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AN INTELLIGENT HYBRID MODEL FOR REDUCING NON-TECHNICAL LOSSES IN ELECTRICAL INDUSTRY

H.Tazarvi[1], J.Shahrabi[2*]

[1]Master of Industrial Engineering, Amirkabir University

[2]Academic Rank: Assistant Professor, Amirkabir University

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ABSTRACT

Non-technical losses, specially electricity theft is a major concern for electricity distribution companies all over the world due to its huge financial impact on their revenue. For developing countries such as Iran, the case is even more important because of the fact that the use of advanced metering infrastructure have not been implemented completely. Since the data mining and its techniques have been widely used nowadays and proven to be useful in so many cases like fraud detection problems, it has been decided to use this science in order to tackle non-technical losses problem for an Iranian company by focusing on meter tampering or it may also be referred as fraud in electricity which plays a huge role in creating none-technical losses. The proposed model proved to be applicable for the company by having a much better performance using multi agent ensemble model of SVM, RF, and NN, in comparison to the company's traditional statistical solution which could merely predict less than ten percent of fraud cases correctly.

Keywords: Fraud detection; Multi agent models; Multi agent ensemble models

Author Correspondence, e-mail: jamalshahrabi@aut.ac.ir

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1. INTRODUCTION

Nowadays everything somehow is related to the electricity and it has become an inseperable part of our daily life that one cannot think of a world without it. So, it is sensible to consider electrical power grids as the backbone of today's society. In order to properly serve the society, there are so many factors that should be took under consideration by the electrical power grids. Two factors which are of utmost importance, however, are managing consumer's consumption and controlling losses in electricity. As a matter of fact, these factors could become so problematic for electrical power grids to force them to take temporary measures such as power outage which disrupts our daily life. A great deal of major problems arises from losses during generation and distribution of the electricity, including financial losses to electricity providers and a decrease of stability and reliability. Losses usually are classified into technical losses and non-technical losses. Technical losses occur naturally and mainly include losses from power dissipation in electrical components, such as in generators, transformers and transmission lines due to internal electrical resistance [1]. Non-technical losses, on the other hand, faced by electricity providers, are the amount of electricity that is consumed, yet not paid for [1]. It mostly includes, but is not limited to, frauds or tampering with the meter, in which consumer deliberately decives the utility by tampering with the meter and making it to show a lower amount of electricity is used than what really is the case [2]. Other types of non-technical losses are: A) stealing electricity by meddling with the electricity cables and putting illegal lines that sometimes could be easily detected as they are often above the ground. B) Billing errors, in which whether the operator gives a higher or lower measures than what the precise measure is, or the office staff mistakes in putting the decimal point at the right place, which inturn, for example results in consumer paying $50 instead of $500. C) Non-payment of bills which refers to the consumers that do not pay their dues, either they believe the electricity should be free for them or they cannot afford to pay for it, or even in some cases the consumer is a wealthy or politically powerful person or organization who knows their electricity will not be cut despite the fact that they do not pay for the electicity [2]. As it has been mentioned earlier frauds or tampering with the meter plays a major role in non-technical losses, and inspections of consumers is the required action to detect these so called frauds in electricity. Carrying out inspections, however, is a costly peocedure, because it needs physical presence of technicians [3]. Hence, it is crucial to have a highly accurate system that can predict the fraudulent consumers so as to reduce the likelihood of losing huge amount of money, not only due to the non-technical losses itself, but also due to the cost of inspections.

As it was mentioned before electrical power grids all over the world need to deal with non-technical losses issue. In developing countries such as Iran, specially, due to the fact that the advanced metering infrastructures are not completely implemented, this issue is more problematic and a solution to tackle this problem is necessary. In this paper, therefore, the aim is to propose a better solution in dealing with electricity theft which is a part of the non-technical losses, than the existing solution. The solution which currently is used for detecting fraudulent consumers is a statistical based solution in which there are some thresholds for a couple of factors, and if a consumer exceeds those thresholds they would be considered as suspect of a fraud investigation process which is both time and money consuming process.

1.1 Importance of The Problem

Non-technical losses not only cause so many problems for electrical power grids but also for the consumers. As matter of fact, electrical power grids mainly lose tremendous amount of money, and consumers would probably, in turn, face the disruption in their daily life by incidents such as power outage. By knowing these consequences of non-technical losses, it is plain this issue so important to be dealt with.

1.2 Research Objectives

The principle objective of this paper is to help Great Tehran Electricity Distribution Center company to achieve higher accuracy in detecting fraudulent consumers which is currently below 10 percent. The second objective is to find the best combination of agents to use in implementing multi agent models which means not only which algorithms to use but also how many to use.

1.3 Paper Structure

The rest of this paper is organized as follows. Chapter 2 provides a literature review of non-technical losses detection and discusses some basic concepts. Chapter 3 describes the model development and validation process. Chapter 4 is about empirical experiments using real data and model verification. Finally, conclusions and future works are explained in the chapter 5.

2. LITERATURE REVIEW & BASIC CONCEPTS

A Utility company is company which supplies utilities, such as gas, electricity, phones, and so on. In this paper gas, electricity, and water firms are referred as utility companies, in addition "NTL" is used as an abbreviation which stands for Non-technical loss. In this section, related works on non-technical losses are categorized based on different utilities. For the electricity utility, however, there is different category which is based on different algorithms that are used in papers.

2.1 Gas & Water

Not much works have been done regarding the reduction of NTLs in gas industry nor the water firms, as [4] implies, "since there are apparent lower levels of gas theft compared to electricity, it is reasonable to assume that gas, being less essential than electricity, is not likely to be stolen". Eyad Hashem S.Humaid, however, has a thesis [5] in fraud detection using data mining techniques for water industry which represents a model that reaches the detection hit rate(True positive rate) of 80 %, whereas by a random manual detection, the rate is between 1 to 10%. He has used SVM (Support Vector Machines) to constitute his model and compared it to ANN (Artificial Neural Networks) and KNN (K Nearest Neighbor).

2.2 Electricity

In this section some related works in this area are reviewed based on different data mining methods that are applied for NTLs detection.

2.2.1 Single Models

The reference [6] which is the base paper for this thesis, used artificial neural networks to identify frauds in electricity industry, they reached the accuracy of 84 percent, precision of 79 percent, recall of 93 percent, and F1 measure of 85 percent in their work. The writers of [7] used the same algorithm in their work, but their results were not as good as the base paper. Although they reached a higher accuracy of 87 percent, in other metrics their result was by far lower than the [6]'s results. The writers of [8, 9] used statistical techniques, data mining and artificial intelligence to detect NTLs and later in [10] they proposed a combined text mining and neural networks model to increase the efficiency in NTLs detection methods which was based on association rules and had the accuracy of about 80%.

SVMs have been used in [11], [12], and [3], since they are quite resilient to the class imbalance problems. The refrence [12] reached the best results among them by using social-spider optimization-based Support Vector Machines, although comparing them by performance metrics is not suitable due to the fact that they used different data sets.

2.2.2 Ensemble & Heuristic Model

An extreme learning machine technique with 54% accuracy was exploited in [13] to analyze abnormal behavior of power utility customers whereby they could detect cases of NTLs in the utility market.

In [14] the writers proposed a hybrid GA-SVM model preselecting suspected customers to be inspected onsite for fraud based on abnormal consumption behavior with a hit rate of 60%, the same hit rate as Jawad Nagi et al. [11] achieved using SVM alone. Caio C.O. Ramos et al. in [15] also used a hybrid approach proposing a new hybrid feature selection algorithm based on Harmony search and Optimum path forest. They, subsequently, validated it in the context of automatic recognition of non-technical losses in power distribution systems. A feature selection based method for NTL analysis was proposed in [16] so as to select the best features in characterizing the electricity customers.

The reference [17] used a new automatic feature analysis method using wavelet techniques and combining multiple classifiers to identify fraud in electricity reaching the classification accuracy of 78% on the training dataset and 70% on the testing dataset.

Luis A. M. Pereira et al. [18] showed how to improve the training phase of a neural network-based classifier using a proposed meta-heuristic technique called Charged System Search, which is based on the interactions between electrically charged particles. Their experiments were carried out in the context of non-technical loss in power distribution systems in a dataset obtained from a Brazilian electrical power company, and have demonstrated the robustness of the proposed technique against with several others nature inspired optimization techniques for training neural networks. They found out CSS and PSO have similar accuracy rates related to NTLs detection and considered using evolutionary techniques instead of the traditional Back propagation algorithm to improve the accuracy rates in Smart Grid applications.

Juan Pablo Kosut et al. in [19] used Adaboost ensemble method for decision tree algorithm to identify frauds. Iñigo Monedero et al. used Pearson coefficient, Bayesian networks and decision trees in [20] detect frauds and other non-technical losses in a power utility. In doing so, they had a help from a powerful software called IBM SPSS Modeler 14 used extensively in data mining.

Quite recently Wenlin Han and Yang Xiao [21], Proposed a new algorithm called NFD which is based on Lagrange polynomial interpolation assisted by Taylor Approximation Precision, making it practical to detect NTL frauds both online and offline in Smart Grid.

A summary of works with regard to NTLs are demonstrated in table 1.1 (Most of them have been reviewed in the previous section):

Table 2.1 A summary of researches regarding NTLs

Paper &Year	Methods	Results
Wavelet Based Feature Extraction and Multiple Classifiers for Electricity Fraud Detection [17] (2002)	proposing **a** new automatic feature analysis method using wavelet techniques and combining multiple classifiers to identify fraud in electricity	For a relatively small amount of data, the classification accuracy reaches 78% on the training dataset and 70% on the testing dataset

Detection of Abnormalities and Electricity Theft using Genetic Support Vector Machines [14] 2008	GA-SVM hybrid model	Detection hit rate of 60% and hence tremendous savings
Nontechnical Loss Detection for Metered Customers in Power Utility Using Support Vector Machines [11] 2010	Classification (SVM)	Detection hit rate of 60% and hence tremendous savings
A novel algorithm for feature selection using Harmony Search and its application for non-technical losses detection [15] 2011	proposing a new hybrid feature selection algorithm based on Harmony search and Optimum path forest	addressing the problem of selecting the most relevant features in order to identify possible illegal consumers
Detection of frauds and other non-technical losses in a power utility using Pearson coefficient, Bayesian networks and decision trees [20] 2012	Pearson coefficient, Bayesian networks and decision trees	The system has reached a success rate of 38%. Where the rate of success of the company in its routine inspections was less than 10%, and it resulted in Recovering about 2 millions of kWh

CYBER PHYSICAL SYSTEMS FOR SMARTER ENERGY GRIDS: EXPERIENCES AT IBM RESEARCH—INDIA [22] 2013	Classification, Regression	20-50% fuel saving
Smart Grid Energy Fraud Detection Using Artificial Neural Networks [6] 2015	Artificial Neural Networks	Achieving 84% accuracy in detecting frauds
A novel detector to detect colluded non-technical loss frauds in smart grid [23] 2016	Classification (recursive least squares)	Proposing a detector, named CNFD, which can detect a specific kind of frauds in Smart grid
NFD: Non-technical loss fraud detection in Smart Grid [21] 2017	Proposing a new algorithm called NFD which is based on Lagrange polynomial interpolation assisted by Taylor Approximation Precision	identifying tampered meters by striking a balance between the budget and the detection time

2.3 Research Motivation

"Data mining technology is rapidly becoming strategically important to many data-rich firms [24]." With the growing applications of Data Mining, as a matter of fact, the smart world that we live in, considers this science as one of the best solutions in quantitative problems. So we do not have to solve our new dynamic complex problems by our traditional methods which were always simplifying problems in order to be able to solve them. Now that we have access to great technology that allows us to analyze data, we should certainly use the most of this advantage to reduce losses in electricity, instead of just changing metering infrastructures, although in order to get the best result changing infrastructure may be necessary. As studies such as the ones that are in the table above show, the world is using data mining to solve these kinds of problems, so this question comes to mind “why wouldn’t we do the same?”, because the fact is no single method can be considered as the best method for detecting NTLs. It has been decided to use Data Mining and its techniques, consequently, to figure out a way to overcome our electrical loss problem and eventually save the money that would have been wasted because of the losses for electrical companies. A couple of studies that are carried out towards this problem demonstrate that every case has specific features depending on the country, customers and the company’s policy. By purifying the data and analyzing it, the goal is to find the meaningful patterns so as to design a hybrid model which combines different methods to find the most appropriate one to reduce Non-Technical losses and also find possible hidden knowledge beneath these losses which are exclusive for Iran’ circumstances, because there is a high possibility there could be other factors causing losses which may be unknown as of the moment, similarly for example, there could be new ways of electricity theft which is a main factor of Non-Technical losses, so the goal is to gather the best possible features in order to have a proper Model.

