Journal of Theoretical and Applied Information Technology
31st December 2018. Vol.96. No 24

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

AN EFFICIENT HYBRID MODEL FOR RELIABLE CLASSIFICATION OF HIGH DIMENSIONAL DATA USING K-MEANS CLUSTERING AND BAGGING ENSEMBLE CLASSIFIER

[1]HAYDER K. FATLAWI [2]ABBAS F. H. ALHARAN [3]NABEEL SALIH ALI*

[1,3] Information Technology Research and Development Center, University of Kufa, Iraq.
[2]Computer Department, College of Education for Girls, University of Kufa, Iraq.

[1]Hayder.fatlawi@uokufa.edu.iq, [2]Abbasf.abood@uokufa.edu.iq, [3]Nabeel@uokufa.ed.iq

ABSTRACT

Data mining is playing a significant role in the digital era, and there are traditional techniques to classify, cluster the large data, etc. Today, the variety of data and its size has grown increasingly. Preprocessing of the data impose and need high computational resources due to raising the number of data attributes. Thus, attributes reduction deem a vital and significant part of the data pre-processing due to its ability to reduce the required computational resources. In this study, a hybrid model is proposed to eliminate irrelevant attributes with N number of goodness evaluation metrics by using K-Means Clustering and Bagging Ensemble Classifier. The proposed model was implanted with five different datasets. The model can minimize the number of the attributes up to (70%). Hence, the results with reduction can be increased the efficiency of the classification performance from the computation time standpoint.

Keywords: *k-means clustering, Bagging classification, Attributes reduction.*

1. INTRODUCTION

Data mining concerns with discovering the hidden patterns and predicting unknown values in a large amount of data [1, 2]. Techniques of data mining have been increased attention by researchers due to raises the need for large and complex data analysis [3]. According to digital universe statistics, the approximate size of the data in 2005 was 130 Exabytes and is expected to reach 40,000 Exabytes, with increasing factor 300[4]. The high dimensionality of data (i.e., the large number of attributes in data) represents a significant challenge faces data mining techniques, whereas, the increasing of attributes lead to dramatically increase in the required computing resourced [5].

On the other hands, most solutions to this challenge focused on reducing the attributes by choosing the most correlated attributes with the target of classification (or removing the most irrelative attributes) [1,6,7]. The importance of an attribute can be determined using some statistical metrics, and the selection of the most suitable parameter represents another challenge [1, 2, 6]. The difficulty of this challenge increases when several metrics are used.

In the current work, a hybrid and multi-stage model is proposed to solve the mentioned challenges due to the ability to deal with any number of metrics to minimize the attributes. The model uses a K-means clustering algorithm to discover the strength patterns of the attributes. Then, reduced the data is classified using bagging ensemble techniques to improve the accuracy of the classification.

2. LITERATURE REVIEW

Attribute selection is a method that used to eliminate undesirable and recurrent attributes from data during processing. Overlooking the un-meaningful attributes from the enormous database minimizes the complexity and time of computation, and maximizes the quality of learning [8]. Two main categories of attribute selection methods are used which are supervised and unsupervised [9]. Diverse attempts by authors are introduced unsupervised selection methods to eliminate undesirable and recurrent data attributes.

A hybrid approach of clustering using K-means and classification using the RBF function of SVM is presented by [10] to detect intrusions and attacks in the network. K-means algorithm is used for selecting the data attributes as a cluster. The proposed approach proved decreased the complexity of classification while both accuracy and detection of four categories are increased when implemented the proposed method in the KDD CUP 99 dataset.

Besides, an attributes selection method introduced by [11]. The method combining multivariate filter model with ant colony optimization (ACO) algorithm. The selection method was produced precise results after tested via new heuristic measurement.

On the other hands, in the field of text mining, as stated in [12], both clustering and classification based selection attributes have experimented. The authors applied hierarchical clustering (hClust) and k-means clustering with various lengths (5%), (10%), (15%), (20%) and (50%). Using a genetic algorithm of the selected attributes. Two measured are used with results which are average accuracy and F-measure to evaluate the performance of hClust and compare with k-means. The results found the performance of the hClust better than K-means when the length of attributes equal to or greater than (15%).

A hybridization approach of SVR, SOFM, and filter based attribute selection have been introduced by [13] to improve the accuracy of prediction for next day price index. SVR model is constructed for each cluster generated by SOFM according to select attributes. The result proved that the proposed approach better than using only SVR with and without attribute selection.

Also, an unsupervised method for attribute selection is presented by [14]. This method is based on the salient attribute selection by discovering the nearest neighbor and farthest neighbor (FSNF) to be held for clustering (k-means and SOM). Furthermore, filter-based and wrapper-based selection methods are discussed and compared with the proposed method to demonstrate the results. Whereas the filter-based method includes three models (Max-Rel, Var. and IBNF); whilst, the wrapper-based method k-means clustering algorithm is used in the training side.

As alongside with [15] which authors proposed another unsupervised attribute selection method that depends on availing the self-representation capability of attributes. Moreover, the representative attributes matric is influenced by itself to construct regularized attributes. The discordant is reduced by using L1, 2-norm, where the selected attributes are the most affection to construct other attributes. The presented method is evaluated by three criteria classification performance, clustering performance, and the redundancy.

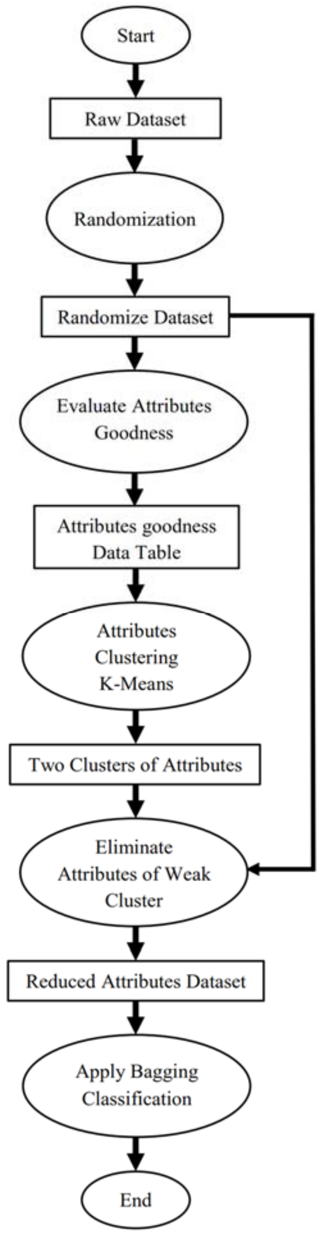
Likewise, [16] proposed an approach to predict early failures detection in the air pressure system of the trunks (Scania) to reduce the cost of the maintenance process. The conducted approach used the random forest to predict the classes of features (created as histograms), and it calculates the value of each class. Data (includes 60000 rows and 171 columns) has been used for training and evaluating the performance of the discussed approach. The results prove that the product approach has reduced the main cost around (0.6) compared to the traditional case (without approach).

