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Developing an Intelligent Material Classification System for Plastic and Other Materials

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***Abstract**: This paper was created within the EU Horizon project - RECICLARM - which conducted waste management research with the purpose of recycling up to 70% of Europe's waste [1]. Our investigation focused on developing an algorithm capable of accurately classifying materials including plastic onces in categories of interest with the help of machine learning. Various types of materials and input variables have been documented and considered while prototyping and testing the intelligent classification algorithm, which resulted in a precise and efficient solution.*

***Keywords**: Machine learning, material classification, material detection, CDW*

1. Introduction

Annually, Europe generates 750 million tons of Construction and Demolition Waste (CDW) [2], yet the recovery rate stands at less than 50%, leading to significant environmental concerns. Furthermore, the reclaimed materials (mostly plastics) predominantly find usage in lower-grade applications. Given that humans have created 8.3 billion metric tons of plastics since large-scale production of the synthetic materials began in the early 1950s [3], plastic is a huge problem in waste management. The improper handling of plastic materials [4] has emerged as a significant global pollution issue, intricately linked to unsustainable production and consumption practices. On a wider scope, the growth of CDW presents a significant challenge to the sustainability of the construction industry. At the project level, CDW impacts profitability and productivity, while nationally, it can cause environmental problems and impose a financial burden on governments [5]. The EU Horizon RECICLARM[1] aims to surmount these challenges by enhancing overall recycling rates, thereby elevating the technical and economic value of recycled materials and products. It offers a pivotal opportunity to revolutionize current practices in the construction industry, promoting a substantial increase in recycled material utilization.

Material classification is a visual recognition task related to texture classification, focused on categorizing images of textures and materials, but is challenging due to intra-class variability and sensitivity to acquisition conditions like viewpoint or lighting [6]. The technical solution developed for the EU Horizon RECICLARM project introduces a new methodology for sorting CDW into distinct, high-purity fractions of smaller sizes. These refined fractions are tailored for superior applications within the building industry, elevating the standards of material utilization and resource efficiency.

EU Horizon RECICLARM is based on three main technologies: mechatronic architecture, classification and sensor system. In this article we are going to focus on the classification algorithm.

In the following subsection a literature review is provided. In the next subsections, by the presentation of the classification of materials, the data collection methodology, the classification algorithm and the mechanism implementation are described. The last section is dedicated to conclusions.

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[1] https://beiaro.eu/reciclarm/

1.1. Related work

This research presents an effective machine vision-based method for automatically classifying materials placed on conveyor belts. The application can be used in various fields, ranging from manufacturing and assembly lines to electronic systems, where keeping track of the quantity of connected components is crucial. In manufacturing processes where items are affixed to a galvanic frame, this solution optimizes the efficiency by providing a reliable and quick method for classifying materials, further streamlining assembly lines, reducing errors, and enhancing overall production efficiency.

Another research is presented in [7]. With the progress of industrialization and urbanization, the accumulation of heavy metal contamination in agricultural soils has become a significant concern, posing risks to human health. To address this issue, visible and near-infrared (Vis-NIR) spectroscopy offers a promising approach for the swift monitoring of heavy metal variations. In this research, the potential of fractional-order derivative (FOD), an optimal band combination algorithm, and various mathematical models were investigated to estimate soil heavy metal concentrations using Vis-NIR spectroscopy.

For this study, 80 soil samples were taken from an agricultural zone in Suzi River Basin (Liaoning Province-China). Laboratory measurements were conducted to obtain the spectra for Hg (mercury), Cr (chromium), and Cu (copper) in the samples. Spectral preprocessing involved applying FODs ranging from 0 to 2, with incremental steps of 0.2. The optimal band combination algorithm was then utilized on the spectra after FOD preprocessing. Subsequently, four mathematical models, namely, PLSR (partial least squares regression), ANFIS (adaptive neural fuzzy inference system), RF (random forest), and GRNN (generalized regression neural network), were employed to estimate the concentration of Hg, Cr, and Cu.

The results demonstrated that high-order FOD exhibited excellent performance in revealing hidden information and distinguishing minor absorbing peaks. Additionally, the optimal band combination algorithm effectively mitigated the spectral noise introduced by high-order FOD. The combination of the optimal band combination algorithm and FOD facilitated the extraction of additional spectral information. Furthermore, compared to ANFIS, PLSR, and RF, GRNN notably enhanced the estimation accuracy for all studied heavy metals.

