

TITLE OF THE PROJECT: BANK NOTE AUTHENTICATION

1 INTRODUCTION:

1.1 Overview

Despite a decrease in the use of currency due to the recent growth in the use of electronic financial transactions, real money transactions remain very important in the global market. While performing transactions with real money, touching and counting notes by hand, is still a common practice in daily life, various types of automated machines, such as ATMs and banknote counters, are essential for large-scale and safe transactions. This paper presents studies that have been conducted in counterfeit banknote detection and describes the advantages and drawbacks of the methods presented in those studies. This study also describes the technological challenges faced by such banknote recognition techniques and presents future directions of research to overcome them.

1.2 Purpose

Lot of miscreants induces fake notes into the market which resemble exactly the original note. Hence, there is a need for an efficient authentication system which **predicts accurately whether the given note is genuine or not.**

2 LITERATURE SURVEY:

2.1 Existing problem

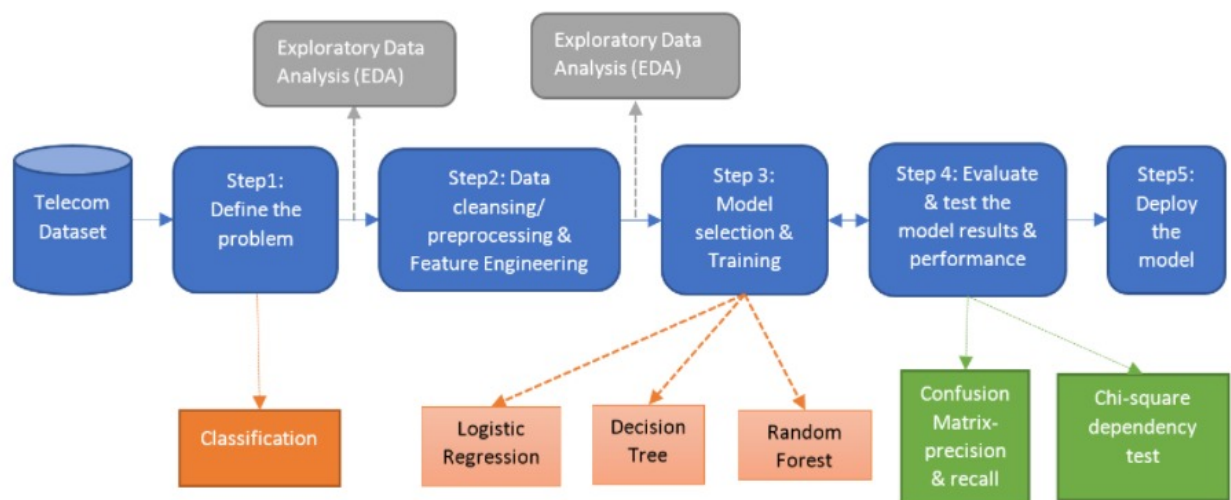
Banknotes are one of the most important assets of a country. Some miscreants introduce fake notes which bear a resemblance to original note to create discrepancies of the money in the financial market. It is difficult for humans to tell true and fake banknotes apart especially because they have a lot of similar features. Fake notes are created with precision, hence there is need for an efficient algorithm which accurately predicts whether a banknote is genuine or not.

2.2 Proposed solution

This paper evaluates supervised machine learning algorithms to classify genuine and fake notes. As the fake notes are prepared with precision, it is difficult to differentiate them from genuine ones. A recognition system must be installed to detect legitimacy of the note. The features will be given as input to the machine learning algorithm which will predict if the note is true or fake. The dataset used to train these algorithms was collected by extracting features from banknote images. The dataset also classifies all the samples into a particular class i.e. genuine or forged. This is a classification project, since the variable to be predicted is binary (fraudulent or legal). The goal here is to model the probability that a banknote is fraudulent, as a function of its features.

3 THEORITICAL ANALYSIS:

3.1 Block diagram



3.2 Hardware / Software designing

Hardware Requirement:

- >Windows 7 and above (64-bit)
- > RAM: 4GB
- > Processor: Minimum Pentium 2 266 MHz processor
- > Browsers: Chrome

Software Required:

- >Java JDK 10
- >Weka
- >Eclipse IDE

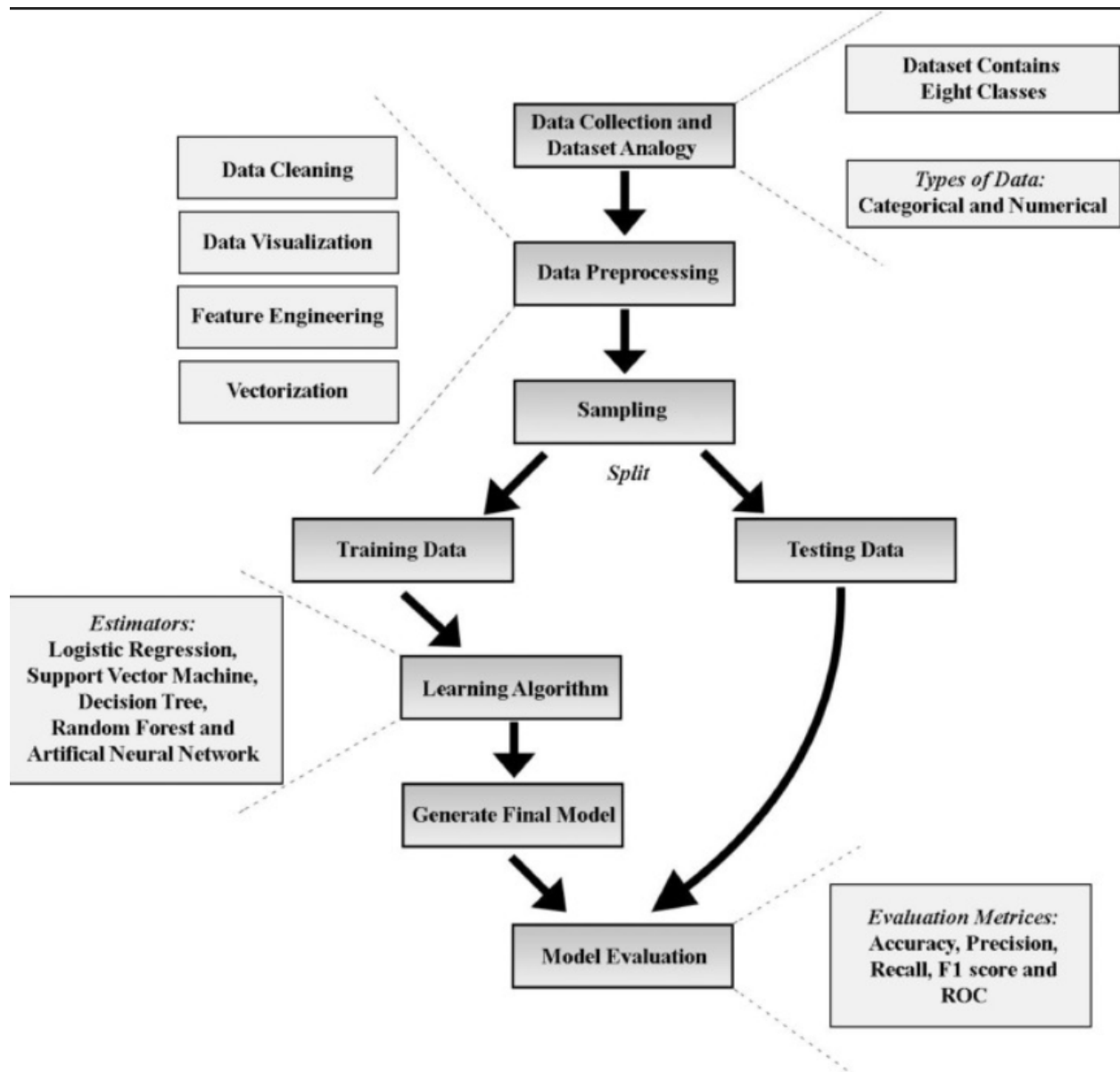
4 EXPERIMENTAL INVESTIGATIONS:

The data file banknote_authentication.csv is the source of information for the classification problem. The number of instances (rows) in the data set is 1372, and the number of variables (columns) is 5.

In that way, this problem has the following variables:

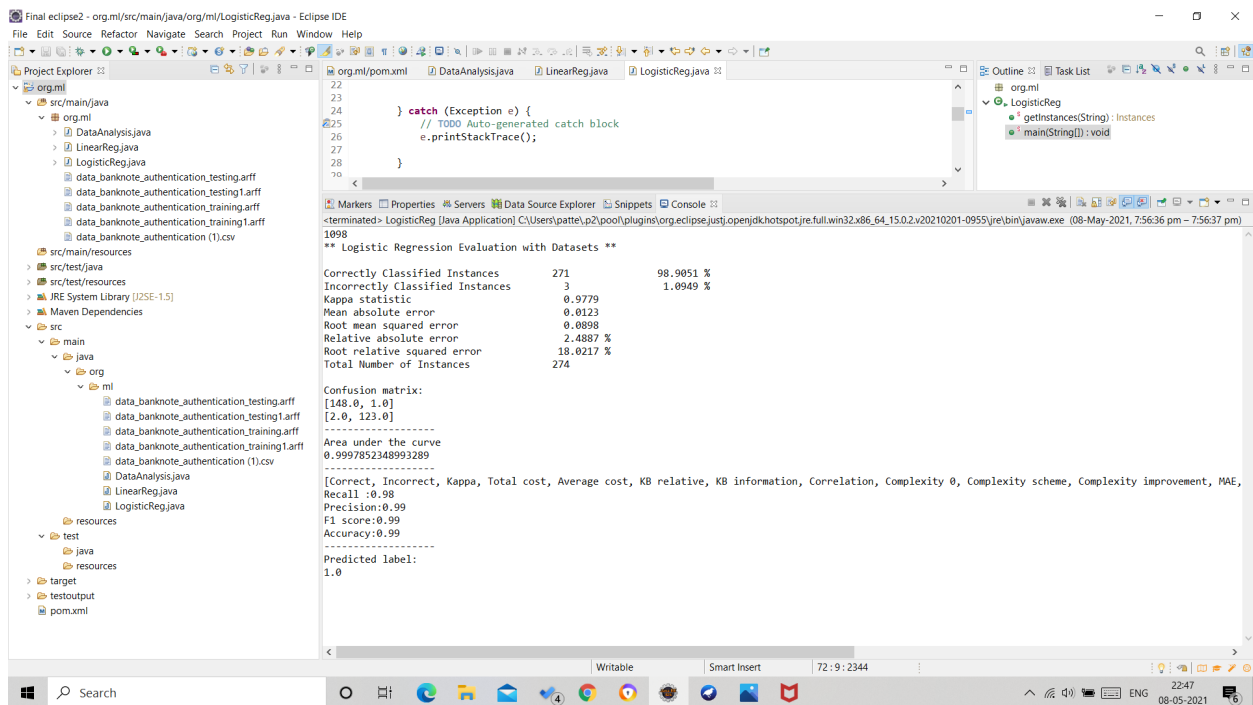
- >variance_of_wavelet_transformed, used as input.
- >skewness_of_wavelet_transformed, used as input.
- >curtosis_of_wavelet_transformed, used as input.
- >entropy_of_image, used as input.
- >counterfeit, used as the target. It can only have two values: 0 (non-counterfeit) or 1 (counterfeit). Extensive experiments have been performed on banknotes dataset using the various models to find the best model suitable for classification of the notes. ROC and other metrics have been calculated to compare the performances of both the techniques. The result shows that back-propagation neural network outperforms support vector machine and gives 100% success rate. These techniques are an efficient way of solving the problem for all banking machines that accept all types of notes.

5 FLOWCHART:



6 RESULT:

Final findings (Output) of the project along with screenshots.



The screenshot shows the Eclipse IDE interface with the following components:

- Project Explorer:** Displays the project structure for 'org.ml', including source files like 'DataAnalysis.java', 'LinearReg.java', and 'LogisticReg.java', and test resources.
- Code Editor:** Shows the 'LogisticReg.java' file with a catch block for exceptions.
- Console:** Displays the output of the application, including a header 'Logistic Regression Evaluation with Datasets **', performance metrics, a confusion matrix, and the area under the curve.

Console Output:

```
<terminated> LogisticReg [Java Application] C:\Users\patte.p2\pool\plugins\org.eclipse.just.openjdkhotspot.jre.full.win32.x86_64.15.0.2.v20210201-0955\jre\bin\javaw.exe (08-May-2021, 7:56:36 pm)
1098
** Logistic Regression Evaluation with Datasets **
Correctly Classified Instances      271      98.9051 %
Incorrectly Classified Instances    3      1.0949 %
Kappa statistic                    0.9779
Mean absolute error                 0.0123
Root mean squared error             0.0898
Relative absolute error             2.4887 %
Root relative squared error        18.0217 %
Total Number of Instances          274

Confusion matrix:
[148.0, 1.0]
[2.0, 123.0]
-----
Area under the curve
0.9997852348993289
-----
[Correct, Incorrect, Kappa, Total cost, Average cost, KB relative, KB information, Correlation, Complexity 0, Complexity scheme, Complexity improvement, MAE,
Recall :0.98
Precision:0.99
F1 score:0.99
Accuracy:0.99
-----
Predicted label:
1.0
```

Preprocess

Classify

Cluster

Associate

Select attributes

Visualize

Classifier

Choose

Logistic -R 1.0E-8 -M -1 -num-decimal-places 4

Test options

☐ Use training set

☐ Supplied test set

☒ Cross-validation

Folds10

☐ Percentage split

%66

More options...

(Nom) Class

Start

Stop

Result list (right-click for options)

19:54:10 - functions.Logistic

Classifier output

=== Run information ===

Scheme: weka.classifiers.functions.Logistic -R 1.0E-8 -M -1 -num-decimal-places 4
Relation: data_banknote_authentication_2-weka.filters.unsupervised.attribute.NumericToNominal-R5
Instances: 1372
Attributes: 5
Variance
Skewness
Curtosis
Entropy
Class
Test mode: 10-fold cross-validation

=== Classifier model (full training set) ===

Logistic Regression with ridge parameter of 1.0E-8

Coefficients...

