ÇUKUROVA UNIVERSITY
INSTITUTE OF NATURAL AND APPLIED SCIENCES

Msc THESIS

Ezgi AKÇA

DEVELOPMENT OF A NEW SOFTWARE FOR RESTING METABOLIC RATE PREDICTION USING MACHINE LEARNING METHODS

DEPARTMENT OF COMPUTER ENGINEERING

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We certify that the thesis titled above was reviewed and approved for the award of degree of the Master of Science by the board of jury on

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ABSTRACT

Msc THESIS

DEVELOPMENT OF A NEW SOFTWARE FOR RESTING METABOLIC RATE PREDICTION USING MACHINE LEARNING METHODS

Ezgi AKÇA

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Resting metabolic rate(RMR) indicates the number of calories that are needed to carry out basic functions in mammals like blood circulation, brain functions, breathing, fuel ventilation, temperature regulation, etc. at complete rest. Accurate prediction of RMR plays a critical role to detect an individual’s establish daily calorie needs, risk of heart disease and stroke, hypertension, diabetes, and internal age so nutritionists calculate RMR of patients within the specified period and able to prepare diet lists for them to help their wellness goals. In this thesis, it was objected to develop a novel web-based application that can predict the individual’s RMR using different machine learning methods. The application has been developed using DTREG predictive modeling software library, Visual Studio, and C# programming language. Three different machine learning methods which are General Regression Neural Network (GRNN), Multi-Layer Perceptron (MLP), Support Vector Machines (SVM) have been integrated into the software. Different prediction models have been assessed according to their Root Mean Square Error (RMSE) metrics. As a result, it has been proven that this software can be used for RMR prediction, producing acceptable error rates under certain circumstances.

Key words: Resting Metabolic Rate, Software Development, Prediction, Multilayer Perceptron, Basal Metabolic Rate

ÖZ

YÜKSEK LİSANS TEZİ

MAKİNE ÖĞRENME YÖNTEMLERİNİ KULLANARAK İSTİRAHAT METABOLİK HIZ TAHMİNİ İÇİN YENİ BİR YAZILIMIN GELİŞTİRİLMESİ

Ezgi AKÇA

ÇUKUROVA ÜNİVERSİTESİ
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Dinlenme metabolik hızı(DMH) kan dolaşımı, beyin fonksiyonları, nefes alma, sıcaklık düzenleme vb. gibi memeli canlılarda temel fonksiyonları yerine getirmek için gereken kalori miktarını ifade eder. Doğru DMH tahmini bireyin günlük kalori ihtiyacını, kalp hastalığı ve felç riskini, hipertansiyonu, diyabeti ve vücut iç yaşını tespit etmede kritik bir rol oynar. Beslenme uzmanları belirtilen süre zarflarında hastalarının DMH'lerini hesaplayabilir ve sağlık hedeflerine yardımcı olmak için onlara diyet listesi hazırlayabilirler. Bu tezde, bireyin DMH değerini farklı makine öğrenmesi yöntemleri kullanarak tahmin edebilecek yeni bir web tabanlı uygulama geliştirilmesi amaçlanmıştır. Uygulama DTREG tahmin modelleme yazılımı kütüphanesi, Visual Studio ve C # programlama dili kullanılarak geliştirilmiştir. Genel Regresyon Sinir Ağı (GRNN), Çok Katmanlı Algılayıcı (MLP), Destek Vektör Makineleri (SVM) olmak üzere üç farklı makine öğrenme yöntemi yazılıma entegre edildi. Farklı tahmin modelleri, Kök Ortalama Kare Hatası (RMSE) ölçümlerine göre değerlendirilmiştir. Sonuç olarak, bu yazılımın DMH tahmini için kullanılabileceği ve bazı durumlarda kabul edilebilir hata oranları ürettiği kanıtlanmıştır.

Anahtar Kelimeler: Dinlenme Metabolik Hızı, Yazılım Geliştirme, Tahmin, Bazal Metabolizma Hızı

EXTENDED ABSTRACT

Resting Metabolic Rate (RMR) is an estimation of how many calories the body will burn to carry out basic functions at complete rest. RMR is an important part of the total daily energy expenditure (TDEE) of the body or the total amount of calories which are burned every day. Knowledge of an individual’s RMR, is a critical piece of information to appropriately establish daily calorie needs. This information is crucial to lose weight, gain weight and maintain optimal body weight without hindering basic functions of body. If an individual's value of RMR is high, the body's chance of storing calories as fat decreases and if it is low, it takes more time for the body to convert the received food into usable energy, and therefore the body will have a greater chance of storing unused foods as fat. Theoretically the person with low RMR, has higher risk to contract an obesity related diseas than normal people. Thus, with the early detection of low RMR, the susceptibility of an individual to obesity is able to understood and the risk of contracting these critical diseases can be reduced by personalized diet plan or necessary interventions.

In practice, the most accurate method for measuring RMR is the Douglas bag system, which is known as indirect calorimetry technique. It is considered the gold standard to calculate RMR in practice. However, measurement of actual RMR with Douglas bag, requires strict restrictions such as clinical situations, expensive equipment, expert requirement for the use of the system, cost of the test and preparation process of the individual. That’s why simple RMR prediction equations are used to calculate RMR. Harris-Benedict (1919), Mifflin-St. Jeor (1952) and Owen et. al. (1987) equations are the most commonly used linear equations by dietitian due to ease of use but they are not fully reliable because of high error rate, limited number and insufficient use of variables. In recent years, several studies which are based on resting energy expenditure with the usage of machine learning methods have been added to the academical literature but none of these studies have been designed as a RMR calculator that can be used in general.

The main purpose of this thesis work, is to develop a new software which can predict RMR of an individual. The software has been developed with the integration of three different machine learning methods which are General Regression Neural Network (GRNN), Multilayer Perceptron (MLP), Support Vector Machines (SVM). The optimization of the parameters in the selected methods has been implemented in the software, in order to achieve diversity.

In this study, 260 female and 150 male patients with different body compositions were gathered in 2 separate data sets. Data sets have been obtained from nutritionist Müzda Irmak in Turkey. These data sets contain various variables which have been obtained from Tanita. A Tanita is a smart scale which scans the entire body and provides a wide range of measurements which are body fat (kg), muscle (kg), bone weight (kg), liquid (kg) etc. in body. These measurements are much more accurate than those provided by calculators and are trusted by doctors and experts worldwide.

In the software which is developed for this thesis, MLP, GRNN, SVM algorithms have been used. MLP is one of the most popular and widely- used machine learning algorithms which can be seen in the other similar studies related to the subject in the literature. In this method, prediction model consists of three different type of layers, including the input layer, the hidden layers and the output layer in total.

SVM is a supervised learning algorithm which can be apply classification or regression analysis. The objective of the support vector machine algorithm in the classification problems is to find a hyperplane in an N-dimensional space that distinctly classifies the data points. SVM can be learned nonlinear complex problem. In this study, SVM models are created by using Support Vector Regression(SVR) which is the version of SVM used for regression problem. The Support Vector Regression (SVR) uses the same principles as the SVM for classification, with only a few minor differences. Cost (C), epsilon (ε) and gamma (γ) values determine the performance of SVM-based models.

GRNN is a specialized neural network algorithm for regression analysis. The GRNN architecture contains four basic layers which are input layer, pattern layer, summation layer and output layer. GRNN can obtained a prediction against input which is fed into network. In the GRNN model, only one unknown parameter is “sigma ” standard deviation value. Sigma can be tuned by training process to an optimum value where the error will be very small. In this thesis work, the functions of .Net Class Library provided by DTREG Predictive Modeling Software are used to implement of Multilayer Perceptron(MLP), Support Vector Machine(SVM), Generalized Regression Neural Network(GRNN) in the parts of software development and creating new model.

When carrying out prediction models, the choice of the form of splitting training-test datasets, which strategy will be used for the missing data blocks, which activation function will be used for the model, are decided by the designer. The extra parameters that must be decided for MLP models are the number of hidden layers, the number of neurons in hidden layers, maximum number of steps for detection of overfitting. For SVM models, firstly which type of SVR model will be used (Nu or Epsilon) should be decided. According to the decided SVR type, Cost (C), Epsilon (ε), Nu parameters should be selected. Gamma (γ), P, Coef, Degree parameters should be set according to the specified activation function. For tuning these parameters, with the usage of grid search or pattern search algorithms can be expected to select these parameters by system itself. In the GRNN model, the method for selecting the sigma value is determined. Then, the minimum limit, maximum limit and step size values which are needed to search for the best sigma value, are the parameters to be decided by the designer to find optimum value for sigma value. The neurons which don’t contribute to the result are removed from network, with the usage of “minimum error” and “minimum neurons” optimization algorithms provided by the software. It has been observed models that have lower error rate with optimization algorithms.

The achieved models were evaluated with respect to Root Mean Squared Error, RMSE ratios. In this study, 17.456 different prediction models have been produced in total, including 8786 models for female patients and 8670 models for male patients. However, the best 720 models have tabled in this thesis. These models were combined with different parameters that may affect the RMR value based on the values of “age, height, weight” or “age, height, BMI (body mass index)”. When the results of these models have been assessed, the first conclusion is that models of GRNN have a lower error rate within all methods.

When error rates are compared, hidden layer size, number of neurons in hidden layer, selection of activation function for MLP models, different cost (C), epsilon (ε) and gamma (γ) values, selection of core function in SVM models, selection of sigma value in GRNN models, have added variety to the prediction models but have observed to not able to decrease in the error rate dramatically.

One of the most important findings has been obtained throughout the study is that the error rates in the predictions are related to the selection of the input parameters. In addition, the option of optimizing the parameters by model is provided lower error rates than manual adjustments in all methods. In general, models of female patient have been obtained lower error rates than model of male patients.

In this thesis work, while the error rates have been ranged between 134.91 and max value for female models, 143.109 and max value for male models. When the RMSE values of the linear estimation equations that are used in the literature have been compared, the machine learning methods are able to produced models which have lower error rate.

According to the results that have been obtained from the whole study, it has been proved that the software developed for this thesis can be used more accurately in prediction of resting metabolic rate from the literature and in prediction equations which are used in practice.

GENİŞLETİLMİŞ ÖZET

Dinlenme metabolizma hızı (DMH), vücudun tamamen dinlenme halindeyken temel fonksiyonlarını yerine getirebilmek için ne kadar kalori harcayacağının bir tahminidir. DMH, vücudun toplam günlük enerji tüketiminin (TDEE) veya her gün yakılan toplam kalori miktarının önemli bir parçasıdır. Bir kişinin DMH bilgisi, o kişinin günlük kalori ihtiyacını doğru bir şekilde tespit etmek için kritik bir bilgi parçasıdır. Bu bilgi, temel vücut fonksiyonlarını engellemeden kilo vermek, kilo almak ve optimum vücut ağırlığını korumak için çok önemlidir. Eğer bir bireyin DMH değeri yüksekse vücudun aldığı kalorileri yağ olarak depolama şansı azalırken, eğer düşükse vücudun alınan yiyecekleri kullanılabilir enerjiye dönüştürmesi daha çok zaman alır ve bu nedenle vücudun kullanılmamış yiyecekleri yağ olarak saklama şansı daha yüksek olacaktır.Düşük DMH'li bir kişinin teorik olarak obezite ile ilişkili hastalıklara yakalanma riski normal insanlara göre çok daha yüksektir. DMH ölçümü beslenme değerlendirmesi ve kilo yönetimi programlarında beslenme uzmanları tarafından yapılmaktadır. Böylece düşük DMH'nin erken tespiti ile bir kişinin obeziteye yatkınlığı anlaşılabilir ve kişiye özel diyet listeleri ya da gerekli müdahaleler ile bu kritik hastalıklara yakalanma riski azaltılabilir.

Pratikte DMH ölçümü için kullanılan en doğru yöntem ise indirekt kalorimtere tekniği olarak bilinen Douglas Bag sistemidir. Douglas Bag sistemi, tek bir nefeste tüketilen O2 ve üretilen CO2 miktarına dayanan solunan gaz analizi yöntemidir. Pratikte DMH'yi hesaplamak için altın standart olarak kabul edilir. Ancak Douglas Bag ile gerçek RMR ölçümü, klinik durumlar, pahalı donanım, sistemin kullanımı için uzman gereksinimi, testin maliyeti ve bireyin hazırlık süreci gibi katı kısıtlamalar gerektirir. Bu nedenle DMH'yi hesaplamak için basit tahmin denklemleri kullanılır Harris-Benedict (1919), Mifflin-St. Jeor (1952) ve Owen ve ark. (1987) denklemleri kullanım kolaylığı nedeniyle diyetisyenlerin en çok kullandığı lineer denklemlerdir. Ancak yüksek hata oranı, sınırlı sayıda ve değişkenlerin yetersiz kullanımı nedeniyle tam olarak güvenilir değildir. Son yıllarda, akademik literatüre makine öğrenme yöntemlerinin kullanımı ile dinlenme enerji harcamasına dayanan bir kaç çalışma eklenmiş, ancak bu çalışmaların hiçbiri genel olarak kullanılabilecek bir DMH hesap makinesi olarak tasarlanmamıştır.

Bu tez çalışmasının temel amacı, bir kişinin DMH'sini tahmin edebilen bilgisayar yazılımının geliştirilmesidir. Yazılım, Genel Regresyon Sinir Ağı (GRNN), Çok Katmanlı Algılayıcı (MLP), Destek Vektör Makineleri (SVM) olmak üzere, üç farklı makine öğrenmesi yönteminin yazılıma entegasyonu ile geliştirilmiştir.Seçilen yöntemlerdeki parametrelerin optimizasyonu, çeşitliliği sağlamak için yazılıma eklenmiştir.

Bu tez çalışması kapsamındaki DMH tahmin denemeleri için farklı vücut kompozisyonlarına sahip toplamda 260 kadın ve 150 erkek hasta verileri 2 ayrı veri setinde toplanmıştır. Veri setleri Türkiye'deki beslenme uzmanı Müzda Irmak'tan temin edilmiştir. Bu veri setleri, Tanita cihazından elde edilen çeşitli değişkenleri içerir. Tanita tüm vücudu tarayan ve vücudun yag(kg), kas(kg), kemik ağırlığı(kg), sıvı(kg)vb. çok çeşitli ölçümlerini sağlayan akıllı bir ölçektir. Bu ölçümler hesap makineleri tarafından yapılanlardan çok daha doğrudur ve dünya çapındaki doktorlar ve uzmanlar tarafından güvenilir kabul edilmektedir.

Bu tez çalışması için geliştirilmiş olan bilgisayar yazılımında MLP, GRNN ve SVM algoritmaları kullanılmıştır. MLP akademik literatürdeki konu ile alakalı diğer benzer çalışmalarda da kullanılmış, popüler olan makine öğrenmesi algoritmalarından birisidir. Bu yöntemde, tahmin modeli giriş katmanı, ara katmanı ve çıkış katmanı olmak üzere toplamda 3 çeşit katmandan oluşmaktadır.

SVM sınıflandırma ve regresyon analizi için kullanılabilen bir denetimli öğrenme modelidir. Sınfılandırma problemlerinde SVM algoritmasının amacı, bir N boyutlu uzayda veri noktalarını belirgin bir şekilde sınıflandıran bir hiper düzlem bulmaktır. SVM lineer olmayan karmaşık problemleri öğrenebilir. Bu çalışmada, SVM'in regresyon problemleri için kullanılan versiyonu olan "Destek Vektör Regresyonu" (SVR) kullanılmıştır. SVR sınıflama problemleri için kullanılan SVM metodu ile küçük farklılıklarla aynı prensipleri korur. Maliyet(C), epsilon (ε) ve gama (γ) değerleri SVM tabanlı modellerin performansını belirler.

GRNN regresyon analizi için özelleşmiş bir yapay sinir ağı algoritmasıdır. GRNN yapısı, giriş katmanı, örüntü katmanı, toplama katmanı ve çıkış katmanı olmak üzere 4 farklı katmanda oluşmaktadır. GRNN ağa beslenen girişe karşı bir tahmin elde edebilir. GRNN modelinde, bilinmeyen tek bir parametre "sigma " standart sapma değeridir. Sigma, eğitim işlemi ile hatanın çok küçük olacağı optimum bir değere ayarlanabilir. Bu çalışmanın yazılım geliştirme ve model oluşturma aşamalarında Çok Katmanlı Algılayıcı (MLP), Destek Vektör Makineleri (SVM) ve Genelleştirilmiş Regresyon Sinir Ağları (GRNN) yöntemleri DTREG öngürü modelleme yazılımı tarafından sağlanan .Net sınıf kütüphanesi bünyesindeki fonksiyonlar kullanılmıştır.

Tahmin modelleri oluşturulurken tasarımcının karar verilmesi gereken başlıca parametreler eğitim-test verisetlerinin ayrılış biçiminin, boş gelen veri blokları için hangi stratejinin kullanılacağının, model için hangi aktifleştirme fonksiyonunun kullanacağının seçimidir. MLP modelleri için, karar verilmesi gereken ekstra parametreler gizli katman sayısı, gizli katmalarda kullanılacak nöron sayısı, “aşırı öğrenme” tespitinde kullanılacak maksimum adım sayısı vb. parametrelerdir. SVM modelleri için, öncelikle hangi tip SVR modelinin kullanılacağına (Nu veya Epsilon) karar verilmelidir. Karar verilen SVR tipine göre, Maliyet (C), Epsilon (ε), Nu parametreleri seçilmelidir. Gamma (γ), P, Coef, Degree parametreleri belirtilen aktivasyon fonksiyonuna göre ayarlanmalıdır. Bu değerler için yazılımda bulunan “ızgara arama” ya da “örüntü arama” algoritmaları kullanılarak sistemin bu parametreleri kendi seçmesi istenebilir. GRNN modelleri için, sigma değeri seçimi için hangi yöntemin kullanılacağı, en iyi sigma değerinin bulunması için aranılacak minimum sınır, maximum sınır ve adım büyüklüğü değerleri tasarımcı tarafından karar verilmesi gereken parametrelerdir. GRNN modelinde, öncelikle sigma değerini seçmek için yöntem belirlenir. Daha sonra, en iyi sigma değerini aramak için gereken minimum limit, maksimum limit ve adım boyutu değerleri, sigma değeri için en uygun değeri bulmak için tasarımcı tarafından kararlaştırılacak parametrelerdir. Sonuca katkıda bulunmayan nöronlar, yazılım tarafından sağlanan "minimum hata" ve "minimum nöron" optimizasyon algoritmaları kullanılarak ağdan atılır. Optimizasyon algoritmaları ile daha düşük hatalı modellerin bulunduğu gözlemlenmiştir. Oluşturulan modeller, Kök Ortalama Kare Hata (Root Mean Squared Error, RMSE) oranlarına göre değerlendirilmiştir.

Bu çalışma kapsamında, kadın hastalar için 8786 model ve erkek hastalar için 8670 model olmak üzere toplamda 17.456 adet tahmin modeli oluşturulmuştur. Ancak bu tezde en iyi 720 model tablolanmıştır. Bu modeller “yaş, boy, kilo” ve “yaş, boy, vki (vücut kitle indeksi)” değerleri temel alınarak RMR değerini etkileyebilecek farklı parametreler ile kombine edilmiştir. Bu modellere ait sonuçlar incelendiğinde varılan ilk sonuç tüm yöntemler içinde GRNN modellerinin daha düşük hata oranlarına sahip olduğudur. Hata oranları karşılaştırıldığında MLP modellerinde gizli katman sayısı, gizli katman nöron sayısı, aktifleştirme fonksiyonu seçimi, SVM modellerinde farklı Maliyet(C), epsilon (ε) ve gama (γ) değerleri, çekirdek fonksiyonu seçimi, GRNN modellerinde sigma değeri seçimi modellerde çeşitlilik sağlasa da farkı değer kombinasyonlarının hata oranlarını önemli derecede düşüremediği gözlemlenmiştir.

Tüm çalışma boyunca elde edilen en önemli bulgulardan birisi de tahmindeki hata oranlarının giriş parametrelerinin seçimiyle ilişkili olduğudur. Bunun dışında tüm yöntemlerde parametrelerin model tarafından optimize edilmesi seçeneği, manuel ayarlamalardan daha düşük hata oranları sağlamıştır.Genel olarak kadın hasta modellerinde, erkek hasta modellerine göre daha düşük hata oranları elde edilmiştir.

Bu tez kapsamında hata değerleri kadın modelleri için 134.91 ve max değerleri, erkek modelleri için 143.109 ve max değerleri arasında oluşmuştur. Elde edilen en iyi sonuçlara bakıldığında, literatürde kullanılan doğrusal tahminleme denklemlerinin RMSE değerleri ile karşılaştırıldığında, makine öğrenmesi yöntemlerinin daha düşük hatalı modeller üretebildiği görülmüştür.

Tüm bu çalışma kapsamında elde edilen değerlere göre, bu tez çalışması için geliştirilmiş olan yazılımın literatürde ve pratikte kullanılan tahmin denklemlerinden daha doğru bir şekilde, dinlenme metabolizma hızı tahmininde kullanılabileceği kanıtlanmıştır.

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LIST OF ABBREVIATIONS

RMR	: Resting Metabolic Rate
BMR	: Basal Metabolic Rate
DBM	: Douglas Bag Method
BSA	: Body Surface Area
ANN	: Artificial Neural Network
REE	: Resting Energy Expenditure
BMI	: Body Mass Index
MLP	: Multi-Layer Perceptrons
GRNN	: General Regression Neural Network
SVM	: Support Vector Machines
MLR	: Multiple Linear Regression
RMSE	: Root Mean Square Errors
W	: Weight
G	: Gender
H	: Height
A	: Age

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1. INTRODUCTION

1.1. Resting Metabolic Rate Prediction

Resting Metabolic Rate (RMR) represents amount of calories that are needed to carry out basic functions in mammals like blood circulation, brain functions, breathing, fuel ventilation, temperature regulation, etc. at complete rest. Put another way, RMR is a prediction of how many calories would be burned if an individual was to do nothing but rest. For most people, Resting metabolic rate is the largest single component of overall daily energy expenditure (Speakman and Selman, 2003). Knowing the RMR value of an individual is crucial information to be able to establish an approximate daily calorie requirement. This information is crucial to lose or gain weight and maintain optimal body weight without hindering the basic functions of the body. If an individual's value of RMR is high, the body's chance of storing calories as fat decreases and if it is low, it takes more time to convert the received food into usable energy for the body, and therefore the body will have a greater chance of storing unused foods as fat.

Basal Metabolic Rate(BMR) is a minimum number of calories that the body would be burned at complete rest and this rate is a similar measurement to RMR. The estimation of BMR is performed using more restrictive conditions than RMR (BMR vs. RMR: Everything You Need to Know, 2017). The test is carried out in a darken room in the morning when a patient is awake after eight hours of sleep. Digestive system has to be inactive at the time of BMR test. Patients which are taken to the test, have to fast for 12 hours. Subjects must rest at reclined position. Measurement of RMR has much less conditions than testing of BMR that test is usually able to performed after 3 or 4 hours of fasting at any time of a day. BMR and RMR are interchangeable term in the literature. In this thesis, prediction of RMR is carried out due to its ease of measurement in practice.

Obesity is a very impotant health problem that increases the risk of many chronic diseases that can lead to death like insulin resistance, liver fatigue, diabetes, hypertension, heart diseases, respiratory distress, some malignant tumor types, etc. Although there are numerous complicated genetic, environmental and mental factors affecting obesity, it originates the result of the energy imbalance between the calories taken and consumed mostly. The main factors that determine the energy consumption of a person are RMR, physical activity, thermal effect of food and temperature. Theoretically the person with low RMR, has higher risk to contract an obesity related diseas than normal people. RMR measurement is carried out by dietitian in nutrition assessment and weight management programs. Thus, with the early detection of low RMR, the susceptibility of an individual to obesity is able to understood and the risk of contracting these critical diseases can be reduced by personalized diet plan or necessary interventions.

There are four different techniques which are used in academic literature and practice to measure RMR. The first one is direct calorimetry, which provides an energy measurement extended in form of heat. Direct calorimetry is a special and isolated chamber that can detect the heat exchange, which has to be proper in size so that a person, and if necessary, an exercise device and measurement equipment should be fit in. This special structure is used to obtain the amount of energy expenditure or metabolic rate by measuring the amount of generated heat by the body. However, the direct calorimetry technique has several disadvantages. The structure which is used is costly and requires the complex engineering. Subjects should remain in a physically closed chamber for a long time (Boushey C. et. al., 2001). Furthermore, the number of facilities which have infrastructure to carried out these kind of measurements are scarce around the world. Therefore, direct calorimetry technique cannot be applied in practice.

Another method for measuring RMR is the indirect calorimetry technique. Indirect calorimetry measures the amount of heat production from a subject via calculating the amount of oxygen consumption and carbon dioxide elimination.

Douglas bag method (DBM) is one of the indirect calorimetry measurement technique and it is considered the gold standart to calculate RMR in practice. Measurement of actual RMR with this technique, requires strict restrictions such as clinical situations, expensive equipment, expert requirement for the use of the system, cost of the test and preparation process of the individual. Therefore, this technique is not preferred to apply by dietician. DBM based indirect calorimetry technique is shown in Figure 1.1.

Figure 1.1. Douglas bag based indirect calorimetry technique

Simple RMR prediction equations are other techniques which are used to calculate RMR. Table 1 presents the prediction equations. These formulas are widely used by dietitians due to their ease of use but they are not fully reliable because of high error rate, limited number and insufficient use of variables.

Table 1.1. RMR prediction equations

Study	Formula
Harris and Benedict(1919)	Female: RMR = 655.1 + 9.56 × weight (kg) + 1.85 × height (cm) – 4.68 × age (y) Male: RMR = 66.47 + 13.75 × weight (kg) + 5 × height (cm) – 6.76 × age (y)
Robertson and Reid(1952)	BMR = BSA $(m^2)^b$ × 24 × (age-specific value)
Cunningham(1980)	RMR = 500 + 22 × lean body mass
FAO/WHO/UNU(1985)	18-30 y: RMR = 13.3 × weight (kg) + 334 × height (m) + 35 30-60 y: RMR = 8.7 × weight (kg) + 25 × height (m) + 865 >60 y: RMR = 9.2 × weight (kg) + 637 × height (m) + 302
Owen et. al.(1987)	Nonathletes: BMR = 795 + 7.18 × weight (kg) Athletes: BMR = 50.4 + 21.1 × weight (kg)
Mifflin et.al.(1990)	RMR = 9.99 × weight (kg) + 6.25 × height (cm) – 4.92 × age (y)+166(sex; male = 1, female = 0) – 161

BSA, Body Surface Area; **RMR**, Resting Metabolic Rate;

The FitMate™ ,a small (20 x 24 cm) analyzer, was developed by Cosmos, designed for oxygen consumption measurement and energy expenditure during rest and exercise as another RMR measurement technical. (Nieman et. al., 2006) compared the Douglas bag method with the FitMate™ which is used to measure oxygen consumption. The fact that health and fitness professionals use FitMate™ to measure RMR is supported by their findings. In comparision with DBM, FitMate™ is lower cost but this device is still not available in most dietician centers due to its cost. FitMate™ is illustrated in Figure 1.2.

Figure 1.2. FitMate™

The novel technique for measuring RMR is machine learning based methods however few studies have been developed to calculate prediction of RMR using machine learning techniques.

1.2. Thesis Motivation and Purpose

In the literature, to the best of our observation, although there exist several academic studies on RMR prediction by using linear equations and indirect calorimetry methods. However, machine learning techniques were applied limitedly in this field. This thesis aims to develop a web based application which can perform RMR prediction using MLP, GRNN, and SVM which are some of the common machine learning methods.

The main features and options which have been included in the project, and made it possible to develop a software containing all these features together first time in the literature, can be listed as follows:

- Three different machine learning methods which are MLP, SVM, GRNN provided by the development environment
- The different options are able to used to define the part of the data set which will be used for training the model or testing the model

- No validation, use all data rows
- Random percent method
- V-fold-cross-validation method
- Leave-one-out validation

- Two different options are integrated to handle missing predictor variable values in dataset
  - Don't use rows with missing predictors
  - Replace missing predictors with medians
- Different activation(kernel) functions can select to apply the system
- Different optimization techinuques which are specific to machine learning methods can be applied to perform better model
- Variety of models can be increased by selecting different combinations of input variables.

