

# cirrhosis-prediction

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## Cirrhosis Prediction

Cirrhosis is a late stage of scarring (fibrosis) of the liver caused by many forms of liver diseases and conditions, such as hepatitis and chronic alcoholism. The following data contains the information collected from the Mayo Clinic trial in primary biliary cirrhosis (PBC) of the liver conducted between 1974 and 1984. A description of the clinical background for the trial and the covariates recorded here is in Chapter 0, especially Section 0.2 of Fleming and Harrington, Counting

Processes and Survival Analysis, Wiley, 1991. A more extended discussion can be found in Dickson, et al., Hepatology 10:1-7 (1989) and in Markus, et al., N Eng J of Med 320:1709-13 (1989).

A total of 424 PBC patients, referred to Mayo Clinic during that ten-year interval, met eligibility criteria for the randomized placebo-controlled trial of the drug D-penicillamine. The first 312 cases in the dataset participated in the randomized trial and contain largely complete data. The additional 112 cases did not participate in the clinical trial but consented to have basic measurements recorded and to be followed for survival. Six of those cases were lost to follow-up shortly after diagnosis, so the data here are on an additional 106 cases as well as the 312 randomized participants.

### Objectives

1. To build a model that will classify images in detecting the Liver Cirrhosis using Liver Ultrasound Data.
2. To compare or trade off four algorithms such as Logistic Regression (LR), Support Vector Machine (SVM), Multilayer Perceptron (MLP), and Convolutional Neural Networks (CNN) that is suitable in in detecting the Liver Cirrhosis using Liver Ultrasound Data.
3. To test the accuracy of four algorithms such as Logistic Regression (LR), Support Vector Machine (SVM), Multilayer Perceptron (MLP), and Convolutional Neural Networks (CNN) that will be fit in to detect Liver Cirrhosis Detection using Liver Ultrasound Data

## 1 - Packages

```
#install.packages("dplyr")  
  
library(dplyr)
```

```
##  
## Attaching package: 'dplyr'
```

```
## The following objects are masked from 'package:stats':  
##  
## filter, lag
```

```
## The following objects are masked from 'package:base':  
##  
## intersect, setdiff, setequal, union
```

```
library(corrplot)
```

```
## corrplot 0.92 loaded
```

```
library(gplots)
```

```
##  
## Attaching package: 'gplots'
```

```
## The following object is masked from 'package:stats':  
##  
## lowess
```

```
library(tidyverse)
```

```
## — Attaching core tidyverse packages ————— tidyverse 2.0.0 —  
## ✓ forcats 1.0.0 ✓ readr 2.1.4  
## ✓ ggplot2 3.4.4 ✓ stringr 1.5.1  
## ✓ lubridate 1.9.3 ✓ tibble 3.2.1  
## ✓ purrr 1.0.2 ✓ tidyr 1.3.0
```

```
## — Conflicts ————— tidyverse_conflicts() —  
## ✖ dplyr::filter() masks stats::filter()  
## ✖ dplyr::lag() masks stats::lag()  
## i Use the conflicted package (<http://conflicted.r-lib.org/>) to force all conflicts to become errors
```

```
library(finalfit)
library(ROSE)
```

```
## Loaded ROSE 0.0-4
```

```
library(caret)
```

```
## Loading required package: lattice
##
## Attaching package: 'caret'
##
## The following object is masked from 'package:purrr':
##
##     lift
```

```
library(randomForest)
```

```
## randomForest 4.7-1.1
## Type rfNews() to see new features/changes/bug fixes.
##
## Attaching package: 'randomForest'
##
## The following object is masked from 'package:ggplot2':
##
##     margin
##
## The following object is masked from 'package:dplyr':
##
##     combine
```

```
library(ggplot2)
library(e1071)
library(RSNNS)
```

```
## Loading required package: Rcpp
##
## Attaching package: 'RSNNS'
##
## The following objects are masked from 'package:caret':
##
##     confusionMatrix, train
```

```
library(tensorflow)
```

```
##  
## Attaching package: 'tensorflow'  
##  
## The following object is masked from 'package:RSNNS':  
##  
##      train  
##  
## The following object is masked from 'package:caret':  
##  
##      train
```

```
library(keras)  
library(smotefamily)  
  
library(reticulate)  
use_python("/usr/local/bin/python3")
```

