4.08	3.83	3.04	2.04	2.53	2.46	1.8	2.21	1.61	1.69	1.72	1.59	13
7064	4.59	6.66	6.36	5.65	5.34	3.16	3.88	4.33	4.05	3.28	2.27	2.73	2.7	1.82	2.16	1.69	1.87	1.85	1.76	13
7201	4.4	6.6	6.26	5.6	5.32	3.27	4.08	4.59	4.24	3.31	2.22	2.78	2.56	1.92	2.26	1.71	1.84	1.93	1.69	13
7219	4.17	5.76	5.75	5.13	4.89	2.78	3.55	3.95	3.75	2.94	2.06	2.52	2.4	1.68	2.19	1.69	1.71	1.78	1.61	13
5523	4.58	6.6	6.37	5.54	5.14	3.16	4.04	4.5	4.12	3.28	2.12	2.8	2.69	1.82	2.39	1.67	1.95	1.94	1.7	14

5524	4.51	6.55	6.37	5.62	5.25	3.24	4.01	4.53	4.28	3.34	2.26	2.66	2.63	1.93	2.39	1.68	1.94	2	1.63	14
5525	4.91	7.25	6.89	6.13	5.66	3.57	4.38	4.86	4.62	3.49	2.66	3.24	2.78	1.96	2.39	1.92	2	2.08	1.77	14
5526	4.26	6.52	6.34	5.68	5.07	3	3.94	4.36	4.11	3.25	2.3	2.73	2.59	1.95	2.26	1.79	1.91	1.97	1.82	14
5527	4.24	6.46	6.3	5.58	5.11	3.15	3.96	4.3	4.04	3.24	2.32	2.62	2.46	1.85	2.2	1.6	1.82	1.77	1.6	14
5557	4.7	6.96	6.88	6.13	5.63	3.24	4.09	4.68	4.38	3.37	2.48	2.9	2.78	1.98	2.25	1.8	1.91	1.92	1.79	14
5558	2.14	3.2	3.13	2.84	2.63	1.46	1.92	2.2	2.17	1.6	1.19	1.41	1.32	0.96	1.06	0.79	0.86	0.87	0.8	14
5559	4.81	6.96	6.92	6.22	5.71	3.21	4.24	4.75	4.5	3.52	2.48	3.11	2.9	1.84	2.44	1.84	1.99	1.96	1.85	14
5560	4.23	6.62	6.42	5.68	5.21	2.94	3.72	4.3	4.04	3.17	1.82	2.47	2.43	1.55	2.21	1.64	1.91	1.91	1.76	14
5561	4.63	6.33	5.92	5.33	4.98	3.04	3.85	4.34	4.08	3.18	2.27	2.75	2.6	1.75	2.07	1.57	1.75	1.77	1.56	14
7065	4.8	6.73	6.51	5.88	5.51	3.35	4.2	4.68	4.42	3.6	2.38	2.86	2.86	2	2.2	1.6	1.7	1.83	1.59	14
7066	5.15	7.44	7.47	6.63	6.25	3.7	4.37	4.81	4.62	3.73	2.46	2.99	2.89	2.02	2.36	1.79	1.91	1.9	1.78	14
7067	4.76	6.55	6.36	5.7	5.4	3.4	4.09	4.56	4.31	3.35	2.44	3.11	2.79	1.99	2.45	1.77	1.91	1.92	1.68	14
7212	4.79	6.75	6.54	5.63	5.24	3.23	4.03	4.52	4.29	3.38	2.34	2.87	2.63	1.9	2.07	1.63	1.84	1.81	1.77	14
5528	4.62	6.65	6.4	5.53	5.13	3.2	4.15	4.48	4.14	3.28	2.18	2.74	2.61	1.82	2.37	1.73	1.98	2	1.61	15
5529	4.63	6.86	6.81	6.08	5.57	3.36	4.47	5.02	4.71	3.82	2.51	2.95	2.9	2	2.42	1.84	1.97	1.91	1.89	15
5530	4.82	6.31	6.14	5.6	5.06	3.12	3.89	4.26	4.07	3.23	2.36	2.83	2.62	1.88	1.99	1.43	1.69	1.84	1.45	15
5531	4.66	6.32	5.97	5.31	5.03	3.08	3.87	4.43	4.1	3.21	2.29	2.77	2.62	1.75	2.14	1.55	1.79	1.75	1.58	15
5532	4.57	6.74	6.5	5.7	5.5	3.17	4.24	4.67	4.54	3.61	2.6	3.09	2.97	2.25	2.19	1.75	1.91	1.92	1.74	15
5533	4.82	6.43	6.17	5.65	5.1	3.2	3.94	4.29	4.13	3.3	2.38	2.84	2.65	1.87	1.96	1.4	1.7	1.83	1.49	15
5534	4.19	6.45	6.31	5.61	5.19	3.18	3.95	4.34	4.08	3.28	2.37	2.64	2.52	1.88	2.21	1.67	1.83	1.84	1.64	15
5562	4.9	7.55	7.35	6.66	6.12	3.09	4.28	4.88	4.44	3.37	2.17	2.83	2.59	1.52	2.58	1.98	2.06	2.09	1.87	15
5563	4.73	6.98	6.59	6.05	5.47	3.2	4.12	4.66	4.22	3.35	2.37	2.72	2.58	1.82	2.49	1.87	2.04	1.98	1.86	15
6110	4.42	6.46	6.31	5.61	5.19	3.16	4.06	4.64	4.39	3.39	2.37	2.99	2.94	1.78	2.45	1.9	2.09	2.12	1.92	15
5013	4.99	7.13	6.81	6.13	5.81	3.42	4.23	4.62	4.39	3.52	2.6	3.06	2.97	2.06	2.25	1.76	1.94	1.97	1.65	16
5332	4.71	7.13	7.27	6.44	5.61	3.32	4.25	4.83	4.55	3.48	2.41	2.98	2.95	1.99	2.14	1.82	1.98	2.06	1.87	16
5351	4.42	6.59	6.38	5.67	5.19	3	3.74	4.52	4.28	3.31	2.25	2.63	2.43	1.81	2.24	1.59	1.68	1.67	1.66	16
5352	4.87	7.03	6.87	5.97	5.66	3.24	4.15	4.73	4.4	3.45	2.38	2.96	2.84	2.07	2.52	1.89	2.09	2.11	1.94	16
5535	4.35	6.35	6.16	5.44	5.24	2.98	3.75	4.16	3.97	3.1	2.29	2.69	2.52	1.72	2.39	1.69	1.71	1.79	1.67	16
5536	4.67	6.86	6.8	6.15	5.54	3.41	4.51	5.06	4.71	3.82	2.49	2.93	2.89	2.02	2.42	1.84	1.97	1.97	1.94	16
5564	4.78	6.93	6.96	6.22	5.7	3.22	4.28	4.82	4.52	3.54	2.58	3.16	2.96	1.9	2.18	1.84	1.97	1.97	1.84	16
5565	4.98	7.6	7.36	6.69	6.17	3.21	4.16	4.87	4.47	3.35	2.31	2.84	2.56	1.49	2.49	2.05	2.13	2.12	1.96	16
5566	4.19	6.04	6.02	5.25	4.75	2.8	3.66	4.16	3.81	2.97	2.16	2.67	2.44	1.64	1.99	1.57	1.56	1.59	1.46	16
6132	4.74	7.32	7.23	6.4	5.8	3.47	4.3	4.89	4.57	3.68	2.56	3.08	2.89	2.13	2.54	1.95	1.99	2.06	1.77	16
5083	4.61	6.51	6.53	5.86	5.25	3.17	3.94	4.44	4.22	3.22	2.31	2.83	2.62	1.73	2.26	1.63	1.87	1.86	1.69	17

5148	5.1	7.04	7.04	6.31	5.59	3.34	4.38	4.9	4.62	3.54	2.53	3.01	2.87	2.09	2.51	1.69	2	2.05	1.83	17
5292	4.68	6.42	6.35	5.68	5.28	3.18	4	4.58	4.24	3.27	2.26	2.74	2.6	1.95	2.25	1.79	1.92	1.92	1.77	17
5306	4.72	7.16	7.1	6.32	5.77	3.25	4.16	4.77	4.52	3.5	2.51	3.07	2.93	2.05	2.53	1.96	2.15	2.15	1.95	17
5315	4.82	6.8	6.81	6.02	5.55	3.26	4.17	4.61	4.28	3.42	2.41	2.87	2.84	2.03	2.44	1.92	1.99	2.15	1.79	17
5341	4.79	6.83	6.7	5.95	5.65	3.16	4.02	4.59	4.33	3.4	2.35	2.84	2.66	1.87	2.31	1.68	1.79	1.81	1.68	17
5344	4.73	6.62	6.64	5.84	5.33	3.12	3.83	4.45	4.14	3.3	2.13	2.71	2.64	1.96	2.12	1.56	1.61	1.73	1.53	17
5360	4.68	6.75	6.49	5.75	5.28	2.97	3.82	4.33	4.03	3.12	2.19	2.66	2.57	1.69	2.18	1.78	1.93	1.96	1.74	17
5390	4.61	6.54	6.49	5.75	5.31	3.01	3.66	4.23	4.04	3.16	2.12	2.58	2.45	1.76	2.14	1.77	1.94	1.92	1.66	17
5567	4.73	7.09	6.64	6.16	5.55	3.24	4.08	4.68	4.2	3.35	2.35	2.8	2.62	1.85	2.47	1.83	1.99	1.97	1.83	17
5014	4.82	7	6.76	5.97	5.53	3.18	4.03	4.48	4.13	3.35	2.39	2.85	2.72	1.94	2.22	1.68	1.77	1.78	1.61	18
5059	5.01	7.08	6.73	6.06	5.67	3.78	4.35	4.9	4.58	3.62	2.46	3.19	3.04	2.07	2.34	1.86	1.96	2.05	1.83	18
5066	4.44	6.48	6.3	5.67	5.18	2.97	3.79	4.39	4.01	3.21	2.23	2.82	2.57	1.75	2.39	1.88	2.01	2.06	1.78	18
5084	4.58	6.77	6.38	5.69	5.48	3.13	3.92	4.54	4.33	3.4	2.24	2.68	2.72	2.1	2.19	1.75	1.87	1.94	1.81	18
5300	4.97	7.09	6.78	6.15	5.81	3.48	4.24	4.68	4.45	3.55	2.6	3.01	2.95	2.06	2.26	1.8	1.86	1.93	1.66	18
5342	4.64	6.76	6.52	5.81	5.23	3.17	3.85	4.28	3.99	3.21	2.18	2.77	2.51	1.83	2.16	1.69	1.71	1.78	1.67	18
5345	4.62	6.66	6.51	5.65	5.06	3.17	3.86	4.34	4.13	3.34	2.25	2.62	2.58	1.89	2.35	1.81	1.89	1.86	1.8	18
5346	4.62	6.89	6.58	6.08	5.5	3.1	4.1	4.55	4.4	3.38	2.39	2.82	2.73	1.84	2.3	1.93	2.07	2.13	1.81	18
5359	4.86	7.49	6.99	6.11	5.93	3.23	4.15	4.78	4.37	3.42	2.48	3.11	2.82	1.84	2.39	1.79	1.91	1.99	1.8	18
5537	4.73	7.06	6.67	5.98	5.52	3.41	4.34	4.89	4.42	3.56	2.64	3.06	2.84	2.03	2.39	1.89	1.99	1.97	1.86	18

APPENDIX C

NORMALIZED TRAINING DATASET OF INPUT FEATURES AND TARGET FEATURES FOR FEMALE HISPANIC POPULATION USING ANN APPROACH

1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	Age
0.116716	0.145253	0.138737	0.121719	0.140482	0.113974	0.114388	0.113029	0.1	0.120513	0.11326	0.132	0.108333	0.121192	0.1	0.1	0.1	0.158394	0.148855	0.1
0.171642	0.255152	0.239789	0.214027	0.198313	0.173362	0.169065	0.172964	0.175524	0.188889	0.228177	0.164	0.179167	0.269536	0.239759	0.1732824	0.164234	0.216788	0.148855	0.144444
0.121493	0.124242	0.130316	0.125339	0.123133	0.106987	0.1	0.136482	0.141958	0.120513	0.139779	0.144	0.191667	0.184768	0.124096	0.1854962	0.152555	0.193431	0.148855	0.144444
0.166866	0.16303	0.142105	0.210407	0.188675	0.1	0.169065	0.157329	0.141958	0.192308	0.1	0.148	0.1	0.137086	0.153012	0.1122137	0.146715	0.164234	0.136641	0.144444
0.217015	0.242222	0.251579	0.259276	0.229157	0.169869	0.186331	0.201629	0.197902	0.18547	0.263536	0.24	0.266667	0.200662	0.181928	0.240458	0.205109	0.275182	0.228244	0.188889
0.169254	0.251919	0.254947	0.235747	0.238795	0.180349	0.241007	0.25114	0.197902	0.195726	0.276796	0.268	0.25	0.23245	0.201205	0.1916031	0.30438	0.234307	0.185496	0.188889
0.291045	0.334343	0.330737	0.313575	0.304337	0.278166	0.223741	0.25114	0.301399	0.236752	0.329834	0.312	0.316667	0.296026	0.287952	0.1732824	0.275182	0.187591	0.191603	0.233333
0.405672	0.360202	0.359368	0.371493	0.379518	0.260699	0.295683	0.313681	0.304196	0.257265	0.303315	0.28	0.3	0.23245	0.355422	0.2709924	0.240146	0.275182	0.289313	0.233333
0.386567	0.374747	0.364421	0.360633	0.375663	0.323581	0.292806	0.305863	0.368531	0.274359	0.329834	0.328	0.325	0.237748	0.437349	0.3931298	0.415328	0.432847	0.277099	0.233333
0.26	0.384444	0.389684	0.375113	0.366024	0.21179	0.243885	0.264169	0.259441	0.212821	0.356354	0.332	0.316667	0.333113	0.350602	0.1977099	0.245985	0.257664	0.203817	0.233333
0.281493	0.365051	0.376211	0.376923	0.406506	0.274672	0.318705	0.32671	0.318182	0.308547	0.298895	0.344	0.325	0.264238	0.321687	0.1549618	0.205109	0.234307	0.234351	0.233333
0.324478	0.397374	0.406526	0.407692	0.383373	0.299127	0.318705	0.412704	0.41049	0.400855	0.343094	0.356	0.329167	0.444371	0.360241	0.2587786	0.216788	0.391971	0.222137	0.277778
0.329254	0.376364	0.406526	0.387783	0.404578	0.288646	0.310072	0.334528	0.30979	0.277778	0.294475	0.3	0.3	0.216556	0.422892	0.3503817	0.327737	0.374453	0.319847	0.277778

0.374627	0.363434	0.352632	0.322624	0.358313	0.222271	0.246763	0.271987	0.267832	0.236752	0.329834	0.256	0.333333	0.306623	0.316867	0.2770992	0.210949	0.362774	0.234351	0.277778
0.279104	0.365051	0.369474	0.366063	0.36988	0.278166	0.28705	0.303257	0.365734	0.346154	0.382873	0.336	0.279167	0.317219	0.36988	0.4114504	0.415328	0.444526	0.29542	0.277778
0.32209	0.400606	0.399789	0.398643	0.396867	0.299127	0.321583	0.342345	0.427273	0.417949	0.343094	0.356	0.379167	0.407285	0.36988	0.2343511	0.251825	0.281022	0.246565	0.277778
0.386567	0.424848	0.446947	0.451131	0.452771	0.306114	0.356115	0.410098	0.37972	0.342735	0.329834	0.368	0.35	0.301325	0.326506	0.380916	0.374453	0.421168	0.387023	0.322222
0.503582	0.460404	0.492421	0.463801	0.479759	0.435371	0.405036	0.412704	0.416084	0.41453	0.360773	0.36	0.379167	0.444371	0.461446	0.3137405	0.321898	0.356934	0.319847	0.322222
0.360299	0.470101	0.460421	0.452941	0.475904	0.29214	0.361871	0.368404	0.365734	0.315385	0.276796	0.3	0.283333	0.227152	0.254217	0.289313	0.263504	0.316058	0.29542	0.322222
0.470149	0.457172	0.480632	0.478281	0.47012	0.29214	0.32446	0.436156	0.435664	0.421368	0.404972	0.4	0.408333	0.370199	0.30241	0.3320611	0.339416	0.345255	0.29542	0.322222
0.293433	0.37798	0.396421	0.375113	0.366024	0.39345	0.292806	0.300651	0.374126	0.288034	0.404972	0.296	0.2875	0.391391	0.43253	0.3076336	0.275182	0.292701	0.289313	0.322222
0.283881	0.418384	0.433474	0.404072	0.39494	0.194323	0.373381	0.365798	0.348951	0.277778	0.365193	0.3	0.333333	0.317219	0.422892	0.2832061	0.251825	0.292701	0.264885	0.322222
0.427164	0.437778	0.458737	0.434842	0.402651	0.267686	0.393525	0.410098	0.407692	0.366667	0.378453	0.368	0.3625	0.322517	0.408434	0.3320611	0.386131	0.333577	0.270992	0.322222
0.403284	0.392525	0.408211	0.398643	0.398795	0.257205	0.315827	0.334528	0.332168	0.301709	0.307735	0.284	0.320833	0.327815	0.321687	0.2709924	0.339416	0.386131	0.29542	0.322222
0.293433	0.403838	0.421684	0.398643	0.410361	0.264192	0.307194	0.347557	0.41049	0.397436	0.374033	0.356	0.3625	0.327815	0.360241	0.2770992	0.222628	0.356934	0.222137	0.322222
0.534627	0.526667	0.546316	0.51448	0.510602	0.39345	0.468345	0.592508	0.56993	0.530769	0.48895	0.448	0.541667	0.481457	0.490361	0.3259542	0.345255	0.485401	0.240458	0.366667
0.49403	0.478182	0.504211	0.460181	0.472048	0.372489	0.445324	0.467427	0.44965	0.346154	0.404972	0.34	0.329167	0.386093	0.442169	0.3259542	0.432847	0.380292	0.325954	0.366667
0.496418	0.450707	0.460421	0.460181	0.473976	0.379476	0.396403	0.40228	0.416084	0.387179	0.440331	0.356	0.408333	0.407285	0.312048	0.3625954	0.456204	0.485401	0.448092	0.366667
0.515522	0.46202	0.463789	0.452941	0.456627	0.358515	0.38777	0.472638	0.472028	0.428205	0.404972	0.432	0.433333	0.396689	0.485542	0.3442748	0.368613	0.386131	0.344275	0.366667
0.374627	0.471717	0.470526	0.48914	0.491325	0.330568	0.419424	0.506515	0.48042	0.469231	0.440331	0.46	0.445833	0.370199	0.490361	0.3687023	0.368613	0.40365	0.356489	0.366667

0.491642	0.455556	0.463789	0.452941	0.481687	0.355022	0.384892	0.485668	0.494406	0.448718	0.431492	0.444	0.458333	0.396689	0.446988	0.3931298	0.39781	0.415328	0.454198	0.366667
0.601493	0.562222	0.595158	0.561538	0.545301	0.372489	0.433813	0.574267	0.530769	0.469231	0.475691	0.48	0.341667	0.301325	0.350602	0.3503817	0.333577	0.508759	0.332061	0.411111
0.572836	0.605859	0.625474	0.612217	0.593494	0.487773	0.505755	0.506515	0.488811	0.482906	0.577348	0.468	0.5875	0.560927	0.581928	0.4236641	0.40365	0.462044	0.332061	0.411111
0.606269	0.518586	0.521053	0.49819	0.522169	0.571616	0.523022	0.561238	0.575524	0.482906	0.612707	0.552	0.595833	0.598013	0.610843	0.619084	0.450365	0.643066	0.600763	0.411111
0.546567	0.549293	0.553053	0.548869	0.562651	0.484279	0.534532	0.545603	0.533566	0.503419	0.541989	0.528	0.520833	0.529139	0.519277	0.3503817	0.351095	0.368613	0.332061	0.411111
0.51791	0.528283	0.537895	0.50724	0.527952	0.351528	0.517266	0.519544	0.513986	0.380342	0.533149	0.512	0.483333	0.444371	0.533735	0.5519084	0.473723	0.514599	0.338168	0.411111
0.668358	0.647879	0.635579	0.603167	0.574217	0.529694	0.594964	0.576873	0.553147	0.479487	0.546409	0.544	0.5625	0.550331	0.577108	0.5274809	0.514599	0.427007	0.417557	0.455556
0.611045	0.555758	0.574947	0.566968	0.574217	0.449345	0.583453	0.56645	0.586713	0.575214	0.581768	0.596	0.620833	0.545033	0.610843	0.6129771	0.479562	0.654745	0.60687	0.455556
0.556119	0.546061	0.574947	0.543439	0.524096	0.501747	0.523022	0.550814	0.541958	0.503419	0.537569	0.508	0.55	0.513245	0.586747	0.4603053	0.438686	0.60219	0.564122	0.455556
0.603881	0.565455	0.583368	0.557919	0.533735	0.515721	0.546043	0.561238	0.567133	0.520513	0.590608	0.564	0.5625	0.545033	0.572289	0.5152672	0.479562	0.643066	0.441985	0.455556
0.577612	0.568687	0.595158	0.583258	0.597349	0.578603	0.603597	0.579479	0.58951	0.58547	0.608287	0.608	0.591667	0.608609	0.581928	0.4847328	0.456204	0.619708	0.472519	0.455556
0.599104	0.610707	0.645684	0.606787	0.595422	0.501747	0.548921	0.576873	0.572727	0.503419	0.572928	0.588	0.583333	0.518543	0.581928	0.429771	0.432847	0.450365	0.399237	0.455556
0.627761	0.633333	0.649053	0.635747	0.632048	0.536681	0.554676	0.527362	0.558741	0.564957	0.533149	0.528	0.554167	0.629801	0.591566	0.4480916	0.567153	0.613869	0.533588	0.455556
0.649254	0.62202	0.622105	0.585068	0.583855	0.561135	0.609353	0.626384	0.637063	0.626496	0.586188	0.612	0.620833	0.640397	0.586747	0.4480916	0.584672	0.643066	0.478626	0.5
0.706567	0.686667	0.699579	0.677376	0.687952	0.603057	0.643885	0.675896	0.684615	0.626496	0.670166	0.728	0.7125	0.725166	0.63494	0.6312977	0.69562	0.724818	0.661832	0.5
0.651642	0.597778	0.649053	0.650226	0.624337	0.536681	0.571942	0.618567	0.606294	0.599145	0.564088	0.556	0.5625	0.523841	0.644578	0.6618321	0.625547	0.50292	0.631298	0.5
0.56806	0.552525	0.544632	0.49638	0.508675	0.452838	0.494245	0.490879	0.466434	0.452137	0.475691	0.464	0.454167	0.396689	0.475904	0.521374	0.479562	0.485401	0.496947	0.5

0.680299	0.626869	0.682737	0.657466	0.651325	0.421397	0.586331	0.62899	0.667832	0.612821	0.51547	0.608	0.616667	0.613907	0.683133	0.6557252	0.50292	0.584672	0.667939	0.5
0.630149	0.636566	0.691158	0.648416	0.662892	0.58559	0.669784	0.691531	0.676224	0.677778	0.692265	0.676	0.658333	0.640397	0.692771	0.710687	0.648905	0.648905	0.643511	0.544444
0.673134	0.628485	0.649053	0.617647	0.62241	0.58559	0.620863	0.644625	0.642657	0.616239	0.603867	0.608	0.6	0.518543	0.668675	0.5763359	0.409489	0.648905	0.594656	0.544444
0.613433	0.634949	0.655789	0.644796	0.653253	0.547162	0.603597	0.62899	0.634266	0.629915	0.559669	0.532	0.545833	0.624503	0.591566	0.521374	0.321898	0.567153	0.551908	0.544444
0.75194	0.686667	0.681053	0.646606	0.649398	0.693886	0.707194	0.71759	0.720979	0.698291	0.705525	0.744	0.75	0.703974	0.736145	0.6923664	0.666423	0.713139	0.667939	0.544444
0.680299	0.657576	0.672632	0.659276	0.686024	0.620524	0.652518	0.681107	0.69021	0.664103	0.603867	0.644	0.6375	0.603311	0.620482	0.6740458	0.666423	0.678102	0.643511	0.544444
0.64209	0.604242	0.608632	0.594118	0.593494	0.491266	0.577698	0.602932	0.614685	0.602564	0.577348	0.62	0.595833	0.592715	0.615663	0.4541985	0.619708	0.643066	0.496947	0.544444
0.577612	0.562222	0.58	0.556109	0.53759	0.466812	0.488489	0.545603	0.541958	0.489744	0.48011	0.508	0.516667	0.507947	0.586747	0.4419847	0.59635	0.613869	0.435878	0.544444
0.708955	0.659192	0.708	0.671946	0.69759	0.620524	0.678417	0.644625	0.673427	0.629915	0.652486	0.652	0.675	0.619205	0.760241	0.6557252	0.637226	0.713139	0.735115	0.544444
0.694627	0.649495	0.664211	0.617647	0.62241	0.624017	0.695683	0.694137	0.673427	0.684615	0.705525	0.692	0.6375	0.688079	0.731325	0.6496183	0.637226	0.660584	0.619084	0.544444
0.65403	0.628485	0.644	0.619457	0.60506	0.58559	0.61223	0.655049	0.611888	0.582051	0.546409	0.592	0.545833	0.560927	0.639759	0.6129771	0.631387	0.672263	0.637405	0.544444
0.649254	0.67697	0.691158	0.655656	0.655181	0.589083	0.617986	0.657655	0.645455	0.588889	0.572928	0.616	0.633333	0.566225	0.649398	0.6557252	0.613869	0.60219	0.576336	0.544444
0.694627	0.673737	0.652421	0.652036	0.659036	0.617031	0.669784	0.694137	0.698601	0.660684	0.617127	0.644	0.6375	0.582119	0.553012	0.6435115	0.625547	0.69562	0.625191	0.588889
0.708955	0.651111	0.665895	0.623077	0.64747	0.610044	0.678417	0.70456	0.70979	0.684615	0.612707	0.668	0.616667	0.428477	0.692771	0.6923664	0.678102	0.765693	0.643511	0.588889
0.754328	0.691515	0.692842	0.626697	0.682169	0.711354	0.695683	0.691531	0.681818	0.725641	0.634807	0.668	0.695833	0.672185	0.639759	0.6801527	0.608029	0.672263	0.570229	0.588889
0.785373	0.717374	0.765263	0.715385	0.736145	0.721834	0.730216	0.756678	0.734965	0.718803	0.683425	0.7	0.7	0.677483	0.750602	0.7045802	0.69562	0.724818	0.759542	0.588889
0.718507	0.675354	0.692842	0.677376	0.709157	0.631004	0.672662	0.707166	0.712587	0.691453	0.639227	0.68	0.675	0.635099	0.610843	0.6923664	0.654745	0.707299	0.655725	0.588889

0.711343	0.743232	0.755158	0.724434	0.753494	0.739301	0.802158	0.808795	0.807692	0.824786	0.732044	0.792	0.829167	0.772848	0.707229	0.7839695	0.771533	0.748175	0.747328	0.588889
0.771045	0.683434	0.706316	0.695475	0.705301	0.610044	0.661151	0.668078	0.673427	0.67094	0.705525	0.716	0.6875	0.698675	0.736145	0.7229008	0.736496	0.754015	0.698473	0.588889
0.692239	0.652727	0.660842	0.648416	0.643614	0.631004	0.620863	0.636808	0.625874	0.640171	0.625967	0.596	0.5875	0.645695	0.610843	0.6251908	0.643066	0.660584	0.637405	0.588889
0.766269	0.722222	0.729895	0.668326	0.695663	0.683406	0.730216	0.743648	0.762937	0.711966	0.643646	0.692	0.670833	0.598013	0.625301	0.6618321	0.637226	0.736496	0.649618	0.633333
0.744776	0.709293	0.697895	0.657466	0.655181	0.725328	0.738849	0.78013	0.76014	0.735897	0.656906	0.744	0.708333	0.666887	0.615663	0.6496183	0.613869	0.578832	0.643511	0.633333
0.773433	0.764242	0.778737	0.778733	0.770843	0.763755	0.810791	0.816612	0.813287	0.776923	0.785083	0.812	0.795833	0.71457	0.798795	0.7717557	0.789051	0.829927	0.582443	0.633333
0.668358	0.686667	0.738316	0.688235	0.666747	0.679913	0.698561	0.730619	0.737762	0.698291	0.705525	0.724	0.758333	0.672185	0.683133	0.6679389	0.707299	0.771533	0.68626	0.633333
0.72806	0.665657	0.692842	0.604977	0.657108	0.634498	0.684173	0.709772	0.712587	0.691453	0.612707	0.664	0.658333	0.454967	0.731325	0.6801527	0.689781	0.730657	0.643511	0.633333
0.759104	0.723838	0.741684	0.735294	0.724578	0.728821	0.733094	0.730619	0.698601	0.705128	0.679006	0.728	0.704167	0.71457	0.750602	0.759542	0.771533	0.783212	0.759542	0.633333
0.787761	0.720606	0.719789	0.666516	0.695663	0.718341	0.721583	0.720195	0.706993	0.776923	0.687845	0.712	0.725	0.703974	0.740964	0.7229008	0.69562	0.713139	0.625191	0.633333
0.780597	0.756162	0.783789	0.771493	0.738072	0.760262	0.747482	0.764495	0.793706	0.783761	0.709945	0.776	0.808333	0.809934	0.692771	0.7229008	0.713139	0.713139	0.741221	0.633333
0.725672	0.725455	0.728211	0.704525	0.666747	0.683406	0.704317	0.725407	0.718182	0.701709	0.608287	0.664	0.645833	0.576821	0.586747	0.6496183	0.713139	0.660584	0.68626	0.633333
0.754328	0.772323	0.797263	0.749774	0.751566	0.70786	0.779137	0.795765	0.804895	0.759829	0.692265	0.7	0.670833	0.709272	0.644578	0.6801527	0.672263	0.765693	0.649618	0.633333
0.878507	0.9	0.9	0.9	0.9	0.9	0.9	0.881759	0.9	0.886325	0.9	0.876	0.9	0.815232	0.871084	0.7900763	0.824088	0.870803	0.710687	0.633333
0.701791	0.710909	0.729895	0.720814	0.686024	0.69738	0.715827	0.74886	0.743357	0.722222	0.621547	0.684	0.629167	0.629801	0.750602	0.6923664	0.69562	0.70146	0.667939	0.633333
0.763881	0.693131	0.724842	0.680995	0.713012	0.704367	0.689928	0.694137	0.693007	0.681197	0.679006	0.648	0.654167	0.677483	0.745783	0.6923664	0.689781	0.666423	0.729008	0.633333
0.790149	0.735152	0.750105	0.700905	0.734217	0.756769	0.805036	0.821824	0.807692	0.794017	0.798343	0.784	0.791667	0.825828	0.755422	0.7900763	0.80073	0.80073	0.783969	0.677778

0.771045	0.715758	0.706316	0.666516	0.684096	0.714847	0.747482	0.733225	0.734965	0.705128	0.701105	0.692	0.6875	0.640397	0.712048	0.8328244	0.847445	0.806569	0.777863	0.677778
0.72806	0.641414	0.686105	0.626697	0.653253	0.672926	0.689928	0.722801	0.70979	0.722222	0.643646	0.664	0.65	0.439073	0.707229	0.7229008	0.718978	0.765693	0.667939	0.677778
0.790149	0.741616	0.763579	0.702715	0.759277	0.735808	0.770504	0.78013	0.754545	0.732479	0.740884	0.752	0.729167	0.71457	0.726506	0.7778626	0.736496	0.771533	0.722901	0.677778
0.780597	0.773939	0.755158	0.731674	0.722651	0.690393	0.761871	0.782736	0.782517	0.773504	0.665746	0.644	0.679167	0.666887	0.755422	0.7900763	0.742336	0.789051	0.722901	0.677778
0.761493	0.788485	0.800632	0.760633	0.763133	0.746288	0.761871	0.798371	0.807692	0.763248	0.696685	0.732	0.716667	0.688079	0.683133	0.7045802	0.70146	0.759854	0.649618	0.677778
0.778209	0.731919	0.751789	0.713575	0.678313	0.665939	0.695683	0.735831	0.673427	0.64359	0.727624	0.72	0.675	0.693377	0.716867	0.6984733	0.678102	0.69562	0.649618	0.677778
0.735224	0.688283	0.672632	0.633937	0.657108	0.651965	0.735971	0.741042	0.723776	0.67094	0.639227	0.656	0.6375	0.322517	0.625301	0.7045802	0.654745	0.70146	0.667939	0.677778
0.823582	0.759394	0.770316	0.738914	0.732289	0.718341	0.741727	0.74886	0.737762	0.688034	0.709945	0.692	0.720833	0.666887	0.726506	0.7473282	0.730657	0.742336	0.729008	0.677778
0.737612	0.752929	0.748421	0.684615	0.713012	0.742795	0.761871	0.772313	0.757343	0.752991	0.705525	0.736	0.7125	0.698675	0.750602	0.851145	0.818248	0.847445	0.747328	0.677778
0.723284	0.688283	0.699579	0.693665	0.691807	0.721834	0.68705	0.74886	0.712587	0.667521	0.617127	0.66	0.670833	0.582119	0.56747	0.6251908	0.572993	0.625547	0.594656	0.722222
0.771045	0.743232	0.783789	0.796833	0.778554	0.704367	0.72446	0.738436	0.754545	0.763248	0.705525	0.7	0.654167	0.735762	0.687952	0.7290076	0.70146	0.718978	0.735115	0.722222
0.708955	0.701212	0.736632	0.719005	0.709157	0.704367	0.681295	0.694137	0.69021	0.688034	0.656906	0.66	0.666667	0.709272	0.408434	0.7290076	0.748175	0.777372	0.729008	0.722222
0.797313	0.773939	0.797263	0.782353	0.768916	0.784716	0.735971	0.756678	0.788112	0.800855	0.727624	0.8	0.8125	0.76755	0.678313	0.7045802	0.69562	0.713139	0.716794	0.722222
0.766269	0.727071	0.746737	0.704525	0.707229	0.669432	0.753237	0.769707	0.77972	0.742735	0.674586	0.7	0.695833	0.656291	0.707229	0.6740458	0.678102	0.742336	0.680153	0.722222
0.725672	0.675354	0.689474	0.680995	0.662892	0.658952	0.669784	0.681107	0.679021	0.688034	0.590608	0.648	0.708333	0.682781	0.591566	0.6374046	0.555474	0.648905	0.643511	0.722222
0.809254	0.778788	0.790526	0.771493	0.776627	0.767249	0.793525	0.806189	0.782517	0.763248	0.776243	0.796	0.775	0.772848	0.726506	0.8206107	0.829927	0.841606	0.790076	0.722222
0.828358	0.741616	0.780421	0.749774	0.766988	0.746288	0.779137	0.774919	0.76014	0.746154	0.740884	0.752	0.725	0.688079	0.740964	0.7778626	0.736496	0.783212	0.729008	0.722222

