Online Characterization of Mixed Plastic Waste Using Machine Learning and Mid-Infrared Spectroscopy

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Abstract

To recycle the mixed plastic waste (MPW), it is important to obtain the compositional information online in real-time. We present a sensing platform based on a convolutional neural network (CNN) and mid-infrared spectroscopy (MIR) for the rapid and accurate characterization of MPW. The MPW samples are placed on a moving platform to mimic the industrial environment. The MIR spectra are collected at the rate of 100Hz and the proposed CNN architecture can reach an overall prediction accuracy close to 100%. Therefore, the proposed method paves the way towards the online MPW characterization in industrial applications where high throughput is needed.

Synopsis Statement

Combining convolutional neural network framework and mid-infrared spectroscopy for online characterization of mixed plastic waste with 100% accuracy.

Keywords

machine learning; mixed plastic waste; MIR spectra; classification; real-time

1. Introduction

Plastics are inexpensive and durable materials that can be easily molded into a variety of products for a wide range of applications, such as food packaging, construction, and electronics. Along with the rapid growth of plastic production, the growth rate of plastic recycling is worrying. According to the U.S. Environmental Protection Agency (EPA) report in 2018[1], 75.6% of the plastic wastes were landfilled, 15.8% were combusted, while only 8.7% were recycled. Moreover, there is a trend of decreasing recycling rate[2], which imposes severe ecological and environmental concerns. To address the challenges, new recycling methods (pyrolysis[3], plastic alloying[4], etc.) are being investigated, but these solutions require an understanding of the composition of MPW in order to determine the process parameters and to remove potential contaminants[5].

Non-destructive methods such as infrared (IR) spectroscopy, X-ray diffraction, laser-induced breakdown spectroscopy (LIB) and other techniques have been successfully used for the identification of a single plastic component[6-11]. Among these methods, near-infrared spectroscopy (NIR) has become the predominant technology in industry for sorting MPW. However, NIR suffers from low accuracy, partly because it cannot detect black plastics[12-13]. A promising alternative to NIR is mid-infrared spectroscopy (MIR), in which photons are transformed from the IR spectral range into the near infrared spectral range and fast silicon detectors can be used[14]. MIR spectroscopy combines the high accuracy of the infrared spectral range with the high speed of NIR. More importantly, MIR spectroscopy is capable of detecting black plastics, which can improve the accuracy of MPW characterization[15-16].

In order to automize the MPW characterization process towards the industrial applications, machine learning (ML) has been widely used to analyze various spectroscopic data of plastics and the results were very promising[17-20]. However, the spectra were often the average of multiple spectroscopic scans during the data collection to reduce the intrinsic noise and to improve the ML prediction accuracy, which would slow the data collection speed. Moreover, in a typical industrial application, the MPW pellets are moved rapidly on a conveyor belt, which lowers the signal-to-noise ratio (SNR) due to the vibration and disturbance of the moving platform. Therefore, a production ready MPW sorting system needs fast data collection (which we call *online*) equipment and an efficient identification algorithm to process the low SNR data.

In this work, we combined CNN and MIR to classify MPW on a moving platform to mimic the industrial application. The MIR spectra were collected at 100 Hz without averaging. The linear speed of the moving plastics was 0.1 m/s. We demonstrate that the CNN framework (which we call PlasticNet) can achieve 100% overall classification accuracy for MPW. The CNN framework also has a fast prediction rate (~36,000 Hz), which allows the future upgrade of the MIR spectrometer with even faster data collection speed. We believe the proposed method is a promising solution towards a real-time online MPW classification system and will help MPW recycling and reclamation.

2. Experimental Data Collection and Preparation

2.1 MIR Measuring System

The schematic experimental setup is shown in **Figure 1**. The IR source (a 1000 °C Silicon Nitride, Si_3N_4, light source, 4.5 mm in diameter and 17 mm long and is heated by 70 W electric power, Hawkeye Technologies model IR-Si311) was placed at the focus of an aluminum elliptical reflector which focused the light at 200 mm from the front surface of the reflector, projecting the light on a gold diffuser, generating a circular area with around 10 mm diameter. Some of the reflected light from the plastic surface was collected by a 1-inch parabolic gold-coated aluminum mirror (with a focal length of 200 mm) that collimated light from the diffuser, after which a 40 mm CaF_2 lens focused the light into a 200 µm core indium fluoride (InF_3) fiber that was connected to the MIR spectrometer (NLIR S2050, Denmark).

