Predict Module Shunt for Load Cell Steel Lots

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Dissertation submitted to the Faculty of Information Technology, University of Moratuwa, Sri Lanka for the fulfillment of the requirements of Degree of Master of Science in Information Technology.

2020

Declaration

I declare that this thesis is my own work and has not been submitted in any form for another degree or diploma at any university or other institution of tertiary education. Information derived from the published or unpublished work of others has been acknowledged in the text and a list of references is given.

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Acknowledgements

I would like to convey my special thanks to Mr. S. C Premarathne, Senior Lecturer, Faculty of Information Technology, University of Moratuwa for his support, guidance and supervision given to me throughout my project, making it a success.

I'm grateful to my wife and my parents, Mr. Wasantha Sesathpura, Mr. Gayan Kodikara, Mr. Randika Thamel, Mr. Gayan Peris, Mr. Asitha Godakandaarchchi, Mr. Rohan Thushara, Mr. Chinthana Pathirana and Mr. Ruwan Bandara for their enormous support given to me at various points in time during the course of this research.

My sincere gratitude to Mr. Suneth Rodrigo for his kind advices and support given to me.

Finally, I thank all the staff members of Faculty of Information Technology, University of Moratuwa.

Abstract

Load cell is a transducer which converts force into a measurable output. There are many varieties of load cells and strain gage-based load cells are heavily used for weighting systems. To acquire the performance, load cell containing strain gages, module shunt, module gages as a combined circuit. Module shunt does the bigger task to Reduce mV/V value change against temperature. Centering is the process which introduce the module shunt for the upcoming loadcell steel lot. Since the chemical and mechanical properties of the steel bars are differ, the performance of the load cell may be vary. This centering process can be optimize by analysing historical data of chemical composition and Centrering results of the supplier lots. Through the data analysing proper module shunt may be found. That will save lots of time and operations of the centering process.

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Chapter 1

1 Introduction

1.1 Prolegomena

The load cell module shunt does the bigger task to reduce mV/V value change against temperature. Centering is the process which introduce the module shunt for the upcoming loadcell steel lot. Since the chemical properties of the steel bars are different, the performance of the load cell may vary. This centering process can be optimized by analyzing historical data of chemical composition and Centrering results of the supplier lots. Through the data analyzing proper module shunt may be found. That will save lots of time and operations of the centering process.

1.2 Background and Motivation

Since the production orders are increasing day by day, all the people in Flintec are trying to minimize the processing time to manufacture a load cell. Therefore, the people who are doing production need much better decision supporting systems to handle processes to deliver load cells to customers within the promised lead time. So, predicting the module shunt would be a best solution for the people who are doing the Centering process and then the processing time would be decreased. Therefore, data mining and presenting the extracted result through a web-based interface would be an attractive and time-saving solution.

1.3 Aims and Objectives

1.3.1 Aims

This research aim is to predict the module shunt for the next load cell production batches without doing the centering process by analyzing historical steel supplier lot details and historical module shunt details for those supplier lots.

1.3.2 Objectives

- Identify the relationship between chemical composition of steel lot and the module shunt published for those steel supplier lots.
- Save the time wasting for the centering process.
- Introduce Module Shunt Predictor tool for module shunt prediction using chemical composition of steel lots.

1.4 Proposed Solution

Web based tool for predicting module shunt for steels lots through data mining techniques. This tool will predict the appropriate module shunt for the given steel lot by analysing the given chemical composition and this will save lot of time taken to select suitable module shunt for the steel lot.

When a new steel lot received to Flintec stores, the relevant user will enter the supplier lot details with chemical compositions. With the proposed system it will automatically predict a suitable module shunt for the relevant steel lot.

From one station data entry at stores we can have module shunt for the new steel lot without doing the time-consuming centering process. And this will save human hours and production planning teams can get their directions or discussions at the early stages of the production.

1.5 Resource Requirement

IEEE Xplore Digital Library and Google schooler is used to find similar kind of research and data mining techniques used to accomplish their researches. Microsoft sql server 2016 has used since all the historical data in Flintec has stored in there and Microsoft Excel used to manipulate the extracted data form sql server. Microsoft visual studio 2015 is used to develop the web-based tool to predict module shunt and WEKA tool has used for the data mining approaches to find the suitable data mining technique for the data set.

Chapter 2

Literature Review of module shunt prediction

2.1 Introduction

This chapter review the relationship between load cell steel chemical composition and the module shunt used for the load cell steel lot.

2.2 Literature Review

Ma Yanbing and Zhang Zupei [1] has analysed the temperature effect and compensation of strain gauge load cells. This paper describes the temperature-sensitivity relation, the measuring method, the results of regression analysis and shows the possibility and significance of compensation as well. These effects vary with the average level of the temperature and the temperature gradient of the load cell. They are due to the temperature effects of the mechanical and electrical characteristics. Output of load cell depends on the K factor and geometric and mechanic specification of elastic element. Its sensitivity varies with the temperature. The paper describes that the force is applied on the elastic element, the deformation appears with the temperature rising which is more than that generated with the temperature decreasing. so that the output of load cell is increased with temperature. Ma Yanbing and Zhang Zupei further describe that the that the performance of the acting force among metal atoms. which depends on the nature and crystal lattice type of metal atom and it relates closely to atomic distance. For most of metal. except the alloy of special crystic structure. its crystal lattice constant increases with a rise in temperature. the atomic interact decreases. This shows that the chemical structure of the steel has a relation to the performance of the load cell.

Tech Note TN-514 of Vishay Precision Group [2] describes that, Strain gage simulation by increasing the resistance of a bridge arm is not very practical because of the small resistance changes involved. Accurate calibration would require inserting a small, ultra-precise resistor in series with the gage. Furthermore, the electrical contacts for inserting the resistor can introduce a significant uncertainty in the resistance change. On the other hand, decreasing the resistance of a bridge arm by shunting with a larger resistor offers a simple, potentially accurate means of simulating the action of a strain gage. This method, known as shunt calibration, places no particularly severe tolerance requirements on the shunting resistor, and is relatively insensitive to modest variations in contact resistance. It is also more versatile in application and generally simpler to implement.

In the Load cell handbook of PCB Group of Company [3] reports that, Shunt calibration stimulates the mechanical input to a transducer by unbalancing the bridge with a fixed resistor placed across, or in parallel with, one leg of the bridge. For tension shunt calibration, the shunt resistor (RST) is shunted across the +excitation (+P) and +signal (+S) leg of the bridge. For a compression shunt calibration, the shunt resistor (RSC) is shunted across the – excitation (-P) and +signal (+S) leg of the bridge. Shunt calibration is accepted throughout the industry as means of periodic calibration of a signal conditioner and transducer between calibrations of known, applied, traceable, mechanical, input values. Consequently, most all strain gage transducer manufacturers collect and supply shunt calibration data, along with a shunt calibration resistor, as a standard feature.

Above literature review information shows that the module shunt resistor is doing a bigger task in Load cell calibration process and that shunt is used to reduce mV/V value change against temperature. During the literature review, found that there are no such researches have been conducted to identify whether there is a relationship between chemical properties of the load cell steel and the module shunt used for that load cell steel lot.

However this research tries to prove that there is a relationship between load cell steel chemical composition and the module shunt used for those steel lots, Appling the data mining techniques for the data set of chemical composition details of steel and the module shunts which have been used for those steel lots.2.1 Introduction

2.3 Summary

Usage of module shunt in the load cell application and the chemical composition of steel is review through this chapter.

Chapter 3

Technology Adapted

3.1 Introduction

Previous chapter go through the data mining process and this chapter describes the different types of technologies applied to do this research work.

3.2 Microsoft Sql Server 2016

SQL Server is a database server by Microsoft. The Microsoft Relational Database Management System is a software product that primarily stores and retrieves data requested by other applications. SQL is a specialized programming language designed to work with data in relational database management systems.

3.3 Microsoft Excel

Microsoft Excel is a spreadsheet program. That is used to create a grid of text, numbers, and formulas that specify calculations. This is valuable to many companies used to record spending and income, plan budgets, chart data, and present financial results concisely.

3.4 Microsoft PowerBi

Microsoft Power BI is used to find insights within your organization's data. Power BI helps connect disparate datasets, transform and clean up data into data models, and create charts or graphs to provide visualizations of your data. All of these can be shared with other Power BI users in your organization

3.5 WEKA Tool

Weka is a collection of machine learning algorithms developed for data mining process. Algorithms can be applied directly to the dataset or called from your own Java code. Weka includes tools for data pre-processing, classification, regression, clustering, association rules, and visualization.

3.6 .Net framework

The software development platform .Net framework was developed by Microsoft. This framework was for creating applications that run on the Windows platform. In 2002 Microsoft released the first version of the .Net framework. This version was called .Net Framework 1.0. The .Net framework has come a long way since then. The current version is 4.7.1. You can use the .Net framework to create both form-based and web-based applications. You can also develop web services using the .Net framework. The >Net framework also supports many programming languages such as Visual Basic and C #. Therefore, the developer can choose the language for developing the desired application.

3.7 MVC Architecture

ASP.NET provided developers with a new framework for website development. The framework makes it easy to distinguish between the data layer, the business layer, and the method used to display these objects on screen. They called this framework ASP.NET MVC. MVC stands for model, view, controller

3.8 Bootstrap

Bootstrap is a framework that helps you design your website faster and easier. Includes HTML and CSS based design templates for typography, forms, buttons, tables, navigation, modals, image carousels and more. We also provide support for JavaScript plugins

3.9 AngularJs

AngularJS is an open source front-end JavaScript framework. Its purpose is to augment browser-based applications with Model View Controller (MVC) functionality and reduce the amount of JavaScript required to make a web application work.