1.3. Previous Work

In 1919, Harris and Benedict published a monumental work entitled "A Biometric Study of Basal Methabolism in Man" attempting a detailed biometric analysis of BMR. In the study, BMR was measured from 136 males and 103 females at the Camegie Nutrition Laboratoy in Boston. They developed two distinct equations for male and female to predict BMR by using rigorous statistical concepts.

In 1980, Cunningham improved the classical metabolism studies, previously done by Harris and Benedict in 1919, by peforming several regression analysis factors influencing the basal metabolic rate (BMR) with the help of using the data of 223 subjects. He proposed a new equation for BMR prediction, in which lean body mass was the single predictor.

In 1985, FAO/WHO/UNU evaluated their own equations to predict the resting metabolic rate (RMR) in Vietnamese adults. The equations from

FAO/WHO/UNU were compared to the equations derived by linear regression of RMR versus body weight.

In 1987, Owen et. al. investigated 60 lean and obese men with an age interval of 18 to 82 weighing between 60 to 171 kg with specified body compositions. They calculated a prediction for the resting metabolic rate (RMR) with their newly developed regression equations based on the body weight and fat-free mass.

In 1990, Mifflin et. al. worked on another predictive equation for resting energy expenditure (REE). For this study, data from 247 females and 251 males with an age interval of 19 to 78 were used, from which 264 were normal-weight and 234 were obese individuals. Indirect calorimetry was used to obtain the resting energy expenditure (REE) values. To drive relationships between REE and weight, height and age for both men and women, multiple regression analyses were performed.

In 2003, Nieman et al. tested resting metabolic rate (RMR) with a new hand-held device called the BodyGem (HealtheTech Inc., Golden, CO).

In 2004, the hand-held indirect calorimeter BodyGem™ appraised by Melanson et. al. for its validity and reliability. In fact, BodyGem™ measured the RMR values of overweight and obese individuas more accurate than estimated by the Harris-Benedict equations.

In 2006, the FitMate™ metabolic system, capable of measuring oxygen consumption and estimating the resting metabolic rate (RMR), was assessed by Nieman et. al. for its validity and reliability. With this study, FitMate™ is accepted as a valid and reliable system in adults for measuring the oxygen consumption and RMR.

In 2017, with the improvement of technology, Disse et. al. developed and validated an artificial neural network (ANN) model to predict REE in obese subjects, which can calculate more accurate and precise than previous predictive equations independent on BMI subgroups. On this side, a simple ANN-REE calculator is provided for clinical settings.

In addition to the studies presented in the literature, the following studies are carried out by using the software developed for this thesis.

- (Akça et. al., 2020) presented models to predict the resting metabolic rate using three different machine learning methods which are MLP, GRNN and SVM. Two different datasets have been used for the female and male patient which obtained from a dietitian center as the data source. 10- Fold Cross-Validation technique has been used in order to increase the accuracy of the learning model. RMSE has been used as the main error metric by each model. The size of hidden layers has been kept as 3 or 4 layers, while the activation functions have been determined as linear or logistic activation functions for MLP models. For GRNN models, neuron size of pattern layer being optimized by software itself instead of depending on the user's preferation. In the SVM model, kernel function and parameter search method were set as linear function or radial basis function (RBF) and grid search or pattern search techniques respectively. The prediction models have been given RMSE rates ranging between 134.91 and 151.289 for models of female patients while the same range is 143.109 and 199.87 for male patient models. Overall, the software can be used as a good substitute for the resting metabolic rate with acceptable accuracy.

Table 1.2.1. presents detailed information about the studies and the methods used for the Resting Metabolic Rate, in ascending chronological order.

Table 1.2. Summary of studies about Resting Metabolic Rate

Study	Methods
(Harris and Benedict, 1919)	MLR
(Cunningham, 1980)	MLR
(FAO/WHO/UNU, 1985)	MLR
(Owen et. al., 1987)	MLR
(Mifflin et.al., 1990)	MLR
(Nieman D.C. et. al., 2003)	Indirect Calorimetry
(Melanson et.al., 2004)	Indirect Calorimetry
(Nieman D.C. et. al., 2006)	Indirect Calorimetry
(Disse E. et.al., 2017)	MLP
(Akça et. al., 2020)	MLP
(Akça et. al., 2020)	GRNN
(Akça et. al., 2020)	SVM

1.4. Overview of the Dataset

During this study, 2 different data sets, which gather from female and male patients have been used in order to carry out the prediction models. In this project, 260 female and 150 male patients have been obtained from dietician Müzda Irmak in Turkey. Different machine learning models have been created separately for these two datasets.

Data Set 1: It contains female data of 260 rows in total that have different body compositions.

Data Set 2: It contains male data of 150 rows in total that have different body compositions.

These datasets contain various variables which have been provided by Tanita. It is a smart scale which scans the entire body. Tanita is shown in Figure 1.3. This provides a wealth of measurements, such as personal informations, body composition analysis, reference analysis, segmental body composition analysis for impedance, segmental body composition analysis for percentage of fat, segmental body composition analysis for kg of fat, segmental body composition analysis for kg of non-fat, segmental body composition analysis for kg of muscle, mass analysis and others. Measurement of hip circumference in the mass analysis has been added in models of female, but not in models of male patients on the recommendation of nutritionist Müzda Irmak. The variables that are obtained from Tanita is shown in Table 1.4.1. Doctors and experts trust to these measurements more due to being much more accurate than those provided by calculators. (Basal Metabolic Rate, n.d.). Tanita measurements have been used as input variables in machine learning models creation phase. Measurements of RMR are obtained for every patients by FitMate™. Calculated RMR values are used as output variables in the machine learning models generation part.

Figure 1.3. Tanita MC 780 MA

Table 1.3. The variables to be used in the study

Category of datasets	Variables
Personal Information	Age, Size(cm), Weight(kg), Body Mass Index/BMI)
Body Composition Analysis	Percentage of Fat, Fat(kg), Liquid(kg), Non-Fat(kg), Muscle(kg), Bone Weight(kg)
Reference Analysis	Mineral Quantity(kg), Protein Amount(kg),Internal Lubrication, Body Density
Segmental Body Composition Analysis(Impedance)	Right-Leg, Left-Leg, Right-Arm, Left-Arm and Body Impedance
Segmental Body Composition Analysis (Fat-%)	Right-Leg, Left-Leg, Right-Arm, Left-Arm and Body Fat Percentage
Segmental Body Composition Analysis(Fat-kg)	Right-Leg, Left-Leg, Right-Arm, Left-Arm and Body Fat Kilograms
Segmental Body Composition Analysis (Non Fat-kg)	Right-Leg, Left-Leg, Right-Arm, Left-Arm and Body Fat Non-Fat Kilograms
Segmental Body Composition Analysis (Muscle-kg)	Right-Leg, Left-Leg, Right-Arm, Left-Arm and Body Muscle Kilograms
Mass Analysis	Soft Muscle Tissue, Bone Minerals Weight(kg), Skeletal Muscles(kg), Extracellular Liquid(kg), Intercellular Fluid(kg), Cell Mass(kg)
Others	Thyroid, Insulin, Cigarette, Waist, Hip, Lower Belly Circumference
Results	RMR Fitmate

2. OVERVIEW OF METHODS

2.1. Multi-Layer Perceptrons

Multilayer perceptrons (MLPs) are a class of feed-forward artificial neural network(ANN) models that are trained with the back-propagation algorithm and an optimization algorithm. MLPs expect desired output values to be trained, so they can learn how to map input data into desired outputs. This is known as a supervised learning technique. They are able to learn theoretically any nonlinear complex problem with sufficient data samples and a variable number of hidden layers. The components which the network consists of each, perform a biased weighted sum of their inputs and pass the calculated values through a transfer function to produce their output, and the units are designed in a layered feed forward topology (Yüksel et.al., 2018). The MLP networks are able to produce different models with the changing number of hidden layers, the number of neurons in each layer and determining the activation function. The MLP includes at least one hidden neuron and each hidden layer in the neural network extracts the implicit information of the features. Hidden layers capture more and more complex with every layer by discovering relationships between features in the input. The selection of number of hidden layers to use is not certain and depends on the problem complexity as well as the type of data used for the models. After choosing layer size, the designer of MLP has to specify the number of neurons for each hidden layer. As good a starting point as any is to use one hidden layer, with the number of units equal to mean of the neurons in the input and output layers (Panchal et. al., 2011). There are intuitive techniques to choose the number of neurons for each layer in literature. One of the techniques is to keep the number of hidden neurons between the size of the input and the size of the output layer. Another method is to keep the number of hidden neurons less than twice the size of the input layer.

Few hidden nodes in layers cannot accurately represent the solution; therefore, models under-fits to the data, called under-training. On the other hand, overtraining may result in a very complicated network and those networks with too many hidden nodes will tend to over-fit the solution. Creating a neural network with the right number of hidden nodes is the aim to address the problem.

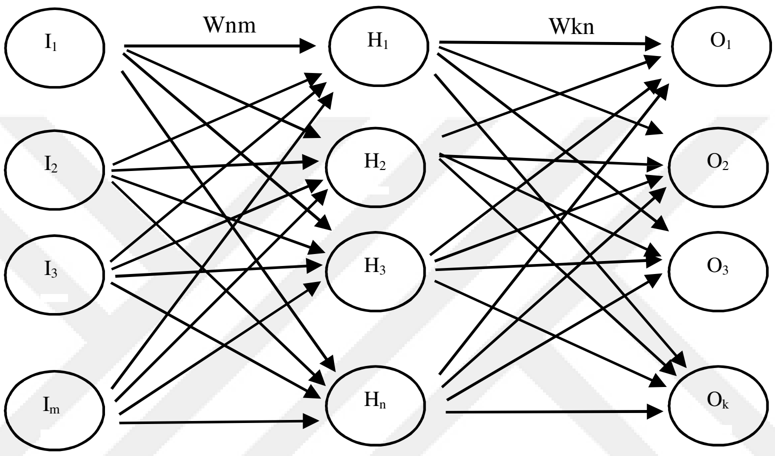

Figure 2.1. An example of MLP structure

In Figure 2.1 shows the number of neurons in the input, hidden and the output layers, which are represented as M, N and K, respectively. The number of hidden layer could be more than one. Each neuron in the hidden layer collects the sum of the output signals from the previous layer. (Isokawa et. al., 2012). Inter neuron connections are called weights. They are used to store acquired pieces of information after the training process. The connection between the n^{th} neuron in the input layer and the m^{th} neuron in the hidden layer is illustrated by Wnm. The output signal of the neuron in the hidden layer, represented by H_n, is formulated by

$$H_n = \mathrm{f}\left(\sum_{m=1}^{m=M} w_{nm}\, I_m\right) \tag{2.1.}$$

and the output signal of the neuron in the output layer, O_k, is denoted as

$$O_k = \mathrm{g}\left(\sum_{n=1}^{n=N} W_{kn}\, H_n\right) \tag{2.2.}$$

where f and g are activation fucntions (kernel function) of the network so that the network can perform an approximation of complex and nonlinear relationships between input and output signals using the nonlinear activation function. There are many options for selection of activation function in literature. The most commonly used functions in practice are relu, leakly-relu, sigmoid, hyperbolic tangent.

In the learning process, weights (w) which are the learnable unit by the network itself are set to minimize the error in the output values produced from the output layer. When the given actual activation value of the output node k is O_k and the expected target group output for node k is T_k, then the difference between the actual output and the expected output is calculated by

$$\Delta_k = T_k - O_k \tag{2.3.}$$

$$E = \frac{1}{2}\left(\sum_p \sum_k (T_k^p - O_k^p)^2\right) \tag{2.4.}$$

For a given training set, the value E is a “cost” function that indicates the performance of network learning. The learning takes place for minimizing the error of the network by updating the weight values through the back-propagation and selected optimization algorithm. Gradient Descent Algorithm is the most common optimization algorithm in machine learning and deep learning which is denoted by

$$\Delta w_{kl}^{(m)} = -\mu \frac{\partial E\left(\left\{w_{ij}^{(n)}\right\}\right)}{\partial w_{kl}^{(m)}} \quad (2.5.)$$

W_{ij} : Input to hidden

W_{jk} : Hidden to output

(n) or (m): The layer

μ : Learning rate

Adam, AdaGrad, RMSProp, SGDNesterov, AdaDelta are different optimization algorithms and able to used with any machine learning techniques in the training process. With the feedforward steps and backpropagation steps, respectively which is one iteration as many times as needed, a certain point can be reached in which the error rate does not decrease anymore and an optimum level of weights is determined for the use in the network.

2.2. Support Vector Machines

SVM is a supervised learning algorithm which can be apply classification or regression analysis. (Vapnik, 1995) developed the principles of SVM. A common task in machine learning is classifying data. Given each data points for a specific problem belongs to one of two classes. Each data point is represented as a n-dimensional vector in the case of support vector machines. Each feature in dataset is known as dimension. The objective of the support vector machine algorithm in the classification problems is to find a hyperplane in an n-dimensional space that distinctly classifies the data points and to decide which class a new data point will be in. In the basic sense, there are many possible hyperplanes that could be chosen to separate the two class of data points. SVM finds a hyperplane that can classify and maximize distance between data points of both classes. Maximizing of the margin, provides more accurate classification for test points to be fed into the network in the future. Hyperplane dimension depends on the number of features of the used data. For example, the hyperplane would be just a line if the number of input features is 2. Similarly, the hyperplane would be a two-dimentional plane, if the number of input features is 3. When the number of features exceeds 3, it will become hard to visualize. Despite designed to solve classification problems, SVMs were lately restructured to solve regression problems. These types of SVMs are nominated as Support Vector Regression (SVR).

2.2.1. Linear Support Vector Regression

Given a set of training instance-target pairs $\{(x_i , y_i)\}$, $x_i \in R_n$, $y_i \in R$, $i = 1, . . . , l$, linear SVR finds a model w such that $w^T x_i$ is close to the target value y_i (Ho and Lin, 2012). Linear support vector regression model is denoted by

$$y_i = w^T . x_i + b, \quad w, x \in R^d, b \in R \tag{2.6.}$$

In (2.6), the target function is denoted by y_i and . represents the dot product in R^d. The main idea is maintained for SVR which are minimizing error, maximizing the margin between hyperplanes and a part of error (ε) is able to tolerated. A loss function should be defined for measuring the empirical risk. The ε-insensitive loss function, which is proposed by Vapnik (Vapnik, 2000), is the most frequently used function. (2.7.), which defined as

$$L_\varepsilon(y) = \begin{cases} 0 & \text{for } |f(x) - y| \le \varepsilon \\ |f(x) - y| - \varepsilon & \text{otherwise} \end{cases} \tag{2.7.}$$

The optimization problem given in (2.8.) (Gunn, 1998) should be solved to find out the optimum values of $\overline{\omega}$ and $\overline{b}$

$$\min \ \frac{1}{2}\|\omega\|^2 + C\sum_{i=1}^{\ell}(\xi_i^- + \xi_i^+) \tag{2.8.}$$

with constraints:

$$\begin{aligned} &\mathrm{y_i} - \langle \omega, x_i \rangle - b \le \varepsilon + \xi_i^+, \\ &\langle \omega, x_i \rangle + b - \mathrm{y_i} \le \varepsilon + \xi_i^+, \\ &\xi_i^+, \xi_i^- \ge 0, \quad \mathrm{i}=1,........,\ell \end{aligned} \tag{2.9.}$$

In (2.9.), there exists toleration for the deviations larger than ε and the tradeoff between the flatness of $f(x)$ is determined by C. The deviations from the ε -tube are represented by the slack variables ξ^- and ξ^+.

The dual optimization problem given in (2.10.)

$$\max_{\alpha,\alpha^*} -\frac{1}{2}\sum_{i=1}^{\ell}\sum_{j=1}^{\ell}(\alpha_i^* - \alpha_i)(\alpha_j^* - \alpha_j)\langle x_i, x_j \rangle - \sum_{i=1}^{\ell} y_i(\alpha_i^* - \alpha_i) - \varepsilon\sum_{i=1}^{\ell}(\alpha_i^* + \alpha_i) \tag{2.10.}$$

with constraints:

$$0 \le \alpha_i, \alpha_i^* \le C, \qquad i = 1,...,\ell \ ,$$
$$\sum_{i=1}^{\ell} (\alpha_i - \alpha_i^*) = 0 \tag{2.11.}$$

has to be solved, which in turn gives the optimum values of the Lagrange multipliers α and α^*, while $\overline{\omega}$ and $\overline{b}$ are given by

$$\overline{\omega} = \sum_{i=1}^{\ell} (\alpha_i^* - \alpha_i) x_i \quad ,$$
$$\overline{b} = -\frac{1}{2} \left\langle \overline{\omega}, (x_r + x_s) \right\rangle \ , \tag{2.12.}$$

where x_r and x_s are support vectors (Gunn, 1998).

2.2.2. Non-linear SVM

Nonlinear SVM can be constructed using a nonlinear mapping ϕ of the input space onto a higher dimension feature space. (2.13.) shows the nonlinear regression model

$$f(x) = \left\langle \omega, \phi(x) \right\rangle + b, \quad \omega, x \in \Re^{\mathrm{d}} \ , b \in \Re \ , \tag{2.13.}$$

where

$$\bar{\omega} = \sum_{i=1}^{\ell} (\alpha_i - \alpha_i^*) \phi(x_i),$$
$$\left\langle \omega, \bar{\phi}(x) \right\rangle = \sum_{i=1}^{\ell} (\alpha_i - \alpha_i^*) \langle \phi(x_i), \phi(x) \rangle = \sum_{i=1}^{\ell} (\alpha_i - \alpha_i^*) K(x_i, x), \tag{2.14}$$
$$\bar{b} = -\frac{1}{2} \sum_{i=1}^{\ell} (\alpha_i - \alpha_i^*)(K(x_i, x_r) + K(x_i, x_s))$$

the support vectors are represented by x_r and x_s . A Kernel function K satisfying Mercer's conditions has been used to explain dot products (Vapnik, 2000).

After $\bar{b}$ is integrated into the kernel function, (2.15.) becomes:

$$\sum_{i=1}^{\ell} (\alpha_i - \alpha_i^*) K(x_i, x) \qquad (2.15.)$$

Many different kernel functions including the RBF, the polynomial function and the sigmoid function exist. However; RBF, as defined in (2.16.) is the most commonly used Kernel function:

$$K(x, x') = \exp\left(-\frac{\|x - x'\|^2}{2\rho^2}\right). \qquad (2.16.)$$

In (2.16.) the width of the RBF function is defined by ρ .

2.3. General Regression Neural Networks

General Regression Neural Network (GRNN) is defined as probabilistic neural network which can be used for regression, prediction, and classification based on function approximation or function estimation algorithm. Similar to other probabilistic neural networks, GRNN requires only fraction of the training samples as a backpropagation neural network would need (Spetch, 1991). It predicts the output of given input data. GRNN estimates the output by using weighted average of training dataset outputs, where the weight is calculated via the Euclidean distance between the training and the test data. The larger the weight or the distance is, the less the weight will be. In the same manner, with a smaller distance, the more weight will be put to the output.

A GRNN consists of four layers, whose names are given in Figure 2.1. The total number of features specifies the number of input neurons. Input layer feeds the input data to the pattern layer. As shown in Figure 2.1, each layer is directly connected to next layer without having any feedback loops. The data points or training samples are repsresented as the circles in the pattern layer. The euclidean distance and activation function are calculated by the pattern layer. Gauss kernel function is commonly used to approach nonlinear complex function in pattern layer of GRNN. Summation layer is composed of two subparts: Numerator and Denominator. In Numerator part, the summation of multiplication of the training output data and the activation function is calculated. The summation of all activation functions is provided by Denominator. The pattern layer of GRNN supplies both the Numerator and Denominator to the next output layer which contains one neuron. This neuron calculates the output by dividing the Numerator part of the Summantion layer by the Denominator part.

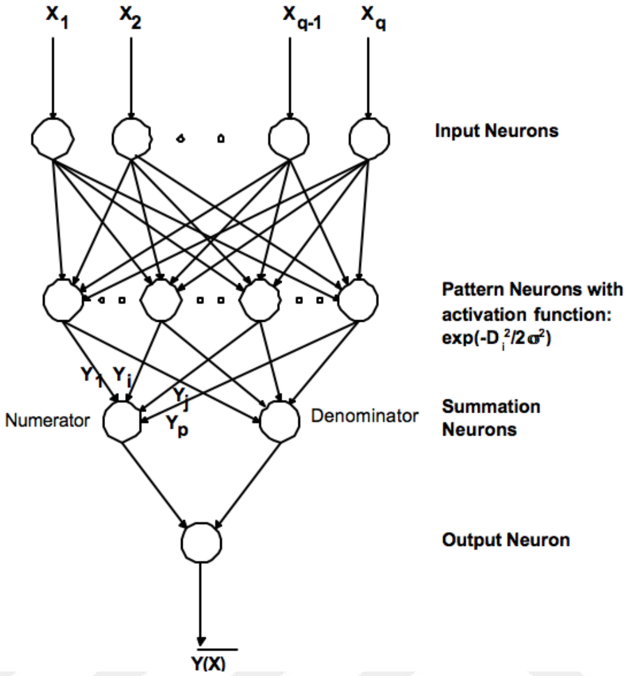

Figure 2.2. A typical GRNN architecture

The joint probability density function applied in GRNN in the normal distribution. Each training sample, X_i is performed as the mean of normal distrubition. The distance, $D_i\ ^2$, represents euclidean distance between the training sample, X_i and the point of test sample, X given by (2.17.). In this case, the conditional expected value of X_i given X, is calculated by (2.18.).

$$D_i^2 = \left(X - X^i\right)^T (X - X^i) \tag{2.17.}$$

$$Y'(X) = \frac{\sum_{i=1}^{n} Y^i exp(-\frac{D_i^2}{2\sigma^2})}{\sum_{i=1}^{n} exp(-\frac{D_i^2}{2\sigma^2})} \tag{2.18.}$$

The value of the training point and the test sample represents how much the training sample is able to contribute to the output of test sample input X. If the distance, D_j, is a small value, the term $exp^{-\left(\frac{d_i^2}{2\sigma^2}\right)}$ becomes a relatively big value.A bigger distance, D_j, results the term $exp^{-\left(\frac{d_i^2}{2\sigma^2}\right)}$ to become small value and for this reason, the effect of the other training samples to the result of prediction is relatively small value. If $D_j = 0$, the term $exp^{-\left(\frac{d_i^2}{2\sigma^2}\right)}$ returns the point of prediction n which is best represented by this training sample. The standard deviation or the spread constant sigma (σ), named in 1991 by Specht, is subject to a search. Modulation of σ can be done by a training process to find an optimum value with a very small error. In other words, the training procedure is necessary to obtain the optimum value of σ. Best practice would be finding the position where the Root Mean Squared Error (RMSE) is minimum. When y_j describes expected output, y_j' is prediction of the network, RMSE is represented by (2.19.).

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{j=1}^{n}\left(y_j - y_j'\right)^2} \tag{2.19.}$$

For searching the optimum value of σ , training sample is splitted into two parts which are the training sample and the test sample. Based on the training data, GRNN is applied on the test data to detect the RMSE for different σ. The σ value giving the minimum error is selected as σ, spread contant of GRNN.

3. SOFTWARE DEVELOPMENT

3.1. Environment

The main purpose of this thesis is to develop a novel web based software that can predict the Resting Metabolic Rate (RMR) using machine learning methods. The software has been developed by using Visual Studio (ASP.NET Framework) , DTREG .Net Class Library, and C# programming language. DTREG .Net Class Library has been integrated the project to apply machine learning methods which are GRNN, MLP and SVM. The user interface consist of two part.The first part is the back end side which is used to create machine learning models.The second one is the front end side that is developed to measure RMR of an individual by appliying generated machine learning models. The back end side is built using Ajax Controller Toolkit and DevExpress components. On the front end side of this project, .Net Core technology is used.

3.2. The Back End Side of The Project

The back end side of the project consists of five parts which are identifying the model name, data set selection, choosing inputs and output variables for the model, model optimization, achieved and saving model.

3.2.1. The Model Name Selection

As shown in Figure 3.1, the user selects a name for the model to be created in this section.

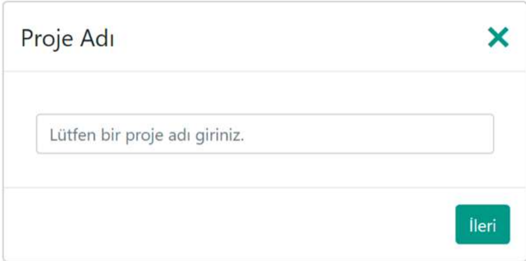

Figure 3.1. The model name selection

3.2.2. Dataset Selection

In this section one of the two different datasets is chosen by the user which gathers from female and male patients. The selected dataset has been used to create the prediction models. Dataset Selection part is displayed on Figure 3.2.

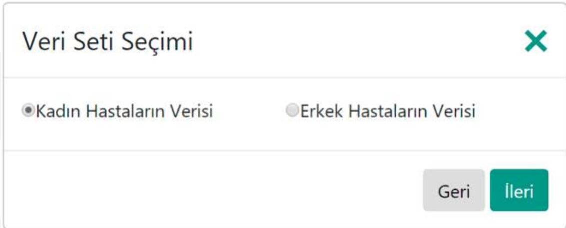

Figure 3.2.The dataset selection

3.2.3. Choosing Inputs and Output Variables

The variables section is devoted to specify the class and category of each variable. Users decide which variables will be selected as inputs or the output of the network. The selected variable in the predictor column is used as a input variable when creating the model. The predictor variable must be selected at least one. The target represents the output which is wanted to estimate by the user. Clearly, the target is RMR for this project. The categorical variable indicates the type of variable. If a variable is discrete like gender, colors, etc., the user should check the categorical checkbox. If a variable is continuous, the user should uncheck the categorical checkbox. Variables are grouped under 11 main headings according to their types. They are listed in Table 2.1 and shown in Figure 3.3.

3.2.4. Model Optimization

In this software, some settings for models of GRNN, MLP, and SVM can be adjusted both manually by the user, and by the software itself via optimization.

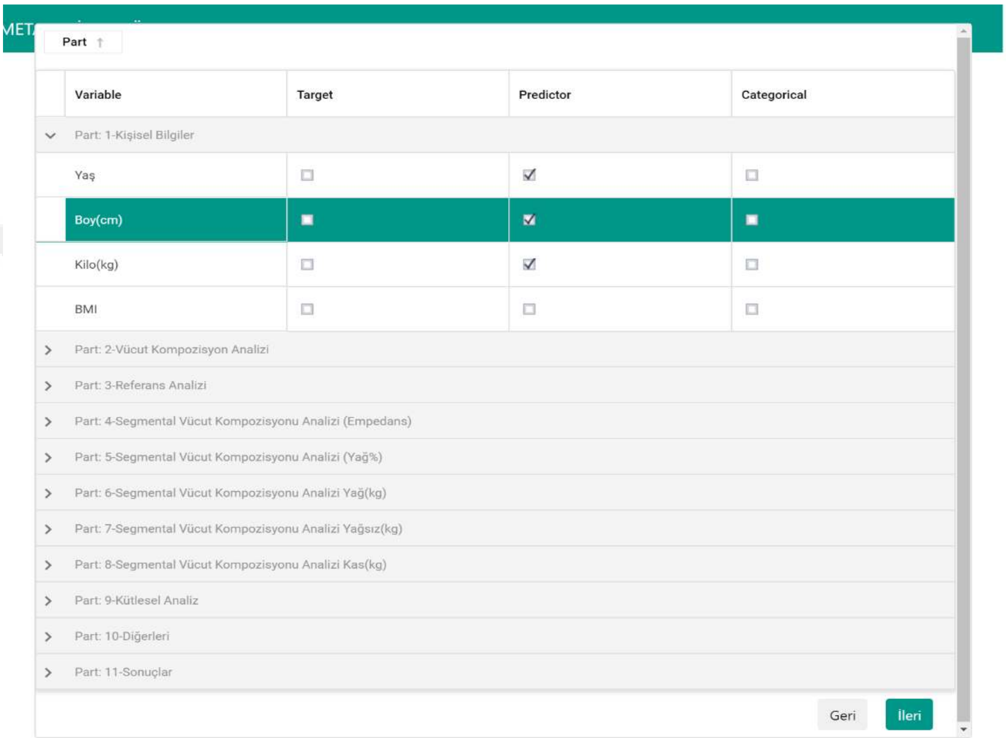

Figure 3.3. Choosing inputs and output variables

3.2.4.1. Settings of MLP Model Optimization

Type of model to build: The type of model provided by DTREG is selected by the user. MLP, GRNN, SVM methods are supported in this project.

