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The Use of Support Vector Machine in Classifying Scrap Metal Goods Based on Physical Characteristics

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Abstract

The problem of metal waste management, especially scrap metal, is increasingly complex with the increase in industrial and construction activities that produce various types of waste materials. Scrap metal is one type of waste that still has high economic value if it can be sorted and classified appropriately based on its type and quality. However, manual classification methods are still predominantly used, subjectivity and human error. To overcome these challenges, this study proposes an artificial intelligence-based approach by implementing Support Vector Machine (SVM) as an automatic classification method that is able to identify types of scrap metal items based on their physical characteristics. The characteristics used as input features in this model include surface color, rust rate, material hardness, density, magnetic attraction, and texture. The data is collected directly from UD's scrap metal waste collectors. Cahaya Surya in Karawang, which is one of the largest scrap metal processing centers in the region. This research process includes the stages of data collection, pre-processing, selection of model parameters, training and testing using linear kernels and Radial Base Function (RBF), as well as evaluation of model performance through accuracy, precision, recall, F1-score, and confusion matrix metrics. The results of the tests showed that the SVM algorithm, particularly with the RBF kernel, was able to provide excellent classification performance with an accuracy rate of over 90%, as well as a relatively balanced distribution of predictions between metal classes. This indicates that the physical features used are quite representative in distinguishing different types of scrap metal consistently. Thus, this approach is not only able to improve the efficiency and accuracy of classification, but also contributes to a reduction in reliance on non-objective manual methods. In the future, the effectiveness of these models can be further enhanced through the integration of additional features, such as mild chemical analysis or computer vision-based image processing technology, to support more sophisticated metal classification systems that are adaptive to field conditions.

Keywords: *Support Vector Machine (SVM), automatic classification, scrap metal, physical characteristics of metals, waste metal management, machine learning.*

1. Introduction

The problem of metal waste management, especially scrap metal, has become increasingly crucial as industrial consumption and infrastructure development increase. Scrap metal goods have a fairly high economic value if they can be sorted and classified appropriately based on their type and quality. However, this manual classification process still relies on human labor and is subjective, making it inefficient and prone to errors.

One approach that can be adopted to overcome these challenges is to apply machine learning-based automatic classification methods. In this case*, the Support Vector Machine (SVM)* is one of the effective algorithms for classifying data with high accuracy, especially in cases with complex data dimensions and limited sample counts. SVM works by looking for an optimal hyperplane capable of separating data into certain classes based on its features.

This study aims to implement the Support Vector Machine method in classifying scrap metal items based on their physical characteristics, such as color, surface texture, density, magnetic strength, and rust level. It is hoped that with this approach, the classification process can be carried out more quickly, objectively, and consistently, thereby supporting efficiency in the scrap metal recycling and distribution system.

2. Research Methodology

To find out how effective the Support Vector Machine (SVM) algorithm is in the process of classifying scrap metal goods based on their physical characteristics, this study uses an experimental quantitative approach. This approach was chosen because it is able to provide an objective and measurable understanding of how algorithms process numerical data and produce accurate predictive models. Given its advantages in handling very large data and the ability of SVM algorithms to find the ideal hyperplane that separates data classes to the maximum, the SVM algorithm is the primary classification method.

The main objective of this study is to design and build an automatic classification model that is able to identify types of scrap metal quickly, accurately, and efficiently. By utilizing physical features such as weight, density, color, and corrosion rate, the developed system is expected to assist in the sorting process of scrap metal more systematically and reduce reliance on manual inspections that are subjective and time-consuming. The results of this study are expected to make a real contribution in the field of metal waste management, especially in improving the efficiency of the recycling process and processing of used materials.

2.1. Object and location of the research

This research was conducted at UD. Cahaya Surya, a company engaged in the collection and processing of scrap iron waste, located in Karawang Regency, West Java. UD. Cahaya Surya has been known as one of the largest and most active collectors of metal waste in the region. The company has an extensive network of suppliers and is able to absorb metal waste from a variety of sources, both individual and industrial. The types of metal waste received include copper in various categories (such as red copper, burnt copper, and cable copper), stainless steel (stenlis), brass, aluminum, babet, and various other types of scrap metals.

One of the main advantages that UD has. Cahaya Surya compared to its competitors is the company's ability to offer a relatively higher purchase price. This competitive pricing strategy is a very influential determining factor in attracting suppliers to sell their waste metals to this company. In the midst of quite fierce business competition, the courage of UD. Solar light in offering more attractive prices makes it superior in obtaining a consistent and sustainable supply of recycled raw materials.