Furthermore, Auto-Associative Multivariate Regression Trees (AAMRT) approach is presented by [17] for unsupervised feature selection to preserve information and reduce data. The AAMRT based on multivariate regression tree (MRT) but the original variables in AAMRT are utilized as response and explanatory variables. Besides, the approach described the MRT and Classification and Regression Trees (CART). Several experiments are applied to different datasets such as Synthetic, Viruses, Flavour, viruses and Bacteria to evaluate The AAMRT approach. The proposed method is effective in selecting and maintaining the important features and expelling the frequent and unimportant features based on their evaluation results.

Moreover, fast feature selection method based on clustering (FAST) is proposed by [18]. The proposed method includes two steps respectively, First: using a graph-theoretic clustering method to divide the attributes into clusters. Second: create the subset of attributes from collecting the most related attributes to a particular class. The Fast method has experimented on 35 datasets with different domains to measure its performance. From the feature selection effectiveness end, FAST results in the best ratio (1.18%) of attribute selection compared with five algorithms namely: FCBF, CFS, Relief, Consist, and FOCUS-SF. Also, the FAST is the faster in running with time 3573 millisecond. Besides, the outcomes of the experiment that FAST produces smaller subsets and improves the accuracy of other classifiers such as Naive Bayes, C4.5, IB1, and RIPPER.

3. METHODOLOGY

Several stages are conducted of the proposed model after randomizing all the raw data to ensure that no date entry patterns remain. These phases include attributes evaluation, k-means clustering, and bagging classification. As we can see in Figure 1 which explains the procedures steps of the hybrid model.



3.1 Attributes Goodness Evaluation

One of the most critical decisions that should be taken during classification model growing is which attribute is most suitable for splitting data? [2]. Also, the question about which is the most suitable splitting value takes a significant role in this process? [1]. Wherefore, the reduction of many attributes leads to an effective decreasing in computing recourses [5]. For more confident elimination of attributes, the evaluation of attributes quality should depend on several metrics. Each measurement could be ranked the attributes differently from the other measure which represents another challenge to be solved.

In this step, k metrics can be applied to the raw data to evaluate the quality of the attributes. Typical and straightforward rule classification method is used to perform the measurement. With N number of attributes, the result of this step is N × K matrix contains the quality of every attribute according to all metrics, such that element i in the matrix represents the goodness of attribute N_i using K_i criterion. This matrix would be used as an input for the next step.

3.2 Attributes Clustering using K-means

Mostly, clustering techniques can be divided into three general types: partitioning, hierarchical, and density-based methods [1,2]. K-means is considered a partitioning method which performed data clustering by produces K partition, and each partition will be a cluster. It begins with selecting random data points for initial partitioning, subsequently; it applies an iterative process to improve the partitioning by changing the position of data points from one cluster to another. The best partitioning is where the data points in a cluster are closer to each other while data points from different clusters are far [2,19]. Furthermore, from the computational time view, k-means could have better performance with a high number of attributes in comparison with hierarchical clustering. In this step, the K-means clustering technique is applied to discover the strength patterns of attributes. The clustering is performed for the data matrix that produced from the previous level, and two clusters are created in the result.

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

3.3 Irrelevant Attributes Removal

According to the distribution of the attributes into two clusters, the decision will be taken to remove the

Figure 1: *Multi-Stage Methodology of the Proposed Model.*

subset of attributes that belong to the weak cluster. The weakness of the cluster is detected by comparing the values of the center elements of the two clusters and the cluster with the lowest values in its center that will be considered the weak cluster. Thereby, all attributes in the weak cluster will be recovered due to the irrelevant to the target in the next classification process.

3.4 Bagging Classification

Instead of creating one single classification model as a result of the training process, an ensemble classifier is created based on the bagging method [2, 6, 21]. Given the reduced dataset DS which contains m attributes and n rows the training include k iterations and for iteration (i<=k), DSi is a randomly sampled subset from DS with replacement. The training process on DSi produces a classification model CMi that could be applied to classify unseen data rows. The ensemble classifier collects the votes from each single classification model CMi and assigns the class with the highest number of votes to the hidden data [20- 24].

4. IMPLEMENTATION AND RESULTS

The implementation includes applying all steps of the proposed model with a sundry and different dataset. Evaluation of classifier's performance is performed by using five accuracy metrics inanition with computational time metric.

4.1 Description of Datasets

In the current study, five different datasets from a variety and diverse fields are used to apply and evaluate the proposed model as follow: (1) bank marketing dataset which depends on phone calls, it contains (17) attributes and (45211) data rows [25]. (2) Diabetes dataset contains clinical care data of 130 US hospitals for ten years (1999-2008), there are (50) attributes and (100000) data rows including in this dataset [26]. (3) MoCap hand postures contain data of 12 users with five different types of hand postures which collected using unlabeled markers, the total number of data rows of this dataset is (78095) and (38) attributes [27, 28]. (4) KDD Cup dataset of the third international competition of knowledge discovery and data mining tools, its task was to develop a network intrusion detector to distinguish between intrusions and standard connections. It contains (42) attributes and (4000000) data rows [29]. (5) APS Failure at Scania Trucks includes (60000) data rows and (171) attributes; also it has two classes: positive class represents failures APS system component and negative level for failures for not related APS components [30].

4.2 Applying Attributes Goodness Evaluation

One of the most critical issues during the growth of a classifier is evaluating of attribute's importance [2, 6]. In each division of the data process, the most relevant attribute with the target of the classification must be chosen. Statistical measures could be used for this task such as Information Gain and Gain Ratio [1, 2]. The best attribute is such an attribute that minimizes the impurity of data. Impurity could be measured using statistical randomness measurement such us Entropy. Therefore, Information Gain is the gain of splitting operation indicates by the impurity of the class Y before and after splitting [2]. The equation (1) explains the calculation of information gain as follow,

$$\textbf{Info. Gain} = \boldsymbol{InG(P)} - \sum_{i=1}^{cn} \frac{\boldsymbol{ND(node\ i)}}{\boldsymbol{ND}}\ \boldsymbol{InG(node\ i)} \quad (\ldots\ldots\ldots\ (1)$$

where InG (P) is the parent node's information gain before splitting, cn is the number of attribute's values, ND is the number of data row in the parent node, ND (node i) is the number of data row in node I, InG (node i) is the information gain of node i. The impurity of data is measured by Information Gain depending on the entropy which tends to select attributes with distinct high values. A high number of values led to generate more branches in each iteration. As a result of that; the number of data rows would be decreased which affects the prediction reliability. Gain Ratio represents an improvement to overcome this problem which weighted the information gain by the number of child nodes of each branch by as shown in the equation (2),

$$\textbf{Gain Ratio} = \frac{\textbf{Info.Gain}}{-\sum_{i=1}^{cn} \textbf{P(node i)log2 P(node i)}} \quad \ldots\ldots\ldots\ldots\ (2)$$

