Automatic Sorting of Alluminium Alloys Based on Spectroscopy Measures

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Abstract
In this paper, we present an approach for classification of aluminium alloys based on spectroscopy measures. We use established pattern recognition techniques for a highly interesting and novel application domain from the area of waste sorting. First, spectrometric data is acquired from aluminium samples using the so called LIBS (Laser Induced Breakdown Spectroscopy). Second, the dimensionality of the feature space achieved in this way is significantly reduced by applying intelligent feature selection schemes. Finally, Nearest Neighbour and Bayes Classifiers as well as Support Vector Machines are used for classification. Comprehensive and comparative evaluation of algorithms integrated in our system provides us with very interesting conclusions.

1. Introduction

Sorting of light metal alloys can be carried out on three different difficulty levels, namely for aluminium consisting of one parent element (about 80 - 88%), multiple major elements (about 0.5 - 20%), and many trace elements (about 0.1 - 1%). While there exist successful approaches for sorting the parent element, sorting of the major elements turns out to be very difficult, and sorting the trace elements even impossible [2].

In this paper, we describe our approach for automatic sorting of the major elements using the LIBS (Laser-Induced Breakdown Spectroscopy) sensor. LIBS is a type of atomic emission spectroscopy which uses a highly energetic laser pulse as the excitation source. The laser is focused to form a plasma, which atomises and excites samples [4]. For our application domain, it yields spectrometric measures of aluminium alloys in form of high-dimensional spectrometric data. Although LIBS itself is a known data acquisition method, there exist no approaches for automatic exploiting this data in order to classify the aluminium alloys. In this paper, we propose known classification techniques to automatically exploit the data delivered by the LIBS technique.

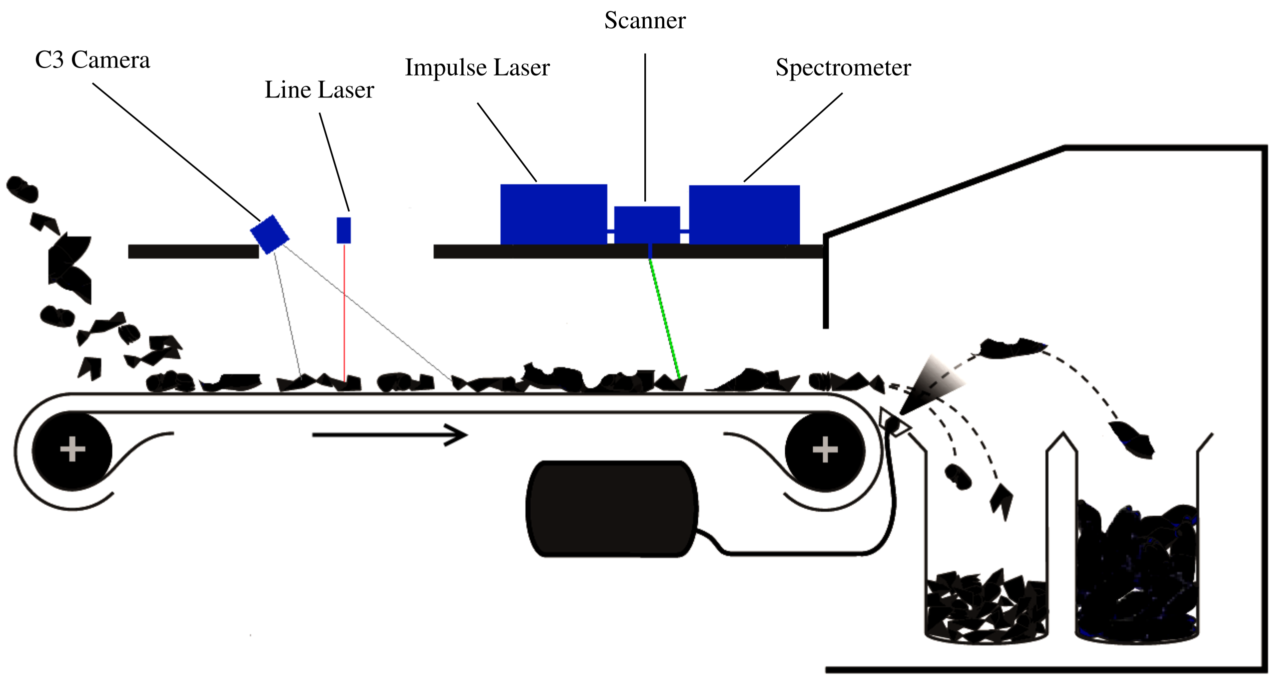

Figure 1. The sorting system and its components.