2.4 Multi Agent Ensemble Learning

Multi agent learning could be categorized as competitive learning and cooperative learning. In competitive learning, agents separately work on a same issue and the outcome of the best agent is the ultimate output. As for the cooperative learning, however, the ultimate output is the combination of a couple of agents’ results. The second approach is generally more preferable in practice due to the fact that aggregating agents’ outputs would usually result in improving the overall performance of the model [25].

According to the past studies, it has been come to the light that the ensemble of agents is more effective than just using an individual model by a single learning agent in the multi agent learning system, because of the fact that ensemble models generally outperform single models, bearing in mind that an agent normally would be defined as an independent learning unit of the multi agent system. “Using ensemble models as the agents in the multi agent systems, are referred as Multi Agent Ensemble Learning” [25].

2.5 Support Vector Machines

Support vector machines (SVM) is one of the greatest algorithms for binary classification. The principal idea behind it is to find the best hyperplane that could separate the data in two classes properly. Since, example data usaually is not linearly seperable, SVM uses a so called kernel trik notion to map the data into a higher dimensional space where the data is separable [26].

2.6 Neural Network

“Artificial neural networks (ANNs) are software implementations of the neuronal structure of our brains.” Brain neurons are capable of changing their output state based on the strength of their electrical or chemical input. The neural network in brain is a vast complex interconnected network of neurons, in which the output of a neuron could be the input for one to dozens of neurons. Feedback is a key factor in the learning process of a neural networks, when the network reaches the desired outcome, it strenghtens the neural connections causing that outcome by adjusting their weights [27].

2.7 Random Forest

Bagging is an ensemble method for the variance reduction of an estimated prediction function. It is normally suitable for high-variance, low-bias procedures, such as trees. The output for classification is the average of votes from a committee of trees where each member casts a vote for the predicted class [28].

Boosting is another ensemble method which works like bagging, however unlike Bagging each member of the committee casts a weighted vote, so for most problems it is a better option to choose compared to Bagging [28].

“Random Forest is a substantial modification of bagging that builds a large collection of de-correlated trees, and then averages them.” Random Forest and Boosting usually reach a similar performance, however, due to simplicity of training and tuning Random Forest, it is more poplular and common in practice [28].

2.8 Measuring Performance

After building a model, knowing its prediction capabilities on a new instance, is of utmost importance. To measure the performance of a predictor, there are commonly used performance metrics, such as accuracy, precision, recall, F1 Score, lift, ROC, etc. The first four ones are used in this paper as performance metrics.

2.8.1 Confusion Matrix

Confusion Matrix as the name suggests gives a matrix as output and describes the complete performance of the model. For instance, assume there is a binary classification problem with the classes “YES” and “NO”. Furthermore, there is a classifier which predicts a class for a given input sample. On testing the model on 165 samples, the following results are derived.

Table 2.2 Confusion Matrix

n=165	**Predicted: NO**	**Predicted: YES**
Actual: NO	50	10
Actual: YES	5	100

There are 4 important terms:

- **True Positives(TP)**: The cases in which the prediction and the actual output is YES.
- **True Negatives(TN)**: The cases in which the prediction and the actual output is NO.
- **False Positives(FP)**: The cases in which the prediction is YES, but the actual output is NO.
- **False Negatives(FN)**: The cases in which the prediction is NO, yet the actual output is YES.

2.8.2 Accuracy

Classification Accuracy or the term accuracy which is commonly used instead, is the ratio of number of correct predictions to the total number of input samples.

$$Accuracy = \frac{TP + TN}{TP + FP + FN + TN} \tag{2.1}$$

Accuracy could be a deceiving metric and it works well only if there are equal number of samples belonging to each class. For instance, consider that there are 96% samples of class A and merley 4% samples of class B in the training set. Then the model can easily achive 96% training accuracy by simply predicting every training sample belonging to class A. but when the same model is tested on a test set with 60% samples of class A and 40% samples of class B, then the test accuracy would drop down to 60%. Classification Accuracy is good performance metric, but it usually gives the wrong impression of having a proper model just for achieving a high accuracy. The real problem arises, when the cost of misclassification of the minor class samples are very high. For example, if the case is about a fatal disease, it is a matter of life or death, and the cost of failing to diagnose the disease is much higher than the cost of sending a healthy person to more tests. To tackle this issue, the following metrics could be used alongside accuracy to have a better evaluation of the adequacy of a model.

2.8.3 Precision

Precision is the ratio of correctly predicted positive observations to the total predicted positive observations. The question this metric answers is, of all instances that are labeled as “YES”, how many actually are “YES”. High precision relates to the low false positive rate.

$$Precision = \frac{TP}{TP + FP} \tag{2.2}$$

2.8.4 Recall

Recall or Sensitivity is the ratio of correctly predicted positive observations to the all observations in actual class. The question recall answers is, of all instances that are actually “YES”, how many are labeled “YES”.

$$Recall = \frac{TP}{TP + FN} \tag{2.5}$$

2.8.5 F1 Score

F1 Score is the weighted average of Precision and Recall. Therefore, this score takes both false positives and false negatives into account. Intuitively, it is not as easy to understand as accuracy, but F1 is normally more useful than accuracy metric, especially, if the classes are not evenly distributed.

$$\boldsymbol{F1\ Score} = \frac{2 * (Recall\ * \ Precision)}{(Recall\ + \ Precision)} \tag{2.6}$$

3. MOEL DEVELOPMENT

As it had been discussed in the first chapter, meter tampering plays a major role in causing non-technical losses. So, in order to reduce non-technical losses, it is a reasonable choice to start diminishing the effects of what is causing the most problems. Hence, the aim of this paper is to detect these so called meter tampering which generally is referred as fraud, by proposing a model competent of classifying fraudulent consumers, so as to prevent or lessen the future possible frauds and saving massive amount of money, accordingly. To verify the proposed fraud detection model it is necessary to evaluate the model using standard data beforehand. The model implementation and selection process is provided in this chapter.

3.1 Standard Data

The standard dataset which is used for the model selection process, is Wisconsin Breast Cancer Original dataset [29] which is widely used for validating classification models, and contains 699 samples obtained from a breast tissue including the two classes malignant which is cancerous tumor and benign which is not a cancerous tumor. Subsequently, data with missing values are removed from dataset; as a result, 683 instances in which 239 of them are malignant and the other 444 are benign remained to use in the experiment. Every record in the database has nine attributes, with all values represented as integer numbers between 1 and 10, and was found to fluctuate notably among benign and malignant instances. The measured nine attributes are:

- Clump thickness
- Uniformity of cell size
- Uniformity of cell shape

- Marginal adhesion
- Single epithelial cell size
- Bare nuclei
- Bland chromatin
- Normal nuclei
- Mitoses

3.2 Model Selection

In this section nine machine learning algorithms have been chosen to participate in model selection process after conducting a thorough research on the most popular algorithms used in data mining problems in general, and more specifically in breast cancer diagnosis and fraud detection. These nine algorithms are:

- ❖ SVM
- ❖ Lib SVM
- ❖ Decision Tree
- ❖ Random Forest
- ❖ Naïve Bayes
- ❖ Neural Network
- ❖ Logistic Regression
- ❖ KNN
- ❖ Gradient Boosted Trees

The model selection process, begins with using these algorithms on their default settings by doing a 10-Fold cross-validation for each algorithm. Afterwards, every algorithm is optimized using the grid search optimization method. The grid search optimization method is a favorite hyper parameter optimization technique that is widely used in the data mining. It basically searches through a manually specified subset of the hyper parameter space of a learning algorithm. To properly optimize every algorithm, their hyper parameters and the extent of searching procedure for every hyper parameter which usually results in getting the best optimizations, are studied and utilized.

The decision for combining the classifiers, was to use the first three best models in terms of precision which is crucial in the breast cancer diagnosis. To be sure that this is a good idea, however, the resolution set to use every possible combination and to analyze the outcomes. Likewise, Majority Voting is used as the ensemble method for aggregating the models.

3.2.1 Single Agent Model

Table 3.1 and Table 3.2 show the performance of every algorithm in their default and optimized settings.

Table 3.1 Performance results on default setting

Model	Accuracy	Precision	Recall	F1 Measure
SVM	0.9693	0.9623	0.9504	0.9563
Lib SVM	0.9722	0.9665	0.9545	0.9605
Decision Tree	0.9429	0.8870	0.9464	0.9158
Random Forest	0.9693	0.9707	0.9431	0.9567
Naïve Bayes	0.9605	0.9707	0.9206	0.9450
Neural Network	0.9663	0.9623	0.9426	0.9524
Logistic Regression	0.9663	0.9456	0.9576	0.9516
KNN	0.9567	0.9277	0.9506	0.9390
Gradient Boosted Trees	0.9610	0.9357	0.9549	0.9452

Results are derived from Rapid Miner 9.1

Table 3.2 Performance results on optimized setting

Model	Accuracy	Precision	Recall	F1 Measure
SVM	0.9780	0.9833	0.9553	0.9691
Lib SVM	0.9751	0.9749	0.9549	0.9648
Decision Tree	0.9619	0.9540	0.9383	0.9461
Random Forest	0.9736	0.9749	0.9510	0.9628
Naïve Bayes	0.9605	0.9707	0.9206	0.9450
Neural Network	0.9751	0.9791	0.9512	0.9649
Logistic Regression	0.9663	0.9456	0.9576	0.9516
KNN	0.9736	0.9623	0.9623	0.9623
Gradient Boosted Trees	0.9707	0.9791	0.9398	0.9590

Results are derived from Rapid Miner 9.1

Table 3.1 shows that Lib SVM algorithm has the best performance in accuracy and F1 measure metrics by its default setting. Random Forest and Naïve Bayes are the best with regards to precision. As for the recall metric, Logistic Regression beats other algorithms by its default setting. Decision Tree algorithm could be considered as the worst algorithm by its default setting according to the table by every metric except recall, in which Naïve Bayes algorithm's performance is worse.

As the Table 3.2 demonstrates, SVM outperforms every single algorithm in all metrics except recall where Logistic Regression and KNN have better performances. Since for the breast cancer diagnosis, other metrics are more important than recall, it can be deduced that for the single agent model SVM is the best option.

3.2.2 Three to Nine Agent Model

After evaluating the single agent models, the next part of the model selection process is to asses all possible combinations, starting with three agent models and ending with nine agent models. Three agent models have 84 possible combinations and their performance results can be seen on Table 3.3.