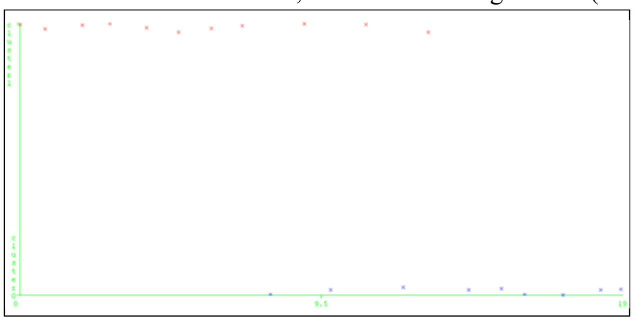
Where P (node i) is the fraction of data instances in the node i to the number of data instances in the parent node. Another three metrics are used in the implementation as follow: OneR which evaluates the goodness of an attribute by using the OneR classifier [31]. Relief Attribute Evaluator: Evaluates the goodness of an attribute by making iterative sampling a data row and considering the value of the given attribute for the nearest data row of the same

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

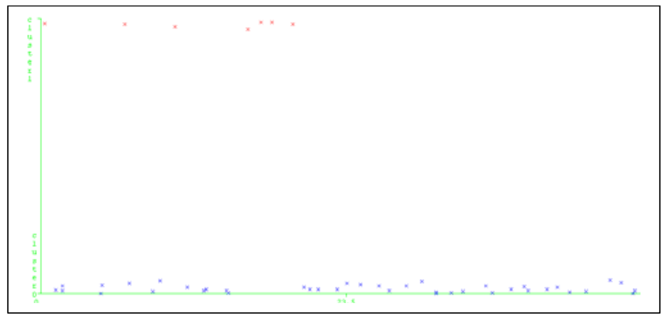
and different class [32-35]. Symmetrical Uncertainty Attribute Evaluator: Evaluates the goodness of an attribute by measuring the symmetrical uncertainty for the class [36-37]. The result of applying those five mercies on five data sets is shown in Tables (1-5) in the appendix section respectively.

4.3 Apply K-means Clustering on Datasets

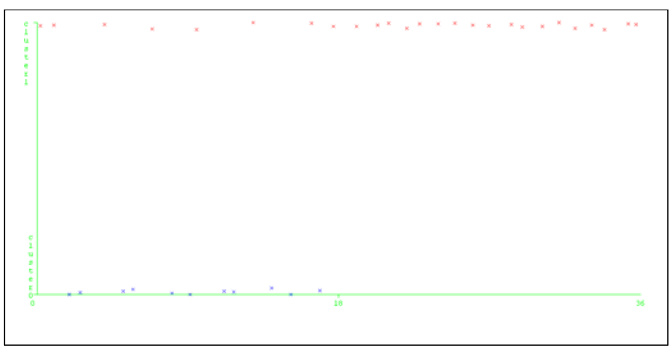
For discovering the strength of the attributes of the five datasets, the k-means algorithm (which explained in Section 3.2) is applied to the data matrix that resulted from the previous step. For each dataset K-mean split the attributes between two clusters: weak and strong, the evaluation of cluster's centroid of five datasets are shown in the Table 1 and Figure 2 present the clustering of attributes of the five datasets consecutively.



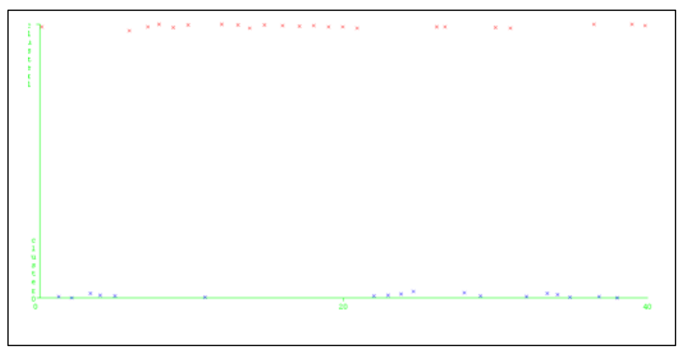
(A) Clustering of Bank Marketing dataset attributes



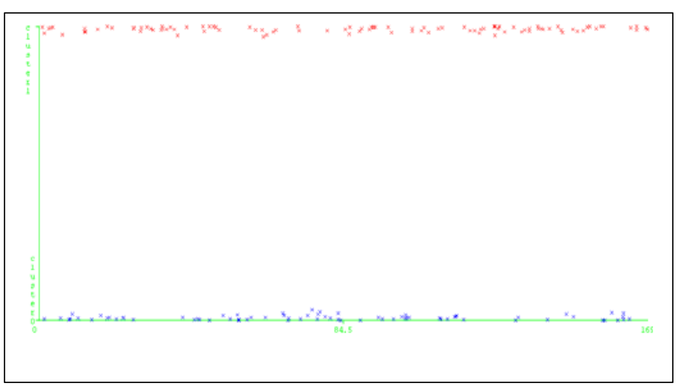
(B) Clustering of Diabetes dataset attributes



(C) Clustering of MoCap Hand Postures dataset attributes



(D) Clustering of KDD Cup 1999 dataset attributes



(E) Clustering of APS Failure dataset attributes

Figure 2: *Clustering of attributes of five datasets*

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

Table 1: *Evaluation of Cluster's centroid of five datasets*

Dataset Name	Original Number of attributes	Reduced Number of attributes	Ratio of attributes Reduction
Bank Marketing	20	8	60%
Diabetes	48	41	15%
MoCap Hand Postures	37	11	70%
KDD cup 1999	41	18	56%
APS Failure	170	71	58%

4.4 Apply Irrelevant Attributes Removal

Each attribute belongs to weak clusters from the previous step is removed resulting in a significant reduction in the dimensionality of datasets. Table 2 clarifies the number of the attribute before and after applying the removal and the ration of attribute reduction.

Table 2: *Ratio of Attributes Reduction in five datasets*

4.5 Apply Bagging Classification

Bagging classification can be characterized by creating the number of sub-dataset from the original dataset and applying classification processes in each one which represents a heavy computational time task. Thereby, the reduction of attributes number provides the efficiency of bagging classification, especially with a big dataset. The improving of computational time on five datasets is shown in Figure 3. Table 3 and Figures (4- 8) represent and illustrate the evaluation of bagging classification accuracy before and after applying the proposed model on five datasets.