0.9	0.819192	0.783789	0.726244	0.774699	0.854585	0.885612	0.9	0.877622	0.831624	0.864641	0.892	0.8875	0.831126	0.63012	0.7473282	0.759854	0.789051	0.674046	0.722222
0.775821	0.775556	0.817474	0.787783	0.80747	0.721834	0.733094	0.741042	0.737762	0.718803	0.683425	0.728	0.7	0.661589	0.779518	0.7412214	0.783212	0.765693	0.759542	0.722222
0.689851	0.712525	0.743368	0.742534	0.751566	0.69738	0.744604	0.738436	0.712587	0.711966	0.723204	0.716	0.7125	0.661589	0.70241	0.7045802	0.759854	0.713139	0.729008	0.722222
0.816418	0.819192	0.830947	0.811312	0.83253	0.819651	0.82518	0.845277	0.84965	0.783761	0.776243	0.784	0.725	0.672185	0.813253	0.8206107	0.835766	0.894161	0.814504	0.722222
0.866567	0.78202	0.839368	0.787783	0.780482	0.770742	0.770504	0.787948	0.785315	0.770085	0.771823	0.736	0.745833	0.815232	0.731325	0.8755725	0.80073	0.829927	0.80229	0.766667
0.842687	0.785253	0.836	0.809502	0.813253	0.739301	0.802158	0.832248	0.793706	0.794017	0.727624	0.74	0.720833	0.762252	0.716867	0.7839695	0.742336	0.789051	0.765649	0.766667
0.756716	0.730303	0.738316	0.708145	0.757349	0.676419	0.721583	0.751466	0.751748	0.735897	0.665746	0.708	0.704167	0.666887	0.615663	0.759542	0.69562	0.736496	0.68626	0.766667
0.794925	0.777172	0.790526	0.796833	0.788193	0.704367	0.730216	0.746254	0.762937	0.776923	0.679006	0.7	0.666667	0.725166	0.673494	0.7656489	0.748175	0.754015	0.741221	0.766667
0.742388	0.683434	0.633895	0.576018	0.603133	0.672926	0.669784	0.688925	0.653846	0.602564	0.643646	0.628	0.566667	0.407285	0.581928	0.6801527	0.625547	0.683942	0.655725	0.766667
0.852239	0.790101	0.812421	0.795023	0.80747	0.763755	0.810791	0.821824	0.818881	0.787179	0.789503	0.804	0.7875	0.672185	0.707229	0.8267176	0.80073	0.853285	0.759542	0.766667
0.704179	0.693131	0.694526	0.690045	0.69759	0.760262	0.698561	0.751466	0.757343	0.75641	0.674586	0.704	0.708333	0.703974	0.683133	0.7534351	0.742336	0.754015	0.741221	0.766667
0.673134	0.668889	0.684421	0.655656	0.666747	0.711354	0.715827	0.730619	0.712587	0.67094	0.683425	0.708	0.675	0.635099	0.721687	0.7534351	0.689781	0.683942	0.716794	0.811111
0.892836	0.846667	0.871368	0.831222	0.840241	0.819651	0.836691	0.840065	0.821678	0.790598	0.780663	0.784	0.758333	0.666887	0.808434	0.8267176	0.829927	0.806569	0.790076	0.811111
0.787761	0.733535	0.753474	0.737104	0.732289	0.700873	0.770504	0.754072	0.748951	0.722222	0.732044	0.72	0.679167	0.624503	0.731325	0.7351145	0.765693	0.777372	0.667939	0.811111
0.797313	0.791717	0.827579	0.816742	0.83253	0.774236	0.782014	0.785342	0.802098	0.776923	0.661326	0.72	0.716667	0.703974	0.726506	0.7900763	0.806569	0.841606	0.747328	0.811111
0.854627	0.791717	0.841053	0.807692	0.826747	0.739301	0.819424	0.845277	0.796503	0.787179	0.727624	0.764	0.729167	0.788742	0.736145	0.7900763	0.724818	0.824088	0.771756	0.811111
0.725672	0.731919	0.768632	0.738914	0.741928	0.624017	0.692806	0.725407	0.729371	0.674359	0.603867	0.604	0.6125	0.492053	0.649398	0.6679389	0.689781	0.736496	0.722901	0.811111

0.766269	0.714141	0.765263	0.720814	0.741928	0.711354	0.733094	0.782736	0.757343	0.698291	0.670166	0.672	0.6875	0.582119	0.721687	0.8145038	0.765693	0.771533	0.796183	0.811111
0.785373	0.741616	0.734947	0.719005	0.699518	0.721834	0.756115	0.754072	0.746154	0.722222	0.705525	0.704	0.704167	0.661589	0.707229	0.8389313	0.829927	0.829927	0.832824	0.811111
0.82597	0.769091	0.790526	0.773303	0.772771	0.760262	0.793525	0.814007	0.802098	0.759829	0.789503	0.808	0.791667	0.76755	0.731325	0.8755725	0.835766	0.864964	0.771756	0.811111
0.744776	0.662424	0.686105	0.626697	0.687952	0.693886	0.721583	0.756678	0.723776	0.752991	0.648066	0.648	0.670833	0.756954	0.654217	0.6801527	0.718978	0.765693	0.759542	0.855556
0.716119	0.752929	0.804	0.766063	0.757349	0.6869	0.735971	0.74886	0.768531	0.739316	0.679006	0.704	0.729167	0.672185	0.625301	0.7229008	0.683942	0.742336	0.692366	0.855556
0.778209	0.738384	0.758526	0.737104	0.722651	0.714847	0.735971	0.722801	0.723776	0.701709	0.732044	0.708	0.7375	0.698675	0.644578	0.7045802	0.678102	0.69562	0.692366	0.855556
0.773433	0.762626	0.778737	0.793213	0.801687	0.791703	0.770504	0.78013	0.790909	0.759829	0.789503	0.78	0.783333	0.809934	0.827711	0.7656489	0.818248	0.876642	0.783969	0.855556
0.742388	0.714141	0.699579	0.652036	0.643614	0.662445	0.664029	0.709772	0.665035	0.636752	0.581768	0.644	0.616667	0.523841	0.63494	0.7045802	0.69562	0.713139	0.68626	0.855556
0.873731	0.817576	0.851158	0.769683	0.788193	0.861572	0.856835	0.881759	0.84965	0.862393	0.767403	0.852	0.829167	0.87351	0.9	0.851145	0.847445	0.888321	0.838931	0.855556
0.725672	0.694747	0.728211	0.702715	0.686024	0.690393	0.756115	0.733225	0.734965	0.698291	0.679006	0.72	0.75	0.698675	0.687952	0.7167939	0.637226	0.707299	0.680153	0.9
0.718507	0.710909	0.718105	0.688235	0.659036	0.599563	0.664029	0.712378	0.693007	0.602564	0.625967	0.656	0.641667	0.545033	0.659036	0.6435115	0.631387	0.660584	0.631298	0.9
0.744776	0.746465	0.758526	0.742534	0.734217	0.714847	0.735971	0.738436	0.720979	0.711966	0.714365	0.764	0.7	0.703974	0.789157	0.7839695	0.794891	0.777372	0.771756	0.9
0.799701	0.720606	0.721474	0.664706	0.709157	0.739301	0.735971	0.733225	0.729371	0.770085	0.679006	0.708	0.725	0.71457	0.606024	0.7412214	0.69562	0.730657	0.625191	0.9

APPENDIX D

NORMALIZED TEST DATASET OF INPUT FEATURES AND TARGET FEATURES FOR FEMALE HISPANIC POPULATION USING ANN APPROACH

1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	Age
0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.111189	0.1	0.130939	0.1	0.108333	0.115894	0.124096	0.1793893	0.146715	0.158394	0.148855	0.144444
0.16209	0.224444	0.214526	0.212217	0.211807	0.141921	0.206475	0.180782	0.203497	0.219658	0.126519	0.12	0.166667	0.12649	0.220482	0.148855	0.135036	0.19927	0.1	0.144444
0.228955	0.30202	0.302105	0.291855	0.312048	0.222271	0.252518	0.256352	0.315385	0.226496	0.325414	0.292	0.295833	0.253642	0.312048	0.3442748	0.345255	0.345255	0.240458	0.188889
0.169254	0.242222	0.224632	0.232127	0.225301	0.145415	0.148921	0.167752	0.161538	0.141026	0.192818	0.116	0.15	0.1	0.148193	0.1977099	0.164234	0.19927	0.148855	0.188889
0.140597	0.227677	0.231368	0.188688	0.194458	0.131441	0.192086	0.20684	0.209091	0.120513	0.148619	0.148	0.191667	0.12649	0.215663	0.1427481	0.111679	0.1	0.142748	0.188889
0.453433	0.442626	0.484	0.465611	0.46241	0.344541	0.410791	0.457003	0.460839	0.407692	0.325414	0.376	0.466667	0.460265	0.5	0.3259542	0.30438	0.327737	0.338168	0.322222
0.367463	0.453939	0.475579	0.454751	0.44506	0.337555	0.410791	0.417915	0.432867	0.335897	0.466851	0.448	0.433333	0.391391	0.451807	0.4480916	0.40365	0.444526	0.319847	0.366667
0.477313	0.458788	0.441895	0.451131	0.472048	0.29214	0.402158	0.428339	0.43007	0.346154	0.400552	0.38	0.375	0.391391	0.413253	0.3564886	0.327737	0.485401	0.350382	0.366667
0.477313	0.415152	0.408211	0.409502	0.414217	0.41441	0.428058	0.438762	0.44965	0.421368	0.334254	0.348	0.366667	0.444371	0.446988	0.3503817	0.368613	0.386131	0.362595	0.366667
0.477313	0.471717	0.477263	0.456561	0.473976	0.41441	0.459712	0.483062	0.483217	0.397436	0.400552	0.416	0.475	0.465563	0.524096	0.380916	0.391971	0.467883	0.356489	0.366667
0.599104	0.53798	0.548	0.547059	0.543373	0.389956	0.520144	0.548208	0.525175	0.493162	0.546409	0.504	0.483333	0.481457	0.533735	0.3625954	0.351095	0.351095	0.454198	0.411111
0.458209	0.552525	0.569895	0.49276	0.551084	0.491266	0.5	0.516938	0.435664	0.404274	0.50221	0.496	0.475	0.465563	0.514458	0.3992366	0.520438	0.543796	0.50916	0.411111
0.572836	0.560606	0.559789	0.541629	0.547229	0.49476	0.540288	0.501303	0.527972	0.404274	0.546409	0.56	0.504167	0.481457	0.572289	0.4969466	0.520438	0.543796	0.374809	0.411111

0.486866	0.492727	0.507579	0.49457	0.493253	0.466812	0.407914	0.467427	0.477622	0.394017	0.471271	0.476	0.466667	0.534437	0.509639	0.4236641	0.456204	0.49708	0.332061	0.411111
0.596716	0.544444	0.564842	0.532579	0.520241	0.466812	0.485612	0.493485	0.486014	0.476068	0.387293	0.48	0.491667	0.433775	0.519277	0.429771	0.49708	0.520438	0.515267	0.411111
0.441493	0.525051	0.514316	0.50181	0.520241	0.466812	0.53741	0.519544	0.530769	0.530769	0.546409	0.52	0.504167	0.497351	0.519277	0.3748092	0.491241	0.537956	0.521374	0.455556
0.558507	0.486263	0.514316	0.5	0.522169	0.484279	0.46259	0.480456	0.474825	0.465812	0.458011	0.432	0.429167	0.454967	0.533735	0.5274809	0.49708	0.520438	0.545802	0.455556
0.58	0.586465	0.638947	0.612217	0.626265	0.459825	0.635252	0.655049	0.637063	0.626496	0.625967	0.636	0.608333	0.608609	0.615663	0.6496183	0.637226	0.637226	0.619084	0.5
0.711343	0.714141	0.726526	0.668326	0.67253	0.655459	0.698561	0.738436	0.706993	0.660684	0.639227	0.664	0.670833	0.656291	0.557831	0.5885496	0.584672	0.467883	0.576336	0.5
0.64209	0.591313	0.642316	0.592308	0.616627	0.547162	0.566187	0.600326	0.575524	0.510256	0.559669	0.58	0.566667	0.486755	0.610843	0.710687	0.672263	0.707299	0.661832	0.5
0.699403	0.701212	0.706316	0.670136	0.691807	0.644978	0.684173	0.686319	0.695804	0.609402	0.643646	0.66	0.645833	0.682781	0.668675	0.7045802	0.683942	0.660584	0.625191	0.5
0.563284	0.539596	0.58	0.592308	0.612771	0.49476	0.531655	0.55342	0.561538	0.541026	0.537569	0.552	0.554167	0.507947	0.56747	0.5458015	0.514599	0.561314	0.503053	0.5
0.663582	0.613939	0.647368	0.619457	0.639759	0.582096	0.546043	0.576873	0.553147	0.544444	0.577348	0.58	0.570833	0.539735	0.610843	0.6068702	0.59635	0.60219	0.594656	0.544444
0.747164	0.673737	0.694526	0.673756	0.670602	0.644978	0.655396	0.688925	0.706993	0.667521	0.652486	0.684	0.725	0.735762	0.70241	0.759542	0.689781	0.736496	0.70458	0.544444
0.64209	0.596162	0.595158	0.585068	0.587711	0.543668	0.609353	0.62899	0.623077	0.605983	0.625967	0.628	0.6375	0.613907	0.586747	0.6007634	0.59635	0.643066	0.558015	0.544444
0.627761	0.573535	0.595158	0.566968	0.562651	0.543668	0.646763	0.639414	0.645455	0.571795	0.634807	0.644	0.6375	0.645695	0.644578	0.619084	0.60219	0.660584	0.551908	0.588889
0.723284	0.69798	0.709684	0.661086	0.676386	0.669432	0.710072	0.743648	0.743357	0.681197	0.612707	0.656	0.6625	0.566225	0.721687	0.6251908	0.625547	0.718978	0.68626	0.588889
0.821194	0.727071	0.756842	0.749774	0.755422	0.770742	0.799281	0.772313	0.771329	0.75641	0.758564	0.764	0.816667	0.719868	0.692771	0.6496183	0.683942	0.666423	0.674046	0.588889
0.775821	0.725455	0.731579	0.657466	0.680241	0.672926	0.698561	0.720195	0.732168	0.739316	0.634807	0.644	0.675	0.619205	0.581928	0.6862595	0.660584	0.777372	0.637405	0.588889
0.716119	0.69798	0.708	0.688235	0.724578	0.651965	0.68705	0.722801	0.720979	0.708547	0.661326	0.684	0.670833	0.645695	0.63494	0.7045802	0.672263	0.70146	0.68626	0.588889

0.694627	0.709293	0.718105	0.728054	0.720723	0.60655	0.658273	0.678502	0.701399	0.691453	0.630387	0.628	0.629167	0.661589	0.668675	0.6496183	0.654745	0.648905	0.637405	0.588889
0.744776	0.693131	0.708	0.680995	0.680241	0.728821	0.733094	0.741042	0.734965	0.711966	0.701105	0.732	0.7	0.74106	0.659036	0.6068702	0.625547	0.648905	0.661832	0.588889
0.799701	0.804646	0.792211	0.804072	0.797831	0.777729	0.764748	0.769707	0.793706	0.763248	0.683425	0.696	0.7125	0.677483	0.731325	0.7534351	0.771533	0.812409	0.735115	0.633333
0.675522	0.64303	0.638947	0.566968	0.574217	0.60655	0.620863	0.688925	0.667832	0.64359	0.603867	0.648	0.625	0.497351	0.644578	0.6740458	0.631387	0.654745	0.655725	0.633333
0.694627	0.722222	0.743368	0.691855	0.670602	0.704367	0.747482	0.767101	0.746154	0.722222	0.785083	0.744	0.733333	0.725166	0.639759	0.7045802	0.707299	0.718978	0.674046	0.677778
0.766269	0.704444	0.696211	0.677376	0.628193	0.655459	0.698561	0.688925	0.69021	0.647009	0.679006	0.648	0.65	0.560927	0.731325	0.7839695	0.754015	0.771533	0.783969	0.677778
0.720896	0.689899	0.713053	0.686425	0.693735	0.704367	0.68705	0.741042	0.701399	0.664103	0.590608	0.656	0.645833	0.582119	0.572289	0.619084	0.59635	0.60219	0.600763	0.677778
0.771045	0.769091	0.778737	0.746154	0.724578	0.774236	0.761871	0.78013	0.790909	0.790598	0.714365	0.776	0.808333	0.778146	0.654217	0.7045802	0.713139	0.718978	0.692366	0.677778
0.749552	0.772323	0.793895	0.787783	0.770843	0.732314	0.758993	0.751466	0.765734	0.72906	0.736464	0.72	0.725	0.688079	0.726506	0.7717557	0.724818	0.759854	0.722901	0.677778
0.892836	0.809495	0.802316	0.760633	0.793976	0.774236	0.796403	0.777524	0.771329	0.787179	0.771823	0.78	0.795833	0.725166	0.779518	0.8206107	0.789051	0.80073	0.832824	0.722222
0.861791	0.78202	0.778737	0.733484	0.766988	0.833624	0.848201	0.847883	0.824476	0.811111	0.780663	0.744	0.745833	0.730464	0.740964	0.8083969	0.765693	0.794891	0.722901	0.722222
0.730448	0.673737	0.679368	0.641176	0.655181	0.651965	0.689928	0.730619	0.726573	0.718803	0.643646	0.672	0.6625	0.460265	0.716867	0.710687	0.718978	0.771533	0.661832	0.766667
0.9	0.819192	0.825895	0.785973	0.805542	0.78821	0.819424	0.785342	0.774126	0.800855	0.709945	0.752	0.779167	0.719868	0.76506	0.8206107	0.812409	0.794891	0.838931	0.766667
0.771045	0.798182	0.815789	0.766063	0.76506	0.714847	0.770504	0.814007	0.816084	0.790598	0.727624	0.704	0.7125	0.682781	0.716867	0.710687	0.70146	0.748175	0.661832	0.766667
0.809254	0.790101	0.834316	0.789593	0.780482	0.70786	0.82518	0.866124	0.841259	0.817949	0.736464	0.816	0.8	0.709272	0.56747	0.6068702	0.771533	0.824088	0.60687	0.811111
0.718507	0.709293	0.726526	0.709955	0.726506	0.679913	0.71295	0.722801	0.701399	0.667521	0.705525	0.664	0.704167	0.71457	0.70241	0.7534351	0.754015	0.748175	0.741221	0.855556
0.787761	0.762626	0.748421	0.738914	0.753494	0.795197	0.784892	0.79316	0.765734	0.790598	0.727624	0.772	0.758333	0.783444	0.673494	0.759542	0.748175	0.777372	0.747328	0.855556

0.685075	0.66404	0.691158	0.652036	0.664819	0.683406	0.698561	0.730619	0.718182	0.694872	0.701105	0.688	0.679167	0.629801	0.716867	0.759542	0.70146	0.678102	0.735115	0.855556
0.754328	0.775556	0.785474	0.775113	0.728434	0.69738	0.72446	0.769707	0.762937	0.718803	0.648066	0.696	0.704167	0.629801	0.76506	0.7412214	0.754015	0.754015	0.722901	0.855556
0.790149	0.769091	0.809053	0.798643	0.776627	0.704367	0.761871	0.808795	0.799301	0.790598	0.771823	0.748	0.775	0.815232	0.846988	0.8816794	0.829927	0.882482	0.796183	0.9
0.864179	0.835354	0.836	0.796833	0.826747	0.861572	0.876978	0.892182	0.863636	0.9	0.89558	0.9	0.870833	0.9	0.880723	0.9	0.9	0.9	0.9	0.9
0.744776	0.693131	0.733263	0.726244	0.711084	0.742795	0.715827	0.741042	0.726573	0.718803	0.692265	0.724	0.716667	0.730464	0.822892	0.7900763	0.806569	0.853285	0.753435	0.9
0.885672	0.801414	0.829263	0.795023	0.786265	0.868559	0.845324	0.881759	0.863636	0.848718	0.789503	0.872	0.8375	0.862914	0.895181	0.8633588	0.847445	0.859124	0.869466	0.9
0.756716	0.743232	0.760211	0.733484	0.766988	0.69738	0.730216	0.761889	0.765734	0.725641	0.648066	0.72	0.6875	0.703974	0.639759	0.759542	0.707299	0.748175	0.710687	0.9
0.682687	0.67697	0.699579	0.666516	0.674458	0.679913	0.715827	0.735831	0.720979	0.694872	0.701105	0.712	0.683333	0.619205	0.707229	0.7473282	0.678102	0.689781	0.70458	0.9

APPENDIX E

NORMALIZED TRAINING DATASET OF INPUT FEATURES AND TARGET FEATURES FOR MALE HISPANIC POPULATION USING ANN APPROACH

1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	Age
0.124299	0.124516	0.123491	0.118944	0.126154	0.128387	0.131549	0.124365	0.136856	0.12392	0.137559	0.146693	0.156667	0.12623	0.1415094	0.137427	0.150286	0.127586	0.110063	0.1
0.172897	0.194194	0.187439	0.196175	0.18	0.185161	0.199155	0.195431	0.204065	0.18505	0.205164	0.205837	0.21	0.200546	0.2169811	0.202924	0.191429	0.224138	0.190566	0.1
0.193458	0.216129	0.2031	0.19326	0.198462	0.187742	0.223944	0.221827	0.240921	0.224917	0.205164	0.208949	0.216667	0.200546	0.190566	0.15614	0.173143	0.145977	0.120126	0.1
0.320561	0.369677	0.351876	0.346266	0.36	0.314194	0.368169	0.400508	0.407859	0.408306	0.385446	0.39572	0.41	0.384153	0.3188679	0.277778	0.305714	0.302299	0.276101	0.144444
0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.144444
0.23271	0.278065	0.247471	0.253005	0.243077	0.234194	0.291549	0.288832	0.271274	0.264784	0.238967	0.240078	0.25	0.26612	0.3264151	0.235673	0.237143	0.242529	0.230818	0.144444
0.223364	0.262581	0.244861	0.236976	0.238462	0.229032	0.302817	0.292893	0.310298	0.29402	0.269014	0.283658	0.273333	0.18306	0.3301887	0.240351	0.26	0.270115	0.200629	0.144444
0.230841	0.248387	0.244861	0.254463	0.24	0.254839	0.284789	0.268528	0.282114	0.280731	0.257746	0.261868	0.28	0.257377	0.2698113	0.259064	0.250857	0.26092	0.195597	0.144444
0.281308	0.323226	0.314029	0.309836	0.306154	0.270323	0.347887	0.349746	0.357995	0.339203	0.31784	0.317899	0.33	0.287978	0.3792453	0.291813	0.356	0.33908	0.281132	0.188889
0.324299	0.358065	0.357096	0.343352	0.352308	0.288387	0.370423	0.36599	0.384011	0.363123	0.374178	0.370817	0.39	0.331694	0.3490566	0.282456	0.333143	0.33908	0.261006	0.188889
0.3	0.33871	0.308809	0.306922	0.303077	0.290968	0.354648	0.337563	0.353659	0.328571	0.31784	0.317899	0.336667	0.253005	0.3830189	0.287135	0.342286	0.343678	0.276101	0.188889
0.350467	0.368387	0.347961	0.357923	0.343077	0.309032	0.354648	0.359898	0.375339	0.339203	0.374178	0.349027	0.363333	0.305464	0.3679245	0.361988	0.273714	0.343678	0.255975	0.233333
0.316822	0.385161	0.380587	0.373953	0.364615	0.306452	0.417746	0.428934	0.453388	0.413621	0.377934	0.426848	0.43	0.384153	0.3943396	0.324561	0.282857	0.32069	0.276101	0.233333

0.118692	0.146452	0.144372	0.139344	0.14	0.13871	0.142817	0.132487	0.141192	0.126578	0.130047	0.14358	0.146667	0.134973	0.1603774	0.132749	0.141143	0.141379	0.120126	0.233333
0.371028	0.416129	0.421044	0.413297	0.401538	0.350323	0.444789	0.441117	0.440379	0.413621	0.426761	0.41751	0.43	0.406011	0.4433962	0.404094	0.392571	0.385057	0.396855	0.277778
0.329907	0.398065	0.388418	0.395811	0.376923	0.332258	0.431268	0.443147	0.455556	0.418937	0.456808	0.470428	0.47	0.397268	0.4358491	0.446199	0.424571	0.458621	0.416981	0.277778
0.356075	0.414839	0.398858	0.400182	0.396923	0.337419	0.410986	0.404569	0.412195	0.392359	0.404225	0.364591	0.363333	0.327322	0.454717	0.436842	0.438286	0.435632	0.422013	0.277778
0.460748	0.474194	0.457586	0.45847	0.436923	0.396774	0.512394	0.510152	0.531436	0.482724	0.535681	0.542023	0.543333	0.493443	0.5415094	0.511696	0.488571	0.509195	0.467296	0.322222
0.481308	0.481935	0.482382	0.46867	0.469231	0.396774	0.501127	0.481726	0.485908	0.456146	0.494366	0.495331	0.513333	0.502186	0.5037736	0.44152	0.470286	0.486207	0.432075	0.322222
0.427103	0.49871	0.483687	0.508015	0.496923	0.456129	0.546197	0.522335	0.531436	0.51196	0.535681	0.532685	0.546667	0.56776	0.4811321	0.427485	0.438286	0.463218	0.406918	0.322222
0.408411	0.429032	0.409299	0.391439	0.404615	0.38129	0.401972	0.422843	0.427371	0.387043	0.370423	0.408171	0.423333	0.384153	0.4283019	0.376023	0.383429	0.412644	0.371698	0.322222
0.382243	0.462581	0.441925	0.430783	0.418462	0.352903	0.46507	0.449239	0.466396	0.413621	0.407981	0.414397	0.423333	0.309836	0.4433962	0.380702	0.424571	0.431034	0.391824	0.322222
0.434579	0.546452	0.526754	0.525501	0.509231	0.492258	0.530423	0.520305	0.533604	0.506645	0.535681	0.532685	0.576667	0.537158	0.5641509	0.511696	0.511429	0.532184	0.512579	0.366667
0.556075	0.546452	0.533279	0.525501	0.530769	0.476774	0.559718	0.550761	0.570461	0.549169	0.535681	0.526459	0.54	0.515301	0.5679245	0.530409	0.534286	0.541379	0.477358	0.366667
0.5	0.515484	0.534584	0.519672	0.504615	0.407097	0.548451	0.54264	0.550949	0.498671	0.546948	0.542023	0.553333	0.54153	0.5679245	0.530409	0.538857	0.527586	0.502516	0.366667
0.458879	0.502581	0.512398	0.506557	0.483077	0.404516	0.50338	0.5	0.535772	0.482724	0.486854	0.482879	0.516667	0.480328	0.4773585	0.44152	0.447429	0.435632	0.477358	0.366667
0.483178	0.490968	0.492822	0.484699	0.469231	0.448387	0.50338	0.481726	0.490244	0.453488	0.464319	0.445525	0.456667	0.423497	0.4886792	0.436842	0.474857	0.5	0.452201	0.366667
0.423364	0.426452	0.436705	0.429326	0.412308	0.370968	0.462817	0.463452	0.453388	0.421595	0.456808	0.429961	0.44	0.388525	0.4283019	0.394737	0.410857	0.435632	0.422013	0.366667
0.492523	0.528387	0.522838	0.521129	0.518462	0.45871	0.510141	0.512183	0.511924	0.525249	0.505634	0.495331	0.506667	0.462842	0.5679245	0.488304	0.465714	0.504598	0.477358	0.366667
0.556075	0.583871	0.580261	0.572131	0.570769	0.523226	0.568732	0.567005	0.570461	0.543854	0.614554	0.601167	0.58	0.528415	0.5716981	0.516374	0.538857	0.545977	0.467296	0.411111

0.471963	0.493548	0.484992	0.480328	0.464615	0.443226	0.50338	0.487817	0.498916	0.461462	0.543192	0.529572	0.516667	0.440984	0.5188679	0.432164	0.442857	0.477011	0.41195	0.411111
0.503738	0.519355	0.512398	0.491985	0.490769	0.481935	0.523662	0.495939	0.492412	0.493355	0.561972	0.5607	0.54	0.510929	0.5490566	0.492982	0.493143	0.536782	0.512579	0.411111
0.535514	0.559355	0.54633	0.545902	0.524615	0.525806	0.548451	0.530457	0.540108	0.517276	0.580751	0.566926	0.566667	0.572131	0.5679245	0.567836	0.538857	0.555172	0.527673	0.411111
0.537383	0.516774	0.500653	0.496357	0.486154	0.494839	0.483099	0.481726	0.50542	0.477409	0.513146	0.495331	0.523333	0.524044	0.545283	0.507018	0.493143	0.509195	0.492453	0.411111
0.578505	0.561935	0.571126	0.586703	0.553846	0.479355	0.521408	0.540609	0.557453	0.514618	0.516901	0.510895	0.543333	0.489071	0.5830189	0.544444	0.557143	0.591954	0.55283	0.411111
0.507477	0.529677	0.512398	0.512386	0.504615	0.445806	0.492113	0.479695	0.503252	0.458804	0.498122	0.473541	0.463333	0.43224	0.5264151	0.460234	0.484	0.495402	0.427044	0.455556
0.514953	0.543871	0.55155	0.573588	0.573846	0.471613	0.525915	0.514213	0.535772	0.509302	0.50939	0.485992	0.486667	0.410383	0.5641509	0.544444	0.520571	0.550575	0.532704	0.455556
0.584112	0.551613	0.56199	0.570674	0.553846	0.481935	0.586761	0.577157	0.609485	0.557143	0.546948	0.585603	0.586667	0.532787	0.5981132	0.516374	0.534286	0.550575	0.532704	0.455556
0.526168	0.516774	0.534584	0.532787	0.538462	0.450968	0.557465	0.54264	0.574797	0.549169	0.55446	0.538911	0.55	0.532787	0.5415094	0.525731	0.511429	0.518391	0.497484	0.455556
0.514953	0.502581	0.515008	0.513843	0.5	0.487097	0.532676	0.524365	0.53794	0.509302	0.535681	0.576265	0.573333	0.524044	0.5528302	0.516374	0.516	0.527586	0.502516	0.455556
0.576636	0.58129	0.595922	0.57796	0.555385	0.520645	0.552958	0.550761	0.561789	0.519934	0.561972	0.526459	0.5	0.440984	0.5679245	0.553801	0.584571	0.578161	0.532704	0.455556
0.571028	0.565806	0.576346	0.569217	0.543077	0.494839	0.557465	0.550761	0.566125	0.522591	0.588263	0.545136	0.536667	0.56776	0.5943396	0.549123	0.525143	0.545977	0.512579	0.5
0.701869	0.687097	0.663785	0.669763	0.68	0.616129	0.672394	0.674619	0.676694	0.631561	0.667136	0.672763	0.66	0.56776	0.6584906	0.638012	0.676	0.66092	0.567925	0.5
0.548598	0.521935	0.517618	0.502186	0.513846	0.456129	0.521408	0.530457	0.529268	0.485382	0.483099	0.495331	0.493333	0.384153	0.545283	0.502339	0.511429	0.532184	0.502516	0.5
0.600935	0.589032	0.622023	0.602732	0.570769	0.530968	0.627324	0.601523	0.644173	0.591694	0.603286	0.62607	0.696667	0.628962	0.6018868	0.567836	0.625714	0.647126	0.598113	0.5
0.54486	0.561935	0.56199	0.537158	0.523077	0.510323	0.570986	0.567005	0.561789	0.527907	0.513146	0.548249	0.526667	0.45847	0.5867925	0.502339	0.529714	0.509195	0.497484	0.5
0.61215	0.617419	0.598532	0.586703	0.603077	0.58	0.629577	0.611675	0.615989	0.594352	0.670892	0.60428	0.61	0.550273	0.7113208	0.656725	0.666857	0.683908	0.663522	0.5

0.561682	0.568387	0.593312	0.576503	0.556923	0.533548	0.566479	0.575127	0.579133	0.570432	0.573239	0.573152	0.586667	0.589617	0.6169811	0.567836	0.584571	0.591954	0.562893	0.5
0.636449	0.625161	0.616803	0.61439	0.598462	0.494839	0.620563	0.627919	0.646341	0.607641	0.588263	0.613619	0.643333	0.598361	0.6358491	0.58655	0.621143	0.628736	0.603145	0.544444
0.628972	0.629032	0.635073	0.621676	0.595385	0.533548	0.62507	0.611675	0.613821	0.57309	0.610798	0.622957	0.623333	0.545902	0.5867925	0.507018	0.548	0.582759	0.406918	0.544444
0.705607	0.630323	0.619413	0.596903	0.590769	0.592903	0.636338	0.615736	0.639837	0.626246	0.633333	0.619844	0.636667	0.642077	0.6132075	0.577193	0.584571	0.578161	0.593082	0.544444
0.578505	0.551613	0.55677	0.56776	0.515385	0.497419	0.58	0.575127	0.585637	0.501329	0.565728	0.5607	0.583333	0.506557	0.5981132	0.577193	0.616571	0.633333	0.567925	0.544444
0.524299	0.555484	0.54894	0.545902	0.523077	0.476774	0.568732	0.581218	0.583469	0.543854	0.501878	0.529572	0.526667	0.454098	0.5943396	0.507018	0.538857	0.550575	0.502516	0.544444
0.591589	0.592903	0.568515	0.557559	0.553846	0.528387	0.58	0.579188	0.576965	0.53588	0.55446	0.570039	0.576667	0.54153	0.590566	0.549123	0.529714	0.591954	0.522642	0.544444
0.63271	0.57871	0.560685	0.548816	0.567692	0.600645	0.595775	0.556853	0.576965	0.543854	0.633333	0.598054	0.616667	0.537158	0.5716981	0.58655	0.593714	0.633333	0.613208	0.544444
0.602804	0.654839	0.66248	0.653734	0.635385	0.569677	0.622817	0.652284	0.67019	0.602326	0.667136	0.66965	0.676667	0.642077	0.6735849	0.666082	0.666857	0.670115	0.633333	0.544444
0.597196	0.62129	0.620718	0.611475	0.610769	0.577419	0.573239	0.595431	0.607317	0.602326	0.580751	0.601167	0.616667	0.633333	0.6169811	0.591228	0.602857	0.637931	0.648428	0.544444
0.606542	0.573548	0.572431	0.56776	0.549231	0.523226	0.566479	0.567005	0.563957	0.509302	0.584507	0.594942	0.58	0.528415	0.6358491	0.600585	0.625714	0.656322	0.593082	0.588889
0.608411	0.625161	0.636378	0.62459	0.624615	0.585161	0.634085	0.640102	0.655014	0.623588	0.637089	0.660311	0.68	0.642077	0.7037736	0.689474	0.644	0.66092	0.683648	0.588889
0.696262	0.674194	0.66248	0.662477	0.636923	0.647097	0.721972	0.713198	0.71355	0.655482	0.644601	0.650973	0.633333	0.510929	0.6773585	0.605263	0.680571	0.670115	0.577987	0.588889
0.664486	0.641935	0.637684	0.630419	0.615385	0.549032	0.62507	0.603553	0.628997	0.634219	0.652113	0.657198	0.653333	0.668306	0.6660377	0.64269	0.653143	0.647126	0.598113	0.588889
0.800935	0.782581	0.769494	0.767395	0.770769	0.724516	0.780563	0.778173	0.793767	0.740532	0.764789	0.766148	0.783333	0.642077	0.7603774	0.736257	0.785714	0.748276	0.703774	0.588889
0.599065	0.608387	0.611582	0.612933	0.576923	0.549032	0.604789	0.605584	0.609485	0.583721	0.61831	0.588716	0.61	0.607104	0.6245283	0.628655	0.666857	0.67931	0.678616	0.588889
0.314953	0.292258	0.289233	0.286521	0.296923	0.272903	0.278028	0.266497	0.282114	0.262126	0.27277	0.252529	0.253333	0.253005	0.2962264	0.268421	0.250857	0.242529	0.240881	0.588889

0.328037	0.306452	0.299674	0.285064	0.295385	0.288387	0.291549	0.290863	0.29729	0.283389	0.314085	0.317899	0.336667	0.301093	0.345283	0.319883	0.328571	0.352874	0.316352	0.588889
0.814019	0.747742	0.761664	0.74408	0.72	0.670323	0.726479	0.733503	0.743902	0.708638	0.72723	0.703891	0.736667	0.712022	0.7641509	0.680117	0.648571	0.734483	0.688679	0.588889
0.630841	0.640645	0.614192	0.602732	0.62	0.525806	0.604789	0.619797	0.633333	0.583721	0.576995	0.576265	0.593333	0.572131	0.654717	0.61462	0.602857	0.610345	0.633333	0.588889
0.56729	0.53871	0.563295	0.554645	0.535385	0.484516	0.528169	0.540609	0.550949	0.509302	0.528169	0.538911	0.563333	0.493443	0.5528302	0.535088	0.520571	0.550575	0.502516	0.588889
0.664486	0.645806	0.636378	0.623133	0.607692	0.528387	0.58	0.577157	0.592141	0.557143	0.588263	0.601167	0.633333	0.620219	0.6358491	0.595906	0.625714	0.633333	0.638365	0.588889
0.645794	0.697419	0.696411	0.704736	0.672308	0.634194	0.649859	0.672589	0.698374	0.655482	0.700939	0.716342	0.723333	0.720765	0.7264151	0.703509	0.703429	0.729885	0.713836	0.633333
0.681308	0.675484	0.689886	0.682878	0.649231	0.605806	0.679155	0.688832	0.683198	0.647508	0.723474	0.722568	0.736667	0.703279	0.7226415	0.689474	0.708	0.72069	0.703774	0.633333
0.784112	0.769677	0.723817	0.728051	0.713846	0.745161	0.758028	0.737563	0.767751	0.732558	0.761033	0.756809	0.73	0.611475	0.7	0.717544	0.717143	0.706897	0.718868	0.633333
0.778505	0.782581	0.736868	0.70765	0.730769	0.758065	0.767042	0.749746	0.778591	0.732558	0.757277	0.756809	0.76	0.633333	0.7113208	0.740936	0.744571	0.729885	0.713836	0.633333
0.757944	0.78129	0.777325	0.774681	0.773846	0.711613	0.796338	0.806599	0.793767	0.788372	0.640845	0.735019	0.726667	0.628962	0.7830189	0.623977	0.589143	0.66092	0.643396	0.633333
0.748598	0.727097	0.717292	0.691621	0.696923	0.750323	0.758028	0.707107	0.730894	0.7299	0.693427	0.731907	0.75	0.742623	0.7603774	0.703509	0.721714	0.757471	0.728931	0.633333
0.642056	0.657419	0.638989	0.612933	0.606154	0.569677	0.613803	0.629949	0.615989	0.589037	0.584507	0.585603	0.6	0.489071	0.6622642	0.661404	0.703429	0.716092	0.653459	0.633333
0.741121	0.719355	0.725122	0.701821	0.696923	0.685806	0.755775	0.749746	0.748238	0.764452	0.723474	0.731907	0.76	0.799454	0.7716981	0.745614	0.735429	0.73908	0.779245	0.633333
0.752336	0.715484	0.727732	0.700364	0.724615	0.696129	0.749014	0.763959	0.791599	0.751163	0.72723	0.731907	0.746667	0.729508	0.7301887	0.740936	0.730857	0.757471	0.754088	0.633333
0.701869	0.721935	0.713377	0.710565	0.670769	0.654839	0.721972	0.72335	0.730894	0.698007	0.689671	0.688327	0.703333	0.729508	0.7566038	0.745614	0.753714	0.771264	0.779245	0.677778
0.681308	0.65871	0.653344	0.637705	0.649231	0.585161	0.647606	0.63401	0.648509	0.615615	0.667136	0.622957	0.616667	0.572131	0.7867925	0.661404	0.612	0.665517	0.648428	0.677778
0.752336	0.683226	0.650734	0.643534	0.661538	0.662581	0.706197	0.715228	0.730894	0.687375	0.712207	0.707004	0.716667	0.646448	0.6962264	0.623977	0.680571	0.688506	0.688679	0.677778