## 2 - Data Preparation & EDA

```
cirrhosis_data <- read.csv("input/cirrhosis.csv")  
  
print(head(cirrhosis_data))
```

```
##      ID N_Days Status      Drug      Age Sex Ascites Hepatomegaly Spiders Edema
## 1  1      400      D D-penicillamine 21464  F      Y      Y      Y      Y
## 2  2      4500     C D-penicillamine 20617  F      N      Y      Y      N
## 3  3      1012     D D-penicillamine 25594  M      N      N      N      S
## 4  4      1925     D D-penicillamine 19994  F      N      Y      Y      S
## 5  5      1504     CL      Placebo 13918  F      N      Y      Y      N
## 6  6      2503     D      Placebo 24201  F      N      Y      N      N
##      Bilirubin Cholesterol Albumin Copper Alk_Phos      SGOT Tryglicerides Platelets
## 1      14.5      261      2.60      156      1718.0 137.95      172      190
## 2      1.1      302      4.14      54      7394.8 113.52      88      221
## 3      1.4      176      3.48      210      516.0 96.10      55      151
## 4      1.8      244      2.54      64      6121.8 60.63      92      183
## 5      3.4      279      3.53      143      671.0 113.15      72      136
## 6      0.8      248      3.98      50      944.0 93.00      63      NA
##      Prothrombin Stage
## 1      12.2      4
## 2      10.6      3
## 3      12.0      4
## 4      10.3      4
## 5      10.9      3
## 6      11.0      3
```

```
cirrhosis_data <- cirrhosis_data %>%
  select(-ID)
```

```
str(cirrhosis_data)
```

```
## 'data.frame':    418 obs. of  19 variables:
## $ N_Days       : int  400 4500 1012 1925 1504 2503 1832 2466 2400 51 ...
## $ Status       : chr   "D" "C" "D" "D" ...
## $ Drug         : chr   "D-penicillamine" "D-penicillamine" "D-penicillamine" "D-pe
nicillamine" ...
## $ Age         : int  21464 20617 25594 19994 13918 24201 20284 19379 15526 25772
...
## $ Sex         : chr   "F" "F" "M" "F" ...
## $ Ascites     : chr   "Y" "N" "N" "N" ...
## $ Hepatomegaly : chr   "Y" "Y" "N" "Y" ...
## $ Spiders     : chr   "Y" "Y" "N" "Y" ...
## $ Edema       : chr   "Y" "N" "S" "S" ...
## $ Bilirubin   : num   14.5 1.1 1.4 1.8 3.4 0.8 1 0.3 3.2 12.6 ...
## $ Cholesterol : int   261 302 176 244 279 248 322 280 562 200 ...
## $ Albumin     : num   2.6 4.14 3.48 2.54 3.53 3.98 4.09 4 3.08 2.74 ...
## $ Copper      : int   156 54 210 64 143 50 52 52 79 140 ...
## $ Alk_Phos    : num   1718 7395 516 6122 671 ...
## $ SGOT        : num   137.9 113.5 96.1 60.6 113.2 ...
## $ Tryglicerides: int   172 88 55 92 72 63 213 189 88 143 ...
## $ Platelets   : int   190 221 151 183 136 NA 204 373 251 302 ...
## $ Prothrombin : num   12.2 10.6 12 10.3 10.9 11 9.7 11 11 11.5 ...
## $ Stage       : int    4 3 4 4 3 3 3 3 2 4 ...
```

```
summary(cirrhosis_data)
```

```

##      N_Days      Status      Drug      Age
##  Min.    : 41    Length:418    Length:418    Min.    : 9598
##  1st Qu.:1093    Class :character    Class :character    1st Qu.:15644
##  Median :1730    Mode  :character    Mode  :character    Median :18628
##  Mean   :1918                                Mean   :18533
##  3rd Qu.:2614                                3rd Qu.:21272
##  Max.   :4795                                Max.   :28650
##
##      Sex      Ascites      Hepatomegaly      Spiders
##  Length:418    Length:418    Length:418    Length:418
##  Class :character    Class :character    Class :character    Class :character
##  Mode  :character    Mode  :character    Mode  :character    Mode  :character
##
##
##
##      Edema      Bilirubin      Cholesterol      Albumin
##  Length:418    Min.    : 0.300    Min.    : 120.0    Min.    :1.960
##  Class :character    1st Qu.: 0.800    1st Qu.: 249.5    1st Qu.:3.243
##  Mode  :character    Median : 1.400    Median : 309.5    Median :3.530
##                                Mean   : 3.221    Mean   : 369.5    Mean   :3.497
##                                3rd Qu.: 3.400    3rd Qu.: 400.0    3rd Qu.:3.770
##                                Max.    :28.000    Max.    :1775.0    Max.    :4.640
##                                NA's    :134
##      Copper      Alk_Phos      SGOT      Tryglicerides
##  Min.    : 4.00    Min.    : 289.0    Min.    : 26.35    Min.    : 33.00
##  1st Qu.: 41.25    1st Qu.: 871.5    1st Qu.: 80.60    1st Qu.: 84.25
##  Median : 73.00    Median : 1259.0    Median :114.70    Median :108.00
##  Mean   : 97.65    Mean   : 1982.7    Mean   :122.56    Mean   :124.70
##  3rd Qu.:123.00    3rd Qu.: 1980.0    3rd Qu.:151.90    3rd Qu.:151.00
##  Max.   :588.00    Max.   :13862.4    Max.   :457.25    Max.   :598.00
##  NA's   :108      NA's   :106      NA's   :106      NA's   :136
##      Platelets      Prothrombin      Stage
##  Min.    : 62.0    Min.    : 9.00    Min.    :1.000
##  1st Qu.:188.5    1st Qu.:10.00    1st Qu.:2.000
##  Median :251.0    Median :10.60    Median :3.000
##  Mean   :257.0    Mean   :10.73    Mean   :3.024
##  3rd Qu.:318.0    3rd Qu.:11.10    3rd Qu.:4.000
##  Max.   :721.0    Max.   :18.00    Max.   :4.000
##  NA's   :11      NA's   :2      NA's   :6

