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Craniofacial Fractures Studies On Association Of Midface And Lower Face With Frontal Bone Injuries Using Integration Of Multilayer Perceptron (Mlp) And Logit Model Approach

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ABSTRACT

Introduction: The number of patients who present with facial injuries every year is on the rise. Most admission requires combined intervention by neurosurgery and maxillofacial team due to frontal bone fractures associated with various types of brain injury. The most common form of skull bone fracture is a frontal bone fracture. A high-impact head injury can fracture the frontal bone and other nearby bones. ***Objectives and Method:*** There is a retrospective study of patients with maxillofacial trauma at Hospital Universiti Sains Malaysia (USM) over five years (1 January 2012 to 31 December 2016). The hospital records of patients who sustained these fractures were analyzed using the newly developed R syntax. This study aims to determine which facial bone fractures are associated with a frontal bone fracture in maxillofacial trauma that occurs at the same time. Therefore, this study proposes an application of Artificial Neural Networks (ANNs) through a feed-forward network toward clinical study data on craniofacial fractures. The most associated bones related to the frontal bone fracture will be determined and will be the input for the multiple logistic regression (MLR). The analysis will be conducted entirely using developed R syntax. The generated syntax is divided into three major sections: Bootstrap (B), Multilayer Perceptron (MLP), and Multiple Logistic Regression. ***Results*:** This type of fracture occurred in 218 patients, with 80.7% male and 19.3% female. There is four variable which was Gender ($\beta_1 = 1.031$; $p < 0.25$; $95\%\ \mathrm{CI}: 1.028, 7.658$), Le Fort III fracture ($\beta_2 = 1.175$; $p < 0.25$; $95\%\ \mathrm{CI}: 0.831, 12.628$), mandibular symphysis fracture ($\beta_3 = -0.935$; $p < 0.25$; $95\%\ \mathrm{CI}: 0.115, 1.342$), and mandibular condylar fracture ($\beta_4 = -1.485$; $p < 0.25$; $95\%\ \mathrm{CI}: 0.028, 1.844$). The above MLP gave the lowest mean absolute deviance (0.0007179404). The accuracy obtained is about 99.928%. ***Conclusions:*** A Multilayer Feed-Forward Neural Network (MLFF) with multiple logistics regression for the modeling and prediction purpose of collected data is a good approach. The result obtained is being tested and checked from an important clinical point of view. This approachable technique was discovered to have superiority in the variable selection for multiple logistic regression modeling. In real life, many of the relationships between inputs and outputs are non-linear as well as complex relationships. As a result, using MLFF for variable selection, especially for modeling purposes, is a very good strategy and was discovered to have superiority of the variable selection for multiple logistic regression modeling.

Keywords: Craniofacial fractures, frontal bone fracture, logistic regression, and multilayer feed-forward neural network

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1. INTRODUCTION

The facial skeleton is made up of 14 bones with varying degrees of tolerance for external forces coming from various directions applied downward; they are quickly fractured by small forces applied in the opposite direction (Ellis, 2013; Nordin *et al.*, 2015). When a facial injury is extremely complex, it is referred to as a Maxillary fracture. Maxillofacial fractures are frequently seen in conjunction with polytrauma, and life-threatening injuries need a prompt multidisciplinary team approach and prolonged hospitalization. Due to the large magnitude of forces during trauma, frontal bone fractures are often associated with concomitant injuries to intracranial, ophthalmological, and maxillofacial (Strong, 2006). Manolidis (2014) stated that the most common findings associated with frontal bone fractures are neurological injuries comprised of open cerebral injury and cerebrospinal fluid (CSF) leak; Ophthalmological issues such as open globe injury, hyphema, relative afferent pupillary defect, traumatic optic neuropathy, disc edema, and corneal defect; and maxillofacial injuries such as Le Fort fracture, complex zygomatic fracture, nasoethmoidal, and mandible fracture. Abosadegh *et al.* (2019) investigated the Epidemiology of Maxillofacial Fractures (MFF) at a Malaysian Teaching Hospital. They discovered that road traffic accident was the most prevalent cause of MFF (83.1%), with motorcycle accidents accounting for most injuries (73.6%).