0.705607	0.663871	0.674225	0.662477	0.641538	0.636774	0.688169	0.698985	0.689702	0.652824	0.700939	0.703891	0.68	0.611475	0.6811321	0.619298	0.598286	0.61954	0.633333	0.677778
0.76729	0.758065	0.742088	0.720765	0.706154	0.724516	0.791831	0.772081	0.750407	0.735216	0.746009	0.778599	0.756667	0.703279	0.8245283	0.745614	0.804	0.798851	0.738994	0.677778
0.714953	0.776129	0.766884	0.755738	0.746154	0.667742	0.721972	0.737563	0.752575	0.716611	0.607042	0.660311	0.71	0.593989	0.6735849	0.703509	0.804	0.785057	0.774214	0.677778
0.815888	0.804516	0.795595	0.758652	0.76	0.745161	0.789577	0.776142	0.785095	0.761794	0.753521	0.787938	0.78	0.698907	0.8320755	0.740936	0.744571	0.752874	0.769182	0.677778
0.795327	0.77871	0.755139	0.748452	0.76	0.74	0.758028	0.751777	0.756911	0.756478	0.753521	0.741245	0.786667	0.712022	0.7415094	0.731579	0.772	0.762069	0.799371	0.677778
0.793458	0.770968	0.756444	0.732423	0.729231	0.74	0.794085	0.786294	0.772087	0.756478	0.697183	0.763035	0.783333	0.712022	0.8283019	0.722222	0.808571	0.803448	0.769182	0.722222
0.780374	0.764516	0.756444	0.74408	0.746154	0.760645	0.787324	0.792386	0.806775	0.772425	0.749765	0.719455	0.763333	0.760109	0.8283019	0.726901	0.804	0.831034	0.733962	0.722222
0.815888	0.817419	0.823002	0.818397	0.804615	0.760645	0.805352	0.822843	0.828455	0.780399	0.832394	0.794163	0.813333	0.781967	0.7754717	0.783041	0.790286	0.794253	0.814465	0.722222
0.337383	0.332258	0.333605	0.33898	0.343077	0.30129	0.316338	0.319289	0.349322	0.309967	0.347887	0.33035	0.326667	0.336066	0.3264151	0.310526	0.310286	0.311494	0.316352	0.722222
0.836449	0.817419	0.828222	0.831512	0.816923	0.752903	0.839155	0.837056	0.854472	0.820266	0.832394	0.859533	0.853333	0.720765	0.8471698	0.801754	0.826857	0.812644	0.844654	0.722222
0.728037	0.773548	0.762969	0.752823	0.74	0.683226	0.721972	0.745685	0.754743	0.727243	0.584507	0.660311	0.696667	0.593989	0.7603774	0.708187	0.790286	0.789655	0.799371	0.722222
0.802804	0.736129	0.697716	0.701821	0.704615	0.709032	0.751268	0.753807	0.763415	0.7299	0.753521	0.747471	0.753333	0.681421	0.7075472	0.675439	0.717143	0.725287	0.698742	0.722222
0.834579	0.787742	0.774715	0.781967	0.786154	0.789032	0.830141	0.822843	0.837127	0.841528	0.794836	0.781712	0.84	0.79071	0.7566038	0.689474	0.694286	0.752874	0.713836	0.722222
0.9	0.879355	0.9	0.891257	0.9	0.879355	0.868451	0.849239	0.880488	0.87608	0.824883	0.822179	0.85	0.799454	0.8169811	0.778363	0.790286	0.785057	0.809434	0.722222
0.827103	0.764516	0.755139	0.755738	0.769231	0.801935	0.805352	0.798477	0.813279	0.775083	0.817371	0.859533	0.816667	0.786339	0.8509434	0.769006	0.790286	0.794253	0.759119	0.722222
0.83271	0.790323	0.77863	0.745537	0.744615	0.758065	0.791831	0.790355	0.808943	0.783056	0.779812	0.784825	0.763333	0.746995	0.7075472	0.703509	0.758286	0.743678	0.804403	0.722222
0.800935	0.777419	0.760359	0.730965	0.727692	0.750323	0.818873	0.782234	0.776423	0.756478	0.719718	0.744358	0.756667	0.712022	0.8207547	0.750292	0.822286	0.831034	0.723899	0.766667

0.802804	0.804516	0.813866	0.811111	0.795385	0.791613	0.890986	0.891878	0.9	0.9	0.843662	0.809728	0.853333	0.79071	0.8396226	0.801754	0.817714	0.789655	0.86478	0.766667
0.808411	0.734839	0.704241	0.698907	0.712308	0.719355	0.755775	0.772081	0.767751	0.737874	0.761033	0.753696	0.76	0.681421	0.7339623	0.666082	0.735429	0.716092	0.708805	0.766667
0.791589	0.789032	0.773409	0.755738	0.784615	0.742581	0.839155	0.820812	0.863144	0.844186	0.877465	0.853307	0.876667	0.9	0.7528302	0.759649	0.790286	0.794253	0.789308	0.766667
0.838318	0.749032	0.730343	0.748452	0.723077	0.750323	0.771549	0.743655	0.774255	0.761794	0.794836	0.775486	0.77	0.73388	0.6660377	0.595906	0.694286	0.752874	0.663522	0.766667
0.720561	0.751613	0.748613	0.742623	0.736923	0.745161	0.773803	0.753807	0.763415	0.756478	0.79108	0.71323	0.726667	0.738251	0.7603774	0.722222	0.753714	0.757471	0.738994	0.766667
0.853271	0.893548	0.884339	0.895628	0.88	0.721935	0.848169	0.863452	0.841463	0.780399	0.715962	0.772374	0.75	0.580874	0.9	0.867251	0.858857	0.872414	0.854717	0.766667
0.763551	0.752903	0.748613	0.742623	0.736923	0.74	0.798592	0.814721	0.830623	0.785714	0.79108	0.822179	0.866667	0.694536	0.8509434	0.829825	0.872571	0.886207	0.879874	0.766667
0.870093	0.839355	0.813866	0.818397	0.832308	0.807097	0.836901	0.81066	0.830623	0.820266	0.877465	0.843969	0.876667	0.81694	0.7754717	0.764327	0.804	0.817241	0.744025	0.811111
0.817757	0.839355	0.873899	0.86357	0.801538	0.78129	0.841408	0.853299	0.865312	0.809635	0.806103	0.819066	0.87	0.786339	0.7339623	0.792398	0.822286	0.858621	0.854717	0.811111
0.763551	0.769677	0.757749	0.751366	0.736923	0.69871	0.726479	0.790355	0.806775	0.764452	0.746009	0.710117	0.696667	0.70765	0.7716981	0.684795	0.685143	0.67931	0.749057	0.811111
0.847664	0.826452	0.821697	0.795082	0.809231	0.760645	0.818873	0.832995	0.832791	0.801661	0.794836	0.81284	0.833333	0.821311	0.8773585	0.825146	0.872571	0.881609	0.889937	0.811111
0.750467	0.73871	0.729038	0.717851	0.744615	0.693548	0.728732	0.717259	0.739566	0.708638	0.761033	0.728794	0.726667	0.668306	0.8283019	0.731579	0.698857	0.734483	0.754088	0.811111
0.830841	0.813548	0.833442	0.831512	0.815385	0.755484	0.848169	0.851269	0.858808	0.825581	0.869953	0.875097	0.873333	0.746995	0.7490566	0.801754	0.817714	0.817241	0.839623	0.811111
0.868224	0.9	0.885644	0.9	0.887692	0.752903	0.821127	0.861421	0.847967	0.775083	0.768545	0.775486	0.74	0.56776	0.8660377	0.9	0.890857	0.886207	0.9	0.811111
0.720561	0.69871	0.710767	0.690164	0.669231	0.647097	0.708451	0.717259	0.704878	0.674086	0.712207	0.722568	0.7	0.633333	0.6773585	0.675439	0.630286	0.642529	0.648428	0.811111
0.799065	0.759355	0.777325	0.779053	0.746154	0.742581	0.771549	0.774112	0.793767	0.740532	0.768545	0.772374	0.76	0.672678	0.7792453	0.703509	0.772	0.766667	0.764151	0.855556
0.890654	0.827742	0.843883	0.844627	0.798462	0.786452	0.870704	0.867513	0.880488	0.825581	0.851174	0.828405	0.843333	0.830055	0.8735849	0.731579	0.831429	0.854023	0.834591	0.855556

0.838318	0.796774	0.813866	0.802368	0.792308	0.765806	0.82338	0.808629	0.806775	0.793688	0.806103	0.784825	0.833333	0.803825	0.8471698	0.839181	0.826857	0.9	0.814465	0.855556
0.83271	0.800645	0.799511	0.792168	0.807692	0.74	0.789577	0.804569	0.817615	0.788372	0.783568	0.775486	0.773333	0.73388	0.7981132	0.726901	0.735429	0.743678	0.759119	0.855556
0.821495	0.773548	0.79168	0.776138	0.758462	0.729677	0.746761	0.776142	0.776423	0.761794	0.700939	0.735019	0.766667	0.773224	0.7264151	0.67076	0.653143	0.706897	0.683648	0.855556
0.821495	0.834194	0.79168	0.822769	0.792308	0.760645	0.803099	0.822843	0.789431	0.775083	0.783568	0.763035	0.76	0.725137	0.8584906	0.797076	0.826857	0.817241	0.834591	0.855556
0.838318	0.822581	0.807341	0.795082	0.789231	0.745161	0.791831	0.782234	0.774255	0.775083	0.798592	0.778599	0.793333	0.764481	0.7641509	0.726901	0.726286	0.729885	0.723899	0.9
0.873832	0.832903	0.803426	0.808197	0.810769	0.9	0.863944	0.867513	0.871816	0.846844	0.824883	0.884436	0.9	0.821311	0.809434	0.811111	0.813143	0.854023	0.834591	0.9
0.793458	0.792903	0.757749	0.754281	0.781538	0.732258	0.767042	0.794416	0.817615	0.788372	0.742254	0.725681	0.793333	0.834426	0.7528302	0.759649	0.772	0.803448	0.824528	0.9
0.866355	0.834194	0.809951	0.821311	0.832308	0.822581	0.839155	0.822843	0.843631	0.828239	0.877465	0.828405	0.87	0.81694	0.7792453	0.783041	0.767429	0.798851	0.749057	0.9
0.804673	0.791613	0.77602	0.771767	0.743077	0.742581	0.751268	0.741624	0.743902	0.737874	0.719718	0.753696	0.723333	0.716393	0.7415094	0.731579	0.698857	0.729885	0.754088	0.9
0.800935	0.808387	0.78385	0.811111	0.784615	0.724516	0.807606	0.796447	0.832791	0.783056	0.798592	0.769261	0.796667	0.720765	0.7943396	0.84386	0.863429	0.890805	0.824528	0.9
0.845794	0.885806	0.837357	0.815483	0.850769	0.758065	0.818873	0.843147	0.826287	0.793688	0.832394	0.859533	0.826667	0.720765	0.8283019	0.778363	0.790286	0.826437	0.819497	0.9
0.821495	0.830323	0.795595	0.796539	0.787692	0.804516	0.86169	0.865482	0.837127	0.830897	0.892488	0.843969	0.833333	0.803825	0.8283019	0.825146	0.826857	0.817241	0.849686	0.9

APPENDIX F

NORMALIZED TEST DATASET OF INPUT FEATURES AND TARGET FEATURES FOR MALE HISPANIC POPULATION USING ANN APPROACH

1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	Age
0.171028	0.160645	0.169168	0.162659	0.183077	0.192903	0.187887	0.183249	0.197561	0.200997	0.201408	0.215175	0.206667	0.178689	0.209434	0.198246	0.218857	0.21954	0.17044	0.1
0.286916	0.305161	0.281403	0.264663	0.270769	0.285806	0.350141	0.343655	0.357995	0.344518	0.347887	0.345914	0.356667	0.331694	0.3490566	0.263743	0.305714	0.311494	0.250943	0.188889
0.290654	0.329677	0.32186	0.321494	0.324615	0.309032	0.372676	0.374112	0.390515	0.35515	0.389202	0.392607	0.41	0.362295	0.3641509	0.324561	0.328571	0.352874	0.296226	0.188889
0.376636	0.390323	0.366232	0.371038	0.341538	0.37871	0.433521	0.426904	0.433875	0.416279	0.385446	0.401946	0.413333	0.340437	0.4132075	0.324561	0.374286	0.389655	0.37673	0.233333
0.309346	0.386452	0.374062	0.362295	0.335385	0.386452	0.426761	0.404569	0.405691	0.381728	0.434272	0.408171	0.416667	0.314208	0.4283019	0.366667	0.383429	0.385057	0.351572	0.233333
0.447664	0.516774	0.526754	0.526958	0.512308	0.471613	0.494366	0.516244	0.535772	0.485382	0.456808	0.470428	0.486667	0.427869	0.5037736	0.41345	0.470286	0.463218	0.381761	0.277778
0.283178	0.360645	0.345351	0.340437	0.313846	0.26	0.332113	0.325381	0.327642	0.296678	0.344131	0.336576	0.32	0.218033	0.3528302	0.282456	0.292	0.371264	0.245912	0.277778
0.45514	0.490968	0.469331	0.46867	0.444615	0.37871	0.456056	0.445178	0.446883	0.424252	0.456808	0.4393	0.453333	0.414754	0.4660377	0.436842	0.438286	0.467816	0.416981	0.322222
0.393458	0.416129	0.402773	0.384153	0.392308	0.332258	0.42	0.441117	0.446883	0.35515	0.449296	0.451751	0.466667	0.449727	0.4509434	0.352632	0.342286	0.458621	0.442138	0.322222
0.43271	0.422581	0.394943	0.391439	0.355385	0.383871	0.417746	0.404569	0.412195	0.365781	0.404225	0.392607	0.38	0.301093	0.4433962	0.422807	0.410857	0.417241	0.386792	0.322222
0.464486	0.483226	0.469331	0.459927	0.470769	0.425161	0.494366	0.477665	0.485908	0.480066	0.460563	0.4393	0.463333	0.419126	0.4660377	0.44152	0.438286	0.444828	0.396855	0.322222
0.443925	0.438065	0.447145	0.439526	0.424615	0.389032	0.42	0.418782	0.433875	0.408306	0.392958	0.420623	0.446667	0.366667	0.4207547	0.408772	0.415429	0.421839	0.386792	0.366667
0.483178	0.516774	0.496737	0.481785	0.470769	0.432903	0.469577	0.467513	0.477236	0.461462	0.479343	0.504669	0.506667	0.480328	0.4962264	0.44152	0.456571	0.477011	0.416981	0.366667

0.516822	0.523226	0.505873	0.515301	0.5	0.456129	0.50338	0.514213	0.520596	0.469435	0.479343	0.476654	0.503333	0.440984	0.4924528	0.427485	0.447429	0.449425	0.452201	0.411111
0.5	0.518065	0.512398	0.516758	0.518462	0.453548	0.521408	0.546701	0.553117	0.503987	0.565728	0.588716	0.593333	0.462842	0.6018868	0.535088	0.575429	0.582759	0.527673	0.411111
0.528037	0.532258	0.526754	0.499271	0.501538	0.507742	0.564225	0.546701	0.555285	0.503987	0.55446	0.557588	0.566667	0.554645	0.5792453	0.511696	0.534286	0.55977	0.51761	0.411111
0.479439	0.485806	0.490212	0.487614	0.449231	0.42	0.471831	0.473604	0.470732	0.421595	0.460563	0.4393	0.443333	0.366667	0.5037736	0.455556	0.452	0.458621	0.442138	0.411111
0.582243	0.558065	0.558075	0.547359	0.526154	0.515484	0.595775	0.585279	0.594309	0.554485	0.558216	0.563813	0.586667	0.519672	0.6018868	0.553801	0.570857	0.573563	0.537736	0.455556
0.576636	0.58129	0.56199	0.521129	0.546154	0.520645	0.58	0.560914	0.581301	0.570432	0.588263	0.598054	0.59	0.475956	0.6433962	0.55848	0.557143	0.587356	0.567925	0.455556
0.520561	0.528387	0.525449	0.502186	0.487692	0.510323	0.53493	0.510152	0.54878	0.519934	0.580751	0.542023	0.56	0.528415	0.6169811	0.530409	0.543429	0.541379	0.492453	0.455556
0.571028	0.564516	0.563295	0.563388	0.564615	0.471613	0.552958	0.579188	0.587805	0.53588	0.50939	0.520233	0.53	0.45847	0.5981132	0.577193	0.534286	0.55977	0.502516	0.455556
0.585981	0.564516	0.580261	0.589617	0.567692	0.507742	0.570986	0.573096	0.594309	0.543854	0.55446	0.5607	0.573333	0.532787	0.6962264	0.55848	0.634857	0.656322	0.58805	0.5
0.65514	0.656129	0.657259	0.662477	0.629231	0.543871	0.577746	0.629949	0.618157	0.527907	0.464319	0.526459	0.516667	0.309836	0.5981132	0.535088	0.593714	0.633333	0.507547	0.5
0.621495	0.600645	0.602447	0.57796	0.56	0.587742	0.600282	0.603553	0.594309	0.583721	0.584507	0.591829	0.606667	0.65082	0.6283019	0.567836	0.575429	0.596552	0.593082	0.5
0.526168	0.532258	0.535889	0.535701	0.518462	0.492258	0.528169	0.534518	0.544444	0.517276	0.498122	0.489105	0.51	0.462842	0.6169811	0.58655	0.543429	0.568966	0.547799	0.544444
0.619626	0.617419	0.625938	0.621676	0.583077	0.543871	0.634085	0.629949	0.633333	0.581063	0.592019	0.579377	0.583333	0.506557	0.6924528	0.591228	0.602857	0.628736	0.628302	0.544444
0.627103	0.634194	0.632463	0.637705	0.596923	0.54129	0.645352	0.67665	0.67019	0.623588	0.610798	0.660311	0.646667	0.628962	0.6396226	0.628655	0.634857	0.642529	0.62327	0.544444
0.585981	0.600645	0.611582	0.589617	0.595385	0.507742	0.570986	0.583249	0.594309	0.591694	0.580751	0.585603	0.603333	0.611475	0.6584906	0.609942	0.634857	0.61954	0.633333	0.588889
0.668224	0.647097	0.637684	0.62459	0.643077	0.564516	0.638592	0.611675	0.644173	0.583721	0.640845	0.622957	0.643333	0.602732	0.6773585	0.661404	0.639429	0.642529	0.628302	0.588889
0.836449	0.813548	0.820392	0.803825	0.778462	0.763226	0.807606	0.81269	0.826287	0.775083	0.768545	0.750584	0.793333	0.764481	0.854717	0.694152	0.753714	0.817241	0.749057	0.633333

0.657009	0.714194	0.715987	0.717851	0.673846	0.662581	0.665634	0.692893	0.70271	0.671429	0.72723	0.716342	0.753333	0.73388	0.7377358	0.708187	0.721714	0.748276	0.738994	0.633333
0.72243	0.702581	0.729038	0.713479	0.689231	0.654839	0.712958	0.715228	0.72439	0.68206	0.776056	0.750584	0.776667	0.738251	0.7792453	0.717544	0.730857	0.743678	0.738994	0.633333
0.726168	0.70129	0.718597	0.722222	0.707692	0.605806	0.735493	0.719289	0.728726	0.687375	0.72723	0.756809	0.756667	0.698907	0.7716981	0.726901	0.744571	0.665517	0.744025	0.633333
0.623364	0.608387	0.603752	0.602732	0.6	0.556774	0.62507	0.609645	0.611653	0.607641	0.595775	0.594942	0.56	0.545902	0.6735849	0.67076	0.648571	0.674713	0.648428	0.633333
0.739252	0.702581	0.706852	0.693078	0.673846	0.672903	0.721972	0.711168	0.722222	0.700664	0.693427	0.66965	0.68	0.685792	0.7377358	0.656725	0.653143	0.688506	0.683648	0.633333
0.720561	0.724516	0.719902	0.703279	0.695385	0.649677	0.681408	0.680711	0.678862	0.64485	0.678404	0.660311	0.696667	0.668306	0.7377358	0.656725	0.666857	0.683908	0.658491	0.677778
0.868224	0.840645	0.841272	0.832969	0.809231	0.773548	0.82338	0.828934	0.843631	0.812292	0.813615	0.775486	0.833333	0.808197	0.8660377	0.712865	0.772	0.854023	0.769182	0.677778
0.757944	0.770968	0.777325	0.771767	0.730769	0.721935	0.758028	0.72132	0.776423	0.761794	0.79108	0.738132	0.77	0.768852	0.7981132	0.745614	0.74	0.757471	0.769182	0.677778
0.785981	0.763226	0.736868	0.720765	0.718462	0.768387	0.767042	0.753807	0.776423	0.743189	0.783568	0.775486	0.763333	0.642077	0.7150943	0.726901	0.653143	0.725287	0.718868	0.677778
0.670093	0.634194	0.646819	0.644991	0.661538	0.649677	0.681408	0.701015	0.709214	0.692691	0.667136	0.678988	0.706667	0.703279	0.7603774	0.694152	0.689714	0.702299	0.713836	0.677778
0.759813	0.770968	0.742088	0.741166	0.756923	0.768387	0.803099	0.804569	0.798103	0.764452	0.734742	0.756809	0.74	0.755738	0.7792453	0.740936	0.758286	0.798851	0.764151	0.677778
0.716822	0.662581	0.67553	0.672678	0.690769	0.641935	0.683662	0.674619	0.69187	0.666113	0.674648	0.675875	0.686667	0.65082	0.7528302	0.731579	0.698857	0.729885	0.723899	0.677778
0.85514	0.854839	0.824307	0.818397	0.809231	0.845806	0.870704	0.859391	0.880488	0.812292	0.9	0.9	0.813333	0.773224	0.8283019	0.839181	0.831429	0.867816	0.804403	0.722222
0.733645	0.760645	0.752529	0.752823	0.718462	0.69871	0.771549	0.757868	0.769919	0.748505	0.764789	0.741245	0.75	0.768852	0.7792453	0.778363	0.790286	0.817241	0.82956	0.722222
0.729907	0.752903	0.747308	0.738251	0.724615	0.737419	0.776056	0.745685	0.754743	0.745847	0.7723	0.707004	0.706667	0.725137	0.7566038	0.689474	0.749143	0.725287	0.718868	0.722222
0.838318	0.733548	0.726427	0.741166	0.716923	0.729677	0.760282	0.737563	0.761247	0.743189	0.787324	0.772374	0.76	0.738251	0.6773585	0.609942	0.689714	0.757471	0.643396	0.766667
0.821495	0.82	0.785155	0.80674	0.78	0.750323	0.812113	0.818782	0.793767	0.775083	0.79108	0.738132	0.746667	0.712022	0.8660377	0.815789	0.849714	0.821839	0.849686	0.766667

0.81028	0.804516	0.812561	0.821311	0.790769	0.804516	0.9	0.9	0.9	0.9	0.83615	0.803502	0.85	0.799454	0.8396226	0.801754	0.817714	0.817241	0.889937	0.811111
0.823364	0.863871	0.868679	0.857741	0.830769	0.82	0.852676	0.865482	0.869648	0.862791	0.862441	0.850195	0.85	0.847541	0.8849057	0.853216	0.826857	0.858621	0.804403	0.811111
0.81215	0.747742	0.753834	0.752823	0.750769	0.745161	0.78507	0.802538	0.798103	0.753821	0.749765	0.744358	0.753333	0.768852	0.7754717	0.778363	0.794857	0.794253	0.804403	0.855556
0.819626	0.843226	0.851713	0.846084	0.826154	0.763226	0.821127	0.841117	0.858808	0.81495	0.843662	0.847082	0.863333	0.812568	0.8811321	0.857895	0.9	0.9	0.894969	0.855556
0.81215	0.790323	0.772104	0.763024	0.750769	0.690968	0.744507	0.751777	0.752575	0.713953	0.723474	0.719455	0.743333	0.655191	0.7490566	0.773684	0.799429	0.812644	0.789308	0.855556
0.799065	0.763226	0.772104	0.763024	0.755385	0.70129	0.708451	0.731472	0.754743	0.724585	0.697183	0.694553	0.703333	0.685792	0.7339623	0.769006	0.804	0.794253	0.749057	0.855556
0.76729	0.755484	0.747308	0.751366	0.735385	0.690968	0.737746	0.763959	0.748238	0.737874	0.738498	0.769261	0.743333	0.681421	0.8283019	0.820468	0.836	0.858621	0.809434	0.9
0.800935	0.77871	0.774715	0.748452	0.716923	0.742581	0.753521	0.753807	0.774255	0.772425	0.746009	0.707004	0.746667	0.742623	0.8132075	0.787719	0.781143	0.766667	0.819497	0.9

APPENDIX G

NORMALIZED DATASET OF INPUT FEATURES AND TARGET FEATURES FOR FEMALE HISPANIC POPULATION FOR FEATURE SELECTION USING GA APPROACH

1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	Age
0.116716	0.145253	0.138737	0.121719	0.140482	0.113974	0.114388	0.113029	0.1	0.120513	0.11326	0.132	0.108333	0.121192	0.1	0.1	0.1	0.158394	0.148855	0.1
0.171642	0.255152	0.239789	0.214027	0.198313	0.173362	0.169065	0.172964	0.175524	0.188889	0.228177	0.164	0.179167	0.269536	0.239759	0.173282	0.164234	0.216788	0.148855	0.144444
0.121493	0.124242	0.130316	0.125339	0.123133	0.106987	0.1	0.136482	0.141958	0.120513	0.139779	0.144	0.191667	0.184768	0.124096	0.185496	0.152555	0.193431	0.148855	0.144444
0.166866	0.16303	0.142105	0.210407	0.188675	0.1	0.169065	0.157329	0.141958	0.192308	0.1	0.148	0.1	0.137086	0.153012	0.112214	0.146715	0.164234	0.136641	0.144444
0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.111189	0.1	0.130939	0.1	0.108333	0.115894	0.124096	0.179389	0.146715	0.158394	0.148855	0.144444
0.16209	0.224444	0.214526	0.212217	0.211807	0.141921	0.206475	0.180782	0.203497	0.219658	0.126519	0.12	0.166667	0.12649	0.220482	0.148855	0.135036	0.19927	0.1	0.144444
0.228955	0.30202	0.302105	0.291855	0.312048	0.222271	0.252518	0.256352	0.315385	0.226496	0.325414	0.292	0.295833	0.253642	0.312048	0.344275	0.345255	0.345255	0.240458	0.188889
0.169254	0.242222	0.224632	0.232127	0.225301	0.145415	0.148921	0.167752	0.161538	0.141026	0.192818	0.116	0.15	0.1	0.148193	0.19771	0.164234	0.19927	0.148855	0.188889
0.140597	0.227677	0.231368	0.188688	0.194458	0.131441	0.192086	0.20684	0.209091	0.120513	0.148619	0.148	0.191667	0.12649	0.215663	0.142748	0.111679	0.1	0.142748	0.188889
0.217015	0.242222	0.251579	0.259276	0.229157	0.169869	0.186331	0.201629	0.197902	0.18547	0.263536	0.24	0.266667	0.200662	0.181928	0.240458	0.205109	0.275182	0.228244	0.188889
0.169254	0.251919	0.254947	0.235747	0.238795	0.180349	0.241007	0.25114	0.197902	0.195726	0.276796	0.268	0.25	0.23245	0.201205	0.191603	0.30438	0.234307	0.185496	0.188889
0.291045	0.334343	0.330737	0.313575	0.304337	0.278166	0.223741	0.25114	0.301399	0.236752	0.329834	0.312	0.316667	0.296026	0.287952	0.173282	0.275182	0.187591	0.191603	0.233333
0.405672	0.360202	0.359368	0.371493	0.379518	0.260699	0.295683	0.313681	0.304196	0.257265	0.303315	0.28	0.3	0.23245	0.355422	0.270992	0.240146	0.275182	0.289313	0.233333

0.386567	0.374747	0.364421	0.360633	0.375663	0.323581	0.292806	0.305863	0.368531	0.274359	0.329834	0.328	0.325	0.237748	0.437349	0.39313	0.415328	0.432847	0.277099	0.233333
0.26	0.384444	0.389684	0.375113	0.366024	0.21179	0.243885	0.264169	0.259441	0.212821	0.356354	0.332	0.316667	0.333113	0.350602	0.19771	0.245985	0.257664	0.203817	0.233333
0.281493	0.365051	0.376211	0.376923	0.406506	0.274672	0.318705	0.32671	0.318182	0.308547	0.298895	0.344	0.325	0.264238	0.321687	0.154962	0.205109	0.234307	0.234351	0.233333
0.324478	0.397374	0.406526	0.407692	0.383373	0.299127	0.318705	0.412704	0.41049	0.400855	0.343094	0.356	0.329167	0.444371	0.360241	0.258779	0.216788	0.391971	0.222137	0.277778
0.329254	0.376364	0.406526	0.387783	0.404578	0.288646	0.310072	0.334528	0.30979	0.277778	0.294475	0.3	0.3	0.216556	0.422892	0.350382	0.327737	0.374453	0.319847	0.277778
0.374627	0.363434	0.352632	0.322624	0.358313	0.222271	0.246763	0.271987	0.267832	0.236752	0.329834	0.256	0.333333	0.306623	0.316867	0.277099	0.210949	0.362774	0.234351	0.277778
0.279104	0.365051	0.369474	0.366063	0.36988	0.278166	0.28705	0.303257	0.365734	0.346154	0.382873	0.336	0.279167	0.317219	0.36988	0.41145	0.415328	0.444526	0.29542	0.277778
0.32209	0.400606	0.399789	0.398643	0.396867	0.299127	0.321583	0.342345	0.427273	0.417949	0.343094	0.356	0.379167	0.407285	0.36988	0.234351	0.251825	0.281022	0.246565	0.277778
0.386567	0.424848	0.446947	0.451131	0.452771	0.306114	0.356115	0.410098	0.37972	0.342735	0.329834	0.368	0.35	0.301325	0.326506	0.380916	0.374453	0.421168	0.387023	0.322222
0.503582	0.460404	0.492421	0.463801	0.479759	0.435371	0.405036	0.412704	0.416084	0.41453	0.360773	0.36	0.379167	0.444371	0.461446	0.31374	0.321898	0.356934	0.319847	0.322222
0.360299	0.470101	0.460421	0.452941	0.475904	0.29214	0.361871	0.368404	0.365734	0.315385	0.276796	0.3	0.283333	0.227152	0.254217	0.289313	0.263504	0.316058	0.29542	0.322222
0.470149	0.457172	0.480632	0.478281	0.47012	0.29214	0.32446	0.436156	0.435664	0.421368	0.404972	0.4	0.408333	0.370199	0.30241	0.332061	0.339416	0.345255	0.29542	0.322222
0.293433	0.37798	0.396421	0.375113	0.366024	0.39345	0.292806	0.300651	0.374126	0.288034	0.404972	0.296	0.2875	0.391391	0.43253	0.307634	0.275182	0.292701	0.289313	0.322222
0.283881	0.418384	0.433474	0.404072	0.39494	0.194323	0.373381	0.365798	0.348951	0.277778	0.365193	0.3	0.333333	0.317219	0.422892	0.283206	0.251825	0.292701	0.264885	0.322222
0.453433	0.442626	0.484	0.465611	0.46241	0.344541	0.410791	0.457003	0.460839	0.407692	0.325414	0.376	0.466667	0.460265	0.5	0.325954	0.30438	0.327737	0.338168	0.322222
0.427164	0.437778	0.458737	0.434842	0.402651	0.267686	0.393525	0.410098	0.407692	0.366667	0.378453	0.368	0.3625	0.322517	0.408434	0.332061	0.386131	0.333577	0.270992	0.322222
0.403284	0.392525	0.408211	0.398643	0.398795	0.257205	0.315827	0.334528	0.332168	0.301709	0.307735	0.284	0.320833	0.327815	0.321687	0.270992	0.339416	0.386131	0.29542	0.322222

0.293433	0.403838	0.421684	0.398643	0.410361	0.264192	0.307194	0.347557	0.41049	0.397436	0.374033	0.356	0.3625	0.327815	0.360241	0.277099	0.222628	0.356934	0.222137	0.322222
0.367463	0.453939	0.475579	0.454751	0.44506	0.337555	0.410791	0.417915	0.432867	0.335897	0.466851	0.448	0.433333	0.391391	0.451807	0.448092	0.40365	0.444526	0.319847	0.366667
0.534627	0.526667	0.546316	0.51448	0.510602	0.39345	0.468345	0.592508	0.56993	0.530769	0.48895	0.448	0.541667	0.481457	0.490361	0.325954	0.345255	0.485401	0.240458	0.366667
0.49403	0.478182	0.504211	0.460181	0.472048	0.372489	0.445324	0.467427	0.44965	0.346154	0.404972	0.34	0.329167	0.386093	0.442169	0.325954	0.432847	0.380292	0.325954	0.366667
0.496418	0.450707	0.460421	0.460181	0.473976	0.379476	0.396403	0.40228	0.416084	0.387179	0.440331	0.356	0.408333	0.407285	0.312048	0.362595	0.456204	0.485401	0.448092	0.366667
0.515522	0.46202	0.463789	0.452941	0.456627	0.358515	0.38777	0.472638	0.472028	0.428205	0.404972	0.432	0.433333	0.396689	0.485542	0.344275	0.368613	0.386131	0.344275	0.366667
0.477313	0.458788	0.441895	0.451131	0.472048	0.29214	0.402158	0.428339	0.43007	0.346154	0.400552	0.38	0.375	0.391391	0.413253	0.356489	0.327737	0.485401	0.350382	0.366667
0.374627	0.471717	0.470526	0.48914	0.491325	0.330568	0.419424	0.506515	0.48042	0.469231	0.440331	0.46	0.445833	0.370199	0.490361	0.368702	0.368613	0.40365	0.356489	0.366667
0.477313	0.415152	0.408211	0.409502	0.414217	0.41441	0.428058	0.438762	0.44965	0.421368	0.334254	0.348	0.366667	0.444371	0.446988	0.350382	0.368613	0.386131	0.362595	0.366667
0.491642	0.455556	0.463789	0.452941	0.481687	0.355022	0.384892	0.485668	0.494406	0.448718	0.431492	0.444	0.458333	0.396689	0.446988	0.39313	0.39781	0.415328	0.454198	0.366667
0.477313	0.471717	0.477263	0.456561	0.473976	0.41441	0.459712	0.483062	0.483217	0.397436	0.400552	0.416	0.475	0.465563	0.524096	0.380916	0.391971	0.467883	0.356489	0.366667
0.601493	0.562222	0.595158	0.561538	0.545301	0.372489	0.433813	0.574267	0.530769	0.469231	0.475691	0.48	0.341667	0.301325	0.350602	0.350382	0.333577	0.508759	0.332061	0.411111
0.572836	0.605859	0.625474	0.612217	0.593494	0.487773	0.505755	0.506515	0.488811	0.482906	0.577348	0.468	0.5875	0.560927	0.581928	0.423664	0.40365	0.462044	0.332061	0.411111
0.599104	0.53798	0.548	0.547059	0.543373	0.389956	0.520144	0.548208	0.525175	0.493162	0.546409	0.504	0.483333	0.481457	0.533735	0.362595	0.351095	0.351095	0.454198	0.411111
0.606269	0.518586	0.521053	0.49819	0.522169	0.571616	0.523022	0.561238	0.575524	0.482906	0.612707	0.552	0.595833	0.598013	0.610843	0.619084	0.450365	0.643066	0.600763	0.411111
0.458209	0.552525	0.569895	0.49276	0.551084	0.491266	0.5	0.516938	0.435664	0.404274	0.50221	0.496	0.475	0.465563	0.514458	0.399237	0.520438	0.543796	0.50916	0.411111
0.572836	0.560606	0.559789	0.541629	0.547229	0.49476	0.540288	0.501303	0.527972	0.404274	0.546409	0.56	0.504167	0.481457	0.572289	0.496947	0.520438	0.543796	0.374809	0.411111

