

**International Journal of  
Engineering Research and Science & Technology**



**ISSN : 2319-5991**

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# GEO TRACKING OF WASTE AND TRIGGERING ALERTS AND MAPPING AREAS WITH HIGH WASTE INDEX

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## ABSTRACT

This article presents the use of automated machine learning for solving a practical problem of a real-life Smart Waste Management system. In particular, the focus of the article is on the problem of detection (i.e., binary classification) of an emptying of a recycling container using sensor measurements. Numerous data-driven methods for solving the problem were investigated in a realistic setting where most of the events were not actual emptyings. The investigated methods included the existing manually engineered model and its modification as well as conventional machine learning algorithms. The use of machine learning allowed improving the classification accuracy and recall of the existing manually engineered model from 86.8 % and 47.9 % to 99.1 % and 98.2 %

respectively when using the best performing solution. This solution used a Random Forest classifier on a set of features based on the filling level at different given time spans. Finally, compared to the baseline existing manually engineered model, the best performing solution also improved the quality of forecasts for emptying time of recycling containers.

## 1.INTRODUCTION

### 1.1 INTRODUCTION

Machine learning is an area with a huge potential for the transformation of many areas of life and science including industrial informatics. In order to hasten the application of machine learning to real-world problems, the automated machine

learning (AutoML) approach has been proposed. This article extends the Auto ML approach with the data-driven methodology applied to industrial problems with existing (e.g., model-based) solutions. When implementing these steps economical and environmental aspects should be taken into account. Waste transportation greatly affects both aspects and its optimisation can significantly increase the positive effects. At the same time, there is a clear requirement that in order to keep recycling stations clean they should be emptied at a right time. It is non-trivial to fulfil this requirement in a scenario with several hundreds of recycling stations (each with several containers) that are spread over a large geographical area.

## 2.LITERATURE SURVEY

### 2.1 INTRODUCTION

#### **“Efficient and Robust Automated Machine Learning,”**

The success of machine learning in a broad range of applications has led to an ever-growing demand for machine learning systems that can be used off the shelf by

non-experts. To be effective in practice, such systems need to automatically choose a good algorithm and feature preprocessing steps for a new dataset at hand, and also set their respective hyperparameters. Recent work has started to tackle this automated machine learning (AutoML) problem with the help of efficient Bayesian optimization methods. In this work we introduce a robust new AutoML system based on scikit-learn (using 15 classifiers, 14 feature preprocessing methods, and 4 data preprocessing methods, giving rise to a structured hypothesis space with 110 hyperparameters). This system, which we dub auto-sklearn, improves on existing AutoML methods by automatically taking into account past performance on similar datasets, and by constructing ensembles from the models evaluated during the optimization. Our system won the first phase of the ongoing ChaLearn AutoML challenge, and our comprehensive analysis on over 100 diverse datasets shows that it substantially outperforms the previous state of the art in AutoML. We also demonstrate the performance gains due to each of our contributions and derive insights into the effectiveness of the individual components of auto-sklearn.

### **“Auto- WEKA: Combined Selection and Hyperparameter Optimization of Classification Algorithms,”**

Many different machine learning algorithms exist; taking into account each algorithm's hyperparameters, there is a staggeringly large number of possible alternatives overall. We consider the problem of simultaneously selecting a learning algorithm and setting its hyperparameters, going beyond previous work that addresses these issues in isolation. We show that this problem can be addressed by a fully automated approach, leveraging recent innovations in Bayesian optimization. Specifically, we consider a wide range of feature selection techniques (combining 3 search and 8 evaluator methods) and all classification approaches implemented in WEKA, spanning 2 ensemble methods, 10 meta-methods, 27 base classifiers, and hyperparameter settings for each classifier. On each of 21 popular datasets from the UCI repository, the KDD Cup 09, variants of the MNIST dataset and CIFAR-10, we show classification performance often much better than using standard selection/hyperparameter optimization methods. We hope that our approach will help non-expert users to more effectively identify machine learning algorithms and

hyperparameter settings appropriate to their applications, and hence to achieve improved performance.

### **“Challenges and Opportunities of Waste Management in IoT-Enabled Smart Cities: A Survey,”**

The new era of Web and Internet of Things (IoT) paradigm is being enabled by the proliferation of various devices like RFIDs, sensors, and actuators. Smart devices (devices having significant computational capabilities, transforming them to `smart things') are embedded in the environment to monitor and collect ambient information. In a city, this leads to Smart City frameworks. Intelligent services could be offered on top of such information related to any aspect of humans' activities. A typical example of services offered in the framework of Smart Cities is IoT-enabled waste management. Waste management involves not only the collection of the waste in the field but also the transport and disposal to the appropriate locations. In this paper, we present a comprehensive and thorough survey of ICT-enabled waste management models. Specifically, we focus on the adoption of smart devices as a key enabling technology in contemporary waste management. We report on the

strengths and weaknesses of various models to reveal their characteristics. This survey sets up the basis for delivering new models in the domain as it reveals the needs for defining novel frameworks for waste management.