In conclusion, these findings offer increased feasibility for the rapid estimation of heavy metal pollution, specifically Hg, Cr, Cu, and other contaminants, in agricultural soil areas. This research highlights the potential of Vis-NIR spectroscopy coupled with advanced preprocessing techniques and GRNN modeling for efficient monitoring and assessment in such scenarios.

According to [8], the increasing request for a categorizing technology that needs minimal manpower and equipment arises from the substantial waste generated during the demolition and remodeling of buildings. In light of the current trend, the most efficient approach involves implementing an artificial intelligence (AI) model for automated categorization. However, applying this technology poses challenges as previous research has predominantly focused on general household waste. Consequently, this study aims to outline the process of developing an AI model capable of distinguishing between different types of construction waste. Additionally, the authors address the difficulties associated with collecting learning data, a common challenge in AI research within specialized fields. To enhance the quantity of learning data in a quantitative manner, the authors employed the Fréchet Inception Distance method, which augmented the data to an appropriate level, effectively doubling or tripling its size. This augmentation aimed to assess the enhancement in the performance of the AI model.

Based on the research conducted on [9], image segmentation and classification are increasingly gaining attention from computer vision and machine learning (ML) researchers. There is a growing demand for accurate and efficient segmentation and recognition mechanisms in emerging systems. This need aligns with the advancements in computational capabilities of modern computer architectures and the development of more effective algorithms for image recognition. Convolutional neural networks (CNNs) are utilized for image classification and recognition, allowing the automation of various industries. This article introduces a CNN-based system for the classification of plastic waste. The challenge of segregating recyclable waste poses a significant hurdle for many countries worldwide. In addition to manual waste segregation, there exist several methods for automated segregation. The article presents a system that classifies waste into the following categories: “polyethylene terephthalate”, “high-density polyethylene”, “polypropylene” and “polystyrene”. The results obtained demonstrate that leveraging image processing and artificial intelligence techniques for automatic waste classification allows the development of effective real-world systems.

Another research [10] reviews machine learning and data mining applications in materials science, focusing on methods like artificial neural networks (ANNs), support vector machines (SVMs), and principal component analysis (PCA). These methods are used to accelerate material characterization, optimize manufacturing processes, and improve material performance prediction. The study highlights the potential of combining experimental and simulation-based data with machine learning to enhance material discovery and optimization.

Based on [11], the increasing global waste volume poses significant challenges related to pollution, waste management, and recycling. Addressing these issues requires innovative strategies, and one promising approach is leveraging artificial intelligence (AI) technology. In this article, the authors examine various applications of AI in waste management, including waste-to-energy systems, smart bins, waste-sorting robots, waste generation models, waste monitoring and tracking, plastic pyrolysis, differentiation between fossil and modern materials, logistics optimization, disposal methods, combating illegal dumping, resource recovery, smart city initiatives, process efficiency enhancement, cost savings, and improvements in public health. By implementing AI in waste logistics, transportation distances can be reduced by up to 36.8%, resulting in cost savings of up to 13.35% and time savings of up to 28.22%. AI algorithms demonstrate high accuracy levels ranging from 72.8% to 99.95% in waste identification and sorting tasks. Additionally, when combined with chemical analysis, AI contributes to advancements in waste pyrolysis, estimation of carbon emissions, and energy conversion processes. The authors also discuss how AI can enhance efficiency and reduce costs in waste management systems tailored for smart cities. Such a solution [12] - that uses AI and robotics in enhancing the efficiency and accuracy of municipal waste sorting - was implemented and tested in Barcelona, showing promising results with regard to the purity of the sorted waste fractions. With the use of AI, other complementary solutions for the improvement of waste management can be applied, such as air quality monitoring [13], Vision-Based on-site waste localization using unmanned aerial vehicle [14] and AI powered chatbots [15]. These technologies enhance the overall efficiency and effectiveness of waste management systems in smart cities, contributing to a more sustainable urban environment.

This study [16] further emphasizes the effectiveness of machine learning techniques, particularly Support Vector Machines (SVM) and Artificial Neural Networks (ANN), in classifying materials like brick, wood, concrete, and asphalt.