A maxillofacial fracture commonly occurs with a frontal bone fracture. In Nigeria between January 1997 and January 2003, a retrospective study involving two university teaching hospitals, namely the University of Benin Teaching Hospital and the Obafemi Awolowo University Teaching Hospital, discovered that 59 out of 102 (58%) patients had maxillofacial fractures in addition to face injury. At Hospital USM, most patients with facial injuries were surgically treated rather than conservatively. There has been a paradigm shift in treating these fractures in the last few decades, from closed reduction to open reduction of internal fixation. This may be attributed to a rise in the number of facial injuries; soft facial implants have become much more frequent (Menon *et al.*, 2011). 45% of patients received surgical treatment in the current report, while only 35% received conservative treatment. The most frequently used surgical technique was the intraoral vestibular approach. It was more widely used in the reduction of the zygomatic arch and zygomatic buttress. This was consistent with the findings of Punjabi *et al.* (2016) and can be explained by the advantages of the former method, which does not result in scarring and allows for a more direct application of force.

Adjacent anatomical structures often complicate injuries to the midface; it is important to diagnose and treat injuries as soon as possible to avoid complications. The most frequent midface fractures are complex zygomatic fractures and LeFort II fractures (Bailey, 2011). Understanding the connection between midface fractures and other injuries allows for more effective patient treatment and the prevention of further complications. The research was conducted in Hospital USM from 2013 to 2018 to determine the frequency, cause, trends, and association of midface fractures with other injuries in this category of patients.

Midface fractures (maxilla and zygoma) are common in all skull fractures and their occurrence varies by country, ranging from 17% in Brazil to 26% in Austria and 60% in Turkey (Chrcanovic *et al.*, 2010). This distinction may result from socioeconomic, cultural, and environmental variables related to shifting trauma patterns (Koorey *et al.*, 1992). The most prevalent fractures, according to Gassner *et al.* (2003), were midface fractures (72.5%) and mandible fractures (24.3%). The orbital fracture occurred on the floor in 22.3 percent of cases, and the typical Le Fort2 fracture was present (45%). Hogg *et al.* (2000) evaluated maximal fractures in the maxilla (23%) and orbit (22%). The primary goal of this research is to determine the relationship between frontal bone fracture and other closely related bones.

The fundamental goal of this study is to create a craniofacial fracture model that focuses on the interaction between frontal bone fractures and all conceivable midface fractures. A maxilla bone fracture occurs when there is bony discontinuity over the maxilla because of an injury such as a car accident. Although the causes of these injuries are different, their effects can be quite devastating depending on the magnitude of forces applied. It is essential to predict the most common type of frontal bone fracture caused by a high-velocity force caused by a traffic road accident. Four fractures were statistically significant ($p < 0.25$) relationship with frontal bone fractures with their clinical importance. Table 2 summarizes the association based on the priority rating.

This information would be useful for anyone dealing with a maxillary bone fracture. This study is expected to provide important information and a deeper understanding of frontal bone fracture and its various relationships. This work contributes to a better understanding of the mechanical behavior of the skull bones, particularly in the context of crashworthiness.

2. MATERIALS AND METHODS

Study Design

A methodology based on a computational retrospective cross-sectional analysis of patients who reported to the Oral and Maxillofacial Surgery unit and related Hospital Universiti Sains Malaysia was conducted between January 1, 2012, and December 31, 2016. Patients with maxillofacial fractures who presented to the emergency room or outpatient department were included in the study. Gender ($x1$), presence of Le Fort III ($x2$), presence of mandibular symphysis fracture ($x3$), and presence of mandibular condylar fracture ($x4$) are the variables chosen. The study was approved by the Universiti Sains Malaysia Research Ethics and Committee (Human) (USM/JEPeM/17040225). The patient's privacy and medical condition are both protected.