### **Smart waste management solution:**

Rapid increase in population, has led to the improper waste management in cities resulting in increased pests and spreading of diseases. Nowadays, the Garbage Collecting Vehicle (GCV) collects the waste twice or thrice in a week. So, the problem is over flowing of wastages on the roads. Hence, to overcome this limitation, in this paper a scheme on smart waste management using Wireless Sensor Networks (WSN) and IoT (Internet of Things) is proposed. The garbage bins are deployed with sensors and are networked together using WSN. The sensors deployed in the garbage bins collect the data for every determined interval. Once the threshold is reached, it raises a request to the GCA (Garbage Collector Agent). This agent collects the requests of all the filled vehicles and communicate using IoT framework. The experimental simulation is done in proteus tool. A hardware prototype is developed for the proposed framework.

Analysis of the proposed scheme provides better results in waste management.

### **“Incorporating Intelligence in Fog Computing for Big Data Analysis in Smart Cities,”**

Data intensive analysis is the major challenge in smart cities because of the ubiquitous deployment of various kinds of sensors. The natural characteristic of geo distribution requires a new computing paradigm to offer location-awareness and latency-sensitive monitoring and intelligent control. Fog Computing that extends the computing to the edge of network and fits this need. In this paper, we introduce a hierarchical distributed Fog Computing architecture to support the integration of massive number of infrastructure components and services in future smart cities. To secure future communities, it is necessary to integrate intelligence in our Fog Computing architecture, e.g., to perform data representation and feature extraction, to identify anomalous and hazardous events, and to offer optimal responses and controls. We analyze case studies using a smart pipeline monitoring system based on fiber optic sensors and sequential learning algorithms to detect events threatening pipeline safety. A working prototype was

constructed to experimentally evaluate event detection performance of the recognition of 12 distinct events. These experimental results demonstrate the feasibility of the system's city-wide implementation in the future.

### 3. EXISTING SYSTEM

The above arguments explain why it is not feasible to use a simple threshold model for the accurate detection of emptying with either the ultrasonic range sensor or the accelerometer. However, it is possible to combine ultrasonic measurements and vibration strength scores in a more complex model with several thresholds. This idea was used to build the existing manually engineered model, which is presented in details it was manually engineered using the expert knowledge of the domain. It is also known that detection performance of the existing manually engineered model is a bottleneck for improving the emptying time predictions. Therefore, we propose using the data-driven approach for improving the quality of the emptying detection part of the system. It should be noted that the acquisition of a dataset used in this article was done as a part of the implementation work in this study.

### ADVANTAGE

- The performance of the existing and the optimised manually engineered models is presented.
- Second, the six conventional classification algorithms are evaluated using the same features as in the existing manually engineered model.
- On the one hand, including additional features often allows achieving better classification performance.
- On the other hand, from the operational point of view it is preferable to use as few features as possible since it improves the interpretability of the solution.
- The compromise between these two conflicting requirements, Recursive Feature Elimination (RFE) method was used to identify the best set of feature.

### 4. Proposed system

Our analysis of an operating Smart Waste Management system revealed that one of these challenges is a problem of an accurate detection of a container being emptied using the measurements from a sensor mounted on top of a container. As it is demonstrated in, the quality of filling

level predictions depends on the correct detection of emptyings. Inaccurate detections devalue filling level predictions, therefore, detection of container emptyings is an integral step in obtaining qualitative predictions. Therefore, this article applies the proposed methodology to the problem of the emptying detection.

#### **DISADVANTAGE:**

- The conventional classification algorithms were applied to the considered problem in order to see if they could improve the performance even further than the optimised manually engineered model.
- In terms of the fair comparison of algorithms, ensemble classifiers should be treated separately, however, in the scope of the considered problem the achieved performance was the main goal.
- The article proposed the iterative data-driven methodology for achieving the highest performance where first the existing solution to the problem was assessed, second this solution was optimised using the collected dataset, next, machine learning algorithms were applied to the problem, and finally, the

feature engineering was used to find if additional features would improve the results.

A recommender framework is a customary system that proposes an item to the user, dependent on their advantage and necessity. These frameworks employ the customers' surveys to break down their sentiment and suggest a recommendation for their exact need. In

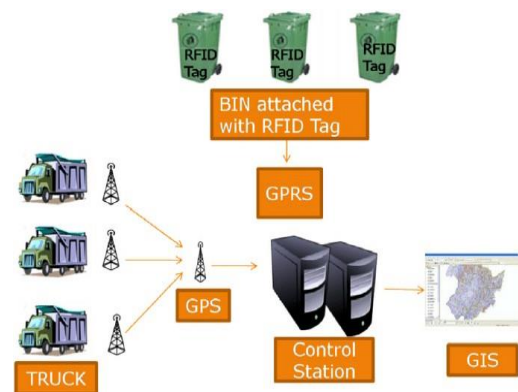
the drug recommender system, medicine is offered on a specific condition dependent on patient reviews using sentiment analysis and feature engineering. Sentiment analysis is a progression of strategies, methods, and tools for distinguishing and extracting emotional data, such as opinion and attitudes, from language [7]. On the other hand, Featuring engineering is the process of making more features from the existing ones; it improves the performance of models.