Dataset Name	Bank Marketing		Diabetes		MoCap Hand Postures		KDD cup 1999		APS Failure	
Cluster No	Cluster 0	Cluster 1	Cluster 0	Cluster 1	Cluster 0	Cluster 1	Cluster 0	Cluster 1	Cluster 0	Cluster 1
Gain Ratio	0.2934	0.045	0.1217	0.1164	0.8839	0.2416	0.623	0.2631	0.1662	0.0942
Info Gain	0.7587	0.1019	0.041	0.6544	0.8088	0.2026	0.6016	0.0453	0.7489	0.1975
OneR	0.7587	0.1019	0.1869	0.2907	0.7328	0.595	0.5471	0.0045	0.324	0.2723
Relief	0.0629	0.3243	0.0903	0.6376	0.1881	0.1664	0.4464	0.0274	0.1489	0.0796
Symmetrical Uncertainty	0.0666	0.0118	0.0014	0.0123	0.098	0.0261	0.5576	0.0531	0.0737	0.022

Journal of Theoretical and Applied Information Technology
31st December 2018. Vol.96. No 24

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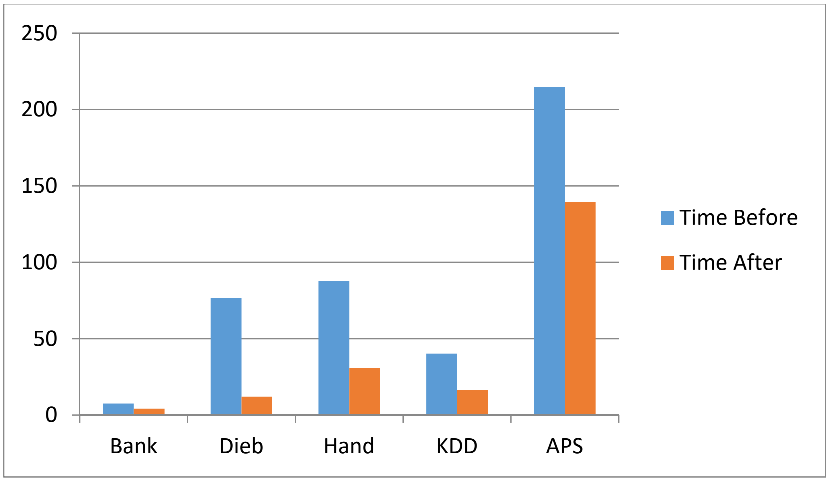

Figure 3: *Comparison of computation time before and after proposed model*

Table 3: *Evaluation the accuracy before and after applying proposed model in five datasets*

Dataset Name	Bank Marketing		Diabetes		MoCap Hand Postures		KDD cup 1999		APS Failure	
	Before	**After**	**Before**	**After**	**Before**	**After**	**Before**	**After**	**Before**	**After**
TP Rate	0.912	0.905	0.533	0.534	0.942	0.891	0.999	0.999	0.966	0.967
Precision	0.894	0.871	0.478	0.482	0.942	0.891	0.999	0.999	0.965	0.967
Recall	0.912	0.905	0.533	0.534	0.942	0.891	0.999	0.999	0.966	0.967
F-Measure	0.894	0.871	0.492	0.497	0.942	0.891	0.999	0.999	0.965	0.967
ROC Area	0.912	0.905	0.559	0.56	0.995	0.984	0.999	0.999	0.992	0.992

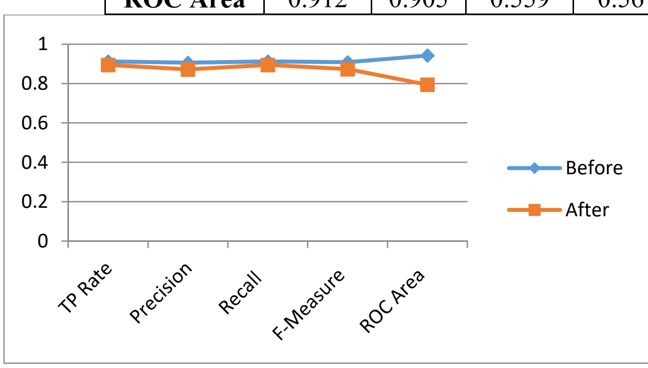

Figure 4: *Comparison of bagging classification accuracy of Bank Marketing dataset before and after improvement*

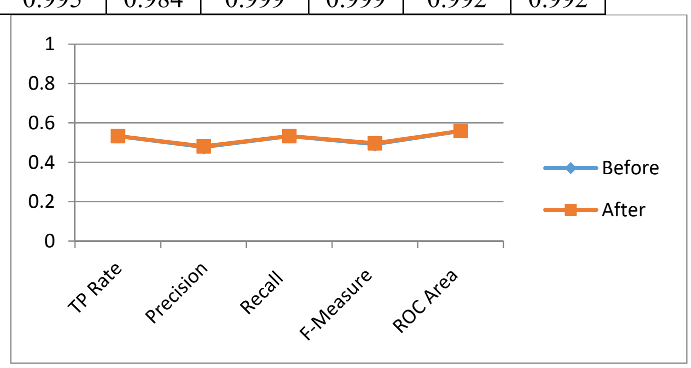

Figure 5: *Comparison of bagging classification accuracy of Diabetes dataset before and after improvement*

Journal of Theoretical and Applied Information Technology
31st December 2018. Vol.96. No 24

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

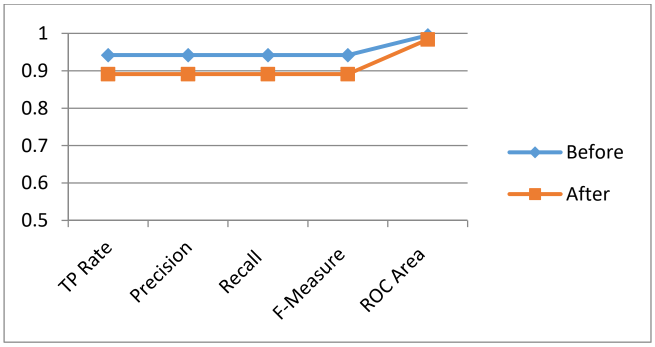

Figure6: *Comparison of bagging classification accuracy of MoCap Hand Postures dataset before and after improvement*

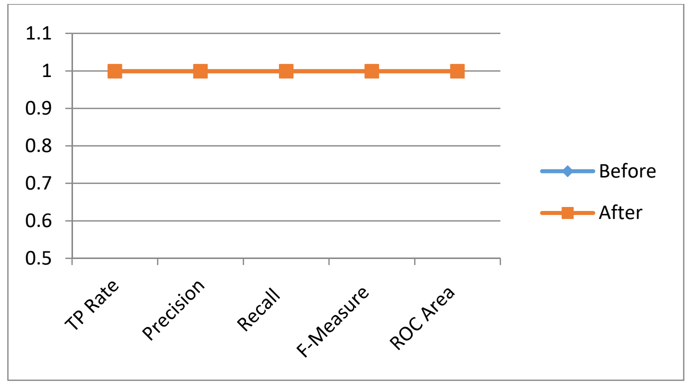

Figure7: *Comparison of bagging classification accuracy of KDD cup 1999 dataset before and after improvement*