Data Collection Procedure

Data on each patient's age, gender, etiology, associated maxillofacial fractures, and treatment approach were gathered from official hospital records and entered into the data collection form that had been prepared previously. The patient’s name and registration number were obtained and written down in a yellow form provided by the recording unit to request the folders. These cases were selected from a pool of maxillofacial trauma cases presented to the Oral Maxillofacial Clinic. Both isolated cases and cases associated with other maxillofacial trauma were included in this study. Patients with incomplete and unavailable hospital records were excluded from this study.

Data Description

We used data from patients with underlying ZCF who visited the Hospital USM outpatient clinic for this study. A total of 218 patients took part in this study. The data summary for the selected variable in the analysis is described in Table 1.

Statistical Analysis

The data were analyzed for the association related to frontal bone fracture. Through the integrated developed syntax, R-Studio software was used to analyze the collected data. In addition to descriptive statistics such as frequencies and means, charts were used to display analyzed data. The advanced approach, such as logistics regression with the multilayer perceptron (MLP), analyses data. A multilayer perceptron (MLP) is a class of feed-forward artificial neural networks. The architecture of MLP consists of an input layer, hidden layer, and output layer.

Bootstrap

Bootstrap starts with a random sample drawn from the population and then computes sample statistics. Following that, the bootstrap copies the initial samples several times to create a pseudo-population, and then the bootstrap draws several samples of substitution. The bootstrap’s capabilities to generate a sample of the same size as the initial sample, with certain results repeated several times and others omitted. Random sampling with substitution yields samples that are not identical to the original sample. The bootstrap calculates statistics for each sample as it draws the sample with replacement (Efron & Tibshirani, 1993).

Multilayer Perceptron (MLP)

The most commonly used artificial neural network, the multilayer perceptron (MLP) technique, will be used. The input, hidden, and output layers make up MLP. The output node of this analysis is singular in the investigation sample since there is only one dependent variable. Equation $\hat{Y} = g_i\left(\sum_{j=1}^{2} n_j + E_3\right)$ constructs an MLP with N input nodes, H hidden nodes, and a single output node. The MLP with N input nodes, H hidden nodes, and a single output node is shown in Figure 1.

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The value $\hat{Y}$ is given as follows $\hat{Y} = g_i\left(\sum_{j=1}^{2} n_j + E_3\right)$, where E_3 the bias for the output node and *g* is an activation function. The value of a hidden node n_j is given as follows $n_j = g_i\left(\sum_{j=1}^{2} h_j + E_2\right)$, where E_2 the bias for the output node and *g* is an activation function. The value of a hidden node h_j is given as follows $h_j = g_i\left(\sum_{j=1}^{2} v_{ji} x_i + E_1\right)$ where E_1 the bias for the output node and *g* is an activation function, where v_{ji} the output *weight* from input node *i* to hidden node *j*, E_1 is the bias for hidden node *j* where *j* =1, 2 and x_i are the independent variables. Figure 1 gives the general architecture of the MLP. The variable chosen from the MLP procedure will be used as input for the multiple logistic regression (Mohamed *et al.*, 2011; Aleng *et al.*, 2012; Mohamed *et al.*, 2012; Aleng *et al.*, 2012).

Logistic Regression Models

When modeling a categorical dependent variable (with two categories) as a function of one or more independent variables, logistic regression can play a very important role. In logistic regression, it is important to have a nominal scale for the dependent variable. In this part, a series of logistic regression models are fitted to investigate the underlying relationship between frontal bone fracture and the specified explanatory factors. The model is fitted through the procedure of Maximum Likelihood Estimation (MLE) (Hosmer & Lemeshow, 2000). Let us define the following multiple logistics regression model for frontal bone fracture as follows.