```

## Handling Missing Values

```
# drop the 6 rows with missing 'Stage'
cirrhosis_data <- cirrhosis_data[complete.cases(cirrhosis_data$Stage), ]

# Numerical columns --> Median
# Impute missing values in numerical columns with the median.
numerical_columns <- sapply(cirrhosis_data, is.numeric)

for (c in names(cirrhosis_data[, numerical_columns])) {
  cirrhosis_data[, c] <- ifelse(is.na(cirrhosis_data[, c]), median(cirrhosis_data[,
c], na.rm = TRUE), cirrhosis_data[, c])
}

# Categorical columns --> Most Frequent
# Impute missing values in categorical columns with the most frequent value
categorical_columns <- sapply(cirrhosis_data, is.factor)

for (c in names(cirrhosis_data[, categorical_columns])) {
  cirrhosis_data[, c] <- ifelse(is.na(cirrhosis_data[, c]), levels(cirrhosis_data[,
c])[which.max(table(cirrhosis_data[, c]))], cirrhosis_data[, c])
}

# Convert 'Stage' to integer
cirrhosis_data$Stage <- as.integer(cirrhosis_data$Stage)

cirrhosis_data <- na.omit(cirrhosis_data)
```

## Missing Values

```
summary(cirrhosis_data)
```



```

##      N_Days      Status      Drug      Age
##  Min.    : 41      Length:312      Length:312      Min.    : 9598
##  1st Qu.:1191      Class :character      Class :character      1st Qu.:15428
##  Median :1840      Mode  :character      Mode  :character      Median :18188
##  Mean   :2006                                     Mean   :18269
##  3rd Qu.:2697                                     3rd Qu.:20715
##  Max.   :4556                                     Max.   :28650
##      Sex      Ascites      Hepatomegaly      Spiders
##  Length:312      Length:312      Length:312      Length:312
##  Class :character      Class :character      Class :character      Class :character
##  Mode  :character      Mode  :character      Mode  :character      Mode  :character
##
##
##
##      Edema      Bilirubin      Cholesterol      Albumin
##  Length:312      Min.    : 0.300      Min.    : 120.0      Min.    :1.96
##  Class :character      1st Qu.: 0.800      1st Qu.: 255.8      1st Qu.:3.31
##  Mode  :character      Median : 1.350      Median : 309.5      Median :3.55
##                                     Mean   : 3.256      Mean   : 364.1      Mean   :3.52
##                                     3rd Qu.: 3.425      3rd Qu.: 392.2      3rd Qu.:3.80
##                                     Max.   :28.000      Max.   :1775.0      Max.   :4.64
##      Copper      Alk_Phos      SGOT      Tryglicerides
##  Min.    : 4.00      Min.    : 289.0      Min.    : 26.35      Min.    : 33.0
##  1st Qu.: 41.75      1st Qu.: 871.5      1st Qu.: 80.60      1st Qu.: 87.0
##  Median : 73.00      Median : 1259.0      Median :114.70      Median :108.0
##  Mean   : 97.49      Mean   : 1982.7      Mean   :122.56      Mean   :123.1
##  3rd Qu.:123.00      3rd Qu.: 1980.0      3rd Qu.:151.90      3rd Qu.:145.2
##  Max.   :588.00      Max.   :13862.4      Max.   :457.25      Max.   :598.0
##      Platelets      Prothrombin      Stage
##  Min.    : 62.0      Min.    : 9.00      Min.    :1.000
##  1st Qu.:200.0      1st Qu.:10.00      1st Qu.:2.000
##  Median :255.5      Median :10.60      Median :3.000
##  Mean   :261.8      Mean   :10.73      Mean   :3.032
##  3rd Qu.:322.0      3rd Qu.:11.10      3rd Qu.:4.000
##  Max.   :563.0      Max.   :17.10      Max.   :4.000

```

## Recode and Mutate Data

```
cirrhosis_data <- cirrhosis_data %>%
  mutate(
    Sex = recode(Sex, 'M' = 0, 'F' = 1),
    Ascites = recode(Ascites, 'N' = 0, 'Y' = 1),
    Drug = recode(Drug, 'D-penicillamine' = 0, 'Placebo' = 1),
    Hepatomegaly = recode(Hepatomegaly, 'N' = 0, 'Y' = 1),
    Spiders = recode(Spiders, 'N' = 0, 'Y' = 1),
    Edema = recode(Edema, 'N' = 0, 'Y' = 1, 'S' = -1),
    Status = recode(Status, 'C' = 0, 'CL' = 1, 'D' = -1),
  )
```

```
str(cirrhosis_data)
```

```
## 'data.frame':    312 obs. of  19 variables:
## $ N_Days      : int  400 4500 1012 1925 1504 2503 1832 2466 2400 51 ...
## $ Status      : num  -1 0 -1 -1 1 -1 0 -1 -1 -1 ...
## $ Drug        : num   0 0 0 0 1 1 1 1 0 1 ...
## $ Age         : int  21464 20617 25594 19994 13918 24201 20284 19379 15526 25772
## ...
## $ Sex         : num   1 1 0 1 1 1 1 1 1 1 ...
## $ Ascites     : num   1 0 0 0 0 0 0 0 0 1 ...
## $ Hepatomegaly : num   1 1 0 1 1 1 1 0 0 0 ...
## $ Spiders     : num   1 1 0 1 1 0 0 0 1 1 ...
## $ Edema       : num   1 0 -1 -1 0 0 0 0 0 1 ...
## $ Bilirubin   : num  14.5 1.1 1.4 1.8 3.4 0.8 1 0.3 3.2 12.6 ...
## $ Cholesterol : num  261 302 176 244 279 248 322 280 562 200 ...
## $ Albumin     : num   2.6 4.14 3.48 2.54 3.53 3.98 4.09 4 3.08 2.74 ...
## $ Copper      : num  156 54 210 64 143 50 52 52 79 140 ...
## $ Alk_Phos    : num  1718 7395 516 6122 671 ...
## $ SGOT        : num  137.9 113.5 96.1 60.6 113.2 ...
## $ Tryglicerides: num  172 88 55 92 72 63 213 189 88 143 ...
## $ Platelets   : int   190 221 151 183 136 249 204 373 251 302 ...
## $ Prothrombin : num  12.2 10.6 12 10.3 10.9 11 9.7 11 11 11.5 ...
## $ Stage       : int    4 3 4 4 3 3 3 3 2 4 ...
## - attr(*, "na.action")= 'omit' Named int [1:100] 313 314 315 316 317 318 319 320
321 322 ...
## ..- attr(*, "names")= chr [1:100] "314" "315" "316" "318" ...
```