0.546567	0.549293	0.553053	0.548869	0.562651	0.484279	0.534532	0.545603	0.533566	0.503419	0.541989	0.528	0.520833	0.529139	0.519277	0.350382	0.351095	0.368613	0.332061	0.411111
0.486866	0.492727	0.507579	0.49457	0.493253	0.466812	0.407914	0.467427	0.477622	0.394017	0.471271	0.476	0.466667	0.534437	0.509639	0.423664	0.456204	0.49708	0.332061	0.411111
0.51791	0.528283	0.537895	0.50724	0.527952	0.351528	0.517266	0.519544	0.513986	0.380342	0.533149	0.512	0.483333	0.444371	0.533735	0.551908	0.473723	0.514599	0.338168	0.411111
0.596716	0.544444	0.564842	0.532579	0.520241	0.466812	0.485612	0.493485	0.486014	0.476068	0.387293	0.48	0.491667	0.433775	0.519277	0.429771	0.49708	0.520438	0.515267	0.411111
0.668358	0.647879	0.635579	0.603167	0.574217	0.529694	0.594964	0.576873	0.553147	0.479487	0.546409	0.544	0.5625	0.550331	0.577108	0.527481	0.514599	0.427007	0.417557	0.455556
0.611045	0.555758	0.574947	0.566968	0.574217	0.449345	0.583453	0.56645	0.586713	0.575214	0.581768	0.596	0.620833	0.545033	0.610843	0.612977	0.479562	0.654745	0.60687	0.455556
0.556119	0.546061	0.574947	0.543439	0.524096	0.501747	0.523022	0.550814	0.541958	0.503419	0.537569	0.508	0.55	0.513245	0.586747	0.460305	0.438686	0.60219	0.564122	0.455556
0.603881	0.565455	0.583368	0.557919	0.533735	0.515721	0.546043	0.561238	0.567133	0.520513	0.590608	0.564	0.5625	0.545033	0.572289	0.515267	0.479562	0.643066	0.441985	0.455556
0.441493	0.525051	0.514316	0.50181	0.520241	0.466812	0.53741	0.519544	0.530769	0.530769	0.546409	0.52	0.504167	0.497351	0.519277	0.374809	0.491241	0.537956	0.521374	0.455556
0.558507	0.486263	0.514316	0.5	0.522169	0.484279	0.46259	0.480456	0.474825	0.465812	0.458011	0.432	0.429167	0.454967	0.533735	0.527481	0.49708	0.520438	0.545802	0.455556
0.577612	0.568687	0.595158	0.583258	0.597349	0.578603	0.603597	0.579479	0.58951	0.58547	0.608287	0.608	0.591667	0.608609	0.581928	0.484733	0.456204	0.619708	0.472519	0.455556
0.599104	0.610707	0.645684	0.606787	0.595422	0.501747	0.548921	0.576873	0.572727	0.503419	0.572928	0.588	0.583333	0.518543	0.581928	0.429771	0.432847	0.450365	0.399237	0.455556
0.627761	0.633333	0.649053	0.635747	0.632048	0.536681	0.554676	0.527362	0.558741	0.564957	0.533149	0.528	0.554167	0.629801	0.591566	0.448092	0.567153	0.613869	0.533588	0.455556
0.649254	0.62202	0.622105	0.585068	0.583855	0.561135	0.609353	0.626384	0.637063	0.626496	0.586188	0.612	0.620833	0.640397	0.586747	0.448092	0.584672	0.643066	0.478626	0.5
0.706567	0.686667	0.699579	0.677376	0.687952	0.603057	0.643885	0.675896	0.684615	0.626496	0.670166	0.728	0.7125	0.725166	0.63494	0.631298	0.69562	0.724818	0.661832	0.5
0.651642	0.597778	0.649053	0.650226	0.624337	0.536681	0.571942	0.618567	0.606294	0.599145	0.564088	0.556	0.5625	0.523841	0.644578	0.661832	0.625547	0.50292	0.631298	0.5
0.58	0.586465	0.638947	0.612217	0.626265	0.459825	0.635252	0.655049	0.637063	0.626496	0.625967	0.636	0.608333	0.608609	0.615663	0.649618	0.637226	0.637226	0.619084	0.5

0.711343	0.714141	0.726526	0.668326	0.67253	0.655459	0.698561	0.738436	0.706993	0.660684	0.639227	0.664	0.670833	0.656291	0.557831	0.58855	0.584672	0.467883	0.576336	0.5
0.56806	0.552525	0.544632	0.49638	0.508675	0.452838	0.494245	0.490879	0.466434	0.452137	0.475691	0.464	0.454167	0.396689	0.475904	0.521374	0.479562	0.485401	0.496947	0.5
0.64209	0.591313	0.642316	0.592308	0.616627	0.547162	0.566187	0.600326	0.575524	0.510256	0.559669	0.58	0.566667	0.486755	0.610843	0.710687	0.672263	0.707299	0.661832	0.5
0.680299	0.626869	0.682737	0.657466	0.651325	0.421397	0.586331	0.62899	0.667832	0.612821	0.51547	0.608	0.616667	0.613907	0.683133	0.655725	0.50292	0.584672	0.667939	0.5
0.699403	0.701212	0.706316	0.670136	0.691807	0.644978	0.684173	0.686319	0.695804	0.609402	0.643646	0.66	0.645833	0.682781	0.668675	0.70458	0.683942	0.660584	0.625191	0.5
0.563284	0.539596	0.58	0.592308	0.612771	0.49476	0.531655	0.55342	0.561538	0.541026	0.537569	0.552	0.554167	0.507947	0.56747	0.545802	0.514599	0.561314	0.503053	0.5
0.630149	0.636566	0.691158	0.648416	0.662892	0.58559	0.669784	0.691531	0.676224	0.677778	0.692265	0.676	0.658333	0.640397	0.692771	0.710687	0.648905	0.648905	0.643511	0.544444
0.673134	0.628485	0.649053	0.617647	0.62241	0.58559	0.620863	0.644625	0.642657	0.616239	0.603867	0.608	0.6	0.518543	0.668675	0.576336	0.409489	0.648905	0.594656	0.544444
0.613433	0.634949	0.655789	0.644796	0.653253	0.547162	0.603597	0.62899	0.634266	0.629915	0.559669	0.532	0.545833	0.624503	0.591566	0.521374	0.321898	0.567153	0.551908	0.544444
0.75194	0.686667	0.681053	0.646606	0.649398	0.693886	0.707194	0.71759	0.720979	0.698291	0.705525	0.744	0.75	0.703974	0.736145	0.692366	0.666423	0.713139	0.667939	0.544444
0.663582	0.613939	0.647368	0.619457	0.639759	0.582096	0.546043	0.576873	0.553147	0.544444	0.577348	0.58	0.570833	0.539735	0.610843	0.60687	0.59635	0.60219	0.594656	0.544444
0.680299	0.657576	0.672632	0.659276	0.686024	0.620524	0.652518	0.681107	0.69021	0.664103	0.603867	0.644	0.6375	0.603311	0.620482	0.674046	0.666423	0.678102	0.643511	0.544444
0.64209	0.604242	0.608632	0.594118	0.593494	0.491266	0.577698	0.602932	0.614685	0.602564	0.577348	0.62	0.595833	0.592715	0.615663	0.454198	0.619708	0.643066	0.496947	0.544444
0.577612	0.562222	0.58	0.556109	0.53759	0.466812	0.488489	0.545603	0.541958	0.489744	0.48011	0.508	0.516667	0.507947	0.586747	0.441985	0.59635	0.613869	0.435878	0.544444
0.747164	0.673737	0.694526	0.673756	0.670602	0.644978	0.655396	0.688925	0.706993	0.667521	0.652486	0.684	0.725	0.735762	0.70241	0.759542	0.689781	0.736496	0.70458	0.544444
0.64209	0.596162	0.595158	0.585068	0.587711	0.543668	0.609353	0.62899	0.623077	0.605983	0.625967	0.628	0.6375	0.613907	0.586747	0.600763	0.59635	0.643066	0.558015	0.544444
0.708955	0.659192	0.708	0.671946	0.69759	0.620524	0.678417	0.644625	0.673427	0.629915	0.652486	0.652	0.675	0.619205	0.760241	0.655725	0.637226	0.713139	0.735115	0.544444

0.694627	0.649495	0.664211	0.617647	0.62241	0.624017	0.695683	0.694137	0.673427	0.684615	0.705525	0.692	0.6375	0.688079	0.731325	0.649618	0.637226	0.660584	0.619084	0.544444
0.65403	0.628485	0.644	0.619457	0.60506	0.58559	0.61223	0.655049	0.611888	0.582051	0.546409	0.592	0.545833	0.560927	0.639759	0.612977	0.631387	0.672263	0.637405	0.544444
0.649254	0.67697	0.691158	0.655656	0.655181	0.589083	0.617986	0.657655	0.645455	0.588889	0.572928	0.616	0.633333	0.566225	0.649398	0.655725	0.613869	0.60219	0.576336	0.544444
0.627761	0.573535	0.595158	0.566968	0.562651	0.543668	0.646763	0.639414	0.645455	0.571795	0.634807	0.644	0.6375	0.645695	0.644578	0.619084	0.60219	0.660584	0.551908	0.588889
0.694627	0.673737	0.652421	0.652036	0.659036	0.617031	0.669784	0.694137	0.698601	0.660684	0.617127	0.644	0.6375	0.582119	0.553012	0.643511	0.625547	0.69562	0.625191	0.588889
0.723284	0.69798	0.709684	0.661086	0.676386	0.669432	0.710072	0.743648	0.743357	0.681197	0.612707	0.656	0.6625	0.566225	0.721687	0.625191	0.625547	0.718978	0.68626	0.588889
0.821194	0.727071	0.756842	0.749774	0.755422	0.770742	0.799281	0.772313	0.771329	0.75641	0.758564	0.764	0.816667	0.719868	0.692771	0.649618	0.683942	0.666423	0.674046	0.588889
0.775821	0.725455	0.731579	0.657466	0.680241	0.672926	0.698561	0.720195	0.732168	0.739316	0.634807	0.644	0.675	0.619205	0.581928	0.68626	0.660584	0.777372	0.637405	0.588889
0.716119	0.69798	0.708	0.688235	0.724578	0.651965	0.68705	0.722801	0.720979	0.708547	0.661326	0.684	0.670833	0.645695	0.63494	0.70458	0.672263	0.70146	0.68626	0.588889
0.708955	0.651111	0.665895	0.623077	0.64747	0.610044	0.678417	0.70456	0.70979	0.684615	0.612707	0.668	0.616667	0.428477	0.692771	0.692366	0.678102	0.765693	0.643511	0.588889
0.694627	0.709293	0.718105	0.728054	0.720723	0.60655	0.658273	0.678502	0.701399	0.691453	0.630387	0.628	0.629167	0.661589	0.668675	0.649618	0.654745	0.648905	0.637405	0.588889
0.754328	0.691515	0.692842	0.626697	0.682169	0.711354	0.695683	0.691531	0.681818	0.725641	0.634807	0.668	0.695833	0.672185	0.639759	0.680153	0.608029	0.672263	0.570229	0.588889
0.785373	0.717374	0.765263	0.715385	0.736145	0.721834	0.730216	0.756678	0.734965	0.718803	0.683425	0.7	0.7	0.677483	0.750602	0.70458	0.69562	0.724818	0.759542	0.588889
0.718507	0.675354	0.692842	0.677376	0.709157	0.631004	0.672662	0.707166	0.712587	0.691453	0.639227	0.68	0.675	0.635099	0.610843	0.692366	0.654745	0.707299	0.655725	0.588889
0.744776	0.693131	0.708	0.680995	0.680241	0.728821	0.733094	0.741042	0.734965	0.711966	0.701105	0.732	0.7	0.74106	0.659036	0.60687	0.625547	0.648905	0.661832	0.588889
0.711343	0.743232	0.755158	0.724434	0.753494	0.739301	0.802158	0.808795	0.807692	0.824786	0.732044	0.792	0.829167	0.772848	0.707229	0.783969	0.771533	0.748175	0.747328	0.588889
0.771045	0.683434	0.706316	0.695475	0.705301	0.610044	0.661151	0.668078	0.673427	0.67094	0.705525	0.716	0.6875	0.698675	0.736145	0.722901	0.736496	0.754015	0.698473	0.588889

0.692239	0.652727	0.660842	0.648416	0.643614	0.631004	0.620863	0.636808	0.625874	0.640171	0.625967	0.596	0.5875	0.645695	0.610843	0.625191	0.643066	0.660584	0.637405	0.588889
0.766269	0.722222	0.729895	0.668326	0.695663	0.683406	0.730216	0.743648	0.762937	0.711966	0.643646	0.692	0.670833	0.598013	0.625301	0.661832	0.637226	0.736496	0.649618	0.633333
0.744776	0.709293	0.697895	0.657466	0.655181	0.725328	0.738849	0.78013	0.76014	0.735897	0.656906	0.744	0.708333	0.666887	0.615663	0.649618	0.613869	0.578832	0.643511	0.633333
0.773433	0.764242	0.778737	0.778733	0.770843	0.763755	0.810791	0.816612	0.813287	0.776923	0.785083	0.812	0.795833	0.71457	0.798795	0.771756	0.789051	0.829927	0.582443	0.633333
0.668358	0.686667	0.738316	0.688235	0.666747	0.679913	0.698561	0.730619	0.737762	0.698291	0.705525	0.724	0.758333	0.672185	0.683133	0.667939	0.707299	0.771533	0.68626	0.633333
0.72806	0.665657	0.692842	0.604977	0.657108	0.634498	0.684173	0.709772	0.712587	0.691453	0.612707	0.664	0.658333	0.454967	0.731325	0.680153	0.689781	0.730657	0.643511	0.633333
0.759104	0.723838	0.741684	0.735294	0.724578	0.728821	0.733094	0.730619	0.698601	0.705128	0.679006	0.728	0.704167	0.71457	0.750602	0.759542	0.771533	0.783212	0.759542	0.633333
0.787761	0.720606	0.719789	0.666516	0.695663	0.718341	0.721583	0.720195	0.706993	0.776923	0.687845	0.712	0.725	0.703974	0.740964	0.722901	0.69562	0.713139	0.625191	0.633333
0.780597	0.756162	0.783789	0.771493	0.738072	0.760262	0.747482	0.764495	0.793706	0.783761	0.709945	0.776	0.808333	0.809934	0.692771	0.722901	0.713139	0.713139	0.741221	0.633333
0.725672	0.725455	0.728211	0.704525	0.666747	0.683406	0.704317	0.725407	0.718182	0.701709	0.608287	0.664	0.645833	0.576821	0.586747	0.649618	0.713139	0.660584	0.68626	0.633333
0.754328	0.772323	0.797263	0.749774	0.751566	0.70786	0.779137	0.795765	0.804895	0.759829	0.692265	0.7	0.670833	0.709272	0.644578	0.680153	0.672263	0.765693	0.649618	0.633333
0.799701	0.804646	0.792211	0.804072	0.797831	0.777729	0.764748	0.769707	0.793706	0.763248	0.683425	0.696	0.7125	0.677483	0.731325	0.753435	0.771533	0.812409	0.735115	0.633333
0.878507	0.9	0.9	0.9	0.9	0.9	0.9	0.881759	0.9	0.886325	0.9	0.876	0.9	0.815232	0.871084	0.790076	0.824088	0.870803	0.710687	0.633333
0.675522	0.64303	0.638947	0.566968	0.574217	0.60655	0.620863	0.688925	0.667832	0.64359	0.603867	0.648	0.625	0.497351	0.644578	0.674046	0.631387	0.654745	0.655725	0.633333
0.701791	0.710909	0.729895	0.720814	0.686024	0.69738	0.715827	0.74886	0.743357	0.722222	0.621547	0.684	0.629167	0.629801	0.750602	0.692366	0.69562	0.70146	0.667939	0.633333
0.763881	0.693131	0.724842	0.680995	0.713012	0.704367	0.689928	0.694137	0.693007	0.681197	0.679006	0.648	0.654167	0.677483	0.745783	0.692366	0.689781	0.666423	0.729008	0.633333
0.694627	0.722222	0.743368	0.691855	0.670602	0.704367	0.747482	0.767101	0.746154	0.722222	0.785083	0.744	0.733333	0.725166	0.639759	0.70458	0.707299	0.718978	0.674046	0.677778

0.766269	0.704444	0.696211	0.677376	0.628193	0.655459	0.698561	0.688925	0.69021	0.647009	0.679006	0.648	0.65	0.560927	0.731325	0.783969	0.754015	0.771533	0.783969	0.677778
0.790149	0.735152	0.750105	0.700905	0.734217	0.756769	0.805036	0.821824	0.807692	0.794017	0.798343	0.784	0.791667	0.825828	0.755422	0.790076	0.80073	0.80073	0.783969	0.677778
0.720896	0.689899	0.713053	0.686425	0.693735	0.704367	0.68705	0.741042	0.701399	0.664103	0.590608	0.656	0.645833	0.582119	0.572289	0.619084	0.59635	0.60219	0.600763	0.677778
0.771045	0.715758	0.706316	0.666516	0.684096	0.714847	0.747482	0.733225	0.734965	0.705128	0.701105	0.692	0.6875	0.640397	0.712048	0.832824	0.847445	0.806569	0.777863	0.677778
0.72806	0.641414	0.686105	0.626697	0.653253	0.672926	0.689928	0.722801	0.70979	0.722222	0.643646	0.664	0.65	0.439073	0.707229	0.722901	0.718978	0.765693	0.667939	0.677778
0.790149	0.741616	0.763579	0.702715	0.759277	0.735808	0.770504	0.78013	0.754545	0.732479	0.740884	0.752	0.729167	0.71457	0.726506	0.777863	0.736496	0.771533	0.722901	0.677778
0.780597	0.773939	0.755158	0.731674	0.722651	0.690393	0.761871	0.782736	0.782517	0.773504	0.665746	0.644	0.679167	0.666887	0.755422	0.790076	0.742336	0.789051	0.722901	0.677778
0.771045	0.769091	0.778737	0.746154	0.724578	0.774236	0.761871	0.78013	0.790909	0.790598	0.714365	0.776	0.808333	0.778146	0.654217	0.70458	0.713139	0.718978	0.692366	0.677778
0.761493	0.788485	0.800632	0.760633	0.763133	0.746288	0.761871	0.798371	0.807692	0.763248	0.696685	0.732	0.716667	0.688079	0.683133	0.70458	0.70146	0.759854	0.649618	0.677778
0.749552	0.772323	0.793895	0.787783	0.770843	0.732314	0.758993	0.751466	0.765734	0.72906	0.736464	0.72	0.725	0.688079	0.726506	0.771756	0.724818	0.759854	0.722901	0.677778
0.778209	0.731919	0.751789	0.713575	0.678313	0.665939	0.695683	0.735831	0.673427	0.64359	0.727624	0.72	0.675	0.693377	0.716867	0.698473	0.678102	0.69562	0.649618	0.677778
0.735224	0.688283	0.672632	0.633937	0.657108	0.651965	0.735971	0.741042	0.723776	0.67094	0.639227	0.656	0.6375	0.322517	0.625301	0.70458	0.654745	0.70146	0.667939	0.677778
0.823582	0.759394	0.770316	0.738914	0.732289	0.718341	0.741727	0.74886	0.737762	0.688034	0.709945	0.692	0.720833	0.666887	0.726506	0.747328	0.730657	0.742336	0.729008	0.677778
0.737612	0.752929	0.748421	0.684615	0.713012	0.742795	0.761871	0.772313	0.757343	0.752991	0.705525	0.736	0.7125	0.698675	0.750602	0.851145	0.818248	0.847445	0.747328	0.677778
0.723284	0.688283	0.699579	0.693665	0.691807	0.721834	0.68705	0.74886	0.712587	0.667521	0.617127	0.66	0.670833	0.582119	0.56747	0.625191	0.572993	0.625547	0.594656	0.722222
0.892836	0.809495	0.802316	0.760633	0.793976	0.774236	0.796403	0.777524	0.771329	0.787179	0.771823	0.78	0.795833	0.725166	0.779518	0.820611	0.789051	0.80073	0.832824	0.722222
0.771045	0.743232	0.783789	0.796833	0.778554	0.704367	0.72446	0.738436	0.754545	0.763248	0.705525	0.7	0.654167	0.735762	0.687952	0.729008	0.70146	0.718978	0.735115	0.722222

0.708955	0.701212	0.736632	0.719005	0.709157	0.704367	0.681295	0.694137	0.69021	0.688034	0.656906	0.66	0.666667	0.709272	0.408434	0.729008	0.748175	0.777372	0.729008	0.722222
0.797313	0.773939	0.797263	0.782353	0.768916	0.784716	0.735971	0.756678	0.788112	0.800855	0.727624	0.8	0.8125	0.76755	0.678313	0.70458	0.69562	0.713139	0.716794	0.722222
0.766269	0.727071	0.746737	0.704525	0.707229	0.669432	0.753237	0.769707	0.77972	0.742735	0.674586	0.7	0.695833	0.656291	0.707229	0.674046	0.678102	0.742336	0.680153	0.722222
0.725672	0.675354	0.689474	0.680995	0.662892	0.658952	0.669784	0.681107	0.679021	0.688034	0.590608	0.648	0.708333	0.682781	0.591566	0.637405	0.555474	0.648905	0.643511	0.722222
0.809254	0.778788	0.790526	0.771493	0.776627	0.767249	0.793525	0.806189	0.782517	0.763248	0.776243	0.796	0.775	0.772848	0.726506	0.820611	0.829927	0.841606	0.790076	0.722222
0.861791	0.78202	0.778737	0.733484	0.766988	0.833624	0.848201	0.847883	0.824476	0.811111	0.780663	0.744	0.745833	0.730464	0.740964	0.808397	0.765693	0.794891	0.722901	0.722222
0.828358	0.741616	0.780421	0.749774	0.766988	0.746288	0.779137	0.774919	0.76014	0.746154	0.740884	0.752	0.725	0.688079	0.740964	0.777863	0.736496	0.783212	0.729008	0.722222
0.9	0.819192	0.783789	0.726244	0.774699	0.854585	0.885612	0.9	0.877622	0.831624	0.864641	0.892	0.8875	0.831126	0.63012	0.747328	0.759854	0.789051	0.674046	0.722222
0.775821	0.775556	0.817474	0.787783	0.80747	0.721834	0.733094	0.741042	0.737762	0.718803	0.683425	0.728	0.7	0.661589	0.779518	0.741221	0.783212	0.765693	0.759542	0.722222
0.689851	0.712525	0.743368	0.742534	0.751566	0.69738	0.744604	0.738436	0.712587	0.711966	0.723204	0.716	0.7125	0.661589	0.70241	0.70458	0.759854	0.713139	0.729008	0.722222
0.816418	0.819192	0.830947	0.811312	0.83253	0.819651	0.82518	0.845277	0.84965	0.783761	0.776243	0.784	0.725	0.672185	0.813253	0.820611	0.835766	0.894161	0.814504	0.722222
0.866567	0.78202	0.839368	0.787783	0.780482	0.770742	0.770504	0.787948	0.785315	0.770085	0.771823	0.736	0.745833	0.815232	0.731325	0.875573	0.80073	0.829927	0.80229	0.766667
0.842687	0.785253	0.836	0.809502	0.813253	0.739301	0.802158	0.832248	0.793706	0.794017	0.727624	0.74	0.720833	0.762252	0.716867	0.783969	0.742336	0.789051	0.765649	0.766667
0.756716	0.730303	0.738316	0.708145	0.757349	0.676419	0.721583	0.751466	0.751748	0.735897	0.665746	0.708	0.704167	0.666887	0.615663	0.759542	0.69562	0.736496	0.68626	0.766667
0.730448	0.673737	0.679368	0.641176	0.655181	0.651965	0.689928	0.730619	0.726573	0.718803	0.643646	0.672	0.6625	0.460265	0.716867	0.710687	0.718978	0.771533	0.661832	0.766667
0.9	0.819192	0.825895	0.785973	0.805542	0.78821	0.819424	0.785342	0.774126	0.800855	0.709945	0.752	0.779167	0.719868	0.76506	0.820611	0.812409	0.794891	0.838931	0.766667
0.794925	0.777172	0.790526	0.796833	0.788193	0.704367	0.730216	0.746254	0.762937	0.776923	0.679006	0.7	0.666667	0.725166	0.673494	0.765649	0.748175	0.754015	0.741221	0.766667

0.742388	0.683434	0.633895	0.576018	0.603133	0.672926	0.669784	0.688925	0.653846	0.602564	0.643646	0.628	0.566667	0.407285	0.581928	0.680153	0.625547	0.683942	0.655725	0.766667
0.852239	0.790101	0.812421	0.795023	0.80747	0.763755	0.810791	0.821824	0.818881	0.787179	0.789503	0.804	0.7875	0.672185	0.707229	0.826718	0.80073	0.853285	0.759542	0.766667
0.771045	0.798182	0.815789	0.766063	0.76506	0.714847	0.770504	0.814007	0.816084	0.790598	0.727624	0.704	0.7125	0.682781	0.716867	0.710687	0.70146	0.748175	0.661832	0.766667
0.704179	0.693131	0.694526	0.690045	0.69759	0.760262	0.698561	0.751466	0.757343	0.75641	0.674586	0.704	0.708333	0.703974	0.683133	0.753435	0.742336	0.754015	0.741221	0.766667
0.673134	0.668889	0.684421	0.655656	0.666747	0.711354	0.715827	0.730619	0.712587	0.67094	0.683425	0.708	0.675	0.635099	0.721687	0.753435	0.689781	0.683942	0.716794	0.811111
0.892836	0.846667	0.871368	0.831222	0.840241	0.819651	0.836691	0.840065	0.821678	0.790598	0.780663	0.784	0.758333	0.666887	0.808434	0.826718	0.829927	0.806569	0.790076	0.811111
0.787761	0.733535	0.753474	0.737104	0.732289	0.700873	0.770504	0.754072	0.748951	0.722222	0.732044	0.72	0.679167	0.624503	0.731325	0.735115	0.765693	0.777372	0.667939	0.811111
0.797313	0.791717	0.827579	0.816742	0.83253	0.774236	0.782014	0.785342	0.802098	0.776923	0.661326	0.72	0.716667	0.703974	0.726506	0.790076	0.806569	0.841606	0.747328	0.811111
0.854627	0.791717	0.841053	0.807692	0.826747	0.739301	0.819424	0.845277	0.796503	0.787179	0.727624	0.764	0.729167	0.788742	0.736145	0.790076	0.724818	0.824088	0.771756	0.811111
0.725672	0.731919	0.768632	0.738914	0.741928	0.624017	0.692806	0.725407	0.729371	0.674359	0.603867	0.604	0.6125	0.492053	0.649398	0.667939	0.689781	0.736496	0.722901	0.811111
0.766269	0.714141	0.765263	0.720814	0.741928	0.711354	0.733094	0.782736	0.757343	0.698291	0.670166	0.672	0.6875	0.582119	0.721687	0.814504	0.765693	0.771533	0.796183	0.811111
0.809254	0.790101	0.834316	0.789593	0.780482	0.70786	0.82518	0.866124	0.841259	0.817949	0.736464	0.816	0.8	0.709272	0.56747	0.60687	0.771533	0.824088	0.60687	0.811111
0.785373	0.741616	0.734947	0.719005	0.699518	0.721834	0.756115	0.754072	0.746154	0.722222	0.705525	0.704	0.704167	0.661589	0.707229	0.838931	0.829927	0.829927	0.832824	0.811111
0.82597	0.769091	0.790526	0.773303	0.772771	0.760262	0.793525	0.814007	0.802098	0.759829	0.789503	0.808	0.791667	0.76755	0.731325	0.875573	0.835766	0.864964	0.771756	0.811111
0.744776	0.662424	0.686105	0.626697	0.687952	0.693886	0.721583	0.756678	0.723776	0.752991	0.648066	0.648	0.670833	0.756954	0.654217	0.680153	0.718978	0.765693	0.759542	0.855556
0.716119	0.752929	0.804	0.766063	0.757349	0.6869	0.735971	0.74886	0.768531	0.739316	0.679006	0.704	0.729167	0.672185	0.625301	0.722901	0.683942	0.742336	0.692366	0.855556
0.778209	0.738384	0.758526	0.737104	0.722651	0.714847	0.735971	0.722801	0.723776	0.701709	0.732044	0.708	0.7375	0.698675	0.644578	0.70458	0.678102	0.69562	0.692366	0.855556

0.718507	0.709293	0.726526	0.709955	0.726506	0.679913	0.71295	0.722801	0.701399	0.667521	0.705525	0.664	0.704167	0.71457	0.70241	0.753435	0.754015	0.748175	0.741221	0.855556
0.787761	0.762626	0.748421	0.738914	0.753494	0.795197	0.784892	0.79316	0.765734	0.790598	0.727624	0.772	0.758333	0.783444	0.673494	0.759542	0.748175	0.777372	0.747328	0.855556
0.773433	0.762626	0.778737	0.793213	0.801687	0.791703	0.770504	0.78013	0.790909	0.759829	0.789503	0.78	0.783333	0.809934	0.827711	0.765649	0.818248	0.876642	0.783969	0.855556
0.742388	0.714141	0.699579	0.652036	0.643614	0.662445	0.664029	0.709772	0.665035	0.636752	0.581768	0.644	0.616667	0.523841	0.63494	0.70458	0.69562	0.713139	0.68626	0.855556
0.873731	0.817576	0.851158	0.769683	0.788193	0.861572	0.856835	0.881759	0.84965	0.862393	0.767403	0.852	0.829167	0.87351	0.9	0.851145	0.847445	0.888321	0.838931	0.855556
0.685075	0.66404	0.691158	0.652036	0.664819	0.683406	0.698561	0.730619	0.718182	0.694872	0.701105	0.688	0.679167	0.629801	0.716867	0.759542	0.70146	0.678102	0.735115	0.855556
0.754328	0.775556	0.785474	0.775113	0.728434	0.69738	0.72446	0.769707	0.762937	0.718803	0.648066	0.696	0.704167	0.629801	0.76506	0.741221	0.754015	0.754015	0.722901	0.855556
0.790149	0.769091	0.809053	0.798643	0.776627	0.704367	0.761871	0.808795	0.799301	0.790598	0.771823	0.748	0.775	0.815232	0.846988	0.881679	0.829927	0.882482	0.796183	0.9
0.864179	0.835354	0.836	0.796833	0.826747	0.861572	0.876978	0.892182	0.863636	0.9	0.89558	0.9	0.870833	0.9	0.880723	0.9	0.9	0.9	0.9	0.9
0.725672	0.694747	0.728211	0.702715	0.686024	0.690393	0.756115	0.733225	0.734965	0.698291	0.679006	0.72	0.75	0.698675	0.687952	0.716794	0.637226	0.707299	0.680153	0.9
0.718507	0.710909	0.718105	0.688235	0.659036	0.599563	0.664029	0.712378	0.693007	0.602564	0.625967	0.656	0.641667	0.545033	0.659036	0.643511	0.631387	0.660584	0.631298	0.9
0.744776	0.693131	0.733263	0.726244	0.711084	0.742795	0.715827	0.741042	0.726573	0.718803	0.692265	0.724	0.716667	0.730464	0.822892	0.790076	0.806569	0.853285	0.753435	0.9
0.744776	0.746465	0.758526	0.742534	0.734217	0.714847	0.735971	0.738436	0.720979	0.711966	0.714365	0.764	0.7	0.703974	0.789157	0.783969	0.794891	0.777372	0.771756	0.9
0.799701	0.720606	0.721474	0.664706	0.709157	0.739301	0.735971	0.733225	0.729371	0.770085	0.679006	0.708	0.725	0.71457	0.606024	0.741221	0.69562	0.730657	0.625191	0.9
0.885672	0.801414	0.829263	0.795023	0.786265	0.868559	0.845324	0.881759	0.863636	0.848718	0.789503	0.872	0.8375	0.862914	0.895181	0.863359	0.847445	0.859124	0.869466	0.9
0.756716	0.743232	0.760211	0.733484	0.766988	0.69738	0.730216	0.761889	0.765734	0.725641	0.648066	0.72	0.6875	0.703974	0.639759	0.759542	0.707299	0.748175	0.710687	0.9
0.682687	0.67697	0.699579	0.666516	0.674458	0.679913	0.715827	0.735831	0.720979	0.694872	0.701105	0.712	0.683333	0.619205	0.707229	0.747328	0.678102	0.689781	0.70458	0.9

APPENDIX H

NORMALIZED DATASET OF INPUT FEATURES AND TARGET FEATURES FOR MALE HISPANIC POPULATION FOR FEATURE SELECTION USING GA APPROACH

1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	Age
0.124299	0.124516	0.123491	0.118944	0.126154	0.128387	0.131549	0.124365	0.136856	0.12392	0.137559	0.146693	0.156667	0.12623	0.141509	0.137427	0.150286	0.127586	0.110063	0.1
0.171028	0.160645	0.169168	0.162659	0.183077	0.192903	0.187887	0.183249	0.197561	0.200997	0.201408	0.215175	0.206667	0.178689	0.209434	0.198246	0.218857	0.21954	0.17044	0.1
0.172897	0.194194	0.187439	0.196175	0.18	0.185161	0.199155	0.195431	0.204065	0.18505	0.205164	0.205837	0.21	0.200546	0.216981	0.202924	0.191429	0.224138	0.190566	0.1
0.193458	0.216129	0.2031	0.19326	0.198462	0.187742	0.223944	0.221827	0.240921	0.224917	0.205164	0.208949	0.216667	0.200546	0.190566	0.15614	0.173143	0.145977	0.120126	0.1
0.320561	0.369677	0.351876	0.346266	0.36	0.314194	0.368169	0.400508	0.407859	0.408306	0.385446	0.39572	0.41	0.384153	0.318868	0.277778	0.305714	0.302299	0.276101	0.144444
0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.144444
0.23271	0.278065	0.247471	0.253005	0.243077	0.234194	0.291549	0.288832	0.271274	0.264784	0.238967	0.240078	0.25	0.26612	0.326415	0.235673	0.237143	0.242529	0.230818	0.144444
0.223364	0.262581	0.244861	0.236976	0.238462	0.229032	0.302817	0.292893	0.310298	0.29402	0.269014	0.283658	0.273333	0.18306	0.330189	0.240351	0.26	0.270115	0.200629	0.144444
0.230841	0.248387	0.244861	0.254463	0.24	0.254839	0.284789	0.268528	0.282114	0.280731	0.257746	0.261868	0.28	0.257377	0.269811	0.259064	0.250857	0.26092	0.195597	0.144444
0.286916	0.305161	0.281403	0.264663	0.270769	0.285806	0.350141	0.343655	0.357995	0.344518	0.347887	0.345914	0.356667	0.331694	0.349057	0.263743	0.305714	0.311494	0.250943	0.188889
0.290654	0.329677	0.32186	0.321494	0.324615	0.309032	0.372676	0.374112	0.390515	0.35515	0.389202	0.392607	0.41	0.362295	0.364151	0.324561	0.328571	0.352874	0.296226	0.188889
0.281308	0.323226	0.314029	0.309836	0.306154	0.270323	0.347887	0.349746	0.357995	0.339203	0.31784	0.317899	0.33	0.287978	0.379245	0.291813	0.356	0.33908	0.281132	0.188889
0.324299	0.358065	0.357096	0.343352	0.352308	0.288387	0.370423	0.36599	0.384011	0.363123	0.374178	0.370817	0.39	0.331694	0.349057	0.282456	0.333143	0.33908	0.261006	0.188889

