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Modeling the Factors Associated with BMI among Type 2 Diabetes Mellitus Patients: A Hybrid Model Approach

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Authors' contributions

This work was carried out in collaboration among all authors. All authors read and approved the final manuscript.

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ABSTRACT

Background: Diabetes mellitus is a chronic illness that results in abnormally high blood sugar levels. It can result in a range of complications.
Objective: The purpose of this study is to present an ideal variable selection strategy utilizing proven Multiple Linear Regression (MLR) models and to validate the variable using Multilayer Perceptron Neural Network (MLP) models. This will validate a factor linked with body mass index (BMI) status in individuals with dyslipidemia and type 2 diabetes mellitus.

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Materials and Methods: Thirty-nine patients were selected from Hospital Universiti Sains Malaysia (USM). Many variables, including BMI, gender, age, race, coronary heart disease status, waist circumference, alanine transferase, triglycerides, and dyslipidemia, were assessed in this retrospective analysis using advanced computational statistical modelling approaches. This study uses R-Studio software and syntax. Each sample's statistics were generated using a hybrid model combining bootstrap and multiple linear regression.

Results: R's statistical approach demonstrates that regression modelling is superior to R-squared performance. The hybrid model may better predict the outcome by separating the datasets into a training and testing set. The well-known bootstrap-integrated MLR technique was used to determine the validity of the variables. The eight variables examined in this case are gender (β_1: -2.329; p < 0.25), age (β_2: -0.151; p < 0.25), race (β_3: 2.504; p < 0.25), coronary heart disease status (β_4: -0.481; p < 0.25), waist circumference (β_5: 0.572; p < 0.25), alanine transferase (β_6: 0.002; p < 0.25), triglycerides (β_7: 0.046; p < 0.25), and dyslipidemia (β_8: 30.769; p < 0.25). There is a linear model that has a 9.019188 MSE.lm in this case.

Conclusion: This study will develop and extensively evaluate a novel hybrid approach combining bootstrapping and multiple linear regression. The R syntax for this procedure was chosen to ensure that the researcher comprehends the example completely. The statistical methods used to conduct this research study using R show that regression modelling is better than R-squared values for the predicted mean squared error. Thus, the study's conclusion shows that the hybrid model technique is superior. This vital conclusion helps us better understand the hybrid method's relative contribution to the result in this case.

Keywords: BMI; Modelling; multiple linear regression; predicted mean square error; type 2 diabetes mellitus.

1. INTRODUCTION

Diabetes mellitus is a metabolic disorder caused by various factors [1]. It can result in the progressive development of multidimensional complications in the human body's vascular system [2]. Micro-vascular endpoint complications may include retinopathy, nephropathy, and neuropathy, whereas macro-vascular endpoint complications may include stroke, peripheral vascular disease, and ischemic cardiovascular disease [3,4]. Diabetes mellitus has been identified as a potentially independent risk factor for premature death and reduced life expectancy [5]. There is a lot of evidence that the number of people with diabetes mellitus is rising at an alarming rate, especially in middle-aged adults [6]. Diabetes mellitus is now considered a risk factor for coronary heart disease [7]. According to Mooradian in diabetes mellitus, dyslipidemia is one of the most critical risk factors for cardiovascular disease [8].

Diabetes is a common, long-term disease that can be dangerous to people's health and is very common. People with diabetes have high blood sugar caused by either a lack of insulin production or an inability to use insulin properly [9]. Diabetes can cause long-term damage and dysfunction of many tissues, including the eyes, kidneys, heart, blood vessels, and nerves [10]. Diabetes can be divided into T1D (type 1) and T2D (type 2). Most people with type 1 diabetes are in their twenties or thirties or even younger. Increased thirst, frequent urination, and raised blood glucose levels are among clinical indications of diabetes [11]. There are no effective oral medications for treating this kind of diabetes, so insulin is the only treatment option for patients. Obesity, hypertension, dyslipidemia, arteriosclerosis, and other conditions are frequently associated with type 2 diabetes in the middle-aged and elderly population [12,13].

The term "dyslipidemia" largely supplanted the previous term "hyperlipidemia" refers to abnormal changes in body composition, most notably in body fat and lipid profiles. Dyslipidemia is a substantial risk factor for coronary heart disease in people with diabetes mellitus since it is associated with decreased high-density lipoprotein (HDL) cholesterol, increased plasma triglycerides, and increased small-density lipoprotein (LDL) cholesterol [14].