Number Of Network Layers: The total number of layers are determined in the network. The parameter values must be either 3 or 4. 3 total layers selection provides 1 hidden layer, and 4 total layers selection corresponds to 2 hidden layers. The default selection for the network is 3 total layer.

Neuron Number: The number of neurons in each hidden layer is one of the basic parameters of a neural network. Identifying fixed number of neurons or determining the optimal number of neurons are provided by DTREG.

Automatically optimized hidden layer 1: Specifying how many neurons to be used in each hidden layer is one of the challenges in constructing MLP network. If inadequate number of neurons are selected, the model may not constitute a complex data model. In the similar manner, if excessive number of neurons are chosen, the model may not interpret the data which leads to poor generalization of new data. Checking this box will assist DTREG to produce multiple network with variety number of neurons in hidden layer 1, and to examine how well the models correlate with the help of using cross validation or hold-out sample.

Maximum, Mininum and Step Size for automatic search: If the automatic search to find the optimum number of neurons is enabled, minimum and maximum number of neurons are set in these fields to try. The number of neurons to be added to each trial is specified by the step size.

Maximum Number of Steps without a Change: During the DTREG search for the optimum number of neurons for the hidden layer 1, the models are started to be generated with the minimum specified number of neurons building up to the maximum neuron size. The error of each model is calculated before increasing the number of neurons. If any improvement is not served during this process, it assumes that the optimal size has been reached, and therefore it stops the search.

Row percentage to use for search: DTREG uses randomly selected subsection of the rows in dataset when it preforms the search for the optimal number of neurons with this option.

Cross validate folds: DTREG evaluates the success of each model during the search by using cross validation. When this radio button is selected, the number of cross validation folds should be selected by user.

Hold-out sample percentage: Selected portion of the data records hold out from each trial model and then use the held-out rows to evaluate the produced model.

Use training data: When DTREG uses the training data to create the network, it evaluates the suitability of the neural network by using the same set of data. This option will not be beneficial in case of creating a new network which will be applied to a new dataset outside of the training data.

Number of neurons for hidden layers: If the automatic search for the optimal number of neurons don't enable, the number of neuron size should be chosen manually. If the layer size is selected 4, the neuron size of second hidden layer must be set by the user.

Use test data to detect over fitting: This option enables DTREG to set apart certain percentage of the training rows by checking them for over fitting as a model tuning performance.

Percent training rows to hold out: This option is used for specified detection of the percentage of the training rows which are held out and used for testing the over fitting. Due to being separated, rows have no contribution to the process of parameter optimization.

Maximum steps without change: In case of the calculated error will not be under specified iteration steps, the training process will be stopped and the best established parameters will be selected for the model.

Hidden layer activation function: Linear or logistic (sigmoid) activation functions are able to select for hidden layers. A sigmoid function is default selection.

Output layer activation function: Linear or logistic (sigmoid) activation functions are able to select for output layer in regression analysis. A linear function is default selection.

Model testing and validation: DTREG evaluates the neural network model once it has been created. There are four different choice for the testing process. If no validation, use all data rows option is selected, DTREG doesn't do any validation of produced model. If random percent option is chosen, the random percent of the rows of the dataset is held out and then the model's error is evaluated with this rows. In the V-fold cross validation option, dataset is divided into equal parts by a specified number of V. When V-1 parts are used to create model, the remaning piece is held out to test of created model. This process is repeated V times and the model's error is calculated by the average of results. The leave-one-out validation performes 1-fold cross validation.

How to handle missing predictor variable values: The rows of dataset may contain missing values for any of the predictor variables. In this case, if the first option is picked, the row will be excluded from the model building process. When the second option is chosen, the missing values are replaced with the meadian value of the predictor variable.

Settings of MLP Model Optimization are shown in Figure 3.4.

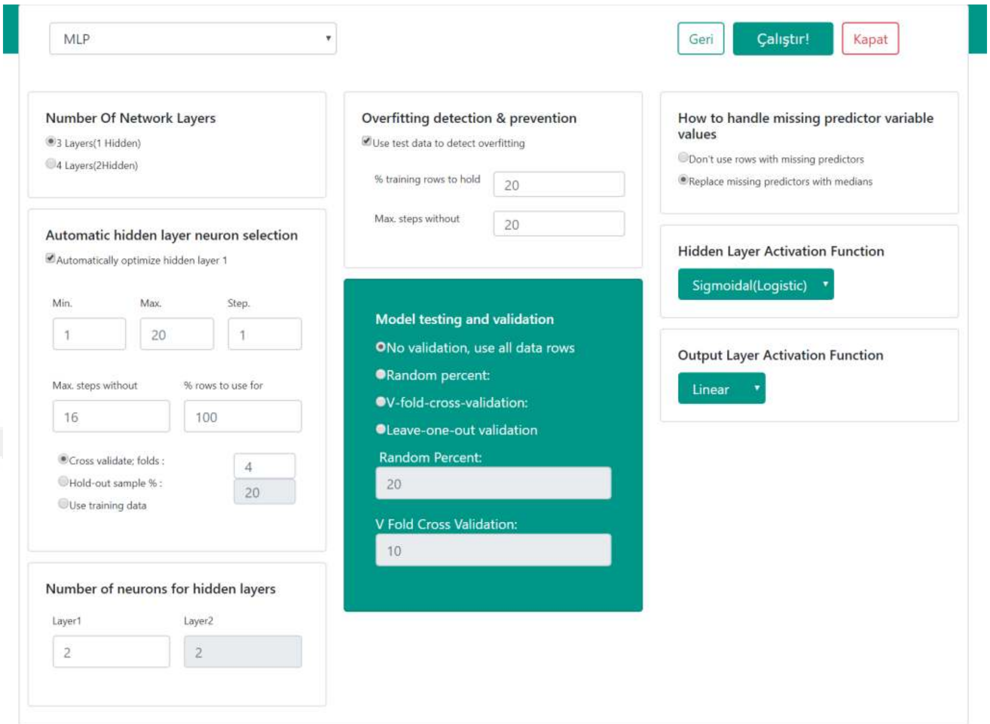

Figure 3.4. Settings of MLP Model Optimization

3.2.4.2. Settings of GRNN Model Optimization

Sigma values for model: The sigma values control the radius of influence of each training point in the model to predict the output. This software provides two types of sigma values.

Single sigma for whole model: If this option is selected, single sigma value is used for all points.

Sigma for each variable: When this option is chosen, different sigma value is calculated for each predictor variable, which allows the impact of each variable on nearby points to be different.

Report sigma values: This option allows DTREG to show the calculated sigma values in the project report.

Starting sigma search control: Min, max,step parameters control the range of sigma values used during the search.

Remove unnecessary neurons: When selected, unnecessary neurons of the pattern layer are removed from the network. In case of not being selected, all training rows will be used to create the model.

Minimize error: This option allows DTREG to remove the neurons until the error of leave-one-out validation remains constant or decreases.

Minimize neurons: This option allows DTREG to remove the neurons until the error of leave-one-out validation exceeds the error from the evaluation of all neurons.

Number of neurons: This option is used for removing the least significant neurons until only the designated number of neurons remain.

Retrain after removing neurons: If this box is selected, the network will be retrained with the remaining neurons in pattern layer after unnecessary neurons are pruned.

Type of kernel function: Two different types of kernel functions are able to use in pattern layer which are gaussian and reciprocal functions. Gaussian function is commonly used kernel function in GRNN. The equation of the Gaussian function represented by (3.1).

$$g(x) = \frac{1}{\sigma\sqrt{2\pi}} e^{\left(\frac{-x^2}{2\sigma^2}\right)} \tag{3.1.}$$

Settings of GRNN Model Optimization are illustrated in Figure 3.5.

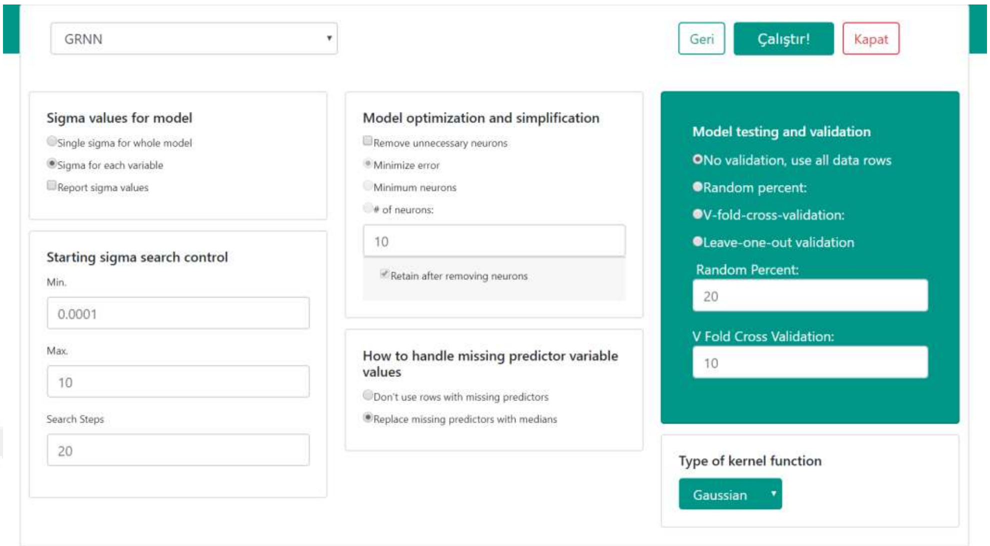

Figure 3.5. Settings of GRNN Model Optimization

3.2.4.3. Settings of SVM Model Optimization

Type of SVM Model: DTREG provides different types of SVM models. ε-SVR or ν-SVR models are able to select for regression models with a continuous target variable. In practice, the results are similar that generated by the different types of models for most application but it isn't known which one is the best option for a specific problem without trying each one.

Kernel Function: A kernel function maps input instances into an m-dimensional space where a hyperplane can separate the data. Four different kernel functions are supported by DTREG namely linear, polynomial, radial basis, and sigmoid (S-shaped) functions. Among these functions, radial basis function (RBF) has been considered the most successful one. However, it is not possible to know which function would be a better option for certain applications without performing each combination.

Stopping Criteria(Epsilon): This represents a tolerance value (ε) that controls when DTREG stops the iterative learning process. If the tolerance is reduced, more accurate models can be generated but the chance of overfitting is increased. When tolerance increases, the computation time of models decreases.

Use shrinking heuristics: A SVM model searches hyperplanes that maximize margins between the feature vectors. Points nearby to hyperplane are valuable for a solution called support vectors. Shrinking option ignores points that are far from hyperplanes which are unlikely to influence the choice of the best separating hyperplane. DTREG recommends that shrinking be enabled.

Parameter optimization search control: Determining the model parameters of SVM such as C, Degree, P, Gamma, etc. influences the model accuracy greatly. DTEG has two options to arrange parameters which are a grid search and a pattern search algorithm.

Do grid search for optimal parameters: If this option is chosen, a grid search algorithm will search for the best value of each parameter using geometric steps. The user has to determine the lower and upper bound for each relevant parameter.

Intervals for grid search: This value identifies the number of tested values between the high and low values.

Refinement iteration value: It is the value specified in the field to the right of intervals. Once DTREG identifies the best parameters candidates by grid search algorithm, small grid search will be performed in the close-range of the optimal point to further improve the optimal values.

Do pattern search for optimal parameters: If this option is chosen, DTREG will apply a pattern search algorithm to try to select the optimal parameter values.

Intervals for pattern search: This option allows to control the starting step size in the pattern search. Setting the first step is important to equalize the number of required steps for crossing the entire search range to the specified number of intervals.

Tolerance: This option has the control over ending the pattern search. The search will be stopped after the value of all parameters divided by the step size reaches less than the tolerance value.

Percent rows to use for search: It identifies the percentage of the training dataset will be operated by DTREG for the seach.

Cross validate; folds: This option allows DTREG to search optimal parameter using V-fold cross validation technique. In case of not being selected, DTREG will operate the optimal parameters examining the calculated errors from the training dataset.

Minimize total error: DTREG computes Root Mean Square Error(RMSE) for regression when performing a search for optimal parameters.

Model Parameters: The user has to determine the number of parameters which are C, Nu, Gamma, Degree, etc. that apply to the SVM according to the kernel function which is chosen.

Settings of SVM Model Optimization are presented in Figure 3.6.

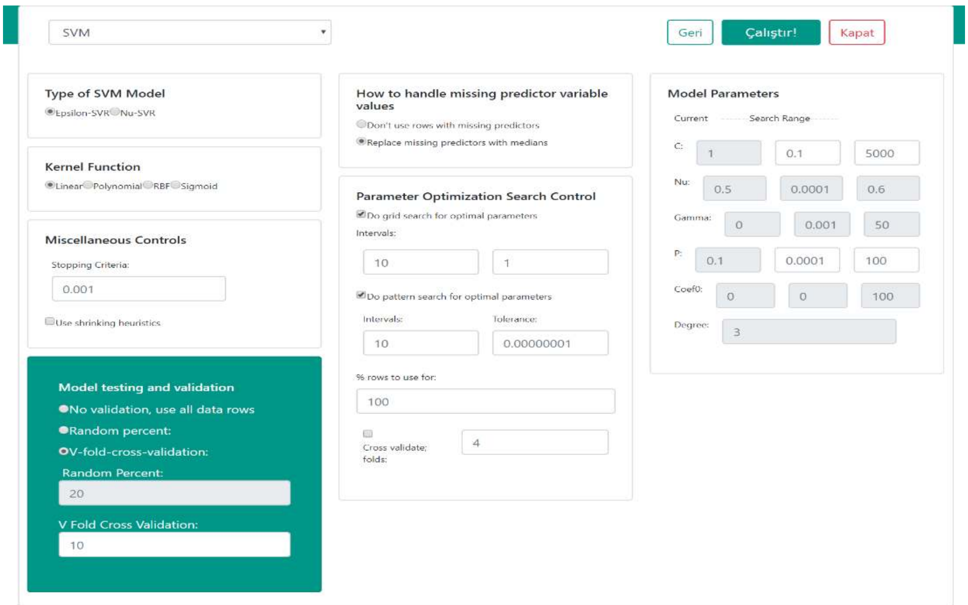

Figure 3.6. Settings of SVM Model Optimization

3.2.5. Avhieved And Saving Model

After the determination of the method and its parameters, the machine learning model is generated via the software. The training and test RMSEs are presented to the user. Finally, the produced model can be saved or deleted. RMSE values of the generated model are presented in Figure 3.7.

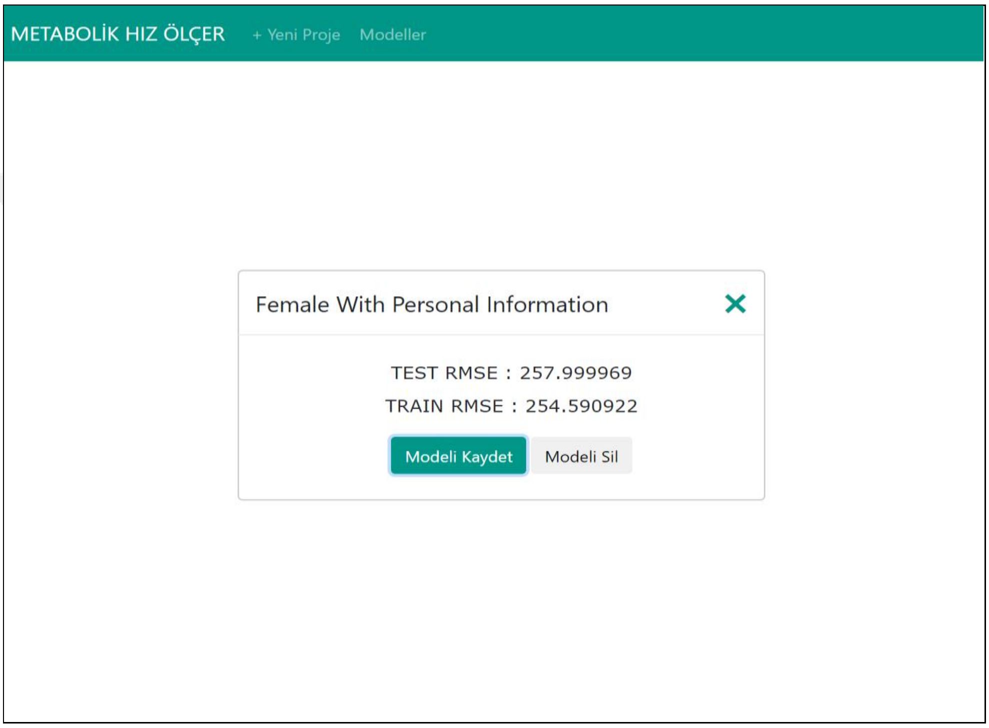

Figure 3.7. RMSE values of the generated model

3.3. The Front End Side of The Project

After machine learning models are generated for female and male patients on the back end side, these models can be used to calculate RMR of a person by the application developed Smartiks Software Incorporation. This program is designed for dietitians. The main features of the application which have been developed are listed below.

3.3.1. Login Page

The user is able to log in to the system with username and password on this page. If 'remember me' checkbox is selected, the user will be redirected to the main page when the system is operated again.

3.3.2. Main Page

The user is able to add a new patient, search a patient according to name, edit or delete already existed patient, add date based visit for the patient, calculate RMR for each patient.

3.3.3. Screenshots

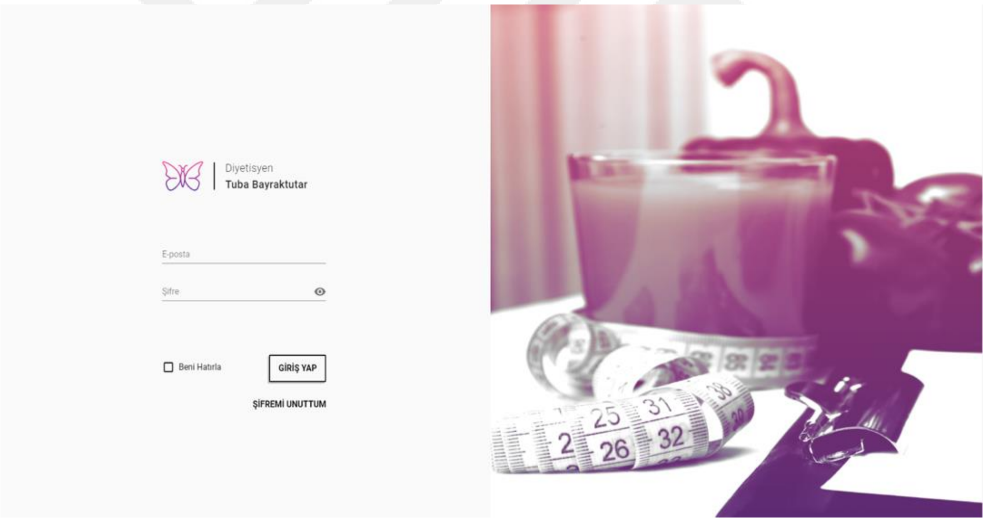

Figure 3.8. Login page

Figure 3.9. Main page

Figure 3.10. Preparing predictor variables

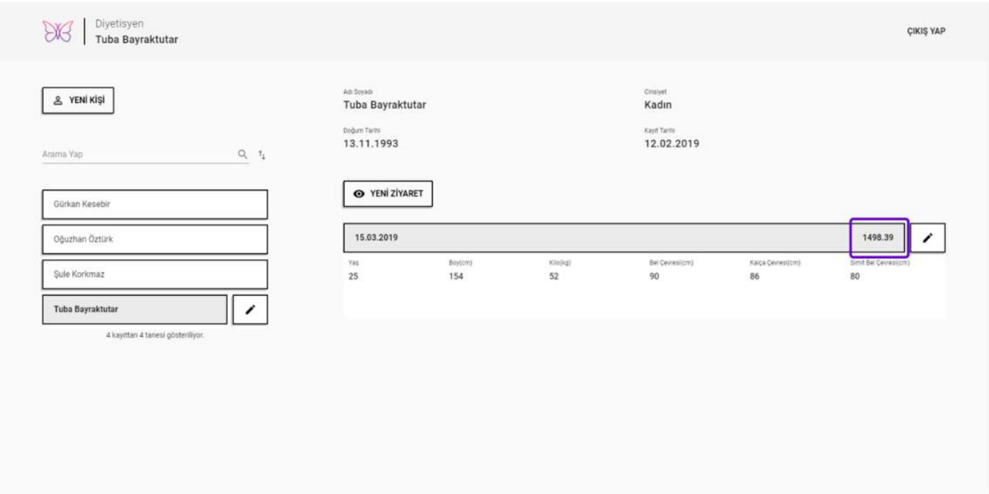

Figure 3.11. Calculating RMR of the patient

4. RESULTS AND DISCUSSIONS

In this thesis, results are divided into two main groups with respect to female and male patient prediction results. The results of each group have been occurred by two subgroups included tuple of age and BMI or age, height and weight. Each subgroup's results consist of 10 different categories which is built a combination of remaining predictor variables. The predictor variables that will be subset for each category are shown in Table 4.1.

Table 4.1. The variables to be used in the study

Category No	Predictor Variables
1	Percentage of Fat, Fat(kg), Liquid(kg), Non-Fat(kg), Muscle(kg), Bone Weight(kg)
2	Mineral Quantity(kg), Protein Amount(kg),Internal Lubrication, Body Density
3	Right-Leg, Left-Leg, Right-Arm, Left-Arm and Body Impedance
4	Right-Leg, Left-Leg, Right-Arm, Left-Arm and Body Fat Percentage
5	Right-Leg, Left-Leg, Right-Arm, Left-Arm and Body Fat Kilograms
6	Right-Leg, Left-Leg, Right-Arm, Left-Arm and Body Fat Non-Fat Kilograms
7	Right-Leg, Left-Leg, Right-Arm, Left-Arm and Body Muscle Kilograms
8	Soft Muscle Tissue, Bone Minerals Weight(kg), Skeletal Muscles(kg), Extracellular Liquid(kg), Intercellular Fluid(kg), Cell Mass(kg)
9	Waist, Hip (for female patients), Lower Belly Circumference
10	Thyroid, Insulin, Cigarette

After determining the combinations of these predictor variables, the model parameters have been chosen for building the prediction models which are as follows:

Selected Settings For The Prediction Models

GRNN Models: Minimum number of errors, minimum neurons, and 10 of neurons optimization techniques.

MLP Models:

- Hidden layer 1, linear activation function for the neurons in hidden and output layers
- Hidden layer 1, linear activation function for the neurons in hidden layer, and sigmoid (S-shaped, logistic) activation function for the neurons in output layer
- Hidden layer 1, the sigmoid (logistic) activation function for the neurons in hidden layer, and linear activation function for the neurons in output layer
- Hidden layer 1, sigmoid (logistic) activation function for the neurons in hidden and output layers
- Hidden layer 2, linear activation function for the neurons in hidden and output layers
- Hidden layer 2, linear activation function for the neurons in hidden layers, and sigmoid (logistic) activation function for the neurons in output layer
- Hidden layer 2, sigmoid (logistic) activation function for the neurons in hidden layers, and linear activation function for the neurons in output layer
- Hidden layer 2, sigmoid (logistic) activation function for the neurons in hidden and output layers

SVM Models:

- Linear kernel function, 'do grid search' optimization technique
- Linear kernel function, 'do pattern search' optimization technique
- RBF kernel function, 'do grid search' optimization technique
- RBF kernel function, 'do pattern search' optimization technique

The evaluation of the performance and the accuracy of these distinct models is executed with the *RMSE* values which have been calculated using 10-fold cross validation method. *RMSE* equation is given in 4.1.

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(Y - Y')^2} \qquad (4.1.)$$

In (4.1.) Y is the target value, Y' is the predicted value, and n is the number of samples in a test subset.

The table of results is represented as the following. The tables from 4.2 to 4.31 show the results of female patients based on age and BMI subgroups while the tables from 4.32 to 4.61 present the results of female patients based on age, height, and weight. The tables from 4.62 to 4.91 represent the results of male patients based on age and BMI subgroups while the tables from 4.92 to 4.121 show the results of male patients based on age, height, and weight.