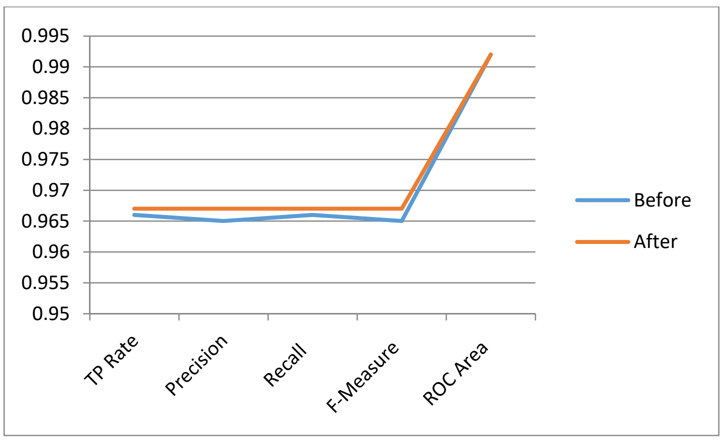

Figure8: *Comparison of bagging classification accuracy of APS Failure dataset before and after improvement*

The performance of the classifier is measured by five common metrics as follow: (1) True Positive (TP), which related to the number of the positive examples that correctly predicted (2) Precision and (3) Recall which used widely in applications where the value of the successful detection of one of the classes is more significant than the detection of the other classes. Precision measures the fraction of the data rows that belong to the positive group, and the classifier has declared as a positive class. Recall calculates the fraction of positive examples that correctly predicted by the classifier [1].

Building a model that maximizes both precision and recall is the key challenge of the classification algorithms. Precision and recall can be summarized into another metric known as the (4) F1 measure as shown in equation (3).

F1 = 2* (Recall* Precision) / (Recall+ Precision) ………… (3)

(5) A receiver operating characteristic (ROC) curve is a graphical approach for displaying the tradeoff between true positive rate and false positive rate of a classifier. In a ROC curve, the true positive rate (TPR) is plotted along the y-axis and the false positive rate (FPR) is shown on the x-axis [1, 2].

5. RESULTS DISCUSSIONS

To shed light on the proposed hybrid model results and their significant findings among other methods and approaches that have been proposed before to improve the classifications performance and its reliability, accuracy, effectiveness, and efficiency for high dimensional data. The proposed method is compared with some prior works regarding classification accuracy and consumed time. Table 4 shows that the proposed method has better classification accuracy and time for bank marketing dataset with 90.5 and 4.23 respectively.

Table 4: *classification accuracy and time consumption for Bank marketing*

work	Classifier	Accuracy	Time (s)
2015 [38]	MLPNN	88.63	1767.75

2016 [39]	LT-SVDD	90	4.96
Proposed model	Bagging	90.5	4.23

Table 5 shows that applying the proposed method on KDD Cup 1999 dataset is superior on five works regarding classification with accuracy 99.9 and it consumes 16.6 seconds compared with the work of Shah and Trivedi, who use back-propagation neural network algorithm for classification.

Table 5: *classification accuracy and time consumption for KDD Cup 1999*

work	Classifier	Accuracy	Time(s)
2015 [40]	BPNN	96.7%	1548
2016 [41]	LSTM-RNN	96.93	-
2017 [42]	Multi-level hybrid SVM and ELM.	95.75	-
2018[43]	REPTree	99.67	
Proposed model	Bagging	99.9	16.6

Table 6 demonstrate that the proposed method has an accuracy better than the work of Schlag et al. for APS Failure dataset, but the consumption time is a little more.

Table 6: *classification accuracy and time consumption for APS Failure*

work	Classifier	Accuracy	Time(s)
2018 [44]	LPSVM	95	110.85
Proposed model	Bagging	96.7	139.36

6. CONCLUSIONS AND FUTURE WORK

In this article, a multi-phase model is proposed to eliminate irrelevant attributes with N number of goodness evaluation metrics via using K-Means Clustering and Bagging Ensemble Classifier. The hybrid model used the K-means clustering algorithm to discover the strength patterns of the attributes as well minimized data is classified using bagging ensemble techniques to improve the accuracy of the classification (see Tables (1-5) in the appendix). The model is evaluated with five different datasets, and the results were efficient due to its ability to deal with any number of metrics to reduce the attributes of the huge data up to (70%) (See Tables (4-6)). In the future directions, we intend to apply more advanced clustering techniques instead of k-means as well, applying soft computing techniques for choosing a suitable number of clusters.

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ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

APPENDICES

Table 1: Bank Marketing Dataset Attributes Evaluation Using PART With Five Metrics

Attribute Name	GainRatio	InfoGain	OneR	Releif	Symm
age	0.011883	0.018439	0.018439	0.0198	0.017905
job	0.004773	0.014223	0.014223	0.14063	0.008156
marital	0.001562	0.002069	0.002069	0.07408	0.002258
education	0.001349	0.003448	0.003448	0.14278	0.00225
default	0.011256	0.008331	0.008331	0.04785	0.01335
housing	8.78E-05	9.97E-05	9.97E-05	0.06619	0.000121
loan	0	1.93E-05	1.93E-05	0.04517	3.02E-05
contact	0.017742	0.016801	0.016801	0.01689	0.023097
month	0.014382	0.038097	0.038097	0.04081	0.024136
day_of_week	0.0002	0.000465	0.000465	0.20365	0.000328
duration	0.03364	0.109413	0.109413	0.06741	0.058192
campaign	0.002452	0.004285	0.004285	0.00336	0.003799
pdays	0.19567	0.044484	0.044484	0.0014	0.121009
previous	0.040006	0.027733	0.027733	0.0026	0.046179
poutcome	0.064022	0.043834	0.043834	0.01801	0.073514
emp.var.rate	0.034411	0.078586	0.078586	0.00433	0.056301
cons.price.idx	0.030057	0.098004	0.098004	0.00724	0.052012
cons.conf.idx	0.032945	0.097628	0.097628	0.00701	0.05625
euribor3m	0.030647	0.10257	0.10257	0.00373	0.053218
nr.employed	0.037894	0.08963	0.08963	0.00392	0.062391

Table 2: Diabetes Dataset Attributes Evaluation Using PART With Five Metrics

Attributes	GainRatio	InfoGain	OneR	Releif	Symm
patient_nbr	0.00854371	0.033077	53.3793	0.012637	0.007151
race	0.00066143	0.000666	53.9119	0.000562	0.004198
gender	0.00027471	0.000274	53.9119	0.000232	0.001815
age	0.00087077	0.002311	53.9119	0.00115	0.01196
weight	0.000003	6.17E-06	54.0908	3.61E-06	-1.6E-05
admission_type_id	0.00234096	0.002944	53.9119	0.002246	0.00211
discharge_disposition_id	0.0150935	0.028613	53.9041	0.017557	0.003087
admission_source_id	0.00516324	0.008335	53.9345	0.005598	0.002977
time_in_hospital	0.00192447	0.003718	53.9119	0.002256	0.001371
payer_code	0.00088832	0.002192	53.9198	0.001144	0.008239
medical_specialty	0.00120801	0.004347	53.9267	0.001752	0.017418
num_lab_procedures	0.00080491	0.001682	53.909	0.000974	0.00139
num_procedures	0.00104724	0.00192	53.9119	0.001201	0.003221
num_medications	0.00330751	0.006624	53.9119	0.003935	0.001866