#### **Advantages**

- The system is more effective since it presents the proposed algorithm used in natural language processing responsible for counting the number of times of all the tokens in review or document..
- The system has exact sentiment analysis prediction techniques for Data Cleaning and Visualization.

### 5. System Architecture

The proposed framework introduces hybrid network architecture that offers a cost-effective waste level monitoring system. The proposal deals with two different types of smart waste bins to segregate biodegradable and non-biodegradable waste at source levels that help to minimize the cost of separating collected waste.



### 6. MODULES INVOLVED

#### Outline of the considered Smart Waste Management system

The considered Smart Waste Management system was created to address the challenge of efficient waste transportation. The system aims at optimising the waste management where a particular goal is to predict when a recycling container is going to be full. It is currently being deployed at every recycling station throughout the whole Sweden and the first 1;500 recycling containers have been operating in the test mode for over a year in the southern part of Sweden. Each



recycling container in the system is equipped with a sensor, which is mounted inside the container. The sensors used in the system are a customised hardware solution. The hardware is equipped with an ultrasonic range sensor, an accelerometer, and a GSM module. The ultrasonic sensor measures a filling level of a recycling container regularly throughout the day at a configurable interval.

### **Motivation for the accurate emptying detection in Smart Waste Management systems**

Recall that the goal of a Smart Waste Management system is to predict emptying time, i.e., the time when a recycling container will be full enough to be emptied. In the considered system, it is defined that a recycling container should be emptied when its filling level reaches 90:0 %. The statistics gathered from the live deployments have shown that the filling rate mostly follows either a line or a simple polynomial function. Therefore, the system can predict the filling level by fitting a regression model to the measurements reported by the ultrasonic sensor. The fitted regression model is used to extrapolate the filling level in the near future. Thus, given the regression model it is possible to estimate the emptying time. A crucial prerequisite for this approach to

function is that the regression model is built using only ultrasonic measurements obtained after the last emptying.

### **Smart waste management system:**

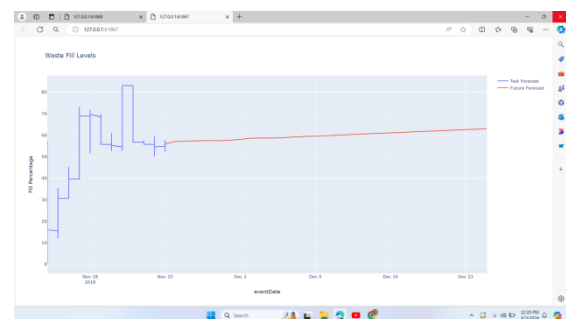
A Smart Waste Management system implementing elements of Internet of Things is an enabling technology addressing the challenges of the waste transportation optimisation. It will allow each recycling container reporting its filling level. The advanced functionality of such a system will enable predicting the expected emptying time of a recycling container, i.e., the time when the container's filling level will achieve a certain critical value. Filling level predictions will allow avoiding redundant transportation without violating the overfilling requirement. However, the quality of filling level predictions will determine the efficiency of a Smart Waste Management system. There are several technical challenges for achieving a high quality predictions. Our analysis of an operating Smart Waste Management system revealed that one of these challenges is a problem of an accurate detection of a container being emptied using the measurements from a sensor mounted on top of a container.

### **Challenges in emptying detection**

A simple solution to emptying detection would be a single threshold-based model where the values measured by either the ultrasonic sensor or accelerometer exceeded the threshold would lead to detection. There are, however, practical limitations for the use of such model. Due to the physical characteristics of the ultrasonic sensor, objects other than the actual waste level could be measured. For example, recycling containers usually have supporting structures or other parts related to the emptying mechanism, which interfere with ultrasonic pulses and, thus, create a false echo. Due to the false echo, the filling level will never reach zero even when the recycling container is actually empty. This fact invalidates the idea of measuring the absence of the waste for emptying detection. In the case of the accelerometer, since recycling containers are emptied by lifting them with a crane this event should trigger a single distinct vibration sample. However, in reality an emptying is not the only event, which generates vibration samples. Extra vibrations are often registered when waste is thrown in a recycling container. Thus, the use of accelerometer measurements could lead to many false detections.

## OUTPUT SCREENS

### Waste fill levels



### Actual vs prediction plot



## 7. Conclusion

This article presented the use of automated machine learning approach for industrial informatics with the show-case of the accurate detection of emptying a recycling container using the measurements from the

sensor mounted on top of the container. The article proposed the iterative data-driven methodology for achieving the highest performance where first the existing solution to the problem was assessed, second this solution was optimised using the collected dataset, next, machine learning algorithms were applied to the problem, and finally, the feature engineering was used to find if additional features would improve the results. There are several limitations to this study. First, it was not directly quantifying to which extend inaccurate detection of emptying affects filling level predictions. Second, the investigated solutions assume availability of filling level measurements and vibration strength scores. Third, the computational complexity of the investigated solutions was not taken into account. During the investigation, several solutions were considered: the existing manually engineered model, the optimised manually engineered model, conventional machines learning algorithms and conventional machine learning algorithms with the extended features.

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