Table 4.2. *RMSE* values for females (Age, BMI,Category-1)

No	Model Type	Pedictor Variables	RMSE
1	GRNN - Minimize error	Age, BMI, Liquid(kg), Non-Fat(kg), Bone Weight (kg), Fat(kg)	142.567
2	GRNN - Minimize error	Age, BMI, Liquid(kg), Bone Weight (kg)	142.756
3	GRNN - Minimize error	Age, BMI, Bone Weight (kg), Fat(kg)	142.781
4	GRNN - Minimize error	Age, BMI, Non-Fat(kg), Bone Weight (kg), Fat(kg)	142.818
5	GRNN - Minimize error	Age, BMI, Fat(%), Liquid(kg), Non-Fat(kg), Bone Weight (kg)	142.839
6	GRNN - Minimize error	Age, BMI, Non-Fat(kg), Bone Weight (kg)	142.969

Table 4.3. *RMSE* values for females (Age, BMI, Category-1)

No	Model Type	Pedictor Variables	RMSE
7	MLP - 3 Layers Linear -Logistic	Age, BMI, Fat(%), Liquid(kg), Bone Weight (kg)	149.541
8	MLP - 4 Layers Linear - Linear	Age, BMI, Non-Fat(kg), Muscle(kg), Bone Weight (kg), Fat(kg)	149.602
9	MLP - 3 Layers Logistic - Linear	Age, BMI, Bone Weight (kg), Fat(kg)	149.623
10	MLP - 3 Layers Logistic - Linear	Age, BMI, Liquid(kg)	149.842
11	MLP - 3 Layers - Linear - Linear	Age, BMI, Liquid(kg), Non-Fat(kg), Bone Weight (kg), Fat(kg)	149.882
12	MLP - 3 Layers - Linear - Linear	Age, BMI, Liquid(kg)	150.006

Table 4.4. *RMSE* values for females (Age, BMI, Category-1)

No	Model Type	Pedictor Variables	RMSE
13	SVM - RBF - DoGridSearch	Age, BMI, Liquid(kg), Non-Fat(kg), Bone Weight (kg), Fat(kg)	148.935
14	SVM - RBF - DoPatternSearch	Age, BMI, Liquid(kg), Non-Fat(kg), Bone Weight (kg), Fat(kg)	148.935
15	SVM - RBF - DoGridSearch	Age, BMI, Fat(%), Muscle(kg)	149.023
16	SVM - RBF - DoPatternSearch	Age, BMI, Fat(%), Muscle(kg)	149.023
17	SVM - RBF - DoGridSearch	Age, BMI, Muscle(kg)	149.126
18	SVM - RBF - DoPatternSearch	Age, BMI, Muscle(kg)	149.126

Table 4.5. *RMSE* values for females (Age, BMI, Category-2)

No	Model Type	Pedictor Variables	RMSE
19	GRNN - Minimize error	Age, BMI, Protein Amount(kg), Internal Lubrication	142.623
20	GRNN - Minimize error	Age, BMI, Mineral Quantity(kg), Protein Amount(kg), Internal Lubrication	143.633
21	GRNN - Minimize error	Age, BMI, Mineral Quantity(kg), Protein Amount(kg)	144.93
22	GRNN -Minimum neurons	Age, BMI, Protein Amount(kg), Internal Lubrication	147.267
23	GRNN - Minimize error	Age, BMI, Internal Lubrication	147.962
24	GRNN - Minimize error	Age, BMI, Mineral Quantity(kg), Internal Lubrication	148.005

Table 4.6. *RMSE* values for females (Age, BMI, Category-2)

No	Model Type	Pedictor Variables	RMSE
25	MLP - 3 Layers - Logistic - Linear	Age, BMI, Protein Amount(kg), Internal Lubrication, Body Density	149.125
26	MLP - 4 Layers - Logistic - Linear	Age, BMI, Internal Lubrication	149.91
27	MLP - 3 Layers - Linear - Linear	Age, BMI, Mineral Quantity(kg), Protein Amount(kg), Internal Lubrication	150.14
28	MLP - 3 Layers - Linear - Logistic	Age, BMI, Protein Amount(kg), Body Density	150.17
29	MLP - 3 Layers - Linear - Linear	Age, BMI, Internal Lubrication	150.046
30	MLP - 4 Layers - Linear - Linear	Age, BMI, Internal Lubrication	150.56

Table 4.7. *RMSE* values for females (Age, BMI, Category-2)

No	Model Type	Pedictor Variables	RMSE
31	SVM - RBF - DoGridSearch	Age, BMI, Body Density	149.299
32	SVM - RBF - DoPatternSearch	Age, BMI, Body Density	149.299
33	SVM - RBF - DoPatternSearch	Age, BMI, Protein Amount(kg), Internal Lubrication	149.588
34	SVM - RBF - DoGridSearch	Age, BMI, Protein Amount(kg), Internal Lubrication	149.589
35	SVM - RBF - DoGridSearch	Age, BMI, Protein Amount(kg), Body Density	149.627
36	SVM - RBF - DoPatternSearch	Age, BMI, Protein Amount(kg), Body Density	149.627

Table 4.8. *RMSE* values for females (Age, BMI, Category-3)

No	Model Type	Pedictor Variables	RMSE
37	GRNN - Minimize error	Age, BMI, Left-Arm Impedance	146.748
38	GRNN - Minimize error	Age, BMI, Left-Leg, Right-Arm, Left-Arm, Body Impedance	146.831
39	GRNN - Minimize error	Age, BMI, Right-Leg , Right-Arm, Left-Arm, Body Impedance	146.839
40	GRNN - Minimize error	Age, BMI, Right-Leg, Left-Leg, Left-Arm, Body Impedance	146.856
41	GRNN - Minimize error	Age, BMI, Right-Leg, Left-Arm, Body Impedance	146.918
42	GRNN - Minimize error	Age, BMI, Right-Leg, Left-Leg, Right-Arm, Left-Arm, Body Impedance	146.986

Table 4.9. *RMSE* values for females (Age, BMI, Category-3)

No	Model Type	Pedictor Variables	RMSE
43	MLP - 3 Layers - Linear - Linear	Age, BMI, Left-Leg, Right-Arm, Body Impedance	148.924
44	MLP - 3 Layers - Linear - Linear	Age, BMI, Right-Leg, Left-Leg, Left-Arm Impedance	149.125
45	MLP - 4 Layers - Linear - Linear	Age, BMI, Left-Leg, Left-Arm, Body Impedance	149.206
46	MLP - 4 Layers - Linear - Linear	Age, BMI, Left-Arm	149.256
47	MLP - 4 Layers - Linear - Linear	Age, BMI, Right-Leg, Left-Arm, Body Impedance	149.395
48	MLP - 3 Layers - Logistic - Linear	Age, BMI, Left-Leg, Right-Arm, Left-Arm, Body Impedance	149.482

Table 4.10. *RMSE* values for females (Age, BMI, Category-3)

No	Model Type	Pedictor Variables	RMSE
49	SVM - RBF - DoGridSearch	Age, BMI, Right-Leg, Left-Leg-Impedance	149.193
50	SVM - RBF - DoPatternSearch	Age, BMI, Right-Leg, Left-Leg-Impedance	149.196
51	SVM - Linear - DoGridSearch	Age, BMI, Right-Leg, Left-Leg-Impedance	149.502
52	SVM - Linear - DoGridSearch	Age, BMI, Right-Leg-Impedance	149.504
53	SVM - Linear - DoPatternSearch	Age, BMI, Right-Leg, Left-Leg-Impedance	149.605
54	SVM - RBF - DoGridSearch	Age, BMI, Right-Arm-Impedance	149.643

Table 4.11. *RMSE* values for females (Age, BMI, Category-4)

No	Model Type	Pedictor Variables	RMSE
55	GRNN - Minimize error	Age, BMI, Right-Leg-Fat Percentage	139.676
56	GRNN - Minimize error	Age, BMI, Right-Leg-Fat, Left-Leg-Fat, Left-Arm-Fat Percentage	146.084
57	GRNN - Minimize error	Age, BMI, Left-Leg-Fat, Left-Arm-Fat Percentage	146.259
58	GRNN - Minimize error	Age, BMI, Right-Leg-Fat, Left-Leg-Fat, Right-Arm-Fat, Body-Fat Percentage	146.327
59	GRNN - Minimize error	Age, BMI, Left-Leg-Fat, Right-Arm-Fat, Left-Arm-Fat Percentage	146.418
60	GRNN - Minimize error	Age, BMI, Left-Leg-Fat, Right-Arm-Fat, Left-Arm-Fat, Body-Fat Percentage	146.449

Table 4.12. *RMSE* values for females (Age, BMI,Category-4)

No	Model Type	Pedictor Variables	RMSE
61	MLP - 3 Layers - Logistic - Linear	Age, BMI, Left-Leg-Fat Percentage	149.205
62	MLP - 3 Layers - Logistic - Linear	Age, BMI, Right-Leg-Fat, Left-Leg-Fat, Right-Arm-Fat Percentage	149.487
63	MLP - 3 Layers - Logistic - Linear	Age, BMI, Right-Leg-Fat, Left-Leg-Fat, Left-Arm-Fat Percentage	149.719
64	MLP - 3 Layers - Logistic - Linear	Age, BMI, Left-Leg-Fat, Right-Arm-Fat Percentage	149.772
65	MLP - 3 Layers - Logistic - Logistic	Age, BMI, Left-Leg-Fat, Right-Arm-Fat, Body-Fat Percentage	149.979
66	MLP - 3 Layers - Logistic - Linear	Age, BMI, Right-Leg-Fat, Left-Leg-Fat, Body-Fat Percentage	150.066

Table 4.13. *RMSE* values for females (Age, BMI, Category-4)

No	Model Type	Pedictor Variables	RMSE
67	SVM - RBF - DoGridSearch	Age, BMI, Right-Leg-Fat, Left-Leg-Fat Percentage	148.626
68	SVM - RBF - DoPatternSearch	Age, BMI, Right-Leg-Fat, Left-Leg-Fat Percentage	148.626
69	SVM - RBF - DoGridSearch	Age, BMI, Left-Leg-Fat, Right-Arm-Fat Percentage	149.097
70	SVM - RBF - DoPatternSearch	Age, BMI, Left-Leg-Fat, Right-Arm-Fat Percentage	149.099
71	SVM - RBF - DoGridSearch	Age, BMI, Right-Leg-Fat Percentage	149.185
72	SVM - RBF - DoPatternSearch	Age, BMI, Right-Leg-Fat Percentage	149.185

Table 4.14. *RMSE* values for females (Age, BMI,Category-5)

No	Model Type	Pedictor Variables	RMSE
73	GRNN - Minimize error	Age, BMI, Right-Leg-Fat (kg), Left-Leg-Fat (kg), Left-Arm-Fat (kg)	140.297
74	GRNN - Minimize error	Age, BMI, Left-Leg-Fat (kg), Right-Arm-Fat (kg)	140.475
75	GRNN - Minimize error	Age, BMI, Left-Leg-Fat (kg), Right-Arm-Fat (kg), Left-Arm-Fat (kg)	145.523
76	GRNN - Minimize error	Age, BMI, Right-Leg-Fat (kg), Left-Leg-Fat (kg), Right-Arm-Fat (kg), Left-Arm-Fat (kg)	145.714
77	GRNN - Minimize error	Age, BMI, Right-Leg-Fat (kg), Left-Leg-Fat (kg)	145.893
78	GRNN - Minimize error	Age, BMI, Right-Leg-Fat (kg), Left-Leg-Fat (kg), Right-Arm-Fat (kg)	145.912

Table 4.15. *RMSE* values for females (Age, BMI,Category-5)

No	Model Type	Pedictor Variables	RMSE
79	MLP - 3 Layers - Logistic - Linear	Age, BMI, Left-Leg-Fat (kg), Right-Arm-Fat (kg), Left-Arm-Fat (kg), Body-Fat (kg)	149.852
80	MLP - 4 Layers - Linear - Logistic	Age, BMI, Right-Arm-Fat (kg)	149.924
81	MLP - 4 Layers - Linear - Linear	Age, BMI, Right-Leg-Fat (kg), Left-Leg-Fat (kg), Right-Arm-Fat (kg)	150
82	MLP - 4 Layers - Logistic - Linear	Age, BMI, Right-Leg-Fat (kg), Right-Arm-Fat (kg), Body-Fat (kg)	150.008
83	MLP - 4 Layers - Linear - Logistic	Age, BMI, Left-Leg-Fat (kg), Right-Arm-Fat (kg), Body-Fat (kg)	150.052
84	MLP - 4 Layers - Linear - Logistic	Age, BMI, Right-Leg-Fat (kg), Right-Arm-Fat (kg), Left-Arm-Fat (kg)	150.054

Table 4.16. *RMSE* values for females (Age, BMI, Category-5)

No	Model Type	Pedictor Variables	RMSE
85	SVM - RBF - DoGridSearch	Age, BMI, Right-Leg-Fat (kg)	149.258
86	SVM - RBF - DoGridSearch	Age, BMI, Left-Leg-Fat (kg), Right-Arm-Fat (kg)	149.462
87	SVM - RBF - DoGridSearch	Age, BMI, Left-Leg-Fat (kg), Body-Fat (kg)	149.466
88	SVM - RBF - DoPatternSearch	Age, BMI, Left-Leg-Fat (kg), Body-Fat (kg)	149.468
89	SVM - RBF - DoPatternSearch	Age, BMI, Left-Leg-Fat (kg), Right-Arm-Fat (kg)	149.474
90	SVM - RBF - DoGridSearch	Age, BMI, Right-Arm-Fat (kg)	149.512

Table 4.17. *RMSE* values for females (Age, BMI,Category-6)

No	Model Type	Pedictor Variables	RMSE
91	GRNN - Minimize error	Age, BMI, Right-Leg-Non-Fat(kg), Left-Leg-Non-Fat(kg)	144.017
92	GRNN - Minimize error	Age, BMI, Right-Leg-Non-Fat(kg), Left-Leg-Non-Fat(kg), Right-Arm-Non-Fat(kg), Left-Arm-Non-Fat(kg)	144.663
93	GRNN - Minimize error	Age, BMI, Right-Leg-Non-Fat(kg), Left-Leg-Non-Fat(kg), Right-Arm-Non-Fat(kg)	144.769
94	GRNN - Minimize error	Age, BMI, Right-Leg-Non-Fat(kg), Left-Leg-Non-Fat(kg), Right-Arm-Non-Fat(kg), Body-Non-Fat(kg)	144.918
95	GRNN - Minimize error	Age, BMI, Right-Leg-Non-Fat(kg), Left-Leg-Non-Fat(kg), Left-Arm-Non-Fat(kg), Body-Non-Fat(kg)	145.179
96	GRNN - Minimize error	Age, BMI, Left-Leg-Non-Fat(kg), Left-Arm-Non-Fat(kg)	145.248

Table 4.18. *RMSE* values for females (Age, BMI, Category-6)

No	Model Type	Pedictor Variables	RMSE
97	MLP - 3 Layers - Linear - Linear	Age, BMI, Right-Arm-Non-Fat(kg)	149.718
98	MLP - 4 Layers - Linear - Linear	Age, BMI, Left-Leg-Non-Fat(kg), Body-Non-Fat(kg)	149.768
99	MLP - 3 Layers - Linear - Logistic	Age, BMI, Right-Leg-Non-Fat(kg), Left-Leg-Non-Fat(kg), Right-Arm-Non-Fat(kg), Body-Non-Fat(kg)	149.799
100	MLP - 3 Layers - Linear - Linear	Age, BMI, Right-Leg-Non-Fat(kg), Left-Leg-Non-Fat(kg), Right-Arm-Non-Fat(kg), Left-Arm-Non-Fat(kg), Body-Non-Fat(kg)	149.826
101	MLP - 3 Layers - Linear - Logistic	Age, BMI, Right-Leg-Non-Fat(kg), Right-Arm-Non-Fat(kg), Left-Arm-Non-Fat(kg), Body-Non-Fat(kg)	149.938
102	MLP - 4 Layers - Linear - Linear	Age, BMI, Right-Leg-Non-Fat(kg), Right-Arm-Non-Fat(kg)	150.024

Table 4.19. *RMSE* values for females (Age, BMI, Category-6)

No	Model Type	Pedictor Variables	RMSE
103	SVM - RBF - DoGridSearch	Age, BMI, Right-Leg, Left-Leg, Left-Arm, Body Non-Fat(kg)	148.962
104	SVM - RBF - DoPatternSearch	Age, BMI, Right-Leg, Left-Leg, Left-Arm, Body Non-Fat(kg)	148.972
105	SVM - RBF - DoGridSearch	Age, BMI, Right-Arm-Non-Fat(kg)	149.468
106	SVM - RBF - DoPatternSearch	Age, BMI, Right-Arm-Non-Fat(kg)	149.468
107	SVM - RBF - DoPatternSearch	Age, BMI, Right-Leg, Left-Leg, Body Non-Fat(kg)	149.503
108	SVM - Linear - DoGridSearch	Age, BMI, Right-Leg, Left-Leg, Right-Arm, Left-Arm Non-Fat(kg)	149.517

Table 4.20. *RMSE* values for females (Age, BMI, Category-7)

No	Model Type	Pedictor Variables	RMSE
109	GRNN - Minimize error	Age, BMI, Right-Leg, Left-Leg, Left-Arm Muscle(kg)	144.016
110	GRNN - Minimize error	Age, BMI, Right-Leg,Left-Leg, Right-Arm, Left-Arm Muscle(kg)	144.026
111	GRNN - Minimize error	Age, BMI, Right-Leg-Muscle(kg), Right-Arm-Muscle(kg)	144.078
112	GRNN - Minimize error	Age, BMI, Right-Leg, Left-Leg, Right-Arm-Muscle(kg)	144.244
113	GRNN - Minimize error	Age, BMI, Right-Leg-Muscle(kg), Body-Muscle(kg)	145.206
114	GRNN - Minimize error	Age, BMI, Right-Leg-Muscle(kg), Left-Leg, Right-Arm, Body-Muscle(kg)	145.207

Table 4.21. *RMSE* values for females (Age, BMI, Category-7)

No	Model Type	Pedictor Variables	RMSE
115	MLP - 3 Layers - Linear - Logistic	Age, BMI, Right-Leg,Left-Leg, Right-Arm, Left-Arm, Body Muscle(kg)	148.279
116	MLP - 3 Layers - Linear - Linear	Age, BMI, Right-Leg, Left-Leg, Left-Arm, Body Muscle(kg)	148.562
117	MLP - 4 Layers - Linear - Linear	Age, BMI, Right-Leg, Left-Leg, Left-Arm, Body Muscle(kg)	148.767
118	MLP - 3 Layers - Linear - Linear	Age, BMI, Right-Leg, Left-Leg, Right-Arm, Left-Arm, Body-Muscle(kg)	148.865
119	MLP - 3 Layers - Logistic - Linear	Age, BMI, Left-Leg-Muscle(kg), Left-Arm-Muscle(kg), Body-Muscle(kg)	148.891
120	MLP - 4 Layers - Linear - Linear	Age, BMI, Right-Leg, Left-Leg, Right-Arm, Body Muscle(kg)	149.046

Table 4.22. *RMSE* values for females (Age, BMI, Category-7)

No	Model Type	Pedictor Variables	RMSE
121	SVM - Linear - DoGridSearch	Age, BMI, Right-Leg, Left-Leg, Right-Arm, Left-Arm, Body Muscle(kg)	147.869
122	SVM - Linear - DoPatternSearch	Age, BMI, Right-Leg, Left-Leg, Right-Arm, Left-Arm, Body Muscle(kg)	147.944
123	SVM - RBF - DoGridSearch	Age, BMI, Right-Leg, Left-Leg, Left-Arm, Body Muscle(kg)	148.409
124	SVM - RBF - DoPatternSearch	Age, BMI, Right-Leg, Left-Leg, Left-Arm, Body-Muscle(kg)	148.419
125	SVM - RBF - DoGridSearch	Age, BMI, Body-Muscle(kg)	148.436
126	SVM - Linear - DoPatternSearch	Age, BMI, Left-Arm, Body-Muscle(kg)	148.446

Table 4.23. *RMSE* values for females (Age, BMI, Category-8)

No	Model Type	Pedictor Variables	RMSE
127	GRNN - Minimize error	Age, BMI, Skeletal Muscles(kg), Extracellular Liquid(kg), Cell Mass(kg)	142.168
128	GRNN - Minimize error	Age, BMI, Intercellular Fluid(kg), Cell Mass(kg)	142.243
129	GRNN - Minimize error	Age, BMI, Skeletal Muscles(kg)	142.257
130	GRNN - Minimize error	Age, BMI, Cell Mass(kg)	142.263
131	GRNN - Minimize error	Age, BMI, Extracellular Liquid(kg), Intercellular Fluid(kg), Cell Mass(kg)	142.273
132	GRNN - Minimize error	Age, BMI, Soft Muscle Tissue(kg), Intercellular Fluid(kg), Cell Mass(kg)	142.308

Table 4.24. *RMSE* values for females (Age, BMI, Category-8)

No	Model Type	Pedictor Variables	RMSE
133	MLP - 4 Layers - Logistic - Linear	Age, BMI, Soft Muscle Tissue(kg), Bone Minerals Weight(kg)	148.406
134	MLP - 3 Layers - Logistic - Linear	Age, BMI, Soft Muscle Tissue(kg), Extracellular Liquid(kg)	148.559
135	MLP - 3 Layers - Logistic - Linear	Age, BMI, Intercellular Fluid(kg)	148.642
136	MLP - 3 Layers - Logistic - Linear	Age, BMI, Skeletal Muscles(kg), Extracellular Liquid(kg), Intercellular Fluid(kg)	148.691
137	MLP - 3 Layers - Logistic - Logistic	Age, BMI, Bone Minerals Weight(kg)	148.705
138	MLP - 4 Layers - Linear - Linear	Age, BMI, Soft Muscle Tissue(kg), Bone Minerals Weight(kg), Skeletal Muscles(kg), Extracellular Liquid(kg), Intercellular Fluid(kg)	148.728

Table 4.25. *RMSE* values for females (Age, BMI, Category-8)

No	Model Type	Pedictor Variables	RMSE
139	SVM - RBF - DoPatternSearch	Age, BMI, Bone Minerals Weight(kg)	147.324
140	SVM - RBF - DoGridSearch	Age, BMI, Bone Minerals Weight(kg)	147.334
141	SVM - RBF - DoGridSearch	Age, BMI, Skeletal Muscles(kg), Intercellular Fluid(kg), Cell Mass(kg)	147.889
142	SVM - RBF - DoPatternSearch	Age, BMI, Skeletal Muscles(kg), Intercellular Fluid(kg), Cell Mass(kg)	147.935
143	SVM - RBF - DoGridSearch	Age, BMI, Soft Muscle Tissue(kg), Skeletal Muscles(kg), Cell Mass(kg)	147.937
144	SVM - RBF - DoPatternSearch	Age, BMI, Soft Muscle Tissue(kg), Skeletal Muscles(kg), Cell Mass(kg)	147.937

Table 4.26. *RMSE* values for females (Age, BMI, Category-9)

No	Model Type	Pedictor Variables	RMSE
145	GRNN - Minimize error	Age, BMI, Waist Circumference(cm), Hip Circumference(cm)	139.084
146	GRNN - Minimize error	Age, BMI, Hip Circumference(cm)	139.154
147	GRNN - Minimize error	Age, BMI, Hip Circumference(cm), Lower Belly Circumference(cm)	139.272
148	GRNN - Minimize error	Age, BMI, Waist Circumference(cm), Hip Circumference(cm), Lower Belly Circumference(cm)	139.364
149	GRNN -#10 of neurons	Age, BMI, Hip Circumference(cm), Lower Belly Circumference(cm)	143.885
150	GRNN - Minimum neurons	Age, BMI, Waist Circumference(cm), Hip Circumference(cm)	144.054

Table 4.27. *RMSE* values for females (Age, BMI, Category-9)

No	Model Type	Pedictor Variables	RMSE
151	MLP - 3 Layers - Logistic - Linear	Age, BMI, Hip Circumference(cm)	146.178
152	MLP - 4 Layers - Linear - Linear	Age, BMI, Hip Circumference(cm)	146.566
153	MLP - 3 Layers - Logistic - Logistic	Age, BMI, Hip Circumference(cm)	146.839
154	MLP - 3 Layers - Linear - Linear	Age, BMI, Hip Circumference(cm)	146.854
155	MLP - 4 Layers - Linear - Linear	Age, BMI, Waist Circumference(cm), Hip Circumference(cm)	147.125
156	MLP - 4 Layers - Linear - Logistic	Age, BMI, Waist Circumference(cm), Hip Circumference(cm)	147.141

Table 4.28. *RMSE* values for females (Age, BMI, Category-9)

No	Model Type	Pedictor Variables	RMSE
157	SVM - RBF - DoPatternSearch	Age, BMI, Hip Circumference(cm)	143.922
158	SVM - RBF - DoGridSearch	Age, BMI, Hip Circumference(cm)	143.947
159	SVM - RBF - DoGridSearch	Age, BMI, Waist Circumference(cm), Hip Circumference(cm)	145.138
160	SVM - RBF - DoPatternSearch	Age, BMI, Waist Circumference(cm), Hip Circumference(cm)	145.138
161	SVM - RBF - DoPatternSearch	Age, BMI, Waist Circumference(cm), Hip Circumference(cm), Lower Belly Circumference(cm)	145.528
162	SVM - RBF - DoGridSearch	Age, BMI, Waist Circumference(cm), Hip Circumference(cm), Lower Belly Circumference(cm)	145.538

Table 4.29. *RMSE* values for females (Age, BMI, Category-10)

No	Model Type	Pedictor Variables	RMSE
163	GRNN - Minimize error	Age, BMI, Thyroid, Insulin, Cigarette	144.646
164	GRNN - Minimize error	Age, BMI, Thyroid, Insulin	144.661
165	GRNN - Minimize error	Age, BMI, Thyroid, Cigarette	146.808
166	GRNN - Minimize error	Age, BMI, Thyroid	147.458
167	GRNN - Minimize error	Age, BMI, Insulin, Cigarette	147.589
168	GRNN - Minimize error	Age, BMI, Insulin	147.609

Table 4.30. *RMSE* values for females (Age, BMI, Category-10)

No	Model Type	Pedictor Variables	RMSE
169	MLP - 3 Layers - Logistic - Logistic	Age, BMI, Thyroid, Insulin	150.523
170	MLP - 3 Layers - Linear - Logistic	Age, BMI, Thyroid	150.537
171	MLP - 3 Layers - Linear - Linear	Age, BMI, Thyroid, Insulin	150.541
172	MLP - 4 Layers - Linear - Logistic	Age, BMI, Thyroid, Insulin	150.561
173	MLP - 4 Layers - Linear - Linear	Age, BMI, Insulin	150.608
174	MLP - 3 Layers - Logistic - Linear	Age, BMI, Thyroid, Insulin	150.646

Table 4.31. *RMSE* values for females (Age, BMI, Category-10)

No	Model Type	Pedictor Variables	RMSE
175	SVM - RBF - DoGridSearch	Age, BMI, Thyroid, Insulin, Cigarette	148.834
176	SVM - RBF - DoPatternSearch	Age, BMI, Thyroid, Insulin, Cigarette	148.834
177	SVM - RBF - DoGridSearch	Age, BMI, Thyroid, Insulin	148.982
178	SVM - Linear - DoGridSearch	Age, BMI, Thyroid, Insulin	149.359
179	SVM - RBF - DoPatternSearch	Age, BMI, Thyroid, Insulin	149.367
180	SVM - RBF - DoPatternSearch	Age, BMI, Thyroid, Cigarette	149.512

Table 4.32. *RMSE* values for females (Age, Height, Weight, Category-1)

No	Model Type	Pedictor Variables	RMSE
181	GRNN - Minimize error	Age, Height(cm), Weight(kg), Fat(%), Liquid(kg), Bone Weight (kg)	134.91
182	GRNN - Minimize error	Age, Height(cm), Weight(kg), Fat(%), Bone Weight (kg)	135.017
183	GRNN - Minimize error	Age, Height(cm), Weight(kg), Bone Weight (kg), Fat(kg)	135.09
184	GRNN - Minimize error	Age, Height(cm), Weight(kg), Fat(%), Non-Fat(kg), Bone Weight (kg)	135.222
185	GRNN - Minimize error	Age, Height(cm), Weight(kg), Non-Fat(kg), Bone Weight (kg), Fat(kg)	135.352
186	GRNN - Minimize error	Age, Height(cm), Weight(kg), Liquid(kg), Non-Fat(kg), Bone Weight (kg)	135.464

Table 4.33. *RMSE* values for females (Age, Height, Weight, Category-1)

No	Model Type	Pedictor Variables	RMSE
187	MLP - 4 Layers - Linear - Linear	Age, Height(cm), Weight(kg), Liquid(kg), Non-Fat(kg), Muscle(kg), Bone Weight (kg), Fat(kg)	149.445
188	MLP - 4 Layers - Linear - Linear	Age, Height(cm), Weight(kg), Liquid(kg), Non-Fat(kg), Bone Weight (kg), Fat(kg)	150.242
189	MLP - 4 Layers - Linear - Linear	Age, Height(cm), Weight(kg), Liquid(kg), Bone Weight (kg), Fat(kg)	150.281
190	MLP - 3 Layers - Sigmoidal - Linear	Age, Height(cm), Weight(kg), Bone Weight (kg), Fat(kg)	150.295
191	MLP - 4 Layers - Linear - Linear	Age, Height(cm), Weight(kg), Non-Fat(kg), Bone Weight (kg), Fat(kg)	150.323
192	MLP - 4 Layers - Linear - Linear	Age, Height(cm), Weight(kg), Liquid(kg), Bone Weight (kg)	150.338

Table 4.34. *RMSE* values for females (Age, Height, Weight, Category-1)

No	Model Type	Pedictor Variables	RMSE
193	SVM - RBF - DoGridSearch	Age, Height(cm), Weight(kg), Liquid, Non-Fat, Muscle, Bone Weight, Fat(kg)	149.688
194	SVM - RBF - DoPatternSearch	Age, Height(cm), Weight(kg), Liquid, Non-Fat, Muscle, Bone Weight , Fat(kg)	149.688
195	SVM - Linear - DoGridSearch	Age, Height(cm), Weight(kg), Liquid, Non-Fat, Muscle, Bone Weight , Fat(kg)	149.719
196	SVM - RBF - DoGridSearch	Age, Height(cm), Weight(kg), Liquid(kg), Non-Fat(kg), Muscle(kg), Bone Weight (kg)	149.801
197	SVM - Linear - DoPatternSearch	Age, Height(cm), Weight(kg), Liquid(kg), Non-Fat(kg), Muscle(kg)	149.805
198	SVM - RBF - DoGridSearch	Age, Height(cm), Weight(kg), Fat(%), Liquid(kg), Non-Fat(kg), Muscle(kg), Bone Weight (kg)	149.816

Table 4.35. *RMSE* values for females (Age, Height, Weight, Category-2)