number_outpatient	0.01343898	0.008942	54.4592	0.008814	0.001368
number_emergency	0.02108132	0.01343	55.0724	0.013425	0.00055
number_inpatient	0.02943808	0.044576	56.4825	0.030979	0.00829
diag_1	0.00532257	0.036408	54.4121	0.008876	0.016579
diag_2	0.00454018	0.029716	54.0839	0.007515	0.009509
diag_3	0.00423976	0.027461	53.7822	0.007005	0.015707
number_diagnoses	0.00488394	0.010136	53.907	0.005895	0.003254
max_glu_serum	0.00096921	0.000365	53.9119	0.000419	0.001985
A1Cresult	0.00055737	0.000504	53.9119	0.000444	0.003011
metformin	0.0009337	0.000757	53.9119	0.000696	0.004112
repaglinide	0.00338757	0.000412	53.9119	0.000555	-1.4E-05
nateglinide	0.00042869	2.65E-05	53.9119	3.72E-05	0.00014
chlorpropamide	0.00675607	6.91E-05	53.9158	0.000101	3.53E-05
glimepiride	0.00037095	0.000119	53.9119	0.000141	0.000561
acetohexamide	0.08394652	1.49E-05	53.9119	2.19E-05	0
glipizide	0.00061396	0.000378	53.9119	0.000382	0.001113
glyburide	0.00012785	7.09E-05	53.9119	7.4E-05	0.001775
tolbutamide	0.0043928	1.35E-05	53.9119	1.97E-05	0
pioglitazone	0.00052883	0.00021	53.9119	0.000238	0.000639
rosiglitazone	0.00085944	0.000306	53.9119	0.000355	0.001585
acarbose	0.00778687	0.000238	53.9375	0.000341	-1.3E-05
miglitol	0.01761629	9E-05	53.9149	0.000131	1.48E-05
troglitazone	0.02367811	1.15E-05	53.9119	1.69E-05	8.11E-06
tolazamide	0.00774476	3.85E-05	53.9119	5.62E-05	2.47E-05
examide	0	0	53.9119	0	0
citoglipton	0	0	53.9119	0	0
insulin	0.00207525	0.003642	53.9119	0.002336	0.003064
glyburide-metformin	0.00133457	8.12E-05	53.9119	0.000114	7.28E-05
glipizide-metformin	0.00748296	1.37E-05	53.9139	2.01E-05	0
glimepiride-pioglitazone	0.0839465	1.49E-05	53.9119	2.19E-05	0
metformin-rosiglitazone	0.05219336	1.75E-05	53.9119	2.57E-05	0
metformin-pioglitazone	0.04930581	8.76E-06	53.9119	1.28E-05	0
change	0.00153624	0.00153	53.9119	0.001297	-0.0007
diabetesMed	0.00354371	0.002757	53.9119	0.002575	0.002003

Table 3: Mocap Hand Postures Dataset Attributes Evaluation Using PART With Five Metrics

Attr	GainRatio	InfoGain	OneR	Relief	Symm
User	0.00723	0.025	24.8259	0.269573	0.00865
X0	0.04299	0.2575	33.4089	0.068946	0.06197
Y0	0.07679	0.5093	43.1174	0.052394	0.11377
Z0	0.06609	0.3684	37.3656	0.060442	0.09332

X1	0.03929	0.2266	31.8044	0.067202	0.05603
Y1	0.07335	0.4906	42.4542	0.049285	0.10891
Z1	0.06435	0.3475	36.8687	0.05829	0.09001
X2	0.04084	0.2299	32.4178	0.07102	0.05784
Y2	0.07526	0.4984	43.047	0.052953	0.11146
Z2	0.066	0.3494	37.4757	0.047177	0.09177
X3	0.0398	0.227	32.8864	0.063677	0.05658
Y3	0.07515	0.4877	43.8742	0.035766	0.11071
Z3	0.06506	0.349	37.7894	0.050979	0.09082
X4	0.03678	0.2137	33.4396	0.075438	0.05257
Y4	0.06996	0.4561	44.2827	0.041644	0.10319
Z4	0.06124	0.3285	38.5884	0.057336	0.08549
X5	0.02811	0.1662	37.1299	0.053686	0.04038
Y5	0.05335	0.3462	45.3557	0.051653	0.07858
Z5	0.04216	0.2259	39.9956	0.040582	0.05883
X6	0.02035	0.1202	43.4235	0.044292	0.02922
Y6	0.03482	0.225	48.2073	0.045295	0.05124
Z6	0.02964	0.1517	45.7988	0.064715	0.04078
X7	0.01408	0.0816	44.2583	0.012321	0.02011
Y7	0.01968	0.1151	46.9525	0	0.02818
Z7	0.0155	0.073	44.7014	0.022944	0.02077
X8	0.01119	0.0569	43.896	0	0.01537
Y8	0.01208	0.0676	44.7987	0	0.01708
Z8	0.01171	0.0537	44.2289	0	0.01555
X9	0.00809	0.039	41.5796	0.059157	0.01093
Y9	0.0082	0.0441	42.0739	0.031278	0.01146
Z9	0.00835	0.0329	40.8869	0.067289	0.01051
X10	0.00239	0.0112	34.9211	0.043535	0.00319
Y10	0.00323	0.0172	35.5959	0.014054	0.0045
Z10	0.00589	0.0219	36.4257	0.050997	0.00725
X11	0	0	20.9678	1.09E-16	0
Y11	0	0	20.9678	1.09E-16	0
Z11	0	0	20.9678	1.09E-16	0

Table 4: KDD Cup 1999 Dataset Attributes Evaluation Using PART With Five Metrics

Attr	GainRatio	InfoGain	OneR	Releif	Symm
att1	0.128	0.02566	56.8012	0	0.02922
att2	0.7656	0.749869	78.0186	0.432155	0.591564
att3	0.6457	1.451671	98.5533	0.814374	0.763265
att4	0.8512	0.772744	76.7197	0.513637	0.627327
att5	0.5621	1.388518	97.1475	0.000239	0.689811