## 3 - Preprocessing Data

```
#Upsampling
balancedData <- SMOTE(
  X = cirrhosis_data,
  target = cirrhosis_data$Stage,
  K = 3)

#Standardize
scaledData <- balancedData$data
```

```
X <- subset(scaledData, select = -c(Status, N_Days, Stage, class))
y <- scaledData$Stage

X_matrix <- as.matrix(sapply(X, as.numeric))
```

```
#Splitting the data 80/20
set.seed(23)
split <- createDataPartition(scaledData$Stage, p = 0.8, list = FALSE)
X_train <- X_matrix[split, ]
X_test <- X_matrix[-split, ]
y_train <- y[split]
y_test <- y[-split]
```

## 4 - Modelling

### Random Forest

```
rf_model <- randomForest(x = X_train, y = factor(y_train), ntree = 500)

# Make predictions on the test set
predictions <- predict(rf_model, newdata = X_test)

# Evaluate the model
conf_matrix <- table(predictions, y_test)
print(conf_matrix)
```

```
##           y_test
## predictions  1  2  3  4
##           1 58  4  3  0
##           2  0  1  0  2
##           3  0  7 15  6
##           4  0  1  6 13
```

```
accuracy <- sum(diag(conf_matrix)) / sum(conf_matrix)
print(paste("Accuracy:", round(accuracy, 4)))
```

```
## [1] "Accuracy: 0.75"
```

```
# Feature importance
importance(rf_model)
```

```
##              MeanDecreaseGini
## Drug              14.185748
## Age              22.565158
## Sex              6.064978
## Ascites          1.796973
## Hepatomegaly     36.645801
## Spiders          10.495472
## Edema            2.446834
## Bilirubin        35.717158
## Cholesterol      20.481980
## Albumin          28.290631
## Copper           18.491163
## Alk_Phos         21.426696
## SGOT             24.696566
## Tryglicerides    25.902124
## Platelets        21.301023
## Prothrombin      21.171215
```

## SVM

```
svm_model = svm(x = X_train,
                y = y_train,
                type = 'C-classification',
                kernel = 'linear')

# Make predictions on the test set
predictions <- predict(svm_model, newdata = X_test)

# Evaluate the model
conf_matrix <- table(predictions, y_test)
conf_matrix
```

```
##           y_test
## predictions  1  2  3  4
##           1 58  7  4  1
##           2  0  0  0  1
##           3  0  3 15  6
##           4  0  3  5 13
```

```
accuracy <- (sum(diag(conf_matrix)) / sum(conf_matrix))
print(paste("Accuracy:", round(accuracy, 4)))
```

```
## [1] "Accuracy: 0.7414"
```

```
# dataframe to matrix
```

```
matrixX_train <- as.matrix(X_train)
matrixy_train <- as.matrix(y_train)
matrixX_test  <- as.matrix(X_test)
matrixy_test  <- as.matrix(y_test)
```