Frontal Bone Skull = β_0 + β_1Gender + β_2 Le Fort III Fracture +β_3 Mandibular Symphysis Fracture + β_4 Mandibular Condylar Fracture + ε

where

$\beta_0,...,\beta_4$ are regression coefficients

is a random error ε is a random error

Methodology Building using R Syntax with Modification

Below is the R syntax for the Multiple Logistic Regression (MLR) modeling with embedded bootstrapping and Multilayer Perceptron (MLP). The full syntax of the calculation is given as follows.

```
###################################DATA INPUT##############################


# /STEP 1-DATASET FOR A SKULL BONE FRACTURE/

Input = ("
gender Lefort symphysis condylar Frontal
1  0  0  0  0
1  0  0  0  1
1  0  0  0  0
1  0  0  0  1
0  0  0  0  0
⋮     ⋮     ⋮
1  0  0  0  0
0  0  0  0  0
1  0  0  0  1
0  0  0  0  1
")
data1 = read.table(textConnection(Input), header = TRUE)
```

######################## **PERFORMING BOOTSTRAP**############################

#/Performing Bootstrap for 1000/

```
mydata <- rbind.data.frame (data1, stringsAsFactors = FALSE)
iboot <- sample(1:nrow(mydata),size=1000, replace = TRUE)
bootdata <- mydata[iboot,]
print (bootdata)
```

#########**PERFORMING MULTIPLE LOGISTICS & MODEL FITTING**####################

#/Performing Multiple Logistics & Model Fitting/

```
model <-glm(Frontal~gender+Lefort+symphysis+condylar, data=data1,family = "binomial")
summary(model)
```

#/Overall p-value for model/

```
anova(model, update(model, ~1), test="Chisq")
```

###############**MULTILAYER PERCEPTRON MODEL (MLP)**##########################

#/MultiLayer Perceptron Model (MLP)/

#/***STEP 2-Install the Neuralnet Package/***

```
if(!require(neuralnet)){install.packages("neural net")}
library ("neuralnet")
```

#/STEP 3- Checking For the Missing Values/

```
apply(bootdata, 2, function(x) sum(is.na(x)))
```

#/STEP 4 - Max-Min Data Normalization/

```
normalize <- function(x) {return ((x - min(x))/(max(x) - min(x)))}
maxmindf <- as.data.frame(lapply(bootdata, normalize))
```

#/STEP 5-Determine the Training and Testing of the Dataset/

#/70% for Training and 30% For Testing/

```
index = sample(1:nrow(bootdata),round(0.70*nrow(bootdata)))
Training <- as.data.frame(bootdata[index,])
Testing <- as.data.frame(bootdata[-index,])
```

#STEP 6 -Print Dataset -Training and Testing Data Set/

```
#print(Training)
#print(Testing)
```

#/STEP 7-Plotting the Architecture of MLP Neural Network/

```
nn <- neuralnet(Frontal~gender+Lefort+symphysis+condylar,data=Training, hidden=3,act.fct = "logistic", linear.output =
FALSE, stepmax = 100000)
plot(nn)
options(warn=-1)
nn$result.matrix
```

#/Testing the Accuracy of The Model- Predicted Result/

#/STEP 8-Predicted Results are Compared to the Actual Results/

```
Temp_test <- subset(Testing, select = c("gender","Lefort","symphysis","condylar"))
head(Temp_test)
```

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```
nn.results <- compute(nn, Temp_test)
results <- data.frame(actual = Testing$Frontal, prediction = nn.results$net.result)

#/STEP 9-Use the Predicted Mean Squared Error NN (MSE-forecasts the Network) as a
#/Measure of How Far the Predictions are From the Real Data/
predicted <- compute(nn,Testing[,1:4])
MSE.net <- sum((Testing$Frontal - predicted$net.result)^2)/nrow(Testing)