att6	0.5103	0.787882	74.0475	0.000212	0.508336
att7	1	0.000327	56.8031	0.00027	0.00042
att8	1	0.002628	56.8164	0	0.003372
att9	0	0	56.8012	0	0
att10	0.4005	0.021701	56.9662	0.000645	0.026958
att11	0.3895	0.000696	56.8012	0	0.000894
att12	0.7146	0.714519	72.1516	0.502149	0.559174
att13	0.8068	0.018521	56.9747	2.82E-05	0.023463
att14	0	0	56.8012	2.86E-05	0
att15	0	0	56.8012	0	0
att16	0.0837	0.002199	56.8012	0	0.00278
att17	0.0782	0.001055	56.8012	4.77E-06	0.001344
att18	0	0	56.8012	1.91E-05	0
att19	0.084	0.002261	56.8012	0.001314	0.002857
att20	0	0	56.8012	0	0
att21	0	0	56.8012	0	0
att22	0.0818	0.001796	56.8012	0.001001	0.002276
att23	0.4221	1.377399	97.2753	0.365748	0.571693
att24	0.2411	0.870868	78.6338	0.301388	0.337019
att25	0.9196	0.747999	76.6139	0.500137	0.631441
att26	0.9121	0.715417	76.4165	0.499866	0.611424
att27	0.3496	0.07313	57.2818	0.026931	0.082869
att28	0.2555	0.057262	56.8012	0.025552	0.064344
att29	0.6087	0.744118	76.4813	0.403561	0.535693
att30	0.8348	0.752617	76.6015	0.045597	0.612545
att31	0.2221	0.245488	56.8012	0.086606	0.18451
att32	0.2735	0.457017	59.2769	0.29733	0.28327
att33	0.3934	0.752724	74.9154	0.396057	0.433954
att34	0.4369	0.761018	75.7308	0.322406	0.461578
att35	0.4044	0.741163	74.6645	0.069738	0.437476
att36	0.3965	0.910599	76.6739	0.393067	0.472727
att37	0.4206	0.431957	57.4783	0.023424	0.334491
att38	0.7876	0.752207	76.5223	0.480489	0.599183
att39	0.808	0.728052	76.4365	0.502253	0.592686
att40	0.2418	0.093149	57.1416	0.02713	0.095984
att41	0.2353	0.07883	56.8012	0.023349	0.083381

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

Table 5: APS Failure At Scania Trucks Dataset Attributes Evaluation Using PART With Five Metrics

Attr	GainRatio	InfoGain	OneR	Releif	Symm
aa_000	0.05934	0.064103	98.33	0.054689	0.10661
ab_000	0.0037	0.000361	98.333	0.000392	0.00328
ac_000	0.008	0.019968	98.327	0.265256	0.01525
ad_000	0.00636	0.013099	98.333	0.006316	0.01201
ae_000	0	0	98.333	-9.3E-05	0
af_000	0	0	98.333	0	0
ag_000	0.2031	0.006434	98.35	0.000156	0.08358
ag_001	0.25861	0.028653	98.553	0.000703	0.24586
ag_002	0.10036	0.036919	98.66	0.008036	0.15064
ag_003	0.03405	0.038504	98.568	0.021426	0.06146
ag_004	0.02363	0.044395	98.26	0.040342	0.04437
ag_005	0.02553	0.051223	98.37	0.047157	0.04813
ag_006	0.01437	0.03262	98.377	0.019729	0.02726
ag_007	0.01623	0.019712	98.323	0.009639	0.02949
ag_008	0.00828	0.013952	98.313	0.002146	0.01544
ag_009	0.00429	0.004478	98.328	0.000753	0.00768
ah_000	0.05195	0.061986	98.375	0.056081	0.09425
ai_000	0.05221	0.029577	98.265	0.003095	0.08588
aj_000	0.01008	0.008367	98.307	0.000238	0.01757
ak_000	0.01265	0.000661	98.333	-1.6E-06	0.00758
al_000	0.03049	0.042637	98.608	0.011215	0.05607
am_0	0.03095	0.043673	98.557	0.011537	0.05697
an_000	0.06387	0.060726	98.39	0.054605	0.11317
ao_000	0.06177	0.060299	98.422	0.053296	0.10979
ap_000	0.07629	0.063032	98.317	0.026606	0.1329
aq_000	0.04844	0.063605	98.39	0.03549	0.08863
ar_000	0.02515	0.007097	98.335	0.018774	0.03509
as_000	0.21424	0.000455	98.338	-5E-06	0.00731
at_000	0.01005	0.005562	98.36	0.000173	0.01646
au_000	0.14573	0.001777	98.352	-3E-06	0.02642
av_000	0.01094	0.023991	98.303	0.007113	0.02072
ax_000	0.01025	0.018241	98.327	0.005582	0.01919
ay_000	0.05491	0.004526	98.372	0.00515	0.04422
ay_001	0.06152	0.004588	98.338	0.000474	0.04661
ay_002	0.13411	0.005903	98.392	0.000989	0.07099
ay_003	0.09683	0.005794	98.377	0.003475	0.06362

ay_004	0.03603	0.008809	98.405	0.001471	0.04804
ay_005	0.01276	0.016536	98.367	0.001761	0.02331
ay_006	0.01228	0.0177	98.332	0.01994	0.02263
ay_007	0.01706	0.034644	98.205	0.012751	0.03218
ay_008	0.04585	0.037672	98.3	0.039881	0.07982
ay_009	0.16956	0.013839	98.452	0.027207	0.13574
az_000	0.0347	0.052378	98.263	0.005495	0.06419
az_001	0.03004	0.050065	98.397	0.008983	0.05597
az_002	0.02984	0.050026	98.413	0.001489	0.05563
az_003	0.01022	0.019601	98.305	0.00305	0.01921
az_004	0.01439	0.03291	98.308	0.0141	0.02732
az_005	0.0275	0.04772	98.298	0.039267	0.05137
az_006	0.00526	0.008302	98.327	0.009957	0.00977
az_007	0.01168	0.016143	98.403	0.034495	0.02146
az_008	0.01312	0.007291	98.333	8.3E-05	0.02151
az_009	0.0203	0.004705	98.33	-9.5E-05	0.02658
ba_000	0.03624	0.051533	98.343	0.033332	0.06674
ba_001	0.0278	0.050886	98.283	0.027294	0.05212
ba_002	0.0437	0.051837	98.212	0.039741	0.07923
ba_003	0.02831	0.052333	98.38	0.031388	0.05311
ba_004	0.02873	0.051322	98.398	0.027023	0.05378
ba_005	0.02339	0.046223	98.38	0.027373	0.04405
ba_006	0.02024	0.038741	98.267	0.019439	0.03805
ba_007	0.01437	0.030778	98.287	0.025147	0.02718
ba_008	0.02335	0.029829	98.278	0.016011	0.04263
ba_009	0.02497	0.024091	98.298	0.029467	0.04433
bb_000	0.05867	0.063643	98.397	0.043317	0.10545
bc_000	0.00954	0.019603	98.297	0.016249	0.01801
bd_000	0.01116	0.027465	98.307	0.00295	0.02127
be_000	0.01158	0.023246	98.327	0.006178	0.02183
bf_000	0.00659	0.008907	98.325	0.00696	0.01209
bg_000	0.05181	0.061828	98.372	0.056242	0.09399
bh_000	0.06955	0.06131	98.308	0.031641	0.12216
bi_000	0.03628	0.055474	98.273	0.012981	0.06718
bj_000	0.06444	0.065734	98.372	0.026949	0.11509
bk_000	0.0159	0.026885	98.377	0.121054	0.02965
bl_000	0.01282	0.024102	98.31	0.132517	0.02408
bm_000	0.01971	0.032717	98.292	0.135327	0.03671
bn_000	0.02835	0.038516	98.332	0.136182	0.05201
bo_000	0.0365	0.041953	98.218	0.124863	0.06599
bp_000	0.04267	0.044582	98.263	0.125308	0.07639