0.3	0.33871	0.308809	0.306922	0.303077	0.290968	0.354648	0.337563	0.353659	0.328571	0.31784	0.317899	0.336667	0.253005	0.383019	0.287135	0.342286	0.343678	0.276101	0.188889
0.350467	0.368387	0.347961	0.357923	0.343077	0.309032	0.354648	0.359898	0.375339	0.339203	0.374178	0.349027	0.363333	0.305464	0.367925	0.361988	0.273714	0.343678	0.255975	0.233333
0.316822	0.385161	0.380587	0.373953	0.364615	0.306452	0.417746	0.428934	0.453388	0.413621	0.377934	0.426848	0.43	0.384153	0.39434	0.324561	0.282857	0.32069	0.276101	0.233333
0.118692	0.146452	0.144372	0.139344	0.14	0.13871	0.142817	0.132487	0.141192	0.126578	0.130047	0.14358	0.146667	0.134973	0.160377	0.132749	0.141143	0.141379	0.120126	0.233333
0.376636	0.390323	0.366232	0.371038	0.341538	0.37871	0.433521	0.426904	0.433875	0.416279	0.385446	0.401946	0.413333	0.340437	0.413208	0.324561	0.374286	0.389655	0.37673	0.233333
0.309346	0.386452	0.374062	0.362295	0.335385	0.386452	0.426761	0.404569	0.405691	0.381728	0.434272	0.408171	0.416667	0.314208	0.428302	0.366667	0.383429	0.385057	0.351572	0.233333
0.371028	0.416129	0.421044	0.413297	0.401538	0.350323	0.444789	0.441117	0.440379	0.413621	0.426761	0.41751	0.43	0.406011	0.443396	0.404094	0.392571	0.385057	0.396855	0.277778
0.329907	0.398065	0.388418	0.395811	0.376923	0.332258	0.431268	0.443147	0.455556	0.418937	0.456808	0.470428	0.47	0.397268	0.435849	0.446199	0.424571	0.458621	0.416981	0.277778
0.356075	0.414839	0.398858	0.400182	0.396923	0.337419	0.410986	0.404569	0.412195	0.392359	0.404225	0.364591	0.363333	0.327322	0.454717	0.436842	0.438286	0.435632	0.422013	0.277778
0.447664	0.516774	0.526754	0.526958	0.512308	0.471613	0.494366	0.516244	0.535772	0.485382	0.456808	0.470428	0.486667	0.427869	0.503774	0.41345	0.470286	0.463218	0.381761	0.277778
0.283178	0.360645	0.345351	0.340437	0.313846	0.26	0.332113	0.325381	0.327642	0.296678	0.344131	0.336576	0.32	0.218033	0.35283	0.282456	0.292	0.371264	0.245912	0.277778
0.45514	0.490968	0.469331	0.46867	0.444615	0.37871	0.456056	0.445178	0.446883	0.424252	0.456808	0.4393	0.453333	0.414754	0.466038	0.436842	0.438286	0.467816	0.416981	0.322222
0.393458	0.416129	0.402773	0.384153	0.392308	0.332258	0.42	0.441117	0.446883	0.35515	0.449296	0.451751	0.466667	0.449727	0.450943	0.352632	0.342286	0.458621	0.442138	0.322222
0.460748	0.474194	0.457586	0.45847	0.436923	0.396774	0.512394	0.510152	0.531436	0.482724	0.535681	0.542023	0.543333	0.493443	0.541509	0.511696	0.488571	0.509195	0.467296	0.322222
0.43271	0.422581	0.394943	0.391439	0.355385	0.383871	0.417746	0.404569	0.412195	0.365781	0.404225	0.392607	0.38	0.301093	0.443396	0.422807	0.410857	0.417241	0.386792	0.322222
0.481308	0.481935	0.482382	0.46867	0.469231	0.396774	0.501127	0.481726	0.485908	0.456146	0.494366	0.495331	0.513333	0.502186	0.503774	0.44152	0.470286	0.486207	0.432075	0.322222
0.427103	0.49871	0.483687	0.508015	0.496923	0.456129	0.546197	0.522335	0.531436	0.51196	0.535681	0.532685	0.546667	0.56776	0.481132	0.427485	0.438286	0.463218	0.406918	0.322222

0.464486	0.483226	0.469331	0.459927	0.470769	0.425161	0.494366	0.477665	0.485908	0.480066	0.460563	0.4393	0.463333	0.419126	0.466038	0.44152	0.438286	0.444828	0.396855	0.322222
0.408411	0.429032	0.409299	0.391439	0.404615	0.38129	0.401972	0.422843	0.427371	0.387043	0.370423	0.408171	0.423333	0.384153	0.428302	0.376023	0.383429	0.412644	0.371698	0.322222
0.382243	0.462581	0.441925	0.430783	0.418462	0.352903	0.46507	0.449239	0.466396	0.413621	0.407981	0.414397	0.423333	0.309836	0.443396	0.380702	0.424571	0.431034	0.391824	0.322222
0.434579	0.546452	0.526754	0.525501	0.509231	0.492258	0.530423	0.520305	0.533604	0.506645	0.535681	0.532685	0.576667	0.537158	0.564151	0.511696	0.511429	0.532184	0.512579	0.366667
0.556075	0.546452	0.533279	0.525501	0.530769	0.476774	0.559718	0.550761	0.570461	0.549169	0.535681	0.526459	0.54	0.515301	0.567925	0.530409	0.534286	0.541379	0.477358	0.366667
0.5	0.515484	0.534584	0.519672	0.504615	0.407097	0.548451	0.54264	0.550949	0.498671	0.546948	0.542023	0.553333	0.54153	0.567925	0.530409	0.538857	0.527586	0.502516	0.366667
0.458879	0.502581	0.512398	0.506557	0.483077	0.404516	0.50338	0.5	0.535772	0.482724	0.486854	0.482879	0.516667	0.480328	0.477358	0.44152	0.447429	0.435632	0.477358	0.366667
0.443925	0.438065	0.447145	0.439526	0.424615	0.389032	0.42	0.418782	0.433875	0.408306	0.392958	0.420623	0.446667	0.366667	0.420755	0.408772	0.415429	0.421839	0.386792	0.366667
0.483178	0.490968	0.492822	0.484699	0.469231	0.448387	0.50338	0.481726	0.490244	0.453488	0.464319	0.445525	0.456667	0.423497	0.488679	0.436842	0.474857	0.5	0.452201	0.366667
0.423364	0.426452	0.436705	0.429326	0.412308	0.370968	0.462817	0.463452	0.453388	0.421595	0.456808	0.429961	0.44	0.388525	0.428302	0.394737	0.410857	0.435632	0.422013	0.366667
0.483178	0.516774	0.496737	0.481785	0.470769	0.432903	0.469577	0.467513	0.477236	0.461462	0.479343	0.504669	0.506667	0.480328	0.496226	0.44152	0.456571	0.477011	0.416981	0.366667
0.492523	0.528387	0.522838	0.521129	0.518462	0.45871	0.510141	0.512183	0.511924	0.525249	0.505634	0.495331	0.506667	0.462842	0.567925	0.488304	0.465714	0.504598	0.477358	0.366667
0.556075	0.583871	0.580261	0.572131	0.570769	0.523226	0.568732	0.567005	0.570461	0.543854	0.614554	0.601167	0.58	0.528415	0.571698	0.516374	0.538857	0.545977	0.467296	0.411111
0.471963	0.493548	0.484992	0.480328	0.464615	0.443226	0.50338	0.487817	0.498916	0.461462	0.543192	0.529572	0.516667	0.440984	0.518868	0.432164	0.442857	0.477011	0.41195	0.411111
0.516822	0.523226	0.505873	0.515301	0.5	0.456129	0.50338	0.514213	0.520596	0.469435	0.479343	0.476654	0.503333	0.440984	0.492453	0.427485	0.447429	0.449425	0.452201	0.411111
0.5	0.518065	0.512398	0.516758	0.518462	0.453548	0.521408	0.546701	0.553117	0.503987	0.565728	0.588716	0.593333	0.462842	0.601887	0.535088	0.575429	0.582759	0.527673	0.411111
0.503738	0.519355	0.512398	0.491985	0.490769	0.481935	0.523662	0.495939	0.492412	0.493355	0.561972	0.5607	0.54	0.510929	0.549057	0.492982	0.493143	0.536782	0.512579	0.411111

0.535514	0.559355	0.54633	0.545902	0.524615	0.525806	0.548451	0.530457	0.540108	0.517276	0.580751	0.566926	0.566667	0.572131	0.567925	0.567836	0.538857	0.555172	0.527673	0.411111
0.537383	0.516774	0.500653	0.496357	0.486154	0.494839	0.483099	0.481726	0.50542	0.477409	0.513146	0.495331	0.523333	0.524044	0.545283	0.507018	0.493143	0.509195	0.492453	0.411111
0.578505	0.561935	0.571126	0.586703	0.553846	0.479355	0.521408	0.540609	0.557453	0.514618	0.516901	0.510895	0.543333	0.489071	0.583019	0.544444	0.557143	0.591954	0.55283	0.411111
0.528037	0.532258	0.526754	0.499271	0.501538	0.507742	0.564225	0.546701	0.555285	0.503987	0.55446	0.557588	0.566667	0.554645	0.579245	0.511696	0.534286	0.55977	0.51761	0.411111
0.479439	0.485806	0.490212	0.487614	0.449231	0.42	0.471831	0.473604	0.470732	0.421595	0.460563	0.4393	0.443333	0.366667	0.503774	0.455556	0.452	0.458621	0.442138	0.411111
0.507477	0.529677	0.512398	0.512386	0.504615	0.445806	0.492113	0.479695	0.503252	0.458804	0.498122	0.473541	0.463333	0.43224	0.526415	0.460234	0.484	0.495402	0.427044	0.455556
0.514953	0.543871	0.55155	0.573588	0.573846	0.471613	0.525915	0.514213	0.535772	0.509302	0.50939	0.485992	0.486667	0.410383	0.564151	0.544444	0.520571	0.550575	0.532704	0.455556
0.584112	0.551613	0.56199	0.570674	0.553846	0.481935	0.586761	0.577157	0.609485	0.557143	0.546948	0.585603	0.586667	0.532787	0.598113	0.516374	0.534286	0.550575	0.532704	0.455556
0.582243	0.558065	0.558075	0.547359	0.526154	0.515484	0.595775	0.585279	0.594309	0.554485	0.558216	0.563813	0.586667	0.519672	0.601887	0.553801	0.570857	0.573563	0.537736	0.455556
0.526168	0.516774	0.534584	0.532787	0.538462	0.450968	0.557465	0.54264	0.574797	0.549169	0.55446	0.538911	0.55	0.532787	0.541509	0.525731	0.511429	0.518391	0.497484	0.455556
0.576636	0.58129	0.56199	0.521129	0.546154	0.520645	0.58	0.560914	0.581301	0.570432	0.588263	0.598054	0.59	0.475956	0.643396	0.55848	0.557143	0.587356	0.567925	0.455556
0.514953	0.502581	0.515008	0.513843	0.5	0.487097	0.532676	0.524365	0.53794	0.509302	0.535681	0.576265	0.573333	0.524044	0.55283	0.516374	0.516	0.527586	0.502516	0.455556
0.576636	0.58129	0.595922	0.57796	0.555385	0.520645	0.552958	0.550761	0.561789	0.519934	0.561972	0.526459	0.5	0.440984	0.567925	0.553801	0.584571	0.578161	0.532704	0.455556
0.520561	0.528387	0.525449	0.502186	0.487692	0.510323	0.53493	0.510152	0.54878	0.519934	0.580751	0.542023	0.56	0.528415	0.616981	0.530409	0.543429	0.541379	0.492453	0.455556
0.571028	0.564516	0.563295	0.563388	0.564615	0.471613	0.552958	0.579188	0.587805	0.53588	0.50939	0.520233	0.53	0.45847	0.598113	0.577193	0.534286	0.55977	0.502516	0.455556
0.571028	0.565806	0.576346	0.569217	0.543077	0.494839	0.557465	0.550761	0.566125	0.522591	0.588263	0.545136	0.536667	0.56776	0.59434	0.549123	0.525143	0.545977	0.512579	0.5
0.701869	0.687097	0.663785	0.669763	0.68	0.616129	0.672394	0.674619	0.676694	0.631561	0.667136	0.672763	0.66	0.56776	0.658491	0.638012	0.676	0.66092	0.567925	0.5

0.548598	0.521935	0.517618	0.502186	0.513846	0.456129	0.521408	0.530457	0.529268	0.485382	0.483099	0.495331	0.493333	0.384153	0.545283	0.502339	0.511429	0.532184	0.502516	0.5
0.585981	0.564516	0.580261	0.589617	0.567692	0.507742	0.570986	0.573096	0.594309	0.543854	0.55446	0.5607	0.573333	0.532787	0.696226	0.55848	0.634857	0.656322	0.58805	0.5
0.65514	0.656129	0.657259	0.662477	0.629231	0.543871	0.577746	0.629949	0.618157	0.527907	0.464319	0.526459	0.516667	0.309836	0.598113	0.535088	0.593714	0.633333	0.507547	0.5
0.600935	0.589032	0.622023	0.602732	0.570769	0.530968	0.627324	0.601523	0.644173	0.591694	0.603286	0.62607	0.696667	0.628962	0.601887	0.567836	0.625714	0.647126	0.598113	0.5
0.54486	0.561935	0.56199	0.537158	0.523077	0.510323	0.570986	0.567005	0.561789	0.527907	0.513146	0.548249	0.526667	0.45847	0.586792	0.502339	0.529714	0.509195	0.497484	0.5
0.61215	0.617419	0.598532	0.586703	0.603077	0.58	0.629577	0.611675	0.615989	0.594352	0.670892	0.60428	0.61	0.550273	0.711321	0.656725	0.666857	0.683908	0.663522	0.5
0.621495	0.600645	0.602447	0.57796	0.56	0.587742	0.600282	0.603553	0.594309	0.583721	0.584507	0.591829	0.606667	0.65082	0.628302	0.567836	0.575429	0.596552	0.593082	0.5
0.561682	0.568387	0.593312	0.576503	0.556923	0.533548	0.566479	0.575127	0.579133	0.570432	0.573239	0.573152	0.586667	0.589617	0.616981	0.567836	0.584571	0.591954	0.562893	0.5
0.526168	0.532258	0.535889	0.535701	0.518462	0.492258	0.528169	0.534518	0.544444	0.517276	0.498122	0.489105	0.51	0.462842	0.616981	0.58655	0.543429	0.568966	0.547799	0.544444
0.636449	0.625161	0.616803	0.61439	0.598462	0.494839	0.620563	0.627919	0.646341	0.607641	0.588263	0.613619	0.643333	0.598361	0.635849	0.58655	0.621143	0.628736	0.603145	0.544444
0.628972	0.629032	0.635073	0.621676	0.595385	0.533548	0.62507	0.611675	0.613821	0.57309	0.610798	0.622957	0.623333	0.545902	0.586792	0.507018	0.548	0.582759	0.406918	0.544444
0.705607	0.630323	0.619413	0.596903	0.590769	0.592903	0.636338	0.615736	0.639837	0.626246	0.633333	0.619844	0.636667	0.642077	0.613208	0.577193	0.584571	0.578161	0.593082	0.544444
0.578505	0.551613	0.55677	0.56776	0.515385	0.497419	0.58	0.575127	0.585637	0.501329	0.565728	0.5607	0.583333	0.506557	0.598113	0.577193	0.616571	0.633333	0.567925	0.544444
0.619626	0.617419	0.625938	0.621676	0.583077	0.543871	0.634085	0.629949	0.633333	0.581063	0.592019	0.579377	0.583333	0.506557	0.692453	0.591228	0.602857	0.628736	0.628302	0.544444
0.524299	0.555484	0.54894	0.545902	0.523077	0.476774	0.568732	0.581218	0.583469	0.543854	0.501878	0.529572	0.526667	0.454098	0.59434	0.507018	0.538857	0.550575	0.502516	0.544444
0.591589	0.592903	0.568515	0.557559	0.553846	0.528387	0.58	0.579188	0.576965	0.53588	0.55446	0.570039	0.576667	0.54153	0.590566	0.549123	0.529714	0.591954	0.522642	0.544444
0.63271	0.57871	0.560685	0.548816	0.567692	0.600645	0.595775	0.556853	0.576965	0.543854	0.633333	0.598054	0.616667	0.537158	0.571698	0.58655	0.593714	0.633333	0.613208	0.544444

0.602804	0.654839	0.66248	0.653734	0.635385	0.569677	0.622817	0.652284	0.67019	0.602326	0.667136	0.66965	0.676667	0.642077	0.673585	0.666082	0.666857	0.670115	0.633333	0.544444
0.597196	0.62129	0.620718	0.611475	0.610769	0.577419	0.573239	0.595431	0.607317	0.602326	0.580751	0.601167	0.616667	0.633333	0.616981	0.591228	0.602857	0.637931	0.648428	0.544444
0.627103	0.634194	0.632463	0.637705	0.596923	0.54129	0.645352	0.67665	0.67019	0.623588	0.610798	0.660311	0.646667	0.628962	0.639623	0.628655	0.634857	0.642529	0.62327	0.544444
0.606542	0.573548	0.572431	0.56776	0.549231	0.523226	0.566479	0.567005	0.563957	0.509302	0.584507	0.594942	0.58	0.528415	0.635849	0.600585	0.625714	0.656322	0.593082	0.588889
0.585981	0.600645	0.611582	0.589617	0.595385	0.507742	0.570986	0.583249	0.594309	0.591694	0.580751	0.585603	0.603333	0.611475	0.658491	0.609942	0.634857	0.61954	0.633333	0.588889
0.608411	0.625161	0.636378	0.62459	0.624615	0.585161	0.634085	0.640102	0.655014	0.623588	0.637089	0.660311	0.68	0.642077	0.703774	0.689474	0.644	0.66092	0.683648	0.588889
0.696262	0.674194	0.66248	0.662477	0.636923	0.647097	0.721972	0.713198	0.71355	0.655482	0.644601	0.650973	0.633333	0.510929	0.677358	0.605263	0.680571	0.670115	0.577987	0.588889
0.664486	0.641935	0.637684	0.630419	0.615385	0.549032	0.62507	0.603553	0.628997	0.634219	0.652113	0.657198	0.653333	0.668306	0.666038	0.64269	0.653143	0.647126	0.598113	0.588889
0.800935	0.782581	0.769494	0.767395	0.770769	0.724516	0.780563	0.778173	0.793767	0.740532	0.764789	0.766148	0.783333	0.642077	0.760377	0.736257	0.785714	0.748276	0.703774	0.588889
0.599065	0.608387	0.611582	0.612933	0.576923	0.549032	0.604789	0.605584	0.609485	0.583721	0.61831	0.588716	0.61	0.607104	0.624528	0.628655	0.666857	0.67931	0.678616	0.588889
0.314953	0.292258	0.289233	0.286521	0.296923	0.272903	0.278028	0.266497	0.282114	0.262126	0.27277	0.252529	0.253333	0.253005	0.296226	0.268421	0.250857	0.242529	0.240881	0.588889
0.328037	0.306452	0.299674	0.285064	0.295385	0.288387	0.291549	0.290863	0.29729	0.283389	0.314085	0.317899	0.336667	0.301093	0.345283	0.319883	0.328571	0.352874	0.316352	0.588889
0.814019	0.747742	0.761664	0.74408	0.72	0.670323	0.726479	0.733503	0.743902	0.708638	0.72723	0.703891	0.736667	0.712022	0.764151	0.680117	0.648571	0.734483	0.688679	0.588889
0.630841	0.640645	0.614192	0.602732	0.62	0.525806	0.604789	0.619797	0.633333	0.583721	0.576995	0.576265	0.593333	0.572131	0.654717	0.61462	0.602857	0.610345	0.633333	0.588889
0.56729	0.53871	0.563295	0.554645	0.535385	0.484516	0.528169	0.540609	0.550949	0.509302	0.528169	0.538911	0.563333	0.493443	0.55283	0.535088	0.520571	0.550575	0.502516	0.588889
0.664486	0.645806	0.636378	0.623133	0.607692	0.528387	0.58	0.577157	0.592141	0.557143	0.588263	0.601167	0.633333	0.620219	0.635849	0.595906	0.625714	0.633333	0.638365	0.588889
0.668224	0.647097	0.637684	0.62459	0.643077	0.564516	0.638592	0.611675	0.644173	0.583721	0.640845	0.622957	0.643333	0.602732	0.677358	0.661404	0.639429	0.642529	0.628302	0.588889

0.645794	0.697419	0.696411	0.704736	0.672308	0.634194	0.649859	0.672589	0.698374	0.655482	0.700939	0.716342	0.723333	0.720765	0.726415	0.703509	0.703429	0.729885	0.713836	0.633333
0.681308	0.675484	0.689886	0.682878	0.649231	0.605806	0.679155	0.688832	0.683198	0.647508	0.723474	0.722568	0.736667	0.703279	0.722642	0.689474	0.708	0.72069	0.703774	0.633333
0.784112	0.769677	0.723817	0.728051	0.713846	0.745161	0.758028	0.737563	0.767751	0.732558	0.761033	0.756809	0.73	0.611475	0.7	0.717544	0.717143	0.706897	0.718868	0.633333
0.836449	0.813548	0.820392	0.803825	0.778462	0.763226	0.807606	0.81269	0.826287	0.775083	0.768545	0.750584	0.793333	0.764481	0.854717	0.694152	0.753714	0.817241	0.749057	0.633333
0.657009	0.714194	0.715987	0.717851	0.673846	0.662581	0.665634	0.692893	0.70271	0.671429	0.72723	0.716342	0.753333	0.73388	0.737736	0.708187	0.721714	0.748276	0.738994	0.633333
0.72243	0.702581	0.729038	0.713479	0.689231	0.654839	0.712958	0.715228	0.72439	0.68206	0.776056	0.750584	0.776667	0.738251	0.779245	0.717544	0.730857	0.743678	0.738994	0.633333
0.778505	0.782581	0.736868	0.70765	0.730769	0.758065	0.767042	0.749746	0.778591	0.732558	0.757277	0.756809	0.76	0.633333	0.711321	0.740936	0.744571	0.729885	0.713836	0.633333
0.726168	0.70129	0.718597	0.722222	0.707692	0.605806	0.735493	0.719289	0.728726	0.687375	0.72723	0.756809	0.756667	0.698907	0.771698	0.726901	0.744571	0.665517	0.744025	0.633333
0.757944	0.78129	0.777325	0.774681	0.773846	0.711613	0.796338	0.806599	0.793767	0.788372	0.640845	0.735019	0.726667	0.628962	0.783019	0.623977	0.589143	0.66092	0.643396	0.633333
0.748598	0.727097	0.717292	0.691621	0.696923	0.750323	0.758028	0.707107	0.730894	0.7299	0.693427	0.731907	0.75	0.742623	0.760377	0.703509	0.721714	0.757471	0.728931	0.633333
0.642056	0.657419	0.638989	0.612933	0.606154	0.569677	0.613803	0.629949	0.615989	0.589037	0.584507	0.585603	0.6	0.489071	0.662264	0.661404	0.703429	0.716092	0.653459	0.633333
0.741121	0.719355	0.725122	0.701821	0.696923	0.685806	0.755775	0.749746	0.748238	0.764452	0.723474	0.731907	0.76	0.799454	0.771698	0.745614	0.735429	0.73908	0.779245	0.633333
0.623364	0.608387	0.603752	0.602732	0.6	0.556774	0.62507	0.609645	0.611653	0.607641	0.595775	0.594942	0.56	0.545902	0.673585	0.67076	0.648571	0.674713	0.648428	0.633333
0.752336	0.715484	0.727732	0.700364	0.724615	0.696129	0.749014	0.763959	0.791599	0.751163	0.72723	0.731907	0.746667	0.729508	0.730189	0.740936	0.730857	0.757471	0.754088	0.633333
0.739252	0.702581	0.706852	0.693078	0.673846	0.672903	0.721972	0.711168	0.722222	0.700664	0.693427	0.66965	0.68	0.685792	0.737736	0.656725	0.653143	0.688506	0.683648	0.633333
0.701869	0.721935	0.713377	0.710565	0.670769	0.654839	0.721972	0.72335	0.730894	0.698007	0.689671	0.688327	0.703333	0.729508	0.756604	0.745614	0.753714	0.771264	0.779245	0.677778
0.720561	0.724516	0.719902	0.703279	0.695385	0.649677	0.681408	0.680711	0.678862	0.64485	0.678404	0.660311	0.696667	0.668306	0.737736	0.656725	0.666857	0.683908	0.658491	0.677778

0.681308	0.65871	0.653344	0.637705	0.649231	0.585161	0.647606	0.63401	0.648509	0.615615	0.667136	0.622957	0.616667	0.572131	0.786792	0.661404	0.612	0.665517	0.648428	0.677778
0.752336	0.683226	0.650734	0.643534	0.661538	0.662581	0.706197	0.715228	0.730894	0.687375	0.712207	0.707004	0.716667	0.646448	0.696226	0.623977	0.680571	0.688506	0.688679	0.677778
0.868224	0.840645	0.841272	0.832969	0.809231	0.773548	0.82338	0.828934	0.843631	0.812292	0.813615	0.775486	0.833333	0.808197	0.866038	0.712865	0.772	0.854023	0.769182	0.677778
0.705607	0.663871	0.674225	0.662477	0.641538	0.636774	0.688169	0.698985	0.689702	0.652824	0.700939	0.703891	0.68	0.611475	0.681132	0.619298	0.598286	0.61954	0.633333	0.677778
0.76729	0.758065	0.742088	0.720765	0.706154	0.724516	0.791831	0.772081	0.750407	0.735216	0.746009	0.778599	0.756667	0.703279	0.824528	0.745614	0.804	0.798851	0.738994	0.677778
0.757944	0.770968	0.777325	0.771767	0.730769	0.721935	0.758028	0.72132	0.776423	0.761794	0.79108	0.738132	0.77	0.768852	0.798113	0.745614	0.74	0.757471	0.769182	0.677778
0.785981	0.763226	0.736868	0.720765	0.718462	0.768387	0.767042	0.753807	0.776423	0.743189	0.783568	0.775486	0.763333	0.642077	0.715094	0.726901	0.653143	0.725287	0.718868	0.677778
0.714953	0.776129	0.766884	0.755738	0.746154	0.667742	0.721972	0.737563	0.752575	0.716611	0.607042	0.660311	0.71	0.593989	0.673585	0.703509	0.804	0.785057	0.774214	0.677778
0.815888	0.804516	0.795595	0.758652	0.76	0.745161	0.789577	0.776142	0.785095	0.761794	0.753521	0.787938	0.78	0.698907	0.832075	0.740936	0.744571	0.752874	0.769182	0.677778
0.670093	0.634194	0.646819	0.644991	0.661538	0.649677	0.681408	0.701015	0.709214	0.692691	0.667136	0.678988	0.706667	0.703279	0.760377	0.694152	0.689714	0.702299	0.713836	0.677778
0.795327	0.77871	0.755139	0.748452	0.76	0.74	0.758028	0.751777	0.756911	0.756478	0.753521	0.741245	0.786667	0.712022	0.741509	0.731579	0.772	0.762069	0.799371	0.677778
0.759813	0.770968	0.742088	0.741166	0.756923	0.768387	0.803099	0.804569	0.798103	0.764452	0.734742	0.756809	0.74	0.755738	0.779245	0.740936	0.758286	0.798851	0.764151	0.677778
0.716822	0.662581	0.67553	0.672678	0.690769	0.641935	0.683662	0.674619	0.69187	0.666113	0.674648	0.675875	0.686667	0.65082	0.75283	0.731579	0.698857	0.729885	0.723899	0.677778
0.793458	0.770968	0.756444	0.732423	0.729231	0.74	0.794085	0.786294	0.772087	0.756478	0.697183	0.763035	0.783333	0.712022	0.828302	0.722222	0.808571	0.803448	0.769182	0.722222
0.780374	0.764516	0.756444	0.74408	0.746154	0.760645	0.787324	0.792386	0.806775	0.772425	0.749765	0.719455	0.763333	0.760109	0.828302	0.726901	0.804	0.831034	0.733962	0.722222
0.85514	0.854839	0.824307	0.818397	0.809231	0.845806	0.870704	0.859391	0.880488	0.812292	0.9	0.9	0.813333	0.773224	0.828302	0.839181	0.831429	0.867816	0.804403	0.722222
0.733645	0.760645	0.752529	0.752823	0.718462	0.69871	0.771549	0.757868	0.769919	0.748505	0.764789	0.741245	0.75	0.768852	0.779245	0.778363	0.790286	0.817241	0.82956	0.722222

0.729907	0.752903	0.747308	0.738251	0.724615	0.737419	0.776056	0.745685	0.754743	0.745847	0.7723	0.707004	0.706667	0.725137	0.756604	0.689474	0.749143	0.725287	0.718868	0.722222
0.815888	0.817419	0.823002	0.818397	0.804615	0.760645	0.805352	0.822843	0.828455	0.780399	0.832394	0.794163	0.813333	0.781967	0.775472	0.783041	0.790286	0.794253	0.814465	0.722222
0.337383	0.332258	0.333605	0.33898	0.343077	0.30129	0.316338	0.319289	0.349322	0.309967	0.347887	0.33035	0.326667	0.336066	0.326415	0.310526	0.310286	0.311494	0.316352	0.722222
0.836449	0.817419	0.828222	0.831512	0.816923	0.752903	0.839155	0.837056	0.854472	0.820266	0.832394	0.859533	0.853333	0.720765	0.84717	0.801754	0.826857	0.812644	0.844654	0.722222
0.728037	0.773548	0.762969	0.752823	0.74	0.683226	0.721972	0.745685	0.754743	0.727243	0.584507	0.660311	0.696667	0.593989	0.760377	0.708187	0.790286	0.789655	0.799371	0.722222
0.802804	0.736129	0.697716	0.701821	0.704615	0.709032	0.751268	0.753807	0.763415	0.7299	0.753521	0.747471	0.753333	0.681421	0.707547	0.675439	0.717143	0.725287	0.698742	0.722222
0.834579	0.787742	0.774715	0.781967	0.786154	0.789032	0.830141	0.822843	0.837127	0.841528	0.794836	0.781712	0.84	0.79071	0.756604	0.689474	0.694286	0.752874	0.713836	0.722222
0.9	0.879355	0.9	0.891257	0.9	0.879355	0.868451	0.849239	0.880488	0.87608	0.824883	0.822179	0.85	0.799454	0.816981	0.778363	0.790286	0.785057	0.809434	0.722222
0.827103	0.764516	0.755139	0.755738	0.769231	0.801935	0.805352	0.798477	0.813279	0.775083	0.817371	0.859533	0.816667	0.786339	0.850943	0.769006	0.790286	0.794253	0.759119	0.722222
0.83271	0.790323	0.77863	0.745537	0.744615	0.758065	0.791831	0.790355	0.808943	0.783056	0.779812	0.784825	0.763333	0.746995	0.707547	0.703509	0.758286	0.743678	0.804403	0.722222
0.800935	0.777419	0.760359	0.730965	0.727692	0.750323	0.818873	0.782234	0.776423	0.756478	0.719718	0.744358	0.756667	0.712022	0.820755	0.750292	0.822286	0.831034	0.723899	0.766667
0.802804	0.804516	0.813866	0.811111	0.795385	0.791613	0.890986	0.891878	0.9	0.9	0.843662	0.809728	0.853333	0.79071	0.839623	0.801754	0.817714	0.789655	0.86478	0.766667
0.838318	0.733548	0.726427	0.741166	0.716923	0.729677	0.760282	0.737563	0.761247	0.743189	0.787324	0.772374	0.76	0.738251	0.677358	0.609942	0.689714	0.757471	0.643396	0.766667
0.808411	0.734839	0.704241	0.698907	0.712308	0.719355	0.755775	0.772081	0.767751	0.737874	0.761033	0.753696	0.76	0.681421	0.733962	0.666082	0.735429	0.716092	0.708805	0.766667
0.791589	0.789032	0.773409	0.755738	0.784615	0.742581	0.839155	0.820812	0.863144	0.844186	0.877465	0.853307	0.876667	0.9	0.75283	0.759649	0.790286	0.794253	0.789308	0.766667
0.838318	0.749032	0.730343	0.748452	0.723077	0.750323	0.771549	0.743655	0.774255	0.761794	0.794836	0.775486	0.77	0.73388	0.666038	0.595906	0.694286	0.752874	0.663522	0.766667
0.720561	0.751613	0.748613	0.742623	0.736923	0.745161	0.773803	0.753807	0.763415	0.756478	0.79108	0.71323	0.726667	0.738251	0.760377	0.722222	0.753714	0.757471	0.738994	0.766667

0.853271	0.893548	0.884339	0.895628	0.88	0.721935	0.848169	0.863452	0.841463	0.780399	0.715962	0.772374	0.75	0.580874	0.9	0.867251	0.858857	0.872414	0.854717	0.766667
0.821495	0.82	0.785155	0.80674	0.78	0.750323	0.812113	0.818782	0.793767	0.775083	0.79108	0.738132	0.746667	0.712022	0.866038	0.815789	0.849714	0.821839	0.849686	0.766667
0.763551	0.752903	0.748613	0.742623	0.736923	0.74	0.798592	0.814721	0.830623	0.785714	0.79108	0.822179	0.866667	0.694536	0.850943	0.829825	0.872571	0.886207	0.879874	0.766667
0.870093	0.839355	0.813866	0.818397	0.832308	0.807097	0.836901	0.81066	0.830623	0.820266	0.877465	0.843969	0.876667	0.81694	0.775472	0.764327	0.804	0.817241	0.744025	0.811111
0.817757	0.839355	0.873899	0.86357	0.801538	0.78129	0.841408	0.853299	0.865312	0.809635	0.806103	0.819066	0.87	0.786339	0.733962	0.792398	0.822286	0.858621	0.854717	0.811111
0.763551	0.769677	0.757749	0.751366	0.736923	0.69871	0.726479	0.790355	0.806775	0.764452	0.746009	0.710117	0.696667	0.70765	0.771698	0.684795	0.685143	0.67931	0.749057	0.811111
0.847664	0.826452	0.821697	0.795082	0.809231	0.760645	0.818873	0.832995	0.832791	0.801661	0.794836	0.81284	0.833333	0.821311	0.877358	0.825146	0.872571	0.881609	0.889937	0.811111
0.750467	0.73871	0.729038	0.717851	0.744615	0.693548	0.728732	0.717259	0.739566	0.708638	0.761033	0.728794	0.726667	0.668306	0.828302	0.731579	0.698857	0.734483	0.754088	0.811111
0.81028	0.804516	0.812561	0.821311	0.790769	0.804516	0.9	0.9	0.9	0.9	0.83615	0.803502	0.85	0.799454	0.839623	0.801754	0.817714	0.817241	0.889937	0.811111
0.830841	0.813548	0.833442	0.831512	0.815385	0.755484	0.848169	0.851269	0.858808	0.825581	0.869953	0.875097	0.873333	0.746995	0.749057	0.801754	0.817714	0.817241	0.839623	0.811111
0.868224	0.9	0.885644	0.9	0.887692	0.752903	0.821127	0.861421	0.847967	0.775083	0.768545	0.775486	0.74	0.56776	0.866038	0.9	0.890857	0.886207	0.9	0.811111
0.720561	0.69871	0.710767	0.690164	0.669231	0.647097	0.708451	0.717259	0.704878	0.674086	0.712207	0.722568	0.7	0.633333	0.677358	0.675439	0.630286	0.642529	0.648428	0.811111
0.823364	0.863871	0.868679	0.857741	0.830769	0.82	0.852676	0.865482	0.869648	0.862791	0.862441	0.850195	0.85	0.847541	0.884906	0.853216	0.826857	0.858621	0.804403	0.811111
0.799065	0.759355	0.777325	0.779053	0.746154	0.742581	0.771549	0.774112	0.793767	0.740532	0.768545	0.772374	0.76	0.672678	0.779245	0.703509	0.772	0.766667	0.764151	0.855556
0.890654	0.827742	0.843883	0.844627	0.798462	0.786452	0.870704	0.867513	0.880488	0.825581	0.851174	0.828405	0.843333	0.830055	0.873585	0.731579	0.831429	0.854023	0.834591	0.855556
0.81215	0.747742	0.753834	0.752823	0.750769	0.745161	0.78507	0.802538	0.798103	0.753821	0.749765	0.744358	0.753333	0.768852	0.775472	0.778363	0.794857	0.794253	0.804403	0.855556
0.819626	0.843226	0.851713	0.846084	0.826154	0.763226	0.821127	0.841117	0.858808	0.81495	0.843662	0.847082	0.863333	0.812568	0.881132	0.857895	0.9	0.9	0.894969	0.855556