Table 3.3 Performance results of three agent models

Model(3 agents)	Accuracy	Precision	Recall	F1 Measure
SVM_NN_GBT	0.9780	0.9874	0.9516	0.9692
SVM_ Lib SVM_NN	0.9824	0.9916	0.9595	0.9753
SVM_NN_DT	0.9751	0.9791	0.9512	0.9649
SVM_NN_RF	0.9824	0.9916	0.9595	0.9753
SVM_NN_NB	0.9780	0.9874	0.9516	0.9692
SVM_NN_LR	0.9780	0.9791	0.9590	0.9689
SVM_NN_KNN	0.9736	0.9623	0.9623	0.9623
SVM_ Lib SVM_DT	0.9736	0.9707	0.9547	0.9627
SVM_ Lib SVM_RF	0.9766	0.9791	0.9551	0.9669
SVM_ Lib SVM_NB	0.9736	0.9749	0.9510	0.9628
SVM_ Lib SVM_LR	0.9722	0.9665	0.9545	0.9605
SVM_ Lib SVM_KNN	0.9780	0.9791	0.9590	0.9689
SVM_ Lib SVM_GBT	0.9795	0.9833	0.9592	0.9711
SVM_DT_RF	0.9722	0.9707	0.9508	0.9607
SVM_DT_NB	0.9707	0.9707	0.9469	0.9587
SVM_DT_LR	0.9707	0.9623	0.9544	0.9583
SVM_DT_KNN	0.9766	0.9749	0.9588	0.9668
SVM_DT_GBT	0.9750	0.9833	0.9476	0.9651
SVM_RF_NB	0.9707	0.9707	0.9469	0.9587
SVM_RF_LR	0.9722	0.9665	0.9545	0.9605
SVM_RF_KNN	0.9780	0.9791	0.9590	0.9689
SVM_RF_GBT	0.9795	0.9833	0.9592	0.9711

Model(3 agents)	Accuracy	Precision	Recall	F1 Measure
SVM_NB_LR	0.9722	0.9665	0.9545	0.9605
SVM_NB_KNN	0.9736	0.9749	0.9510	0.9628
SVM_NB_GBT	0.9766	0.9833	0.9514	0.9671
SVM_LR_KNN	0.9751	0.9707	0.9587	0.9647
SVM_LR_GBT	0.9751	0.9749	0.9549	0.9648
SVM_KNN_GBT	0.9751	0.9749	0.9549	0.9648
Lib SVM_DT_RF	0.9722	0.9707	0.9508	0.9607
Lib SVM_DT_NB	0.9707	0.9665	0.9506	0.9585
Lib SVM_DT_NN	0.9693	0.9665	0.9467	0.9565
Lib SVM_DT_LR	0.9722	0.9665	0.9545	0.9605
Lib SVM_DT_KNN	0.9751	0.9749	0.9549	0.9648
Lib SVM_DT_GBT	0.9693	0.9707	0.9431	0.9567
Lib SVM_RF_NB	0.9736	0.9749	0.9510	0.9628
Lib SVM_RF_NN	0.9766	0.9791	0.9551	0.9669
Lib SVM_RF_LR	0.9736	0.9707	0.9547	0.9627
Lib SVM_RF_KNN	0.9766	0.9791	0.9551	0.9669
Lib SVM_RF_GBT	0.9766	0.9791	0.9551	0.9669
Lib SVM_NB_NN	0.9751	0.9791	0.9512	0.9649
Lib SVM_NB_LR	0.9707	0.9665	0.9506	0.9585
Lib SVM_NB_KNN	0.9751	0.9791	0.9512	0.9649
Lib SVM_NB_GBT	0.9736	0.9749	0.9510	0.9628
Lib SVM_NN_LR	0.9766	0.9707	0.9627	0.9667
Lib SVM_NN_KNN	0.9810	0.9791	0.9669	0.9730
Lib SVM_NN_GBT	0.9780	0.9874	0.9516	0.9692
Lib SVM_LR_KNN	0.9751	0.9665	0.9625	0.9645
Lib SVM_LR_GBT	0.9736	0.9665	0.9585	0.9625
Lib SVM_KNN_GBT	0.9766	0.9791	0.9551	0.9669
DT_RF_NB	0.9722	0.9707	0.9508	0.9607
DT_RF_NN	0.9678	0.9665	0.9429	0.9545
DT_RF_LR	0.9707	0.9665	0.9506	0.9585
DT_RF_KNN	0.9736	0.9749	0.9510	0.9628
DT_RF_GBT	0.9678	0.9707	0.9393	0.9547
DT_NB_NN	0.9649	0.9623	0.9388	0.9504
DT_NB_LR	0.9693	0.9665	0.9467	0.9565
DT_NB_KNN	0.9707	0.9707	0.9469	0.9587
DT_NB_GBT	0.9663	0.9707	0.9355	0.9528
DT_NN_LR	0.9678	0.9540	0.9540	0.9540
DT_NN_KNN	0.9751	0.9707	0.9587	0.9647
DT_NN_GBT	0.9722	0.9749	0.9472	0.9608
DT_LR_KNN	0.9722	0.9582	0.9622	0.9602
DT_LR_GBT	0.9678	0.9623	0.9465	0.9544
DT_KNN_GBT	0.9707	0.9749	0.9433	0.9588
RF_NB_NN	0.9722	0.9749	0.9472	0.9608

Model(3 agents)	Accuracy	Precision	Recall	F1 Measure
RF_NB_LR	0.9707	0.9707	0.9469	0.9587
RF_NB_KNN	0.9721	0.9747	0.9467	0.9605
RF_NB_GBT	0.9707	0.9707	0.9469	0.9587
RF_NN_LR	0.9766	0.9707	0.9627	0.9667
RF_NN_KNN	0.9810	0.9791	0.9669	0.9730
RF_NN_GBT	0.9780	0.9874	0.9516	0.9692
RF_LR_KNN	0.9751	0.9665	0.9625	0.9645
RF_LR_GBT	0.9736	0.9665	0.9585	0.9625
RF_KNN_GBT	0.9766	0.9791	0.9551	0.9669
NB_NN_LR	0.9722	0.9665	0.9545	0.9605
NB_NN_KNN	0.9780	0.9791	0.9590	0.9689
NB_NN_GBT	0.9736	0.9833	0.9438	0.9631
NB_LR_KNN	0.9707	0.9623	0.9544	0.9583
NB_LR_GBT	0.9707	0.9665	0.9506	0.9585
NB_KNN_GBT	0.9751	0.9749	0.9549	0.9648
NN_LR_KNN	0.9766	0.9665	0.9665	0.9665
NN_LR_GBT	0.9751	0.9749	0.9549	0.9648
NN_KNN_GBT	0.9766	0.9791	0.9551	0.9669
LR_KNN_GBT	0.9751	0.9707	0.9587	0.9647

Results are derived from Rapid Miner 9.1

According to the table, there are two models that have the best performances in every metrics. One is multi agent model of SVM_ Lib SVM_NN, and the other one is multi agent ensemble model of SVM_ NN_RF. The given name multi agent ensemble is due to the Random Forest participation, which is an ensemble of Decision Trees, in the multi agent model.

The subsequent phase after testing three agent models is to test five agent models. There are 126 possible combinations for the five agent models which is the highest number of combinations in all categories. The performance outcomes of every five agent model can be seen in the following table.

Table 3.4 Performance results of five agent models

Model(5 agents)	Accuracy	Precision	Recall	F1 Measure
SVM_ Lib SVM_DT_RF_NB	**0.9722**	**0.9707**	**0.9508**	**0.9607**
SVM_ Lib SVM_DT_RF_NN	**0.9766**	**0.9791**	**0.9551**	**0.9669**
SVM_ Lib SVM_DT_RF_LR	**0.9722**	**0.9665**	**0.9545**	**0.9605**
SVM_ Lib SVM_DT_RF_KNN	**0.9766**	**0.9791**	**0.9551**	**0.9669**

Model(5 agents)	Accuracy	Precision	Recall	F1 Measure
SVM_ Lib SVM_DT_RF_GBT	0.9751	0.9749	0.9549	0.9648
SVM_ Lib SVM_DT_NB_NN	0.9751	0.9749	0.9549	0.9648
SVM_ Lib SVM_DT_NB_LR	0.9707	0.9665	0.9506	0.9585
SVM_ Lib SVM_DT_NB_KNN	0.9751	0.9749	0.9549	0.9648
SVM_ Lib SVM_DT_NB_GBT	0.9751	0.9749	0.9549	0.9648
SVM_ Lib SVM_DT_NN_LR	0.9751	0.9707	0.9587	0.9647
SVM_ Lib SVM_DT_NN_KNN	0.9795	0.9833	0.9592	0.9711
SVM_ Lib SVM_DT_NN_GBT	0.9766	0.9833	0.9514	0.9671
SVM_ Lib SVM_DT_LR_KNN	0.9736	0.9665	0.9585	0.9625
SVM_ Lib SVM_DT_LR_GBT	0.9751	0.9707	0.9587	0.9647
SVM_ Lib SVM_DT_KNN_GBT	0.9780	0.9791	0.9590	0.9689
SVM_ Lib SVM_RF_NB_NN	0.9766	0.9791	0.9551	0.9669
SVM_ Lib SVM_RF_NB_LR	0.9722	0.9707	0.9508	0.9607
SVM_ Lib SVM_RF_NB_KNN	0.9766	0.9791	0.9551	0.9669
SVM_ Lib SVM_RF_NB_GBT	0.9751	0.9749	0.9549	0.9648
SVM_ Lib SVM_RF_NN_LR	0.9780	0.9791	0.9590	0.9689
SVM_ Lib SVM_RF_NN_KNN	0.9795	0.9833	0.9592	0.9711
SVM_ Lib SVM_RF_NN_GBT	0.9810	0.9874	0.9593	0.9732
SVM_ Lib SVM_RF_LR_KNN	0.9766	0.9749	0.9588	0.9668
SVM_ Lib SVM_RF_LR_GBT	0.9766	0.9749	0.9588	0.9668
SVM_ Lib SVM_RF_KNN_GBT	0.9795	0.9833	0.9592	0.9711
SVM_ Lib SVM_NB_NN_LR	0.9751	0.9749	0.9549	0.9648
SVM_ Lib SVM_NB_NN_KNN	0.9795	0.9833	0.9592	0.9711
SVM_ Lib SVM_NB_NN_GBT	0.9795	0.9833	0.9592	0.9711
SVM_ Lib SVM_NB_LR_KNN	0.9736	0.9707	0.9547	0.9627
SVM_ Lib SVM_NB_LR_GBT	0.9751	0.9749	0.9549	0.9648
SVM_ Lib SVM_NB_KNN_GBT	0.9766	0.9791	0.9551	0.9669
SVM_ Lib SVM_NN_LR_KNN	0.9795	0.9791	0.9630	0.9710
SVM_ Lib SVM_NN_LR_GBT	0.9795	0.9833	0.9592	0.9711
SVM_ Lib SVM_NN_KNN_GBT	0.9810	0.9874	0.9593	0.9732
SVM_ Lib SVM_LR_KNN_GBT	0.9751	0.9707	0.9587	0.9647
SVM_DT_RF_NB_NN	0.9722	0.9707	0.9508	0.9607
SVM_DT_RF_NB_LR	0.9707	0.9707	0.9469	0.9587
SVM_DT_RF_NB_KNN	0.9722	0.9707	0.9508	0.9607
SVM_DT_RF_NB_GBT	0.9722	0.9707	0.9508	0.9607
SVM_DT_RF_NN_LR	0.9751	0.9707	0.9587	0.9647
SVM_DT_RF_NN_KNN	0.9795	0.9833	0.9592	0.9711
SVM_DT_RF_NN_GBT	0.9766	0.9833	0.9514	0.9671
SVM_DT_RF_LR_KNN	0.9736	0.9665	0.9585	0.9625
SVM_DT_RF_LR_GBT	0.9751	0.9707	0.9587	0.9647
SVM_DT_RF_KNN_GBT	0.9780	0.9791	0.9590	0.9689
SVM_DT_NB_NN_LR	0.9736	0.9707	0.9547	0.9627
SVM_DT_NB_NN_KNN	0.9780	0.9791	0.9590	0.9689