This paper is structured as follows. In Section 2. the data acquisition process by LIBS is shorty described. Section 3. presents our method to feature selection. In Section 4. the implemented classification algorithms are overviewed. The experiments and results are described in Section 5., while Section 6. closes the paper providing some interesting conclusions and plans for the future work.

2. Data Acquisition

The system is mounted above a conveyor band that is moving objects for acquisition (see Figure 1). First, a camera and a line laser determine the altitude profile of the objects which simplifies their further segmentation. Second, a scanner equipped with two mirrors deflects the emitted light towards a spectrometer. Finally, the objects are sorted in two fractions. The object recognition itself is performed by the c3 camera and the line laser. The camera takes object being illuminated by the line laser in the way presented in Figure 2. In our setup we use the Nd:YAG laser with a impulse frequence of 40Hz. The analysis of the radiance is performed by a multi-channel integrated spectrometer (see Figure 1) using the so called LIBS (Laser Induced Breakdown Spectroscopy) approach. LIBS is a type of atomic emission spectroscopy which uses a highly energetic laser pulse as the excitation source. The laser is focused to form a plasma, which atomises and excites samples. For our application domain, it yields spectrometric measures of aluminium alloys in form of high-dimensional spectrometric data. Figure 3 shows exemplary LIBS spectra for different metallic elements.

3. Feature Selection

As the raw data contains many channels from the spectrometer and even more data may be provided by other means, it is important to select the best features out of the data for a successful separation. All channels can be used for classification, but unnecessary ones lead in general to lower classification

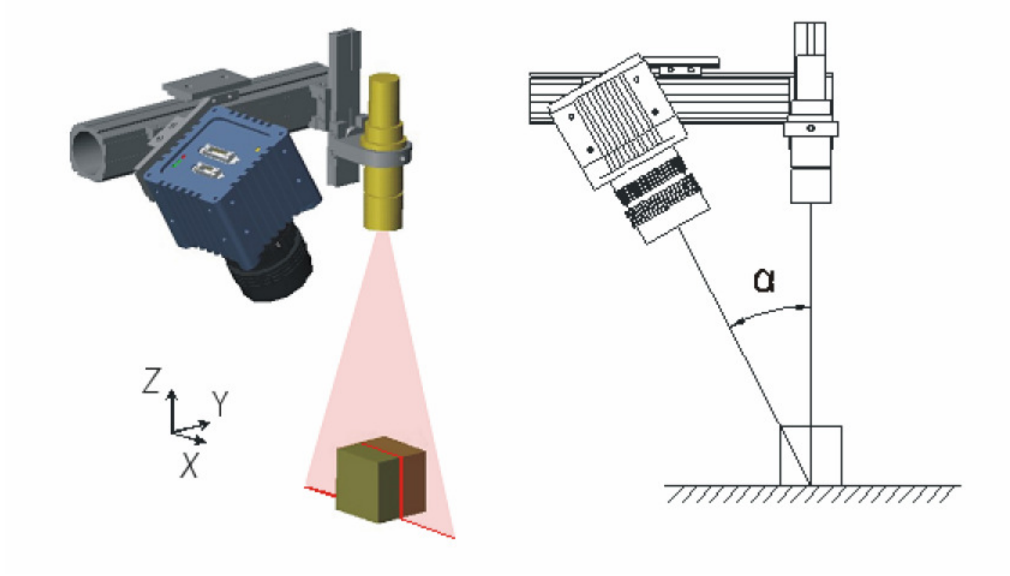

Figure 2. The camera setup for object recognition.