Recent advancements in AI-based plastic sorting systems have significantly improved the efficiency and accuracy of recycling processes. A study by Peršak et al. developed an efficient vision-based sorting system for transparent polycarbonate plastic granulate, utilizing machine vision and air separation technology. The system employs an industrial camera and backlight illumination to detect defects in plastic granulates, which are then classified using the k-Nearest Neighbors algorithm and separated pneumatically. The results demonstrated the system's promising capabilities in handling transparent plastics, highlighting its potential application in the recycling industry [17]. Similarly, another study by Chen et al. proposed a deep learning-based vision detection scheme for waste plastic sorting. This scheme integrates the YOLOX object detection model with the DeepSORT multiple object tracking algorithm, optimized for plastic detection and tracking. The system uses virtual detection lines to filter and extract information dynamically, achieving real-time and effective sorting of complex plastic objects [18].

Utilizing AI for material classification represents an emerging research domain. The recent partnership [19] between Bollegraaf, world’s largest builder of recycling facilities, and Greyparrot, AI waste analytics leader, highlights the growing interest in this field. Together, they aim to retrofit existing recycling facilities with AI capabilities, significantly enhancing the efficiency and accuracy of sorting processes. This collaboration leverages Bollegraaf's extensive recycling infrastructure and Greyparrot's advanced AI systems to create fully automated and intelligent sorting facilities, revolutionizing global waste management and boosting recycling rates. Another key player in waste management, Urbaser, has announced an investment [20] in AI-powered waste sorting technology in Spain. Set to be installed in Valencia, this technology uses computer vision to detect and sort waste, improving sustainability and recycling rates by accurately identifying and classifying materials that were previously challenging to sort.

Within the framework of the EU research project RECICLARM, our article introduces a contribution to this innovative research avenue.

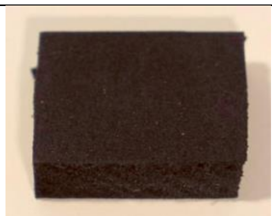
2. Materials and methods

The developed model underwent training using a diverse range of material samples to refine its ability to classify materials detected on the conveyor belt. Following this training phase, simulation results validated our approach, showcasing the model's accuracy in correctly identifying samples with variations in color, shape, or size.

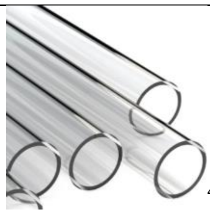
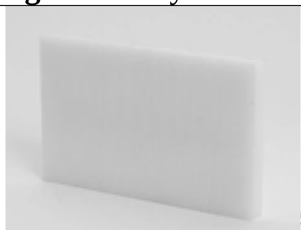
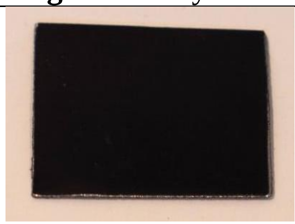
This section delves into the overview of the material samples specifically chosen and employed for training the model.

Table 1 shows images containing a short collection of sorted sample materials examples. The measurement results of the CDW samples were performed using the Bruker Vertex 80 Fourier-Transform infrared (FTIR) spectrometer.

Table 1. Exemplification of materials samples

	Material sample	Image example
1.	Plastic Foil	 [2] **Figure 1.** Plastic foil
2.	PVC	 [3] **Figure 2.** PVC conveyor belt
3.	Polymer	 **Figure 3**. Polymer foam

[2]Source: https://i.pinimg.com/564x/00/09/ed/0009ed760b2fcd775450da8440d58d79.jpg
[3]Source: https://www.iksonic.com/shop/conveyor-belts/black-color-and-pvc-material-high-quality-treadmill-conveyor-belt/

4.	PMMA	 [4] **Figure 4**. PMMA
5.	Polyamide	 **Figure 5.** Polyamide foil
6.	Polyacetal	 [5] **Figure 6.** Polyacetal
7.	Anodised Aluminium	 **Figure 7**. Anodised aluminium
8.	Raw Aluminium	 **Figure 8.** Raw aluminium
9.	Copper	 **Figure 9**. Copper
10.	Asphalt	 **Figure 10.** Asphalt with mineral aggregate