0.838318	0.796774	0.813866	0.802368	0.792308	0.765806	0.82338	0.808629	0.806775	0.793688	0.806103	0.784825	0.833333	0.803825	0.84717	0.839181	0.826857	0.9	0.814465	0.855556
0.83271	0.800645	0.799511	0.792168	0.807692	0.74	0.789577	0.804569	0.817615	0.788372	0.783568	0.775486	0.773333	0.73388	0.798113	0.726901	0.735429	0.743678	0.759119	0.855556
0.821495	0.773548	0.79168	0.776138	0.758462	0.729677	0.746761	0.776142	0.776423	0.761794	0.700939	0.735019	0.766667	0.773224	0.726415	0.67076	0.653143	0.706897	0.683648	0.855556
0.81215	0.790323	0.772104	0.763024	0.750769	0.690968	0.744507	0.751777	0.752575	0.713953	0.723474	0.719455	0.743333	0.655191	0.749057	0.773684	0.799429	0.812644	0.789308	0.855556
0.799065	0.763226	0.772104	0.763024	0.755385	0.70129	0.708451	0.731472	0.754743	0.724585	0.697183	0.694553	0.703333	0.685792	0.733962	0.769006	0.804	0.794253	0.749057	0.855556
0.821495	0.834194	0.79168	0.822769	0.792308	0.760645	0.803099	0.822843	0.789431	0.775083	0.783568	0.763035	0.76	0.725137	0.858491	0.797076	0.826857	0.817241	0.834591	0.855556
0.838318	0.822581	0.807341	0.795082	0.789231	0.745161	0.791831	0.782234	0.774255	0.775083	0.798592	0.778599	0.793333	0.764481	0.764151	0.726901	0.726286	0.729885	0.723899	0.9
0.873832	0.832903	0.803426	0.808197	0.810769	0.9	0.863944	0.867513	0.871816	0.846844	0.824883	0.884436	0.9	0.821311	0.809434	0.811111	0.813143	0.854023	0.834591	0.9
0.76729	0.755484	0.747308	0.751366	0.735385	0.690968	0.737746	0.763959	0.748238	0.737874	0.738498	0.769261	0.743333	0.681421	0.828302	0.820468	0.836	0.858621	0.809434	0.9
0.793458	0.792903	0.757749	0.754281	0.781538	0.732258	0.767042	0.794416	0.817615	0.788372	0.742254	0.725681	0.793333	0.834426	0.75283	0.759649	0.772	0.803448	0.824528	0.9
0.866355	0.834194	0.809951	0.821311	0.832308	0.822581	0.839155	0.822843	0.843631	0.828239	0.877465	0.828405	0.87	0.81694	0.779245	0.783041	0.767429	0.798851	0.749057	0.9
0.804673	0.791613	0.77602	0.771767	0.743077	0.742581	0.751268	0.741624	0.743902	0.737874	0.719718	0.753696	0.723333	0.716393	0.741509	0.731579	0.698857	0.729885	0.754088	0.9
0.800935	0.77871	0.774715	0.748452	0.716923	0.742581	0.753521	0.753807	0.774255	0.772425	0.746009	0.707004	0.746667	0.742623	0.813208	0.787719	0.781143	0.766667	0.819497	0.9
0.800935	0.808387	0.78385	0.811111	0.784615	0.724516	0.807606	0.796447	0.832791	0.783056	0.798592	0.769261	0.796667	0.720765	0.79434	0.84386	0.863429	0.890805	0.824528	0.9
0.845794	0.885806	0.837357	0.815483	0.850769	0.758065	0.818873	0.843147	0.826287	0.793688	0.832394	0.859533	0.826667	0.720765	0.828302	0.778363	0.790286	0.826437	0.819497	0.9
0.821495	0.830323	0.795595	0.796539	0.787692	0.804516	0.86169	0.865482	0.837127	0.830897	0.892488	0.843969	0.833333	0.803825	0.828302	0.825146	0.826857	0.817241	0.849686	0.9

APPENDIX I

GENERATED CSV FILE OF DATASET OF LATEST POPULATION FOR FEMALE HISPANIC POPULATION AFTER FEATURE SELECTION USING GA APPROACH

# Bone 1	Bone 2	Bone 3	Bone 4	Bone 5	Bone 6	Bone 7	Bone 8	Bone 9	Bone10	Bone11	Bone12	Bone13	Bone14	Bone15	Bone16	Bone17	Bone18	Bone19
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APPENDIX J

GENERATED CSV FILE OF DATASET OF LATEST POPULATION FOR MALE HISPANIC POPULATION AFTER FEATURE SELECTION USING GA APPROACH

# Bone1	Bone2	Bone3	Bone4	Bone5	Bone6	Bone7	Bone8	Bone9	Bone10	Bone11	Bone12	Bone13	Bone14	Bone15	Bone16	Bone17	Bone18	Bone19
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1	0	0	0	0	0	1	0	0	0	0	0	1	1	1	1	0	0	1
1	0	0	0	0	0	1	0	0	0	0	0	1	1	1	1	0	0	1
1	0	0	0	0	0	1	0	0	0	0	0	1	1	1	1	0	0	1
1	0	0	0	0	0	1	0	0	0	0	0	1	1	1	1	0	0	1
1	0	0	0	0	0	1	0	0	0	0	0	1	1	1	1	0	0	1
1	0	0	0	0	0	1	0	0	0	0	0	1	1	1	1	0	0	1
1	0	0	0	0	0	1	0	0	0	0	0	1	1	1	1	0	0	1
1	0	0	0	0	0	1	0	0	0	0	0	1	1	1	1	0	0	1
1	0	0	0	0	0	1	0	0	0	0	0	1	1	1	1	0	0	1

1	0	0	0	0	0	1	0	0	0	0	0	1	1	1	1	0	0	1
1	0	0	0	0	0	1	0	0	0	0	0	1	1	1	1	0	0	1
1	0	0	0	0	0	1	0	0	0	0	0	1	1	1	1	0	0	1
1	0	0	0	0	0	1	0	0	0	0	0	1	1	1	1	0	0	1
1	0	0	0	0	0	1	0	0	0	0	0	1	1	1	1	0	0	1
1	0	0	0	0	0	1	0	0	0	0	0	1	1	1	1	0	0	1

APPENDIX K

NORMALIZED TRAINING DATASET OF SELECTED INPUT FEATURES AND SELECTED TARGET FEATURES FOR FEMALE HISPANIC POPULATION USING GA-ANN APPROACH

4	5	6	11	15	16	18	19	Age
0.121719	0.140482	0.113974	0.11326	0.1	0.1	0.158394	0.148855	0.1
0.214027	0.198313	0.173362	0.228177	0.239759	0.173282	0.216788	0.148855	0.144444
0.125339	0.123133	0.106987	0.139779	0.124096	0.185496	0.193431	0.148855	0.144444
0.210407	0.188675	0.1	0.1	0.153012	0.112214	0.164234	0.136641	0.144444
0.259276	0.229157	0.169869	0.263536	0.181928	0.240458	0.275182	0.228244	0.188889
0.235747	0.238795	0.180349	0.276796	0.201205	0.191603	0.234307	0.185496	0.188889
0.313575	0.304337	0.278166	0.329834	0.287952	0.173282	0.187591	0.191603	0.233333
0.371493	0.379518	0.260699	0.303315	0.355422	0.270992	0.275182	0.289313	0.233333
0.360633	0.375663	0.323581	0.329834	0.437349	0.39313	0.432847	0.277099	0.233333
0.375113	0.366024	0.21179	0.356354	0.350602	0.19771	0.257664	0.203817	0.233333
0.376923	0.406506	0.274672	0.298895	0.321687	0.154962	0.234307	0.234351	0.233333
0.407692	0.383373	0.299127	0.343094	0.360241	0.258779	0.391971	0.222137	0.277778
0.387783	0.404578	0.288646	0.294475	0.422892	0.350382	0.374453	0.319847	0.277778
0.322624	0.358313	0.222271	0.329834	0.316867	0.277099	0.362774	0.234351	0.277778
0.366063	0.36988	0.278166	0.382873	0.36988	0.41145	0.444526	0.29542	0.277778
0.398643	0.396867	0.299127	0.343094	0.36988	0.234351	0.281022	0.246565	0.277778
0.451131	0.452771	0.306114	0.329834	0.326506	0.380916	0.421168	0.387023	0.322222
0.463801	0.479759	0.435371	0.360773	0.461446	0.31374	0.356934	0.319847	0.322222
0.452941	0.475904	0.29214	0.276796	0.254217	0.289313	0.316058	0.29542	0.322222
0.478281	0.47012	0.29214	0.404972	0.30241	0.332061	0.345255	0.29542	0.322222
0.375113	0.366024	0.39345	0.404972	0.43253	0.307634	0.292701	0.289313	0.322222
0.404072	0.39494	0.194323	0.365193	0.422892	0.283206	0.292701	0.264885	0.322222
0.434842	0.402651	0.267686	0.378453	0.408434	0.332061	0.333577	0.270992	0.322222
0.398643	0.398795	0.257205	0.307735	0.321687	0.270992	0.386131	0.29542	0.322222
0.398643	0.410361	0.264192	0.374033	0.360241	0.277099	0.356934	0.222137	0.322222
0.51448	0.510602	0.39345	0.48895	0.490361	0.325954	0.485401	0.240458	0.366667

0.460181	0.472048	0.372489	0.404972	0.442169	0.325954	0.380292	0.325954	0.366667
0.460181	0.473976	0.379476	0.440331	0.312048	0.362595	0.485401	0.448092	0.366667
0.452941	0.456627	0.358515	0.404972	0.485542	0.344275	0.386131	0.344275	0.366667
0.48914	0.491325	0.330568	0.440331	0.490361	0.368702	0.40365	0.356489	0.366667
0.452941	0.481687	0.355022	0.431492	0.446988	0.39313	0.415328	0.454198	0.366667
0.561538	0.545301	0.372489	0.475691	0.350602	0.350382	0.508759	0.332061	0.411111
0.612217	0.593494	0.487773	0.577348	0.581928	0.423664	0.462044	0.332061	0.411111
0.49819	0.522169	0.571616	0.612707	0.610843	0.619084	0.643066	0.600763	0.411111
0.548869	0.562651	0.484279	0.541989	0.519277	0.350382	0.368613	0.332061	0.411111
0.50724	0.527952	0.351528	0.533149	0.533735	0.551908	0.514599	0.338168	0.411111
0.603167	0.574217	0.529694	0.546409	0.577108	0.527481	0.427007	0.417557	0.455556
0.566968	0.574217	0.449345	0.581768	0.610843	0.612977	0.654745	0.60687	0.455556
0.543439	0.524096	0.501747	0.537569	0.586747	0.460305	0.60219	0.564122	0.455556
0.557919	0.533735	0.515721	0.590608	0.572289	0.515267	0.643066	0.441985	0.455556
0.583258	0.597349	0.578603	0.608287	0.581928	0.484733	0.619708	0.472519	0.455556
0.606787	0.595422	0.501747	0.572928	0.581928	0.429771	0.450365	0.399237	0.455556
0.635747	0.632048	0.536681	0.533149	0.591566	0.448092	0.613869	0.533588	0.455556
0.585068	0.583855	0.561135	0.586188	0.586747	0.448092	0.643066	0.478626	0.5
0.677376	0.687952	0.603057	0.670166	0.63494	0.631298	0.724818	0.661832	0.5
0.650226	0.624337	0.536681	0.564088	0.644578	0.661832	0.50292	0.631298	0.5
0.49638	0.508675	0.452838	0.475691	0.475904	0.521374	0.485401	0.496947	0.5
0.657466	0.651325	0.421397	0.51547	0.683133	0.655725	0.584672	0.667939	0.5
0.648416	0.662892	0.58559	0.692265	0.692771	0.710687	0.648905	0.643511	0.544444
0.617647	0.62241	0.58559	0.603867	0.668675	0.576336	0.648905	0.594656	0.544444
0.644796	0.653253	0.547162	0.559669	0.591566	0.521374	0.567153	0.551908	0.544444
0.646606	0.649398	0.693886	0.705525	0.736145	0.692366	0.713139	0.667939	0.544444
0.659276	0.686024	0.620524	0.603867	0.620482	0.674046	0.678102	0.643511	0.544444
0.594118	0.593494	0.491266	0.577348	0.615663	0.454198	0.643066	0.496947	0.544444
0.556109	0.53759	0.466812	0.48011	0.586747	0.441985	0.613869	0.435878	0.544444
0.671946	0.69759	0.620524	0.652486	0.760241	0.655725	0.713139	0.735115	0.544444
0.617647	0.62241	0.624017	0.705525	0.731325	0.649618	0.660584	0.619084	0.544444
0.619457	0.60506	0.58559	0.546409	0.639759	0.612977	0.672263	0.637405	0.544444
0.655656	0.655181	0.589083	0.572928	0.649398	0.655725	0.60219	0.576336	0.544444
0.652036	0.659036	0.617031	0.617127	0.553012	0.643511	0.69562	0.625191	0.588889

0.623077	0.64747	0.610044	0.612707	0.692771	0.692366	0.765693	0.643511	0.588889
0.626697	0.682169	0.711354	0.634807	0.639759	0.680153	0.672263	0.570229	0.588889
0.715385	0.736145	0.721834	0.683425	0.750602	0.70458	0.724818	0.759542	0.588889
0.677376	0.709157	0.631004	0.639227	0.610843	0.692366	0.707299	0.655725	0.588889
0.724434	0.753494	0.739301	0.732044	0.707229	0.783969	0.748175	0.747328	0.588889
0.695475	0.705301	0.610044	0.705525	0.736145	0.722901	0.754015	0.698473	0.588889
0.648416	0.643614	0.631004	0.625967	0.610843	0.625191	0.660584	0.637405	0.588889
0.668326	0.695663	0.683406	0.643646	0.625301	0.661832	0.736496	0.649618	0.633333
0.657466	0.655181	0.725328	0.656906	0.615663	0.649618	0.578832	0.643511	0.633333
0.778733	0.770843	0.763755	0.785083	0.798795	0.771756	0.829927	0.582443	0.633333
0.688235	0.666747	0.679913	0.705525	0.683133	0.667939	0.771533	0.68626	0.633333
0.604977	0.657108	0.634498	0.612707	0.731325	0.680153	0.730657	0.643511	0.633333
0.735294	0.724578	0.728821	0.679006	0.750602	0.759542	0.783212	0.759542	0.633333
0.666516	0.695663	0.718341	0.687845	0.740964	0.722901	0.713139	0.625191	0.633333
0.771493	0.738072	0.760262	0.709945	0.692771	0.722901	0.713139	0.741221	0.633333
0.704525	0.666747	0.683406	0.608287	0.586747	0.649618	0.660584	0.68626	0.633333
0.749774	0.751566	0.70786	0.692265	0.644578	0.680153	0.765693	0.649618	0.633333
0.9	0.9	0.9	0.9	0.871084	0.790076	0.870803	0.710687	0.633333
0.720814	0.686024	0.69738	0.621547	0.750602	0.692366	0.70146	0.667939	0.633333
0.680995	0.713012	0.704367	0.679006	0.745783	0.692366	0.666423	0.729008	0.633333
0.700905	0.734217	0.756769	0.798343	0.755422	0.790076	0.80073	0.783969	0.677778
0.666516	0.684096	0.714847	0.701105	0.712048	0.832824	0.806569	0.777863	0.677778
0.626697	0.653253	0.672926	0.643646	0.707229	0.722901	0.765693	0.667939	0.677778
0.702715	0.759277	0.735808	0.740884	0.726506	0.777863	0.771533	0.722901	0.677778
0.731674	0.722651	0.690393	0.665746	0.755422	0.790076	0.789051	0.722901	0.677778
0.760633	0.763133	0.746288	0.696685	0.683133	0.70458	0.759854	0.649618	0.677778
0.713575	0.678313	0.665939	0.727624	0.716867	0.698473	0.69562	0.649618	0.677778
0.633937	0.657108	0.651965	0.639227	0.625301	0.70458	0.70146	0.667939	0.677778
0.738914	0.732289	0.718341	0.709945	0.726506	0.747328	0.742336	0.729008	0.677778
0.684615	0.713012	0.742795	0.705525	0.750602	0.851145	0.847445	0.747328	0.677778
0.693665	0.691807	0.721834	0.617127	0.56747	0.625191	0.625547	0.594656	0.722222
0.796833	0.778554	0.704367	0.705525	0.687952	0.729008	0.718978	0.735115	0.722222
0.719005	0.709157	0.704367	0.656906	0.408434	0.729008	0.777372	0.729008	0.722222
0.782353	0.768916	0.784716	0.727624	0.678313	0.70458	0.713139	0.716794	0.722222

0.704525	0.707229	0.669432	0.674586	0.707229	0.674046	0.742336	0.680153	0.722222
0.680995	0.662892	0.658952	0.590608	0.591566	0.637405	0.648905	0.643511	0.722222
0.771493	0.776627	0.767249	0.776243	0.726506	0.820611	0.841606	0.790076	0.722222
0.749774	0.766988	0.746288	0.740884	0.740964	0.777863	0.783212	0.729008	0.722222
0.726244	0.774699	0.854585	0.864641	0.63012	0.747328	0.789051	0.674046	0.722222
0.787783	0.80747	0.721834	0.683425	0.779518	0.741221	0.765693	0.759542	0.722222
0.742534	0.751566	0.69738	0.723204	0.70241	0.70458	0.713139	0.729008	0.722222
0.811312	0.83253	0.819651	0.776243	0.813253	0.820611	0.894161	0.814504	0.722222
0.787783	0.780482	0.770742	0.771823	0.731325	0.875573	0.829927	0.80229	0.766667
0.809502	0.813253	0.739301	0.727624	0.716867	0.783969	0.789051	0.765649	0.766667
0.708145	0.757349	0.676419	0.665746	0.615663	0.759542	0.736496	0.68626	0.766667
0.796833	0.788193	0.704367	0.679006	0.673494	0.765649	0.754015	0.741221	0.766667
0.576018	0.603133	0.672926	0.643646	0.581928	0.680153	0.683942	0.655725	0.766667
0.795023	0.80747	0.763755	0.789503	0.707229	0.826718	0.853285	0.759542	0.766667
0.690045	0.69759	0.760262	0.674586	0.683133	0.753435	0.754015	0.741221	0.766667
0.655656	0.666747	0.711354	0.683425	0.721687	0.753435	0.683942	0.716794	0.811111
0.831222	0.840241	0.819651	0.780663	0.808434	0.826718	0.806569	0.790076	0.811111
0.737104	0.732289	0.700873	0.732044	0.731325	0.735115	0.777372	0.667939	0.811111
0.816742	0.83253	0.774236	0.661326	0.726506	0.790076	0.841606	0.747328	0.811111
0.807692	0.826747	0.739301	0.727624	0.736145	0.790076	0.824088	0.771756	0.811111
0.738914	0.741928	0.624017	0.603867	0.649398	0.667939	0.736496	0.722901	0.811111
0.720814	0.741928	0.711354	0.670166	0.721687	0.814504	0.771533	0.796183	0.811111
0.719005	0.699518	0.721834	0.705525	0.707229	0.838931	0.829927	0.832824	0.811111
0.773303	0.772771	0.760262	0.789503	0.731325	0.875573	0.864964	0.771756	0.811111
0.626697	0.687952	0.693886	0.648066	0.654217	0.680153	0.765693	0.759542	0.855556
0.766063	0.757349	0.6869	0.679006	0.625301	0.722901	0.742336	0.692366	0.855556
0.737104	0.722651	0.714847	0.732044	0.644578	0.70458	0.69562	0.692366	0.855556
0.793213	0.801687	0.791703	0.789503	0.827711	0.765649	0.876642	0.783969	0.855556
0.652036	0.643614	0.662445	0.581768	0.63494	0.70458	0.713139	0.68626	0.855556
0.769683	0.788193	0.861572	0.767403	0.9	0.851145	0.888321	0.838931	0.855556
0.702715	0.686024	0.690393	0.679006	0.687952	0.716794	0.707299	0.680153	0.9
0.688235	0.659036	0.599563	0.625967	0.659036	0.643511	0.660584	0.631298	0.9
0.742534	0.734217	0.714847	0.714365	0.789157	0.783969	0.777372	0.771756	0.9
0.664706	0.709157	0.739301	0.679006	0.606024	0.741221	0.730657	0.625191	0.9

APPENDIX L

NORMALIZED TEST DATASET OF SELECTED INPUT FEATURES AND SELECTED TARGET FEATURES FOR FEMALE HISPANIC POPULATION USING GA-ANN APPROACH

4	5	6	11	15	16	18	19	Age
0.1	0.1	0.1	0.130939	0.124096	0.179389	0.158394	0.148855	0.144444
0.212217	0.211807	0.141921	0.126519	0.220482	0.148855	0.19927	0.1	0.144444
0.291855	0.312048	0.222271	0.325414	0.312048	0.344275	0.345255	0.240458	0.188889
0.232127	0.225301	0.145415	0.192818	0.148193	0.19771	0.19927	0.148855	0.188889
0.188688	0.194458	0.131441	0.148619	0.215663	0.142748	0.1	0.142748	0.188889
0.465611	0.46241	0.344541	0.325414	0.5	0.325954	0.327737	0.338168	0.322222
0.454751	0.44506	0.337555	0.466851	0.451807	0.448092	0.444526	0.319847	0.366667
0.451131	0.472048	0.29214	0.400552	0.413253	0.356489	0.485401	0.350382	0.366667
0.409502	0.414217	0.41441	0.334254	0.446988	0.350382	0.386131	0.362595	0.366667
0.456561	0.473976	0.41441	0.400552	0.524096	0.380916	0.467883	0.356489	0.366667
0.547059	0.543373	0.389956	0.546409	0.533735	0.362595	0.351095	0.454198	0.411111
0.49276	0.551084	0.491266	0.50221	0.514458	0.399237	0.543796	0.50916	0.411111
0.541629	0.547229	0.49476	0.546409	0.572289	0.496947	0.543796	0.374809	0.411111
0.49457	0.493253	0.466812	0.471271	0.509639	0.423664	0.49708	0.332061	0.411111
0.532579	0.520241	0.466812	0.387293	0.519277	0.429771	0.520438	0.515267	0.411111
0.50181	0.520241	0.466812	0.546409	0.519277	0.374809	0.537956	0.521374	0.455556
0.5	0.522169	0.484279	0.458011	0.533735	0.527481	0.520438	0.545802	0.455556
0.612217	0.626265	0.459825	0.625967	0.615663	0.649618	0.637226	0.619084	0.5
0.668326	0.67253	0.655459	0.639227	0.557831	0.58855	0.467883	0.576336	0.5
0.592308	0.616627	0.547162	0.559669	0.610843	0.710687	0.707299	0.661832	0.5
0.670136	0.691807	0.644978	0.643646	0.668675	0.70458	0.660584	0.625191	0.5
0.592308	0.612771	0.49476	0.537569	0.56747	0.545802	0.561314	0.503053	0.5
0.619457	0.639759	0.582096	0.577348	0.610843	0.60687	0.60219	0.594656	0.544444
0.673756	0.670602	0.644978	0.652486	0.70241	0.759542	0.736496	0.70458	0.544444
0.585068	0.587711	0.543668	0.625967	0.586747	0.600763	0.643066	0.558015	0.544444
0.566968	0.562651	0.543668	0.634807	0.644578	0.619084	0.660584	0.551908	0.588889

0.661086	0.676386	0.669432	0.612707	0.721687	0.625191	0.718978	0.68626	0.588889
0.749774	0.755422	0.770742	0.758564	0.692771	0.649618	0.666423	0.674046	0.588889
0.657466	0.680241	0.672926	0.634807	0.581928	0.68626	0.777372	0.637405	0.588889
0.688235	0.724578	0.651965	0.661326	0.63494	0.70458	0.70146	0.68626	0.588889
0.728054	0.720723	0.60655	0.630387	0.668675	0.649618	0.648905	0.637405	0.588889
0.680995	0.680241	0.728821	0.701105	0.659036	0.60687	0.648905	0.661832	0.588889
0.804072	0.797831	0.777729	0.683425	0.731325	0.753435	0.812409	0.735115	0.633333
0.566968	0.574217	0.60655	0.603867	0.644578	0.674046	0.654745	0.655725	0.633333
0.691855	0.670602	0.704367	0.785083	0.639759	0.70458	0.718978	0.674046	0.677778
0.677376	0.628193	0.655459	0.679006	0.731325	0.783969	0.771533	0.783969	0.677778
0.686425	0.693735	0.704367	0.590608	0.572289	0.619084	0.60219	0.600763	0.677778
0.746154	0.724578	0.774236	0.714365	0.654217	0.70458	0.718978	0.692366	0.677778
0.787783	0.770843	0.732314	0.736464	0.726506	0.771756	0.759854	0.722901	0.677778
0.760633	0.793976	0.774236	0.771823	0.779518	0.820611	0.80073	0.832824	0.722222
0.733484	0.766988	0.833624	0.780663	0.740964	0.808397	0.794891	0.722901	0.722222
0.641176	0.655181	0.651965	0.643646	0.716867	0.710687	0.771533	0.661832	0.766667
0.785973	0.805542	0.78821	0.709945	0.76506	0.820611	0.794891	0.838931	0.766667
0.766063	0.76506	0.714847	0.727624	0.716867	0.710687	0.748175	0.661832	0.766667
0.789593	0.780482	0.70786	0.736464	0.56747	0.60687	0.824088	0.60687	0.811111
0.709955	0.726506	0.679913	0.705525	0.70241	0.753435	0.748175	0.741221	0.855556
0.738914	0.753494	0.795197	0.727624	0.673494	0.759542	0.777372	0.747328	0.855556
0.652036	0.664819	0.683406	0.701105	0.716867	0.759542	0.678102	0.735115	0.855556
0.775113	0.728434	0.69738	0.648066	0.76506	0.741221	0.754015	0.722901	0.855556
0.798643	0.776627	0.704367	0.771823	0.846988	0.881679	0.882482	0.796183	0.9
0.796833	0.826747	0.861572	0.89558	0.880723	0.9	0.9	0.9	0.9
0.726244	0.711084	0.742795	0.692265	0.822892	0.790076	0.853285	0.753435	0.9
0.795023	0.786265	0.868559	0.789503	0.895181	0.863359	0.859124	0.869466	0.9
0.733484	0.766988	0.69738	0.648066	0.639759	0.759542	0.748175	0.710687	0.9
0.666516	0.674458	0.679913	0.701105	0.707229	0.747328	0.689781	0.70458	0.9

APPENDIX M

NORMALIZED TRAINING DATASET OF SELECTED INPUT FEATURES AND SELECTED TARGET FEATURES FOR MALE HISPANIC POPULATION USING GA-ANN APPROACH

1	7	13	14	15	16	19	Age
0.124299	0.131549	0.156667	0.12623	0.141509	0.137427	0.110063	0.1
0.172897	0.199155	0.21	0.200546	0.216981	0.202924	0.190566	0.1
0.193458	0.223944	0.216667	0.200546	0.190566	0.15614	0.120126	0.1
0.320561	0.368169	0.41	0.384153	0.318868	0.277778	0.276101	0.144444
0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.144444
0.23271	0.291549	0.25	0.26612	0.326415	0.235673	0.230818	0.144444
0.223364	0.302817	0.273333	0.18306	0.330189	0.240351	0.200629	0.144444
0.230841	0.284789	0.28	0.257377	0.269811	0.259064	0.195597	0.144444
0.281308	0.347887	0.33	0.287978	0.379245	0.291813	0.281132	0.188889
0.324299	0.370423	0.39	0.331694	0.349057	0.282456	0.261006	0.188889
0.3	0.354648	0.336667	0.253005	0.383019	0.287135	0.276101	0.188889
0.350467	0.354648	0.363333	0.305464	0.367925	0.361988	0.255975	0.233333
0.316822	0.417746	0.43	0.384153	0.39434	0.324561	0.276101	0.233333
0.118692	0.142817	0.146667	0.134973	0.160377	0.132749	0.120126	0.233333
0.371028	0.444789	0.43	0.406011	0.443396	0.404094	0.396855	0.277778
0.329907	0.431268	0.47	0.397268	0.435849	0.446199	0.416981	0.277778
0.356075	0.410986	0.363333	0.327322	0.454717	0.436842	0.422013	0.277778
0.460748	0.512394	0.543333	0.493443	0.541509	0.511696	0.467296	0.322222
0.481308	0.501127	0.513333	0.502186	0.503774	0.44152	0.432075	0.322222
0.427103	0.546197	0.546667	0.56776	0.481132	0.427485	0.406918	0.322222
0.408411	0.401972	0.423333	0.384153	0.428302	0.376023	0.371698	0.322222
0.382243	0.46507	0.423333	0.309836	0.443396	0.380702	0.391824	0.322222
0.434579	0.530423	0.576667	0.537158	0.564151	0.511696	0.512579	0.366667
0.556075	0.559718	0.54	0.515301	0.567925	0.530409	0.477358	0.366667
0.5	0.548451	0.553333	0.54153	0.567925	0.530409	0.502516	0.366667
0.458879	0.50338	0.516667	0.480328	0.477358	0.44152	0.477358	0.366667

0.483178	0.50338	0.456667	0.423497	0.488679	0.436842	0.452201	0.366667
0.423364	0.462817	0.44	0.388525	0.428302	0.394737	0.422013	0.366667
0.492523	0.510141	0.506667	0.462842	0.567925	0.488304	0.477358	0.366667
0.556075	0.568732	0.58	0.528415	0.571698	0.516374	0.467296	0.411111
0.471963	0.50338	0.516667	0.440984	0.518868	0.432164	0.41195	0.411111
0.503738	0.523662	0.54	0.510929	0.549057	0.492982	0.512579	0.411111
0.535514	0.548451	0.566667	0.572131	0.567925	0.567836	0.527673	0.411111
0.537383	0.483099	0.523333	0.524044	0.545283	0.507018	0.492453	0.411111
0.578505	0.521408	0.543333	0.489071	0.583019	0.544444	0.55283	0.411111
0.507477	0.492113	0.463333	0.43224	0.526415	0.460234	0.427044	0.455556
0.514953	0.525915	0.486667	0.410383	0.564151	0.544444	0.532704	0.455556
0.584112	0.586761	0.586667	0.532787	0.598113	0.516374	0.532704	0.455556
0.526168	0.557465	0.55	0.532787	0.541509	0.525731	0.497484	0.455556
0.514953	0.532676	0.573333	0.524044	0.55283	0.516374	0.502516	0.455556
0.576636	0.552958	0.5	0.440984	0.567925	0.553801	0.532704	0.455556
0.571028	0.557465	0.536667	0.56776	0.59434	0.549123	0.512579	0.5
0.701869	0.672394	0.66	0.56776	0.658491	0.638012	0.567925	0.5
0.548598	0.521408	0.493333	0.384153	0.545283	0.502339	0.502516	0.5
0.600935	0.627324	0.696667	0.628962	0.601887	0.567836	0.598113	0.5
0.54486	0.570986	0.526667	0.45847	0.586792	0.502339	0.497484	0.5
0.61215	0.629577	0.61	0.550273	0.711321	0.656725	0.663522	0.5
0.561682	0.566479	0.586667	0.589617	0.616981	0.567836	0.562893	0.5
0.636449	0.620563	0.643333	0.598361	0.635849	0.58655	0.603145	0.544444
0.628972	0.62507	0.623333	0.545902	0.586792	0.507018	0.406918	0.544444
0.705607	0.636338	0.636667	0.642077	0.613208	0.577193	0.593082	0.544444
0.578505	0.58	0.583333	0.506557	0.598113	0.577193	0.567925	0.544444
0.524299	0.568732	0.526667	0.454098	0.59434	0.507018	0.502516	0.544444
0.591589	0.58	0.576667	0.54153	0.590566	0.549123	0.522642	0.544444
0.63271	0.595775	0.616667	0.537158	0.571698	0.58655	0.613208	0.544444
0.602804	0.622817	0.676667	0.642077	0.673585	0.666082	0.633333	0.544444
0.597196	0.573239	0.616667	0.633333	0.616981	0.591228	0.648428	0.544444
0.606542	0.566479	0.58	0.528415	0.635849	0.600585	0.593082	0.588889
0.608411	0.634085	0.68	0.642077	0.703774	0.689474	0.683648	0.588889
0.696262	0.721972	0.633333	0.510929	0.677358	0.605263	0.577987	0.588889

0.664486	0.62507	0.653333	0.668306	0.666038	0.64269	0.598113	0.588889
0.800935	0.780563	0.783333	0.642077	0.760377	0.736257	0.703774	0.588889
0.599065	0.604789	0.61	0.607104	0.624528	0.628655	0.678616	0.588889
0.314953	0.278028	0.253333	0.253005	0.296226	0.268421	0.240881	0.588889
0.328037	0.291549	0.336667	0.301093	0.345283	0.319883	0.316352	0.588889
0.814019	0.726479	0.736667	0.712022	0.764151	0.680117	0.688679	0.588889
0.630841	0.604789	0.593333	0.572131	0.654717	0.61462	0.633333	0.588889
0.56729	0.528169	0.563333	0.493443	0.55283	0.535088	0.502516	0.588889
0.664486	0.58	0.633333	0.620219	0.635849	0.595906	0.638365	0.588889
0.645794	0.649859	0.723333	0.720765	0.726415	0.703509	0.713836	0.633333
0.681308	0.679155	0.736667	0.703279	0.722642	0.689474	0.703774	0.633333
0.784112	0.758028	0.73	0.611475	0.7	0.717544	0.718868	0.633333
0.778505	0.767042	0.76	0.633333	0.711321	0.740936	0.713836	0.633333
0.757944	0.796338	0.726667	0.628962	0.783019	0.623977	0.643396	0.633333
0.748598	0.758028	0.75	0.742623	0.760377	0.703509	0.728931	0.633333
0.642056	0.613803	0.6	0.489071	0.662264	0.661404	0.653459	0.633333
0.741121	0.755775	0.76	0.799454	0.771698	0.745614	0.779245	0.633333
0.752336	0.749014	0.746667	0.729508	0.730189	0.740936	0.754088	0.633333
0.701869	0.721972	0.703333	0.729508	0.756604	0.745614	0.779245	0.677778
0.681308	0.647606	0.616667	0.572131	0.786792	0.661404	0.648428	0.677778
0.752336	0.706197	0.716667	0.646448	0.696226	0.623977	0.688679	0.677778
0.705607	0.688169	0.68	0.611475	0.681132	0.619298	0.633333	0.677778
0.76729	0.791831	0.756667	0.703279	0.824528	0.745614	0.738994	0.677778
0.714953	0.721972	0.71	0.593989	0.673585	0.703509	0.774214	0.677778
0.815888	0.789577	0.78	0.698907	0.832075	0.740936	0.769182	0.677778
0.795327	0.758028	0.786667	0.712022	0.741509	0.731579	0.799371	0.677778
0.793458	0.794085	0.783333	0.712022	0.828302	0.722222	0.769182	0.722222
0.780374	0.787324	0.763333	0.760109	0.828302	0.726901	0.733962	0.722222
0.815888	0.805352	0.813333	0.781967	0.775472	0.783041	0.814465	0.722222
0.337383	0.316338	0.326667	0.336066	0.326415	0.310526	0.316352	0.722222
0.836449	0.839155	0.853333	0.720765	0.84717	0.801754	0.844654	0.722222
0.728037	0.721972	0.696667	0.593989	0.760377	0.708187	0.799371	0.722222
0.802804	0.751268	0.753333	0.681421	0.707547	0.675439	0.698742	0.722222
0.834579	0.830141	0.84	0.79071	0.756604	0.689474	0.713836	0.722222

0.9	0.868451	0.85	0.799454	0.816981	0.778363	0.809434	0.722222
0.827103	0.805352	0.816667	0.786339	0.850943	0.769006	0.759119	0.722222
0.83271	0.791831	0.763333	0.746995	0.707547	0.703509	0.804403	0.722222
0.800935	0.818873	0.756667	0.712022	0.820755	0.750292	0.723899	0.766667
0.802804	0.890986	0.853333	0.79071	0.839623	0.801754	0.86478	0.766667
0.808411	0.755775	0.76	0.681421	0.733962	0.666082	0.708805	0.766667
0.791589	0.839155	0.876667	0.9	0.75283	0.759649	0.789308	0.766667
0.838318	0.771549	0.77	0.73388	0.666038	0.595906	0.663522	0.766667
0.720561	0.773803	0.726667	0.738251	0.760377	0.722222	0.738994	0.766667
0.853271	0.848169	0.75	0.580874	0.9	0.867251	0.854717	0.766667
0.763551	0.798592	0.866667	0.694536	0.850943	0.829825	0.879874	0.766667
0.870093	0.836901	0.876667	0.81694	0.775472	0.764327	0.744025	0.811111
0.817757	0.841408	0.87	0.786339	0.733962	0.792398	0.854717	0.811111
0.763551	0.726479	0.696667	0.70765	0.771698	0.684795	0.749057	0.811111
0.847664	0.818873	0.833333	0.821311	0.877358	0.825146	0.889937	0.811111
0.750467	0.728732	0.726667	0.668306	0.828302	0.731579	0.754088	0.811111
0.830841	0.848169	0.873333	0.746995	0.749057	0.801754	0.839623	0.811111
0.868224	0.821127	0.74	0.56776	0.866038	0.9	0.9	0.811111
0.720561	0.708451	0.7	0.633333	0.677358	0.675439	0.648428	0.811111
0.799065	0.771549	0.76	0.672678	0.779245	0.703509	0.764151	0.855556
0.890654	0.870704	0.843333	0.830055	0.873585	0.731579	0.834591	0.855556
0.838318	0.82338	0.833333	0.803825	0.84717	0.839181	0.814465	0.855556
0.83271	0.789577	0.773333	0.73388	0.798113	0.726901	0.759119	0.855556
0.821495	0.746761	0.766667	0.773224	0.726415	0.67076	0.683648	0.855556
0.821495	0.803099	0.76	0.725137	0.858491	0.797076	0.834591	0.855556
0.838318	0.791831	0.793333	0.764481	0.764151	0.726901	0.723899	0.9
0.873832	0.863944	0.9	0.821311	0.809434	0.811111	0.834591	0.9
0.793458	0.767042	0.793333	0.834426	0.75283	0.759649	0.824528	0.9
0.866355	0.839155	0.87	0.81694	0.779245	0.783041	0.749057	0.9
0.804673	0.751268	0.723333	0.716393	0.741509	0.731579	0.754088	0.9
0.800935	0.807606	0.796667	0.720765	0.79434	0.84386	0.824528	0.9
0.845794	0.818873	0.826667	0.720765	0.828302	0.778363	0.819497	0.9
0.821495	0.86169	0.833333	0.803825	0.828302	0.825146	0.849686	0.9