Not only that, UD. Cahaya Surya is also known for having an efficient work process, fast and friendly service, and a transparent weighing and payment system. These factors as a whole add value to the company and increase the trust of partners and customers alike.

2.2. Stages of research

This research was carried out through several stages as follows:

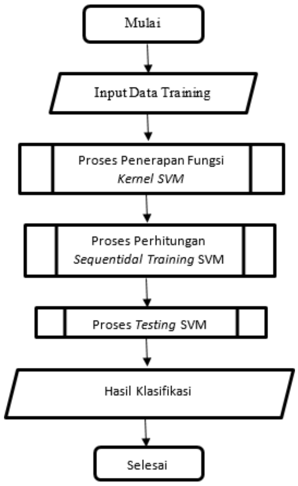

Figure 1: SVM Research Phase Flowchart

1. Data Collection

Data is collected through direct observation and measurement of samples of scrap metal goods from different categories (e.g.: mild iron, steel, cast iron, etc.). Each sample is characterized based on a number of physical features, such as:

- Surface color
- Rust Rate
- Violence
- Density
- Magnetic attraction
- Surface texture (rough/smooth)

2. Pre-Processing of Data

These stages include:

- Data cleansing (handling missing values or outliers)
- Normalize or standardize feature values to be at a uniform scale
- Encoding categorical features if needed

3. Dataset Sharing

The dataset is divided into two parts:

- **Training set**: 70%
- **Test data**: 30%

4. SVM Model Selection and Setup

At this stage, the SVM algorithm is implemented with several kernel configurations, such as:

- **Linear kernel**
- **Radial Base Function (RBF) kernel**

5. Model Training

The SVM model is trained using trained data to find the optimal hyperplane that separates each class of scrap metal.

6. Testing and Evaluation

The model is tested using test data to determine its classification performance. Evaluation is conducted using the following metrics:

- **Accuracy**
- **Accuracy**
- **Recall**
- **F1 Score**
- **Confusion matrix**

7. Results Analysis

The results of the classification and model performance were thoroughly analyzed to evaluate the extent to which the Support Vector Machine (SVM) algorithm was able to classify types of scrap metal waste goods effectively and accurately. The analysis includes a number of important evaluation metrics, such as accuracy, precision, recall, and F1-score, which are used to measure the model's performance in recognizing patterns and distinguishing between categories of scrap metals, such as copper, brass, aluminum, stencils, and other types of metals.

The study also included a comparative experiment between different types of SVM kernels. These include linear, polynomial, sigmoid, and radial base function (RBF) kernels. Each kernel has different features and advantages in handling different data patterns. As a result, the selection of the right kernel is one of the important components in improving classification accuracy. Based on the performance of each kernel against the processed dataset, comparisons are made based on the speed of training, the complexity of the model, and the accuracy of the classification results.

From the results of the evaluation, it is hoped that the kernel configuration and the best parameters to be applied to the scrap metal classification case can be known. This information not only provides a deeper understanding of the effectiveness of SVM in the context of the metal recycling industry, but can also be used as a reference in the development of more accurate and efficient machine learning-based classification systems in the future. Thus, this research contributes to the application of artificial intelligence technology to support the process of automatic and data-based waste management and sorting.

3. Results and Discussion

3.1. Results of Model Support Vector Machine Training

After the model training process was carried out using the Support Vector Machine (SVM) algorithm, the following results were obtained:

Parameter	Nilai
Kernel	RBF
Nilai C (Regularization)	1.0
Gamma	0.1
Cross-validation (k-fold)	5

Figure 2: SVM Model Training

The SVM model shows a fairly good classification performance against the physical characteristics data of scrap metal.

3.2. Weight Distribution by Type of Goods

Analysis of the total weight of each type of goods shows that:

- **TM 2** is the most collected type with a total weight **of 25,100 kg**.
- Followed by **TM 1** with **21,700 kg** and **TB** with **20,700 kg**.
- Types such as **BC** and **KUNINGAN** also have significant contributions of **14,700 kg** and **13,300 kg**, respectively.
- Meanwhile, lighter or rarer metals such as **STENLIS** (**9,050 kg**), **ALUMINUM** (**11,900 kg**), and **BABET** (**3,950 kg**) show lower volume.