Because insulin resistance or deficiency affects enzymes and pathways involved in lipid metabolism, lipid abnormalities are common in diabetes mellitus [15]. Furthermore, the lipid particle composition of diabetic dyslipidemia is thought to be more atherogenic than that of other forms of dyslipidemia. Diabetic patients' normal lipid levels may be more atherogenic than those of nondiabetic patients. Atherosclerosis and dyslipidemia are causally connected. Hyperglycaemia, obesity, and insulin resistance contribute considerably to the advancement of atherosclerosis in diabetes [16-18].

2. MATERIALS AND METHODS

2.1 Data Collection

This study analyzed a dataset from the outpatient clinic at Hospital Universiti Sains Malaysia (U.S.M), Kelantan, Malaysia. The dataset contains nine attributes: body mass index, gender, age, race, coronary heart disease, waist circumference, alanine transferase, triglycerides, and dyslipidaemia. In this dataset, 39 patients took part in the study. The data descriptions for the research variables are summarised in Table 1.

2.2 Study Design

This paper outlines a methodology based on the design of computational retrospective research. This study constructs a multilayer perceptron with multiple linear regression using a retrospective approach and advanced computational statistical modeling techniques. This methodology was built using the testing and training datasets for M.L.P. and Multiple Linear Regression. B.M.I. (Y), Gender (X1), Age (X2), Race (X3), Coronary Heart Disease status (X4), Wc (X5), Alt (X6), Tg (X7), and Dys (X8) were used to demonstrate the case study.

2.3 Computational Biometry Modelling

The simulation data were analysed using multiple linear regression.

The R-Studio software developed the R-syntax with a successful combination model that used bootstrap, multiple linear regression, and multilayer perceptron approaches. These advanced techniques led to the superiority of the hybrid model technique. This section investigated the relationship between the total number of cases and the selected explanatory variables by fitting a set of linear regression models. The data was divided into two categories: training and testing. Modelling was done with the training data, while validation will be done with the testing data.

Table 1. Data description of the selected variables

Variable	Code	Description
BMI	Y	BMI Reading
Gender	X_1	Gender 0 = Male 1 = Female
Age	X_2	Age
Race	X_3	Race 0 = Malay 1 = Chinese 2 = Indian 3 = Others
Chd	X_4	Coronary Heart Disease 0 = Yes 1 = No
Wc	X_5	Waist Circumference
Alt	X_6	Alanine Transferase
Tg	X_7	Triglycerides
Dys	X_8	Dyslipidaemia

$$Y = \beta_0 + \beta_1(Gender) + \beta_2(Age) + \beta_3(Race) + \beta_4(Chd) + \beta_5(Wc) + \beta_6(Alt) + \beta_7(Tg) + \beta_8(Dys) \ldots\ldots(1)$$

where $\beta_0, \ldots, \beta_8$ are parameters, and *Y* is the reading of body mass index.

2.4 Bootstrap

Bootstrap started by calculating sample statistics after a population sample has been chosen randomly. A pseudo-population was formed by replicating a large number of substitution samples numerous times after the original samples were copied. Random sampling produced samples that differ from the original sample in the case of replacement sampling. The bootstrap is a statistical technique used to calculate statistics for each sample taken with replacement [19,20]. Table 2 shows the model's result. The R software was used to fit the linear regression. The following is the complete step-by-step procedure:

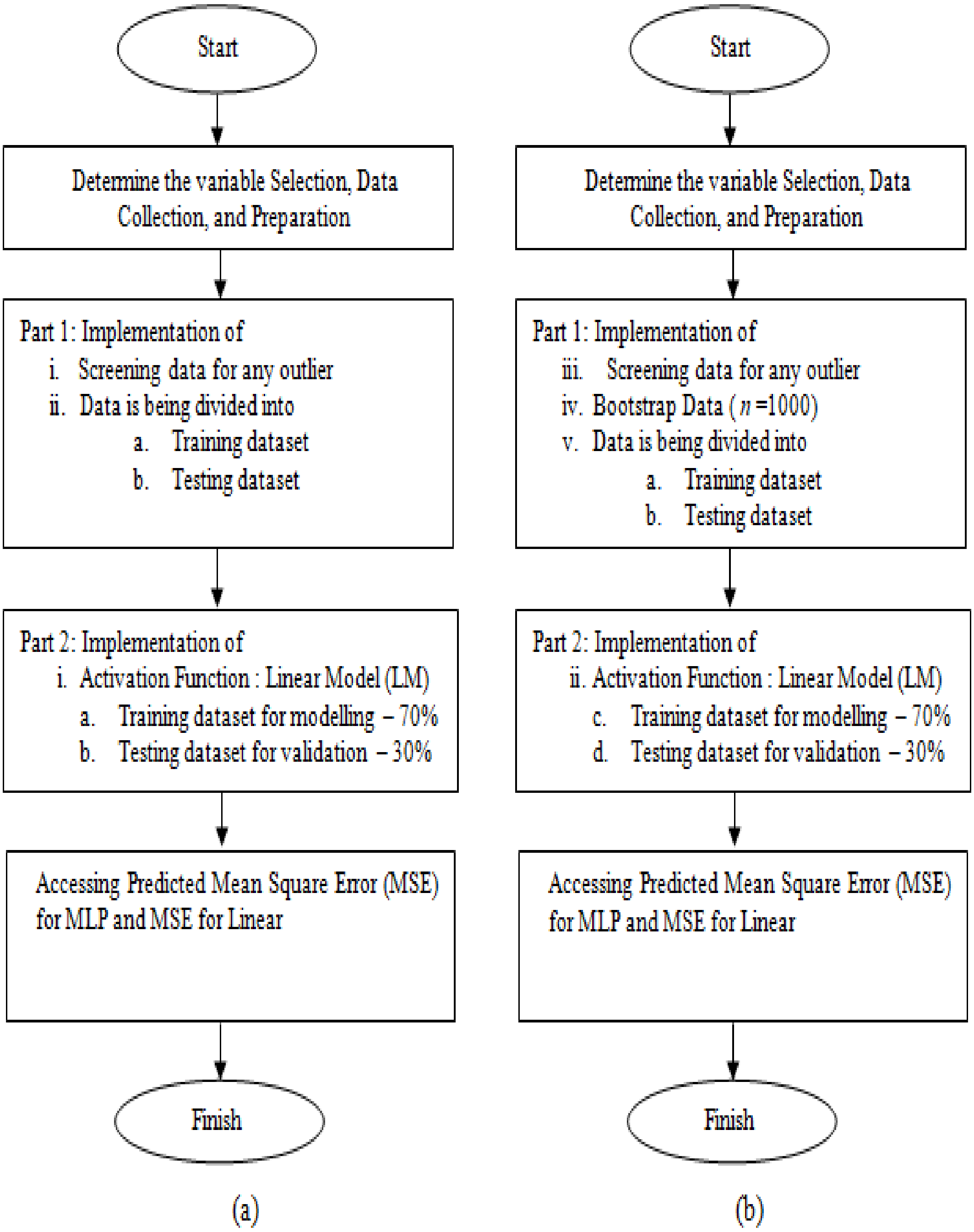

Fig. 1. Flowchart illustrating the proposed statistical linear modelling technique

An essential aspect of this type of study is that it uses a model that affects clinical variables. A bootstrapping method will be developed after the data has been prepared. By repeating each observation numerous times and eliminating some of them, the bootstrap approach generates a sample of the same size as the original sample [19-22]. Fig. 1 illustrates how this works to help you better grasp it.