APPENDIX N

NORMALIZED TEST DATASET OF SELECTED INPUT FEATURES AND SELECTED TARGET FEATURES FOR MALE HISPANIC POPULATION USING GA-ANN APPROACH

1	7	13	14	15	16	19	Age
0.171028	0.187887	0.206667	0.178689	0.209434	0.198246	0.17044	0.1
0.286916	0.350141	0.356667	0.331694	0.349057	0.263743	0.250943	0.188889
0.290654	0.372676	0.41	0.362295	0.364151	0.324561	0.296226	0.188889
0.376636	0.433521	0.413333	0.340437	0.413208	0.324561	0.37673	0.233333
0.309346	0.426761	0.416667	0.314208	0.428302	0.366667	0.351572	0.233333
0.447664	0.494366	0.486667	0.427869	0.503774	0.41345	0.381761	0.277778
0.283178	0.332113	0.32	0.218033	0.35283	0.282456	0.245912	0.277778
0.45514	0.456056	0.453333	0.414754	0.466038	0.436842	0.416981	0.322222
0.393458	0.42	0.466667	0.449727	0.450943	0.352632	0.442138	0.322222
0.43271	0.417746	0.38	0.301093	0.443396	0.422807	0.386792	0.322222
0.464486	0.494366	0.463333	0.419126	0.466038	0.44152	0.396855	0.322222
0.443925	0.42	0.446667	0.366667	0.420755	0.408772	0.386792	0.366667
0.483178	0.469577	0.506667	0.480328	0.496226	0.44152	0.416981	0.366667
0.516822	0.50338	0.503333	0.440984	0.492453	0.427485	0.452201	0.411111
0.5	0.521408	0.593333	0.462842	0.601887	0.535088	0.527673	0.411111
0.528037	0.564225	0.566667	0.554645	0.579245	0.511696	0.51761	0.411111
0.479439	0.471831	0.443333	0.366667	0.503774	0.455556	0.442138	0.411111
0.582243	0.595775	0.586667	0.519672	0.601887	0.553801	0.537736	0.455556
0.576636	0.58	0.59	0.475956	0.643396	0.55848	0.567925	0.455556
0.520561	0.53493	0.56	0.528415	0.616981	0.530409	0.492453	0.455556
0.571028	0.552958	0.53	0.45847	0.598113	0.577193	0.502516	0.455556
0.585981	0.570986	0.573333	0.532787	0.696226	0.55848	0.58805	0.5
0.65514	0.577746	0.516667	0.309836	0.598113	0.535088	0.507547	0.5
0.621495	0.600282	0.606667	0.65082	0.628302	0.567836	0.593082	0.5
0.526168	0.528169	0.51	0.462842	0.616981	0.58655	0.547799	0.544444
0.619626	0.634085	0.583333	0.506557	0.692453	0.591228	0.628302	0.544444

0.627103	0.645352	0.646667	0.628962	0.639623	0.628655	0.62327	0.544444
0.585981	0.570986	0.603333	0.611475	0.658491	0.609942	0.633333	0.588889
0.668224	0.638592	0.643333	0.602732	0.677358	0.661404	0.628302	0.588889
0.836449	0.807606	0.793333	0.764481	0.854717	0.694152	0.749057	0.633333
0.657009	0.665634	0.753333	0.73388	0.737736	0.708187	0.738994	0.633333
0.72243	0.712958	0.776667	0.738251	0.779245	0.717544	0.738994	0.633333
0.726168	0.735493	0.756667	0.698907	0.771698	0.726901	0.744025	0.633333
0.623364	0.62507	0.56	0.545902	0.673585	0.67076	0.648428	0.633333
0.739252	0.721972	0.68	0.685792	0.737736	0.656725	0.683648	0.633333
0.720561	0.681408	0.696667	0.668306	0.737736	0.656725	0.658491	0.677778
0.868224	0.82338	0.833333	0.808197	0.866038	0.712865	0.769182	0.677778
0.757944	0.758028	0.77	0.768852	0.798113	0.745614	0.769182	0.677778
0.785981	0.767042	0.763333	0.642077	0.715094	0.726901	0.718868	0.677778
0.670093	0.681408	0.706667	0.703279	0.760377	0.694152	0.713836	0.677778
0.759813	0.803099	0.74	0.755738	0.779245	0.740936	0.764151	0.677778
0.716822	0.683662	0.686667	0.65082	0.75283	0.731579	0.723899	0.677778
0.85514	0.870704	0.813333	0.773224	0.828302	0.839181	0.804403	0.722222
0.733645	0.771549	0.75	0.768852	0.779245	0.778363	0.82956	0.722222
0.729907	0.776056	0.706667	0.725137	0.756604	0.689474	0.718868	0.722222
0.838318	0.760282	0.76	0.738251	0.677358	0.609942	0.643396	0.766667
0.821495	0.812113	0.746667	0.712022	0.866038	0.815789	0.849686	0.766667
0.81028	0.9	0.85	0.799454	0.839623	0.801754	0.889937	0.811111
0.823364	0.852676	0.85	0.847541	0.884906	0.853216	0.804403	0.811111
0.81215	0.78507	0.753333	0.768852	0.775472	0.778363	0.804403	0.855556
0.819626	0.821127	0.863333	0.812568	0.881132	0.857895	0.894969	0.855556
0.81215	0.744507	0.743333	0.655191	0.749057	0.773684	0.789308	0.855556
0.799065	0.708451	0.703333	0.685792	0.733962	0.769006	0.749057	0.855556
0.76729	0.737746	0.743333	0.681421	0.828302	0.820468	0.809434	0.9
0.800935	0.753521	0.746667	0.742623	0.813208	0.787719	0.819497	0.9

APPENDIX O

NORMALIZED AND DENORMALIZED TRAINING DATASET OF TARGET FEATURE, OUTPUTS AND ERRORS FOR FEMALE HISPANIC POPULATION USING ANN APPROACH AND GA-ANN APPROACH

ANN						GA-ANN					
Normalized			Denormalized			Normalized			Denormalized		
Target	Output	Error	Target	Output	Error	Target	Output	Error	Target	Output	Error
0.1	0.165005	-0.065	0	1.462611	-1.46261	0.1	0.171634	-0.07163	0	1.611771	-1.61177
0.144444	0.190916	-0.04647	1	2.045608	-1.04561	0.144444	0.189427	-0.04498	1	2.012104	-1.0121
0.144444	0.165951	-0.02151	1	1.483898	-0.4839	0.144444	0.179772	-0.03533	1	1.794876	-0.79488
0.144444	0.166355	-0.02191	1	1.49299	-0.49299	0.144444	0.187721	-0.04328	1	1.973727	-0.97373
0.188889	0.210397	-0.02151	2	2.483925	-0.48393	0.188889	0.22601	-0.03712	2	2.835234	-0.83523
0.188889	0.213796	-0.02491	2	2.560415	-0.56042	0.188889	0.198552	-0.00966	2	2.21741	-0.21741
0.233333	0.199852	0.033482	3	2.246662	0.753338	0.233333	0.217863	0.015471	3	2.651913	0.348087
0.233333	0.249125	-0.01579	3	3.355302	-0.3553	0.233333	0.257367	-0.02403	3	3.54076	-0.54076
0.233333	0.258167	-0.02483	3	3.558764	-0.55876	0.233333	0.3014	-0.06807	3	4.531506	-1.53151
0.233333	0.21353	0.019804	3	2.554417	0.445583	0.233333	0.215141	0.018192	3	2.59068	0.40932
0.233333	0.226293	0.007041	3	2.841582	0.158418	0.233333	0.234879	-0.00155	3	3.034768	-0.03477
0.277778	0.272924	0.004854	4	3.890786	0.109214	0.277778	0.288693	-0.01091	4	4.245586	-0.24559
0.277778	0.298052	-0.02027	4	4.456169	-0.45617	0.277778	0.294839	-0.01706	4	4.38387	-0.38387
0.277778	0.233847	0.043931	4	3.011561	0.988439	0.277778	0.233691	0.044087	4	3.008042	0.991958
0.277778	0.259419	0.018359	4	3.586929	0.413071	0.277778	0.298597	-0.02082	4	4.468434	-0.46843
0.277778	0.225638	0.05214	4	2.826858	1.173142	0.277778	0.260345	0.017432	4	3.607773	0.392227
0.322222	0.372989	-0.05077	5	6.142257	-1.14226	0.322222	0.374523	-0.0523	5	6.176775	-1.17678
0.322222	0.328678	-0.00646	5	5.145265	-0.14526	0.322222	0.354026	-0.0318	5	5.715575	-0.71557
0.322222	0.360633	-0.03841	5	5.864244	-0.86424	0.322222	0.34286	-0.02064	5	5.464356	-0.46436
0.322222	0.316239	0.005983	5	4.865374	0.134626	0.322222	0.33135	-0.00913	5	5.205382	-0.20538
0.322222	0.254069	0.068153	5	3.466552	1.533448	0.322222	0.282388	0.039835	5	4.103723	0.896277
0.322222	0.277989	0.044233	5	4.004751	0.995249	0.322222	0.228218	0.094004	5	2.884915	2.115085
0.322222	0.308152	0.01407	5	4.683414	0.316586	0.322222	0.283879	0.038343	5	4.137286	0.862714
0.322222	0.293569	0.028653	5	4.35531	0.64469	0.322222	0.289841	0.032381	5	4.271426	0.728574

0.322222	0.237513	0.084709	5	3.094052	1.905948	0.322222	0.258517	0.063705	5	3.566638	1.433362
0.366667	0.382985	-0.01632	6	6.367157	-0.36716	0.366667	0.33729	0.029377	6	5.339021	0.660979
0.366667	0.385612	-0.01895	6	6.426271	-0.42627	0.366667	0.325615	0.041052	6	5.076329	0.923671
0.366667	0.394984	-0.02832	6	6.637145	-0.63714	0.366667	0.397414	-0.03075	6	6.691818	-0.69182
0.366667	0.308296	0.058371	6	4.686659	1.313341	0.366667	0.314863	0.051804	6	4.834407	1.165593
0.366667	0.332302	0.034365	6	5.226793	0.773207	0.366667	0.319778	0.046889	6	4.944994	1.055006
0.366667	0.336106	0.030561	6	5.312377	0.687623	0.366667	0.340566	0.0261	6	5.412744	0.587256
0.411111	0.461114	-0.05	7	8.125059	-1.12506	0.411111	0.420094	-0.00898	7	7.20212	-0.20212
0.411111	0.431339	-0.02023	7	7.45512	-0.45512	0.411111	0.421975	-0.01086	7	7.244428	-0.24443
0.411111	0.470856	-0.05974	7	8.34426	-1.34426	0.411111	0.507079	-0.09597	7	9.159269	-2.15927
0.411111	0.359218	0.051893	7	5.832397	1.167603	0.411111	0.367116	0.043995	7	6.010118	0.989882
0.411111	0.382208	0.028904	7	6.349669	0.650331	0.411111	0.366599	0.044512	7	5.998486	1.001514
0.455556	0.523232	-0.06768	8	9.522714	-1.52271	0.455556	0.492174	-0.03662	8	8.823917	-0.82392
0.455556	0.461715	-0.00616	8	8.138577	-0.13858	0.455556	0.495258	-0.0397	8	8.893304	-0.8933
0.455556	0.497084	-0.04153	8	8.934396	-0.9344	0.455556	0.471262	-0.01571	8	8.353396	-0.3534
0.455556	0.470471	-0.01492	8	8.335596	-0.3356	0.455556	0.487025	-0.03147	8	8.708065	-0.70807
0.455556	0.456702	-0.00115	8	8.025785	-0.02579	0.455556	0.505609	-0.05005	8	9.126196	-1.1262
0.455556	0.439313	0.016243	8	7.634543	0.365457	0.455556	0.433893	0.021663	8	7.512591	0.487409
0.455556	0.505834	-0.05028	8	9.131257	-1.13126	0.455556	0.532839	-0.07728	8	9.738887	-1.73889
0.5	0.506475	-0.00647	9	9.145679	-0.14568	0.5	0.499801	0.000199	9	8.995521	0.004479
0.5	0.600891	-0.10089	9	11.27005	-2.27005	0.5	0.627338	-0.12734	9	11.86511	-2.86511
0.5	0.571437	-0.07144	9	10.60734	-1.60734	0.5	0.58216	-0.08216	9	10.8486	-1.8486
0.5	0.487631	0.012369	9	8.721686	0.278314	0.5	0.453523	0.046477	9	7.954264	1.045736
0.5	0.512127	-0.01213	9	9.272865	-0.27286	0.5	0.542091	-0.04209	9	9.947051	-0.94705
0.544444	0.595767	-0.05132	10	11.15476	-1.15476	0.544444	0.587552	-0.04311	10	10.96991	-0.96991
0.544444	0.553968	-0.00952	10	10.21427	-0.21427	0.544444	0.557872	-0.01343	10	10.30212	-0.30212
0.544444	0.541957	0.002487	10	9.944042	0.055958	0.544444	0.54965	-0.00521	10	10.11713	-0.11713
0.544444	0.618901	-0.07446	10	11.67526	-1.67526	0.544444	0.636096	-0.09165	10	12.06216	-2.06216
0.544444	0.627328	-0.08288	10	11.86488	-1.86488	0.544444	0.648409	-0.10396	10	12.3392	-2.3392
0.544444	0.456461	0.087984	10	8.02037	1.97963	0.544444	0.465071	0.079373	10	8.214105	1.785895
0.544444	0.466552	0.077892	10	8.247431	1.752569	0.544444	0.457793	0.086651	10	8.050347	1.949653
0.544444	0.598431	-0.05399	10	11.2147	-1.2147	0.544444	0.612853	-0.06841	10	11.53919	-1.53919
0.544444	0.571471	-0.02703	10	10.60809	-0.60809	0.544444	0.556475	-0.01203	10	10.27069	-0.27069
0.544444	0.633798	-0.08935	10	12.01045	-2.01045	0.544444	0.611742	-0.0673	10	11.5142	-1.5142

0.544444	0.623278	-0.07883	10	11.77376	-1.77376	0.544444	0.611675	-0.06723	10	11.51269	-1.51269
0.588889	0.650968	-0.06208	11	12.39678	-1.39678	0.588889	0.654289	-0.0654	11	12.47149	-1.47149
0.588889	0.634459	-0.04557	11	12.02533	-1.02533	0.588889	0.624107	-0.03522	11	11.79241	-0.79241
0.588889	0.629638	-0.04075	11	11.91686	-0.91686	0.588889	0.647308	-0.05842	11	12.31444	-1.31444
0.588889	0.705017	-0.11613	11	13.61289	-2.61289	0.588889	0.694349	-0.10546	11	13.37285	-2.37285
0.588889	0.639809	-0.05092	11	12.1457	-1.1457	0.588889	0.665245	-0.07636	11	12.71802	-1.71802
0.588889	0.721033	-0.13214	11	13.97323	-2.97323	0.588889	0.723771	-0.13488	11	14.03485	-3.03485
0.588889	0.595922	-0.00703	11	11.15826	-0.15826	0.588889	0.638663	-0.04977	11	12.11991	-1.11991
0.588889	0.624415	-0.03553	11	11.79933	-0.79933	0.588889	0.633244	-0.04436	11	11.998	-0.998
0.633333	0.688122	-0.05479	12	13.23276	-1.23276	0.633333	0.676039	-0.04271	12	12.96087	-0.96087
0.633333	0.675302	-0.04197	12	12.9443	-0.9443	0.633333	0.665002	-0.03167	12	12.71255	-0.71255
0.633333	0.699173	-0.06584	12	13.48139	-1.48139	0.633333	0.723146	-0.08981	12	14.02078	-2.02078
0.633333	0.684366	-0.05103	12	13.14825	-1.14825	0.633333	0.674208	-0.04087	12	12.91968	-0.91968
0.633333	0.633679	-0.00035	12	12.00777	-0.00777	0.633333	0.598614	0.034719	12	11.21882	0.781179
0.633333	0.71815	-0.08482	12	13.90837	-1.90837	0.633333	0.733728	-0.10039	12	14.25888	-2.25888
0.633333	0.645973	-0.01264	12	12.2844	-0.2844	0.633333	0.659332	-0.026	12	12.58498	-0.58498
0.633333	0.713715	-0.08038	12	13.80859	-1.80859	0.633333	0.748327	-0.11499	12	14.58737	-2.58737
0.633333	0.730492	-0.09716	12	14.18607	-2.18607	0.633333	0.711662	-0.07833	12	13.76239	-1.76239
0.633333	0.738803	-0.10547	12	14.37308	-2.37308	0.633333	0.718778	-0.08544	12	13.9225	-1.9225
0.633333	0.775643	-0.14231	12	15.20197	-3.20197	0.633333	0.78832	-0.15499	12	15.48719	-3.48719
0.633333	0.694537	-0.0612	12	13.37707	-1.37707	0.633333	0.697372	-0.06404	12	13.44087	-1.44087
0.633333	0.654974	-0.02164	12	12.48692	-0.48692	0.633333	0.654846	-0.02151	12	12.48403	-0.48403
0.677778	0.720806	-0.04303	13	13.96813	-0.96813	0.677778	0.706399	-0.02862	13	13.64398	-0.64398
0.677778	0.734824	-0.05705	13	14.28355	-1.28355	0.677778	0.722081	-0.0443	13	13.99682	-0.99682
0.677778	0.670179	0.007598	13	12.82903	0.170966	0.677778	0.654504	0.023274	13	12.47634	0.523661
0.677778	0.710441	-0.03266	13	13.73492	-0.73492	0.677778	0.701583	-0.0238	13	13.53561	-0.53561
0.677778	0.753488	-0.07571	13	14.70348	-1.70348	0.677778	0.724524	-0.04675	13	14.05178	-1.05178
0.677778	0.73946	-0.06168	13	14.38786	-1.38786	0.677778	0.732736	-0.05496	13	14.23656	-1.23656
0.677778	0.68625	-0.00847	13	13.19063	-0.19063	0.677778	0.6603	0.017478	13	12.60674	0.393256
0.677778	0.708137	-0.03036	13	13.68307	-0.68307	0.677778	0.655945	0.021833	13	12.50876	0.491242
0.677778	0.731759	-0.05398	13	14.21457	-1.21457	0.677778	0.717746	-0.03997	13	13.89928	-0.89928
0.677778	0.749635	-0.07186	13	14.6168	-1.6168	0.677778	0.735311	-0.05753	13	14.2945	-1.2945
0.722222	0.695498	0.026725	14	13.3987	0.601302	0.722222	0.697951	0.024271	14	13.4539	0.546097
0.722222	0.705544	0.016679	14	13.62473	0.375271	0.722222	0.739204	-0.01698	14	14.38209	-0.38209

0.722222	0.764601	-0.04238	14	14.95352	-0.95352	0.722222	0.778627	-0.0564	14	15.2691	-1.2691
0.722222	0.703282	0.01894	14	13.57385	0.426153	0.722222	0.750573	-0.02835	14	14.63789	-0.63789
0.722222	0.690281	0.031941	14	13.28133	0.718675	0.722222	0.670247	0.051975	14	12.83056	1.169437
0.722222	0.652539	0.069683	14	12.43213	1.567866	0.722222	0.681663	0.040559	14	13.08741	0.912587
0.722222	0.760857	-0.03863	14	14.86928	-0.86928	0.722222	0.764147	-0.04193	14	14.94332	-0.94332
0.722222	0.718841	0.003382	14	13.92391	0.076085	0.722222	0.730861	-0.00864	14	14.19438	-0.19438
0.722222	0.753209	-0.03099	14	14.6972	-0.6972	0.722222	0.741087	-0.01887	14	14.42446	-0.42446
0.722222	0.724093	-0.00187	14	14.04209	-0.04209	0.722222	0.732278	-0.01006	14	14.22625	-0.22625
0.722222	0.699648	0.022574	14	13.49209	0.507914	0.722222	0.695299	0.026923	14	13.39423	0.605767
0.722222	0.785771	-0.06355	14	15.42985	-1.42985	0.722222	0.781922	-0.0597	14	15.34325	-1.34325
0.766667	0.775306	-0.00864	15	15.19438	-0.19438	0.766667	0.781423	-0.01476	15	15.33202	-0.33202
0.766667	0.770097	-0.00343	15	15.07719	-0.07719	0.766667	0.763863	0.002804	15	14.93691	0.063094
0.766667	0.699794	0.066872	15	13.49537	1.504625	0.766667	0.711916	0.05475	15	13.76812	1.231879
0.766667	0.733795	0.032872	15	14.26038	0.73962	0.766667	0.758179	0.008488	15	14.80903	0.190971
0.766667	0.690702	0.075965	15	13.2908	1.709204	0.766667	0.635281	0.131385	15	12.04383	2.956167
0.766667	0.762453	0.004214	15	14.90519	0.094814	0.766667	0.770714	-0.00405	15	15.09107	-0.09107
0.766667	0.709332	0.057335	15	13.70997	1.290029	0.766667	0.733014	0.033653	15	14.24282	0.757182
0.811111	0.675023	0.136088	16	12.93802	3.061976	0.811111	0.674608	0.136503	16	12.92869	3.071312
0.811111	0.791055	0.020056	16	15.54873	0.45127	0.811111	0.779898	0.031213	16	15.2977	0.702301
0.811111	0.702278	0.108834	16	13.55125	2.448754	0.811111	0.699832	0.11128	16	13.49621	2.503791
0.811111	0.771042	0.040069	16	15.09844	0.901563	0.811111	0.789259	0.021852	16	15.50832	0.491679
0.811111	0.768822	0.042289	16	15.04849	0.951513	0.811111	0.763169	0.047942	16	14.92131	1.078687
0.811111	0.73492	0.076191	16	14.28571	1.714291	0.811111	0.700234	0.110877	16	13.50528	2.494724
0.811111	0.759866	0.051245	16	14.84699	1.153014	0.811111	0.738253	0.072858	16	14.36069	1.639311
0.811111	0.768394	0.042717	16	15.03887	0.96113	0.811111	0.758581	0.05253	16	14.81808	1.181924
0.811111	0.758427	0.052684	16	14.81462	1.185382	0.811111	0.771859	0.039253	16	15.11682	0.883182
0.855556	0.693997	0.161559	17	13.36493	3.635071	0.855556	0.66678	0.188775	17	12.75256	4.247441
0.855556	0.735337	0.120219	17	14.29507	2.704926	0.855556	0.736593	0.118963	17	14.32334	2.676665
0.855556	0.704995	0.15056	17	13.6124	3.387603	0.855556	0.709957	0.145598	17	13.72404	3.275957
0.855556	0.719926	0.135629	17	13.94834	3.051658	0.855556	0.750149	0.105407	17	14.62835	2.371648
0.855556	0.725594	0.129962	17	14.07586	2.924139	0.855556	0.692093	0.163462	17	13.3221	3.677897
0.855556	0.781936	0.07362	17	15.34355	1.656449	0.855556	0.775605	0.079951	17	15.20111	1.798887
0.9	0.6807	0.2193	18	13.06576	4.93424	0.9	0.692208	0.207792	18	13.32468	4.67532
0.9	0.672943	0.227057	18	12.89121	5.108787	0.9	0.635281	0.264719	18	12.04382	5.956181

0.9	0.709247	0.190753	18	13.70805	4.291952	0.9	0.720846	0.179154	18	13.96904	4.03096
0.9	0.689351	0.210649	18	13.2604	4.739598	0.9	0.707722	0.192278	18	13.67374	4.326263

APPENDIX P

NORMALIZED AND DENORMALIZED TEST DATASET OF TARGET FEATURE, OUTPUTS AND ERRORS FOR FEMALE HISPANIC POPULATION USING ANN APPROACH AND GA-ANN APPROACH AND THEIR DENORMALIZED TEST SET SQUARE ERRORS

ANN							GA-ANN						
Normalized			Denormalized				Normalized			Denormalized			
Target	Output	Error	Target	Output	Error	Error^2	Target	Output	Error	Target	Output	Error	Error^2
0.144444	0.160235	-0.01579	1	1.35528	-0.35528	0.1262236	0.144444	0.171211	-0.02677	1	1.602258	-0.60226	0.3627149
0.144444	0.185898	-0.04145	1	1.93271	-0.93271	0.8699482	0.144444	0.188988	-0.04454	1	2.00224	-1.00224	1.0044851
0.188889	0.217836	-0.02895	2	2.651318	-0.65132	0.4242148	0.188889	0.239164	-0.05027	2	3.131187	-1.13119	1.2795851
0.188889	0.208893	-0.02	2	2.450083	-0.45008	0.202575	0.188889	0.205634	-0.01675	2	2.376769	-0.37677	0.1419548
0.188889	0.190312	-0.00142	2	2.032009	-0.03201	0.0010246	0.188889	0.173359	0.01553	2	1.650577	0.349423	0.1220967
0.322222	0.314485	0.007737	5	4.825922	0.174078	0.0303032	0.322222	0.318016	0.004206	5	4.905369	0.094631	0.008955
0.366667	0.330118	0.036549	6	5.177644	0.822356	0.6762698	0.366667	0.337291	0.029376	6	5.339039	0.660961	0.4368701
0.366667	0.320472	0.046195	6	4.960624	1.039376	1.0803034	0.366667	0.320741	0.045926	6	4.966668	1.033332	1.0677757
0.366667	0.333974	0.032693	6	5.264418	0.735582	0.5410809	0.366667	0.351957	0.01471	6	5.669032	0.330968	0.1095401
0.366667	0.360853	0.005814	6	5.869192	0.130808	0.0171107	0.366667	0.355153	0.011514	6	5.740944	0.259056	0.0671099
0.411111	0.361824	0.049287	7	5.891033	1.108967	1.2298072	0.411111	0.334841	0.076271	7	5.283911	1.716089	2.9449606
0.411111	0.499053	-0.08794	7	8.978694	-1.97869	3.9152298	0.411111	0.412348	-0.00124	7	7.027829	-0.02783	0.0007745
0.411111	0.402584	0.008527	7	6.808137	0.191862	0.0368112	0.411111	0.43861	-0.0275	7	7.618726	-0.61873	0.3828213
0.411111	0.358334	0.052777	7	5.812521	1.187479	1.4101061	0.411111	0.404148	0.006963	7	6.843336	0.156664	0.0245435
0.411111	0.475403	-0.06429	7	8.446568	-1.44657	2.0925581	0.411111	0.48125	-0.07014	7	8.578115	-1.57811	2.4904463
0.455556	0.418337	0.037219	8	7.162575	0.837425	0.7012808	0.455556	0.392133	0.063422	8	6.572998	1.427002	2.0363357
0.455556	0.447337	0.008218	8	7.815088	0.184912	0.0341925	0.455556	0.47282	-0.01726	8	8.388447	-0.38845	0.1508907
0.5	0.538355	-0.03835	9	9.86298	-0.86298	0.7447344	0.5	0.519588	-0.01959	9	9.440739	-0.44074	0.194251
0.5	0.659258	-0.15926	9	12.58331	-3.58331	12.840116	0.5	0.611188	-0.11119	9	11.50172	-2.50172	6.2586081
0.5	0.617134	-0.11713	9	11.63552	-2.63552	6.9459483	0.5	0.613335	-0.11334	9	11.55004	-2.55004	6.5026916
0.5	0.643955	-0.14395	9	12.23898	-3.23898	10.491005	0.5	0.646051	-0.14605	9	12.28615	-3.28615	10.798797
0.5	0.446576	0.053424	9	7.797965	1.202035	1.4448877	0.5	0.504036	-0.00404	9	9.090821	-0.09082	0.0082484
0.544444	0.55614	-0.0117	10	10.26316	-0.26316	0.0692529	0.544444	0.580103	-0.03566	10	10.80231	-0.80231	0.6437025

0.544444	0.641034	-0.09659	10	12.17328	-2.17328	4.7231265	0.544444	0.678766	-0.13432	10	13.02223	-3.02223	9.1338448
0.544444	0.525876	0.018569	10	9.582207	0.417793	0.1745513	0.544444	0.538444	0.006	10	9.864999	0.135001	0.0182252
0.588889	0.510719	0.07817	11	9.241172	1.758828	3.0934744	0.588889	0.51797	0.070919	11	9.40432	1.59568	2.5461933
0.588889	0.677289	-0.0884	11	12.98901	-1.98901	3.9561596	0.588889	0.642245	-0.05336	11	12.20051	-1.20051	1.4412173
0.588889	0.676841	-0.08795	11	12.97893	-1.97893	3.9161718	0.588889	0.696297	-0.10741	11	13.41669	-2.41669	5.8403941
0.588889	0.7105	-0.12161	11	13.73625	-2.73625	7.4870672	0.588889	0.692444	-0.10355	11	13.32999	-2.32999	5.4288405
0.588889	0.66258	-0.07369	11	12.65805	-1.65805	2.7491175	0.588889	0.672237	-0.08335	11	12.87533	-1.87533	3.516855
0.588889	0.63075	-0.04186	11	11.94189	-0.94189	0.8871492	0.588889	0.649932	-0.06104	11	12.37348	-1.37348	1.8864476
0.588889	0.644503	-0.05561	11	12.25132	-1.25132	1.5658051	0.588889	0.655515	-0.06663	11	12.49909	-1.49909	2.2472766
0.633333	0.7633	-0.12997	12	14.92424	-2.92424	8.5511858	0.633333	0.775129	-0.1418	12	15.19039	-3.19039	10.178607
0.633333	0.633228	0.000105	12	11.99764	0.002363	5.586E-06	0.633333	0.58855	0.044783	12	10.99238	1.007624	1.0153071
0.677778	0.710951	-0.03317	13	13.74639	-0.74639	0.5570933	0.677778	0.67701	0.000768	13	12.98272	0.017276	0.0002985
0.677778	0.722019	-0.04424	13	13.99543	-0.99543	0.9908809	0.677778	0.700183	-0.02241	13	13.50413	-0.50413	0.254145
0.677778	0.692657	-0.01488	13	13.33478	-0.33478	0.1120801	0.677778	0.686474	-0.0087	13	13.19567	-0.19567	0.0382849
0.677778	0.72904	-0.05126	13	14.15341	-1.15341	1.3303506	0.677778	0.741731	-0.06395	13	14.43896	-1.43896	2.0706008
0.677778	0.735931	-0.05815	13	14.30844	-1.30844	1.7120282	0.677778	0.744738	-0.06696	13	14.5066	-1.5066	2.2698366
0.722222	0.7472	-0.02498	14	14.56199	-0.56199	0.3158322	0.722222	0.747734	-0.02551	14	14.57401	-0.57401	0.3294915
0.722222	0.768505	-0.04628	14	15.04137	-1.04137	1.0844461	0.722222	0.75182	-0.0296	14	14.66595	-0.66595	0.4434849
0.766667	0.668945	0.097722	15	12.80126	2.198745	4.8344794	0.766667	0.648801	0.117866	15	12.34801	2.651988	7.0330389
0.766667	0.777541	-0.01087	15	15.24468	-0.24468	0.0598674	0.766667	0.776177	-0.00951	15	15.21399	-0.21399	0.0457933
0.766667	0.743967	0.0227	15	14.48925	0.51075	0.2608654	0.766667	0.710237	0.05643	15	13.73032	1.269677	1.6120799
0.811111	0.754291	0.05682	16	14.72155	1.278452	1.6344391	0.811111	0.730238	0.080873	16	14.18035	1.819646	3.3111118
0.855556	0.708331	0.147225	17	13.68745	3.312554	10.973016	0.855556	0.696038	0.159518	17	13.41085	3.589153	12.882022
0.855556	0.744206	0.111349	17	14.49464	2.505358	6.2768201	0.855556	0.756936	0.098619	17	14.78106	2.218936	4.923677
0.855556	0.671879	0.183676	17	12.86728	4.132715	17.079336	0.855556	0.659169	0.196386	17	12.58131	4.418687	19.524793
0.855556	0.749239	0.106317	17	14.60787	2.392127	5.7222714	0.855556	0.736191	0.119364	17	14.31431	2.685692	7.2129436
0.9	0.749722	0.150278	18	14.61873	3.381266	11.432958	0.9	0.753526	0.146474	18	14.70434	3.295661	10.86138
0.9	0.779885	0.120115	18	15.29742	2.70258	7.3039394	0.9	0.777513	0.122487	18	15.24403	2.755965	7.5953434
0.9	0.705995	0.194005	18	13.63488	4.365124	19.054303	0.9	0.733892	0.166108	18	14.26258	3.737422	13.968326
0.9	0.773929	0.126071	18	15.1634	2.836596	8.0462773	0.9	0.786697	0.113303	18	15.45068	2.549322	6.4990433
0.9	0.71777	0.18223	18	13.89982	4.100182	16.811488	0.9	0.735001	0.164999	18	14.28753	3.712467	13.782411
0.9	0.670333	0.229667	18	12.83249	5.16751	26.703157	0.9	0.663309	0.236691	18	12.67444	5.325557	28.361559

APPENDIX Q

NORMALIZED AND DENORMALIZED TRAINING DATASET OF TARGET FEATURE, OUTPUTS AND ERRORS FOR MALE HISPANIC POPULATION USING ANN APPROACH AND GA-ANN APPROACH

ANN						GA-ANN					
Normalized			Denormalized			Normalized			Denormalized		
Target	Output	Error	Target	Output	Error	Target	Output	Error	Target	Output	Error
0.1	0.172571	-0.07257	0	1.632857	-1.63286	0.1	0.166519	-0.06652	0	1.496672	-1.49667
0.1	0.207328	-0.10733	0	2.414884	-2.41488	0.1	0.189582	-0.08958	0	2.015598	-2.0156
0.1	0.175667	-0.07567	0	1.702509	-1.70251	0.1	0.181696	-0.0817	0	1.838155	-1.83815
0.144444	0.254243	-0.1098	1	3.470469	-2.47047	0.144444	0.243028	-0.09858	1	3.218131	-2.21813
0.144444	0.186174	-0.04173	1	1.938922	-0.93892	0.144444	0.170479	-0.02603	1	1.585769	-0.58577
0.144444	0.215885	-0.07144	1	2.607419	-1.60742	0.144444	0.20733	-0.06289	1	2.414928	-1.41493
0.144444	0.162137	-0.01769	1	1.398087	-0.39809	0.144444	0.17621	-0.03177	1	1.714721	-0.71472
0.144444	0.196641	-0.0522	1	2.174425	-1.17443	0.144444	0.195107	-0.05066	1	2.139917	-1.13992
0.188889	0.207155	-0.01827	2	2.410987	-0.41099	0.188889	0.218731	-0.02984	2	2.671457	-0.67146
0.188889	0.21969	-0.0308	2	2.693025	-0.69303	0.188889	0.23199	-0.0431	2	2.969769	-0.96977
0.188889	0.195742	-0.00685	2	2.1542	-0.1542	0.188889	0.221564	-0.03268	2	2.73519	-0.73519
0.233333	0.262522	-0.02919	3	3.656738	-0.65674	0.233333	0.253572	-0.02024	3	3.455374	-0.45537
0.233333	0.208481	0.024852	3	2.440825	0.559175	0.233333	0.211307	0.022026	3	2.504407	0.495593
0.233333	0.175958	0.057376	3	1.709046	1.290954	0.233333	0.166172	0.067161	3	1.488871	1.511129
0.277778	0.303618	-0.02584	4	4.581398	-0.5814	0.277778	0.297836	-0.02006	4	4.451309	-0.45131
0.277778	0.260344	0.017434	4	3.607738	0.392262	0.277778	0.252396	0.025382	4	3.428909	0.571091
0.277778	0.300283	-0.02251	4	4.506367	-0.50637	0.277778	0.314114	-0.03634	4	4.817573	-0.81757
0.322222	0.320653	0.001569	5	4.964702	0.035298	0.322222	0.354719	-0.0325	5	5.73117	-0.73117
0.322222	0.381886	-0.05966	5	6.342426	-1.34243	0.322222	0.394602	-0.07238	5	6.628536	-1.62854
0.322222	0.360614	-0.03839	5	5.863814	-0.86381	0.322222	0.310325	0.011897	5	4.73231	0.26769