[4]Source: https://www.rimetplast.it/wp-content/uploads/2017/04/pmma-1-1000x600.jpg
[5]Source: https://bbs-industrie.com/wp-content/uploads/2020/10/pom-c_DSC9319.jpg
[6]Source: https://www.cutmy.co.uk/media/catalog/variant/s/t/steamed_beech_veneered_mdf_.jpg

11.	Concrete Aggregate	 **Figure 11.** Concrete aggregate
12.	Cement - Sample 1	 **Figure 12.** Cement sample 1
13.	Cement - Sample 2	 **Figure 13.** Cement sample 2
14.	Brick	 **Figure 14.** Brick
15.	Brick (contaminated with soil and mortar paste)	 **Figure 15.** Contaminated brick
16.	Wood	 **Figure 16.** Unprocessed wood
17.	Wood Tongue Depressor	 **Figure 17.** Wood stick
18.	Stained Wood	 **Figure 18.** Stained wood

19.	Beech MDF	 **Figure 19.** Beech MDF
20.	Wenge MDF	 **Figure 20.** Wenge MDF
21.	Cardboard	 **Figure 21.** Cardboard
22.	Felt	 **Figure 22**. Felt
23.	Black Felt	 **Figure 23**. Black felt
24.	Stone - Sample 1	 **Figure 24.** Stone sample 1
25.	Stone - Sample 2	 **Figure 25.** Stone sample 2
26.	Glass with coating	 **Figure 26.** Glass with coating

27.	H-ZF1 Optical Glass	 **Figure 27.** Optical glass

FTIR stands for Fourier Transform Infrared Spectroscopy, and it represents a methodology used for collecting data for classification purposes in various fields, including chemistry, materials science, pharmaceuticals, and more. FTIR spectroscopy analyzes how molecules interact with infrared light. Every molecule absorbs light at specific frequencies, generating a unique fingerprint based on its chemical composition.

FTIR collects data by passing infrared light through a sample and measuring the absorbance at different wavelengths. The resulting spectrum represents the molecular composition of the sample. The resulting data can be used for classification by creating libraries or databases of known spectra. When analyzing an unknown sample, its spectrum can be compared to these libraries to identify or classify its components. Classification involves pattern recognition where software or algorithms compare the spectral pattern of the unknown sample to known patterns. This helps classify compounds, identify substances, or detect differences between samples.

Twenty-seven different measurements of the CDW sample were performed with the Bruker Vertex 80v FTIR spectrometer. Based on these, eight classes of materials were identified that cover the materials described in Table 1.

Table 2. Identified classes of materials

1.	Plastics	5.	Materials based on bricks and clay
2.	Metals	6.	Wood and wood derivatives
3.	Materials based on asphalt and tar	7.	Natural rock
4.	Concrete, cement-based materials	8.	Glass

Our simulations were performed for a combination of angles of incidence (15, 25, 35, 45 degrees) and reflection (15, 25, 35, 45 degrees). A total of 16 measurement configurations were identified for each CDW sample. The measurement range was set from 350cm^{-1} to 7500 or 8000cm^{-1}, meaning 1.25 micrometers (or 1.33 micrometers) to ~28.5 micrometers. To optimize the scan time, the sampling varied between these being set to 1/2 cm^{-1}, 1/9 cm^{-1}; 1/18 cm^{-1}.

The data was exported in two forms: the intensity of light incident on the sensor and the calculated reflectance of the sample. The second form was obtained by correcting the measured light intensity reflected from the sample by the source spectrum obtained by replacing the CDW material with a mirror.

3. Results and discussions

The classification algorithm for construction and demolition waste processes data from partners to classify materials on the conveyor belt. It involves steps like importing, transforming data into a .csv file, analyzing relevant characteristics, training a Random Forest classifier, and refining the model based on results.

Material classification is a multiclass problem because it involves predicting one material label from a set of more than two possible labels. The challenge is to treat this classification as a predictive modelling problem by using a representative number of examples from each class, building a model, and learning the problem.