No	Model Type	Pedictor Variables	RMSE
199	GRNN - Minimize error	Age, Height(cm), Weight(kg), Mineral Quantity(kg), Protein Amount(kg), Internal Lubrication	143.996
200	GRNN - Minimize error	Age, Height(cm), Weight(kg), Protein Amount(kg), Internal Lubrication	144.674
201	GRNN - Minimize error	Age, Height(cm), Weight(kg), Mineral Quantity(kg), Protein Amount(kg)	145.245
202	GRNN - Minimize error	Age, Height(cm), Weight(kg), Internal Lubrication	145.411
203	GRNN - Minimize error	Age, Height(cm), Weight(kg), Protein Amount(kg)	145.898
204	GRNN - Minimize error	Age, Height(cm), Weight(kg), Mineral Quantity(kg)	147.468

Table 4.36. *RMSE* values for females (Age, Height, Weight, Category-2)

No	Model Type	Pedictor Variables	RMSE
205	MLP - 4 Layers - Linear - Linear	Age, Height(cm), Weight(kg), Body Density	150.562
206	MLP - 4 Layers - Linear - Linear	Age, Height(cm), Weight(kg), Protein Amount(kg), Body Density	150.775
207	MLP - 3 Layers - Logistic - Linear	Age, Height(cm), Weight(kg), Protein Amount(kg), Body Density	150.875
208	MLP - 4 Layers - Linear - Linear	Age, Height(cm), Weight(kg), Internal Lubrication, Body Density	150.987
209	MLP - 4 Layers - Logistic - Logistic	Age, Height(cm), Weight(kg), Protein Amount(kg)	151.069
210	MLP - 3 Layers - Linear - Linear	Age, Height(cm), Weight(kg), Protein Amount(kg), Internal Lubrication	151.289

Table 4.37. *RMSE* values for females (Age, Height, Weight, Category-2)

No	Model Type	Pedictor Variables	RMSE
211	SVM - RBF - DoGridSearch	Age, Height(cm), Weight(kg), Body Density	150.398
212	SVM - RBF - DoPatternSearch	Age, Height(cm), Weight(kg), Body Density	150.398
213	SVM - RBF - DoGridSearch	Age, Height(cm), Weight(kg), Protein Amount(kg), Internal Lubrication, Body Density	150.406
214	SVM - RBF - DoPatternSearch	Age, Height(cm), Weight(kg), Protein Amount(kg), Internal Lubrication, Body Density	150.406
215	SVM - Linear - DoGridSearch	Age, Height(cm), Weight(kg), Protein Amount(kg), Internal Lubrication	150.436
216	SVM - Linear - DoPatternSearch	Age, Height(cm), Weight(kg), Internal Lubrication, Body Density	150.436

Table 4.38. *RMSE* values for females (Age, Height, Weight, Category-3)

No	Model Type	Pedictor Variables	RMSE
217	GRNN - Minimize error	Age, Height(cm), Weight(kg), Right-Arm, Left-Arm, Body Impedance	146.377
218	GRNN - Minimize error	Age, Height(cm), Weight(kg), Right-Leg, Left-Leg, Body Impedance	146.411
219	GRNN - Minimize error	Age, Height(cm), Weight(kg), Left-Leg, Right-Arm, Left-Arm, Body Impedance	146.495
220	GRNN - Minimize error	Age, Height(cm), Weight(kg), Right Leg, Left-Leg, Left-Arm, Body Impedance	146.555
221	GRNN - Minimize error	Age, Height(cm), Weight(kg), Right-Leg, Right-Arm, Left-Arm, Body Impedance	146.569
222	GRNN - Minimize error	Age, Height(cm), Weight(kg), Right-Leg, Left-Leg, Right-Arm, Left-Arm, Body Impedance	146.639

Table 4.39. *RMSE* values for females (Age, Height, Weight, Category-3)

No	Model Type	Pedictor Variables	RMSE
223	MLP - 4 Layers - Linear - Linear	Age, Height(cm), Weight(kg), Right-Leg, Left-Leg, Right-Arm, Body Impedance	149.422
224	MLP - 3 Layers - Logistic - Linear	Age, Height(cm), Weight(kg), Left-Leg Impedance	150.065
225	MLP - 4 Layers - Linear - Linear	Age, Height(cm), Weight(kg), Right-Leg, Right-Arm, Left-Arm, Body Impedance	150.196
226	MLP - 3 Layers - Logistic - Linear	Age, Height(cm), Weight(kg), Right-Arm Impedance	150.228
227	MLP - 3 Layers - Linear - Logistic	Age, Height(cm), Weight(kg), Right-Leg, Left-Leg, Right-Arm, Left-Arm Impedance	150.236
228	MLP - 4 Layers - Linear - Linear	Age, Height(cm), Weight(kg), Right-Leg, Left-Leg Impedance	150.275

Table 4.40. *RMSE* values for females (Age, Height, Weight, Category-3)

No	Model Type	Pedictor Variables	RMSE
229	SVM - RBF - DoGridSearch	Age, Height(cm), Weight(kg), Right-Arm-Impedance	149.905
230	SVM - RBF - DoPatternSearch	Age, Height(cm), Weight(kg), Right-Arm-Impedance	149.905
231	SVM - RBF - DoPatternSearch	Age, Height(cm), Weight(kg), Left-Leg-Impedance	149.941
232	SVM - RBF - DoGridSearch	Age, Height(cm), Weight(kg), Left-Leg-Impedance	149.947
233	SVM - Linear - DoGridSearch	Age, Height(cm), Weight(kg), Right-Leg, Left-Leg-Impedance	150.017
234	SVM - Linear - DoPatternSearch	Age, Height(cm), Weight(kg), Right-Leg, Left-Leg-Impedance	150.065

Table 4.41. *RMSE* values for females (Age, Height, Weight, Category-4)

No	Model Type	Pedictor Variables	RMSE
235	GRNN - Minimize error	Age, Height(cm), Weight(kg), Left-Leg-Fat, Left-Arm-Fat (%)	146.025
236	GRNN - Minimize error	Age, Height(cm), Weight(kg), Left-Leg-Fat, Right-Arm-Fat, Body-Fat(%)	146.139
237	GRNN - Minimize error	Age, Height(cm), Weight(kg), Right-Leg-Fat, Left-Leg-Fat, Body-Fat (%)	146.151
238	GRNN - Minimize error	Age, Height(cm), Weight(kg), Left-Leg-Fat, Right-Arm-Fat (%)	146.159
239	GRNN - Minimize error	Age, Height(cm), Weight(kg), Right-Leg-Fat, Left-Leg-Fat, Right-Arm-Fat, Left-Arm-Fat, Body-Fat (%)	146.253
240	GRNN - Minimize error	Age, Height(cm), Weight(kg), Right-Leg-Fat, Left-Leg-Fat (%)	146.317

Table 4.42. *RMSE* values for females (Age, Height, Weight, Category-4)

No	Model Type	Pedictor Variables	RMSE
241	MLP - 4 Layers - Sigmoidal - Linear	Age, Height(cm), Weight(kg), Right-Leg-Fat Percentage, Left-Leg-Fat Percentage, Body-Fat Percentage	150.352
242	MLP - 4 Layers - Sigmoidal - Linear	Age, Height(cm), Weight(kg), Right-Leg-Fat Percentage, Right-Arm-Fat Percentage, Body-Fat Percentage	150.416
243	MLP - 4 Layers - Linear - Linear	Age, Height(cm), Weight(kg), Left-Leg-Fat Percentage, Left-Arm-Fat Percentage	150.419
244	MLP - 3 Layers - Sigmoidal - Linear	Age, Height(cm), Weight(kg), Right-Leg-Fat Percentage, Right-Arm-Fat Percentage	150.507
245	MLP - 4 Layers - Sigmoidal - Logistic	Age, Height(cm), Weight(kg), Right-Arm-Fat Percentage, Left-Arm-Fat Percentage	150.548
246	MLP - 3 Layers - Sigmoidal - Linear	Age, Height(cm), Weight(kg), Right-Arm-Fat Percentage, Body-Fat Percentage	150.572

Table 4.43. *RMSE* values for females (Age, Height, Weight, Category-4)

No	Model Type	Pedictor Variables	RMSE
247	SVM - RBF - DoGridSearch	Age, Height(cm), Weight(kg), Left-Leg-Fat, Body-Fat (%)	149.802
248	SVM - RBF - DoPatternSearch	Age, Height(cm), Weight(kg), Left-Leg-Fat , Body-Fat (%)	149.802
249	SVM - RBF - DoGridSearch	Age, Height(cm), Weight(kg), Right-Leg-Fat , Left-Leg-Fat , Right-Arm-Fat, Left-Arm-Fat , Body-Fat (%)	149.888
250	SVM - RBF - DoPatternSearch	Age, Height(cm), Weight(kg), Right-Leg-Fat , Left-Leg-Fat , Right-Arm-Fat , Left-Arm-Fat , Body-Fat (%)	149.888
251	SVM - RBF - DoGridSearch	Age, Height(cm), Weight(kg), Left-Leg-Fat , Right-Arm-Fat , Body-Fat (%)	149.995
252	SVM - RBF - DoPatternSearch	Age, Height(cm), Weight(kg), Left-Leg-Fat , Right-Arm-Fat , Body-Fat (%)	149.995

Table 4.44. *RMSE* values for females (Age, Height, Weight, Category-5)

No	Model Type	Pedictor Variables	RMSE
253	GRNN - Minimize error	Age, Boy(cm), Kilo(kg), Right-Arm-Fat (kg), Left-Arm-Fat (kg)	141.405
254	GRNN - Minimize error	Age, Boy(cm), Kilo(kg), Left-Leg-Fat (kg)	144.799
255	GRNN - Minimize error	Age, Boy(cm), Kilo(kg), Right-Leg-Fat (kg), Left-Leg-Fat (kg), Left-Arm-Fat (kg)	144.865
256	GRNN - Minimize error	Age, Boy(cm), Kilo(kg), Left-Leg-Fat (kg), Right-Arm-Fat (kg)	145.139
257	GRNN - Minimize error	Age, Boy(cm), Kilo(kg), Left-Leg-Fat (kg), Left-Arm-Fat (kg)	145.144
258	GRNN - Minimize error	Age, Boy(cm), Kilo(kg), Right-Leg-Fat (kg), Left-Leg-Fat (kg), Right-Arm-Fat (kg), Left-Arm-Fat (kg)	145.465

Table 4.45. *RMSE* values for females (Age, Height, Weight, Category-5)

No	Model Type	Pedictor Variables	RMSE
259	MLP - 3 Layers - Logistic - Linear	Age, Boy(cm), Kilo(kg), Right-Leg-Fat (kg), Left-Leg-Fat (kg), Right-Arm-Fat (kg), Left-Arm-Fat (kg), Body-Fat (kg)	149.887
260	MLP - 3 Layers - Logistic - Linear	Age, Boy(cm), Kilo(kg), Right-Leg-Fat (kg), Left-Leg-Fat (kg), Right-Arm-Fat (kg)	150.004
261	MLP - 3 Layers - Logistic - Linear	Age, Boy(cm), Kilo(kg), Right-Leg-Fat (kg), Body-Fat (kg)	150.022
262	MLP - 3 Layers - Logistic - Linear	Age, Boy(cm), Kilo(kg), Left-Arm-Fat (kg), Body-Fat (kg)	150.025
263	MLP - 4 Layers - Logistic - Logistic	Age, Boy(cm), Kilo(kg), Left-Leg-Fat (kg), Body-Fat (kg)	150.217
264	MLP - 3 Layers - Logistic - Logistic	Age, Boy(cm), Kilo(kg), Right-Leg-Fat (kg), Body-Fat (kg)	150.224

Table 4.46. *RMSE* values for females (Age, Height, Weight, Category-5)

No	Model Type	Pedictor Variables	RMSE
265	SVM - RBF - DoGridSearch	Age, Boy(cm), Kilo(kg), Right-Leg-Fat (kg), Left-Leg-Fat (kg), Left-Arm-Fat (kg), Body-Fat (kg)	149.335
266	SVM - RBF - DoPatternSearch	Age, Boy(cm), Kilo(kg), Right-Leg-Fat (kg), Left-Leg-Fat (kg), Left-Arm-Fat (kg), Body-Fat (kg)	149.335
267	SVM - RBF - DoPatternSearch	Age, Boy(cm), Kilo(kg), Right-Arm-Fat (kg), Body-Fat (kg)	149.503
268	SVM - RBF - DoGridSearch	Age, Boy(cm), Kilo(kg), Right-Arm-Fat (kg), Body-Fat (kg)	149.511
269	SVM - RBF - DoGridSearch	Age, Boy(cm), Kilo(kg), Left-Arm-Fat (kg), Body-Fat (kg)	149.638
270	SVM - RBF - DoPatternSearch	Age, Boy(cm), Kilo(kg), Left-Arm-Fat (kg), Body-Fat (kg)	149.654

Table 4.47. *RMSE* values for females (Age, Height, Weight, Category-6)

No	Model Type	Pedictor Variables	RMSE
271	GRNN - Minimize error	Age, Height(cm), Weight(kg), Right-Leg Non-Fat(kg)	144.153
272	GRNN - Minimize error	Age, Height(cm), Weight(kg), Right-Leg, Left-Leg Non-Fat(kg)	144.161
273	GRNN - Minimize error	Age, Height(cm), Weight(kg), Right-Leg, Right-Arm, Left-Arm, Body Non-Fat(kg)	144.368
274	GRNN - Minimize error	Age, Height(cm), Weight(kg), Right-Leg, Right-Arm Non-Fat(kg)	144.405
275	GRNN - Minimize error	Age, Height(cm), Weight(kg), Right-Leg, Right-Arm, Body-Non-Fat(kg)	144.525
276	GRNN - Minimize error	Age, Height(cm), Weight(kg), Right-Leg, Left-Arm Non-Fat(kg)	144.766

Table 4.48. *RMSE* values for females (Age, Height, Weight, Category-6)

No	Model Type	Pedictor Variables	RMSE
277	MLP - 3 Layers - Linear - Logistic	Age, Height(cm), Weight(kg), Right-Leg, Left-Leg, Right-Arm, Left-Arm, Body Non-Fat(kg)	150.158
278	MLP - 4 Layers - Linear - Logistic	Age, Height(cm), Weight(kg), Right-Arm, Left-Arm Non-Fat(kg)	150.198
279	MLP - 3 Layers - Logistic - Linear	Age, Height(cm), Weight(kg), Left-Leg, Right-Arm Non-Fat(kg)	150.329
280	MLP - 4 Layers - Linear - Linear	Age, Height(cm), Weight(kg), Right-Leg, Left-Leg, Left-Arm-Non-Fat(kg)	150.495
281	MLP - 3 Layers - Linear - Linear	Age, Height(cm), Weight(kg), Left-Leg, Left-Arm Non-Fat(kg)	150.502
282	MLP - 4 Layers - Linear - Linear	Age, Height(cm), Weight(kg), Right-Leg, Right-Arm, Left-Arm, Body Non-Fat(kg)	150.544

Table 4.49. *RMSE* values for females (Age, Height, Weight, Category-6)

No	Model Type	Pedictor Variables	RMSE
283	SVM - Linear - DoGridSearch	Age, Height(cm), Weight(kg), Left-Leg-Non-Fat(kg)	149.329
284	SVM - Linear - DoPatternSearch	Age, Height(cm), Weight(kg), Left-Leg-Non-Fat(kg)	149.384
285	SVM - Linear - DoPatternSearch	Age, Height(cm), Weight(kg), Left-Leg, Right-Arm, Left-Arm-Non-Fat(kg)	149.581
286	SVM - Linear - DoGridSearch	Age, Height(cm), Weight(kg), Left-Leg-Non-Fat(kg), Right-Arm-Non-Fat(kg), Left-Arm-Non-Fat(kg)	149.652
287	SVM - Linear - DoGridSearch	Age, Height(cm), Weight(kg), Right-Arm, Left-Arm, Body-Non-Fat(kg)	150.028
288	SVM - Linear - DoPatternSearch	Age, Height(cm), Weight(kg), Left-Leg, Left-Arm, Body-Non-Fat(kg)	150.059

Table 4.50. *RMSE* values for females (Age, Height, Weight, Category-7)

No	Model Type	Pedictor Variables	RMSE
289	GRNN - Minimize error	Age, Height(cm), Weight(kg), Right-Leg-Muscle(kg), Left-Leg-Muscle(kg)	144.146
290	GRNN - Minimize error	Age, Height(cm), Weight(kg), Right-Leg-Muscle(kg), Left-Leg-Muscle(kg), Right-Arm-Muscle(kg)	144.384
291	GRNN - Minimize error	Age, Height(cm), Weight(kg), Right-Leg-Muscle(kg), Right-Arm-Muscle(kg)	144.523
292	GRNN - Minimize error	Age, Height(cm), Weight(kg), Right-Leg-Muscle(kg), Left-Leg-Muscle(kg), Left-Arm-Muscle(kg)	144.603
293	GRNN - Minimize error	Age, Height(cm), Weight(kg), Right-Leg-Muscle(kg), Body-Muscle(kg)	145.342
294	GRNN - Minimize error	Age, Height(cm), Weight(kg), Right-Leg-Muscle(kg), Right-Arm-Muscle(kg), Body-Muscle(kg)	145.426

Table 4.51. *RMSE* values for females (Age, Height, Weight, Category-7)

No	Model Type	Pedictor Variables	RMSE
295	MLP - 3 Layers - Linear - Logistic	Age, Height(cm), Weight(kg), Left-Arm, Body Muscle(kg)	148.693
296	MLP - 3 Layers - Linear - Logistic	Age, Height(cm), Weight(kg), Right-Arm, Left-Arm, Body Muscle(kg)	148.889
297	MLP - 3 Layers - Logistic - Linear	Age, Height(cm), Weight(kg), Right-Arm, Left-Arm, Body Muscle(kg)	149.164
298	MLP - 3 Layers - Linear - Linear	Age, Height(cm), Weight(kg), Right-Leg, Left-Leg, Right-Arm, Left-Arm, Body Muscle(kg)	149.185
299	MLP - 4 Layers - Linear - Logistic	Age, Height(cm), Weight(kg), Right-Arm, Left-Arm Muscle(kg)	149.488
300	MLP - 3 Layers - Logistic - Logistic	Age, Height(cm), Weight(kg), Right-Leg, Left-Leg, Right-Arm, Left-Arm, Body-Muscle(kg)	149.733

Table 4.52. *RMSE* values for females (Age, Height, Weight, Category-7)

No	Model Type	Pedictor Variables	RMSE
301	SVM - Linear - DoPatternSearch	Age, Height(cm), Weight(kg), Left-Leg-Muscle(kg), Right-Arm-Muscle(kg), Left-Arm-Muscle(kg)	147.767
302	SVM - Linear - DoGridSearch	Age, Height(cm), Weight(kg), Left-Leg, Right-Arm, Left-Arm-Muscle(kg)	147.833
303	SVM - Linear - DoPatternSearch	Age, Height(cm), Weight(kg), Right-Leg, Left-Leg, Right-Arm, Left-Arm, Body Muscle(kg)	148.495
304	SVM - Linear - DoGridSearch	Age, Height(cm), Weight(kg), Right-Leg, Left-Leg, Right-Arm, Left-Arm, Body Muscle(kg)	148.529
305	SVM - Linear - DoGridSearch	Age, Height(cm), Weight(kg), Left-Arm, Body Muscle(kg)	148.606
306	SVM - Linear - DoPatternSearch	Age, Height(cm), Weight(kg), Right-Leg, Left-Leg, Right-Arm, Left-Arm-Muscle(kg)	148.624

Table 4.53. *RMSE* values for females (Age, Height, Weight, Category-8)

No	Model Type	Pedictor Variables	RMSE
307	GRNN - Minimize error	Age, Height(cm), Weight(kg), Soft Muscle Tissue(kg)	136.919
308	GRNN - Minimize error	Age, Height(cm), Weight(kg), Soft Muscle Tissue(kg), Cell Mass(kg)	137.553
309	GRNN - Minimize error	Age, Height(cm), Weight(kg), Soft Muscle Tissue(kg), Extracellular Liquid(kg)	137.654
310	GRNN - Minimize error	Age, Height(cm), Weight(kg), Soft Muscle Tissue(kg), Skeletal Muscles(kg)	137.834
311	GRNN - Minimize error	Age, Height(cm), Weight(kg), Soft Muscle Tissue(kg), Intercellular Fluid(kg), Cell Mass(kg)	138.124
312	GRNN - Minimize error	Age, Height(cm), Weight(kg), Soft Muscle Tissue(kg), Intercellular Fluid(kg)	138.273

Table 4.54. *RMSE* values for females (Age, Height, Weight, Category-8)

No	Model Type	Pedictor Variables	RMSE
313	MLP - 4 Layers - Linear - Linear	Age, Height(cm), Weight(kg), Bone Minerals (kg), Cell Mass(kg)	148.876
314	MLP - 4 Layers - Linear - Linear	Age, Height(cm), Weight(kg), Bone Minerals (kg), Intercellular Fluid(kg)	148.883
315	MLP - 4 Layers - Linear - Logistic	Age, Height(cm), Weight(kg), Soft Muscle Tissue(kg), Bone Minerals (kg), Extracellular Liquid(kg), Intercellular Fluid(kg), Cell Mass(kg)	148.902
316	MLP - 4 Layers - Logistic - Linear	Age, Height(cm), Weight(kg), Bone Minerals (kg), Skeletal Muscles(kg), Extracellular Liquid(kg), Intercellular Fluid(kg), Cell Mass(kg)	148.908
317	MLP - 4 Layers - Logistic - Linear	Age, Height(cm), Weight(kg), Bone Minerals (kg), Extracellular Liquid(kg)	148.982
318	MLP - 4 Layers - Linear - Linear	Age, Height(cm), Weight(kg), Soft Muscle Tissue(kg), Bone Minerals (kg), Extracellular Liquid(kg), Intercellular Fluid(kg), Cell Mass(kg)	149.021

Table 4.55. *RMSE* values for females (Age, Height, Weight, Category-8)

No	Model Type	Pedictor Variables	RMSE
319	SVM - Linear - DoGridSearch	Age, Height(cm), Weight(kg), Bone Minerals Weight(kg)	149.058
320	SVM - RBF - DoGridSearch	Age, Height(cm), Weight(kg), Bone Minerals Weight(kg)	149.067
321	SVM - RBF - DoPatternSearch	Age, Height(cm), Weight(kg), Bone Minerals Weight(kg)	149.068
322	SVM - Linear - DoGridSearch	Age, Height(cm), Weight(kg), Soft Muscle Tissue(kg), Skeletal Muscles(kg)	149.079
323	SVM - Linear - DoPatternSearch	Age, Height(cm), Weight(kg), Soft Muscle Tissue(kg), Skeletal Muscles(kg)	149.079
324	SVM - Linear - DoPatternSearch	Age, Height(cm), Weight(kg), Bone Minerals Weight(kg)	149.085

Table 4.56. *RMSE* values for females (Age, Height, Weight, Category-9)

No	Model Type	Pedictor Variables	RMSE
325	GRNN - Minimize error	Age, Height(cm), Weight(kg), Hip, Lower Belly Circumference(cm)	137.465
326	GRNN - Minimize error	Age, Height(cm), Weight(kg), Hip Circumference(cm)	138.421
327	GRNN - Minimize error	Age, Height(cm), Weight(kg), Waist(cm), Hip Circumference(cm)	138.499
328	GRNN - Minimize error	Age, Height(cm), Weight(kg), Waist(cm), Hip , Lower Belly Circumference(cm)	139.429
329	GRNN - Minimum neurons	Age, Height(cm), Weight(kg), Waist(cm), Hip Circumference(cm)	142.598
330	GRNN -#10 of neurons	Age, Height(cm), Weight(kg), Waist(cm), Hip Circumference(cm)	142.803

Table 4.57. *RMSE* values for females (Age, Height, Weight, Category-9)

No	Model Type	Pedictor Variables	RMSE
331	MLP - 3 Layers - Linear - Logistic	Age, Height(cm), Weight(kg), Waist(cm), Hip, Lower Belly Circumference(cm)	146.849
332	MLP - 3 Layers - Logistic - Logistic	Age, Height(cm), Weight(kg), Hip Circumference(cm)	147.028
333	MLP - 4 Layers - Linear - Linear	Age, Height(cm), Weight(kg), Waist(cm), Hip Circumference(cm)	147.183
334	MLP - 4 Layers - Linear - Logistic	Age, Height(cm), Weight(kg), Hip Circumference(cm)	147.208
335	MLP - 3 Layers - Linear - Logistic	Age, Height(cm), Weight(kg), Waist(cm), Hip Circumference(cm)	147.336
336	MLP - 3 Layers - Logistic - Linear	Age, Height(cm), Weight(kg), Hip Circumference(cm)	147.458

Table 4.58. *RMSE* values for females (Age, Height, Weight, Category-9)

No	Model Type	Pedictor Variables	RMSE
337	SVM - RBF - DoGridSearch	Age, Height(cm), Weight(kg), Waist(cm), Hip , Lower Belly Circumference(cm)	145.663
338	SVM - RBF - DoPatternSearch	Age, Height(cm), Weight(kg), Waist(cm), Hip , Lower Belly Circumference(cm)	145.663
339	SVM - Linear - DoGridSearch	Age, Height(cm), Weight(kg), Waist(cm), Hip Circumference(cm)	145.748
340	SVM - Linear - DoPatternSearch	Age, Height(cm), Weight(kg), Waist(cm), Hip , Lower Belly Circumference(cm)	146.019
341	SVM - RBF - DoGridSearch	Age, Height(cm), Weight(kg), Hip , Lower Belly Circumference(cm)	146.054
342	SVM - Linear - DoGridSearch	Age, Height(cm), Weight(kg), Hip, Lower Belly Circumference(cm)	146.126

Table 4.59. *RMSE* values for females (Age, Height, Weight, Category-10)

No	Model Type	Pedictor Variables	RMSE
343	GRNN - Minimize error	Age, Height(cm), Weight(kg), Thyroid, Cigarette	140.858
344	GRNN - Minimize error	Age, Height(cm), Weight(kg), Thyroid, Insulin, Cigarette	141.847
345	GRNN - Minimize error	Age, Height(cm), Weight(kg), Thyroid, Insulin	143.577
346	GRNN - Minimize error	Age, Height(cm), Weight(kg), Thyroid	144.165
347	GRNN - Minimize error	Age, Height(cm), Weight(kg), Insulin, Cigarette	147.141
348	GRNN - Minimize error	Age, Height(cm), Weight(kg), Cigarette	147.248

Table 4.60. *RMSE* values for females (Age, Height, Weight, Category-10)

No	Model Type	Pedictor Variables	RMSE
349	MLP - 4 Layers - Logistic - Linear	Age, Height(cm), Weight(kg), Thyroid, Insulin	149.951
350	MLP - 4 Layers - Linear - Linear	Age, Height(cm), Weight(kg), Thyroid, Insulin, Cigarette	150.107
351	MLP - 4 Layers - Logistic - Logistic	Age, Height(cm), Weight(kg), Thyroid	150.261
352	MLP - 4 Layers - Logistic - Linear	Age, Height(cm), Weight(kg), Thyroid, Insulin, Cigarette	150.815
353	MLP - 3 Layers - Linear - Logistic	Age, Height(cm), Weight(kg), Thyroid	150.878
354	MLP - 4 Layers - Logistic - Logistic	Age, Height(cm), Weight(kg), Thyroid, Insulin, Cigarette	150.913

Table 4.61. *RMSE* values for females (Age, Height, Weight, Category-10)

No	Model Type	Pedictor Variables	RMSE
355	SVM - RBF - DoPatternSearch	Age, Height(cm), Weight(kg), Thyroid, Insulin, Cigarette	149.702
356	SVM - RBF - DoGridSearch	Age, Height(cm), Weight(kg), Thyroid, Insulin, Cigarette	149.747
357	SVM - RBF - DoGridSearch	Age, Height(cm), Weight(kg), Thyroid, Insulin	150.054
358	SVM - RBF - DoGridSearch	Age, Height(cm), Weight(kg), Thyroid, Cigarette	150.383
359	SVM - RBF - DoPatternSearch	Age, Height(cm), Weight(kg), Thyroid, Cigarette	150.383
360	SVM - RBF - DoGridSearch	Age, Height(cm), Weight(kg), Thyroid	150.411