## MLP

```
model_mlp <- keras_model_sequential()
input_shape <- dim(X_train)[2]

model_mlp %>%
  layer_dense(units = 32, activation = 'relu', input_shape = input_shape) %>%
  layer_dense(units = 64, activation = 'relu') %>%
  layer_dense(units = 32, activation = 'relu') %>%
  layer_dense(units = 5, activation = 'softmax') %>%
  compile(
    optimizer = 'adam',
    loss = 'sparse_categorical_crossentropy',
    metrics = c('accuracy'))

summary(model_mlp)
```

```
## Model: "sequential"
```

```
##
## Layer (type)                Output Shape                Param #
## =====
## dense_3 (Dense)             (None, 32)                  544
## dense_2 (Dense)             (None, 64)                  2112
## dense_1 (Dense)             (None, 32)                  2080
## dense (Dense)               (None, 5)                   165
## =====
## Total params: 4901 (19.14 KB)
## Trainable params: 4901 (19.14 KB)
## Non-trainable params: 0 (0.00 Byte)
##
```

```
model_mlp %>% fit(matrixX_train, matrixy_train, epochs = 20, validation_data = list(m
atrixX_test, matrixy_test))
```

```
## Epoch 1/20
## 15/15 - 0s - loss: 378.8661 - accuracy: 0.3141 - val_loss: 223.1509 - val_accurac
y: 0.5086 - 483ms/epoch - 32ms/step
## Epoch 2/20
## 15/15 - 0s - loss: 95.0060 - accuracy: 0.3205 - val_loss: 70.0251 - val_accuracy:
0.3103 - 70ms/epoch - 5ms/step
## Epoch 3/20
## 15/15 - 0s - loss: 51.6143 - accuracy: 0.3803 - val_loss: 52.1501 - val_accuracy:
0.4052 - 49ms/epoch - 3ms/step
## Epoch 4/20
## 15/15 - 0s - loss: 52.1113 - accuracy: 0.3312 - val_loss: 73.0927 - val_accuracy:
0.1724 - 50ms/epoch - 3ms/step
## Epoch 5/20
## 15/15 - 0s - loss: 45.1129 - accuracy: 0.3803 - val_loss: 57.0884 - val_accuracy:
0.2931 - 50ms/epoch - 3ms/step
## Epoch 6/20
## 15/15 - 0s - loss: 23.6788 - accuracy: 0.3868 - val_loss: 35.1046 - val_accuracy:
0.5000 - 48ms/epoch - 3ms/step
## Epoch 7/20
## 15/15 - 0s - loss: 33.0452 - accuracy: 0.3226 - val_loss: 76.1884 - val_accuracy:
0.5000 - 53ms/epoch - 4ms/step
## Epoch 8/20
## 15/15 - 0s - loss: 43.3555 - accuracy: 0.3462 - val_loss: 33.5154 - val_accuracy:
0.5431 - 49ms/epoch - 3ms/step
## Epoch 9/20
## 15/15 - 0s - loss: 36.5277 - accuracy: 0.3675 - val_loss: 41.8665 - val_accuracy:
0.1379 - 46ms/epoch - 3ms/step
## Epoch 10/20
```

```
## 15/15 - 0s - loss: 19.0711 - accuracy: 0.4017 - val_loss: 35.9004 - val_accuracy:
0.3276 - 48ms/epoch - 3ms/step
## Epoch 11/20
## 15/15 - 0s - loss: 24.9486 - accuracy: 0.3462 - val_loss: 43.3852 - val_accuracy:
0.5000 - 48ms/epoch - 3ms/step
## Epoch 12/20
## 15/15 - 0s - loss: 28.1007 - accuracy: 0.3739 - val_loss: 29.1176 - val_accuracy:
0.2241 - 48ms/epoch - 3ms/step
## Epoch 13/20
## 15/15 - 0s - loss: 23.3510 - accuracy: 0.4038 - val_loss: 39.1374 - val_accuracy:
0.2328 - 45ms/epoch - 3ms/step
## Epoch 14/20
## 15/15 - 0s - loss: 35.9711 - accuracy: 0.3419 - val_loss: 48.1245 - val_accuracy:
0.2586 - 48ms/epoch - 3ms/step
## Epoch 15/20
## 15/15 - 0s - loss: 36.2496 - accuracy: 0.4017 - val_loss: 29.7412 - val_accuracy:
0.2414 - 46ms/epoch - 3ms/step
## Epoch 16/20
## 15/15 - 0s - loss: 27.6098 - accuracy: 0.3504 - val_loss: 53.3075 - val_accuracy:
0.4828 - 46ms/epoch - 3ms/step
## Epoch 17/20
## 15/15 - 0s - loss: 32.7499 - accuracy: 0.3419 - val_loss: 39.1943 - val_accuracy:
0.2500 - 43ms/epoch - 3ms/step
## Epoch 18/20
## 15/15 - 0s - loss: 36.5610 - accuracy: 0.3440 - val_loss: 82.3010 - val_accuracy:
0.2500 - 46ms/epoch - 3ms/step
## Epoch 19/20
## 15/15 - 0s - loss: 48.4172 - accuracy: 0.3632 - val_loss: 44.0441 - val_accuracy:
0.2500 - 46ms/epoch - 3ms/step
## Epoch 20/20
## 15/15 - 0s - loss: 32.2664 - accuracy: 0.3547 - val_loss: 20.2731 - val_accuracy:
0.2414 - 44ms/epoch - 3ms/step
```

```
score <- model_mlp %>% evaluate(matrixX_test, matrixy_test)
```

```
## 4/4 - 0s - loss: 20.2731 - accuracy: 0.2414 - 24ms/epoch - 6ms/step
```

```
score
```

```
##      loss  accuracy
## 20.2731247 0.2413793
```