Chapter 4

A novel approach for predicting module shunt

4.1 Introduction

Chapter 3 described the different technologies and tools used for this research work and this chapter will include our approach to predict module shunt and input, output, data selection, date pre-processing and data transforming.

4.2 Hypothesis

Using data mining techniques can predict the module shunt for a load cell steel lot depending on the chemical composition of that supplier steel lot.

The module shunt predictor tool can predict the module shunt for the load cell steel supplier lot using data mining classification model and can eliminate the time-consuming Centering process accordingly.

4.3 Input

As the inputs for this prediction two sql data tables are used, one sql table is having Supplier lot number, lot received date, Suppler, Data entered user, Chemical composition of C, Cr, Cu, Mn, Ni and Si.

date	sup_lot	C	Cu	Cr	Si	Mn	Ni	Entered_by
2011-02-03 00:00:00.000	100804248	0.023	3.35	15.34	0.4	0.65	4.27	1240
2011-02-07 00:00:00.000	100804250	0.023	3.27	15.41	0.3	0.52	4.58	1240
2011-02-07 00:00:00.000	100804253	0.025	3.26	15.26	0.36	0.56	4.38	1240
2011-02-21 00:00:00.000	101208408	0.023	3.3	15.45	0.38	0.52	4.29	1240
2011-03-31 00:00:00.000	101208410	0.021	3.19	15.13	0.33	0.52	4.43	237

Figure - 4.3.1: tbl_steel_chemical_composition – Sql Table

When new steel lot received to Flintec stores, an authorized user will enter the supplier lot number and chemical composition details of that steel lot via a web-based system called

Product Process Tracking System and the data will store in sql table called tbl_steel_chemical_composition.

The other sql table is having Supplier lot, Module shunt, Tested date and data entered user.

supplier_lot	shunt_published	date	operator
100804248	191	2011-02-08 00:00:00.000	729
100804250	158	2011-02-13 00:00:00.000	729
100804253	78.7	2011-02-20 00:00:00.000	729
101208408	160	2011-02-25 00:00:00.000	729
101208410	165	2011-04-06 00:00:00.000	729

Figure - 4.3.2: tbl_shunt_published_data – Sql Table

After the Centering process has completed against a steel supplier lot, the selected module shunt will store in tbl_shunt_published_data sql table via the same Product process tracking system by an operator in Product audit department.

4.4 Output

Predicted results or the predicted patterns identified will be the output of this data mining approach. Relationship between chemical composition and the module shunt will be identified as the output of this process. The extracted results from the data mining process will be applied to a web-based system called Module Shunt Predictor Tool. Finally, this web-based tool will be the output of the process.

4.5 Process

In this process of predicting module shunt for load cell steel lots with data mining, all the standard steps in knowledge discovery process which include data selection to evaluation are carried out. Throughout the process the data set is cleaned, formatted and prepared for mining and interpretation.

4.5.1 Data Selection

Flintec Transducers Pvt Ltd is tracking all load cell related information properly due to customer requirements. Flintec inhouse IT department has developed several data tracking and automation systems to track those load cell process related data. All those data are stored in a central sql database which is called "Flintecdata" .When the load cell steel bars are received to Flintec stores via the suppliers, They are sending the standard document with this steel lots which is having Supplier lot number and the chemical compositions of the steel. Those chemicals are C, Cr, Cu, Mn, Ni and Si. The authorized person form Flintec will inspect the steel lots and after the GRN process the steel lot details are inserted to a web system which is called Product process tracking system.

The stored data is consisting with Supplier Lot Number, Lot Received Date, Suppler, Data entered user, Chemical composition of C, Cr, Cu, Mn, Ni and Si. This is the one data set which is used for this data mining process.

After load cells have received to Flintec Product audit department, they will do the Centering process and the centering result will be inserted to the Product process tracking system then all the data will be stored in sql server. That data is consisting of Supplier lot, Module Shunt, Tested date and data entered user. This is the second data set which is required to do the data mining process.

4.5.2 Data Pre-Processing

Data pre-processing refers to the steps that are applied to make data more suitable for data mining. Real-world data is often incomplete, inconsistent, lacks certain behaviors or trends, and can contain many errors. Data pre-processing is a proven way to solve these problems.

Incomplete data generally means missing attribute values, missing certain attributes, or containing only aggregated data. Noisy data means that it contains errors and outliers. Inconsistency means there is a code or name mismatch. To get useful data that can be used for data mining, you need to do data cleaning.

4.5.3 Data Transformation

This is the step that transforms or consolidates the data into a form suitable for mining by performing operations such as summarization and aggregation. A vast amount of data is available, and useful information is provided to support such normalization as decision-making, smoothing, aggregation, generalization, and strategies used within the data transformation process. And a huge need to adjust to knowledge. Smoothing is used to remove noise from the data, aggregation is used to build summaries and data cubes, generalization is used to the concept of ascending hierarchy, and normalization is used to scale within a small specified range. will be used.

4.5.4 Data Mining

This is an important part of this research that used intelligent methods to extract data patterns. Not only that, the discovery of interesting knowledge also involves finding associations, changes, anomalies, and important structures in chemical composition datasets. Associations use relationships between a particular item in a data transaction and other items in the same transaction to predict patterns. In classification, the method aims to learn different functions that map each item of selected data to one of a set of predefined classes.

Predictive analytics in predictive mining is related to regression techniques. The key idea behind it is to discover relationships between dependent and independent variables, relationships between independent variables. Sequential pattern analysis looks for similar patterns of data transactions over a period of time. Business analysts can use these patterns to identify relationships between data. Descriptive cluster analysis takes unsorted data and uses automated methods to classify this data into groups. Most of the mathematical models applied for classification are also applicable for cluster analysis. Predictive or descriptive mining tasks are selected according to the task they are trying to accomplish through survey questions

4.5.5 Evaluation/Interpretation

The data interpretation stage is the most important stage because it integrates the knowledge from the mined data. There are two important issues. One issue is how to determine business value from the knowledge patterns found during the data mining stage. Another issue is the technique or visualization tool used to display the data mining results. Therefore, in order to maximize efficiency, it is necessary to evaluate the mined patterns for goals or objectives. Choosing the right visualization tools is important for the proper interpretation of knowledge patterns. Many visualization packages and tools are available, including pie charts, histograms, plots, trees and distribution networks.

4.5.6 Users

Flintec Product Audit department who are responsible for performing the centering process and Flintec Gaging department who are responsible for applying gages to load cells are the users who required these data for their day today jobs.

4.6 Summary

This chapter describes the approach of data mining to predict module shunt and the next chapter will go through the implementation process of module shunt predictor tool.

Chapter 5

Implementation

5.1 Introduction

In chapter 5, we described overall design of the proposed solution. This chapter provides implementation details of software and algorithms used with sample outputs.

5.2 Overall Implementation

The Mod Shunt Predictor tool, a web-based solution is the final implementation which is developed in .Net 4.6 framework and MVC 5 architecture. Backend of the system used Microsoft sql server 2016 and Bootstrap 4 is used for the front-end responsive web designing. AngularJs also used as the scripting language. The data mining results or the extracted tree from Random Tree classification has implemented inside the system and it will show the predicted module shunt for the given chemical composition. Figure 5.2.1 shows a screen shot of the Mod Shunt Predictor tool.

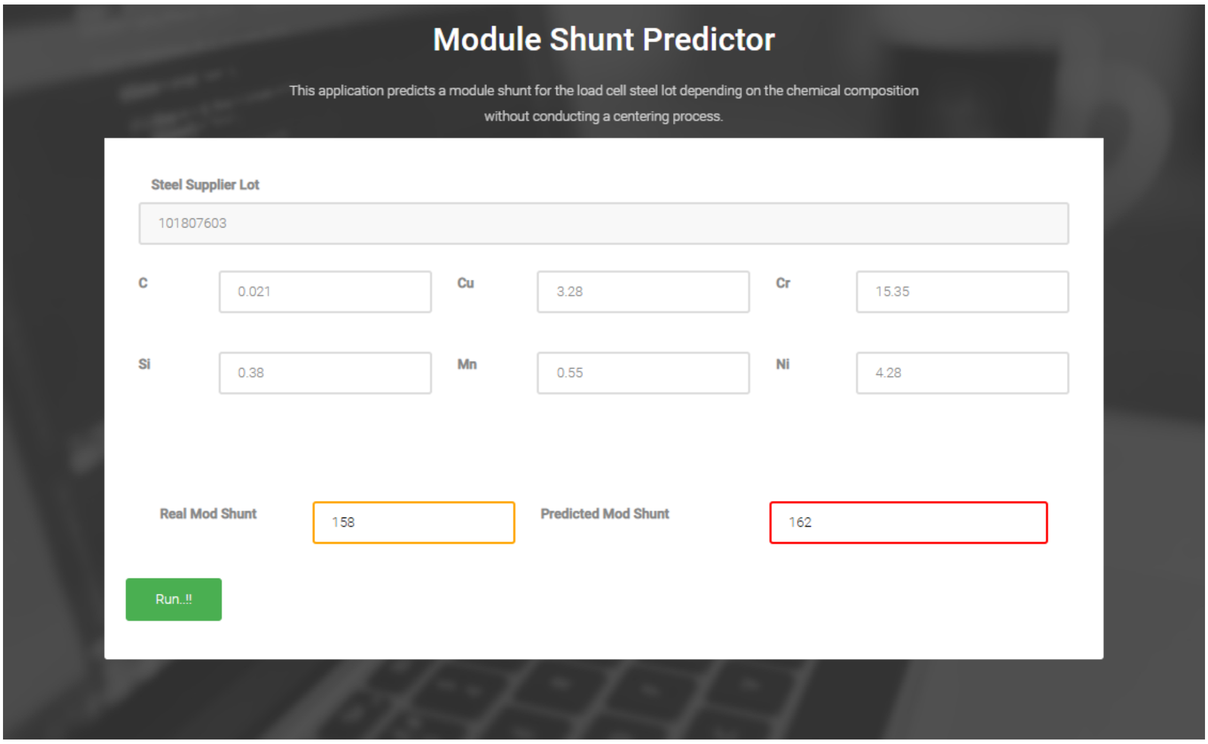

Figure - 5.2.1: Mod Shunt Predictor – User Interface

This web-based module, the module shunt predictor tool is very easy to use, and this is working on any web browser which is an advantage for users to involve with this solution. The main goal of this web-based tool is to predict module shunt easily depending on the inbuilt Random tree algorithm. If the users select a previous steel supplier lot, they can find which module shunt had used and if they click run button the system will predial a appropriate module shunt using the given chemical composition values.