The details of the MIR spectrometer can be found in our previous work[15]. Briefly, the MIR spectrometer (NLIR S2050) is based on sum-frequency generation in a $\chi(2)$-nonlinear $LiNbO_3$ crystal that upconverts mid-infrared light from the band 2.0 µm – 5.0 µm to the near-visible region 695 nm – 877 nm[21-24]. The advantages of the upconversion spectrometer are that most thermal noise is not upconverted[25-26] and that Silicon-based CMOS-array detectors have much higher detectivities than the traditional MIR detectors such as HgCdTe (MCT) or PbSe array detectors. The CMOS detector has 2048 pixels, and the spectral resolution is < 6 cm^{-1}.

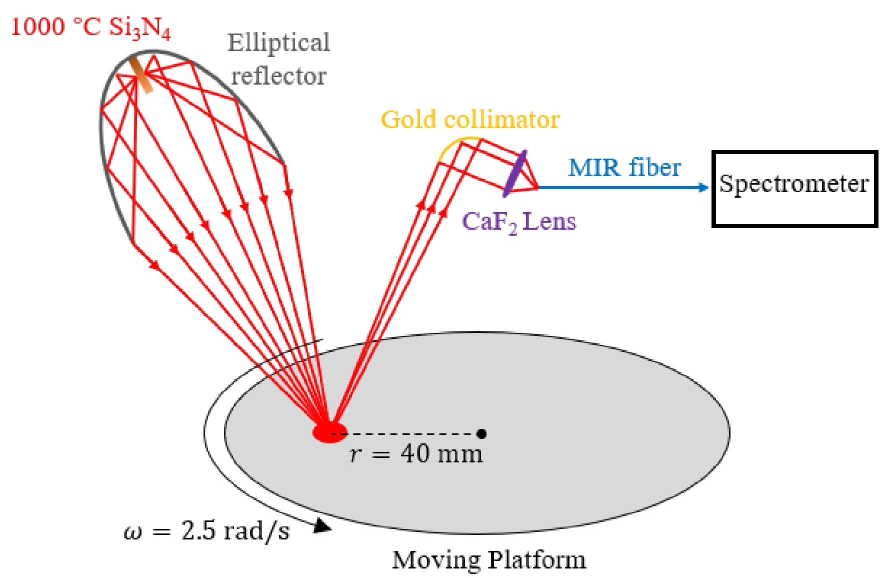

Figure 1. Experimental setup. The MPW samples are placed on a moving platform to mimic the industrial application.

The MPW samples were placed on the moving platform to mimic the conveyor belt in the industrial application. The platform was driven by a 12V DC motor. The angular velocity was set to 2.5 rad/s and the focal point of the MIR source was 40 mm away from the center of the platform, which corresponded to the sample linear speed of 100 m/s. The platform surface was Urethane which was a typical conveyor belt material used in industry.

2.2 Data Collection

In this work we considered 4 commercially available plastic materials commonly found in the MPW, including light blue color polystyrene (PS), black color polyethylene (PE), deep blue color polypropylene (PP), and white color polyvinyl chloride (PVC). All plastic samples were 1 mm thick sheets purchased from ePlastics (San Diego, California, United States). In addition, the Urethane platform surface was also considered, and it is called the background (BK) in the following context.