Variable	Class
=====	
Variance	7.0594
Skewness	4.191
Curtosis	5.2075
Entropy	0.6053
Intercept	-7.3219

Odds Ratios...

Variable	Class
=====	
Variance	2590.0439
Skewness	66.0952
Curtosis	197.0461

Status

OK

Log

x 0

Windows taskbar showing search, task view, and various application icons (Edge, File Explorer, Mail, etc.). System clock shows 22:50 on 08-05-2021.

7 ADVANTAGES & DISADVANTAGES :

Following are the benefits or advantages :

- ➡ Features are automatically deduced and optimally tuned for desired outcome. Features are not required to be extracted ahead of time. This avoids time consuming machine learning techniques.
- ➡ Robustness to natural variations in the data is automatically learned.
- ➡ The same neural network based approach can be applied to many different applications and data types.
- ➡ The deep learning architecture is flexible to be adapted to new problems in the future.

Following are the drawbacks or disadvantages:

- ➡ It requires very large amount of data in order to perform better than other techniques.
- ➡ It is extremely expensive to train due to complex data models. Moreover deep learning requires expensive GPUs and hundreds of machines. This increases cost to the users.
- ➡ There is no standard theory to guide you in selecting right deep learning tools as it requires knowledge of topology, training method and other parameters. As a result it is difficult to be adopted by less skilled people.
- ➡ It is not easy to comprehend output based on mere learning and requires classifiers to do so. Convolutional neural network based algorithms perform such tasks.

8 APPLICATIONS:

There are wide range of applications of the project built.

If a bank note is verified whether it is fake or not then the government can identify the culprits and punish them.

The economy of the country can be observed keenly .

Illegal activities can be stopped.

Since it indulges machine learning the conclusions of the model are accurate.

9 CONCLUSION:

Banknote authentication is an important task. It is difficult to manually detect fake bank notes. Machine learning algorithms can help in this regard. In this document it is explained how to solve the problem of banknote authentication using machine learning techniques. We concluded that the logistic regression is the best algorithm for banknote authentication with an accuracy of 99.63%.

10 FUTURE SCOPE:

In future, this work can be extended by categorizing the notes into different categories as Genuine, Low-Quality forgery, High-Quality forgery, Inappropriate ROI.

11 BIBILOGRAPHY:

References of previous works or websites visited/books referred for analysis about the project, solution previous findings etc.

<https://www.ijcaonline.org/archives/volume179/number20/shahani-2018-ijca-916343.pdf>

<https://medium.com/geekculture/building-a-machine-learning-model-for-banknote-authentication-f9c6855a9057>

<https://www.neuraldesigner.com/learning/examples/banknote-authentication>

<https://www.vshsolutions.com/blogs/banknote-authentication-using-machine-learning-algorithms/>

APPENDIX :

A. Source Code Attach the code for the solution built.

package org.ml;

```

import java.io.IOException;

import tech.tablesaw.api.Table;
import tech.tablesaw.plotly.Plot;
import tech.tablesaw.plotly.components.Figure;
import tech.tablesaw.plotly.components.Layout;
import tech.tablesaw.plotly.traces.BoxTrace;
import tech.tablesaw.plotly.traces.HistogramTrace;

public class DataAnalysis {

    public static void main(String args[])
    {
        System.out.println("DataAnalysis");

        try {
            Table bank_data =
Table.read().csv("C:\\Users\\patte\\Desktop\\Final
eclipse2\\org.ml\\src\\main\\java\\org\\ml\\data_banknote_authentication (1).csv");
            System.out.println(bank_data.shape());

            System.out.println(bank_data.first(4));
            System.out.println(bank_data.last(4));

            System.out.println(bank_data.structure());

            System.out.println(bank_data.summary());

            Layout layout1 = Layout.builder().title("Distribution of
VARIANCE").build();
            HistogramTrace trace1=
HistogramTrace.builder(bank_data.nCol("Variance")).build();
            Plot.show(new Figure(layout1,trace1));

            ///Layout layout3 = Layout.builder().title("").build();
            ///BoxTrace trace3=

```

```

BoxTrace.builder(bank_data.categoricalColumn("Skewness"),bank_data.nCol("Variance"
)).build();

        ///Plot.show(new Figure(layout3,trace3));

        Layout l2 = Layout.builder().title("Class Distribution").build();
        BoxTrace t2 =
BoxTrace.builder(bank_data.categoricalColumn("Class"),bank_data.nCol("Skewness")).b
uild();

        Plot.show(new Figure(l2,t2));

    } catch (IOException e) {
        //
        e.printStackTrace();
    }
}
}
}

```