```
clc;
clear;
```

```
%DATA LOADED TO MATLAB
%https://www.kaggle.com/code/davegn/rice-type-classification
Table = 'C:\Users\dimin\OneDrive - City, University of
London\Desktop\RiceClassification.csv';
opts = detectImportOptions(Table);
opts.VariableNamingRule = 'preserve';
data = readtable('C:\Users\dimin\OneDrive - City, University of
London\Desktop\RiceClassification.csv', opts)
originalHeaders = data.Properties.VariableDescriptions;
```

```
%EXPLORATORY DATA ANALYSIS
data.id = [];%Removing the identification column as it is not needed
summary(data);%Printing a statistics summary for the dataset
```

```
%Pie chart which shows the percentage of each class type in the dataset.
%This was created to understand how balanced the target variable is.
class(data.Class);%Checking the data type of the Class column in the dataset
if ~iscategorical(data.Class)
    data.Class = categorical(data.Class)
end%Checking if the Class data type is categorical and if not converting it
to.
counts = countcats(data.Class);%Counting the number of each classification
categories = categories(data.Class);%Obtaining the unique categories in the
Class column

pie(counts);%Creating a pie chart using the counts of each class
legendLabels = {'Gonen', 'Jasmine'}
legend(legendLabels, 'Location', 'bestoutside');
title('Percentage of Rice Class');
```

```
%Histograms showing the distribution of the X variables of the dataset
%This was created in order to understand the distributions of the variables
%in the dataset.
dataWithoutClass = removevars(data, 'Class');%Removing the Class column from
the dataset, by creating a new one where Class is absent

numericVars = varfun(@isnumeric, dataWithoutClass, 'OutputFormat',
'uniform');%Identifying the numerical variables in the dataset and making sure
that the result is a single array
numericData = dataWithoutClass(:, numericVars);%Making sure that only columns
with numerical variables are present
```

```
numNumericVars = sum(numericVars);%Counting the number of numerical variables
present
%Determining the number of rows and columns to calculate the size of the
%subplot
numRows = ceil(sqrt(numNumericVars));
numCols = numRows;

figure;%Creating the subplot
for i = 1:numNumericVars
    subplot(numRows, numCols, i);
    histogram(dataWithoutClass{:, i});
    title(dataWithoutClass.Properties.VariableNames{i});
end
sgtitle('Distribution of Variables');
```

```
%Correlation Matrix Heatmap computation
%This was computed in order to observe the relationships between the
%variables of the dataset.
numericArray = table2array(numericData);%Converting the numerical table to a
numerical array
corrMatrix = corr(numericArray, 'Rows', 'complete');%Computation of the
correlation matrix excluding any rows with missing values
figure('Position', [100, 100, 1000, 800]);%Stating the dimensions of the
heatmap
heatmap(numericData.Properties.VariableNames,
numericData.Properties.VariableNames, corrMatrix, 'Colormap', jet, 'Title',
'Correlation Matrix Heatmap');%Specifying colour, title etc..
```

```
%DATA PRE-PROCESSING
% Min-Max Normalization
numericData = data(:, varfun(@isnumeric, data, 'OutputFormat', 'uniform'));
%Extracting numeric values from the dataset
minVals = min(table2array(numericData), [], 1);%Calculating the minimum values
maxVals = max(table2array(numericData), [], 1);%Calculating the maximum values
normData = (table2array(numericData) - minVals) ./ (maxVals -
minVals);%Applying the normalization
data{:, varfun(@isnumeric, data, 'OutputFormat', 'uniform')} =
normData;%Placing the normalized values back to the dataset
```

%Data Transformations: Applying the Box-Cox Transformation %This was done in order to change the distributions of some variables so %that they are closer to normal distributions, even though MLP is generally %robust to non-normal data.

```
variables = data.Properties.VariableNames;%Obtaining all the variable names
from the dataset
lambdas = struct();%Creating a structure to store the lamba values obtained
for var = variables%Iterating over each variable in the dataset
    if strcmp(var, 'Class') || ~isnumeric(data.(var{1}))%If the variable is
Class or non-numeric it is skipped.
        continue;
    end
    minValue = min(data.(var{1})); Finding the minimum value of the variable
that is checked at that moment
    adjustment = 0;%Initializing adjustment factor to 0
    if minValue <= 0%If the minimum value is less or equal to 0, it is made
positive since the Box-Cox transformation only works with positive values
        adjustment = abs(minValue) + 1;
        adjustedData = data.(var{1}) + adjustment;
    else
        adjustedData = data.(var{1});
    end
    [transformed, lambda] = boxcox(adjustedData); %Applying the transformation
    data.(var{1}) = transformed; Updating the original dataset with the
transformed data
    lambdas.(var{1}) = lambda;%Storing the lamba values
end
```

```
%This subplot contains histograms of the transformed variables. Comparing
%to the previous subplot, it can be observed that the variables now are
%closer to normality.