Model(5 agents)	Accuracy	Precision	Recall	F1 Measure
SVM_DT_NB_NN_GBT	0.9766	0.9833	0.9514	0.9671
SVM_DT_NB_LR_KNN	0.9722	0.9665	0.9545	0.9605
SVM_DT_NB_LR_GBT	0.9736	0.9707	0.9547	0.9627
SVM_DT_NB_KNN_GBT	0.9766	0.9791	0.9551	0.9669
SVM_DT_NN_LR_KNN	0.9780	0.9749	0.9628	0.9688
SVM_DT_NN_LR_GBT	0.9766	0.9833	0.9514	0.9671
SVM_DT_NN_KNN_GBT	0.9766	0.9833	0.9514	0.9671
SVM_DT_LR_KNN_GBT	0.9751	0.9707	0.9587	0.9647
SVM_RF_NB_NN_LR	0.9736	0.9707	0.9547	0.9627
SVM_RF_NB_NN_KNN	0.9795	0.9833	0.9592	0.9711
SVM_RF_NB_NN_GBT	0.9795	0.9833	0.9592	0.9711
SVM_RF_NB_LR_KNN	0.9722	0.9665	0.9545	0.9605
SVM_RF_NB_LR_GBT	0.9736	0.9707	0.9547	0.9627
SVM_RF_NB_KNN_GBT	0.9766	0.9791	0.9551	0.9669
SVM_RF_NN_LR_KNN	0.9795	0.9791	0.9630	0.9710
SVM_RF_NN_LR_GBT	0.9795	0.9833	0.9592	0.9711
SVM_RF_NN_KNN_GBT	0.9810	0.9874	0.9593	0.9732
SVM_RF_LR_KNN_GBT	0.9751	0.9707	0.9587	0.9647
SVM_NB_NN_LR_KNN	0.9766	0.9749	0.9588	0.9668
SVM_NB_NN_LR_GBT	0.9780	0.9833	0.9553	0.9691
SVM_NB_NN_KNN_GBT	0.9780	0.9833	0.9553	0.9691
SVM_NB_LR_KNN_GBT	0.9722	0.9707	0.9508	0.9607
SVM_NN_LR_KNN_GBT	0.9780	0.9749	0.9628	0.9688
Lib SVM_DT_RF_NB_NN	0.9736	0.9749	0.9510	0.9628
Lib SVM_DT_RF_NB_LR	0.9707	0.9665	0.9506	0.9585
Lib SVM_DT_RF_NB_KNN	0.9736	0.9749	0.9510	0.9628
Lib SVM_DT_RF_NB_GBT	0.9722	0.9707	0.9508	0.9607
Lib SVM_DT_RF_NN_LR	0.9736	0.9707	0.9547	0.9627
Lib SVM_DT_RF_NN_KNN	0.9766	0.9791	0.9551	0.9669
Lib SVM_DT_RF_NN_GBT	0.9736	0.9791	0.9474	0.9630
Lib SVM_DT_RF_LR_KNN	0.9736	0.9707	0.9547	0.9627
Lib SVM_DT_RF_LR_GBT	0.9722	0.9665	0.9545	0.9605
Lib SVM_DT_RF_KNN_GBT	0.9766	0.9791	0.9551	0.9669
Lib SVM_DT_NB_NN_LR	0.9722	0.9665	0.9545	0.9605
Lib SVM_DT_NB_NN_KNN	0.9766	0.9791	0.9551	0.9669
Lib SVM_DT_NB_NN_GBT	0.9722	0.9749	0.9472	0.9608
Lib SVM_DT_NB_LR_KNN	0.9722	0.9665	0.9545	0.9605
Lib SVM_DT_NB_LR_GBT	0.9722	0.9665	0.9545	0.9605
Lib SVM_DT_NB_KNN_GBT	0.9736	0.9749	0.9510	0.9628
Lib SVM_DT_NN_LR_KNN	0.9780	0.9749	0.9628	0.9688
Lib SVM_DT_NN_LR_GBT	0.9722	0.9707	0.9508	0.9607
Lib SVM_DT_NN_KNN_GBT	0.9766	0.9833	0.9514	0.9671
Lib SVM_DT_LR_KNN_GBT	0.9736	0.9665	0.9585	0.9625

Model(5 agents)	Accuracy	Precision	Recall	F1 Measure
Lib SVM_RF_NB_NN_LR	**0.9751**	**0.9749**	**0.9549**	**0.9648**
Lib SVM_RF_NB_NN_KNN	**0.9766**	**0.9791**	**0.9551**	**0.9669**
Lib SVM_RF_NB_NN_GBT	**0.9766**	**0.9791**	**0.9551**	**0.9669**
Lib SVM_RF_NB_LR_KNN	**0.9751**	**0.9749**	**0.9549**	**0.9648**
Lib SVM_RF_NB_LR_GBT	**0.9736**	**0.9707**	**0.9547**	**0.9627**
Lib SVM_RF_NB_KNN_GBT	**0.9751**	**0.9791**	**0.9512**	**0.9649**
Lib SVM_RF_NN_LR_KNN	**0.9795**	**0.9791**	**0.9630**	**0.9710**
Lib SVM_RF_NN_LR_GBT	**0.9780**	**0.9791**	**0.9590**	**0.9689**
Lib SVM_RF_NN_KNN_GBT	**0.9795**	**0.9833**	**0.9592**	**0.9711**
Lib SVM_RF_LR_KNN_GBT	**0.9766**	**0.9749**	**0.9588**	**0.9668**
Lib SVM_NB_NN_LR_KNN	**0.9795**	**0.9791**	**0.9630**	**0.9710**
Lib SVM_NB_NN_LR_GBT	**0.9766**	**0.9749**	**0.9588**	**0.9668**
Lib SVM_NB_NN_KNN_GBT	**0.9780**	**0.9833**	**0.9553**	**0.9691**
Lib SVM_NB_LR_KNN_GBT	**0.9736**	**0.9707**	**0.9547**	**0.9627**
Lib SVM_NN_LR_KNN_GBT	**0.9795**	**0.9791**	**0.9630**	**0.9710**
DT_RF_NB_NN_LR	**0.9722**	**0.9707**	**0.9508**	**0.9607**
DT_RF_NB_NN_KNN	**0.9736**	**0.9749**	**0.9510**	**0.9628**
DT_RF_NB_NN_GBT	**0.9693**	**0.9707**	**0.9431**	**0.9567**
DT_RF_NB_LR_KNN	**0.9722**	**0.9707**	**0.9508**	**0.9607**
DT_RF_NB_LR_GBT	**0.9722**	**0.9707**	**0.9508**	**0.9607**
DT_RF_NB_KNN_GBT	**0.9707**	**0.9707**	**0.9469**	**0.9587**
DT_RF_NN_LR_KNN	**0.9780**	**0.9749**	**0.9628**	**0.9688**
DT_RF_NN_LR_GBT	**0.9722**	**0.9707**	**0.9508**	**0.9607**
DT_RF_NN_KNN_GBT	**0.9766**	**0.9833**	**0.9514**	**0.9671**
DT_RF_LR_KNN_GBT	**0.9736**	**0.9665**	**0.9585**	**0.9625**
DT_NB_NN_LR_KNN	**0.9766**	**0.9707**	**0.9627**	**0.9667**
DT_NB_NN_LR_GBT	**0.9722**	**0.9707**	**0.9508**	**0.9607**
DT_NB_NN_KNN_GBT	**0.9736**	**0.9791**	**0.9474**	**0.9630**
DT_NB_LR_KNN_GBT	**0.9722**	**0.9665**	**0.9545**	**0.9605**
DT_NN_LR_KNN_GBT	**0.9751**	**0.9749**	**0.9549**	**0.9648**
RF_NB_NN_LR_KNN	**0.9780**	**0.9749**	**0.9628**	**0.9688**
RF_NB_NN_LR_GBT	**0.9751**	**0.9707**	**0.9587**	**0.9647**
RF_NB_NN_KNN_GBT	**0.9780**	**0.9833**	**0.9553**	**0.9691**
RF_NB_LR_KNN_GBT	**0.9722**	**0.9665**	**0.9545**	**0.9605**
RF_NN_LR_KNN_GBT	**0.9795**	**0.9791**	**0.9630**	**0.9710**
NB_NN_LR_KNN_GBT	**0.9766**	**0.9749**	**0.9588**	**0.9668**

Results are derived from Rapid Miner 9.1

There are three models that have the best performances in five agent models unlike the three agent models. The first one is multi agent ensemble model of SVM_ Lib SVM_RF_NN_GBT, the second one is multi agent model of SVM_ Lib SVM_NN_KNN_GBT and the third one is multi agent ensemble model of SVM_RF_NN_KNN_GBT. These models have the best performance in every metrics. The accuracy of these models is 98 percent, almost same as their precision. Their recall is 96 percent. And as for the F1 measure the accuracy is 97 percent.

The next part of the model selection process is testing seven agent models which means testing 36 possible combinations. Table 3.5 contains the performances results of these models based on the four metrics.

Table 3.5 Performance results of seven agent models

Model(7 agents)	Accuracy	Precision	Recall	F1 Measure
SVM_ Lib SVM_DT_RF_NB_NN_LR	**0.9736**	**0.9707**	**0.9547**	**0.9627**
SVM_ Lib SVM_DT_RF_NB_NN_KNN	**0.9766**	**0.9791**	**0.9551**	**0.9669**
SVM_ Lib SVM_DT_RF_NB_NN_GBT	**0.9751**	**0.9749**	**0.9549**	**0.9648**
SVM_ Lib SVM_DT_RF_NB_LR_KNN	**0.9736**	**0.9707**	**0.9547**	**0.9627**
SVM_ Lib SVM_DT_RF_NB_LR_GBT	**0.9736**	**0.9707**	**0.9547**	**0.9627**
SVM_ Lib SVM_DT_RF_NB_KNN_GBT	**0.9751**	**0.9749**	**0.9549**	**0.9648**
SVM_ Lib SVM_DT_RF_NN_LR_KNN	**0.9780**	**0.9791**	**0.9590**	**0.9689**
SVM_ Lib SVM_DT_RF_NN_LR_GBT	**0.9766**	**0.9749**	**0.9588**	**0.9668**
SVM_ Lib SVM_DT_RF_NN_KNN_GBT	**0.9795**	**0.9833**	**0.9592**	**0.9711**
SVM_ Lib SVM_DT_RF_LR_KNN_GBT	**0.9766**	**0.9749**	**0.9588**	**0.9668**
SVM_ Lib SVM_DT_NB_NN_LR_KNN	**0.9766**	**0.9749**	**0.9588**	**0.9668**
SVM_ Lib SVM_DT_NB_NN_LR_GBT	**0.9766**	**0.9749**	**0.9588**	**0.9668**
SVM_ Lib SVM_DT_NB_NN_KNN_GBT	**0.9780**	**0.9791**	**0.9590**	**0.9689**
SVM_ Lib SVM_DT_NB_LR_KNN_GBT	**0.9766**	**0.9749**	**0.9588**	**0.9668**
SVM_ Lib SVM_DT_NN_LR_KNN_GBT	**0.9780**	**0.9791**	**0.9590**	**0.9689**
SVM_ Lib SVM_RF_NB_NN_LR_KNN	**0.9780**	**0.9791**	**0.9590**	**0.9689**
SVM_ Lib SVM_RF_NB_NN_LR_GBT	**0.9766**	**0.9749**	**0.9588**	**0.9668**
SVM_ Lib SVM_RF_NB_NN_KNN_GBT	**0.9780**	**0.9791**	**0.9590**	**0.9689**
SVM_ Lib SVM_RF_NB_LR_KNN_GBT	**0.9766**	**0.9749**	**0.9588**	**0.9668**
SVM_ Lib SVM_RF_NN_LR_KNN_GBT	**0.9795**	**0.9833**	**0.9592**	**0.9711**
SVM_ Lib SVM_NB_NN_LR_KNN_GBT	**0.9780**	**0.9791**	**0.9590**	**0.9689**
SVM_DT_RF_NB_NN_LR_KNN	**0.9751**	**0.9707**	**0.9587**	**0.9647**
SVM_DT_RF_NB_NN_LR_GBT	**0.9751**	**0.9707**	**0.9587**	**0.9647**
SVM_DT_RF_NB_NN_KNN_GBT	**0.9780**	**0.9791**	**0.9590**	**0.9689**
SVM_DT_RF_NB_LR_KNN_GBT	**0.9751**	**0.9707**	**0.9587**	**0.9647**
SVM_DT_RF_NN_LR_KNN_GBT	**0.9780**	**0.9791**	**0.9590**	**0.9689**
SVM_DT_NB_NN_LR_KNN_GBT	**0.9780**	**0.9791**	**0.9590**	**0.9689**
SVM_RF_NB_NN_LR_KNN_GBT	**0.9780**	**0.9791**	**0.9590**	**0.9689**
Lib SVM_DT_RF_NB_NN_LR_KNN	**0.9751**	**0.9749**	**0.9549**	**0.9648**

Lib SVM_DT_RF_NB_NN_LR_GBT	**0.9736**	**0.9707**	**0.9547**	**0.9627**
Lib SVM_DT_RF_NB_NN_KNN_GBT	**0.9766**	**0.9791**	**0.9551**	**0.9669**
Lib SVM_DT_RF_NB_LR_KNN_GBT	**0.9736**	**0.9707**	**0.9547**	**0.9627**
Lib SVM_DT_RF_NN_LR_KNN_GBT	**0.9780**	**0.9791**	**0.9590**	**0.9689**
Lib SVM_DT_NB_NN_LR_KNN_GBT	**0.9766**	**0.9749**	**0.9588**	**0.9668**
Lib SVM_RF_NB_NN_LR_KNN_GBT	**0.9780**	**0.9791**	**0.9590**	**0.9689**
DT_RF_NB_NN_LR_KNN_GBT	**0.9751**	**0.9707**	**0.9587**	**0.9647**

Results are derived from Rapid Miner 9.1

SVM_ Lib SVM_DT_RF_NN_KNN_GBT and SVM_ Lib SVM_RF_NN_LR_KNN_GBT multi agent ensemble models have the highest accuracy, precision, recall and F1 measure performances among other seven agent models which are 98%, 98%, 96%, and 97 %, respectively.