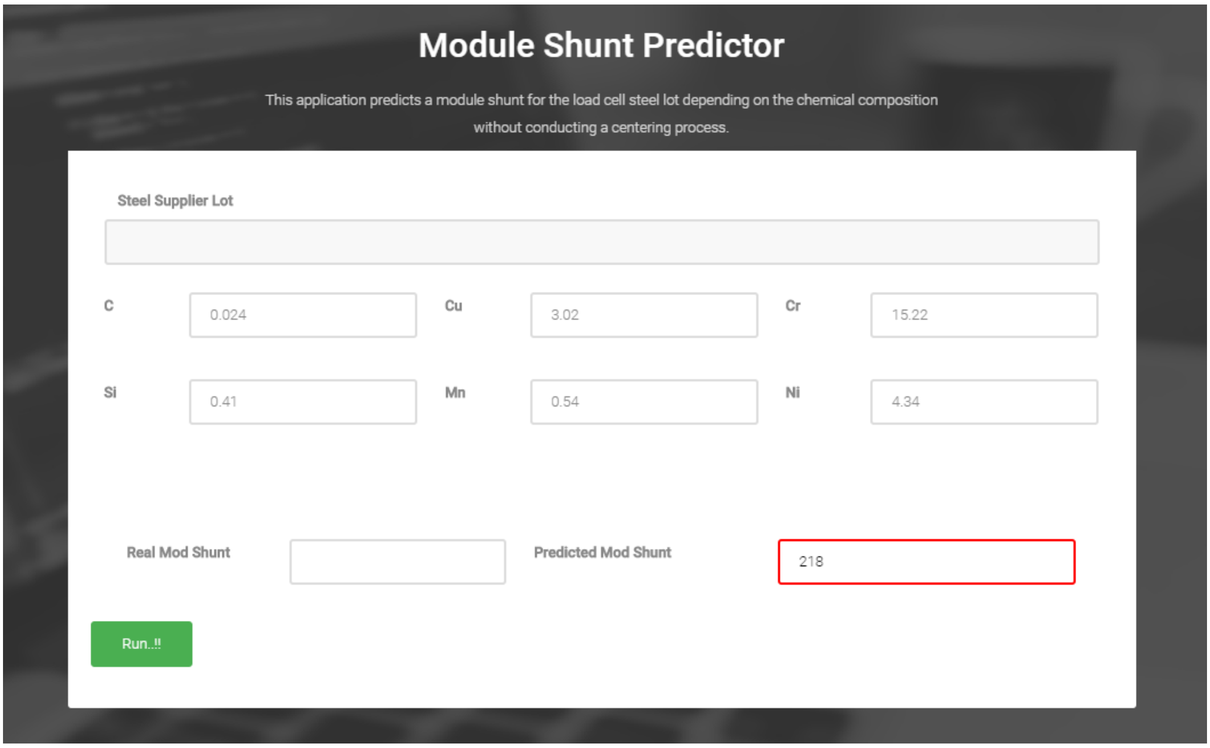

Figure - 5.2.2: Predicting Module shunt for new steel supplier lot – User Interface

This module shunt predictor tool can be used to predict module shunt for a new supplier lot and can be used to find module shunts of previous steel lots. Therefore, while stores operator is entering chemical composition values, system will automatically give the predicted module shunt for the current steel suppler lot.

5.3 Data Collection and Preprocessing

Flintec Transducers Pvt Ltd is tracking all load cell related information properly due to customer requirements. Flintec inhouse IT department has developed several data tracking and automation systems to track those load cell process related data. All those data are stored in a central sql database which is called “Flintecdata” .When the load cell steel bars are received to Flintec stores via the suppliers, They are sending the standared document with this steel lots which is having Supplier lot number and the chemical compositions of the steel. Those chemicals are C, Cr, Cu, Mn, Ni and Si. The authorized person form Flintec will inspect the steel lots and after the GRN process the steel lot details are inserted to a web system which is called Product process tracking system.

The stored data is consisting with Supplier Lot Number, Lot Received Date, Suppler, Data entered user, Chemical composition of C, Cr, Cu, Mn, Ni and Si. This is the one data set which is used for this data mining process.

After load cells have received to Flintec Product audit department, they will do the Centering process and the Centering result will be inserted to the Product process tracking system then all the data will be stored in sql server. That data is consist of Supplier lot, Module Shunt, Tested date and data entered user. This is the second data set which is required to do the data mining process.

For the data mining task, data set one and data set two was joined through sql query. Since both data sets are having steel suppler lot as a unique key. After joining the two data sets C, Cr, Cu, Mn, Ni, Si and Module shunt is extracted via sql query manipulation. Those collected data exported to csv format and done the pre-processing mechanism using WEKA tool.

That data set consists of lots of missing values, noisy values and redundant values. Then we eliminate those redundant and noisy values in the data set to use for the data mining tasks. Figure - 5.3.1 and Figure - 5.3.2 shows removing noisy or the outlier values using WEKA tool.