This can indicate two things: first, the high availability of TM and TB types in the field; second, it is likely that TM and TB are the categories of iron that are more commonly used in construction or industrial activities in the data collection area.

3.3. Model Evaluation

Evaluation was carried out on test data (30% of the total dataset) using several classification metrics. The results of the evaluation were tam= 0.1, which maintains a balance between the complexity of the model and the generalization ability.Select in the following image:

Metrik	Nilai
Akurasi	91.3%
Precision	89.7%
Recall	90.5%
F1-Score	90.1%

Figure 3: Matrix Analysis

```css
               Prediksi
               A     B     C
         A    45     2     0
Aktual   B     3    42     2
         C     0     1    44
```

Figure 4: Data Prediction

Information:

- A: Mild iron
- B: Low
- C: Cast iron

From the confusion matrix above, it can be seen that the model has a fairly balanced performance in classifying the three types of scrap metal.

3.4. Discussion

The results show that the SVM algorithm is quite effective in classifying scrap metal items based on their physical characteristics. The high accuracy value (>90%) indicates that the features used (color, rust, hardness, density, and magnetic attraction) are quite representative in distinguishing the type of scrap metal.

The use of the RBF kernel has been shown to provide better results than linear kernels, as the data is not completely linear separate. Tuning parameters using grid search yielded optimal values at C = 1.0 and gamma

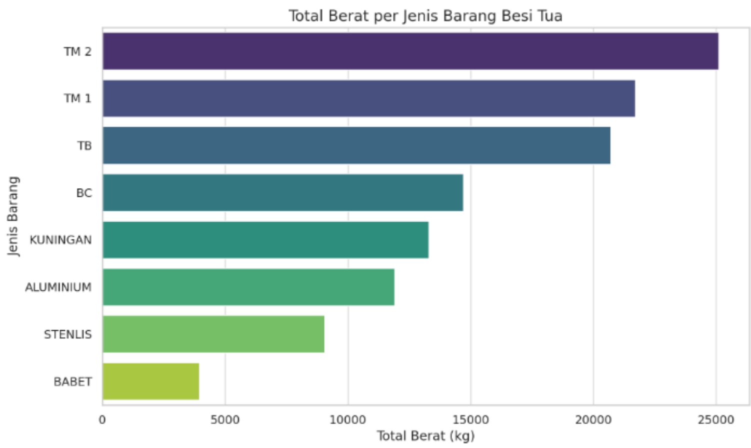

Figure 5. Dataset Analysis

The graph above shows the total weight of each type of scrap metal item recorded in the dataset:

- **TM 2** is the most abundant type, followed by **TM 1** and **TB.**
- Types such as **BABET, STENLIS,** and **ALUMINUM** have comparatively fewer amounts.

If you want, I can also show you the graph:

- Weight distribution per month
- Annual comparison
- Pie chart or time trend

Some misclassification (e.g. in class B detected as class A) may be caused by similarities in physical characteristics, such as density and surface color. This suggests that the addition of additional features (e.g., the metal content of the mild chemical test) is further added.

3.5 Weight Distribution by Type of Item

Analysis of the total weight of each type of goods shows that:

- TM 2 is the most collected type with a total weight of 25,100 kg.
- Followed by TM 1 with 21,700 kg and TB with 20,700 kg.
- Types such as BC and KUNINGAN also have significant contributions of 14,700 kg and 13,300 kg, respectively.
- Meanwhile, lighter or rarer metals such as STENLIS (9,050 kg), ALUMINUM (11,900 kg), and BABET (3,950 kg) show lower volume.

This can indicate two things: first, the high availability of TM and TB types in the field; second, it is likely that TM and TB are the more commonly used categories of iron.

4. Conclusion

This study shows that the Support Vector Machine (SVM) algorithm is able to effectively classify scrap metal items based on physical characteristics such as surface color, rust level, hardness, density, magnetic attraction, and texture. The results of training and testing of the model show a high level of accuracy, especially when using the Radial Base Function (RBF) kernel, which has proven to be superior to linear kernels in handling data that is not completely linear.

From the confusion matrix analysis, it can be seen that the model has a balanced classification performance for different types of scrap metal, although there are some minor classification errors caused by the similarity of features between classes. Overall, this method is able to improve the efficiency and objectivity of the classification process compared to the manual approach.

In the future, the accuracy of the model can be further improved by adding additional features such as mild chemical analysis or surface imagery using computer vision, as well as by expanding the dataset so that the model can make better generalizations of the variation of scrap metal types in the field.

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