As for the last set of combinations, there is only one possible combination for nine agent models which is to combine all of the single models as a separate agent by majority voting. The below table shows the outcome of using all the models as a separate agent in the model.

Table 3.6 Performance results of nine agent model

Model(9 agents)	**Accuracy**	**Precision**	**Recall**	**F1 Measure**
SVM_ Lib SVM_DT_RF_NB_NN_LR_KNN_GBT	**0.9766**	**0.9749**	**0.9588**	**0.9668**

Results are derived from Rapid Miner 9.1

3.2.3 The Chosen Model

With all the acquired information from the single agent models to the nine agent model, it is time to choose the superior one as the final model and later on the next section compare it with other models in different papers that used the same data.

The following charts are illustrated to have a better understanding of each agent based category's best possible performances.

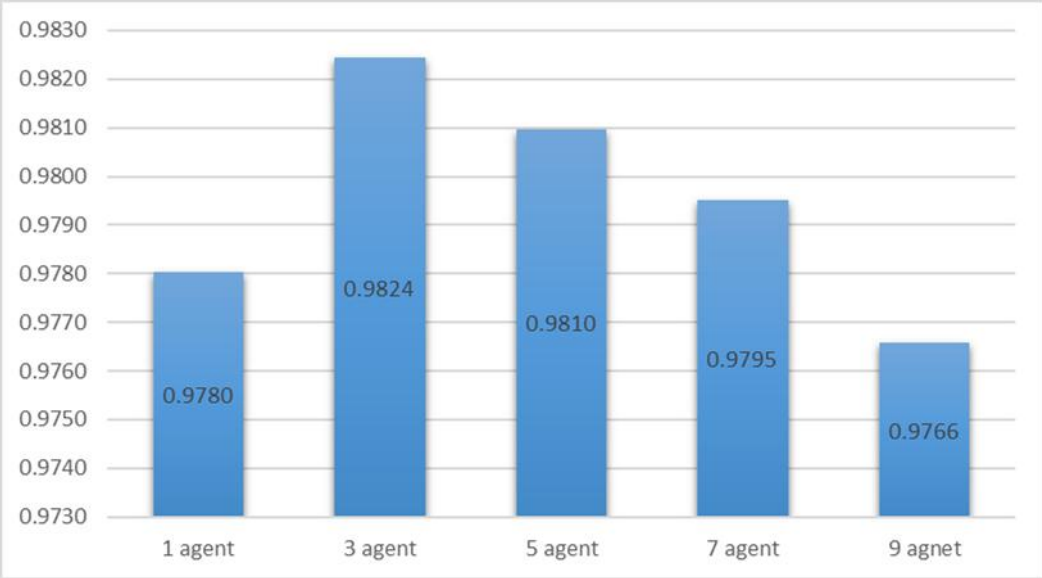

Fig.3.1 Comparison of the best possible performance of every agent in terms of Accuracy

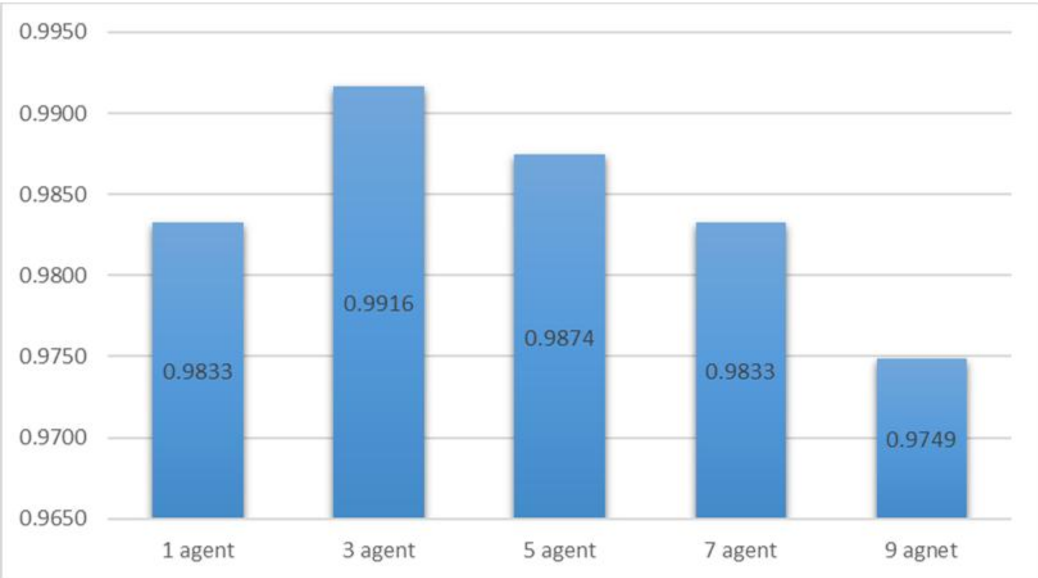

Fig.3.2 Comparison of the best possible performance of every agent in terms of Precision

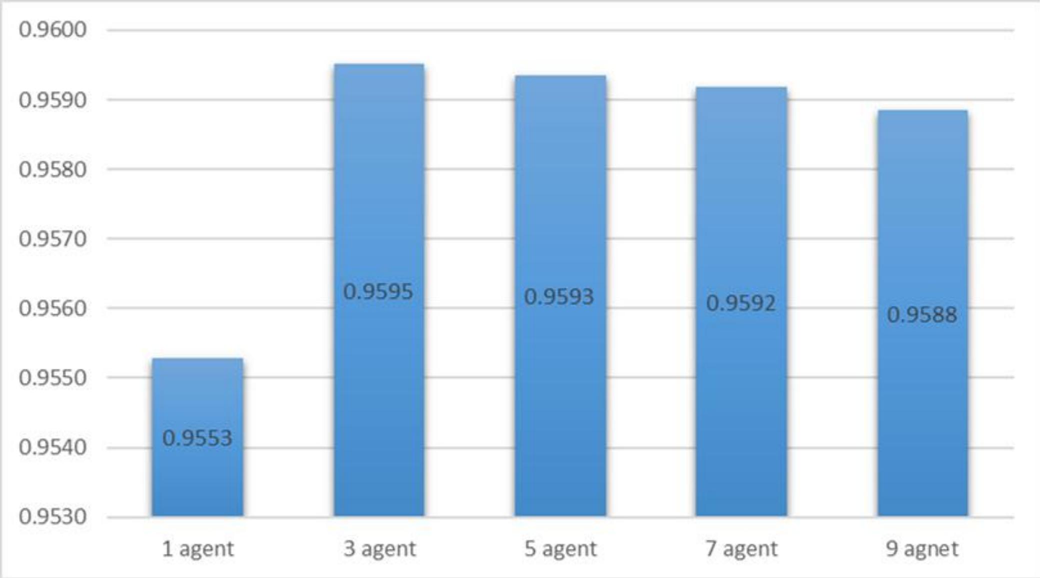

Fig.3.3 Comparison of the best possible performance of every agent in terms of Recall

Fig.3.4 Comparison of the best possible performance of every agent in terms of F1 measure

The first evident information the charts display is that the three agent models stand out as the best models in by every metrics. To further investigate the charts, the accuracy and the F1 measure charts show that apart from three agent models the next best options are 5, 7, 1, and 9 agent models. As for the precision, the single agent model surpasses the 7 agent models and takes the third place. Finally, for recall metric, the performances are very similar between all multi agent models. For the single agent model, on the other hand, the case is somehow different and it has the worst performance although it is not a bad performance.

Now the question is which one of the three agent models to choose as the final model. To answer this question, two factors should be considered, execution time and diversity.

Even though execution time could have a major impact on choosing the models, for these two models, nevertheless, does not have any significance. The reason is the difference between the models execution time is only one second. The multi agent model's execution time is two seconds and the multi agent ensemble model's execution time is three seconds.

"In an ensemble or multi agent model, the combination of the output of several classifiers is only useful if they disagree on some inputs. The measure of disagreement is referred as the diversity of the ensemble" [30]. Since SVM and Lib SVM almost work the same, it is better to use the multi agent ensemble model of Support Vector Machines, Random Forest, and Neural Networks. In the empirical phase which is in chapter 4, however, the SVM, Lib SVM, NN model is also tested to show this fact that the multi agent ensemble model is the solely best model.

3.3 Model Validation

To validate this model, it should be compared to the best models in other papers that used the same standard data. The Table 3.7 provides information about some of these papers. The reason why only the metric accuracy, is used for the comparison is due the fact that most of these papers used only accuracy as their performance metrics and to have a good comparison the metric should be the same. The table is sorted in order of improvement in accuracy. Likewise, it demonstrates that the best accuracy is 98% which is about 0.25% lower than the proposed model. Therefore, the authenticity of the proposed multi agent ensemble model is verified, and it is time to use this model in empirical test with real electricity consumption data to test its competency in fraud detection in electrical industry.

Table 3.7 Perfomances of papers that used breast cancer wisocsin original dataset

Paper &Year	**Method**	**Accuracy(%)**
[31] 2017	Random Forest	96.2
[32] 2014	Extreme Learning Machine Neural Networks	96.4
[33] 2012	Hybrid approach of Functional Networks , Type-2 Fuzzy Logic and SVM	96.85
[34] 2017	Dynamic ensemble selection with Probabilistic Classifier Chains	97
[35] 2016	SVM	97.13
[36] 2017	Multi agent model of Naive Bayes, SVM, J48	97.13
[37] 2017	Bayesian Network	97.22
[38] 2018	deep learning-based stacking ensemble method	97.22
[39] 2012	SMO+J48+NB+Instance Based for K-Nearest neighbor	97.28
[40] 2018	Naive Bayes	97.36
[41] 2014	Multi boost SMO	97.8
[42] 2012	Hybrid approach of bagging with cart decision tree algorithm	97.85
[43] 2015	Multi agent model of on-line dictionary learning and SVM	98

4. EMPERICAL EXPERIMANTATION WITH REAL CONSUMPTION DATA

4.1 Great Tehran Electricity Distribution Center

The Regional Electrical Companies have been tasked to do the distribution of the electricity in the country up to the level of 63 kilo volts for a long time. Over time, the tasks of doing the higher voltages, electricity production and transmission have also been added to their responsibility, which in turn prompted some difficulties. In Order to deal with these difficulties, the headquarters of the electrical industry carried out a research which resulted in assigning utilities to independent non-governmental sector, where electricity distribution centers were created. The creation of electricity distribution centers refined the structure of Iran's utilities. Although there were some major issues, these companies found their way to evolve and gaining an independent identity, similar to production and transmission sectors. [44] The Great Tehran Electricity Distribution Center is one of these companies which provides the real consumer's consumption data for the purpose of this paper.

4.2 Data Preparation

As the saying goes at least 80 percent of data mining process belongs to data preparation. Especially, when there is no contract and no certainty of getting good results from these companies point of view, they do not cooperate with students who want to put use of their data.

By doing a thorough research on the best features used in fraud detection in electrical industry on different worth reading papers and combining them with each other the following features were requested to be provided by the company in order to use in this thesis to acquire the best possible results:

- Consumer's code
- Consumption type (Commercial, Industrial, Domestic, Other)
- Reader's Code
- Meter Status (Operational, Broken)
- Building Location
- Number of Meters in the Building
- Number of People in the Building

- Number of People in the House
- paid bills per invoices ratio
- Monthly consumption for at least 5 years
- Fraud Status (Yes, No)

Due to lack of cooperation from the Great Tehran Electricity Distribution Center, however, the below features merely were provided from the requested features:

- Consumer's code
- Consumption type (Domestic, General, Commercial)
- Monthly consumption for at about 5 years
- Fraud Status (Yes, No)

The given data is consumption data for 919 consumers of 200 thousand consumers in the Sadat Abad district in Tehran from the month Februray of the year 2013 to the month July of the year 2018. The data contains all 404 fraudulent consumers of the whole consumers in Sadat Abad district, plus 515 random non-fraudulent consumers from the 200 thousand consumers.

The first and the most time consuming step in the data preparation phase was to organize the existing data set to represent the monthly average consumptions values, as the initial data set was disorganized and provided datum from various time periods throughout the year. This data set was thoroughly examined and adjusted to meet the desired criteria.

The next part was to deal with the missing values. Since the majority of missing values belonged to the last two months of the data set, these two months were removed from the data set. Moreover, a few consumers had a lot of missing values in their consumption data, so the decision was set to remove these consumers, as well.