2.5 The Syntax in R

```
#/Complete Dataset for a patient with Type 2 Diabetes/
#/Mellitus with Dyslipidaemia disease /

Input =("
BMI Gender Age Race Chd Wc Alt Tg Dys
23.90 0 58 0 1 35 10 1.40 1
21.09 1 36 0 1 30 89 1.28 1
34.60 0 47 0 1 33 23 1.04 1
23.62 0 50 0 1 33 31 0.90 1
29.40 0 47 0 1 32 24 1.41 1
20.31 1 46 0 1 29 22 1.87 1
?      ?      ?
?      ?      ?
27.80 0 56 0 0 96 42 1.14 0
22.30 0 51 0 1 35 24 0.97 1
24.03 0 58 1 1 30 15 0.97 1
29.33 1 57 0 1 33 26 1.43 1
19.53 1 53 0 1 28 25 2.47 1
25.80 1 71 0 1 94 9 1.50 0
")
data = read.table(textConnection(Input),header=TRUE)
#/Performing Bootstrap for 1000
mydata <- rbind.data.frame(data, stringsAsFactors = FALSE)
iboot <- sample(1:nrow(mydata),size=1000, replace = TRUE)
bootdata <- mydata[iboot,]

#/install the neuralnet package/
if(!require(neuralnet)){install.packages("neuralnet")}
library("neuralnet")

#/Checking for the missing values/.
apply(bootdata, 2, function(x) sum(is.na(x)))

#/Scaling the data for normalization
# Method (usually called feature scaling) to get all the scaled data
# in the range [0,1]/
max_data <- apply(bootdata, 2, max)
min_data <- apply(bootdata, 2, min)
data_scaled <- scale(bootdata,center = min_data, scale = max_data - min_data)

#/Randomly split the data into 70:30
#70 percent of the data at our disposal to train the network
#30 percent to test the network/

index = sample(1:nrow(bootdata),round(0.70*nrow(bootdata)))
train_data <- as.data.frame(data_scaled[index,])
test_data <- as.data.frame(data_scaled[-index,])

# Print Data
print(train_data)
print(test_data )
```

```
#/Build the network
#BMI 3 hidden layers have 3 and 2 neurons respectfully
#Input layer = 8/
#Output layer = 1/

n = names(bootdata)
f = as.formula(paste("BMI ~", paste(n[!n %in% "BMI"], collapse = " + ")))
nn = neuralnet(f,data=train_data,hidden=c(2),linear.output=T)
plot(nn)
options(warn=-1)

#/30 percent of the available data to do this:
#using only the first 2 columns representing the input variables
#of the network and 1 is the output for N.N./
predicted <- compute(nn,test_data[,1:8])

#/Use the Mean Squared Error N.N. (MSE-forecasts the network) as a measure of how
far
#away our predictions are from the real data/
MSE.net <- sum((test_data$BMI - predicted$net.result)^2)/nrow(test_data)
MSE.net

# /Fit a Linear Regression Model
# Use Mean Squared Error (MSE) as a Measure of Prediction Performance/
#/Predict the Values for the Test Set and Calculate the MSE/
Model <- lm(BMI~Gender+Age+Race+Chd+Wc+Alt+Tg+Dys, data=bootdata)
summary(Model)
test <- data[-index,]
predict_lm <- predict(Model,test)
MSE.lm <- sum((predict_lm - test$BMI)^2)/nrow(test)
MSE.lm

#/Printing the Value of M.S.E. for Linear Model and Neural Network/
print(paste(MSE.lm,MSE.net))

#Predicted data
data$PredictedBMI <- predict(Model,data)
distPred <- predict(Model, data)
preds <- predict(Model, data)
modelEval <- cbind(data$BMI, preds)
colnames(modelEval) <- c('Actual','Predicted')
modelEval <- as.data.frame(modelEval)
print (modelEval)
```

3. RESULTS

3.1 The Result of Regression Modelling

3.1.1Regression model without bootstrapping

Table 2 displays the outcomes of multiple linear regression with a training dataset, with BMI as the dependent variable and the study's outcome. In this case, the mean square error net (MSE.net) prediction is 0.167656, while the Predicted Mean Square Error (MSE.lm) is 8.509776. These values indicate the difference between the predicted and actual values. Also, the table shows how widely distributed our predictive data is and how well obtained model predicts. Interestingly, similar data will have a small spread following, demonstrating our forecast data's accuracy and reliability. A 70/30 split means that 70% of the data is used to train the network, and 30% is used to test the network. The findings of the multiple regression analysis are shown in Table 2. The model is illustrated below.

3.1.2 Regression model with bootstrapping

The bootstrapping technique was used in this section. Table 3 shows the results of multiple linear regression using a training set, where BMI served as the study's outcome. It also shows how dispersed our predictive data is and how accurate our model predicts future events. Mean Square Error prediction for the linear model's (MSE.lm) is 9.019188, while the mean square error net prediction for the neural network(MSE.net) is 0.202656. The difference between predicted and actual values is shown in these numbers. Our forecast data is accurate and reliable based on this small spread. The training and testing data are split 70:30, which means that 70% of the data is used to train the network, and 30% is used for testing. Table 3 illustrates the multiple regression analysis results. The model can be seen below.