In the first phase, the classification algorithm was based on the Random Forest principle, a regression - based learning method, mostly by building a multitude of Decision Trees at the time of learning. This type of algorithm tends to learn the training dataset very well. However, this leads to the phenomenon of overfitting - meaning that the algorithm learns the training data set so well that it will only know this data. In such cases, no machine learning is done and the algorithm will perform poorly in tests on new datasets. To counteract this overlearning effect, a deep neural network Multinomial Naive Bayes classifier was used in the next iterations of the algorithm.

The identified classes resulting from the infrared image database are short-wave infrared and long-wave infrared.

The CDW database consists of 27 files related to each material. The classes that were considered in the database are listed in Table 3.

Table 3. Classes used in input data

1.	PVC	8.	Copper	15.	Wood	22.	Black Felt
2.	Polymer Foam	9.	Asphalt	16.	Wood stick	23.	Plastic Foil
3.	PMMA	10.	Concrete aggregate	17.	Stained wood	24.	Stone sample 1
4.	Polyamide	11.	Cement sample 1	18.	Beech MDF	25.	Stone sample 2
5.	Polyacetal	12.	Cement sample 2	19.	Wenge MDF	26.	Glass with coating
6.	Anodised aluminium	13.	Brick	20.	Cardboard	27.	Optical glass
7.	Raw aluminium	14.	Contaminated brick	21.	Felt		

The data used to train the model are saved in two different types of files for the purpose of experimentation: a file named *class_angleOfLightIncidence_angleOfLightReflection* with the extension *.dpt* (ex: AluminumAnoda_15_15.dpt), and another file containing the calculated reflectance (corrected data for the source spectrum) whose name contains the addition *_Ssc* (ex: AluminiumAnoda_ 15_15_Ssc.dpt).

The material training database contains 4 different angles corresponding to light incidence (15, 25, 35, 45 degrees) and 4 different angles of measured reflection (15, 25, 35, 45 degrees). Thus, there are 16 combinations of angles of incidence and reflection (16 files per material class for light incidence and 16 files for measured reflection).

For example, a record in the file "AluminiumAnoda_15_15.dpt" has the following structure:

350.05283919,0.05265756
350.1733808,0.05103086
350.29392241,0.0485783
350.41446402,0.04575773
350.53500563,0.04312359
350.65554724,0.04116087

An example of a record from the file "AluminiumAnoda_15_15_Ssc.dpt" has the following structure:

350.05283919,3.703e-05
350.1733808,3.632e-05
350.29392241,3.502e-05
350.41446402,3.343e-05
350.53500563,3.195e-05
350.65554724,3.092e-05

The following paragraphs describe how to develop and evaluate a model for the multiclass classification of materials related to the RECICLARM project, based on the database described above.

Each of the 27 material classes listed above has two columns for each file type and several records (rows). The logic applied was to extract features from files containing experimental data and build the database of material features. Analysis of the resulting experimental files is based on the recorded signal data.

The developed classification algorithm is used to classify new materials coming onto the conveyor belt and is based on already existing data for each material class.

The steps followed in the experimental development regarding data classification were the following:

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1. Import and convert data from existing files to a .csv format to facilitate compatibility with scikit-learn, often abbreviated as sklearn, which is a popular machine learning library in Python.
2. Review and view relevant features based on the .csv file.
3. Training the data with the Random Forest classifier implemented with the sklearn functions.
4. Displaying the results and improving the classifier (if applicable).

The resulting file with the .csv extension has the following structure (Figure 28):

Figure 28. Input data for experimenting with the classifier module

The algorithm developed and used for the classification of materials from construction and demolition is presented below.

Four scripts (training script, prediction script, listener script and talker script) work together in a distributed robotics context using the Robot Operating System (ROS) to create a ML pipeline for classifying different materials. The application could be useful, for example, in scenarios where a robot needs to recognize and interact with various materials in its environment.

3.1. Training script

The training script is the first one used and it is designed to listen to the ROS topic "/data", which publishes a set of features describing different materials. When the script receives a message on this topic, it uses the received features to incrementally train a Multinomial Naive Bayes classifier. The trained classifier is saved to disk for future use.