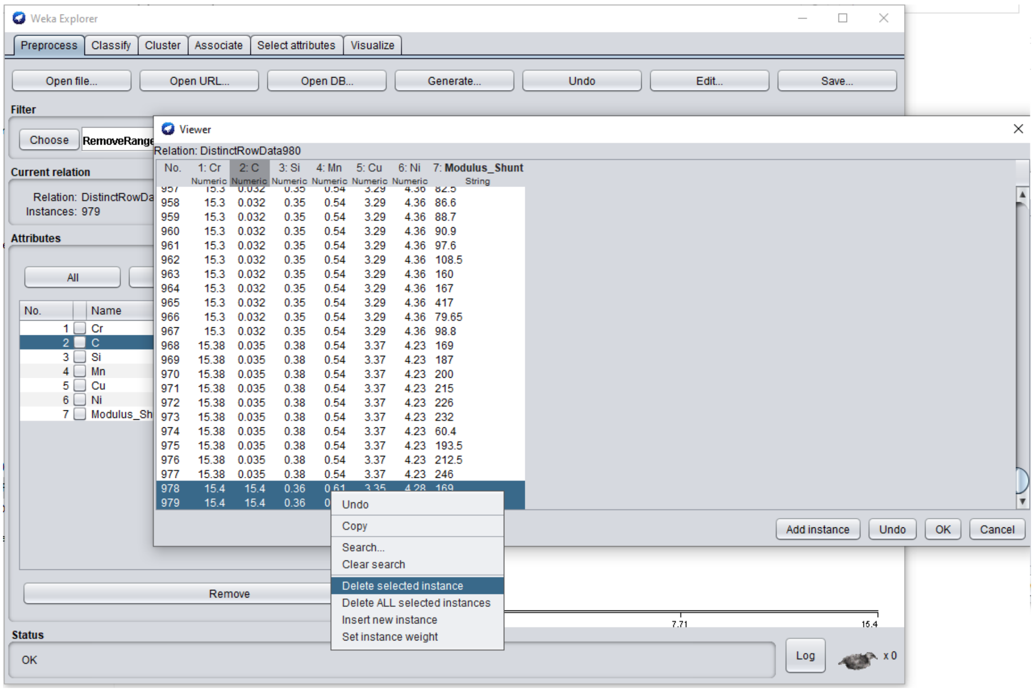

Figure - 5.3.1: Remove noisy data or remove outlier values – WEKA Tool

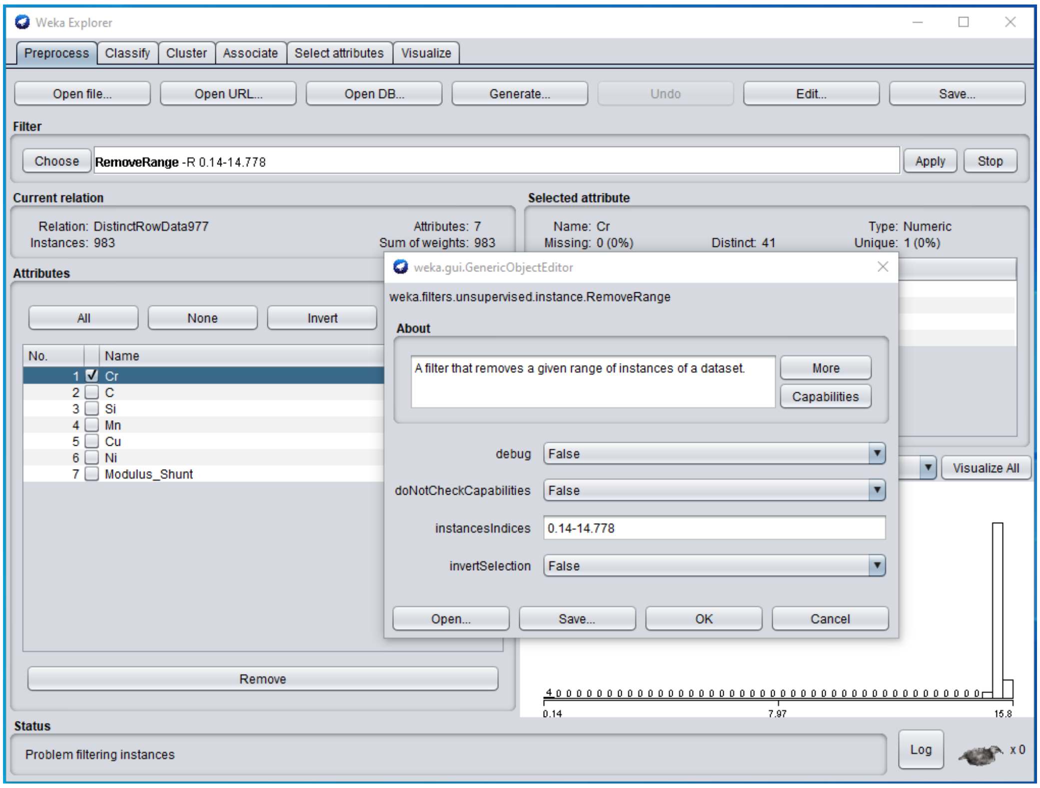

Figure - 5.3.2: Remove noisy data or remove outlier values – WEKA Tool

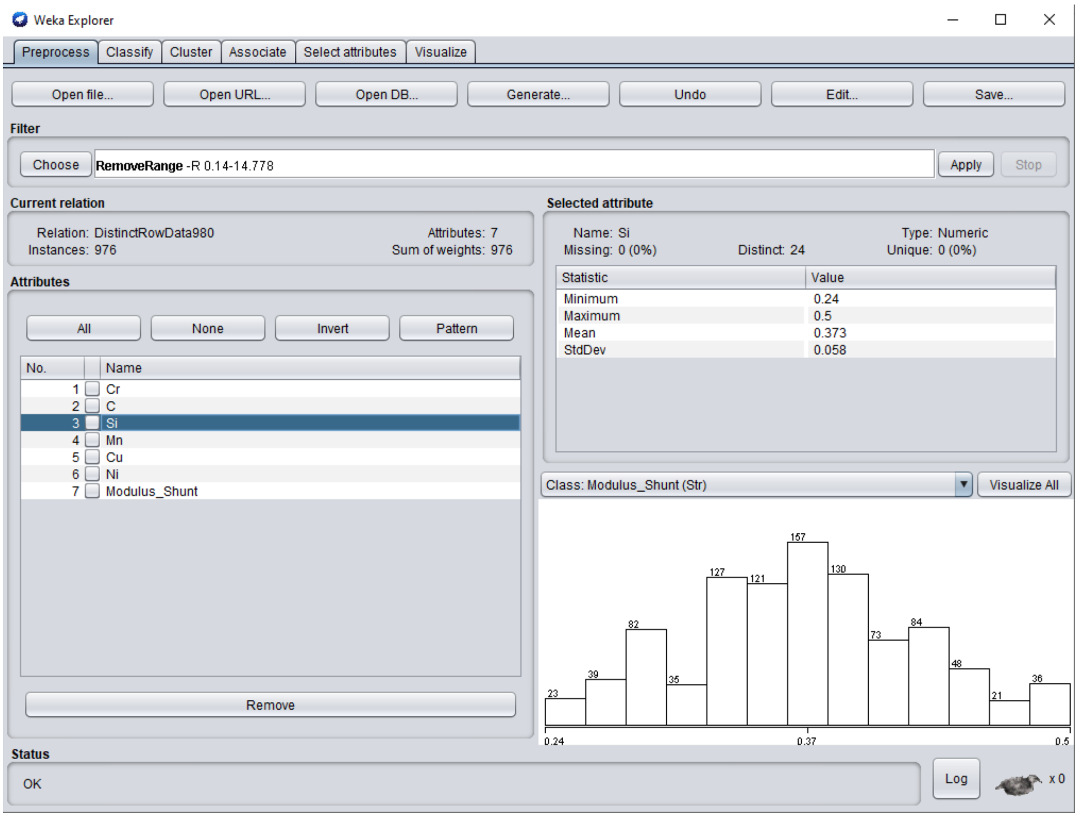

Figure - 5.3.3: After removing outliers of Si – WEKA Tool

5.4 Implementation of Mod Shunt Predictor User Interface

The Mod Shunt Predictor is a totally web based system and used ASP.net MVC 5 framework for the development. For the front-end design Bootstrap 4 has used and therefore user can experience the responsive feeling when using the system. AngulaJs is used as the client-side scripting language which is better to handle user requests via the system.

5.5 Implementation of Back end

Microsoft sql server 2016 has used as the back-end database management system. The pre-processed data in csv file again inserted to Microsoft sql server since there are two main advantages. The first one is ,it's easy to access sql server via ASP.net MVC web system and the next advantage is we can integrate the current data entering system which is called Product

Process Tracking system with Mod Shunt Predictor system due to both the systems are using same sql server database.

5.6 Summary

This chapter described overall implementation details of each module of the proposed solution. It also mentioned software and data mining techniques for models development with align to design. Next chapter evaluates all the modules implemented in the solution.

Chapter 6

Evaluation

6.1 Introduction

This chapter describes the how the selected data mining techniques are applicable for the proposed solution and how the data set behave according to the applied data mining techniques.

6.2 Evaluation of Classification Techniques

Efficiency or the performance finding of machine learning model is difficult since that is connected with the data set used or the business environment of the data. It is very important to find the correct evaluation measure to predict the results.

Evaluation mechanisms are different and here we try to evaluate the data mining classification techniques we have used to find the suitable classifier for the data det. The main aim of classification functions is to accurately predict the target class for every scenario in the selected data set.

The pre-processed data set has cross validated using 10 folds inside the WEKA tool. In 10-fold cross validation the data set is divide into 10 pieces or folds then hold out each fold for training and testing with the remaining 9 folds together. Which will give averaged 10 evaluation results.

Random Tree, Random Forest, J48, Naïve Bayes, KStar and Decision Table are the different datamining techniques used for the evaluation. For the evaluation of these different techniques, confusion metric is used and Accuracy, Recall and the Precision are the different, measurements used for this evaluation.

6.2.1 Confusion Metric

Confusion metric is a table drawn to describe the performance of a classification technique. The output of the classification can be two or more classes. So, the confusion metric is consists with four different predicted and actual values.

		Actual Values	
		Positive	Negative
Predicted Values	Positive	TP	FP
	Negative	FN	TN

Table 6.2.1 confusion Metric

This table is very useful to measure Recall, Precision, Accuracy and ROC curve.

To understand the above terminologies, need to know True Positive (TP), False Positive (FP), False Negative (FN) and True Negative (TN).

True Positive (TP) - Prediction is positive and it is true

True Negative (TN) - Prediction is negative and it is true

False Positive (FP) - Prediction is positive and it is false. This is called as Type 1 Error

False Negative (FN) - Prediction is negative and its false. This is called as Type 2 Error

Accuracy, Recall, Precision and ROC curve are the different measurements used to evaluate the classification techniques.

6.2.2 Accuracy

Proportion of correct classifications (true and negatives) from overall number of cases.

$$\textbf{Accuracy} = \frac{\textbf{TP} + \textbf{TN}}{\textbf{TP+TN+FP+FN}}$$

6.2.3 Recall

How much we have predicted accurately out of all positive classes. This value should be near to 1.0 to point out that the used classification model is perfect.

$$\textbf{Recall} = \frac{\textbf{TP}}{\textbf{TP} + \textbf{FN}}$$

6.2.4 Precision

Which are actually positive out of all positive classes.

$$\textbf{Precision} = \frac{\textbf{TP}}{\textbf{TP} + \textbf{FP}}$$

6.2.5 ROC Curve

Receiver operating characteristic curve represents how capable of distinguishing between classes in the selected model. If the value of ROC curve is near to 1.0, it is the proper classification model to use for the implementation.

Following table 6.2.2 shows how the different data mining techniques have applied to see the performance of the model.

Data mining Technique	TP Rate	FP Rate	Precision	Recall	F-Measure	ROC Area
Random Tree	0.814	0.008	0.833	0.814	0.824	0.951
Random Forest	0.814	0.008	0.833	0.814	0.824	0.938
J48	0.814	0.007	0.854	0.814	0.833	0.9
Naive Bayes	0.721	0.015	0.689	0.721	0.705	0.97
KStar	0.721	0.031	0.525	0.721	0.608	0.938
Decision Table	0.651	0.004	0.875	0.651	0.747	0.932

Table 6.2.2 Classification Technique Evaluation

Above classification technique comparison table consists of several measures TP rate, FP rate, Precision, Recall, F-Measure and ROC area. According to the data mining theories a better classification models are having ROC area near to 1.0, Higher TP rate and lower FP rate.

According to the results in above Table 6.2.2 Random tree is having the highest ROC area value than Random forest, J48, Naive Bayes, KStar and Decision Table models. Therefore, Random tree model is having showing higher performance for module shunt prediction data set. Other than that Random tree, Random forest and J48 models are having highest TP rates So, those three models are having same rate at TP rate. Since Random tree, Random forest and J48 models are showing the highest performance over module shunt prediction data set those three models can be selected but depending on the highest ROC area value in random tree model ,we can evaluate that Random tree model is the best performing classifier for the module shunt predictor data set.

6.3 Summary

This chapter concludes with test results used to evaluate the data model. Final chapter will summarize the overall research and highlights the significance findings of the research.

Chapter 7

Conclusion and Further work

7.1 Introduction

In this research, we have studied the relationship between chemical composition (C, Cu, Cr, Si, Mn, Ni) of steels bars which used to manufacture Load cells and the Module shunt which is a resistor used in load cell wiring. Depending on the results found via data mining approach conducted through the Weka tool , we have go through in built classification algorithms in Weka and extract the relationship using Random Forest algorithm and we have developed a web based system called Mod Shunt Predictor based on the results extracted via the research study.