The spectra were collected by placing the plastic samples on the moving platform. For the ML training/validation/testing, pure plastic sheets were cut to the same size as the platform, as shown in **Figure 2a**. 500 spectra of each plastic sample were collected at the measurement rate of 100 Hz. Therefore, a total of 2,500 spectra were used for the ML training/validation/testing. For the ML prediction, binary and quaternary mixed plastic samples were measured as unseen data. The binary mixed plastic samples were measured by covering approximately half of the platform surface with one plastic and the other half with another plastic, as shown in **Figure 2b**. The reason of designing such binary mix was to generate the spectra dataset in which each component contributes approximately half the number of the spectra. For example, the binary mix of BK/PS dataset should have ~50% BK spectrum and ~50% of PVC spectrum. Therefore, the binary mixes can be used as the unseen data to effectively validate the accuracy of the proposed ML model. For the prediction of quaternary mixed plastic samples, the plastic sheets were cut into small flakes with sizes approximately 20×20 mm^2 to 25×25 mm^2, then different types of plastic samples were placed on the moving platform to mimic MPW on a conveyor belt, as shown in **Figure 2c**. 4 binary combinations (BK/PS, BK/PVC, PE/PVC, PS/PP) and 1 quaternary combination (BK/PVC/PP/PS) were used, and 500 spectra of each combination were collected for the ML prediction.

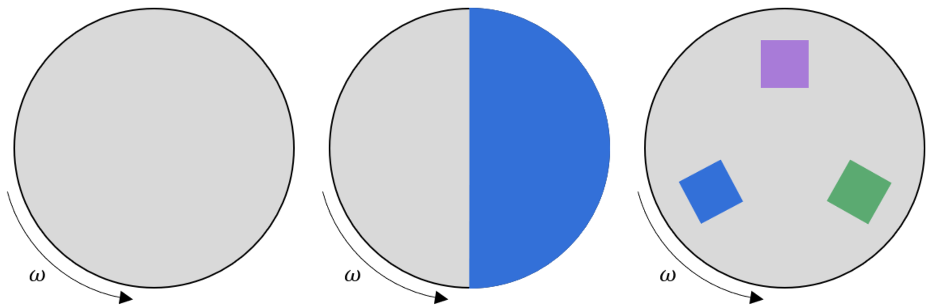

Figure 2. Data collection methods for single, binary, and quaternary MPW samples. (a) The platform is covered by a single plastic sheet; (b) Half of the platform is covered by one plastic component, and the other half is covered by another component; (c) 3 plastic flakes are placed on the platform.

2.2 Data Processing

Each spectrum had 975 data points ranging from wavenumber 2000 to 3500 cm^{-1} (encoded in a vector of $\mathbb{R}^{975}$), with each point representing the intensity of a given wavenumber. To increase classification accuracy, we investigated data preprocessing methods such as smoothing and detrending. A rolling average with a window size of 30 was used for smoothing. Detrending is accomplished by removing the linear trend (background) from the spectra. All spectra were normalized to the range of [0, 1] to facilitate ML analysis

$$\hat{x} = \frac{x - \min(x)}{\max(x) - \min(x)}$$

where $x \in \mathbb{R}^{975}$ was the original spectrum and $\hat{x} \in \mathbb{R}^{975}$ was the normalized spectrum. **Figure 3** shows the PE spectra measured at 100 Hz with various preprocessing methods. The spectra of the other 5 samples are shown in **Figure S1-4**. There was significant noise in the raw data as shown in **Figure 3(a)** which was due to the intrinsic electronics noise at high measurement rate (systematic noise) and the extrinsic noise due to the vibration of the moving platform. We explored the effectiveness of various preprocessing methods on the ML prediction accuracy and provided the best practices for preprocessing of the high noise MIR data.