The key parts of this code are:

Import of necessary libraries

The script imports NumPy for numerical operations, Joblib for saving/loading the model, and MultinomialNB from sklearn which is a Naive Bayes classifier suitable for discrete features.

```
import numpy as np
import joblib
from sklearn.naive bayes import MultinomialNB
import glob,os
import sys
import rospy
from std_msgs.msg import Int32MultiArray
```

Materials definition

Different types of materials are defined as classes that the classifier can predict. The materials are stored in a dictionary with integer labels ranging from 0 to 7.

```
jsonAllMaterials={ 0:"Aluminium", 1:"Asphalt", 2:"Brick", 3:"Cement", 4:"Concrete", 5:"Glass", 6:"Stone", 7:"Wood",}
```

Setup function

This function loads an existing trained classifier if available, otherwise, it starts creating a new one. It also sets up the list of all materials (classes).

```
def setup()
global clf
global allMaterials
 if os.path.isfile(saveClassifier):
clf = joblib.load(saveClassifier)
print("Found Previous Calssifier")
for key,value in jsonAllMaterials.items():
allMaterials.append(value)
```

Listener function

This function sets up a ROS node and a subscriber to the "/data" topic. It enters a loop that waits for data to be received on this topic.

```
def listener():
print("Listening for training...")
rospy.init_node('listener', anonymous=True)
rospy.Subscriber("data", Int32MultiArray, callback)
rospy.spin()
```

Callback function

This function is invoked when new data is received from the ROS topic "/data". It logs that data has been received, and it extracts the material type from the received data. The data is used to train the classifier on this material type. It then logs the competition of the training process.

```
def callback(data):
rospy.loginfo(rospy.get_caller_id() + "Data received")
flatten_df=list(data.data)
material=jsonAllMaterials[flatten_df.pop()]
trainOn(flatten_df, material)
rospy.loginfo(rospy.get_caller_id() + "Done training on "+material)
```

TrainOn function

This function trains the classifier with the received data. The ”partial_fit()” function is used, which is suitable for incremental training. After training, the classifier is saved to a file.

```
def trainOn(flatten_df,material):
print("Training...")
with np.errstate(all="ignore"):
clf.partial_fit([flatten_df],[material],classes=allMaterials);
```

```
joblib.dump(clf, saveClassifier)
print("Done...")
```

In the main part of the script, the setup function is called to initialize the classifier, then the listener function is invoked to start receiving data. This script is written in Python and uses the ROS framework for receiving data, which is often used in robotics for inter-process communication. The data is expected to be in the form of an array of integer values, with the material type as the last element of the array.

3.2. Prediction script

The second script is the prediction one and it represents the counterpart of the first script. It listens to the same “/data" ROS topic for incoming data, processes the features received, and utilizes the previously trained Multinomial Naive Bayes classifier to make predictions about the material type. These predictions are then published on the "/label" topic, along with additional information such as the time and spatial coordinates. Here are its key parts:

Imports and global variables

The script imports necessary modules and initializes a global publisher (pub) to the “/label” ROS topic. It also sets up the file path to the saved classifier and initializes a Multinomial Naive Bayes classifier (clf). It then defines a dictionary (jsonAllMaterials) to map numerical labels to their corresponding materials.

Setup function

This function attempts to load a previously trained classifier from a file. If no saved classifier is found, it prints a message and exits the program.

```
def setup():
global clf
global allMaterials
if os.path.isfile(saveClassifier):
clf = joblib.load(saveClassifier)
print("Found Previous Classifier")
else:
print("There is no save, please check file save")
sys.exit()
```

Listener function

This function initializes a ROS node and subscribes to the “/data” topic. It enters a loop that waits for data to be published on this topic.

```
def listener():
print("Listening for predicting...")
rospy.init_node('listener', anonymous=True)
rospy.Subscriber("data", Int32MultiArray, callback)
rospy.spin()
```

Callback function

This function is called when a new message is received on the “/data” ROS topic. It first extracts time and location information (nsec, sec, y, x) from the received message and then uses the remaining data to predict the material type. Finally, it sends a message to the “/label” topic with the location, time, and predicted material label.

```
def callback(data):
rospy.loginfo(rospy.get_caller_id() + "Data received")
flatten_df=list(data.data)
nsec=flatten_df.pop()
sec=flatten_df.pop()
y=flatten_df.pop()
x=flatten_df.pop()
material=predict(flatten_df)
rospy.loginfo(rospy.get_caller_id() + "Predicting: "+material)
for key,value in jsonAllMaterials.items():
if value=material:
msgArr = Int32MultiArray()
msgArr.data = [x,y,sec,nsec,key]
pub.publish(msgArr)
break
```

Predict function

This function uses the trained classifier to predict the material type based on the input data. It prints and returns the predicted material.

```
def predict(flatten_df):
class_code= clf.predict([flatten_df])
print("The predicted material is: ",class_code[0])
return class_code[0]
```

In the main part of the script the setup function is called to load the classifier, and then the listener function is called to start receiving data.