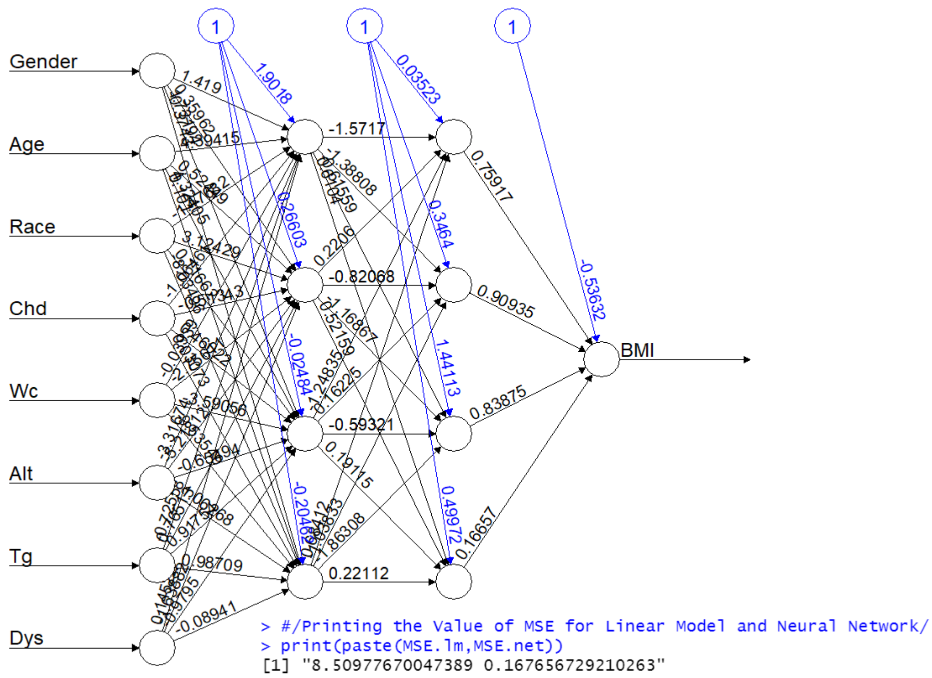

Fig. 2. The architecture of the best (MLP) model with eight input variables, two hidden layers, and one output node (Proposed Model)

Mse.lm 8.509776 mse.net 0.167656

Table 2. Result of multiple linear regression (MLR)

Variable	Estimate	Std. Error	t-Value	P-Value
(Intercept)	-13.569	12.214	-1.111	0.276
Gender	-2.289	1.409	-1.625	0.115
Age	-0.154	0.085	-1.805	0.082
Race	2.171	1.849	1.174	0.249
Chd	-0.237	3.126	-0.076	0.940
Wc	0.553	0.104	5.299	1.11e-05*
Alt	0.001	0.041	0.035	0.973
Tg	0.046	1.131	0.041	0.968
Dys	29.209	6.554	4.456	0.0001*

*Multiple Linear Regression was applied; *Significant at the level of the 0.05; R^2 : 60.21%*

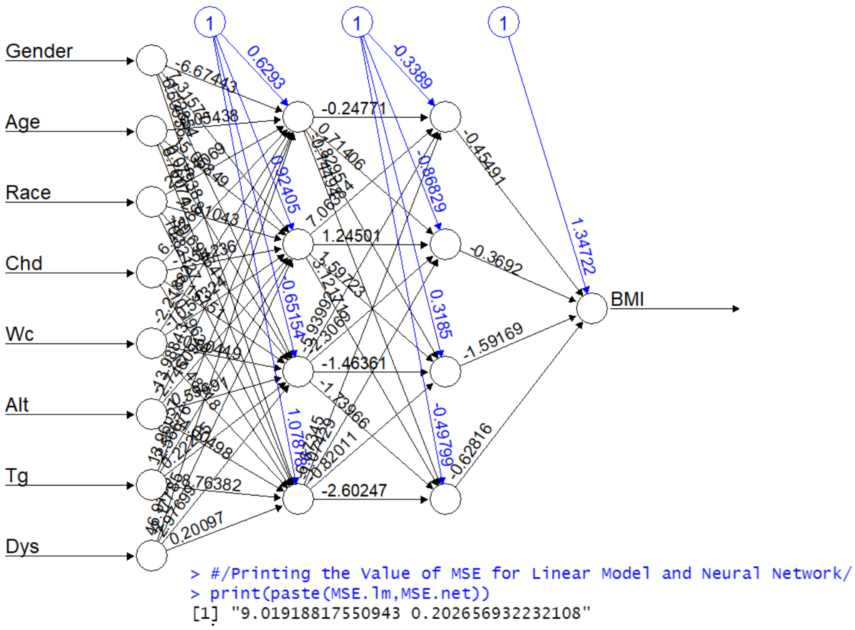

Fig. 3. The architecture of the best (MLP) model with eight input variables, two hidden layers, and one output node