#/STEP 10-Printing the Predicted Mean Square Error/
MSE.net

################NEURAL NETWORK PARAMETER OUTPUT################
#/STEP 11-Neural Network Parameter Output/
library(neuralnet)
nn <-  neuralnet(Frontal ~gender+Lefort+symphysis+condylar,data=Training, hidden=4,act.fct = "logistic", linear.output = FALSE, stepmax = 1000000)
nn$result.matrix

######################MODEL VALIDATION CALCULATION###############
#/STEP 12- Model Validate/
results <- data.frame(actual = Testing$Frontal, prediction = nn.results$net.result)
results

####################MODEL ACCURACY CALCULATION##################
#/STEP 13- Model Accuracy/
predicted1=results$prediction*abs(diff(range(bootdata$Frontal)))+min(bootdata$Frontal)
#print(predicted)
actual1=results$actual*abs(diff(range(bootdata$Frontal)))+min(bootdata$Frontal)
#print(actual1)
deviation= ((actual1-predicted1))
#print(deviation)

# /Mean Absolute Deviance/
value=abs(mean(deviation))
print(value)
accuracy_in_percent=(1-value)*100
accuracy_in_percent

##################################THE END##############################
```

3. RESULTS

A total of 218 patients were discovered to have had a frontal bone fracture. Males made up 80.7%, while females made up 19.3 %. The table also showed that the fractures occurred most (36.2%, 79/218) in patients between 11 to 20 years old. Analysis of the etiology of frontal bone fractures showed that motor vehicle accident (74.8%) was the most common cause. Regarding care options, 45.0% of patients underwent surgery, 39.4% underwent conservative treatment, 14.7% declined treatment, and 0.9% underwent surgery elsewhere. The most common surgical approach used was intraoral upper vestibular (33.9%) followed by coronal and lateral eyebrow approach (17.9%), and the least opted were infraorbital, subconjunctival, and upper blepharoplasty approaches (0.9%). The data used in this study is given in Table 2.

Figure 2 shows the architecture of the MLP with one hidden layer, four input nodes, two hidden nodes, and one output node. Gender, Le Fort III Fracture, Mandibular Symphysis Fracture, and Mandibular Condylar Fracture had the lowest

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mean absolute deviance (0.0007179408) given by the above MLP with a combination of fours. The accuracy obtained is about 99.928%.

Table 3 shows the results of combining all possible variables, with the highest accuracy coming from the input of Gender, Le Fort III Fracture, Mandibular Symphysis Fracture, and Mandibular Condylar Fracture. From Table 3, it was found that the gender ($\beta_1 = 1.031$; $p < 0.25$; 95% CI : $1.028, 7.658$), Le Fort III Fracture ($\beta_2 = 1.175$; $p < 0.25$; 95% CI : $0.831, 12.628$), Mandibular Symphysis Fracture ($\beta_3 = -0.935$; $p < 0.25$; 95% CI : $0.115, 1.342$), and Mandibular Condylar Fracture ($\beta_4 = -1.485$; $p < 0.25$; 95% CI : $0.028, 1.844$) have a strong association with Frontal Bone Skull Fracture. The presence of a Le Fort III fracture increases the chances of fracturing the frontal bone threefold compared to those that do not have a Le Fort III fracture. Patients who have a mandibular fracture have a 60.8 percent lower chance of breaking their frontal bone than patients who do not have a mandibular fracture.