3.3. Listener script

Listener script, the third script, listens to the "/label" topic where the predictions are published. Whenever a new prediction is received, it logs the information, providing a real-time view of the classifier's performance. The data received is not processed further in this script, but it could potentially be used for other purposes, like providing feedback to the robot. Here is a breakdown of what the script does:

Imports

It imports rospy, the Python client library for ROS, and Int32MultiArray, a ROS message type that contains an array of 32-bit integers.

Listener function

This function creates a ROS node named "listener" (with the name automatically made unique by rospy), subscribes to the "/label" topic, and enters a loop that waits for data to be received on this topic.

```
def listener():
rospy.init_node('listener', anonymous=True)
rospy.Subscriber("label", Int32MultiArray, callback)
rospy.spin()
```

Callback function

This function is called when new data is received on the "/label" topic. The function simply logs the received data.

```
def callback(data):
rospy.loginfo(rospy.get_caller_id() + "I heard "+str(data.data))
```

In the main part of the script the listener function is invoked, setting up the ROS node and starting the loop to listen for data. This script is very basic and is typically used for debugging purposes to monitor the data being published to a certain topic. It is a simple way to confirm that your data is being sent and received correctly in a ROS-based system.

3.4. Talker script

Lastly, the talker script serves as a simple example of a ROS publisher. It continuously publishes a "talker online" message with the current time stamp on the "/chatter" topic at a frequency of 10 Hz. This script does not interact directly with the other scripts in the given context, but it shows how to set up a basic publisher node in ROS.

This Python script sets up a ROS node that publishes a string message to the ”/chatter” topic at a rate of 10Hz (10 times per second). The message it publishes is the string "talker online" followed by the current time. Here's what each part of the script does:

Imports

It imports rospy, the Python client library for ROS, and String, a ROS message type that can contain a string.

Talker function

This script initializes a ROS node called “talker” and sets up a publisher that broadcasts messages to the ”/chatter” topic at a 10Hz rate. In a continuous loop (until the node is shut down), it creates a string message with "talker online" and the current time, logs this message, and publishes it on the ”/chatter” topic. The script uses a sleep function to maintain the specified 10Hz publish rate.

```
def talker():
pub = rospy.Publisher('chatter', String, queue_size=10)
rospy.init_node('talker', anonymous=True)
rate = rospy.Rate(10) # 10hz
while not rospy.is_shutdown():
talker_str = "talker online %s" % rospy.get_time()
rospy.loginfo(talker_str)
pub.publish(talker_str)
rate.sleep()
```

This is a basic example of a ROS publisher node and serves as an example of how to create a ROS node and publish data.