## CNN

```

CNNmodel <- keras_model_sequential()

CNNmodel %>%
  layer_conv_1d(filters = 32, kernel_size = 3, padding = 'same', activation = 'relu',
input_shape = c(16, 1)) %>%
  layer_max_pooling_1d(pool_size = 2) %>%
  layer_conv_1d(filters = 64, kernel_size = 3, padding = 'same', activation = 'relu')
%>%
  layer_max_pooling_1d(pool_size = 2) %>%
  layer_conv_1d(filters = 32, kernel_size = 3, padding = 'same', activation = 'relu')
%>%
  layer_max_pooling_1d(pool_size = 2) %>%
  layer_dropout(0.25) %>%
  layer_flatten() %>%
  layer_dense(units = 16, activation = 'relu') %>%
  layer_dense(units = 5, activation = 'softmax') %>%
  compile(
    loss = 'sparse_categorical_crossentropy',
    optimizer = 'adam',
    metrics = 'accuracy')
summary(CNNmodel)

```

```

## Model: "sequential_1"
##
## Layer (type)                Output Shape              Param #
## =====
## conv1d_2 (Conv1D)           (None, 16, 32)           128
## max_pooling1d_2 (MaxPooling1D) (None, 8, 32)            0
## conv1d_1 (Conv1D)           (None, 8, 64)            6208
## max_pooling1d_1 (MaxPooling1D) (None, 4, 64)            0
## conv1d (Conv1D)             (None, 4, 32)            6176
## max_pooling1d (MaxPooling1D) (None, 2, 32)            0
## dropout (Dropout)          (None, 2, 32)            0
## flatten (Flatten)           (None, 64)               0
## dense_5 (Dense)             (None, 16)              1040
## dense_4 (Dense)            (None, 5)                85
## =====
## Total params: 13637 (53.27 KB)
## Trainable params: 13637 (53.27 KB)
## Non-trainable params: 0 (0.00 Byte)
##