0.322222	0.366338	-0.04412	5	5.992612	-0.99261	0.322222	0.33592	-0.0137	5	5.308191	-0.30819
0.322222	0.248139	0.074084	5	3.333119	1.666881	0.322222	0.287523	0.0347	5	4.219259	0.780741
0.366667	0.330499	0.036168	6	5.186226	0.813774	0.366667	0.332674	0.033993	6	5.235156	0.764844
0.366667	0.430909	-0.06424	6	7.445459	-1.44546	0.366667	0.47508	-0.10841	6	8.439307	-2.43931
0.366667	0.400609	-0.03394	6	6.763714	-0.76371	0.366667	0.417345	-0.05068	6	7.140267	-1.14027
0.366667	0.36031	0.006356	6	5.856984	0.143016	0.366667	0.397307	-0.03064	6	6.689397	-0.6894
0.366667	0.436837	-0.07017	6	7.578844	-1.57884	0.366667	0.430617	-0.06395	6	7.438873	-1.43887
0.366667	0.395519	-0.02885	6	6.649169	-0.64917	0.366667	0.364779	0.001888	6	5.957523	0.042477
0.366667	0.399004	-0.03234	6	6.727586	-0.72759	0.366667	0.407628	-0.04096	6	6.92162	-0.92162
0.411111	0.475807	-0.0647	7	8.455651	-1.45565	0.411111	0.442613	-0.0315	7	7.708794	-0.70879
0.411111	0.352385	0.058726	7	5.67867	1.32133	0.411111	0.347416	0.063695	7	5.56686	1.43314
0.411111	0.442254	-0.03114	7	7.700722	-0.70072	0.411111	0.44309	-0.03198	7	7.719521	-0.71952
0.411111	0.491892	-0.08078	7	8.817571	-1.81757	0.411111	0.482505	-0.07139	7	8.606369	-1.60637
0.411111	0.48968	-0.07857	7	8.767806	-1.76781	0.411111	0.499551	-0.08844	7	8.989892	-1.98989
0.411111	0.56608	-0.15497	7	10.4868	-3.4868	0.411111	0.553425	-0.14231	7	10.20207	-3.20207
0.455556	0.418726	0.036829	8	7.171346	0.828654	0.455556	0.431625	0.023931	8	7.461555	0.538445
0.455556	0.513724	-0.05817	8	9.308789	-1.30879	0.455556	0.472117	-0.01656	8	8.372623	-0.37262
0.455556	0.503063	-0.04751	8	9.068929	-1.06893	0.455556	0.511397	-0.05584	8	9.256443	-1.25644
0.455556	0.445336	0.01022	8	7.770052	0.229948	0.455556	0.457168	-0.00161	8	8.036278	-0.03628
0.455556	0.457638	-0.00208	8	8.046853	-0.04685	0.455556	0.429479	0.026077	8	7.413273	0.586727
0.455556	0.546596	-0.09104	8	10.0484	-2.0484	0.455556	0.54986	-0.0943	8	10.12185	-2.12185
0.5	0.536275	-0.03627	9	9.816181	-0.81618	0.5	0.527892	-0.02789	9	9.627564	-0.62756
0.5	0.645299	-0.1453	9	12.26923	-3.26923	0.5	0.613822	-0.11382	9	11.56098	-2.56098
0.5	0.512461	-0.01246	9	9.280372	-0.28037	0.5	0.49497	0.00503	9	8.886825	0.113175
0.5	0.449227	0.050773	9	7.857611	1.142389	0.5	0.52493	-0.02493	9	9.560919	-0.56092
0.5	0.446992	0.053008	9	7.807316	1.192684	0.5	0.458223	0.041777	9	8.060014	0.939986
0.5	0.571867	-0.07187	9	10.61701	-1.61701	0.5	0.576743	-0.07674	9	10.72672	-1.72672
0.5	0.522621	-0.02262	9	9.508971	-0.50897	0.5	0.513448	-0.01345	9	9.302589	-0.30259
0.544444	0.525515	0.018929	10	9.574098	0.425902	0.544444	0.590817	-0.04637	10	11.04339	-1.04339

0.544444	0.440878	0.103567	10	7.669754	2.330246	0.544444	0.458818	0.085627	10	8.073402	1.926598
0.544444	0.621997	-0.07755	10	11.74492	-1.74492	0.544444	0.6876	-0.14316	10	13.22101	-3.22101
0.544444	0.534561	0.009883	10	9.777628	0.222372	0.544444	0.523619	0.020826	10	9.531418	0.468582
0.544444	0.420641	0.123804	10	7.214419	2.785581	0.544444	0.43003	0.114414	10	7.425675	2.574325
0.544444	0.548797	-0.00435	10	10.09794	-0.09794	0.544444	0.526863	0.017581	10	9.604424	0.395576
0.544444	0.63918	-0.09474	10	12.13156	-2.13156	0.544444	0.621112	-0.07667	10	11.72502	-1.72502
0.544444	0.578651	-0.03421	10	10.76965	-0.76965	0.544444	0.540208	0.004236	10	9.904683	0.095317
0.544444	0.643991	-0.09955	10	12.23979	-2.23979	0.544444	0.612106	-0.06766	10	11.5224	-1.5224
0.588889	0.614023	-0.02513	11	11.56553	-0.56553	0.588889	0.576067	0.012822	11	10.71151	0.288491
0.588889	0.587804	0.001085	11	10.97558	0.024418	0.588889	0.567007	0.021882	11	10.50766	0.492339
0.588889	0.605487	-0.0166	11	11.37346	-0.37346	0.588889	0.598919	-0.01003	11	11.22569	-0.22569
0.588889	0.528569	0.06032	11	9.642799	1.357201	0.588889	0.62242	-0.03353	11	11.75444	-0.75444
0.588889	0.700331	-0.11144	11	13.50744	-2.50744	0.588889	0.705795	-0.11691	11	13.63039	-2.63039
0.588889	0.618777	-0.02989	11	11.67248	-0.67248	0.588889	0.621765	-0.03288	11	11.7397	-0.7397
0.588889	0.302177	0.286712	11	4.548985	6.451015	0.588889	0.282876	0.306013	11	4.114708	6.885292
0.588889	0.295575	0.293314	11	4.40043	6.59957	0.588889	0.288837	0.300052	11	4.248823	6.751177
0.588889	0.74576	-0.15687	11	14.52959	-3.52959	0.588889	0.75224	-0.16335	11	14.6754	-3.6754
0.588889	0.613522	-0.02463	11	11.55424	-0.55424	0.588889	0.62318	-0.03429	11	11.77155	-0.77155
0.588889	0.523219	0.06567	11	9.522428	1.477572	0.588889	0.500172	0.088717	11	9.003865	1.996135
0.588889	0.618473	-0.02958	11	11.66563	-0.66563	0.588889	0.667352	-0.07846	11	12.76542	-1.76542
0.633333	0.648467	-0.01513	12	12.3405	-0.3405	0.633333	0.618815	0.014519	12	11.67333	0.326672
0.633333	0.654932	-0.0216	12	12.48596	-0.48596	0.633333	0.640328	-0.00699	12	12.15738	-0.15738
0.633333	0.703547	-0.07021	12	13.57981	-1.57981	0.633333	0.735365	-0.10203	12	14.29571	-2.29571
0.633333	0.674681	-0.04135	12	12.93033	-0.93033	0.633333	0.713418	-0.08008	12	13.80189	-1.80189
0.633333	0.67994	-0.04661	12	13.04864	-1.04864	0.633333	0.642078	-0.00874	12	12.19675	-0.19675
0.633333	0.673461	-0.04013	12	12.90286	-0.90286	0.633333	0.706479	-0.07315	12	13.64579	-1.64579
0.633333	0.582738	0.050596	12	10.8616	1.1384	0.633333	0.620006	0.013327	12	11.70014	0.299859
0.633333	0.701061	-0.06773	12	13.52387	-1.52387	0.633333	0.727709	-0.09438	12	14.12344	-2.12344
0.633333	0.749477	-0.11614	12	14.61324	-2.61324	0.633333	0.730584	-0.09725	12	14.18814	-2.18814

0.677778	0.693752	-0.01597	13	13.35943	-0.35943	0.677778	0.711081	-0.0333	13	13.74932	-0.74932
0.677778	0.613899	0.063878	13	11.56274	1.437264	0.677778	0.62726	0.050518	13	11.86335	1.136652
0.677778	0.720978	-0.0432	13	13.972	-0.972	0.677778	0.713451	-0.03567	13	13.80264	-0.80264
0.677778	0.694748	-0.01697	13	13.38183	-0.38183	0.677778	0.649463	0.028315	13	12.36291	0.637086
0.677778	0.679699	-0.00192	13	13.04323	-0.04323	0.677778	0.695068	-0.01729	13	13.38902	-0.38902
0.677778	0.680444	-0.00267	13	13.05999	-0.05999	0.677778	0.715178	-0.0374	13	13.84151	-0.84151
0.677778	0.706112	-0.02833	13	13.63752	-0.63752	0.677778	0.744311	-0.06653	13	14.497	-1.497
0.677778	0.752776	-0.075	13	14.68746	-1.68746	0.677778	0.764773	-0.08699	13	14.95739	-1.95739
0.722222	0.705072	0.017151	14	13.61411	0.385888	0.722222	0.725463	-0.00324	14	14.07293	-0.07293
0.722222	0.72569	-0.00347	14	14.07803	-0.07803	0.722222	0.714331	0.007891	14	13.82245	0.177553
0.722222	0.801988	-0.07977	14	15.79473	-1.79473	0.722222	0.773808	-0.05159	14	15.16069	-1.16069
0.722222	0.354683	0.367539	14	5.730364	8.269636	0.722222	0.312349	0.409873	14	4.777859	9.222141
0.722222	0.752835	-0.03061	14	14.68878	-0.68878	0.722222	0.758122	-0.0359	14	14.80774	-0.80774
0.722222	0.695112	0.02711	14	13.39003	0.609974	0.722222	0.723409	-0.00119	14	14.02671	-0.02671
0.722222	0.748063	-0.02584	14	14.58141	-0.58141	0.722222	0.745263	-0.02304	14	14.51841	-0.51841
0.722222	0.750667	-0.02845	14	14.64002	-0.64002	0.722222	0.740336	-0.01811	14	14.40756	-0.40756
0.722222	0.813307	-0.09108	14	16.0494	-2.0494	0.722222	0.804551	-0.08233	14	15.8524	-1.8524
0.722222	0.789849	-0.06763	14	15.5216	-1.5216	0.722222	0.742455	-0.02023	14	14.45524	-0.45524
0.722222	0.794395	-0.07217	14	15.62388	-1.62388	0.722222	0.806974	-0.08475	14	15.90692	-1.90692
0.766667	0.676968	0.089699	15	12.98177	2.01823	0.766667	0.719706	0.046961	15	13.94338	1.056616
0.766667	0.727742	0.038925	15	14.12419	0.875813	0.766667	0.745156	0.021511	15	14.51601	0.483994
0.766667	0.761329	0.005338	15	14.8799	0.120103	0.766667	0.745202	0.021465	15	14.51704	0.482959
0.766667	0.716616	0.05005	15	13.87387	1.126133	0.766667	0.739303	0.027363	15	14.38433	0.615672
0.766667	0.769363	-0.0027	15	15.06066	-0.06066	0.766667	0.769522	-0.00285	15	15.06424	-0.06424
0.766667	0.706076	0.060591	15	13.63671	1.363288	0.766667	0.690051	0.076616	15	13.27615	1.723849
0.766667	0.791042	-0.02438	15	15.54845	-0.54845	0.766667	0.777576	-0.01091	15	15.24546	-0.24546
0.766667	0.692865	0.073802	15	13.33946	1.660536	0.766667	0.701277	0.06539	15	13.52873	1.471266
0.811111	0.764902	0.046209	16	14.96029	1.039708	0.811111	0.766423	0.044688	16	14.99452	1.005477
0.811111	0.783664	0.027447	16	15.38245	0.617552	0.811111	0.775684	0.035427	16	15.20289	0.797114

0.811111	0.769367	0.041744	16	15.06076	0.939238	0.811111	0.749383	0.061728	16	14.61113	1.388872
0.811111	0.802824	0.008287	16	15.81355	0.186453	0.811111	0.799696	0.011415	16	15.74316	0.256839
0.811111	0.715967	0.095144	16	13.85925	2.140746	0.811111	0.702828	0.108283	16	13.56363	2.436373
0.811111	0.783583	0.027528	16	15.38063	0.619374	0.811111	0.768514	0.042597	16	15.04157	0.958432
0.811111	0.834138	-0.02303	16	16.51811	-0.51811	0.811111	0.811447	-0.00034	16	16.00756	-0.00756
0.811111	0.691439	0.119672	16	13.30738	2.692619	0.811111	0.666363	0.144748	16	12.74317	3.256827
0.855556	0.766086	0.08947	17	14.98693	2.013068	0.855556	0.74685	0.108706	17	14.55412	2.44588
0.855556	0.807282	0.048274	17	15.91384	1.086161	0.855556	0.803392	0.052163	17	15.82633	1.173669
0.855556	0.776523	0.079033	17	15.22177	1.778233	0.855556	0.769001	0.086555	17	15.05252	1.947484
0.855556	0.789478	0.066078	17	15.51325	1.486753	0.855556	0.769883	0.085672	17	15.07238	1.927621
0.855556	0.784492	0.071064	17	15.40106	1.59894	0.855556	0.760717	0.094839	17	14.86613	2.133869
0.855556	0.803659	0.051897	17	15.83232	1.167681	0.855556	0.778915	0.076641	17	15.27558	1.724415
0.9	0.75355	0.14645	18	14.70487	3.295134	0.9	0.764479	0.135521	18	14.95077	3.049228
0.9	0.823126	0.076874	18	16.27033	1.729673	0.9	0.785434	0.114566	18	15.42226	2.577741
0.9	0.795589	0.104411	18	15.65076	2.349243	0.9	0.78482	0.11518	18	15.40844	2.591559
0.9	0.782202	0.117798	18	15.34956	2.650444	0.9	0.766582	0.133418	18	14.9981	3.001898
0.9	0.777406	0.122594	18	15.24162	2.758375	0.9	0.777928	0.122072	18	15.25338	2.746617
0.9	0.73439	0.16561	18	14.27378	3.726219	0.9	0.757506	0.142494	18	14.79389	3.206105
0.9	0.791646	0.108354	18	15.56204	2.437956	0.9	0.771954	0.128046	18	15.11897	2.881027
0.9	0.792467	0.107533	18	15.58052	2.419484	0.9	0.769683	0.130317	18	15.06787	2.932126

APPENDIX R

NORMALIZED AND DENORMALIZED TEST DATASET OF TARGET FEATURE, OUTPUTS AND ERRORS FOR MALE HISPANIC POPULATION USING ANN APPROACH AND GA-ANN APPROACH AND THEIR DENORMALIZED TEST SET SQUARE ERRORS

ANN							GA-ANN						
Normalized			Denormalized				Normalized			Denormalized			
Target	Output	Error	Target	Output	Error	Error^2	Target	Output	Error	Target	Output	Error	Error^2
0.1	0.201324	-0.10132	0	2.279791	-2.27979	5.1974449	0.1	0.183585	-0.08359	0	1.880664	-1.88066	3.5368987
0.188889	0.197235	-0.00835	2	2.187777	-0.18778	0.03526	0.188889	0.215019	-0.02613	2	2.587926	-0.58793	0.3456575
0.188889	0.233506	-0.04462	2	3.003875	-1.00387	1.0077643	0.188889	0.214525	-0.02564	2	2.576813	-0.57681	0.3327132
0.233333	0.279835	-0.0465	3	4.046295	-1.04629	1.0947323	0.233333	0.299638	-0.0663	3	4.491861	-1.49186	2.2256486
0.233333	0.211454	0.02188	3	2.507708	0.492292	0.242351	0.233333	0.219837	0.013496	3	2.696342	0.303658	0.0922084
0.277778	0.366258	-0.08848	4	5.990798	-1.9908	3.9632762	0.277778	0.321419	-0.04364	4	4.981924	-0.98192	0.9641748
0.277778	0.201166	0.076612	4	2.276225	1.723775	2.9714014	0.277778	0.208095	0.069683	4	2.432137	1.567863	2.4581941
0.322222	0.348731	-0.02651	5	5.596441	-0.59644	0.355742	0.322222	0.387335	-0.06511	5	6.465045	-1.46505	2.1463582
0.322222	0.431744	-0.10952	5	7.464246	-2.46425	6.0725074	0.322222	0.342664	-0.02044	5	5.459937	-0.45994	0.2115419
0.322222	0.332151	-0.00993	5	5.223394	-0.22339	0.049905	0.322222	0.369982	-0.04776	5	6.074604	-1.0746	1.154774
0.322222	0.347224	-0.025	5	5.56253	-0.56253	0.3164396	0.322222	0.373251	-0.05103	5	6.148144	-1.14814	1.3182336
0.366667	0.354582	0.012085	6	5.728094	0.271906	0.073933	0.366667	0.368918	-0.00225	6	6.050651	-0.05065	0.0025656
0.366667	0.359656	0.00701	6	5.842269	0.157731	0.024879	0.366667	0.394445	-0.02778	6	6.625014	-0.62501	0.3906426
0.411111	0.481509	-0.0704	7	8.583953	-1.58395	2.5089077	0.411111	0.450218	-0.03911	7	7.879906	-0.87991	0.7742341
0.411111	0.418609	-0.0075	7	7.168705	-0.16871	0.0284614	0.411111	0.382704	0.028408	7	6.36083	0.63917	0.4085383
0.411111	0.469562	-0.05845	7	8.315154	-1.31515	1.7296295	0.411111	0.45401	-0.0429	7	7.965232	-0.96523	0.9316724
0.411111	0.418849	-0.00774	7	7.174108	-0.17411	0.0303137	0.411111	0.412423	-0.00131	7	7.029521	-0.02952	0.0008715
0.455556	0.469473	-0.01392	8	8.313136	-0.31314	0.0980541	0.455556	0.504234	-0.04868	8	9.095267	-1.09527	1.1996099
0.455556	0.402567	0.052988	8	6.807768	1.192232	1.4214163	0.455556	0.491397	-0.03584	8	8.806426	-0.80643	0.6503225
0.455556	0.340921	0.114635	8	5.420717	2.579283	6.6527001	0.455556	0.415008	0.040548	8	7.087681	0.912319	0.8323259
0.455556	0.518221	-0.06267	8	9.409963	-1.40996	1.9879956	0.455556	0.493393	-0.03784	8	8.851337	-0.85134	0.724774
0.5	0.539811	-0.03981	9	9.895757	-0.89576	0.8023803	0.5	0.527366	-0.02737	9	9.615734	-0.61573	0.3791286
0.5	0.642738	-0.14274	9	12.21161	-3.21161	10.314416	0.5	0.576607	-0.07661	9	10.72366	-1.72366	2.9709889

0.5	0.624776	-0.12478	9	11.80746	-2.80746	7.8818342	0.5	0.608032	-0.10803	9	11.43072	-2.43072	5.9084008
0.544444	0.477199	0.067245	10	8.486977	1.513023	2.2892396	0.544444	0.475933	0.068512	10	8.458489	1.541511	2.3762555
0.544444	0.562167	-0.01772	10	10.39876	-0.39876	0.1590132	0.544444	0.575252	-0.03081	10	10.69318	-0.69318	0.480497
0.544444	0.61475	-0.07031	10	11.58187	-1.58187	2.5023213	0.544444	0.5905	-0.04606	10	11.03624	-1.03624	1.0737941
0.588889	0.535541	0.053348	11	9.799663	1.200337	1.4408096	0.588889	0.574432	0.014457	11	10.67472	0.325278	0.105806
0.588889	0.605067	-0.01618	11	11.36402	-0.36402	0.1325071	0.588889	0.629204	-0.04031	11	11.90709	-0.90709	0.8228051
0.633333	0.754195	-0.12086	12	14.71938	-2.71938	7.3950179	0.633333	0.751885	-0.11855	12	14.66741	-2.66741	7.1150809
0.633333	0.650181	-0.01685	12	12.37906	-0.37906	0.1436895	0.633333	0.627768	0.005566	12	11.87477	0.12523	0.0156827
0.633333	0.681152	-0.04782	12	13.07592	-1.07592	1.1576138	0.633333	0.671135	-0.0378	12	12.85053	-0.85053	0.7234027
0.633333	0.658568	-0.02523	12	12.56777	-0.56777	0.3223628	0.633333	0.678144	-0.04481	12	13.00823	-1.00823	1.0165321
0.633333	0.622084	0.01125	12	11.74689	0.253114	0.0640667	0.633333	0.624661	0.008672	12	11.80488	0.195123	0.0380731
0.633333	0.70065	-0.06732	12	13.51462	-1.51462	2.2940737	0.633333	0.70814	-0.07481	12	13.68316	-1.68316	2.8330133
0.677778	0.672703	0.005075	13	12.88582	0.114182	0.0130375	0.677778	0.668477	0.009301	13	12.79072	0.209278	0.0437974
0.677778	0.765351	-0.08757	13	14.9704	-1.9704	3.8824699	0.677778	0.772625	-0.09485	13	15.13407	-2.13407	4.5542406
0.677778	0.633847	0.043931	13	12.01156	0.988439	0.977012	0.677778	0.721206	-0.04343	13	13.97713	-0.97713	0.9547794
0.677778	0.726137	-0.04836	13	14.08809	-1.08809	1.1839369	0.677778	0.722753	-0.04498	13	14.01194	-1.01194	1.024021
0.677778	0.696694	-0.01892	13	13.42562	-0.42562	0.1811511	0.677778	0.636967	0.04081	13	12.08177	0.918231	0.8431488
0.677778	0.789076	-0.1113	13	15.50421	-2.50421	6.2710567	0.677778	0.729651	-0.05187	13	14.16714	-1.16714	1.3622203
0.677778	0.725624	-0.04785	13	14.07654	-1.07654	1.1589414	0.677778	0.696402	-0.01862	13	13.41905	-0.41905	0.1755997
0.722222	0.808195	-0.08597	14	15.93439	-1.93439	3.7418586	0.722222	0.77833	-0.05611	14	15.26242	-1.26242	1.5937016
0.722222	0.723004	-0.00078	14	14.01759	-0.01759	0.0003094	0.722222	0.738726	-0.0165	14	14.37134	-0.37134	0.1378948
0.722222	0.691355	0.030867	14	13.30549	0.694506	0.4823393	0.722222	0.697581	0.024642	14	13.44556	0.554436	0.3073996
0.766667	0.776064	-0.0094	15	15.21143	-0.21143	0.0447025	0.766667	0.764482	0.002185	15	14.95085	0.049152	0.0024159
0.766667	0.791099	-0.02443	15	15.54973	-0.54973	0.3022033	0.766667	0.784245	-0.01758	15	15.39551	-0.39551	0.1564279
0.811111	0.763783	0.047328	16	14.93511	1.064889	1.1339896	0.811111	0.763742	0.047369	16	14.93419	1.065813	1.1359574
0.811111	0.747164	0.063947	16	14.5612	1.4388	2.0701466	0.811111	0.740383	0.070728	16	14.40863	1.591374	2.5324713
0.855556	0.825701	0.029855	17	16.32826	0.671738	0.4512326	0.855556	0.787862	0.067693	17	15.4769	1.523102	2.3198399
0.855556	0.771538	0.084017	17	15.10961	1.89039	3.573573	0.855556	0.770061	0.085494	17	15.07638	1.923624	3.700331
0.855556	0.763251	0.092305	17	14.92314	2.076855	4.3133276	0.855556	0.779566	0.07599	17	15.29023	1.709767	2.9233016
0.855556	0.77824	0.077315	17	15.26041	1.739593	3.0261827	0.855556	0.780163	0.075393	17	15.30366	1.696342	2.8775757
0.9	0.755632	0.144368	18	14.75171	3.248289	10.551383	0.9	0.738611	0.161389	18	14.36874	3.631262	13.186061
0.9	0.714103	0.185897	18	13.81731	4.182687	17.494871	0.9	0.78023	0.11977	18	15.30516	2.694836	7.2621388

APPENDIX S

GA PYTHON SCRIPT FOR FEMALE FEATURE SELECTION

```python
import random
import numpy as np
import matplotlib.pyplot as plt
import pandas as pd
import csv

from os.path import join, dirname
from sklearn.utils import Bunch
from sklearn.model_selection import cross_val_score
from sklearn.linear_model import LinearRegression

SEED = 2018
random.seed(SEED)
np.random.seed(SEED)

#===============================================================================
# Data
#===============================================================================
module_path = dirname(__file__)
data_file_name = join(module_path, 'HISF.csv')
with open(data_file_name) as f:
    data_file = csv.reader(f)
    temp = next(data_file)
    n_samples = int(temp[0])
    n_features = int(temp[1])
    data = np.empty((n_samples, n_features))
    target = np.empty((n_samples,))
    temp = next(data_file)  # names of features
    feature_names = np.array(temp)

    for i, d in enumerate(data_file):
        data[i] = np.asarray(d[:-1], dtype=np.float64)
        target[i] = np.asarray(d[-1], dtype=np.float64)

dataset = Bunch(data=data,
```

```
             target=target,
             # last column is target value
             feature_names=feature_names[:-1],
             filename=data_file_name)

X, y = dataset.data, dataset.target
features = dataset.feature_names
#features = ["Bone1" "Bone2" "Bone3" "Bone4" "Bone5" "Bone6" "Bone7" "Bone8" "Bone9" "Bone10" "Bone11" "Bone12" "Bone13" "Bone14" "Bone15"
"Bone16" "Bone17" "Bone18" "Bone19"]
#features = [Bone1, Bone2, Bone3, Bone4, Bone5, Bone6, Bone7, Bone8, Bone9, Bone10, Bone11, Bone12, Bone13, Bone14, Bone15, Bone16, Bone17,
Bone18, Bone19]


#==============================================================================
# CV MSE before feature selection
#==============================================================================
est = LinearRegression()
score = -1.0 * cross_val_score(est, X, y , cv=5, scoring="neg_mean_squared_error")
print("CV MSE before feature selection: {:.8f}".format(np.mean(score)))

#==============================================================================
# Class performing feature selection with genetic algorithm
#==============================================================================
class GeneticSelector():
    def __init__(self, estimator, n_gen, size, n_best, n_rand,
                 n_children, mutation_rate):
        # Estimator
        self.estimator = estimator
        # Number of generations
        self.n_gen = n_gen
        # Number of chromosomes in population
        self.size = size
        # Number of best chromosomes to select
```

```python
        self.n_best = n_best
        # Number of random chromosomes to select
        self.n_rand = n_rand
        # Number of children created during crossover
        self.n_children = n_children
        # Probablity of chromosome mutation
        self.mutation_rate = mutation_rate

        if int((self.n_best + self.n_rand) / 2) * self.n_children != self.size:
            raise ValueError("The population size is not stable.")

    def initilize(self):
        population = []
        for i in range(self.size):
            chromosome = np.ones(self.n_features, dtype=np.bool)
            mask = np.random.rand(len(chromosome)) < 0.3
            chromosome[mask] = False
            population.append(chromosome)
        return population

    def fitness(self, population):
        X, y = self.dataset
        scores = []
        for chromosome in population:
            score = -1.0 * np.mean(cross_val_score(self.estimator, X[:,chromosome], y,
                                                   cv=5,
                                                   scoring="neg_mean_squared_error"))
            scores.append(score)
        scores, population = np.array(scores), np.array(population)
        inds = np.argsort(scores)
        return list(scores[inds]), list(population[inds,:])

    def select(self, population_sorted):
```

```python
        population_next = []
        for i in range(self.n_best):
            population_next.append(population_sorted[i])
        for i in range(self.n_rand):
            population_next.append(random.choice(population_sorted))
        random.shuffle(population_next)
        return population_next

    def crossover(self, population):
        population_next = []
        for i in range(int(len(population)/2)):
            for j in range(self.n_children):
                chromosome1, chromosome2 = population[i], population[len(population)-1-i]
                child = chromosome1
                mask = np.random.rand(len(child)) > 0.5
                child[mask] = chromosome2[mask]
                population_next.append(child)
        return population_next

    def mutate(self, population):
        population_next = []
        for i in range(len(population)):
            chromosome = population[i]
            if random.random() < self.mutation_rate:
                mask = np.random.rand(len(chromosome)) < 0.05
                chromosome[mask] = False
            population_next.append(chromosome)
        return population_next

    def generate(self, population):
        # Selection, crossover and mutation
        scores_sorted, population_sorted = self.fitness(population)
        population = self.select(population_sorted)
```

```
        population = self.crossover(population)
        population = self.mutate(population)
        # History
        self.chromosomes_best.append(population_sorted[0])
        self.scores_best.append(scores_sorted[0])
        self.scores_avg.append(np.mean(scores_sorted))

        return population

    def fit(self, X, y):

        self.chromosomes_best = []
        self.scores_best, self.scores_avg  = [], []

        self.dataset = X, y
        self.n_features = X.shape[1]
        self.population = []
        population = self.initilize()
        for i in range(self.n_gen):
            population = self.generate(population)

        self.population = population
        return self

    @property
    def support_(self):
        return self.chromosomes_best[-1]

    def plot_scores(self):
        plt.plot(self.scores_best, label='Best')
        plt.plot(self.scores_avg, label='Average')
        plt.legend()
        plt.ylabel('Scores')
```

```
        plt.xlabel('Generation')
        plt.show()

sel = GeneticSelector(estimator=LinearRegression(),
                      n_gen=200, size=200, n_best=40, n_rand=40,
                      n_children=5, mutation_rate=0.05)
sel.fit(X, y)
sel.plot_scores()
score = -1.0 * cross_val_score(est, X[:,sel.support_], y, cv=5, scoring="neg_mean_squared_error")
print("CV MSE after feature selection: {:.8f}".format(np.mean(score)))
#print(sel.population)
np.savetxt('GApopulationFemale.csv', sel.population, fmt='%.2f', delimiter=',', header=" Bone1, Bone2, Bone3, Bone4, Bone5, Bone6, Bone7,
    Bone8, Bone9, Bone10, Bone11, Bone12, Bone13, Bone14, Bone15, Bone16, Bone17, Bone18, Bone19")
```

APPENDIX T

GA PYTHON SCRIPT FOR MALE FEATURE SELECTION

```python
import random
import numpy as np
import matplotlib.pyplot as plt
import pandas as pd
import csv

from os.path import join, dirname
from sklearn.utils import Bunch
from sklearn.model_selection import cross_val_score
from sklearn.linear_model import LinearRegression

SEED = 2018
random.seed(SEED)
np.random.seed(SEED)

#==============================================================================
# Data
#==============================================================================
module_path = dirname(__file__)
data_file_name = join(module_path, 'HISM.csv')
with open(data_file_name) as f:
    data_file = csv.reader(f)
    temp = next(data_file)
    n_samples = int(temp[0])
    n_features = int(temp[1])
    data = np.empty((n_samples, n_features))
    target = np.empty((n_samples,))
    temp = next(data_file)  # names of features
    feature_names = np.array(temp)

    for i, d in enumerate(data_file):
        data[i] = np.asarray(d[:-1], dtype=np.float64)
        target[i] = np.asarray(d[-1], dtype=np.float64)

dataset = Bunch(data=data,
```

```
                target=target,
                # last column is target value
                feature_names=feature_names[:-1],
                filename=data_file_name)

X, y = dataset.data, dataset.target
features = dataset.feature_names
#features = ["Bone1" "Bone2" "Bone3" "Bone4" "Bone5" "Bone6" "Bone7" "Bone8" "Bone9" "Bone10" "Bone11" "Bone12" "Bone13" "Bone14" "Bone15" "Bone16" "Bone17" "Bone18" "Bone19"]
#features = [Bone1, Bone2, Bone3, Bone4, Bone5, Bone6, Bone7, Bone8, Bone9, Bone10, Bone11, Bone12, Bone13, Bone14, Bone15, Bone16, Bone17, Bone18, Bone19]


#==============================================================================
# CV MSE before feature selection
#==============================================================================
est = LinearRegression()
score = -1.0 * cross_val_score(est, X, y , cv=5, scoring="neg_mean_squared_error")
print("CV MSE before feature selection: {:.8f}".format(np.mean(score)))

#==============================================================================
# Class performing feature selection with genetic algorithm
#==============================================================================
class GeneticSelector():
    def __init__(self, estimator, n_gen, size, n_best, n_rand,
                 n_children, mutation_rate):
        # Estimator
        self.estimator = estimator
        # Number of generations
        self.n_gen = n_gen
        # Number of chromosomes in population
        self.size = size
        # Number of best chromosomes to select
```

```python
        self.n_best = n_best
        # Number of random chromosomes to select
        self.n_rand = n_rand
        # Number of children created during crossover
        self.n_children = n_children
        # Probablity of chromosome mutation
        self.mutation_rate = mutation_rate

        if int((self.n_best + self.n_rand) / 2) * self.n_children != self.size:
            raise ValueError("The population size is not stable.")

    def initilize(self):
        population = []
        for i in range(self.size):
            chromosome = np.ones(self.n_features, dtype=np.bool)
            mask = np.random.rand(len(chromosome)) < 0.3
            chromosome[mask] = False
            population.append(chromosome)
        return population

    def fitness(self, population):
        X, y = self.dataset
        scores = []
        for chromosome in population:
            score = -1.0 * np.mean(cross_val_score(self.estimator, X[:,chromosome], y,
                                                    cv=5,
                                                    scoring="neg_mean_squared_error"))
            scores.append(score)
        scores, population = np.array(scores), np.array(population)
        inds = np.argsort(scores)
        return list(scores[inds]), list(population[inds,:])

    def select(self, population_sorted):
```

```python
        population_next = []
        for i in range(self.n_best):
            population_next.append(population_sorted[i])
        for i in range(self.n_rand):
            population_next.append(random.choice(population_sorted))
        random.shuffle(population_next)
        return population_next

    def crossover(self, population):
        population_next = []
        for i in range(int(len(population)/2)):
            for j in range(self.n_children):
                chromosome1, chromosome2 = population[i], population[len(population)-1-i]
                child = chromosome1
                mask = np.random.rand(len(child)) > 0.5
                child[mask] = chromosome2[mask]
                population_next.append(child)
        return population_next

    def mutate(self, population):
        population_next = []
        for i in range(len(population)):
            chromosome = population[i]
            if random.random() < self.mutation_rate:
                mask = np.random.rand(len(chromosome)) < 0.05
                chromosome[mask] = False
            population_next.append(chromosome)
        return population_next

    def generate(self, population):
        # Selection, crossover and mutation
        scores_sorted, population_sorted = self.fitness(population)
        population = self.select(population_sorted)
```

```
            population = self.crossover(population)
            population = self.mutate(population)
            # History
            self.chromosomes_best.append(population_sorted[0])
            self.scores_best.append(scores_sorted[0])
            self.scores_avg.append(np.mean(scores_sorted))

            return population

        def fit(self, X, y):

            self.chromosomes_best = []
            self.scores_best, self.scores_avg  = [], []

            self.dataset = X, y
            self.n_features = X.shape[1]
            self.population = []
            population = self.initilize()
            for i in range(self.n_gen):
                population = self.generate(population)

            self.population = population
            return self

        @property
        def support_(self):
            return self.chromosomes_best[-1]

        def plot_scores(self):
            plt.plot(self.scores_best, label='Best')
            plt.plot(self.scores_avg, label='Average')
            plt.legend()
            plt.ylabel('Scores')
```

```python
            plt.xlabel('Generation')
            plt.show()

sel = GeneticSelector(estimator=LinearRegression(),
                      n_gen=200, size=200, n_best=40, n_rand=40,
                      n_children=5, mutation_rate=0.05)
sel.fit(X, y)
sel.plot_scores()
score = -1.0 * cross_val_score(est, X[:,sel.support_], y, cv=5, scoring="neg_mean_squared_error")
print("CV MSE after feature selection: {:.8f}".format(np.mean(score)))
#print(sel.population)
np.savetxt('GApopulationMale.csv', sel.population, fmt='%.2f', delimiter=',', header=" Bone1, Bone2, Bone3, Bone4, Bone5, Bone6, Bone7,
    Bone8, Bone9, Bone10, Bone11, Bone12, Bone13, Bone14, Bone15, Bone16, Bone17, Bone18, Bone19")
```