4. DISCUSSION

This paper examines the association of frontal bone fracture with Gender, Le Fort III Fracture, Mandibular Symphysis Fracture, and Mandibular Condylar Fracture. On the methodology building perception, the proposed methodology provides a good strategy to determine the most common fracture related to frontal bone fracture. The combining method in this paper allows the researcher to select the factor that has the most associated with the outcome of the study. The bootstrap used in this study, the real strength of the bootstrap is sampling with replacement (Efron & Tibshirani, 1993; Mooney & Robert, 1993). Our findings seem to agree with Ishman and Friedland (2004) and Dahiya *et al.* (1999) in terms of gender distribution and site involvement in frontal bone fracture. Male drivers are more likely to be involved in accidents when driving a right-hand drive vehicle in Malaysia due to the elevated risk of striking on the side, with regards to this, whereas striking on the side is more likely to happen to female drivers. Most patients had moderate head injuries and were treated conservatively. Frontal bone was the most usually injured by depressed fractures of the skull. The previous research has focused on frontal bone fractures, highlighting the frontal bone's compromise with le fort III and the relationship between these two structures and the skull-based.

Fractures of the midface are by far the most common type of injury, followed by fractures of the lower face (mandible) and upper face (frontal bone and superior orbital rim). Also referred to as the inferior jaw, the mandible is the weakest and largest bone in the skeleton of the face. The mandibular symphysis joins the bodies of the right and left mandibles. It connects with the lower jaw to provide open storage for the teeth. The temporomandibular articulation is formed on either side of the temporal bone, articulating with the temporomandibular ligament. The mandibular condylar fracture is also correlating to the frontal bone skull fracture. The relationship between these two structures and the skull is compromised by the frontal bones and mandibular condylar.

5. CONCLUSION