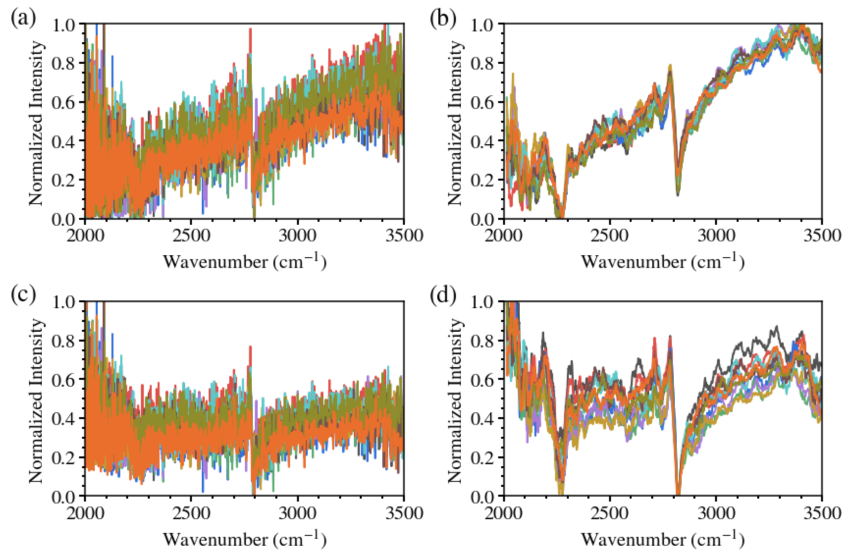

Figure 3. PE spectra measured at 100 Hz with various preprocessing methods. (a) shows the raw spectra; (b) show the smooth preprocessing; (c) shows the detrend preprocessing; (d) shows both the smooth and detrend preprocessing.

2.3 Data Splitting

The spectra of pure plastic samples as well as the Urethane platform surface (BK) were randomly divided into a training set and a test set. A training set was used to fit the parameters of the ML model during the learning process. An independent test set was used to evaluate the performance (accuracy) of the ML model. A total of 30% of the spectra in the training set were randomly chosen as the validation set for tuning the ML architecture. We employed a 5-fold cross-validation method to assess the robustness and generalizability of the ML model. Specifically, the training dataset was randomly split into five subsets of equal size. One of these five subsets was retained for the cross-validation, while the other four were used for the training. The cross-validation was repeated five times, with each subset serving as test data exactly once. Prior to data splitting, the data were partitioned into homogeneous subsets using stratification. In other words, for each fold, each plastic type contributed the same proportion of data (20%) to the training and test sets. The final reported accuracy was the average of all five-fold accuracies. The model was robust and generalizable if the accuracy of the test set for each fold was comparable. The spectra of the binary and quaternary plastic combinations are regarded as unseen dataset to demonstrate the MPW classification ability of the proposed ML models. For predicting the composition of mixtures, the five-fold cross validation model with the highest test set accuracy is utilized.

2.4 Computational Framework

The proposed framework includes a CNN architecture that we refer to as PlasticNet. PlasticNet functions as a 1D CNN since its architecture converts IR spectra to vectors (1D data items). The architecture of the proposed 1D CNN is shown in **Figure 4**. 1D CNNs extract features from IR spectra using convolution and pooling. In our architecture, every convolutional filter is a three-dimensional vector. A convolved signal of a filter is a scalar value indicating the presence (high value) or absence (low value) of the pattern the filter is attempting to identify. A convolution operation transforms a given vector to another vector of the same dimension after a nonlinear transformation (e.g., rectified linear units). These filters are referred to as the convolutional layers. The convolution operation significantly increases the amount of information that must be processed; therefore, it is necessary to summarize this information. We reduce the dimension using a max-pooling operation, which takes a subset of a given vector (in this case, a portion of size 2) and reduces it to a single value by extracting the maximum value. This greatly reduces the number of dimensions of the vector from the convolutional layer and condenses the key information.