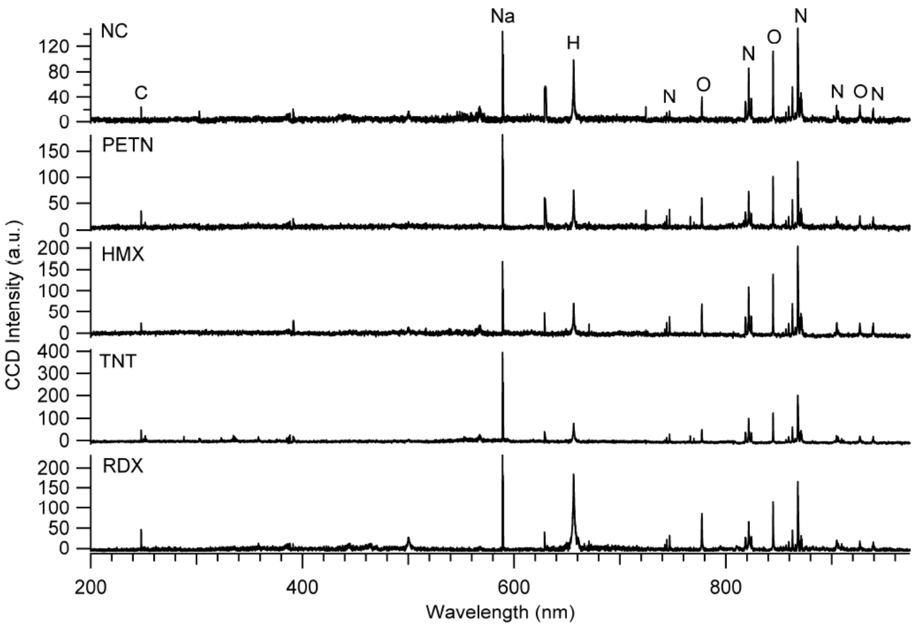

Figure 3. LIBS spectra for different explosives.

rate and slower classification. The impact is depending on the kind of classifier used.

There are many algorithms known, which can be used to find the optimal selection of features for a given problem. Two related algorithms were evaluated for a few problems out of the field of separating aluminium alloys. These were Forward Selection and Backward Selection [6]. The common principle is the continuously optimising of the set of features. While both are able to achieve very good results, they would take far to long for the data set, that was used in this test.

This problem lead to the development of a new feature selection algorithm, using the impact of each channel on a naive Bayes classifier [7] as a way to determine the importance of each channel for a given classification task. Instead of optimising the subset of features step by step, this algorithm calculates the success rate of a classification based on each channel by its own. The goal is not to find an optimal subset of features, but to find a subset, which is good enough for a practical application, fast enough to be able to quickly adapt to new tasks and changing environments. Finding the optimal subset becomes impossible, when you don't specify which classifier will be used in the actual classification. This is because each classifier, and even different configurations of the same classifier will possibly need different subsets of data for the best results.

After this first step, each channel has a success rate and the decision, if this rate is high enough to add this channel to the subset that will be used for the classification can be done with a certain threshold, by looking at the average success rate of all channels or by other means. In this case the average success rate was used.

$$optfeatures = \bigcup_{i=1}^{n} channel_i \mid rate_i < threshold$$

$$optfeatures = \bigcup_{i=1}^{n} channel_i \mid rate_i < rate_{avg}$$

If we want to find a subset, which can be used for different tasks, the decision becomes more difficult. For three different tasks, one channel could score 100% on two tasks and 0% on the third. Should this channel have precedence over a channel which scores 66% in all the tests? Another option is to attach a weight to each channel representing its importance for the classification, but not all classifiers support the consideration of such attributes.

4. Classification

The classifier used for these experiments has to fulfil several requirements. Since there is very little time between data acquisition and decision making, and a minimum rate of classifications needs to be achieved to provide enough throughput for a system which will be used in an industrial environment, the system has to work very fast. The result of the classification is worthless after the object has passed the point of separation, so a fast classifier is not enough, it has to have a low fluctuation on the time needed for the classification.

Obviously the classifier has much influence of the success rate of the classification, which need to be very high (above 95%) for certain tasks. Three well proven classifiers were chosen for the evaluation. The Bayes Classifier [3] and the Nearest Neighbour classifier [5] (kNN) were chosen due to their simplicity and traceability. The Bayes Classifier uses statistical information about the distribution of the data to classify an unknown data point. This classifier is very fast and uses very little memory, because it only needs to store the mean and variance of each channel of each class.

As the Nearest Neighbour Classifier compares the samples with each measurement in the training set, its computational complexity is depending on the size of the training set. For large training data the NN classifier was the only one, which violated the time constraints in the tests. The training set used in the comparison of success rate was with approximately 5000 samples well inside the time limits. The Support Vector Machine (SVM) [1] was chosen, because its good results with data of high dimensionality and flexibility.