The research conducted to identify the relationship and predict the Module shunt depending on the chemical composition of its load cell steel. Since all the attributes are numerical and need to predict the class accurately, we have applied classification algorithms in Weka tool. Depending on the results we have got through classification algorithms, Random tree shows the best results with accuracy, not only that but also Random tree results a tree as a visualization it is very easy to understand and implant a system using that results.

The Mod Shunt Predictor, the web-based system totally based on the results extracted through the Random tree classification, and this can be used in Flintec for selecting a proper module shunt via a proper scientific approach without doing a Centering process. And this will save the valuable production time which was occupied to select a module shunt.

7.2 Limitations

In this research study, we have only gone through the relationship between chemical composition of load cell steel bars and the module shunt. But there may be some other conditions like, the operator who apply the module or the module shunt inbuild issues may be affected to the centering process. Those are not considered in this research study.

7.3 Future Developments

For the future studies, it's better to study module shunt properties and chemical composition of load cells, both together to predict a module shunt.

We hope to further develop the Mod Shunt Predictor tool to predict the module shunt at the initial stage of data entering to the system at steel yard or the stores. Then people who need the information about next steel batches and module shunt required to perform the production can ready early stages of the production.

7.4 Summary

This chapter concludes the thesis by describing the solution given with the data mining to predict the module shunt and the advantages Flintec can gain through the Mod Shunt Predictor tool.