By dealing with the missing values, the data set lessened to 870 consumers including 377 fraudulent and 493 non fraudulent consumers, and 64 moths of average consumption data.

4.3 Creating Subsets

Since the prepared data set merely contains consumptions rates and consumption types as the features, creation of different subsets to use as input of the proposed model seems a good idea so as to achieve better results. To create these different subsets, three approaches have been made:

- ❖ Clustering
- ❖ Feature extraction
- ❖ Subsets based on consumption types

4.3.1 Clustering

The first approach was to use clustering to have at least two different data sets. To do the clustering the K-means algorithm was used. The K-means clustering algorithm aims to partition n observations into K clusters in which each observation belongs to the cluster with the nearest mean, serving as a prototype of the cluster. By using the grid search to find the best K for K- means clustering, the given two clusters were not meaningful. In the next step, even cluster of clustering method have been used which is using a second order cluster to hopefully gain better clusters. This method also failed, however, and clustering the clusters did not result in any achieving any meaningful clusters. The outcome of clustering was not surprising, as a matter of fact, because to have proper clusters the data set should consist much more features.

4.3.2 Feature Extraction

After the failure of the first method, it became evident that more having more feature are necessary to get better results. But due to the lack of cooperation from the company, the only way to get more features was to extract them from the data set. Three features have been extracted from the data set:

- Number of zeros in monthly consumption rates of consumers
- Seasonal consumption rates
- Yearly consumption rate

A couple of different data sets have been created using this method. However, since the performance of the clustering method did not improve, the first method is not used in the model testing phase.

4.3.3 Subsets Based On Consumption Types

The third and the last method is creating subsets based on consumption types and mixing it with the second method to have the best possible materials to evaluate competency of the proposed model.

4.4 Model Results

In this section, the performance results of every data set is discussed using the proposed multi agent ensemble model. Moreover, the best data set is used to compare the model with the basic models and the other multi agent model which have been mentioned earlier in the model selection phase.

The testing process is very similar to the model selection phase in which the data set was breast cancer data. However, unlike the breast cancer data set, the attributes of these data sets have various scales, so normalizing all the features is required. Likewise, the Z-transformation is used to normalize the attributes.

4.4.1 Feature Extraction Approach

Table 4.1 provides the information regarding the performance results of the proposed model using all of the data sets that are derived from implementing the second method of the subset creation, also known as feature extraction method.

Table 4.1 Performance results of the proposed model using feature extraction method

Data Code	Monthly Consumption	Seasonal Consumption	Yearly Consumption	Number of Zeros	Accuracy	Precision	Recall	F1 Measure
22	✓				87.13	84.62	85.52	85.07
31			✓		84.37	87.97	78.33	82.87
32		✓			87.47	87.43	84.06	85.71
33		✓	✓		86.21	81.82	85.47	83.61
34	✓		✓		86.55	84.76	84.08	84.42
35	✓	✓			86.32	84.76	83.64	84.20
36	✓	✓	✓		87.13	85.56	84.66	85.11

Data Code	Monthly Consumption	Seasonal Consumption	Yearly Consumption	Number of Zeros	Accuracy	Precision	Recall	F1 Measure
41	✓			✓	85.98	85.68	82.61	84.11
42		✓		✓	85.75	86.63	81.41	83.94
43			✓	✓	85.17	87.17	80.10	83.48
44	✓	✓		✓	85.63	85.29	82.01	83.62
45	✓		✓	✓	87.47	86.90	84.42	85.64
46		✓	✓	✓	84.60	85.56	80.00	82.69
47	✓	✓	✓	✓	86.21	86.90	82.07	84.42

Results are derived from Rapid Miner 9.1

The following figures are illustrated to have a better visual representation of the upper table.

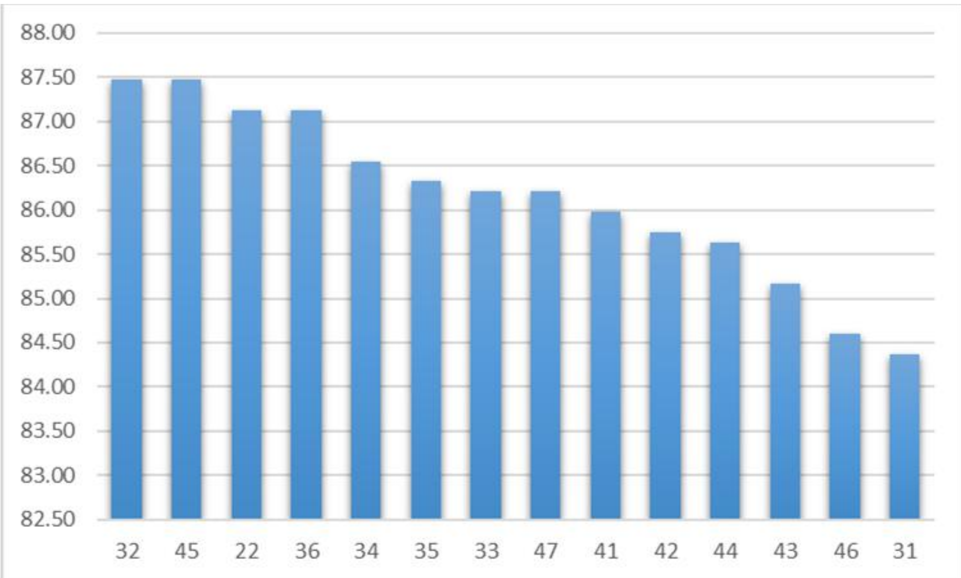

Fig.4.1 Percentage of Accuracy/Dataset Code

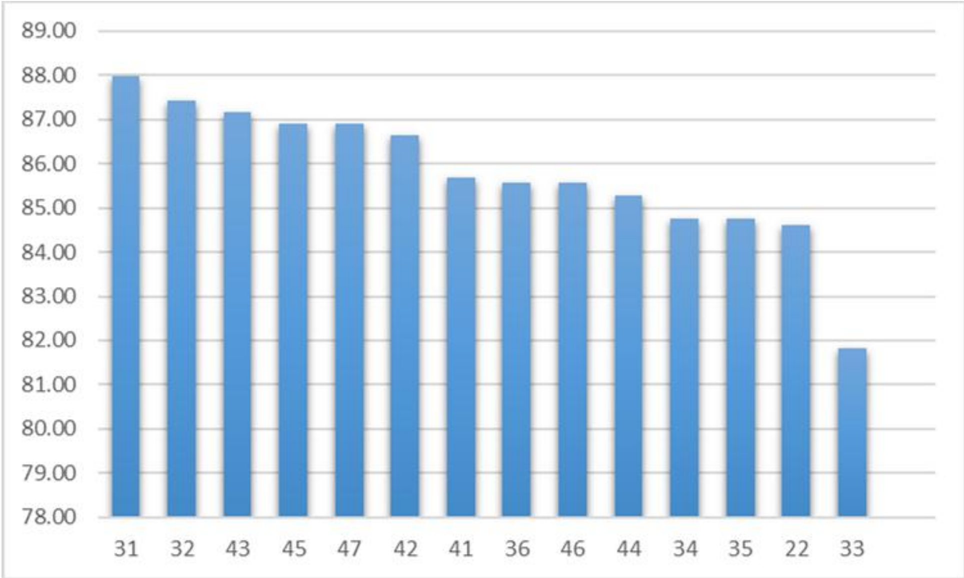

Fig.4.2 Percentage of Precision/Dataset Code

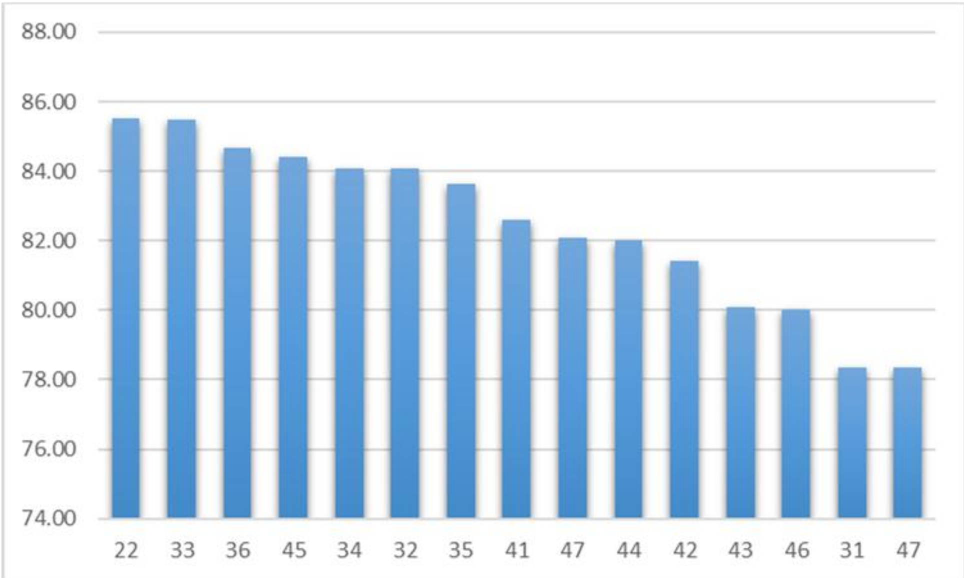

Fig.4.3 Percentage of Recall/Dataset Code

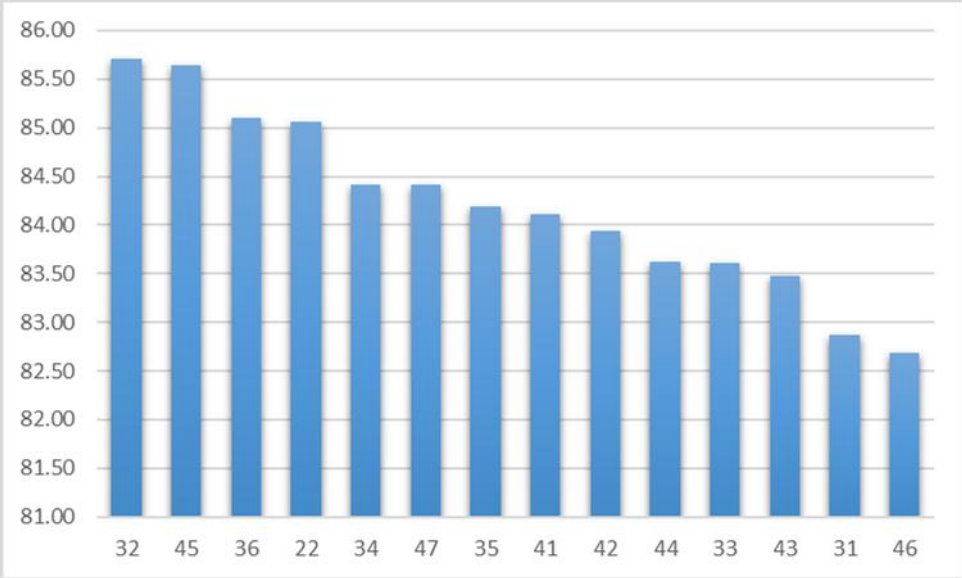

Fig.4.4 Percentage of F1 measure/Dataset Code

The Figure 4.1 shows that the 32 and 45 data sets have the highest overall accuracy of 87.47 percent. Moreover, the 22 and 36 datasets are second best in terms of accuracy, with only having 0.34 percent lower accuracy. On the other hand, the 31 data set has the lowest accuracy which is 84.37 percent.

The next chart which is about precision demonstrates that the 31 and 33 datasets have the best and the worst performances, respectively. The rest of them, however, vary between 84 to 87 percent.

The datasets 22 and 33 have the best performances with regard to the recall, as the recall chart illustrates. In addition, the data sets 31 and 47 have the worst performance which is about 78 percent.

As for the F1 measure, datasets 32 and 45 have the best results, although the other datasets are not far behind in terms of performance. Furthermore, the 46 dataset solely has the lowest performance.

Overall, according to the charts the 32 data set which uses seasonal consumption rates, results in the best model performance, due to the fact that none of the data set result in the dominancy of the model in every metric, it is a wise choice to use F1 measure metric to choose the best data set for this part. Although, the 45 data set helps the model to have a very similar results to using the 32 data set it takes 73 more seconds to be executed than the model using the 32 data set in which the execution time is 26 seconds.