When using the Nearest Neighbour classifier there is only one parameter, which can be optimised to increase the success rate. This is the number of neighbours, which will be used to determine the class of a sample (e.g. the three closest ones).

When using a Support Vector Machine there are many parameters, which can be modified depending on the kernel function used. In this case a ”RBF” kernel was used. The two parameters with the most influence on the success rate of the classification are C (penalty or cost parameter) and gamma, which is a parameter of the ”RBF” kernel. To find common good configuration for this application a grid search was used.

To optimise the preprocessing of the data in a similar way, several normalisation methods and their combination were evaluated

5. Experiments and Results

For testing, a high number of different aluminium alloys have been taken into consideration (see Table 1). All of them are common in the industry.

First of all, approaches for feature selection have been evaluated for specific sorting strategies. Theoretically, the backward and the forward selection should provide the best results. However, they do not fulfil the speed requirements of our application domain. Therefore, finally the Bayes Relevance Selection (BRS) method has been used. The robustness of the feature selection has been exemplary evaluated for the classification of alloys 307 and 23502. The results can be seen in Table 2.

The alloy classification results with the Nearest Neighbour classifier are presented in Table 3.

Unfortunately, the Bayes classifier could not bring satisfying results and achieved an overall classification result of only 23%. Once several normalisation approaches have been applied, the classification performance has increased to 32% which still lies deep underneath the system requirements.

Table 4 presents alloy classification results for the SVM classification scheme. Here, the best classification performance has been achieved and this algorithm has been finally integrated into the industrial sorting system for alloys.

6. Conclusions

In this paper, we have described our system for classification of aluminium alloys based on spectroscopy measures. We have used three established pattern recognition techniques, namely the Near-