variables = data.Properties.VariableNames;
numericVars = variables(~strcmp(variables, 'Class'));
numNumericVars = numel(numericVars);
numRows = ceil(sqrt(numNumericVars));
numCols = ceil(numNumericVars / numRows);
figure;
subplotIndex = 1;
for var = numericVars
    if isnumeric(data.(var{1}))
        subplot(numRows, numCols, subplotIndex);
        histogram(data.(var{1}));
        title(var{1});
        subplotIndex = subplotIndex + 1;
```

```
end
end
sgtitle('Distribution of Transformed Variables');
```

```
%NEURAL NETWORK CONSTRUCTION AND DATA PARTITIONING
X = data{:, {'Area', 'AspectRation', 'ConvexArea', 'Eccentricity',
'EquivDiameter', 'Extent', 'MajorAxisLength', 'MinorAxisLength', 'Perimeter',
'Roundness'}};
%Selecting the specific features from the dataset
Y = data.Class; %Selecting the target variable
cv = cvpartition(size(X, 1), 'HoldOut', 0.3); %Data is splitted to 70%
training and 30% testing data
idx = cv.test;%Creating an index vector
%Splitting the features into datasets according to the index vector
X_{train} = X(\sim idx, :);
Y_train = Y(~idx, :);
X_{\text{test}} = X(idx, :);
Y_{test} = Y(idx, :);
%Convert categorical variables to numerical
%This was done because neural networks require numerical inputs. The
%dummyvar function is used to convert the categorical variable into a set of
dummy/indicator variables.
Y_train = dummyvar(categorical(Y_train));
Y test = dummyvar(categorical(Y test));
```

```
%Hyperparameters to iterate over
learning_rates = [0.01, 0.1, 0.3]; %Defining a set for the learning rate
hidden_sizes = [10, 20, 30]; %Defining a size for the hidden layers
epochs = 1; %Defining the number of epochs
```

```
net.layers{end}.transferFcn = 'logsig';%Specifying the transfer
function for the output layer
        %Start timer to measure training time
        %Training the neural network
        [net, tr] = train(net, X_train', Y_train');
        %Timer stopped
        training time = toc;
        %Testing the network
        Y_pred = net(X_test');%Testing the network on the test set
        Y pred round = Y pred >= 0.50; %Setting a treshold for binary
classification
        test_accuracy = sum(Y_pred_round' == Y_test) /
numel(Y_test);%Calculating the test accuracy of the network
        %Setting up the results obtained to be printed
        result = struct('learning_rate', lr, 'hidden_size', hs, ...
                        'test_accuracy', test_accuracy, 'training_time',
training_time);
        results = [results, result];
    end
end
for i = 1:length(results)%Displaying the results
    fprintf('Learning Rate: %.2f, Hidden Size: %d, Test Accuracy: %.4f,
Training Time: %.2f seconds\n', ...
    results(i).learning_rate, results(i).hidden_size,
results(i).test_accuracy, results(i).training_time);
end
```

```
Y_test = Y_test(:); Reshaping the Y_test array into a vector
Y_pred_round = double(Y_pred_round(:)); Converting Y_pred_rounded into a
double
```

```
%Confusion matrix calculation, based on true labels(Y_test) and the
%predicted labels(Y_pred_rounded)
[C,order] = confusionmat(Y_test,Y_pred_round);
%Confusion matrix visualization
figure;
confusionchart(C,order);
saveas(gcf, 'confusionchart.png');
```

```
%Computation of performance metrics, such as Precision, Recall and F1 %score. These were computed using the elements obtained from the confusion %matrix.

TP = C(2,2);%True positive calculation
TN = C(1,1);%True negative calculation
```

```
FP = C(1,2); False positive calculation
FN = C(2,1); %False negative calculation
precision = TP / (TP + FP);%Calculation of precision which is the ratio of
true positives to all the predicted positives
recall = TP / (TP + FN);%Calculation of recall which is the ratio of true
positives to all actual positives
F1 = 2 * (precision * recall) / (precision + recall);%F1 score calculation,
which is a mean of precision and recall
fprintf('Precision: %.2f\n', precision);
fprintf('Recall: %.2f\n', recall);
fprintf('F1 Score: %.2f\n', F1);
fprintf('True Positive: %.2f/n', TP);
fprintf('True Negative: %.2f/n', TN);
fprintf('False Positive: %.2f/n', FP);
fprintf('False Negative: %.2f/n', FN);
Y_pred = double(Y_pred(:)); Converting the predicted labels to double to
ensure that it is a column vector
```

```
Y_pred = double(Y_pred(:));%Converting the predicted labels to double to
ensure that it is a column vector
Y_test = double(Y_test(:));%Converting the actual labels to double to ensure
that it is a column vector

[X_ROC, Y_ROC, T, AUC] = perfcurve(Y_test, Y_pred, 1);%Computing the RoC
curve, using the false positive rate, true positive rate, the tresholds and
area under the curve
figure;%Creating a figure for the curve
plot(X_ROC, Y_ROC, 'LineWidth', 2);%Plotting the curve
title(sprintf('ROC Curve (AUC = %.2f)', AUC));
xlabel('False Positive Rate');
ylabel('True Positive Rate');
grid on;
saveas(gcf, 'RoC Curve.png');
```