Table 4.62. *RMSE* values for males (Age, BMI, Category-1)

No	Model Type	Pedictor Variables	RMSE
361	GRNN - Minimize error	Age, BMI, Muscle(kg), Bone Weight(kg), Fat(kg)	170.167
362	GRNN - Minimize error	Age, BMI, Liquid(kg), Bone Weight(kg), Fat(kg)	170.628
363	GRNN - Minimize error	Age, BMI, Liquid(kg), Non-Fat(kg), Bone Weight(kg), Fat(kg)	171.833
364	GRNN - Minimize error	Age, BMI, Liquid(kg), Muscle(kg), Bone Weight(kg)	172.094
365	GRNN - Minimize error	Age, BMI, Liquid(kg), Non-Fat(kg), Muscle(kg), Bone Weight(kg)	172.539
366	GRNN - Minimize error	Age, BMI, Bone Weight(kg)	172.544

Table 4.63. *RMSE* values for males (Age, BMI, Category-1)

No	Model Type	Pedictor Variables	RMSE
367	MLP - 3 Layers - Logistic - Linear	Age, BMI, Fat(%), Bone Weight(kg)	186.948
368	MLP - 3 Layers - Logistic - Logistic	Age, BMI, Muscle(kg)	187.366
369	MLP - 3 Layers - Linear - Linear	Age, BMI, Muscle(kg), Fat(kg)	188.515
370	MLP - 3 Layers - Linear - Linear	Age, BMI, Fat(%), Non-Fat(kg), Bone Weight(kg)	188.607
371	MLP - 4 Layers - Logistic - Linear	Age, BMI, Liquid(kg), Non-Fat(kg), Bone Weight(kg), Fat(kg)	188.676
372	MLP - 4 Layers - Linear - Linear	Age, BMI, Fat(%), Non-Fat(kg), Bone Weight(kg)	188.866

Table 4.64. *RMSE* values for males (Age, BMI, Category-1)

No	Model Type	Pedictor Variables	RMSE
373	SVM - Linear - DoGridSearch	Age, BMI, Fat(%), Bone Weight(kg)	188.438
374	SVM - Linear - DoPatternSearch	Age, BMI, Fat(%), Bone Weight(kg)	188.438
375	SVM - RBF - DoPatternSearch	Age, BMI, Bone Weight(kg)	188.806
376	SVM - RBF - DoGridSearch	Age, BMI, Bone Weight(kg)	188.878
377	SVM - RBF - DoPatternSearch	Age, BMI, Liquid(kg), Fat(kg)	189.302
378	SVM - RBF - DoGridSearch	Age, BMI, Liquid(kg), Fat(kg)	189.412

Table 4.65. *RMSE* values for males (Age, BMI, Category-2)

No	Model Type	Pedictor Variables	RMSE
379	GRNN - Minimize error	Age, BMI, Mineral Quantity(kg)	180.473
380	GRNN - Minimize error	Age, BMI, Mineral Quantity(kg), Internal Lubrication	181.608
381	GRNN - Minimize error	Age, BMI, Mineral Quantity(kg), Internal Lubrication, Body Density	181.756
382	GRNN - Minimize error	Age, BMI, Mineral Quantity(kg), Body Density	181.781
383	GRNN - Minimize error	Age, BMI, Internal Lubrication	182.437
384	GRNN - Minimize error	Age, BMI, Body Density	183.006

Table 4.66. *RMSE* values for males (Age, BMI, Category-2)

No	Model Type	Pedictor Variables	RMSE
385	MLP - 3 Layers - Logistic - Linear	Age, BMI, Mineral Quantity(kg), Protein Amount(kg)	187.747
386	MLP - 3 Layers - Logistic - Linear	Age, BMI, Mineral Quantity(kg), Protein Amount(kg), Internal Lubrication, Body Density	187.953
387	MLP - 4 Layers - Linear - Logistic	Age, BMI, Mineral Quantity(kg), Internal Lubrication, Body Density	187.991
388	MLP - 3 Layers - Linear - Linear	Age, BMI, Mineral Quantity(kg), Protein Amount(kg), Internal Lubrication, Body Density	189.522
389	MLP - 3 Layers - Linear - Logistic	Age, BMI, Mineral Quantity(kg)	189.618
390	MLP - 3 Layers - Logistic - Linear	Age, BMI, Mineral Quantity(kg), Protein Amount(kg), Internal Lubrication	189.646

Table 4.67 *RMSE* values for males (Age, BMI,, Category-2)

No	Model Type	Pedictor Variables	RMSE
391	SVM - Linear - DoGridSearch	Age, BMI, Mineral Quantity(kg), Protein Amount(kg), Body Density	187.406
392	SVM - Linear - DoPatternSearch	Age, BMI, Mineral Quantity(kg), Protein Amount(kg), Body Density	187.423
393	SVM - RBF - DoPatternSearch	Age, BMI, Mineral Quantity(kg), Protein Amount(kg), Internal Lubrication, Body Density	187.913
394	SVM - RBF - DoGridSearch	Age, BMI, Mineral Quantity(kg), Protein Amount(kg), Internal Lubrication, Body Density	187.933
395	SVM - RBF - DoPatternSearch	Age, BMI, Protein Amount(kg)	188.027
396	SVM - RBF - DoGridSearch	Age, BMI, Protein Amount(kg)	188.053

Table 4.68. *RMSE* values for males (Age, BMI, Category-3)

No	Model Type	Pedictor Variables	RMSE
397	GRNN - Minimize error	Age, BMI, Right-Leg-Impedance, Left-Leg-Impedance, Left-Arm-Impedance, Body-Impedance	167.703
398	GRNN - Minimize error	Age, BMI, Right-Leg-Impedance, Right-Arm-Impedance, Left-Arm-Impedance, Body-Impedance	167.812
399	GRNN - Minimize error	Age, BMI, Right-Leg-Impedance, Left-Leg-Impedance, Right-Arm-Impedance, Left-Arm-Impedance, Body-Impedance	169.193
400	GRNN - Minimize error	Age, BMI, Left-Leg-Impedance, Right-Arm-Impedance, Body-Impedance	176.583
401	GRNN - Minimize error	Age, BMI, Right-Arm-Impedance, Left-Arm-Impedance	179.019
402	GRNN - Minimize error	Age, BMI, Right-Leg-Impedance, Right-Arm-Impedance, Body-Impedance	179.075

Table 4.69. *RMSE* values for males (Age, Height, Weight, Category-3)

No	Model Type	Pedictor Variables	RMSE
403	MLP - 3 Layers - Logistic - Linear	Age, BMI, Body-Impedance	190.937
404	MLP - 3 Layers - Linear - Linear	Age, BMI, Right-Arm-Impedance, Body-Impedance	192.823
405	MLP - 4 Layers - Linear - Linear	Age, BMI, Right-Arm-Impedance, Left-Arm-Impedance, Body-Impedance	193.649
406	MLP - 3 Layers - Logistic - Linear	Age, BMI, Left-Leg-Impedance	194.265
407	MLP - 3 Layers - Linear - Linear	Age, BMI, Left-Leg-Impedance, Right-Arm-Impedance, Left-Arm-Impedance, Body-Impedance	194.499
408	MLP - 3 Layers - Linear - Linear	Age, BMI, Right-Leg-Impedance, Left-Leg-Impedance, Right-Arm-Impedance	194.602

Table 4.70. *RMSE* values for males (Age, BMI, Category-3)

No	Model Type	Pedictor Variables	RMSE
409	SVM - RBF - DoGridSearch	Age, BMI, Right-Leg-Impedance, Left-Leg-Impedance, Right-Arm-Impedance, Body-Impedance	190.202
410	SVM - Linear - DoGridSearch	Age, BMI, Right-Leg-Impedance, Left-Leg-Impedance, Right-Arm-Impedance, Body-Impedance	190.314
411	SVM - RBF - DoGridSearch	Age, BMI, Right-Arm-Impedance, Body-Impedance	190.425
412	SVM - Linear - DoPatternSearch	Age, BMI, Right-Leg-Impedance, Left-Leg-Impedance, Right-Arm-Impedance, Body-Impedance	190.501
413	SVM - RBF - DoPatternSearch	Age, BMI, Right-Arm-Impedance, Body-Impedance	190.517
414	SVM - RBF - DoPatternSearch	Age, BMI, Right-Leg-Impedance, Right-Arm-Impedance, Body-Impedance	190.943

Table 4.71. *RMSE* values for males (Age, BMI, Category-4)

No	Model Type	Pedictor Variables	RMSE
415	GRNN - Minimize error	Age, BMI, Left-Arm-Fat Percentage, Body-Fat Percentage	177.851
416	GRNN - Minimize error	Age, BMI, Right-Leg-Fat Percentage, Right-Arm-Fat Percentage, Left-Arm-Fat Percentage, Body-Fat Percentage	178.211
417	GRNN - Minimize error	Age, BMI, Left-Leg-Fat Percentage, Right-Arm-Fat Percentage, Left-Arm-Fat Percentage, Body-Fat Percentage	180.582
418	GRNN - Minimize error	Age, BMI, Right-Leg-Fat Percentage, Left-Leg-Fat Percentage, Left-Arm-Fat Percentage	180.649
419	GRNN - Minimize error	Age, BMI, Right-Leg-Fat Percentage, Left-Leg-Fat Percentage, Right-Arm-Fat Percentage, Body-Fat Percentage	180.791
420	GRNN - Minimize error	Age, BMI, Left-Leg-Fat Percentage	180.894

Table 4.72. *RMSE* values for males (Age, BMI, Category-4)

No	Model Type	Pedictor Variables	RMSE
421	MLP - 3 Layers - Linear - Linear	Age, BMI, Left-Leg-Fat Percentage, Right-Arm-Fat Percentage, Body-Fat Percentage	192.196
422	MLP - 3 Layers - Logistic - Linear	Age, BMI, Right-Leg-Fat Percentage, Left-Leg-Fat Percentage, Right-Arm-Fat Percentage, Body-Fat Percentage	192.765
423	MLP - 4 Layers - Linear - Linear	Age, BMI, Right-Arm-Fat Percentage	193.414
424	MLP - 4 Layers - Linear - Linear	Age, BMI, Body-Fat Percentage	193.451
425	MLP - 3 Layers - Linear - Linear	Age, BMI, Right-Arm-Fat Percentage, Body-Fat Percentage	193.674
426	MLP - 3 Layers - Logistic - Linear	Age, BMI, Left-Arm-Fat Percentage, Body-Fat Percentage	193.708

Table 4.73. *RMSE* values for males (Age, BMI, Category-4)

No	Model Type	Pedictor Variables	RMSE
427	SVM - RBF - DoGridSearch	Age, BMI, Left-Leg-Fat Percentage	192.452
428	SVM - RBF - DoPatternSearch	Age, BMI, Left-Leg-Fat Percentage	192.452
429	SVM - RBF - DoPatternSearch	Age, BMI, Body-Fat Percentage	192.506
430	SVM - RBF - DoGridSearch	Age, BMI, Body-Fat Percentage	192.528
431	SVM - RBF - DoPatternSearch	Age, BMI, Right-Arm-Fat Percentage, Body-Fat Percentage	193.017
432	SVM - RBF - DoGridSearch	Age, BMI, Right-Arm-Fat Percentage, Body-Fat Percentage	193.198

Table 4.74. *RMSE* values for males (Age, BMI, Category-5)

No	Model Type	Pedictor Variables	RMSE
433	GRNN - Minimize error	Age, BMI, Left-Leg-Fat (kg)	179.596
434	GRNN - Minimize error	Age, BMI, Right-Leg-Fat (kg), Left-Leg-Fat (kg), Left-Arm-Fat (kg), Body-Fat (kg)	181.184
435	GRNN - Minimize error	Age, BMI, Left-Leg-Fat (kg), Right-Arm-Fat (kg), Body-Fat (kg)	181.341
436	GRNN - Minimize error	Age, BMI, Right-Leg-Fat (kg), Left-Leg-Fat (kg), Right-Arm-Fat (kg), Body-Fat (kg)	181.374
437	GRNN - Minimize error	Age, BMI, Right-Arm-Fat (kg), Left-Arm-Fat (kg), Body-Fat (kg)	181.382
438	GRNN - Minimize error	Age, BMI, Right-Leg-Fat (kg), Left-Leg-Fat (kg), Right-Arm-Fat (kg), Left-Arm-Fat (kg), Body-Fat (kg)	181.392

Table 4.75. *RMSE* values for males (Age, Height, Weight, Category-5)

No	Model Type	Pedictor Variables	RMSE
439	MLP - 4 Layers - Linear - Linear	Age, BMI, Left-Leg-Fat (kg)	187.564
440	MLP - 4 Layers - Linear - Linear	Age, BMI, Left-Leg-Fat (kg), Body-Fat (kg)	189.122
441	MLP - 3 Layers - Linear - Linear	Age, BMI, Left-Leg-Fat (kg), Right-Arm-Fat (kg), Body-Fat (kg)	189.297
442	MLP - 3 Layers - Logistic - Linear	Age, BMI, Right-Leg-Fat (kg), Left-Leg-Fat (kg), Right-Arm-Fat (kg), Body-Fat (kg)	190.391
443	MLP - 3 Layers - Logistic - Logistic	Age, BMI, Right-Arm-Fat (kg), Body-Fat (kg)	190.508
444	MLP - 4 Layers - Linear - Linear	Age, BMI, Right-Leg-Fat (kg), Left-Leg-Fat (kg), Right-Arm-Fat (kg), Body-Fat (kg)	191.115

Table 4.76. *RMSE* values for males (Age, BMI, Category-5)

No	Model Type	Pedictor Variables	RMSE
445	SVM - Linear - DoPatternSearch	Age, BMI, Left-Leg-Fat (kg), Right-Arm-Fat (kg), Body-Fat (kg)	188.463
446	SVM - Linear - DoGridSearch	Age, BMI, Left-Leg-Fat (kg), Right-Arm-Fat (kg), Body-Fat (kg)	188.742
447	SVM - Linear - DoGridSearch	Age, BMI, Left-Leg-Fat (kg), Right-Arm-Fat (kg), Left-Arm-Fat (kg), Body-Fat (kg)	189.109
448	SVM - Linear - DoPatternSearch	Age, BMI, Left-Leg-Fat (kg), Right-Arm-Fat (kg), Left-Arm-Fat (kg), Body-Fat (kg)	189.109
449	SVM - Linear - DoGridSearch	Age, BMI, Right-Leg-Fat (kg), Left-Leg-Fat (kg), Right-Arm-Fat (kg), Body-Fat (kg)	189.115
450	SVM - Linear - DoPatternSearch	Age, BMI, Right-Leg-Fat (kg), Left-Leg-Fat (kg), Right-Arm-Fat (kg), Body-Fat (kg)	189.115

Table 4.77. *RMSE* values for males (Age, BMI, Category-6)

No	Model Type	Pedictor Variables	RMSE
451	GRNN - Minimize error	Age, BMI, Right-Arm-Non-Fat(kg), Body-Non-Fat(kg)	164.017
452	GRNN - Minimize error	Age, BMI, Right-Leg-Non-Fat(kg), Left-Leg-Non-Fat(kg)	165.195
453	GRNN - Minimize error	Age, BMI, Right-Leg-Non-Fat(kg), Left-Leg-Non-Fat(kg), Body-Non-Fat(kg)	165.541
454	GRNN - Minimize error	Age, BMI, Right-Leg-Non-Fat(kg), Left-Leg-Non-Fat(kg), Left-Leg-Non-Fat(kg), Body-Non-Fat(kg)	165.827
455	GRNN - Minimize error	Age, BMI, Right-Leg-Non-Fat(kg), Left-Leg-Non-Fat(kg), Body-Non-Fat(kg)	165.943
456	GRNN - Minimize error	Age, BMI, Right-Leg-Non-Fat(kg), Body-Non-Fat(kg)	166.328

Table 4.78. *RMSE* values for males (Age, BMI, Category-6)

No	Model Type	Pedictor Variables	RMSE
457	MLP - 4 Layers - Linear - Logistic	Age, BMI, Right-Arm-Non-Fat(kg), Left-Leg-Non-Fat(kg), Body-Non-Fat(kg)	181.115
458	MLP - 4 Layers - Linear - Linear	Age, BMI, Right-Leg-Non-Fat(kg), Left-Leg-Non-Fat(kg), Right-Arm-Non-Fat(kg), Left-Leg-Non-Fat(kg), Body-Non-Fat(kg)	182.827
459	MLP - 3 Layers - Linear - Logistic	Age, BMI, Right-Arm-Non-Fat(kg), Left-Leg-Non-Fat(kg)	183.397
460	MLP - 3 Layers - Logistic - Linear	Age, BMI, Right-Leg-Non-Fat(kg), Right-Arm-Non-Fat(kg), Left-Leg-Non-Fat(kg), Body-Non-Fat(kg)	183.953
461	MLP - 3 Layers - Linear - Logistic	Age, BMI, Right-Leg-Non-Fat(kg), Left-Leg-Non-Fat(kg), Right-Arm-Non-Fat(kg), Left-Leg-Non-Fat(kg)	183.954
462	MLP - 3 Layers - Linear - Logistic	Age, BMI, Right-Leg-Non-Fat(kg), Right-Arm-Non-Fat(kg), Left-Leg-Non-Fat(kg)	184.174

Table 4.79. *RMSE* values for males (Age, BMI, Category-6)

No	Model Type	Pedictor Variables	RMSE
463	SVM - Linear - DoPatternSearch	Age, BMI, Right-Leg-Non-Fat(kg), Right-Arm-Non-Fat(kg), Left-Leg-Non-Fat(kg), Body-Non-Fat(kg)	182.883
464	SVM - Linear - DoGridSearch	Age, BMI, Right-Leg-Non-Fat(kg), Right-Arm-Non-Fat(kg), Left-Leg-Non-Fat(kg), Body-Non-Fat(kg)	183.051
465	SVM - Linear - DoPatternSearch	Age, BMI, Right-Arm-Non-Fat(kg), Body-Non-Fat(kg)	183.792
466	SVM - Linear - DoPatternSearch	Age, BMI, Right-Leg-Non-Fat(kg), Right-Arm-Non-Fat(kg), Body-Non-Fat(kg)	183.918
467	SVM - Linear - DoGridSearch	Age, BMI, Right-Leg-Non-Fat(kg), Right-Arm-Non-Fat(kg), Body-Non-Fat(kg)	183.999
468	SVM - Linear - DoPatternSearch	Age, BMI, Right-Arm-Non-Fat(kg), Left-Leg-Non-Fat(kg), Body-Non-Fat(kg)	184.147

Table 4.80. *RMSE* values for males (Age, BMI, Category-7)

No	Model Type	Pedictor Variables	RMSE
469	GRNN - Minimize error	Age, BMI, Left-Leg-Muscle(kg), Right-Arm-Muscle(kg), Left-Arm-Muscle(kg)	164.886
470	GRNN - Minimize error	Age, BMI, Left-Leg-Muscle(kg), Right-Arm-Muscle(kg)	165.165
471	GRNN - Minimize error	Age, BMI, Body-Muscle(kg)	165.193
472	GRNN - Minimize error	Age, BMI, Right-Arm-Muscle(kg), Body-Muscle(kg)	165.923
473	GRNN - Minimize error	Age, BMI, Left-Arm-Muscle(kg), Body-Muscle(kg)	165.979
474	GRNN - Minimize error	Age, BMI, Right-Arm-Muscle(kg), Left-Arm-Muscle(kg), Body-Muscle(kg)	166.331

Table 4.81. *RMSE* values for males (Age, BMI, Category-7)

No	Model Type	Pedictor Variables	RMSE
475	MLP - 4 Layers - Logistic - Logistic	Age, BMI, Left-Leg-Muscle(kg), Left-Arm-Muscle(kg)	196
476	MLP - 4 Layers - Linear - Linear	Age, BMI, Right-Arm-Muscle(kg), Left-Arm-Muscle(kg), Body-Muscle(kg)	182.258
477	MLP - 3 Layers - Linear - Logistic	Age, BMI, Right-Leg-Muscle(kg), Right-Arm-Muscle(kg), Body-Muscle(kg)	182.576
478	MLP - 3 Layers - Linear - Logistic	Age, BMI, Right-Arm-Muscle(kg), Left-Arm-Muscle(kg)	183.925
479	MLP - 3 Layers - Linear - Logistic	Age, BMI, Right-Leg-Muscle(kg), Left-Leg-Muscle(kg), Right-Arm-Muscle(kg)	184.029
480	MLP - 3 Layers - Linear - Logistic	Age, BMI, Right-Leg-Muscle(kg), Right-Arm-Muscle(kg), Left-Arm-Muscle(kg), Body-Muscle(kg)	184.257

Table 4.82. *RMSE* values for males (Age, BMI, Category-7)

No	Model Type	Pedictor Variables	RMSE
481	SVM - Linear - DoGridSearch	Age, BMI, Right-Leg-Muscle(kg), Left-Leg-Muscle(kg), Right-Arm-Muscle(kg)	183.051
482	SVM - Linear - DoPatternSearch	Age, BMI, Right-Leg-Muscle(kg), Left-Leg-Muscle(kg)	183.633
483	SVM - Linear - DoGridSearch	Age, BMI, Right-Leg-Muscle(kg), Left-Leg-Muscle(kg)	183.826
484	SVM - Linear - DoPatternSearch	Age, BMI, Right-Leg-Muscle(kg), Left-Leg-Muscle(kg), Right-Arm-Muscle(kg), Body-Muscle(kg)	183.862
485	SVM - Linear - DoGridSearch	Age, BMI, Right-Leg-Muscle(kg), Left-Leg-Muscle(kg), Right-Arm-Muscle(kg), Body-Muscle(kg)	183.873
486	SVM - RBF - DoGridSearch	Age, BMI, Right-Leg-Muscle(kg), Left-Leg-Muscle(kg), Right-Arm-Muscle(kg)	184.452

Table 4.83. *RMSE* values for males (Age, BMI, Category-8)

No	Model Type	Pedictor Variables	RMSE
487	GRNN - Minimize error	Age, BMI, Skeletal Muscles(kg), Cell Mass(kg)	163.639
488	GRNN - Minimize error	Age, BMI, Soft Muscle Tissue(kg), Skeletal Muscles(kg), Extracellular Liquid(kg), Intercellular Fluid(kg)	165.116
489	GRNN - Minimize error	Age, BMI, Bone Minerals Weight(kg), Extracellular Liquid(kg)	165.311
490	GRNN - Minimize error	Age, BMI, Extracellular Liquid(kg), Intercellular Fluid(kg), Cell Mass(kg)	165.521
491	GRNN - Minimize error	Age, BMI, Extracellular Liquid(kg), Cell Mass(kg)	165.581
492	GRNN - Minimize error	Age, BMI, Soft Muscle Tissue(kg), Intercellular Fluid(kg)	165.642

Table 4.84. *RMSE* values for males (Age, BMI, Category-8)

No	Model Type	Pedictor Variables	RMSE
493	MLP - 3 Layers - Linear - Logistic	Age, BMI, Soft Muscle Tissue, Bone Minerals Weight, Intercellular Fluid, Cell Mass(kg)	182.191
494	MLP - 3 Layers - Linear - Linear	Age, BMI, Soft Muscle Tissue, Bone Minerals Weight, Skeletal Muscles, Intercellular Fluid, Cell Mass(kg)	182.863
495	MLP - 3 Layers - Linear - Logistic	Age, BMI, Soft Muscle Tissue, Bone Minerals Weight, Skeletal Muscles, Cell Mass(kg)	182.883
496	MLP - 3 Layers - Linear - Logistic	Age, BMI, Soft Muscle Tissue, Bone Minerals Weight, Cell Mass (kg)	182.985
497	MLP - 3 Layers - Linear - Logistic	Age, BMI, Soft Muscle Tissue, Skeletal Muscles, Intercellular Fluid (kg)	183.135
498	MLP - 3 Layers - Linear - Linear	Age, BMI, Bone Minerals Weight, Skeletal Muscles, Extracellular Liquid, Intercellular Fluid, Cell Mass (kg)	183.174

Table 4.85. *RMSE* values for males (Age, BMI, Category-8)

No	Model Type	Pedictor Variables	RMSE
499	SVM - RBF - DoPatternSearch	Age, BMI, Soft Muscle Tissue(kg), Extracellular Liquid(kg)	183.251
500	SVM - RBF - DoGridSearch	Age, BMI, Soft Muscle Tissue(kg), Extracellular Liquid(kg)	183.323
501	SVM - RBF - DoGridSearch	Age, BMI, Soft Muscle Tissue(kg), Bone Minerals Weight(kg), Skeletal Muscles(kg), Cell Mass(kg)	183.503
502	SVM - RBF - DoPatternSearch	Age, BMI, Soft Muscle Tissue(kg), Bone Minerals Weight(kg), Skeletal Muscles(kg), Cell Mass(kg)	183.503
503	SVM - Linear - DoGridSearch	Age, BMI, Bone Minerals Weight(kg), Extracellular Liquid(kg), Intercellular Fluid(kg), Cell Mass(kg)	183.524
504	SVM - Linear - DoPatternSearch	Age, BMI, Bone Minerals Weight(kg), Extracellular Liquid(kg), Intercellular Fluid(kg), Cell Mass(kg)	183.561

Table 4.86. *RMSE* values for males (Age, BMI, Category-9)

No	Model Type	Pedictor Variables	RMSE
505	GRNN -#10 of neurons	Age, BMI, Waist Circumference(cm)	175.218
506	GRNN - Minimize error	Age, BMI, Waist Circumference(cm), Lower Belly Circumference(cm)	175.509
507	GRNN - Minimize error	Age, BMI, Waist Circumference(cm)	175.541
508	GRNN - Minimize error	Age, BMI, Lower Belly Circumference(cm)	175.756
509	GRNN -#10 of neurons	Age, BMI, Waist Circumference(cm), Lower Belly Circumference(cm)	182.706
510	GRNN - Minimum neurons	Age, BMI, Waist Circumference(cm), Lower Belly Circumference(cm)	183.854

Table 4.87. *RMSE* values for males (Age, BMI, Category-9)

No	Model Type	Pedictor Variables	RMSE
511	MLP - 3 Layers - Logistic - Linear	Age, BMI, Waist Circumference(cm)	185.077
512	MLP - 3 Layers - Linear - Linear	Age, BMI, Waist Circumference(cm)	185.698
513	MLP - 3 Layers - Logistic - Logistic	Age, BMI, Waist Circumference(cm)	188.391
514	MLP - 3 Layers - Logistic - Linear	Age, BMI, Waist Circumference(cm), Lower Belly Circumference(cm)	189.559
515	MLP - 4 Layers - Linear - Linear	Age, BMI, Waist Circumference(cm), Lower Belly Circumference(cm)	191.476
516	MLP - 3 Layers - Linear - Logistic	Age, BMI, Waist Circumference(cm), Lower Belly Circumference(cm)	192.545

Table 4.88. *RMSE* values for males (Age, BMI, Category-9)

No	Model Type	Pedictor Variables	RMSE
517	SVM - RBF - DoGridSearch	Age, BMI, Waist Circumference(cm)	187.496
518	SVM - RBF - DoPatternSearch	Age, BMI, Waist Circumference(cm)	187.497
519	SVM - Linear - DoPatternSearch	Age, BMI, Waist Circumference(cm)	188.523
520	SVM - Linear - DoGridSearch	Age, BMI, Waist Circumference(cm)	188.549
521	SVM - RBF - DoGridSearch	Age, BMI, Waist Circumference(cm), Lower Belly Circumference(cm)	191.535
522	SVM - RBF - DoPatternSearch	Age, BMI, Waist Circumference(cm), Lower Belly Circumference(cm)	191.535

Table 4.89. *RMSE* values for males (Age, BMI, Category-10)

No	Model Type	Pedictor Variables	RMSE
523	GRNN - Minimize error	Age, BMI, Insulin, Cigarette	176.406
524	GRNN - Minimize error	Age, BMI, Thyroid, Insulin, Cigarette	177.572
525	GRNN - Minimize error	Age, BMI, Thyroid, Insulin	177.806
526	GRNN - Minimize error	Age, BMI, Insulin	179.134
527	GRNN - Minimize error	Age, BMI, Thyroid	180.95
528	GRNN - Minimize error	Age, BMI, Thyroid, Cigarette	181.872