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Appendix A

Data Pre-processing

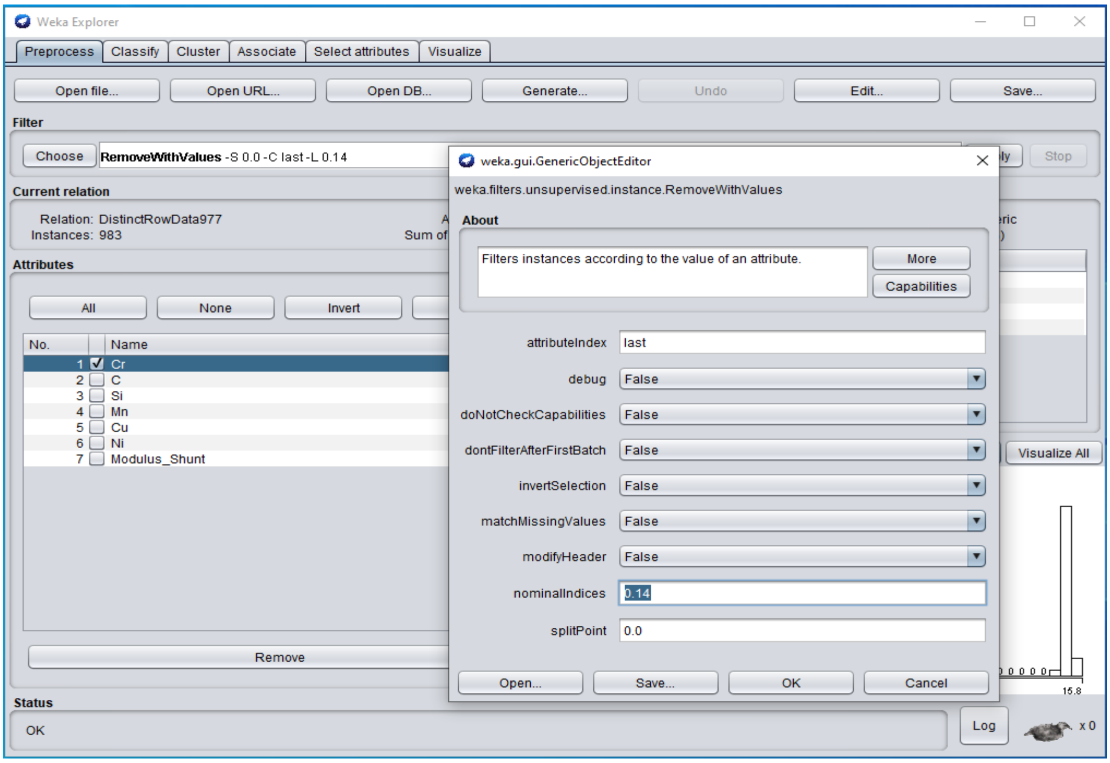

Figure – 8.1: Data pre-processing -remove values– WEKA Tool

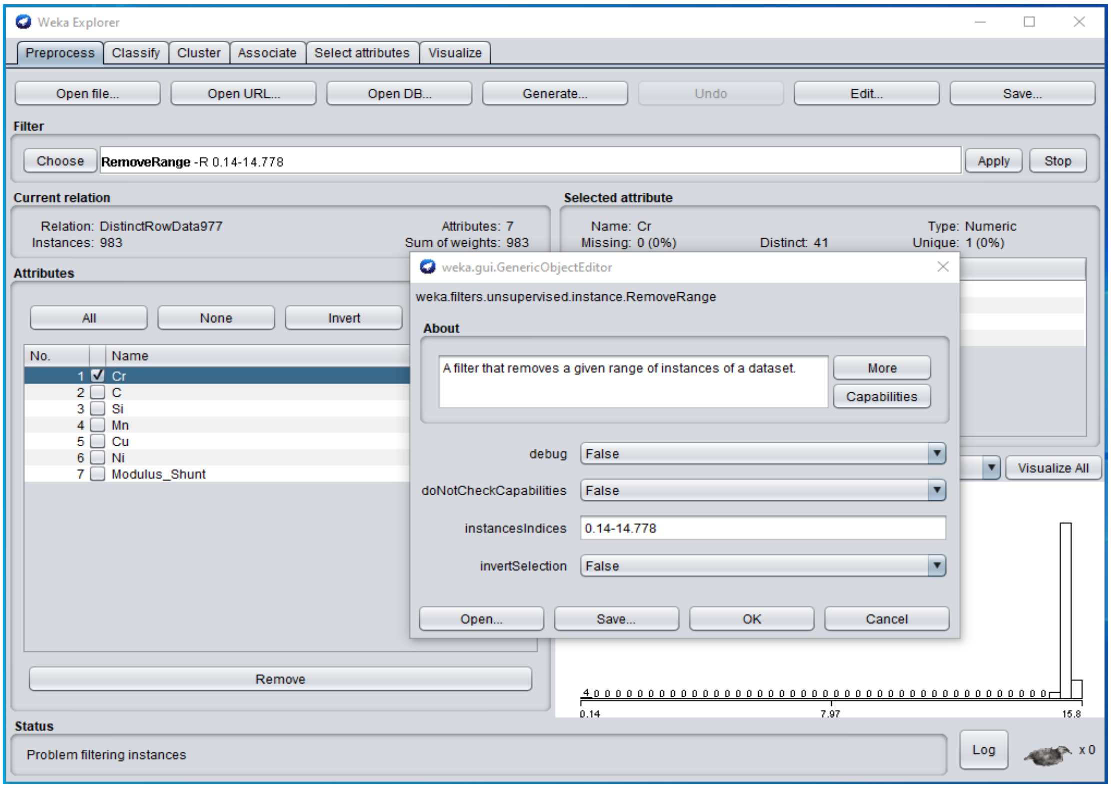

Figure – 8.2: Data pre-processing -remove values– WEKA Tool

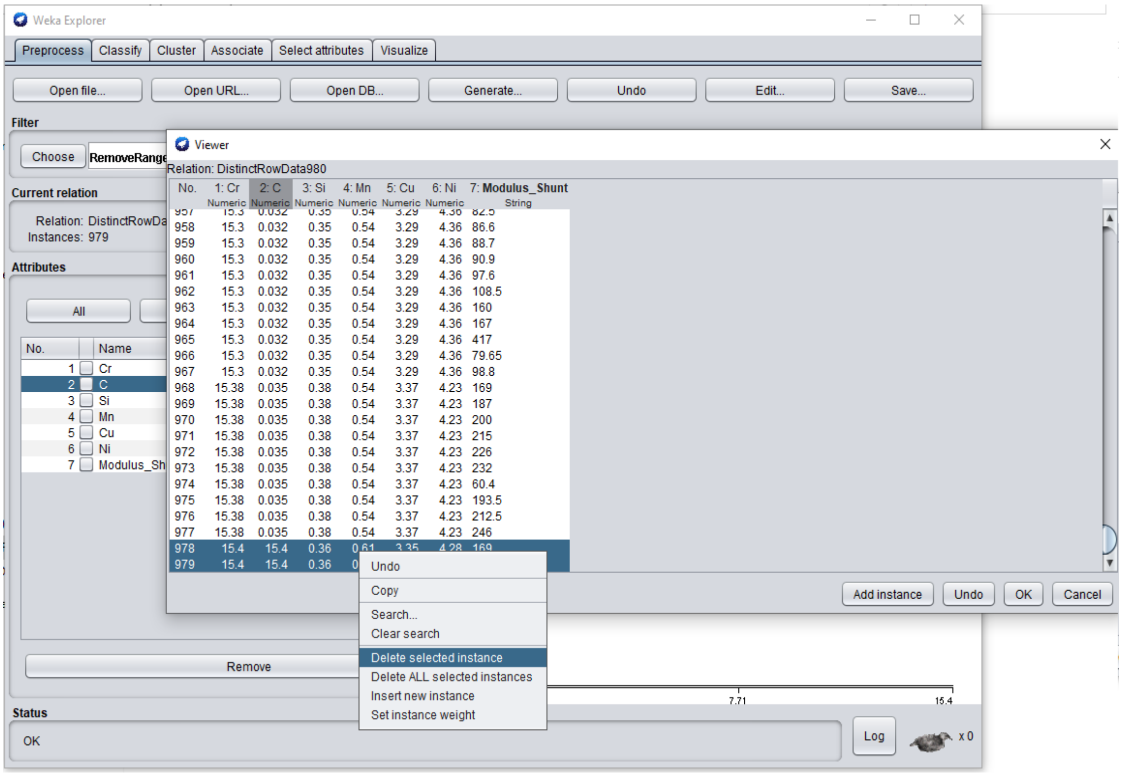

Figure – 8.3: Data pre-processing -delete rows– WEKA Tool

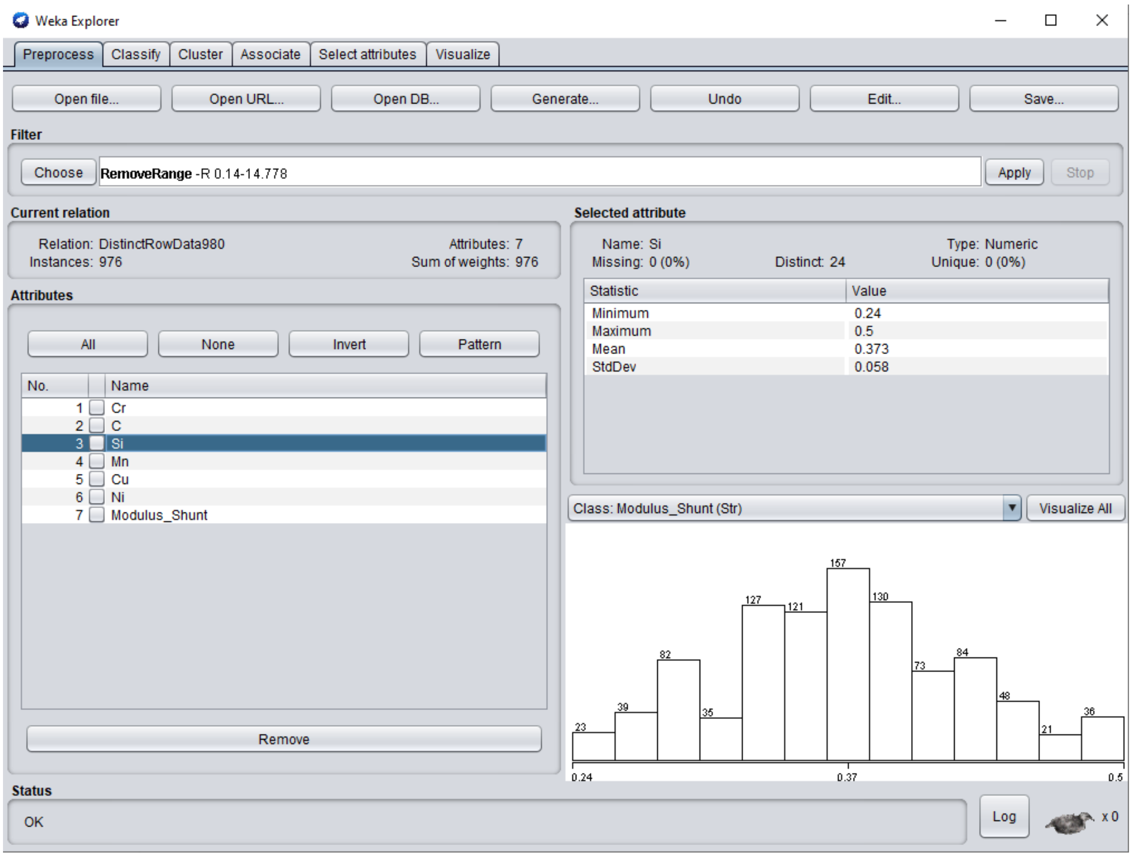

Figure – 8.4: Data pre-processing -after removing outliers of Si

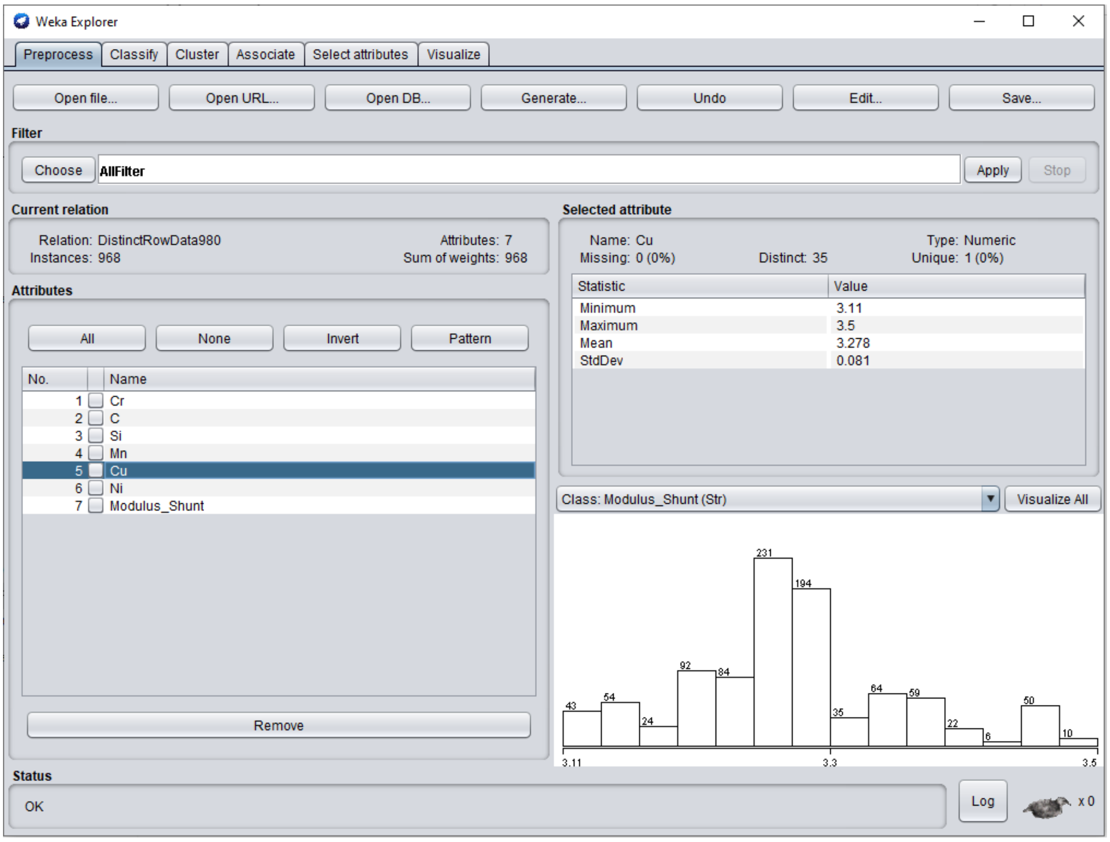

Figure – 8.5: Data pre-processing -after removing outliers of Cu

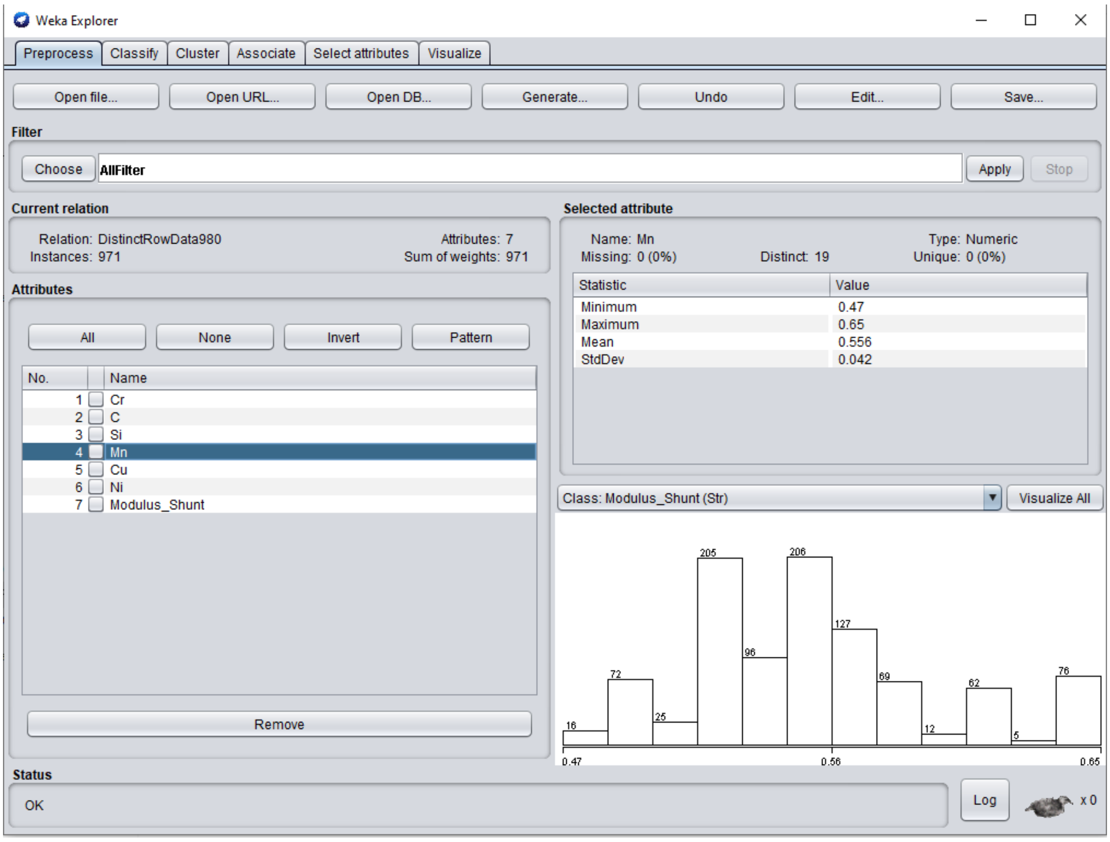

Figure – 8.6: Data pre-processing -after removing outliers of Mn

Appendix B

WEKA Classification.