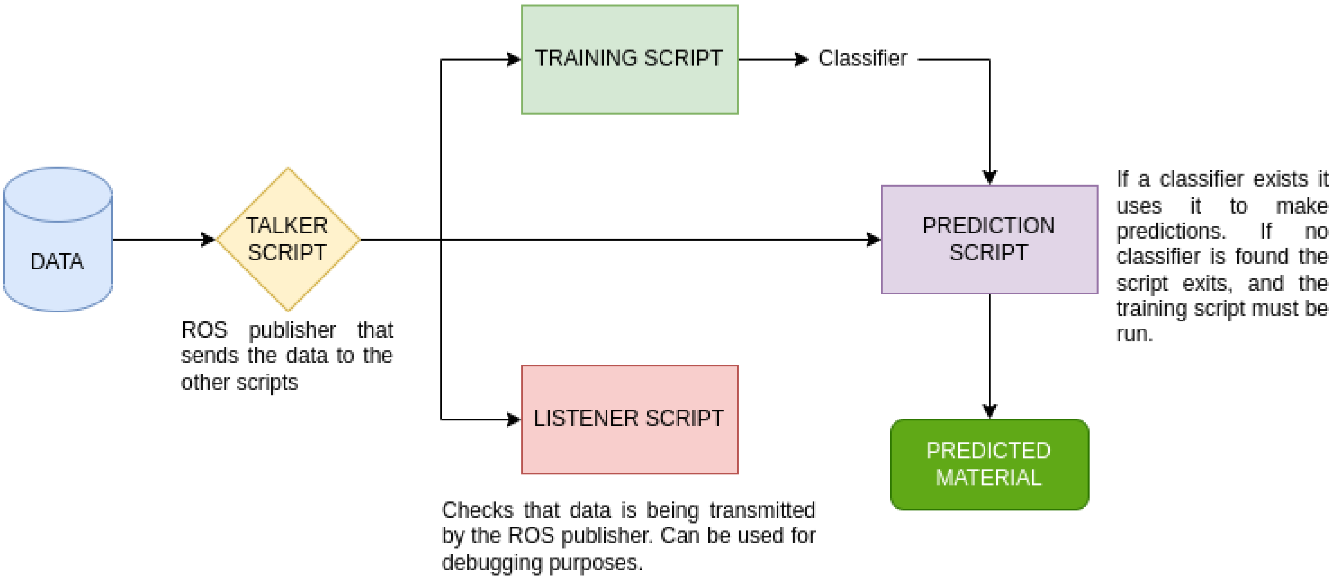

Figure 29. Flow diagram of the RECICLARM ecosystem

Detection of materials using AI

Detection of materials can be achieved through the use of AI algorithms. By combining high-quality cameras, a conveyor belt system, and an AI model, it is possible to accurately classify various materials in real-time. This technology can be applied across a wide range of activities including construction, demolition, sorting, and more.

In the detection process, objects are placed on a conveyor belt, where high-quality cameras capture their characteristics. The image data is sent to an AI system for classification, using the Multinomial Naive Bayes algorithm. Data exchange within the ROS framework is enabled through scripts and AI. The AI classifier can be stored and retrained if new materials are introduced. Initially, the system identifies materials such as Aluminum, Asphalt, Brick, Cement, Concrete, Glass, Stone, and Wood, with the option to expand the list through retraining.

All together, these scripts showcase a common pattern in distributed robotics applications, where different nodes in the system have specialized tasks (like collecting data, processing data, or acting on processed data) and communicate with each other using published messages.

4. Conclusions

This article explores intelligent plastic and other materials classification in the manufacturing industry, whilst various material types and input variables used for the algorithms were outlined. The constructed intelligent system was described and related research was presented with the purpose of efficiency comparison.

The developed intelligent material classification system holds significant potential for enhancing the efficiency and accuracy of plastic recycling processes. By precisely identifying and sorting various types of plastics, the system ensures that higher-quality recycled plastics are produced, which can then be utilized in more demanding applications, thereby increasing the overall value of recycled plastic products. Moreover, implementing this intelligent classification system can substantially reduce the environmental impact of plastic waste management. By boosting the recycling rate of plastic waste, the system helps minimize the volume of waste sent to landfills and reduces the need for extracting virgin plastic materials, contributing to a more sustainable and circular economy.

The scalability and adaptability of the classification algorithm make it suitable for a wide range of applications beyond plastic waste. This methodology can be adapted to classify different types of plastic materials in various industries, including packaging, manufacturing, and electronic waste management, broadening its impact significantly. Furthermore, the system's ability to integrate seamlessly with existing waste management and recycling infrastructures is a key advantage. The use of AI and machine learning allows for continuous improvement and adaptation of the classification models as new data is collected, ensuring that the system remains effective as plastic compositions and recycling requirements evolve.

Economically, the increased efficiency and accuracy in sorting plastic materials can lead to significant benefits. By reducing the need for manual sorting and minimizing errors, the system can lower operational costs for recycling facilities. Additionally, the production of higher-quality recycled plastics can open new market opportunities and increase revenue for recycling companies.

As future work, it is important to note that using the current data together with the improvements mentioned above does not guarantee better classifications, because a large enough dataset is also needed. A new set of data has been obtained from the partners of the project and will be processed in order to continue the experiments aimed at developing a classifier as accurate as possible.

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