4.4.2 Subsets Based On Consumption Types Approach

The next part of model assessment is to use the data sets that are created based on consumption types which are “domestic”, “general” and “commercial”, respectively. There are 227 fraudulent and 82 non fraudulent consumers for “domestic” type. “general” type has 49 fraudulent and 370 non fraudulent consumers. And for the “commercial” type, there are 101 fraudulent and 41 non fraudulent consumers. The following tables shows the performance outcomes of the model by utilizing the third approach of creating subsets.

Table 4.2 Performance results of the proposed model using domestic type subsets

Data Code	Monthly Consumption	Seasonal Consumption	Yearly Consumption	Number of Zeros	Accuracy	Precision	Recall	F1 Measure
221	✓				89.64	97.80	89.16	93.28
311			✓		88.67	98.67	87.45	92.72
321		✓			93.71	99.06	93.78	96.35
331		✓	✓		89.00	98.67	87.80	92.92
341	✓		✓		89.64	98.67	88.49	93.31
351	✓	✓			89.64	98.23	88.80	93.28
361	✓	✓	✓		89.97	98.23	89.16	93.47
411	✓			✓	90.29	98.24	89.56	93.70
421		✓		✓	89.64	98.67	88.49	93.31
431			✓	✓	88.31	98.22	87.35	92.47
441	✓	✓		✓	89.64	98.23	88.80	93.28
451	✓		✓	✓	88.67	97.35	88.35	92.63
461		✓	✓	✓	89.00	98.67	87.80	92.92

Data Code	Monthly Consumption	Seasonal Consumption	Yearly Consumption	Number of Zeros	Accuracy	Precision	Recall	F1 Measure
471	✓	✓	✓	✓	90.29	97.79	89.84	93.64

Results are derived from Rapid Miner 9.1

Table 4.3 Performance results of the proposed model using general type subsets

Data Code	Monthly Consumption	Seasonal Consumption	Yearly Consumption	Number of Zeros	Accuracy	Precision	Recall	F1 Measure
222	✓				88.31	0.00	*	*
312			✓		88.54	0.00	*	*
322		✓			88.54	0.00	*	*
332		✓	✓		88.54	0.00	*	*
342	✓		✓		88.54	0.00	*	*
352	✓	✓			88.54	0.00	*	*
362	✓	✓	✓		88.54	0.00	*	*
412	✓			✓	88.31	0.00	*	*
422		✓		✓	88.54	0.00	*	*
432			✓	✓	88.54	0.00	*	*
442	✓	✓		✓	88.54	0.00	*	*
452	✓		✓	✓	88.54	0.00	*	*

Data Code	Monthly Consumption	Seasonal Consumption	Yearly Consumption	Number of Zeros	Accuracy	Precision	Recall	F1 Measure
462		✓	✓	✓	88.54	0.00	*	*
472	✓	✓	✓	✓	88.31	0.00	0.00	*

Results are derived from Rapid Miner 9.1

Table 4.4 Performance results of the proposed model using commercial type subsets

Data Code	Monthly Consumption	Seasonal Consumption	Yearly Consumption	Number of Zeros	Accuracy	Precision	Recall	F1 Measure
225	✓				85.21	96.04	85.09	90.23
315			✓		85.21	99.00	83.19	90.41
325		✓			85.92	99.00	83.90	90.83
335		✓	✓		84.51	96.00	84.21	89.72
345	✓		✓		84.51	96.00	84.21	89.72
355	✓	✓			84.51	96.00	84.21	89.72
365	✓	✓	✓		84.51	96.00	84.21	89.72
415	✓			✓	85.21	96.04	85.09	90.23
425		✓		✓	84.51	96.00	84.21	89.72
435			✓	✓	84.51	98.00	83.05	89.91
445	✓	✓		✓	84.51	96.00	84.21	89.72

Data Code	Monthly Consumption	Seasonal Consumption	Yearly Consumption	Number of Zeros	Accuracy	Precision	Recall	F1 Measure
455	✓		✓	✓	84.51	96.00	84.21	89.72
465		✓	✓	✓	84.51	97.00	83.62	89.81
475	✓	✓	✓	✓	84.51	96.00	84.21	89.72

Results are derived from Rapid Miner 9.1

The first thing that catches the eye by looking at the Table 4.3 is that something there is an issue with the data based on “general” consumption. In all those cases except the last one, the proposed model did not learn anything and predicted all instances non fraudulent, and for the last case it falsely predicted one instance fraudulent. The reason of this fact is still unknown and the only tool to discover the knowledge beneath it is to have the Great Tehran Electricity Distribution Center company’s cooperation which as for the moment is not the main concern due to the fact that the company stated, “general” consumption consists of mainly ministries and traffic lights consumptions, and not much fraud cases are reported from this kind of consumption in comparison to the “domestic” and “commercial consumptions. Therefore, their principal objective is dealing with these two types of consumptions first rather than focusing on the “general” consumption.

Moving on to the other two tables the following figures are displayed to have a better interpretation of the tables.