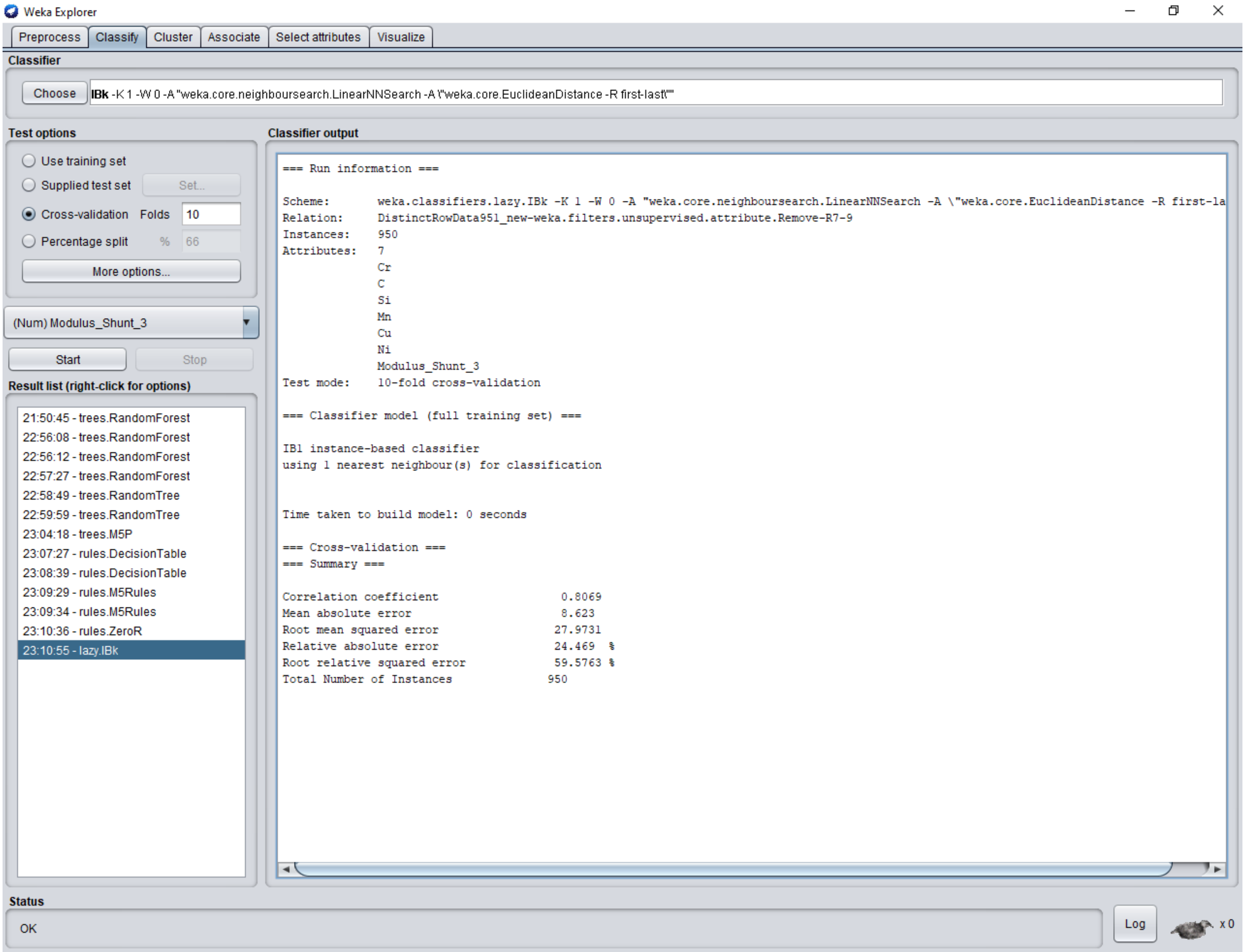

Figure – 8.7: classification-lazy-IBK

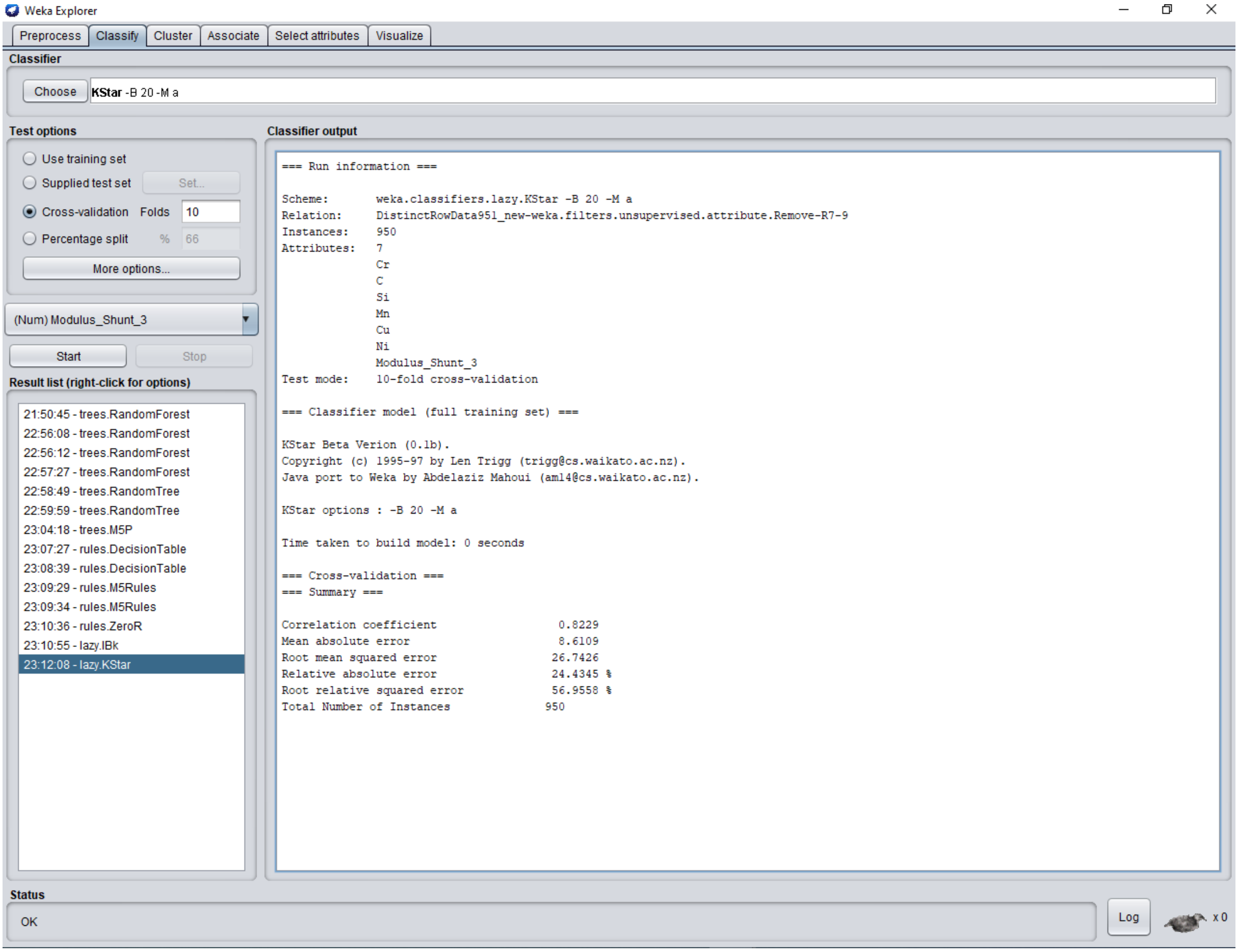

Figure – 8.8: classification-lazy-KStar

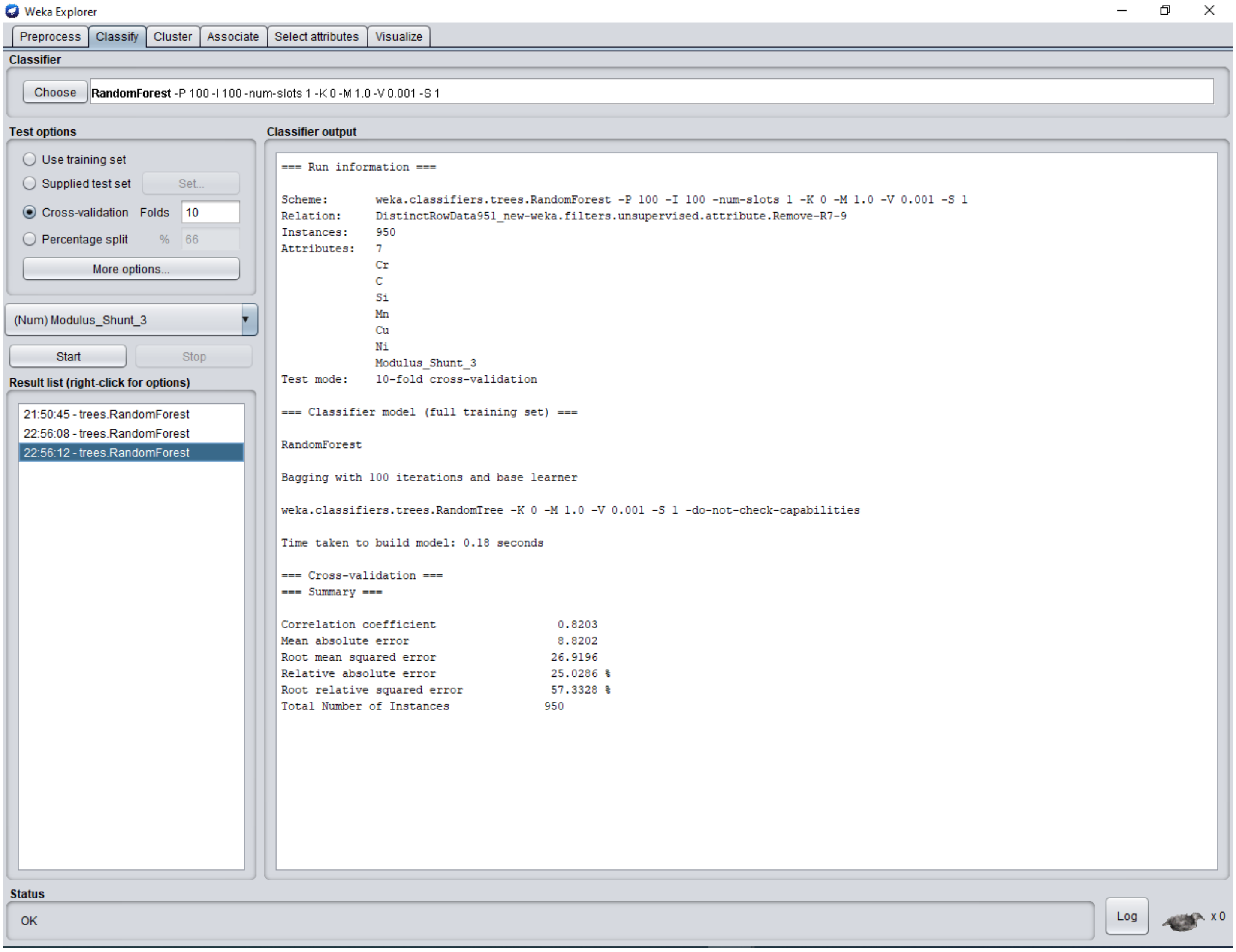