Table 3. Result of multiple linear Regression with combining the bootstrap method training and testing dataset

Variable	Estimate	Std. Error	t-Value	*P*-Value
(Intercept)	-15.539	1.957	-7.942	5.38e-15*
Gender	-2.329	0.239	-9.749	< 2e-16*
Age	-0.151	0.014	-10.469	< 2e-16*
Race	2.504	0.315	7.938	5.54e-15*
Chd	-0.481	0.504	-0.954	0.340
Wc	0.572	0.017	34.289	< 2e-16*
Alt	0.002	0.007	0.242	0.809
Tg	0.046	0.191	0.241	0.809
Dys	30.769	1.037	29.677	< 2e-16*

*Multiple Linear Regression was applied; *Significant at the level of the 0.05; R^2 : 62.58%*

3.1.3 Regression model refinement

The bootstrapping method approach reveals whether the characteristics of the studied variables are significant or not. These significant variables act as a feeder for the new robust multiple linear regression. The insignificant variable will be eliminated from the model. Table 4 summarises the finding, and Fig. 4 shows the validated model.

3.2 Model Evaluation

The model built from the training data set was tested with the testing data set. In this case, the forecast value can be used to determine the model's evaluation. The accuracy of a prediction will be ascertained by comparing the actual and expected values.

The R syntax has developed the method for evaluating models. When two sets of data are compared, the predicted distance between the expected and actual values will be used to determine the difference. The smallest differences are found between the good model and the precise model. This method can be used to evaluate the following techniques.

According to the proposed model, Table 6 summarises the "Actual" and "Predicted" values. The researchers discovered that "actual" and "predicted" values were statistically equivalent. This proved the superiority of the proposed model.

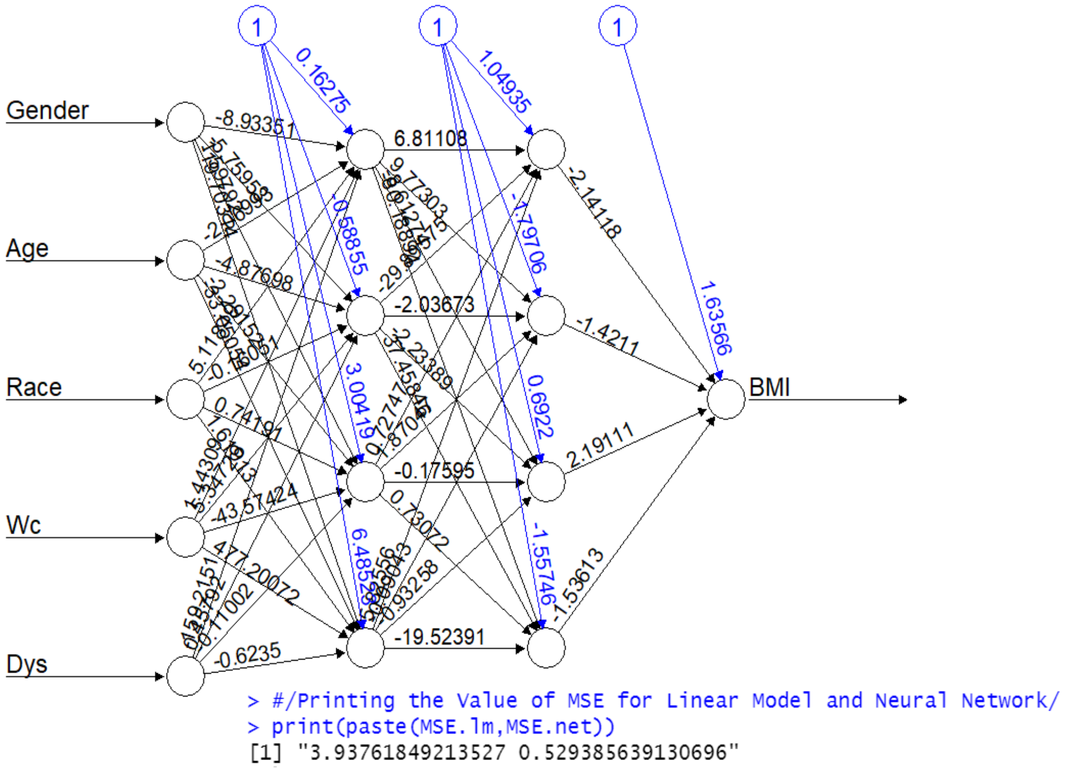

Fig. 4. The architecture of the best (M.L.P.) model with five input variables, two hidden layers, and one output node