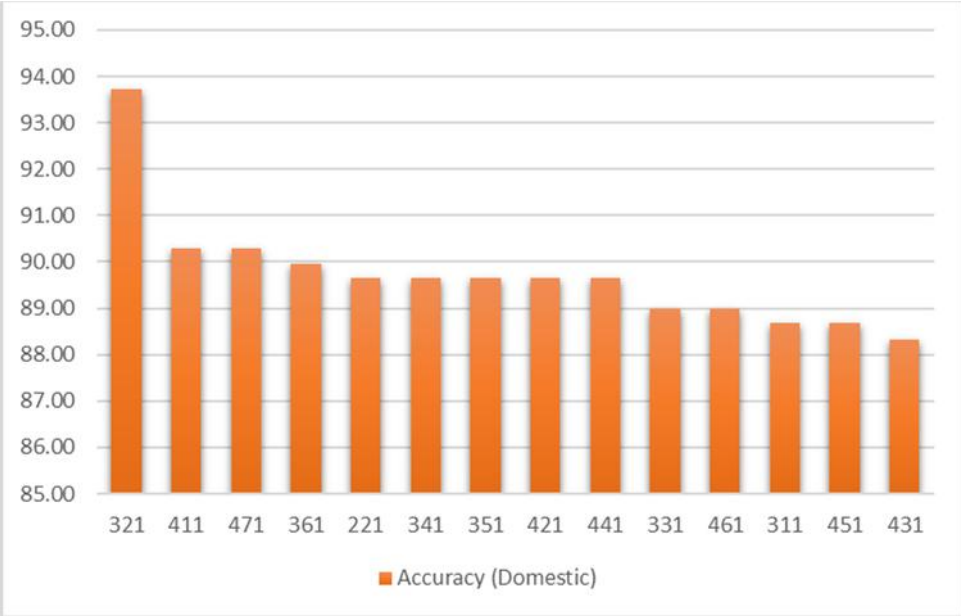

Fig.4.5 Percentage of Accuracy (Domestic)/Dataset Code

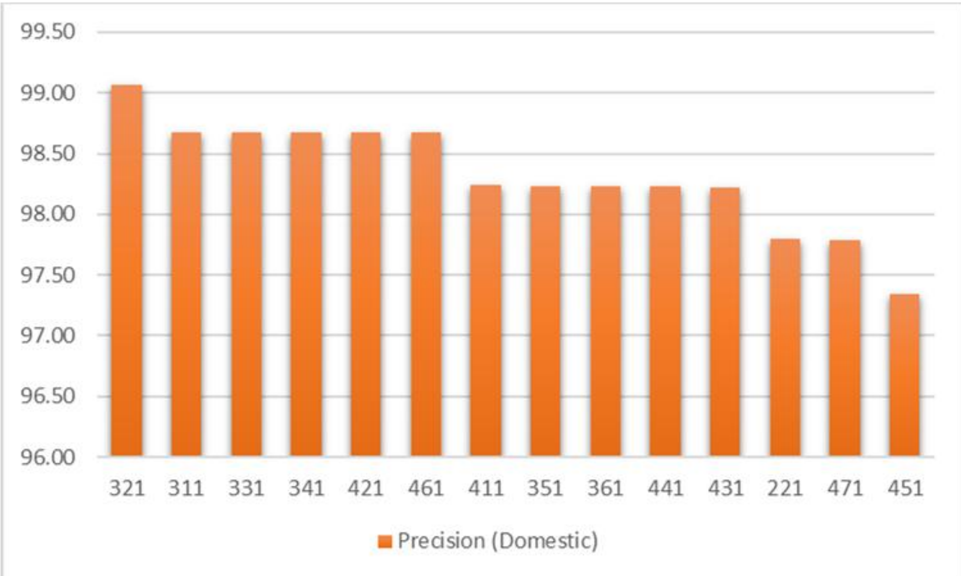

Fig.4.6 Percentage of Precision (Domestic)/Dataset Code

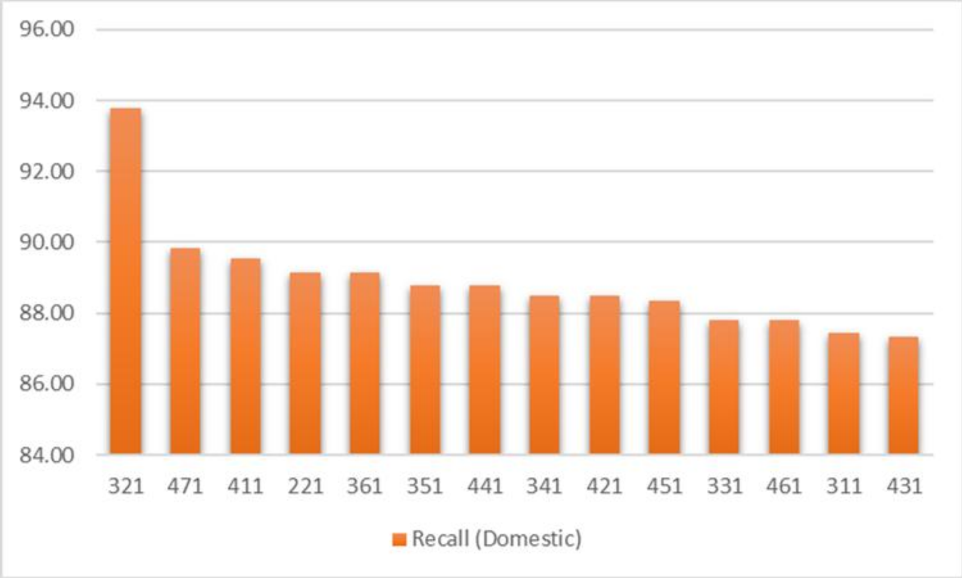

Fig.4.7 Percentage of Recall (Domestic)/Dataset Code

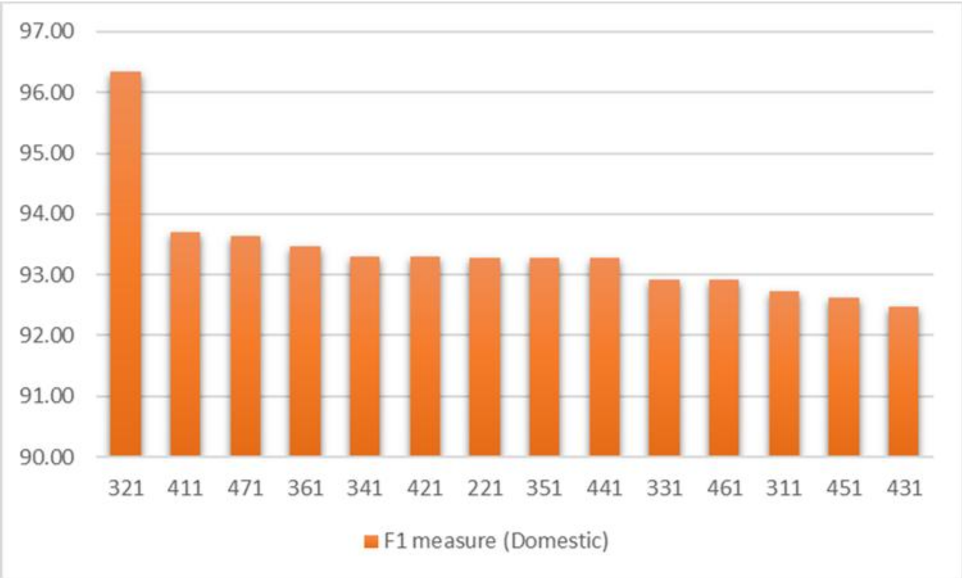

Fig.4.8 Percentage of F1 measure (Domestic)/Dataset Code

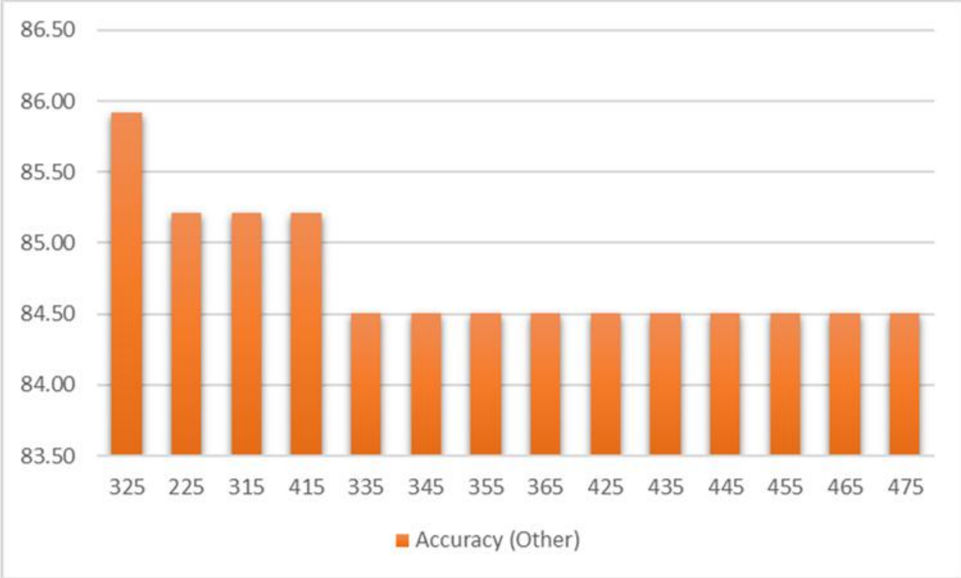

Fig.4.9 Percentage of Accuracy (Commercial)/Dataset Code

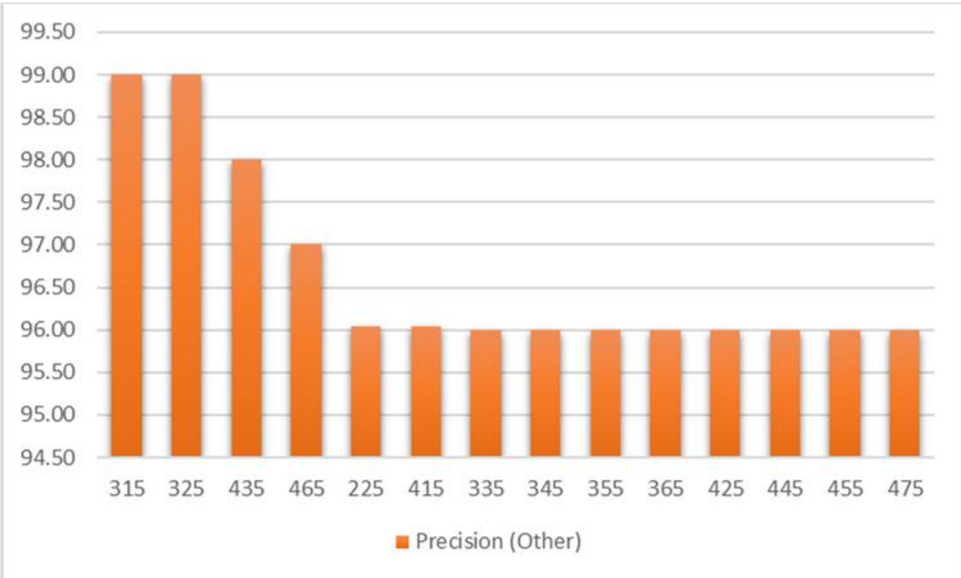

Fig.4.10 Percentage of Precision (Commercial)/Dataset Code

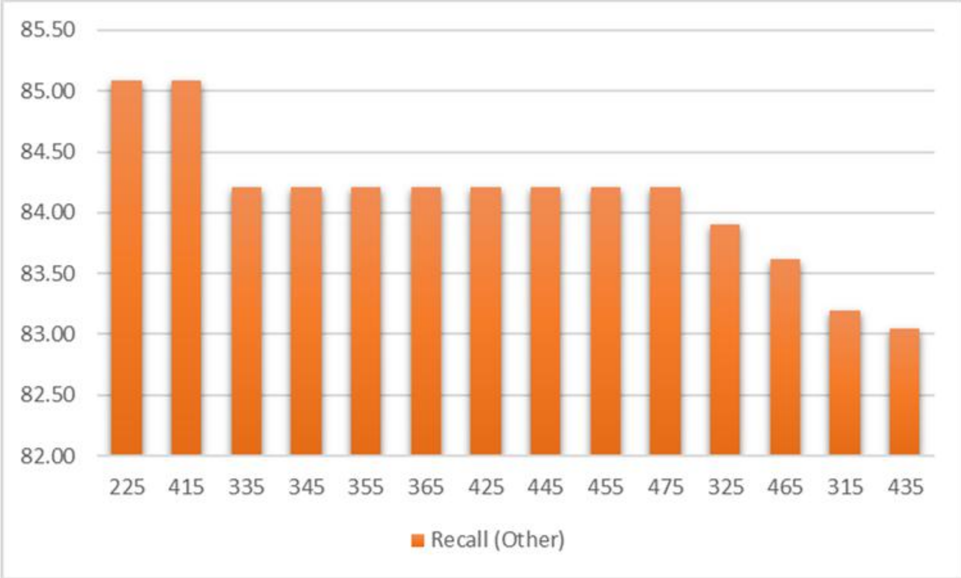

Fig.4.11 Percentage of Recall (Commercial)/Dataset Code

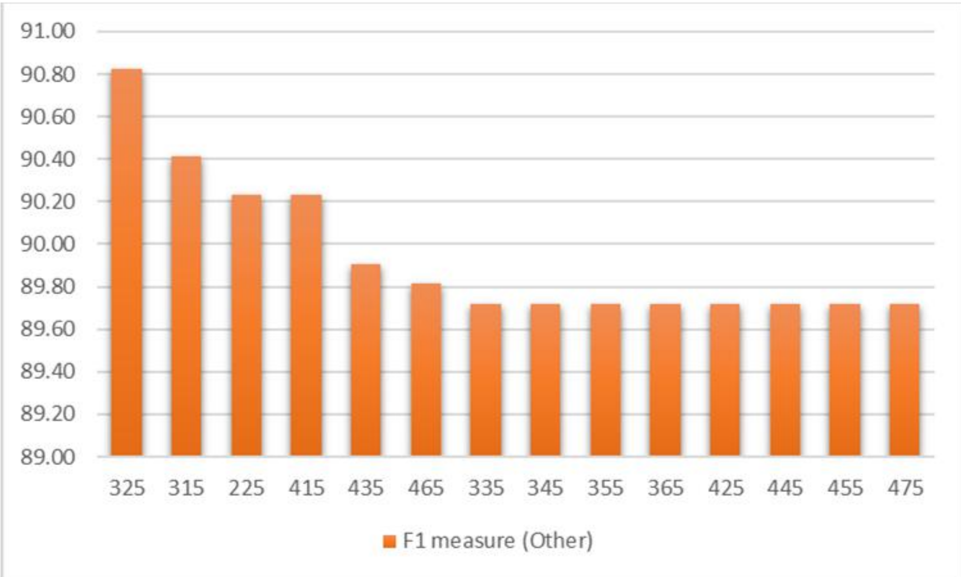

Fig.4.12 Percentage of F1 measure (Commercial)/Dataset Code

The 321 dataset by far has the best overall accuracy, according to the Figure 4.5. As for the rest of the datasets, the accuracy gradually decreases from 90.29 percent to 88.31 percent which is for the 431 dataset.

The 321 dataset also, has an outstanding precision of 99.06 percent, the 4.6 chart shows. The rest of the datasets do not work as perfectly as the 321 dataset. Their performance is still good though, with the worst one being the 451 dataset which hits the precision of 97.35 percent.

The recall chart demonstrates the dominancy of the 321 dataset, as well. The trend for the rest of the dataset is moderate reduction of recall performance from 89.84 to 87.35 percent.

The case is not different for the F1 measure figure, as the 321 dataset has the best performance. The rest of the datasets have almost a similar performance between around 93 to 92 percent.

With regards to the Figure 4.5 to the Figure 4.8 it is evident that the proposed model has an astonishing performance in every metric using the 321 data which is seasonal consumption rates for the “domestic” consumptions.

The chart 4.9 demonstrates that most of the datasets have the 84.51 percent, three data sets have the accuracy of 85.21 percent. Likewise, the best performance even though not so dominant, belongs to the 325 which is 85.92 percent.

The 315 and 325 datasets have the greatest precision of exactly 99 percent which is brilliant. The second and the third best performances are 98 and 97 percent, respectively. The rest of the datasets, however, have almost a same precision of around 96 percent.

According to the recall chart, the 225 and 415 reach the recall accuracy of 85.09 percent. The 435 dataset, on the other hand, has the worst performance which is 83.05 percent.

The final chart shows that the 325 dataset has the best performance of 90.83 percent. The rest of the datasets performances vary between 90.41 to 89.72 percent which is not so different from the best one’s performance.

Overall, regarding the “commercial” type performance charts, the “commercial” consumption type results have a similar trend to the “domestic” consumption results in which using the seasonal data helps the model to have the best performances in every metric, except for the recall metric the case is different and the 225 data set has the best performance.

4.4.3 Final Assessment

Although, detecting frauds is not a matter of life and death like identifying breast cancers, it still is crucial because it could save a massive amount of money for the company. Hence, the most important metric to evaluate the model would arguably be precision, same as the breast cancer diagnosis, if other metrics show a good overall performance, as well of course.

Both “domestic” and “commercial” data sets best performances hit the 99 percent accuracy for the precision metric, yet the issue with the “general” data set should be dealt with, in spite of the fact that it is a minor obstacle for the theory of separating the data sets and having an independent model for each one. So there are two possible choices. One is to settle for the feature extraction approach’s best results which hits the accuracy of 87.47 percent and compare it with its base models and the other multi agent model. The other option, however, is to ignore the “general” type and propose separate models for the other two categories. The second option seems practical and better than the first option. Nonetheless, due to the fact that the whole dataset did not include so many consumers let alone the separated subsets, it is decided to use the first option for now which still has proper results, then after having the companies trust and cooperation, choosing the second option by having a more complete dataset in terms of both features and consumers.

The following table demonstrates the supremacy of the proposed model.

Table 4.5 Final assessment

Model	Accuracy	Precision	Recall	F1 Measure	Execution Time
SVM_NN_RF	87.47	87.43	84.06	85.71	26 s
SVM_ Lib SVM_NN	83.45	68.45	90.78	78.05	24 s
SVM	81.95	79.14	78.93	79.04	16 s
NN	79.54	84.76	72.37	78.08	2 s
RF	86.67	84.76	84.31	84.53	3 s

Results are derived from Rapid Miner 9.1

As the table shows even though the proposed model’s execution time is negligibly more than others, it has the best performance in every metric, except recall which is not of utmost importance.

5. CONCOLUSION & FUTURE WORKS

The experimental results showed that the proposed model works the best using the seasonal data set as the initial data set, and has the potential to become even better by solving the issue arising from separating the data set based on consumption types and having a more complete dataset. As for the verification of the model, the model showed that even though not separating the dataset based on consumption types, lowers the performance results of the model, it still is by far better than the existing solution the company has which is a statistical solution with less than 10 percent success rate in correctly identifying frauds. Furthermore, the multi agent ensemble model proved to be capable in fraud detection problems by combining three optimized models. The final comparison, likewise, demonstrated that the diversity of ensembles is an important factor and although the two multi agent models had the same performances in the model selection phase, in empirical phase the effect of the diversity had its impact on the performances.

As it has been discussed a few times throughout this thesis, due to the lack of cooperation from the Great Tehran Electricity Distribution Center company, the desired attributes and number of consumer's data were not provided. Therefore, for future work, the aim is to gain the company's trust by showing them the achieved results, to finally have their cooperation, not only to get more features and consumer's data that could help the model to enhance its performance, but to solve the "general" consumption type's problem which in turn would notably improve the model's performance, as having separate models seems a wise choice by having sufficient datasets.

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