Figure – 8.9: classification-RandomForest

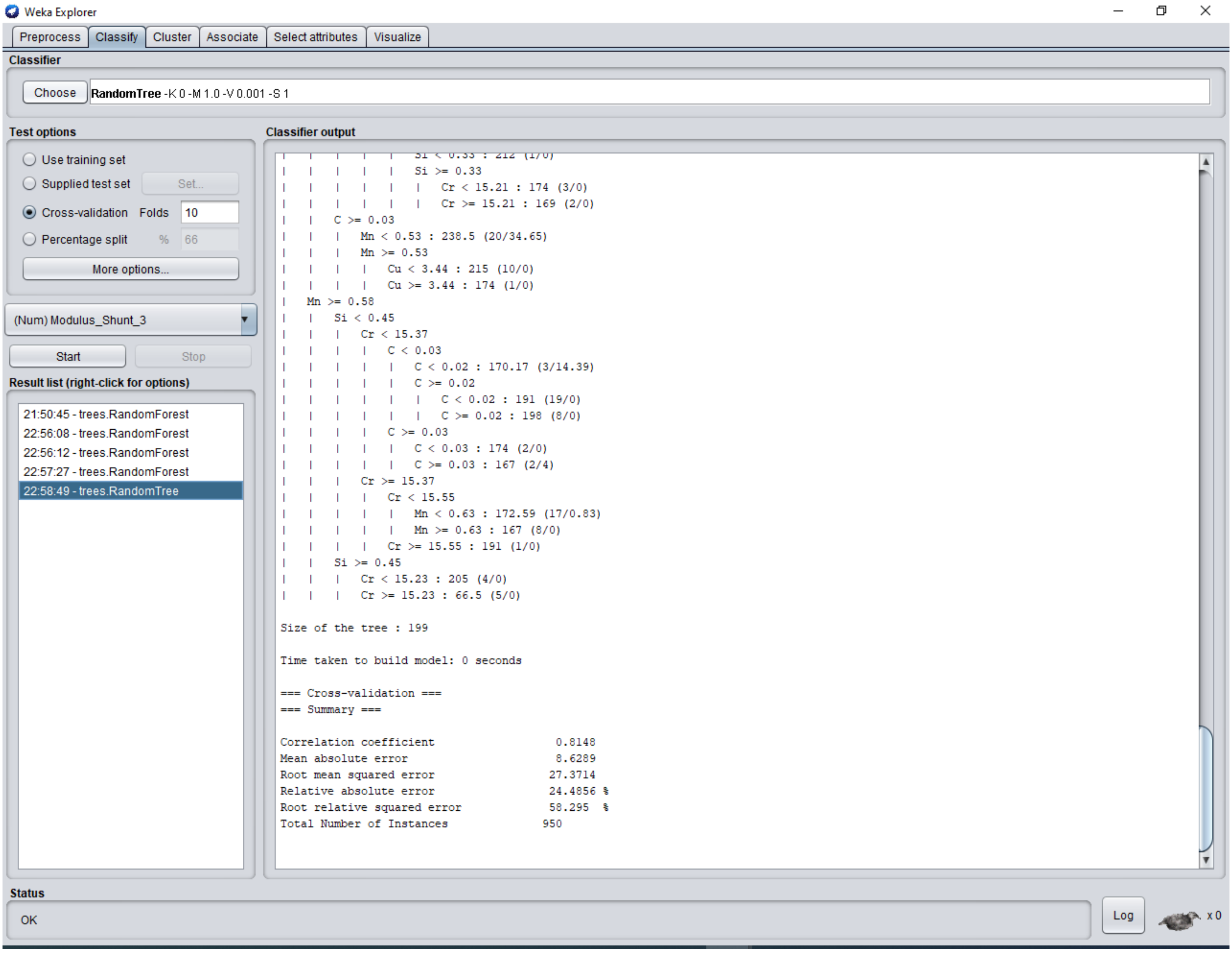

Figure – 8.10: classification-RandomTree

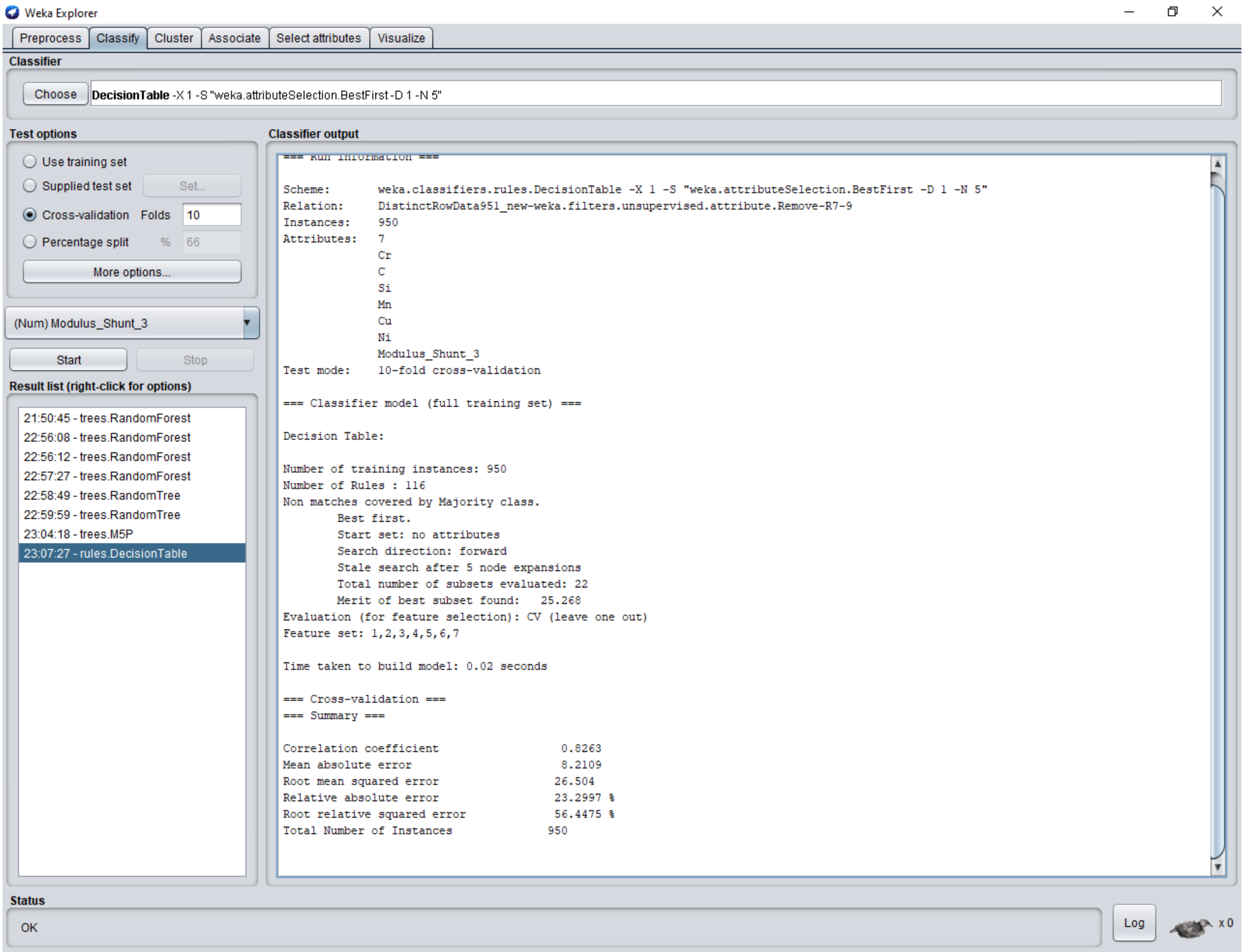

Figure – 8.11: classification-DecisionTree