bq_000	0.04879	0.047191	98.265	0.123496	0.08663
br_000	0.05614	0.048837	98.275	0.135879	0.09845
bs_000	0.00805	0.016204	98.315	0.07371	0.01518
bt_000	0.04907	0.063862	98.313	0.044541	0.0897
bu_000	0.05842	0.063498	98.385	0.043334	0.10503
bv_000	0.05842	0.063498	98.387	0.043334	0.10503
bx_000	0.03845	0.056801	98.345	0.04071	0.07103
by_000	0.0282	0.054189	98.383	0.04887	0.05303
bz_000	0.00445	0.009077	98.322	0.003295	0.0084
ca_000	0.01565	0.020494	98.333	0.241526	0.02863
cb_000	0.00336	0.005144	98.333	0.22544	0.00622
cc_000	0.04115	0.057691	98.382	0.048707	0.0757
cd_000	0.00733	0.000653	98.333	0.122922	0.00618
ce_000	0.0215	0.029061	98.313	0.064487	0.03943
cf_000	0.01004	0.011734	98.322	-6.8E-05	0.01818
cg_000	0.00994	0.018784	98.333	0.010246	0.01867
ch_000	0	0	98.333	0	0
ci_000	0.06587	0.065802	98.365	0.050465	0.11737
cj_000	0.02007	0.019744	98.428	0.011239	0.0357
ck_000	0.05382	0.064663	98.24	0.041375	0.09769
cl_000	0.05676	0.021218	98.293	0.002331	0.08553
cm_000	0.0118	0.022537	98.342	0.019454	0.02217
cn_000	0.11947	0.030809	98.573	0.00315	0.16208
cn_001	0.04297	0.034653	98.585	0.01532	0.07462
cn_002	0.02362	0.036825	98.352	0.022375	0.04381
cn_003	0.03459	0.048335	98.258	0.03386	0.06362
cn_004	0.03719	0.05018	98.365	0.032132	0.0682
cn_005	0.01849	0.03696	98.292	0.021867	0.03485
cn_006	0.01171	0.026223	98.257	0.012264	0.02221
cn_007	0.0117	0.027664	98.242	0.017329	0.02225
cn_008	0.01791	0.02684	98.308	0.021227	0.03312
cn_009	0.00919	0.017001	98.322	0.011429	0.01724
co_000	0.00318	0.006098	98.337	0.00423	0.00597
cp_000	0.00931	0.017557	98.332	0.00209	0.01749
cq_000	0.05842	0.063498	98.385	0.043334	0.10503
cr_000	0.0542	0.000405	98.333	1.1E-06	0.00624
cs_000	0.02061	0.040013	98.275	0.036672	0.03877
cs_001	0.02382	0.044337	98.293	0.035575	0.04471
cs_002	0.0431	0.05406	98.207	0.031969	0.07855
cs_003	0.02856	0.049523	98.222	0.016504	0.05336
cs_004	0.04342	0.05314	98.267	0.021647	0.07894

cs_005	0.02573	0.047213	98.322	0.036052	0.04825
cs_006	0.02329	0.020401	98.287	0.031197	0.04087
cs_007	0.00719	0.017691	98.33	0.00127	0.01369
cs_008	0.00312	0.006113	98.332	7.06E-05	0.00587
cs_009	0.03865	0.00024	98.333	-1E-05	0.00373
ct_000	0.00575	0.012877	98.328	0.01099	0.0109
cu_000	0.00806	0.016207	98.315	0.00176	0.01519
cv_000	0.01335	0.026995	98.283	0.063609	0.02518
cx_000	0.01283	0.025099	98.302	0.033665	0.02415
cy_000	0.02075	0.003221	98.328	0.002444	0.02321
cz_000	0.00304	0.005964	98.327	0.001869	0.00573
da_000	0	0	98.333	-8.3E-05	0
db_000	0.00829	0.007537	98.333	0	0.01462
dc_000	0.01395	0.027909	98.298	0.041415	0.02629
dd_000	0.02812	0.045678	98.248	0.023877	0.05231
de_000	0.02132	0.033453	98.315	0.00985	0.03956
df_000	0.20795	0.003311	98.338	0.003541	0.04791
dg_000	0.02796	0.004606	98.378	0.003945	0.03209
dh_000	0.00319	0.002165	98.333	-1.6E-05	0.00541
di_000	0.00792	0.006573	98.34	0.002364	0.01381
dj_000	0	0	98.333	-2.8E-06	0
dk_000	0	0	98.333	-7.5E-05	0
dl_000	0	0	98.333	3.88E-05	0
dm_000	0	0	98.333	1.73E-05	0
dn_000	0.05118	0.063722	98.355	0.036472	0.0932
do_000	0.01097	0.020683	98.357	0.035351	0.0206
dp_000	0.00756	0.020634	98.36	0.02892	0.01446
dq_000	0.0083	0.00836	98.315	0.011692	0.0148
dr_000	0.00817	0.009199	98.297	0.023004	0.01474
ds_000	0.0212	0.041745	98.277	0.051881	0.03991
dt_000	0.02198	0.041382	98.358	0.062894	0.04128
du_000	0.01184	0.01926	98.317	0.01844	0.02202
dv_000	0.01316	0.021831	98.305	0.005467	0.02451
dx_000	0.00672	0.008785	98.31	0.034744	0.01229
dy_000	0.00596	0.008663	98.323	0.003061	0.01099
dz_000	0.03985	0.000165	98.33	-1.9E-06	0.00261
ea_000	0.00342	0.000359	98.333	-5.8E-05	0.00316
eb_000	0.00684	0.013875	98.337	0.011118	0.0129
ec_00	0.01851	0.032031	98.338	0.018058	0.03458
ed_000	0.01843	0.034386	98.27	0.023878	0.03459
ee_000	0.03067	0.053462	98.295	0.02934	0.05733

ee_001	0.0219	0.04754	98.293	0.014519	0.04146
ee_002	0.0234	0.048593	98.397	0.039534	0.0442
ee_003	0.0219	0.045201	98.367	0.021799	0.04134
ee_004	0.0232	0.043646	98.328	0.02856	0.04357
ee_005	0.03075	0.048769	98.573	0.039454	0.0571
ee_006	0.01687	0.039952	98.385	0.026574	0.03209
ee_007	0.02463	0.024192	98.277	0.018198	0.04381
ee_008	0.009	0.016591	98.335	0.005648	0.01688
ee_009	0.00322	0.005551	98.323	0	0.00602
ef_000	0.02384	0.000195	98.332	1.44E-05	0.00299
eg_000	0.01563	0.00016	98.333	-1.9E-05	0.00241