Table 4.90. *RMSE* values for males (Age, BMI, Category-10)

No	Model Type	Pedictor Variables	RMSE
529	MLP - 3 Layers - Linear - Logistic	Age, BMI, Insulin, Cigarette	191.721
530	MLP - 3 Layers - Linear - Logistic	Age, BMI, Cigarette	192.696
531	MLP - 4 Layers - Linear - Linear	Age, BMI, Thyroid, Cigarette	192.696
532	MLP - 3 Layers - Linear - Linear	Age, BMI, Thyroid, Insulin, Cigarette	193.282
533	MLP - 4 Layers - Linear - Linear	Age, BMI, Cigarette	193.285
534	MLP - 3 Layers - Logistic - Linear	Age, BMI, Cigarette	193.659

Table 4.91. *RMSE* values for males (Age, BMI, Category-10)

No	Model Type	Pedictor Variables	RMSE
535	SVM - Linear - DoGridSearch	Age, BMI, Insulin, Cigarette	180.95
536	SVM - RBF - DoPatternSearch	Age, BMI, Cigarette	182.84
537	SVM - RBF - DoGridSearch	Age, BMI, Cigarette	188.65
538	SVM - Linear - DoGridSearch	Age, BMI, Thyroid	194.98
539	SVM - Linear - DoPatternSearch	Age, BMI, Thyroid	196.46
540	SVM - RBF - DoGridSearch	Age, BMI, Thyroid, Cigarette	199.87

Table 4.92. *RMSE* values for males (Age, Height, Weight, Category-1)

No	Model Type	Pedictor Variables	RMSE
541	GRNN - Minimize error	Age, Height(cm), Weight(kg), Muscle(kg), Bone Weight(kg), Fat(kg)	157.006
542	GRNN - Minimize error	Age, Height(cm), Weight(kg), Non-Fat(kg), Muscle(kg), Bone Weight(kg), Fat(kg)	157.747
543	GRNN - Minimize error	Age, Height(cm), Weight(kg), Fat(%), Non-Fat(kg), Muscle(kg), Bone Weight(kg)	157.915
544	GRNN - Minimize error	Age, Height(cm), Weight(kg), Fat(%), Liquid(kg), Bone Weight(kg)	158.152
545	GRNN - Minimize error	Age, Height(cm), Weight(kg), Liquid(kg), Non-Fat(kg)	158.709
546	GRNN - Minimize error	Age, Height(cm), Weight(kg), Fat(%), Non-Fat(kg), Bone Weight(kg)	159.501

Table 4.93. *RMSE* values for males (Age, Height, Weight, Category-1)

No	Model Type	Pedictor Variables	RMSE
547	MLP - 4 Layers - Linear - Linear	Age, Height(cm), Weight(kg), Bone Weight(kg)	184.152
548	MLP - 4 Layers - Linear - Linear	Age, Height(cm), Weight(kg), Muscle(kg)	187.076
549	MLP - 4 Layers - Logistic - Linear	Age, Height(cm), Weight(kg), Non-Fat(kg), Muscle(kg), Bone Weight(kg), Fat(kg)	187.696
550	MLP - 4 Layers - Linear - Logistic	Age, Height(cm), Weight(kg), Bone Weight(kg), Fat(kg)	188.771
551	MLP - 4 Layers - Linear - Linear	Age, Height(cm), Weight(kg), Fat(%), Non-Fat(kg)	188.896
552	MLP - 3 Layers - Linear - Logistic	Age, Height(cm), Weight(kg), Non-Fat(kg)	189.003

Table 4.94. *RMSE* values for males (Age, Height, Weight, Category-1)

No	Model Type	Pedictor Variables	RMSE
553	SVM - RBF - DoGridSearch	Age, Height(cm), Weight(kg), Fat(%)	185.158
554	SVM - RBF - DoPatternSearch	Age, Height(cm), Weight(kg), Fat(%)	185.231
555	SVM - RBF - DoPatternSearch	Age, Height(cm), Weight(kg), Fat(%), Liquid(kg), Bone Weight(kg)	185.873
556	SVM - RBF - DoGridSearch	Age, Height(cm), Weight(kg), Fat(%), Liquid(kg), Bone Weight(kg)	185.885
557	SVM - RBF - DoGridSearch	Age, Height(cm), Weight(kg), Fat(%), Liquid(kg)	186.189
558	SVM - RBF - DoPatternSearch	Age, Height(cm), Weight(kg), Fat(%), Liquid(kg)	186.189

Table 4.95. *RMSE* values for males (Age, Height, Weight, Category-2)

No	Model Type	Pedictor Variables	RMSE
559	GRNN - Minimize error	Age, Height(cm), Weight(kg), Mineral Quantity(kg)	158.814
560	GRNN - Minimize error	Age, Height(cm), Weight(kg), Mineral Quantity(kg), Internal Lubrication	161.595
561	GRNN - Minimize error	Age, Height(cm), Weight(kg), Mineral Quantity(kg), Body Density	162.378
562	GRNN - Minimize error	Age, Height(cm), Weight(kg), Mineral Quantity(kg), Internal Lubrication, Body Density	164.546
563	GRNN - Minimize error	Age, Height(cm), Weight(kg), Internal Lubrication	167.809
564	GRNN -#10 of neurons	Age, Height(cm), Weight(kg), Mineral Quantity(kg), Body Density	168.044

Table 4.96. *RMSE* values for males (Age, Height, Weight, Category-2)

No	Model Type	Pedictor Variables	RMSE
565	MLP - 3 Layers - Logistic - Linear	Age, Height(cm), Weight(kg), Protein Amount(kg), Body Density	186.256
566	MLP - 4 Layers - Logistic - Logistic	Age, Height(cm), Weight(kg), Mineral Quantity(kg), Protein Amount(kg), Body Density	186.512
567	MLP - 3 Layers - Logistic - Linear	Age, Height(cm), Weight(kg), Protein Amount(kg)	186.766
568	MLP - 3 Layers - Logistic - Logistic	Age, Height(cm), Weight(kg), Protein Amount(kg)	186.925
569	MLP - 3 Layers - Linear - Linear	Age, Height(cm), Weight(kg), Protein Amount(kg)	187.269
570	MLP - 4 Layers - Linear - Linear	Age, Height(cm), Weight(kg), Mineral Quantity(kg), Body Density	187.538

Table 4.97. *RMSE* values for males (Age, Height, Weight, Category-2)

No	Model Type	Pedictor Variables	RMSE
571	SVM - RBF - DoGridSearch	Age, Height(cm), Weight(kg), Body Density	184.569
572	SVM - RBF - DoPatternSearch	Age, Height(cm), Weight(kg), Body Density	184.569
573	SVM - RBF - DoGridSearch	Age, Height(cm), Weight(kg), Protein Amount(kg), Body Density	185.654
574	SVM - RBF - DoPatternSearch	Age, Height(cm), Weight(kg), Protein Amount(kg), Body Density	185.674
575	SVM - RBF - DoPatternSearch	Age, Height(cm), Weight(kg), Internal Lubrication, Body Density	185.914
576	SVM - RBF - DoGridSearch	Age, Height(cm), Weight(kg), Internal Lubrication, Body Density	185.952

Table 4.98. *RMSE* values for males (Age, Height, Weight, Category-3)

No	Model Type	Pedictor Variables	RMSE
577	GRNN - Minimize error	Age, Height(cm), Weight(kg), Left-Leg-Impedance, Right-Arm-Impedance, Left-Arm-Impedance, Body-Impedance	143.109
578	GRNN - Minimize error	Age, Height(cm), Weight(kg), Right-Leg-Impedance, Left-Leg-Impedance, Right-Arm-Impedance, Left-Arm-Impedance, Body-Impedance	143.339
579	GRNN - Minimize error	Age, Height(cm), Weight(kg), Right-Leg-Impedance, Left-Arm-Impedance, Body-Impedance	143.561
580	GRNN - Minimize error	Age, Height(cm), Weight(kg), Right-Leg-Impedance, Left-Arm-Impedance	143.706
581	GRNN - Minimize error	Age, Height(cm), Weight(kg), Right-Leg-Impedance, Left-Leg-Impedance, Left-Arm-Impedance	143.879
582	GRNN - Minimize error	Age, Height(cm), Weight(kg), Right-Leg-Impedance, Left-Leg-Impedance, Right-Arm-Impedance, Left-Arm-Impedance	144.815

Table 4.99. *RMSE* values for males (Age, Height, Weight, Category-3)

No	Model Type	Pedictor Variables	RMSE
583	MLP - 3 Layers - Logistic - Linear	Age, Height(cm), Weight(kg), Body-Impedance	186.838
584	MLP - 3 Layers - Logistic - Linear	Age, Height(cm), Weight(kg), Right-Arm-Impedance	186.908
585	MLP - 3 Layers - Logistic - Linear	Age, Height(cm), Weight(kg), Right-Leg-Impedance, Left-Leg-Impedance, Right-Arm-Impedance	187.437
586	MLP - 4 Layers - Linear - Linear	Age, Height(cm), Weight(kg), Right-Arm-Impedance, Left-Arm-Impedance, Body-Impedance	187.458
587	MLP - 3 Layers - Logistic - Linear	Age, Height(cm), Weight(kg), Right-Arm-Impedance, Left-Arm-Impedance	187.794
588	MLP - 3 Layers - Logistic - Logistic	Age, Height(cm), Weight(kg), Right-Arm-Impedance	187.944

Table 4.100. *RMSE* values for males (Age, Height, Weight, Category-3)

No	Model Type	Pedictor Variables	RMSE
589	SVM - RBF - DoGridSearch	Age, Height(cm), Weight(kg), Right-Arm-Impedance, Left-Arm-Impedance	182.107
590	SVM - RBF - DoPatternSearch	Age, Height(cm), Weight(kg), Right-Arm-Impedance, Left-Arm-Impedance	182.107
591	SVM - RBF - DoPatternSearch	Age, Height(cm), Weight(kg), Right-Arm-Impedance, Body-Impedance	182.343
592	SVM - RBF - DoGridSearch	Age, Height(cm), Weight(kg), Right-Arm-Impedance, Body-Impedance	182.379
593	SVM - RBF - DoGridSearch	Age, Height(cm), Weight(kg), Right-Leg-Impedance, Right-Arm-Impedance, Body-Impedance	184.194
594	SVM - RBF - DoPatternSearch	Age, Height(cm), Weight(kg), Right-Leg-Impedance, Right-Arm-Impedance, Body-Impedance	184.326

Table 4.101. *RMSE* values for males (Age, Height, Weight, Category-4)

No	Model Type	Pedictor Variables	RMSE
595	GRNN - Minimize error	Age, Height(cm), Weight(kg), Right-Arm-Fat Percentage, Left-Arm-Fat Percentage, Body-Fat Percentage	152.969
596	GRNN - Minimize error	Age, Height(cm), Weight(kg), Right-Leg-Fat Percentage, Left-Leg-Fat Percentage, Left-Arm-Fat Percentage, Body-Fat Percentage	167.546
597	GRNN - Minimize error	Age, Height(cm), Weight(kg), Left-Leg-Fat Percentage, Right-Arm-Fat Percentage	167.557
598	GRNN - Minimize error	Age, Height(cm), Weight(kg), Right-Leg-Fat Percentage	167.657
599	GRNN - Minimize error	Age, Height(cm), Weight(kg), Right-Arm-Fat Percentage, Left-Arm-Fat Percentage	167.686
600	GRNN - Minimize error	Age, Height(cm), Weight(kg), Left-Leg-Fat Percentage, Body-Fat Percentage	167.706

Table 4.102. *RMSE* values for males (Age, Height, Weight, Category-4)

No	Model Type	Pedictor Variables	RMSE
601	MLP - 3 Layers - Logistic - Linear	Age, Height(cm), Weight(kg), Right-Leg-Fat Percentage, Left-Leg-Fat Percentage	185.317
602	MLP - 3 Layers - Logistic - Linear	Age, Height(cm), Weight(kg), Left-Leg-Fat Percentage, Left-Arm-Fat Percentage	186.262
603	MLP - 4 Layers - Linear - Linear	Age, Height(cm), Weight(kg), Left-Arm-Fat Percentage	187.024
604	MLP - 4 Layers - Linear - Linear	Age, Height(cm), Weight(kg), Left-Leg-Fat Percentage	187.366
605	MLP - 3 Layers - Linear - Linear	Age, Height(cm), Weight(kg), Left-Arm-Fat Percentage, Body-Fat Percentage	187.924
606	MLP - 3 Layers - Logistic - Linear	Age, Height(cm), Weight(kg), Right-Leg-Fat Percentage, Right-Arm-Fat Percentage, Left-Arm-Fat Percentage, Body-Fat Percentage	187.973

Table 4.103. *RMSE* values for males (Age, Height, Weight, Category-4)

No	Model Type	Pedictor Variables	RMSE
607	SVM - RBF - DoGridSearch	Age, Height(cm), Weight(kg), Body-Fat Percentage	184.158
608	SVM - RBF - DoPatternSearch	Age, Height(cm), Weight(kg), Body-Fat Percentage	184.158
609	SVM - RBF - DoGridSearch	Age, Height(cm), Weight(kg), Left-Arm-Fat Percentage	185.915
610	SVM - RBF - DoPatternSearch	Age, Height(cm), Weight(kg), Left-Arm-Fat Percentage	185.915
611	SVM - RBF - DoGridSearch	Age, Height(cm), Weight(kg), Left-Arm-Fat Percentage, Body-Fat Percentage	186.081
612	SVM - RBF - DoPatternSearch	Age, Height(cm), Weight(kg), Left-Arm-Fat Percentage, Body-Fat Percentage	186.082

Table 4.104. *RMSE* values for males (Age, Height, Weight, Category-5)

No	Model Type	Pedictor Variables	RMSE
613	GRNN - Minimize error	Age, Height(cm), Weight(kg), Right-Leg-Fat (kg), Left-Leg-Fat (kg), Left-Arm-Fat (kg)	167.402
614	GRNN - Minimize error	Age, Height(cm), Weight(kg), Left-Leg-Fat (kg)	167.425
615	GRNN - Minimize error	Age, Height(cm), Weight(kg), Right-Leg-Fat (kg), Left-Arm-Fat (kg)	167.789
616	GRNN - Minimize error	Age, Height(cm), Weight(kg), Left-Leg-Fat (kg), Right-Arm-Fat (kg)	167.853
617	GRNN - Minimize error	Age, Height(cm), Weight(kg), Right-Arm-Fat (kg), Left-Arm-Fat (kg), Body-Fat (kg)	167.862
618	GRNN - Minimize error	Age, Height(cm), Weight(kg), Left-Leg-Fat (kg), Left-Arm-Fat (kg), Body-Fat (kg)	167.867

Table 4.105. *RMSE* values for males (Age, Height, Weight, Category-5)

No	Model Type	Pedictor Variables	RMSE
619	MLP - 3 Layers - Logistic - Linear	Age, Height(cm), Weight(kg), Right-Arm-Fat (kg)	185.947
620	MLP - 3 Layers - Logistic - Linear	Age, Height(cm), Weight(kg), Left-Arm-Fat (kg), Body-Fat (kg)	186.644
621	MLP - 4 Layers - Linear - Linear	Age, Height(cm), Weight(kg), Left-Arm-Fat (kg), Body-Fat (kg)	186.658
622	MLP - 4 Layers - Linear - Linear	Age, Height(cm), Weight(kg), Left-Leg-Fat (kg), Right-Arm-Fat (kg), Body-Fat (kg)	187.176
623	MLP - 4 Layers - Linear - Linear	Age, Height(cm), Weight(kg), Left-Leg-Fat (kg), Left-Arm-Fat (kg), Body-Fat (kg)	187.509
624	MLP - 3 Layers - Logistic - Linear	Age, Height(cm), Weight(kg), Right-Leg-Fat (kg), Right-Arm-Fat (kg)	187.526

Table 4.106. *RMSE* values for males (Age, Height, Weight, Category-5)

No	Model Type	Pedictor Variables	RMSE
625	SVM - Linear - DoGridSearch	Age, Height(cm), Weight(kg), Left-Arm-Fat (kg), Body-Fat (kg)	187.521
626	SVM - Linear - DoPatternSearch	Age, Height(cm), Weight(kg), Left-Arm-Fat (kg), Body-Fat (kg)	187.577
627	SVM - RBF - DoGridSearch	Age, Height(cm), Weight(kg), Left-Arm-Fat (kg)	187.766
628	SVM - RBF - DoPatternSearch	Age, Height(cm), Weight(kg), Left-Arm-Fat (kg)	187.766
629	SVM - RBF - DoPatternSearch	Age, Height(cm), Weight(kg), Body-Fat (kg)	187.843
630	SVM - RBF - DoGridSearch	Age, Height(cm), Weight(kg), Body-Fat (kg)	187.863

Table 4.107. *RMSE* values for males (Age, Height, Weight, Category-6)

No	Model Type	Pedictor Variables	RMSE
631	GRNN - Minimize error	Age, Height(cm), Weight(kg), Right-Leg-Non-Fat(kg), Right-Arm-Non-Fat(kg)	151.684
632	GRNN - Minimize error	Age, Height(cm), Weight(kg), Right-Arm-Non-Fat(kg)	155.272
633	GRNN - Minimize error	Age, Height(cm), Weight(kg), Left-Leg-Non-Fat(kg), Right-Arm-Non-Fat(kg), Left-Arm-Non-Fat(kg)	156.948
634	GRNN - Minimize error	Age, Height(cm), Weight(kg), Right-Leg-Non-Fat(kg), Left-Arm-Non-Fat(kg)	158.642
635	GRNN - Minimize error	Age, Height(cm), Weight(kg), Right-Leg-Non-Fat(kg)	160.419
636	GRNN - Minimize error	Age, Height(cm), Weight(kg), Right-Arm-Non-Fat(kg), Body-Non-Fat(kg)	161.045

Table 4.108. *RMSE* values for males (Age, Height, Weight, Category-6)

No	Model Type	Pedictor Variables	RMSE
637	MLP - 3 Layers - Logistic - Linear	Age, Height(cm), Weight(kg), Right-Arm-Non-Fat, Body-Non-Fat (kg)	178.994
638	MLP - 3 Layers - Logistic - Linear	Age, Height(cm), Weight(kg), Right-Arm-Non-Fat, Left-Arm-Non-Fat, Body-Non-Fat (kg)	179.429
639	MLP - 3 Layers - Logistic - Linear	Age, Height(cm), Weight(kg), Right-Leg-Non-Fat, Left-Arm-Non-Fat, Body-Non-Fat(kg)	181.386
640	MLP - 3 Layers - Linear - Linear	Age, Height(cm), Weight(kg), Left-Leg-Non-Fat, Right-Arm-Non-Fat, Left-Arm-Non-Fat(kg)	181.545
641	MLP - 4 Layers - Logistic - Linear	Age, Height(cm), Weight(kg), Right-Leg-Non-Fat, Left-Leg-Non-Fat, Right-Arm-Non-Fat, Left-Arm-Non-Fat, Body-Non-Fat(kg)	181.764
642	MLP - 3 Layers - Logistic - Linear	Age, Height(cm), Weight(kg), Right-Arm-Non-Fat, Left-Arm-Non-Fat(kg)	182.427

Table 4.109. *RMSE* values for females (Age, Height, Weight, Category-6)

No	Model Type	Pedictor Variables	RMSE
643	SVM - Linear - DoGridSearch	Age, Height(cm), Weight(kg), Right-Leg-Non-Fat, Right-Arm-Non-Fat, Body-Non-Fat(kg)	182.372
644	SVM - Linear - DoPatternSearch	Age, Height(cm), Weight(kg), Right-Leg-Non-Fat, Right-Arm-Non-Fat, Body-Non-Fat(kg)	182.372
645	SVM - Linear - DoPatternSearch	Age, Height(cm), Weight(kg), Right-Leg-Non-Fat, Right-Arm-Non-Fat, Left-Arm-Non-Fat, Body-Non-Fat(kg)	182.705
646	SVM - Linear - DoGridSearch	Age, Height(cm), Weight(kg), Right-Leg-Non-Fat, Right-Arm-Non-Fat, Left-Arm-Non-Fat, Body-Non-Fat(kg)	182.719
647	SVM - Linear - DoPatternSearch	Age, Height(cm), Weight(kg), Right-Leg-Non-Fat, Right-Arm-Non-Fat, Left-Arm-Non-Fat(kg)	182.826
648	SVM - RBF - DoPatternSearch	Age, Height(cm), Weight(kg), Right-Leg-Non-Fat, Right-Arm-Non-Fat, Left-Arm-Non-Fat, Body-Non-Fat(kg)	183.006

Table 4.110. *RMSE* values for males (Age, Height, Weight, Category-7)

No	Model Type	Pedictor Variables	RMSE
649	GRNN - Minimize error	Age, Height(cm), Weight(kg), Right-Arm-Muscle(kg), Body-Muscle(kg)	155.758
650	GRNN - Minimize error	Age, Height(cm), Weight(kg), Right-Arm-Muscle(kg), Left-Arm-Muscle(kg)	156.233
651	GRNN - Minimize error	Age, Height(cm), Weight(kg), Right-Arm-Muscle(kg), Left-Arm-Muscle(kg), Body-Muscle(kg)	156.488
652	GRNN - Minimize error	Age, Height(cm), Weight(kg), Right-Arm-Muscle(kg)	156.743
653	GRNN - Minimize error	Age, Height(cm), Weight(kg), Right-Leg-Muscle(kg), Left-Leg-Muscle(kg), Right-Arm-Muscle(kg), Body-Muscle(kg)	156.759
654	GRNN - Minimize error	Age, Height(cm), Weight(kg), Right-Leg-Muscle(kg), Right-Arm-Muscle(kg), Left-Arm-Muscle(kg)	157.092

Table 4.111. *RMSE* values for males (Age, Height, Weight, Category-7)

No	Model Type	Pedictor Variables	RMSE
655	MLP - 3 Layers - Linear - Logistic	Age, Height(cm), Weight(kg), Right-Arm-Muscle(kg), Body-Muscle(kg)	180.884
656	MLP - 3 Layers - Logistic - Linear	Age, Height(cm), Weight(kg), Left-Leg-Muscle(kg), Left-Arm-Muscle(kg), Body-Muscle(kg)	181.092
657	MLP - 3 Layers - Logistic - Linear	Age, Height(cm), Weight(kg), Left-Leg-Muscle(kg), Body-Muscle(kg)	181.923
658	MLP - 4 Layers - Linear - Logistic	Age, Height(cm), Weight(kg), Right-Leg-Muscle(kg), Left-Leg-Muscle(kg), Left-Arm-Muscle(kg)	182.332
659	MLP - 3 Layers - Linear - Logistic	Age, Height(cm), Weight(kg), Right-Leg-Muscle(kg), Body-Muscle(kg)	182.572
660	MLP - 4 Layers - Linear - Linear	Age, Height(cm), Weight(kg), Right-Leg-Muscle(kg), Right-Arm-Muscle(kg), Left-Arm-Muscle(kg)	182.807

Table 4.112. *RMSE* values for males (Age, Height, Weight, Category-7)

No	Model Type	Pedictor Variables	RMSE
661	SVM - Linear - DoGridSearch	Age, Height(cm), Weight(kg), Right-Leg-Muscle(kg), Right-Arm-Muscle(kg), Left-Arm-Muscle(kg)	182.174
662	SVM - Linear - DoPatternSearch	Age, Height(cm), Weight(kg), Right-Leg-Muscle(kg), Right-Arm-Muscle(kg), Left-Arm-Muscle(kg)	182.174
663	SVM - RBF - DoPatternSearch	Age, Height(cm), Weight(kg), Right-Leg-Muscle(kg), Left-Leg-Muscle(kg), Right-Arm-Muscle(kg)	182.532
664	SVM - Linear - DoGridSearch	Age, Height(cm), Weight(kg), Right-Leg-Muscle(kg), Right-Arm-Muscle(kg), Left-Arm-Muscle(kg), Body-Muscle(kg)	182.629
665	SVM - RBF - DoPatternSearch	Age, Height(cm), Weight(kg), Left-Leg-Muscle(kg)	182.755
666	SVM - RBF - DoGridSearch	Age, Height(cm), Weight(kg), Left-Leg-Muscle(kg)	182.772

Table 4.113. *RMSE* values for males (Age, Height, Weight, Category-8)

No	Model Type	Pedictor Variables	RMSE
667	GRNN - Minimize error	Age, Height(cm), Weight(kg), Cell Mass(kg)	154.086
668	GRNN -#10 of neurons	Age, Height(cm), Weight(kg), Bone Minerals Weight(kg), Cell Mass(kg)	156.478
669	GRNN - Minimize error	Age, Height(cm), Weight(kg), Soft Muscle Tissue(kg), Bone Minerals Weight(kg), Skeletal Muscles(kg), Extracellular Liquid(kg), Cell Mass(kg)	157.579
670	GRNN - Minimize error	Age, Height(cm), Weight(kg), Soft Muscle Tissue(kg), Skeletal Muscles(kg), Extracellular Liquid(kg), Intercellular Fluid(kg), Cell Mass(kg)	157.845
671	GRNN -#10 of neurons	Age, Height(cm), Weight(kg), Intercellular Fluid(kg), Cell Mass(kg)	157.964
672	GRNN - Minimize error	Age, Height(cm), Weight(kg), Bone Minerals Weight(kg), Intercellular Fluid(kg), Cell Mass(kg)	158.383

Table 4.114. *RMSE* values for males (Age, Height, Weight, Category-8)

No	Model Type	Pedictor Variables	RMSE
673	MLP - 4 Layers - Linear - Linear	Age, Height(cm), Weight(kg), Bone Minerals Weight(kg), Skeletal Muscles(kg), Extracellular Liquid(kg)	179.335
674	MLP - 3 Layers - Logistic - Logistic	Age, Height(cm), Weight(kg), Skeletal Muscles(kg), Extracellular Liquid(kg), Cell Mass(kg)	180.705
675	MLP - 3 Layers - Linear - Linear	Age, Height(cm), Weight(kg), Bone Minerals Weight(kg), Extracellular Liquid(kg)	180.814
676	MLP - 3 Layers - Logistic - Linear	Age, Height(cm), Weight(kg), Soft Muscle Tissue(kg), Skeletal Muscles(kg), Extracellular Liquid(kg), Cell Mass(kg)	181.035
677	MLP - 3 Layers - Logistic - Logistic	Age, Height(cm), Weight(kg), Skeletal Muscles(kg), Cell Mass(kg)	181.323
678	MLP - 3 Layers - Linear - Logistic	Age, Height(cm), Weight(kg), Soft Muscle Tissue(kg), Bone Minerals Weight(kg), Extracellular Liquid(kg)	181.351

Table 4.115. *RMSE* values for males (Age, Height, Weight, Category-8)

No	Model Type	Pedictor Variables	RMSE
679	SVM - Linear - DoGridSearch	Age, Height(cm), Weight(kg), Soft Muscle Tissue(kg), Bone Minerals Weight(kg), Extracellular Liquid(kg), Cell Mass(kg)	182.795
680	SVM - Linear - DoPatternSearch	Age, Height(cm), Weight(kg), Soft Muscle Tissue(kg), Bone Minerals Weight(kg), Extracellular Liquid(kg), Cell Mass(kg)	182.947
681	SVM - RBF - DoGridSearch	Age, Height(cm), Weight(kg), Soft Muscle Tissue(kg), Skeletal Muscles(kg), Extracellular Liquid(kg), Cell Mass(kg)	183.152
682	SVM - Linear - DoGridSearch	Age, Height(cm), Weight(kg), Bone Minerals Weight(kg), Skeletal Muscles(kg), Cell Mass(kg)	183.192
683	SVM - Linear - DoGridSearch	Age, Height(cm), Weight(kg), Soft Muscle Tissue, Intercellular Fluid, Cell Mass (kg)	183.276
684	SVM - Linear - DoPatternSearch	Age, Height(cm), Weight(kg), Soft Muscle Tissue(kg), Intercellular Fluid(kg), Cell Mass(kg)	183.286