This research looks at the other bone that may be highly associated with frontal bone fractures. The result indicated that gender, presence of Le Fort III fracture, presence of mandibular symphysis fracture, and presence of mandibular condylar fracture play an important role in frontal bone fracture and may contribute to a better understanding of the mechanical behavior of the skull bones, particularly in terms of crashworthiness. At first, the clinical data was collected dan being bootstrap using the case of resampling technique. The boosting technique tends to larger the samples tend and produce better precision and narrower confidence intervals. It may also disclose important details about the sample analysis, such as the true nature of a relationship between two variables. Secondly, this paper proposed a technique to determine which bones have a high probability related to frontal bone fracture using the multilayer perceptron approach. Through this technique, all related bones will be tested, and those which have a high association will be selected for the modeling purpose. The selected combination of the studied variable with a high impact will be used as an input for multiple logistics regression. This will ensure the model obtained is highly accurate dan reliable. This is very useful for estimating the probabilities of events (predict the odds of being a case), including determining a relationship between features and the probabilities of outcomes.

ETHICAL APPROVAL

Ethical clearance for this study was obtained from the Research Ethics and Committee (Human), Universiti Sains Malaysia (USM/JEPeM/17040225). Both patients' identities and underlying medical conditions were kept confidential.

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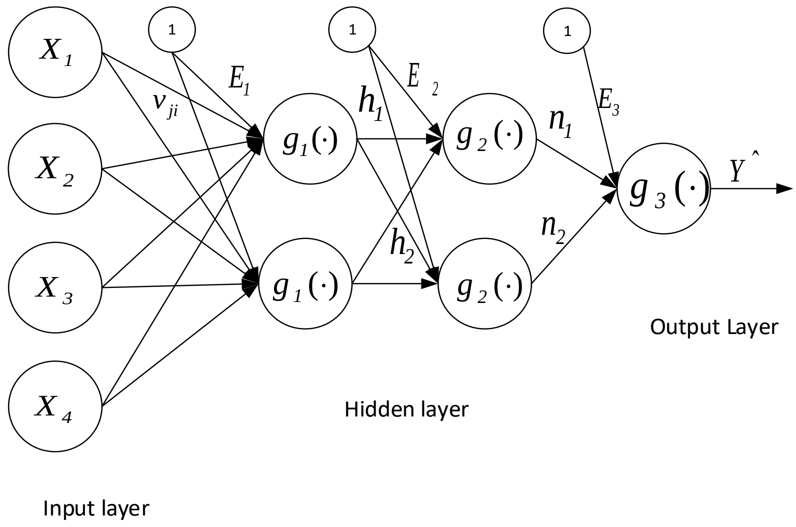

Figure 1: The general architecture of the MLP with two hidden layers, N input nodes, H hidden nodes, and one output node

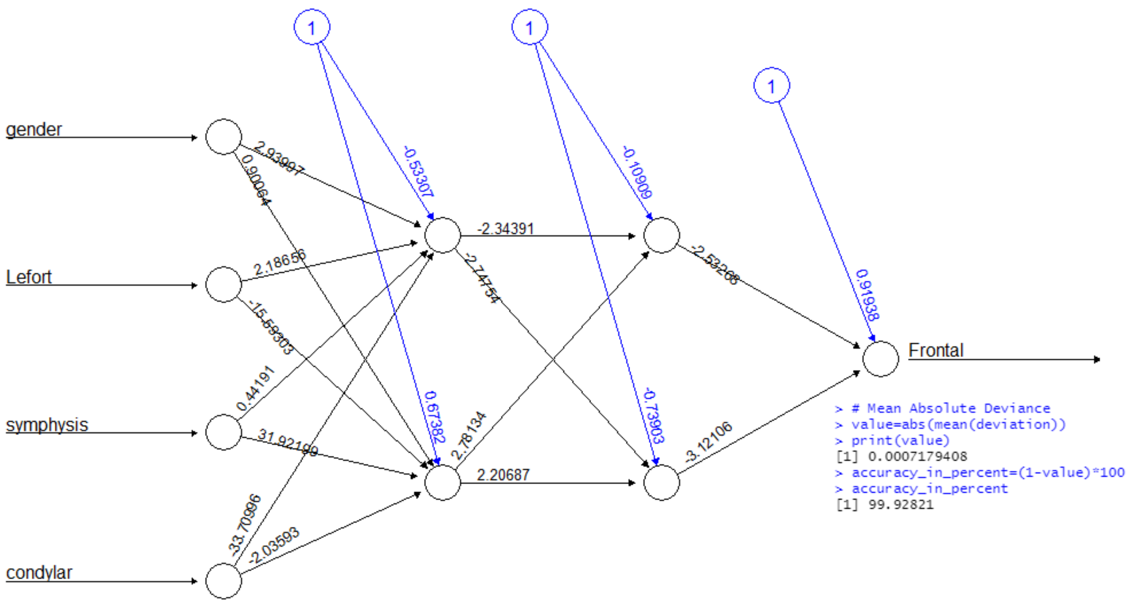

Figure 2: The architecture of the MLP with one hidden layer, 4 input nodes, 2 hidden nodes, and one output node

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Table 1: Data Description of Bone Skull Fracture

Variable	Code	Description
Frontal	Y	Presence of Frontal Bone Skull Fracture 1 = Yes, 0 = No
Gender	X1	Patient's Gender
Le Fort III	X2	Presence of Le Fort III Fracture 1 = Yes, 0 = No
Symphysis	X3	Presence of Mandibular Symphysis Fracture 1 = Yes, 0 = No
Condylar	X4	Presence of Mandibular Condylar Fracture 1 = Yes, 0 = No

Table 2: Possible Combination of Input Variable into MLP Model

Input Variable	Mean Absolute Deviance	Accuracy (%)
a. Gender, Lefort, Symphysis	0.0365	96.345
b. Gender, Lefort, Condylar	0.0149	98.511
c. Lefort, Symphysis, Condylar	0.0438	95.618
d. Symphysis, Condylar, Gender	0.0281	97.189
e. Gender, Lefort, Symphysis, Condylar	0.0087	99.126

Table 3: Logistic Regression Model

	B	S.E.	Wald	df	Sig.	Exp(B)
Gender of Patient	1.031	0.512	4.053	1	0.044	2.805
Presence of Le Fort III Fracture	1.175	0.694	2.865	1	0.091	3.239
Presence of Mandibular Symphysis Fracture	-0.935	0.627	2.223	1	0.136	0.392
Presence of Mandibular Condylar Fracture	-1.485	1.070	1.926	1	0.165	0.226
Constant	-1.882	0.480	15.383	1	0.000	0.152

Multiple logistic regression was applied; the Overall percentage for the classification table is 76.1%;