Number	Producer	Name	Type	Al %[a]%	Si%	Fe%	Cu%	Mn%	Mg%	Cr%	Ni%	Zn%	Ti%	Be%	Bi%	Cd%	Co%	Ga%	Pb%	Sn%	V%	Zr%
15502	Alusuisse	155 / 02	AlFe	97.818	0.5	1	0.1	0.081	0.15	0.051	0.053	0.062	0.065					0.007	0.01	0.011	0.05	0.042
15803	Alusuisse	158 / 03	AlFe	97.8365	0.053	1.98	0.012	0.021	0.02	0.007	0.0085	0.0075	0.013					0.01	0.007	0.005	0.013	0.0055
16301	Alusuisse	163 / 01	AlFe	94.105	0.156	4.93	0.106	0.222	0.084	0.054	0.054	0.176	0.06						0.014	0.0146	0.013	0.0063
23502	Alusuisse	235 / 02	AlCu	92.96	0.94	0.57	0.98	0.94	0.91	0.14	0.15	1	0.125		0.43	0.305			0.43			0.12
32701	Alusuisse	327 / 01	AlMn	97.8997	0.054	0.138	0.025	1.74	0.006	0.005	0.0052	0.052	0.068						0.0063			
33502	Alusuisse	335 / 02	AlMn	97.893	0.101	1.53	0.012	0.4	0.0015	0.012	0.012	0.021	0.0032								0.012	
43502	Alusuisse	435 / 02	AlSi	81.4904	13.03	0.48	1.32	0.304	1	0.053	2.03	0.052	0.058	0.0024			0.052		0.053	0.049	0.0042	0.0145
61102	Alusuisse	611 / 02	AlMgSi	99.49778	0.222	0.07	0.0006	0.0024	0.194	0.0011	0.0007	0.0015	0.0017					0.0054	0.00038	0.00034	0.0011	0.001
63202	Alusuisse	632 / 02	AlMgSi	98.07045	0.68	0.203	0.029	0.421	0.475	0.0206	0.0066	0.0515	0.029						0.0055	0.005	0.0022	
66501	Alusuisse	665 / 01	AlMgSi	94.49	1.72	0.72	1	0.41	1.2	0.11		0.2	0.15									
71102	Alusuisse	711 / 02	AlZn	93.0248	0.4	0.452	0.049	0.204	4.45	0.0092		1.3	0.106	0.005								
87101	Alusuisse	871 / 01	AlZn(Si)	80.8035	9.67	0.155	0.011	0.023	0.295	0.019	0.022	8.94	0.056									
87201	Alusuisse	872 / 01	AlZn(Si)	80.0642	8.76	0.41	0.1	0.2	0.405	0.011	0.011	10	0.037									
87301	Alusuisse	873 / 01	AlZn(Si)	80.7486	7.25	0.26	0.049	0.104	0.535	0.032	0.006	11	0.0154									
132	MBH	54X G13H2	AlSi	83.63	10.1	1.03	1.27	0.2	1.34	0.08	1.23	0.62	0.19						0.15	0.16		
251	MBH	54X G25D1	AlSi	93.481	3.34	0.72	0.01	0.81	0.65	0.14	0.26	0.36	0.098	0.001	0.11				0.004		0.016	
204	MBH	54X GS20J4	AlSi	73.3289	25.5	0.227		0.146	0.005	0.194	0.265	0.224	0.107	0.0017					0.0014			
210	MBH	55X G02D10	AlSiCu	81.66	6.56	0.186	4.65	0.015		0.16	0.96	4.76			0.09		0.059			0.9		
48	MBH	55X G04H8	AlSiCu	87.7235	5.53	0.67	3.34	0.41	0.18	0.05	0.35	1.28	0.18			0.0055	0.021	0.008	0.166	0.076	0.01	
2502	MBH	56X G250J2	AlCu	91.54	0.25	0.45	5.13	0.17	0.04	0.11	1.25	0.2	0.26				0.31					
2504	MBH	56X G250 J4	AlCu	90.76	0.05	0.17	7	0.54		0.04	0.8	0.05	0.16				0.12		0.09	0.16		
121	MBH	57X G12H1	AlCuSi	88.6391	2.52	0.88	5.54	0.032	0.4	0.069	0.31	1.03	0.114	0.0019		0.012	0.113		0.016	0.095	0.15	0.07
123	MBH	57X G12H3	AlCuSi	85.46	1.57	0.89	9.75	0.32	0.25	0.04	0.63	0.6	0.21						0.09	0.19		
125	MBH	57X G12H5	AlCuSi	86.349	0.55	0.19	12.2	0.073	0.028	0.016	0.11	0.072	0.036	0.003		0.023	0.054	0.017	0.068	0.067	0.033	0.045
406	MBH	58X G40H6	AlZn	92.05	0.09	0.08	0.111	0.004		0.005	0.008	7.55	0.064			0.032	0.006					
409	MBH	58X G40H9	AlZn	91.676	0.24	0.47	0.18	0.046	1.12	0.37	0.048	4.9	0.25						0.4	0.13		0.17
771	MBH	59X G77J1	AlMgCu	89.094	0.15	0.21	2.41	0.46	4.83	0.24	0.17	1.91	0.178		0.06	0.004	0.018		0.125	0.126	0.005	0.01
773	MBH	59X G77J3	AlZnMgCu	88.2045	0.37	0.71	2.42	0.594	2.27	0.023	0.43	4.57	0.107		0.046	0.0115			0.075	0.137	0.006	0.026
776	MBH	59X G77J6	AlZn	84.214	0.04	0.054	1.13	0.0024	2.63	0.0046	0.003	11.6	0.023							0.006	0.003	0.29
54	MBH	511X G05H4	AlMg	93.561	0.11	0.14	0.056	0.55	5.1	0.029	0.04	0.062	0.048	0.014					0.15	0.14		
105	MBH	511X G10H5	AlMg	85.507	0.19	0.18	0.02	0.21	13.6		0.07	0.02		0.013					0.19			
30001	MBH	511X G3000B1	AlMg	96.77	0.55	0.27	0.24	1.32	0.16	0.13	0.16	0.09							0.15	0.16		
90912	MBH	514X 9091.2	AlMn	86.81	0.45	0.9	0.44	10.8	0.03	0.06	0.07	0.16	0.15						0.09	0.04		
306	BAM	306	G-AlSi8Cu3	85.516	8.57	1.14	2.636	0.33	0.293		0.296	0.887	0.152						0.18			
307	BAM	307	AlMg 4.5 Mn	93.7163	0.155	0.412	0.1043	0.701	4.576	0.162		0.0634	0.1009	0.0011		0.00489						
308	BAM	308	AlZnMgCu1.5	90.21178	0.0707	0.1634	1.315	0.0342	2.29	0.1962	0.0122	5.67	0.0285	0.00022								0.0078
309	BAM	309	AlSi12	88.02558	11.76	0.0883	0.0048	0.0548	0.00068	0.00047	0.00087	0.00379	0.0556								0.00421	
2	VAW	R-02	Al 99.9999	99.999918				0.000004	0.000062	0.000002		0.000008						0.000004	0.000002			