Table 4. The Final Result of Multiple Linear Regression

Variable	Estimate	Std. Error	t-Value	*P*-Value
(Intercept)	-13.797	1.893	-7.288	6.4e-13
Gender	-2.069	0.217	-9.515	< 2e-16
Age	-0.139	0.013	-10.352	< 2e-16
Race	1.297	0.302	4.297	1.9e-05
Wc	0.547	0.018	31.077	< 2e-16
Dys	28.751	1.089	26.380	< 2e-16

*Multiple Linear Regression was applied; *Significant at the level of the 0.05; R^2 : 59.22%*

Table 5. Displays both the "Actual" and "Predicted" values using the proposed methodology

	Actual	Predicted		Actual	Predicted
1	23.90	26.08856	12	24.50	30.63321
2	21.09	24.25333	13	23.40	25.13303
3	34.60	26.60300	14	23.40	25.13303
4	23.62	26.16097	15	26.60	23.10047
5	29.40	26.04983	16	23.05	25.42426
6	20.31	22.22674	17	27.20	26.53059
7	41.70	40.43463	18	23.70	21.01180
8	22.52	22.44902	19	21.23	22.63257
9	22.60	21.02252	20	34.00	33.73299
10	24.70	26.69079	21	34.00	33.73299
11	21.08	23.76477			

Minimal discrepancies exist between the actual and predicted values. There were no significant differences in the paired-sample t-test as well.

Table 6. Comparison of the "Actual Data" with "Predicted Data"

Paired Samples Test	
Variables	**Mean (S.D.)**
Actual	26.029(5.614)
Predicted	26.324(1.77)
T Statistics (d.f)	-0.446(20)
p-value	0.661
Paired Sample Correlation (P)	0.841
p-value	0.00

**significant at 0.05; Independent samples T-Test was applied; Assumptions normality is fulfilled*

4. DISCUSSION

This study used Multilayer Perceptron to develop and validate the proposed hybrid model. Through this research paper, we were able to effectively use the presented technique, which is particularly helpful for predicting event probability due to its ease of use (predict the odds of being a case). Using the proposed method, one can accurately estimate the predicted value of a dependent variable.

We developed and harmonized a hybrid approach that resulted in a highly accurate and dependable prediction model. The findings revealed that gender, age, race, waist circumference and dyslipidaemia are the most critical factors influencing body mass index. The initial data was stored in a "mega" file created by the bootstrap technique. There were several replacement files generated during the bootstrap procedure. Statistical samples were generated and saved using the bootstrap method. As a final step, the bootstrap approach iteratively repeated this procedure, which took thousands of times. Finally, all of the data has been collected and is now ready to be analysed.

The R syntax algorithm had been used to integrate this proposed methodology with the application concept. The first step in this proposed methodology is to seek expert advice when choosing variables. When it comes to variable selection, the proposed method begins with a consultation with an expert. Then, data for training and testing will be kept apart. The application is linked to method-based methodology via the R syntax algorithm. The first step is to select variables with assistance and guidance. In the following step, the bootstrap technique will be applied to the data set. At this time, 70 per cent of the bootstrap data will be designated as training data, and 30 per cent will be marked as testing data. We will use data from the training dataset to build and test the model. A successful model will have the lowest value of predicted mean square error.

5. CONCLUSION

The study's findings helped the decision-maker achieve the best possible outcome. Data preparation and standardization are among the most challenging aspects of linear modelling. According to this study, statistical formulations, computation in R syntax, and the multiple linear regression package produced highly successful linear modelling.

CONSENT

Both the patient's privacy and medical condition were protected.

ETHICAL APPROVAL

The Human Research Ethics Committee of Universiti Sains Malaysia (JEPeM Code: USM/JEPeM/20090462) reviewed and approved the study.

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COMPETING INTERESTS

Authors have declared that no competing interests exist.

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