```



```
CNNmodel %>%
  fit(
    x = matrixX_train,
    y = matrixy_train,
    epochs = 20,
    validation_data = list(matrixX_test, matrixy_test))

## Epoch 1/20
## 15/15 - 1s - loss: 259.8183 - accuracy: 0.3141 - val_loss: 67.8598 - val_accuracy:
0.5000 - 629ms/epoch - 42ms/step
## Epoch 2/20
## 15/15 - 0s - loss: 90.4796 - accuracy: 0.3504 - val_loss: 41.9381 - val_accuracy:
0.5086 - 57ms/epoch - 4ms/step
## Epoch 3/20
## 15/15 - 0s - loss: 32.0528 - accuracy: 0.2842 - val_loss: 3.6813 - val_accuracy:
0.2069 - 59ms/epoch - 4ms/step
## Epoch 4/20
## 15/15 - 0s - loss: 12.0261 - accuracy: 0.2286 - val_loss: 2.2647 - val_accuracy:
0.5086 - 65ms/epoch - 4ms/step
## Epoch 5/20
## 15/15 - 0s - loss: 6.8257 - accuracy: 0.4359 - val_loss: 1.5914 - val_accuracy: 0.
5000 - 60ms/epoch - 4ms/step
## Epoch 6/20
## 15/15 - 0s - loss: 5.0420 - accuracy: 0.4359 - val_loss: 1.5841 - val_accuracy: 0.
5000 - 65ms/epoch - 4ms/step
## Epoch 7/20
## 15/15 - 0s - loss: 4.7129 - accuracy: 0.4316 - val_loss: 1.5770 - val_accuracy: 0.
5000 - 64ms/epoch - 4ms/step
## Epoch 8/20
## 15/15 - 0s - loss: 4.5016 - accuracy: 0.4103 - val_loss: 1.5685 - val_accuracy: 0.
5000 - 64ms/epoch - 4ms/step
## Epoch 9/20
## 15/15 - 0s - loss: 3.2632 - accuracy: 0.4167 - val_loss: 1.5613 - val_accuracy: 0.
5000 - 62ms/epoch - 4ms/step
## Epoch 10/20
## 15/15 - 0s - loss: 3.3154 - accuracy: 0.4231 - val_loss: 1.5533 - val_accuracy: 0.
5000 - 61ms/epoch - 4ms/step
## Epoch 11/20
## 15/15 - 0s - loss: 2.7117 - accuracy: 0.3996 - val_loss: 1.5457 - val_accuracy: 0.
5000 - 63ms/epoch - 4ms/step
## Epoch 12/20
## 15/15 - 0s - loss: 2.7840 - accuracy: 0.4637 - val_loss: 1.5472 - val_accuracy: 0.
5000 - 62ms/epoch - 4ms/step
## Epoch 13/20
## 15/15 - 0s - loss: 2.3919 - accuracy: 0.4658 - val_loss: 1.5318 - val_accuracy: 0.
5000 - 63ms/epoch - 4ms/step
```

```
## Epoch 14/20
## 15/15 - 0s - loss: 2.2709 - accuracy: 0.4615 - val_loss: 1.5246 - val_accuracy: 0.5000 - 62ms/epoch - 4ms/step
## Epoch 15/20
## 15/15 - 0s - loss: 2.4526 - accuracy: 0.4722 - val_loss: 1.5172 - val_accuracy: 0.5000 - 61ms/epoch - 4ms/step
## Epoch 16/20
## 15/15 - 0s - loss: 2.1170 - accuracy: 0.4509 - val_loss: 1.5100 - val_accuracy: 0.5000 - 61ms/epoch - 4ms/step
## Epoch 17/20
## 15/15 - 0s - loss: 2.2062 - accuracy: 0.4466 - val_loss: 1.5031 - val_accuracy: 0.5000 - 60ms/epoch - 4ms/step
## Epoch 18/20
## 15/15 - 0s - loss: 2.4031 - accuracy: 0.4615 - val_loss: 1.4962 - val_accuracy: 0.5000 - 62ms/epoch - 4ms/step
## Epoch 19/20
## 15/15 - 0s - loss: 2.4706 - accuracy: 0.4637 - val_loss: 1.4901 - val_accuracy: 0.5000 - 61ms/epoch - 4ms/step
## Epoch 20/20
## 15/15 - 0s - loss: 2.0937 - accuracy: 0.4658 - val_loss: 1.4841 - val_accuracy: 0.5000 - 85ms/epoch - 6ms/step
```

```
CNNmodel %>% evaluate(matrixX_test, matrixy_test)
```

```
## 4/4 - 0s - loss: 1.4841 - accuracy: 0.5000 - 26ms/epoch - 6ms/step
```

```
##      loss accuracy
## 1.48409 0.50000
```

```
predictionsTest <- CNNmodel %>% evaluate(matrixX_test, matrixy_test)
```

```
## 4/4 - 0s - loss: 1.4841 - accuracy: 0.5000 - 22ms/epoch - 5ms/step
```

```
predictionsTest
```

```
##      loss accuracy
## 1.48409 0.50000
```