[a] Computed

Table 1. Different aluminium alloys used for experiments

Classifier	Overall Classification Rate	Classification Rate 307	Classification Rate 23502
Bayes, Voting, All Channels	39.4 %	93 %	23 %
Bayes, Voting, BRS for 307	42,1 %	**98 %**	10 %
Bayes, Voting, BRS for 23502	35,7 %	54 %	**76 %**
Bayes, Product, All Channels	69,1 %	87 %	44 %
Bayes, Product, BRS for 307	70,8 %	**93 %**	52 %
Bayes, Product, BRS for 23502	67,0 %	93 %	**64 %**
1NN, All Channels	84,8 %	100 %	72 %
1NN, BRS for 307	85,1 %	**100 %**	88 %
1NN, BRS for 23502	87,9 %	100 %	**98 %**

Table 2. Evaluation for Bayes Relevance Selection (BRS)

Classification Result	Real Class													
	2	32701	125	48	306	23502	123	105	308	210	4060	309	307	87201
2	80	56	0	0	0	0	0	0	0	0	0	5	0	0
32701	18	40	0	0	0	0	0	0	0	0	0	0	0	0
125	2	4	95	0	1	0	0	0	0	0	0	0	0	0
48	0	0	0	30	1	0	0	0	0	0	0	0	0	4
306	0	0	0	43	78	1	15	0	0	0	0	0	0	0
23502	0	0	0	3	7	70	61	0	28	0	0	0	0	0
123	0	0	5	24	12	18	23	0	0	0	0	0	0	0
105	0	0	0	0	0	0	0	100	0	0	0	0	69	0
308	0	0	0	0	0	10	1	0	72	0	0	0	0	13
210	0	0	0	0	0	0	0	0	0	98	1	0	0	0
4060	0	0	0	0	0	0	0	0	0	2	99	0	0	0
309	0	0	0	0	1	0	0	0	0	0	0	95	0	0
307	0	0	0	0	0	1	0	0	0	0	0	0	31	0
87201	0	0	0	0	0	0	0	0	0	0	0	0	0	83
Correct:	80%	40%	94%	30%	77%	69%	23%	100%	72%	98%	99%	94%	31%	82%

Classification Rate = 71.00 % (994/1400)

Table 3. Confusion matrix for alloy classification results with the Nearest Neighbour classifier.

est Neighbour and the Bayes classifiers as well as Support Vector Machines. While Bayes classifier did not provide any satisfying results, Nearest Neighbour approach worked much better. However, the best results have been achieved for Support Vector Machines and this technique will be used in the final realisation of the sorting hardware in the industry.

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Classification Result	Real Class													
	2	48	306	123	105	125	210	4060	307	308	23502	309	32701	87201
2	100	0	0	0	0	0	0	0	0	0	0	1	77	0
48	0	92	0	0	0	0	0	0	0	0	0	0	0	8
306	0	7	100	0	0	0	0	0	0	0	0	0	0	0
123	0	1	0	100	0	0	0	0	0	0	0	0	0	0
105	0	0	0	0	100	0	0	0	12	0	0	0	0	0
125	0	0	0	0	0	100	0	0	0	0	0	0	0	0
210	0	0	0	0	0	0	99	0	0	0	0	0	0	0
4060	0	0	0	0	0	0	1	100	0	0	0	0	0	0
307	0	0	0	0	0	0	0	0	88	1	0	0	0	0
308	0	0	0	0	0	0	0	0	0	98	0	0	0	16
23502	0	0	0	0	0	0	0	0	0	1	100	0	0	0
309	0	0	0	0	0	0	0	0	0	0	0	99	0	0
32701	0	0	0	0	0	0	0	0	0	0	0	0	23	0
87201	0	0	0	0	0	0	0	0	0	0	0	0	0	76
Correct:	100 %	92 %	100 %	100 %	100 %	100 %	99 %	100 %	87 %	98 %	100 %	99 %	23 %	75 %

Classification Rate = 91.07 %

Table 4. Confusion matrix for alloy classification results with the SVM classifier.

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