Table 4.116. *RMSE* values for males (Age, Height, Weight, Category-9)

No	Model Type	Pedictor Variables	RMSE
685	GRNN - Minimize error	Age, Height(cm), Weight(kg), Waist Circumference(cm)	157.094
686	GRNN - Minimize error	Age, Height(cm), Weight(kg), Waist Circumference(cm), Lower Belly Circumference(cm)	160.361
687	GRNN -#10 of neurons	Age, Height(cm), Weight(kg), Waist Circumference(cm), Lower Belly Circumference(cm)	162.733
688	GRNN -#10 of neurons	Age, Height(cm), Weight(kg), Lower Belly Circumference(cm)	163.971
689	GRNN - Minimize error	Age, Height(cm), Weight(kg), Lower Belly Circumference(cm)	164.939
690	GRNN -#10 of neurons	Age, Height(cm), Weight(kg), Waist Circumference(cm)	166.968

Table 4.117. *RMSE* values for males (Age, Height, Weight, Category-9)

No	Model Type	Pedictor Variables	RMSE
691	MLP - 3 Layers - Logistic - Logistic	Age, Height(cm), Weight(kg), Waist Circumference(cm)	177.276
692	MLP - 3 Layers - Linear - Logistic	Age, Height(cm), Weight(kg), Waist Circumference(cm)	181.289
693	MLP - 3 Layers - Linear - Linear	Age, Height(cm), Weight(kg), Lower Belly Circumference(cm)	181.51
694	MLP - 3 Layers - Logistic - Linear	Age, Height(cm), Weight(kg), Waist Circumference(cm), Lower Belly Circumference(cm)	181.834
695	MLP - 3 Layers - Linear - Logistic	Age, Height(cm), Weight(kg), Waist Circumference(cm), Lower Belly Circumference(cm)	182.279
696	MLP - 3 Layers - Logistic - Logistic	Age, Height(cm), Weight(kg), Waist Circumference(cm), Lower Belly Circumference(cm)	182.49

Table 4.118. *RMSE* values for males (Age, Height, Weight, Category-9)

No	Model Type	Pedictor Variables	RMSE
697	SVM - RBF - DoGridSearch	Age, Height(cm), Weight(kg), Lower Belly Circumference(cm)	178.131
698	SVM - RBF - DoPatternSearch	Age, Height(cm), Weight(kg), Lower Belly Circumference(cm)	178.233
699	SVM - RBF - DoPatternSearch	Age, Height(cm), Weight(kg), Waist Circumference(cm)	178.799
700	SVM - RBF - DoGridSearch	Age, Height(cm), Weight(kg), Waist Circumference(cm)	178.801
701	SVM - RBF - DoPatternSearch	Age, Height(cm), Weight(kg), Waist Circumference(cm), Lower Belly Circumference(cm)	183.289
702	SVM - RBF - DoGridSearch	Age, Height(cm), Weight(kg), Waist Circumference(cm), Lower Belly Circumference(cm)	183.448

Table 4.119. *RMSE* values for males (Age, Height, Weight, Category-10)

No	Model Type	Pedictor Variables	RMSE
703	GRNN - Minimize error	Age, Height(cm), Weight(kg), Cigarette	157.967
704	GRNN - Minimize error	Age, Height(cm), Weight(kg), Insulin, Cigarette	158.253
705	GRNN - Minimize error	Age, Height(cm), Weight(kg), Thyroid, Cigarette	158.364
706	GRNN - Minimize error	Age, Height(cm), Weight(kg), Thyroid, Insulin, Cigarette	159.979
707	GRNN - Minimize error	Age, Height(cm), Weight(kg), Thyroid, Insulin	160.785
708	GRNN - Minimize error	Age, Height(cm), Weight(kg), Insulin	161.349

Table 4.120. *RMSE* values for males (Age, Height, Weight, Category-10)

No	Model Type	Pedictor Variables	RMSE
709	MLP - 3 Layers - Logistic - Linear	Age, Height(cm), Weight(kg), Insulin	187.317
710	MLP - 4 Layers - Logistic - Linear	Age, Height(cm), Weight(kg), Thyroid, Cigarette	189.249
711	MLP - 3 Layers - Linear - Linear	Age, Height(cm), Weight(kg), Cigarette	189.652
712	MLP - 3 Layers - Linear - Linear	Age, Height(cm), Weight(kg), Thyroid	190.554
713	MLP - 3 Layers - Linear - Logistic	Age, Height(cm), Weight(kg), Thyroid	190.838
714	MLP - 3 Layers - Linear - Logistic	Age, Height(cm), Weight(kg), Thyroid, Insulin	190.953

Table 4.121. *RMSE* values for males (Age, Height, Weight, Category-10)

No	Model Type	Pedictor Variables	RMSE
715	SVM - RBF - DoGridSearch	Age, Height(cm), Weight(kg), Insulin	186.349
716	SVM - RBF - DoPatternSearch	Age, Height(cm), Weight(kg), Insulin	186.519
717	SVM - RBF - DoGridSearch	Age, Height(cm), Weight(kg), Thyroid	188.409
718	SVM - RBF - DoPatternSearch	Age, Height(cm), Weight(kg), Thyroid	188.451
729	SVM - RBF - DoPatternSearch	Age, Height(cm), Weight(kg), Cigarette	189.348
720	SVM - RBF - DoGridSearch	Age, Height(cm), Weight(kg), Cigarette	189.359

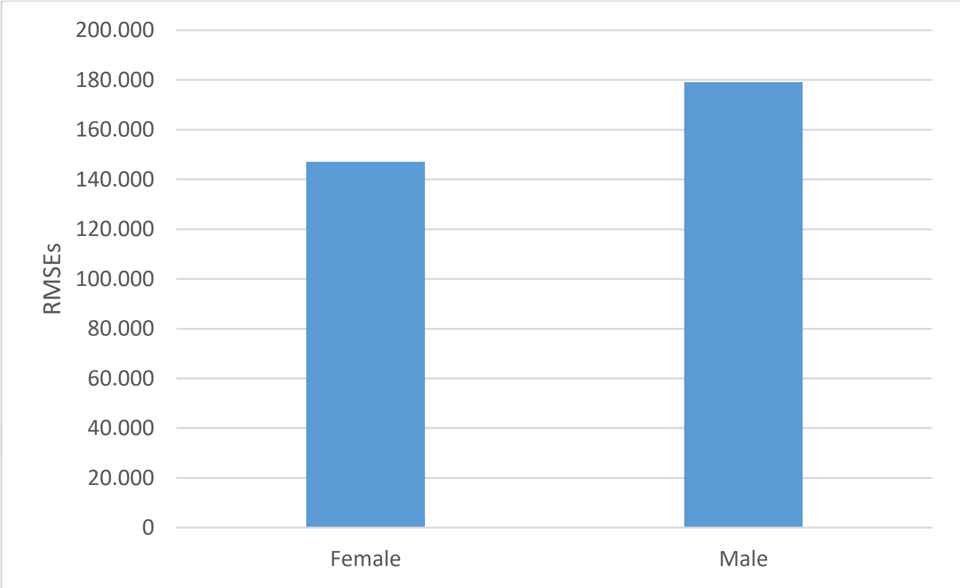

Figure 4.1. The comparison of female and male data sets

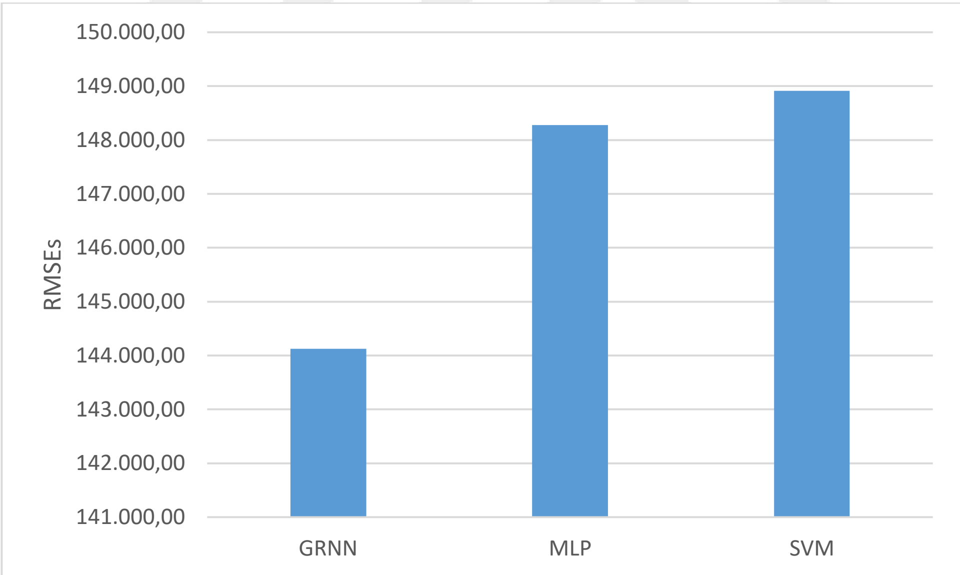

Figure 4.2. The comparison of machine learning techniques for the female data set

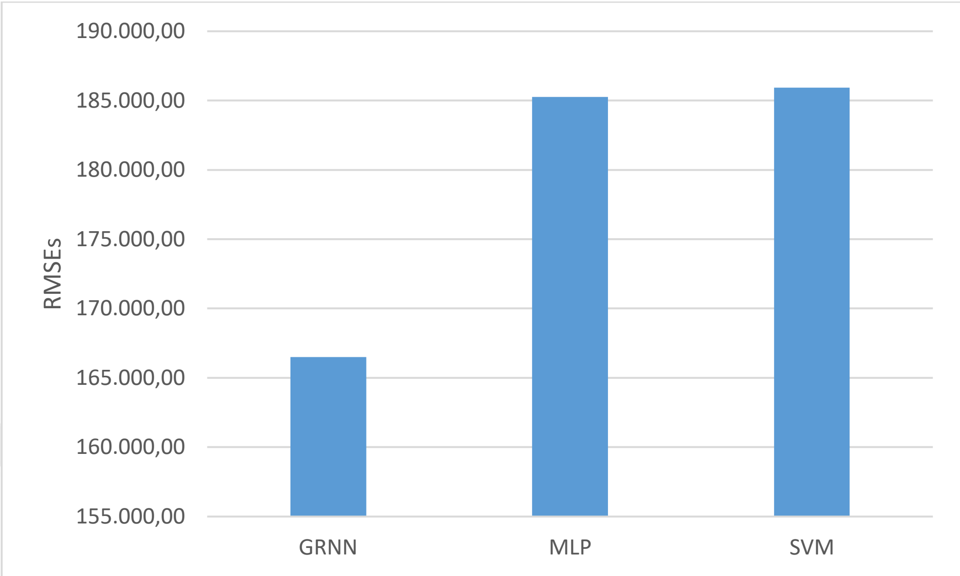

Figure 4.3. The comparison of machine learning techniques for the male data set

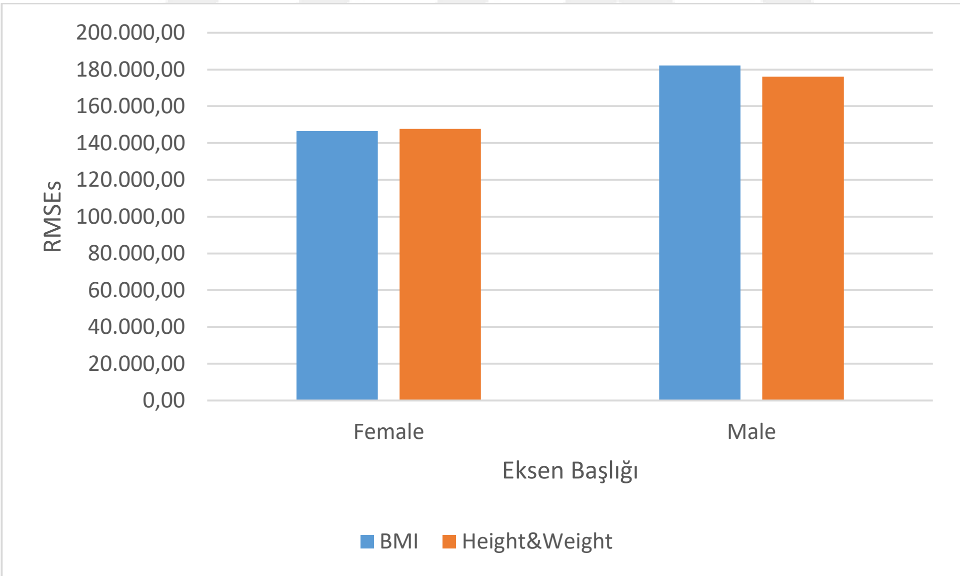

Figure 4.4. The comparison of BMI-based models and Height&Weight-based models for female and male data sets

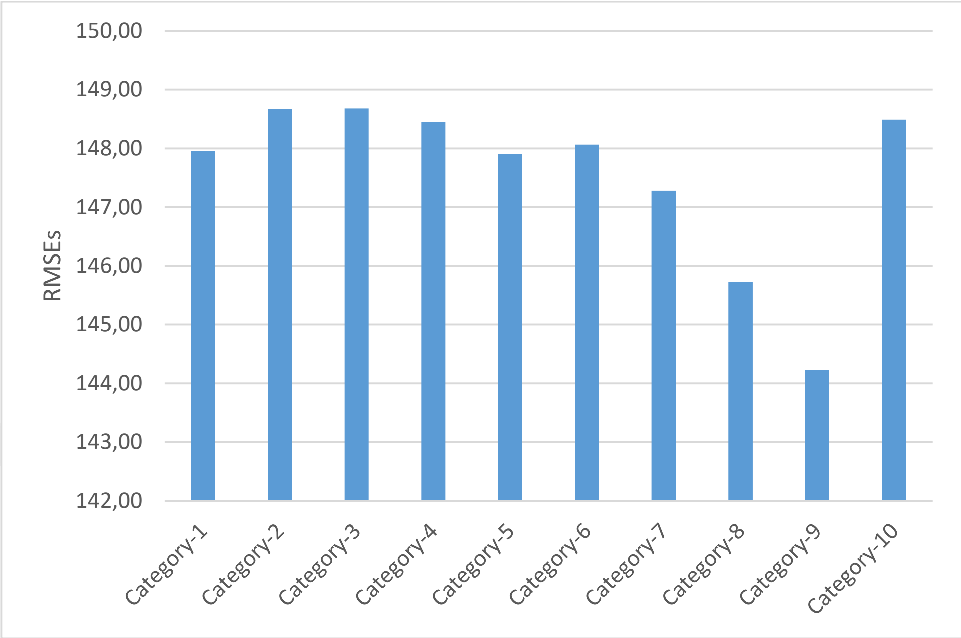

Figure 4.5. The comparison of categories for females

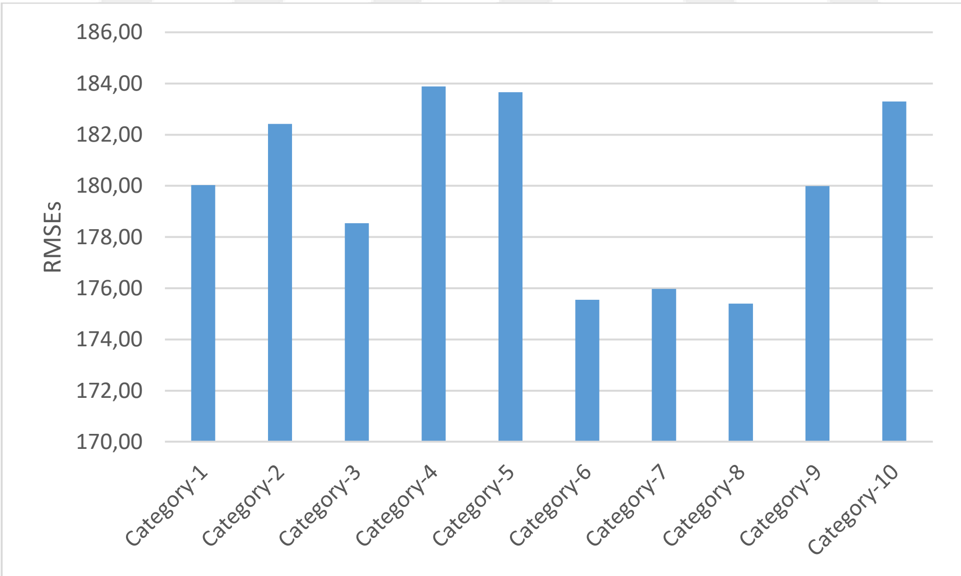

Figure 4.6. The comparison of categories for males

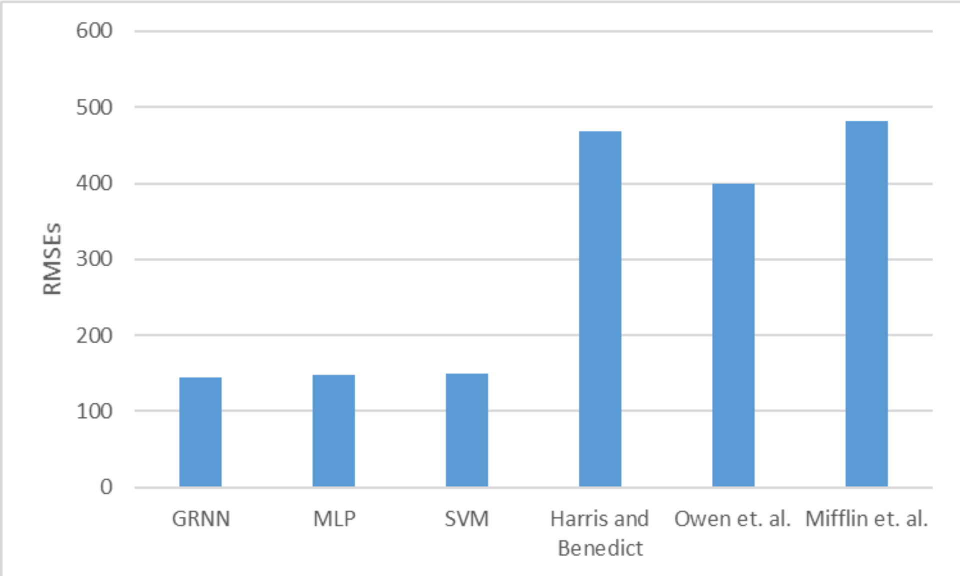

Figure 4.7. The comparison of prediction equations and machine learning models for females

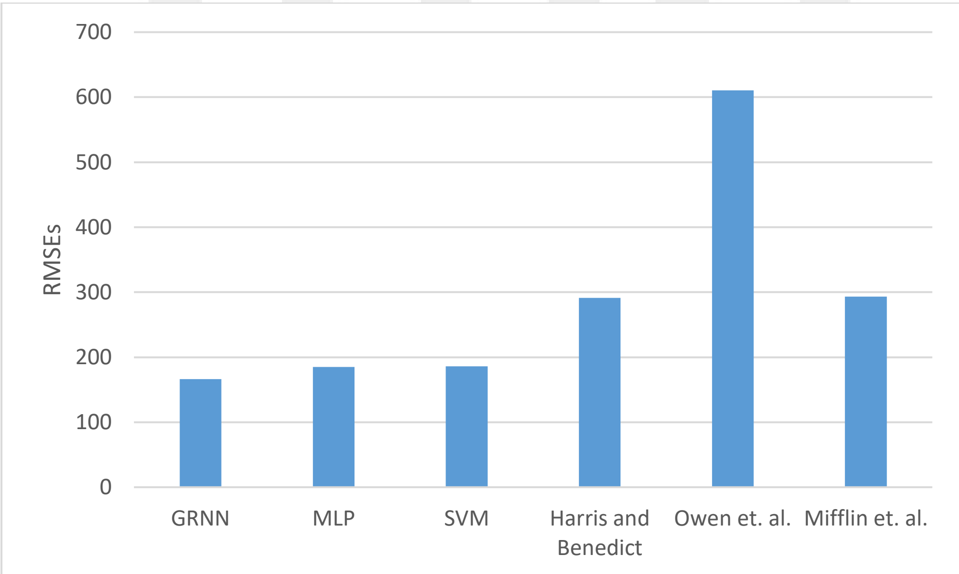

Figure 4.8. The comparison of prediction equations and machine learning models for males

4.1. General Discussion of the Results

When the results have been obtained, it is noticed that the models of the female data set have lower error rates as opposed to models of the male data set. The root arithmetical mean of the RMSE values for all 60 tables is 146.975 for prediction results of female patent while the mean value is 179.116 for 60 tables of male patient prediction results.

When the machine learning methods are compared for prediction results of female and male patients, GRNN has generated better results than MLP and SVM techniques. If MLP and SVM techniques are compared, MLP has slightly better results than SVM technique. According to the overall root mean error rates for female patients, between the three options of machine learning techniques, the arithmetical mean *RMSE* of GRNN models has been calculated as 144.123 while the arithmetical mean *RMSE* for MLP and SVM techniques have been measured as 148.277 and 148.913 for females, respectively. For males, the arithmetical mean *RMSE* of GRNN models has been computed as 166.505 while the arithmetical mean *RMSE* for MLP and SVM techniques have been calculated as 185.262 and 185.919, in the given order.

In this thesis, all of the prediction models have been created using subset of age and BMI or age, height and weight .For female prediction results, BMI-based models have not a dramatic change or improvement on the error rate when compared with prediction results of height and weight-based models. Conversely, it has been observed that height and weight-based prediction models have better *RMSE* according to the BMI-based prediction models for male prediction results. The arithmetical mean *RMSEs* of BMI-based and height,weight-based models are 146.502 and 147.440 in the given order while the same values are 182.199 and 176.120, respectively.

For this thesis the prediction results also have been compared with respect to the prediction variables being used. The prediction results which have been generated with the usage of subsets of 10 different categories in total. Generated models using Category 9 which consists of waist, hip and lower belly circumferenece has lowest the average of *RMSE* for female patients. It is proven that these variables are a high impact on prediction models estimating *RMSE* of female patients. The arithmetical mean *RMSEs* of Category 9-based models calculated as 144.229. It has been observed that Category 6 and Category 8 have been brought about lower results for male patients. While Category 6 consists of right-leg, left-leg, right-arm, left-arm and body fat non-fat kilograms, Category 8 is sets of soft muscle tissue, bone minerals weight(kg), skeletal muscles(kg), extracellular liquid(kg), intercellular fluid(kg) and cell mass(kg). The arithmetical mean *RMSEs* of Category 6-based and Category 8-based models calculated as 175.544 and 175.395, respectively.

For female models, the lowest *RMSE* value has been obtained by model number 181 which is 134.91. The predictor variables are age, height(cm), weight(kg), fat(%), liquid(kg), bone weight (kg) while the machine learning technique is GRNN using minimize-error optimization tenchique for this model. The least favorable prediction model in female models is model number 210 which has been calculated RMSE as 151.289 using prediction variable sets of age, height(cm), weight(kg), protein amount(kg), internal lubrication via MLP with the usage of 1 hidden layer, linear activation function for the neurons of hidden and output layers. The minimum *RMSE* value is 143.109 for male models which have been produced by model number 577. This model has been created with the usage of prediction variables which are age, height(cm), weight(kg), left-leg-impedance, right-arm-impedance, left-arm-impedance, body-impedance and used GRNN technique with the minimize-error optimization technique. The least accurate model in male models is model number 540 that has been measured RMSE as 199.87. The model has been carried out by using predictor variables set of age, BMI, thyroid, cigarette via SVM learning technique applying RBF kernel function and dogridsearch optimization technique at the same time.

The comparison notes the machine learning methods and RMR prediction equations for each individual data set, with respect to the arithmetical mean *RMSE* of the models are listed in the following section.

4.2. The Comparision of Machine Learning Methods and RMR Prediction Equations For Each Data Set

- For the female data set, the arithmetical mean *RMSE* of Harris and Benedict equation has been calculated as 468.595. The range of percentage decrement rates of *RMSE* of Harris and Benedict equation with respect to other machine learning methods are as follows: 69.243% for GRNN, 68.357% for MLP and 68.221% for SVM.
- For the female data set, the average *RMSE* value of Owen et. al. prediction equation has been obtained as 398.730. The range of percentage decrement rates of *RMSE* of this equation according to other machine learning methods are as follows: 63.854% for GRNN, 62.812% for MLP and 62.653% for SVM.
- For the female data set, the mean *RMSE* of Mifflin et. al. equation has been calculated as 481.132. The range of percentage reducing rates of *RMSE* of this equation compared with other machine learning methods are as follows: 70.045% for GRNN, 69.181 % for MLP and 69.049% for SVM.
- For the female data set, when the accuracy of prediction equations are compared among themselves, the Owen et. al. is the best equation resulted in 398.730 RMS value. The second equation is Harris and Benedict which has been calculated *RMSE* as 468.595 and the worst perdiction equation is Mifflin et. al. with 481.132.
- For the male data set, the arithmetical mean *RMSE* of Harris and

Benedict equation has been measured as 291.547. The range of percentage decrement rates of *RMSE* of Harris and Benedict equation with respect to other machine learning methods are as follows: 42.889% for GRNN, 36.455% for MLP and 36.230% for SVM.

- For the male data set, the average *RMSE* value of Owen et. al. prediction equation has been computed as 610.653. The range of percentage decrement rates of *RMSE* of this equation according to other machine learning methods are as follows: 72.733% for GRNN, 69.661% for MLP and 69.554% for SVM.
- For the male data set, the mean *RMSE* of Mifflin et. al. prediction equation has been obtained as 293.349. The range of percentage reducing rates of *RMSE* of this equation compared with other machine learning methods are as follows: 43.24% for GRNN, 36.845 % for MLP and 36.622% for SVM.
- For the male data set, when the accuracy of prediction equations are compared among themselves, Harris and Benedict is the best equation resulted in 291.547 RMS value with respect to Mifflin et. al. and Owen et. al which have been calculated *RMSE* as 293.349, 610.653 respectively.

5. CONCLUSION

The main purpose of this thesis work was to develop a new software which can predict RMR of an individual. The software has been developed by using Visual Studio (ASP.NET Framework) , DTREG .Net Class Library, and C# programming language. DTREG .Net Class Library has been integrated the project to apply machine learning methods which are GRNN, MLP and SVM. The software consists of two parts. The first part has been generated as the back end side which is used to create machine learning models. The second one has been developed as the front end side that is developed to measure RMR of an individual by appliying generated machine learning models. The back end side has been built using Ajax Controller Toolkit and DevExpress components while on the front end side of this project, .Net Core technology has been used for designing.

For this thesis, female and male patients data sets have been obtained from dietician Müzda Irmak in Turkey. The software consists of two main modules. In this software different predictor variables and parameters have been determined in order to obtain various models.17.456 different prediction models have been produced in total, including 8786 models for the female patients and 8670 models for the male patients. However, the best 720 models have tabled in this thesis.The evaluation of prediction models has been made concerning RMSE results, gather from each prediction model.

According to the prediction results, the models of female data set yield better results compared to the models of male data set. If the size of the data set icreases for male patients, the prediction models may generate better results for males. The sets of prediction variables belong to 10 different categories (see the tables 5.82) have leaded to variety in the prediction models. The optimization parameters have brought about variety as like prediction variables but they haven't changed the accuracy of models dramatically.

Throughout the whole process, *RMSE* results for the female models varies between 134.91 and 151.289 while the same range is 143.109 and 199.87 shows that it is feasible to obtain accurate predictions when the predictor variables are selected correctly , the optimum parameters and enough amount of training data is used.

In this thesis, it has been proven that the machine learning methods have been improved the prediction results by between 62.653% and 70.045% for females and between 36.230% and 72.733% for males, when the machine learning methods are compared with RMR prediction equations. The prediction equations widely use in dietitian centers however dietitians can calculate RMR of their patienst more accurately with the usage of this software after this work.

As a result of this thesis work, it has been proven that the developed software can be used to predict RMR of an individual within acceptable error rates.

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CURRICULUM VITAE

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