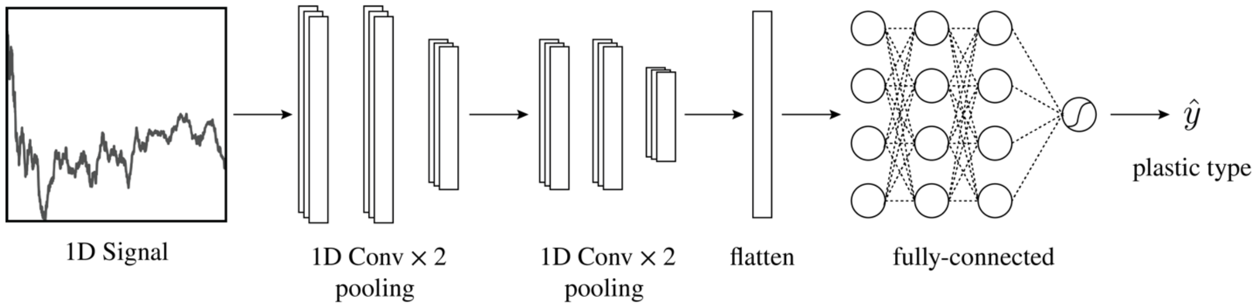

Figure 4. Architecture of PlasticNet. The plastic network inputs a 975 vector and outputs the predicted plastic type. It contains 4 1D convolutional layers (each with 64 filters of dim 3), 2 1D max-pooling layers (each with a window size of 2), a flatten layer, and 3 fully connected layers (each with 64 nodes and a dropout ratio of 0.2). The activation function between the layers is ReLU. The final output activation function is SoftMax.

A 975-dimensional IR vector was fed directly into the PlasticNet. Four convolutional layers, two max-pooling layers, and three fully connected layers were included in the model. Each convolutional layer contained 64 filters of size 3, whereas the max-pooling layer consists of filter of size 2. Each fully connected layer contained 64 nodes. We used rectified linear units (ReLUs) between layers as activation functions. We added a dropout ratio of 0.2 between each of two fully connected layers to prevent overfitting. The activation function of the output layer was SoftMax, and the loss function was categorical cross-entropy. The output vector had a dimension of 5, which corresponded to the probability that the IR spectra originated from a particular type of plastic. Convolutional layers and max-pooling layers were organized recursively in the PlasticNet to extract information at both the local and global scales. In addition, it enabled the condensing of information for the classification and prediction of the corresponding plastic type.

3. Results and Discussion

3.1 ML Training with Various Preprocessing Methods

The performance of the ML models with the test dataset is shown in **Table 1**. The results revealed that all preprocessing methods can achieve close to 100% classification for the single plastic component samples.

Table 1. Overall Classification Accuracies Found with Different Data Processing Methods.

	Raw	Smooth	Detrend	Both smooth and detrend
Accuracy	100%	99.8%	100%	100%

Using the confusion matrix, we gained a deeper understanding of the classification precision of various plastic types. The PlasticNet confusion matrix of the dataset with both smoothing and detrending as preprocessing is shown in **Figure 5**. Each row of the confusion matrix represents instances of the predicted class, and each column represents instances of the true class. Instances correctly classified are in the entries along the diagonal line.

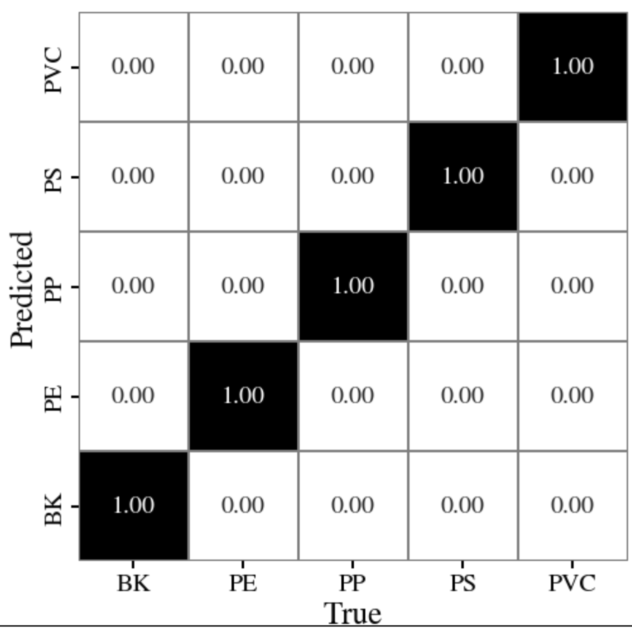

Figure 5. Confusion matrix of PlasticNet with both smooth and detrend preprocessing. The overall accuracy is 100%.

We performed additional principal component analysis (PCA) to determine if the data possessed any inherent clustering based on the type of plastic. **Figure 6** shows the first and second principal components of the MIR spectra, it is evident that clusters are formed according to plastic types. This inherent data clustering facilitated classification.

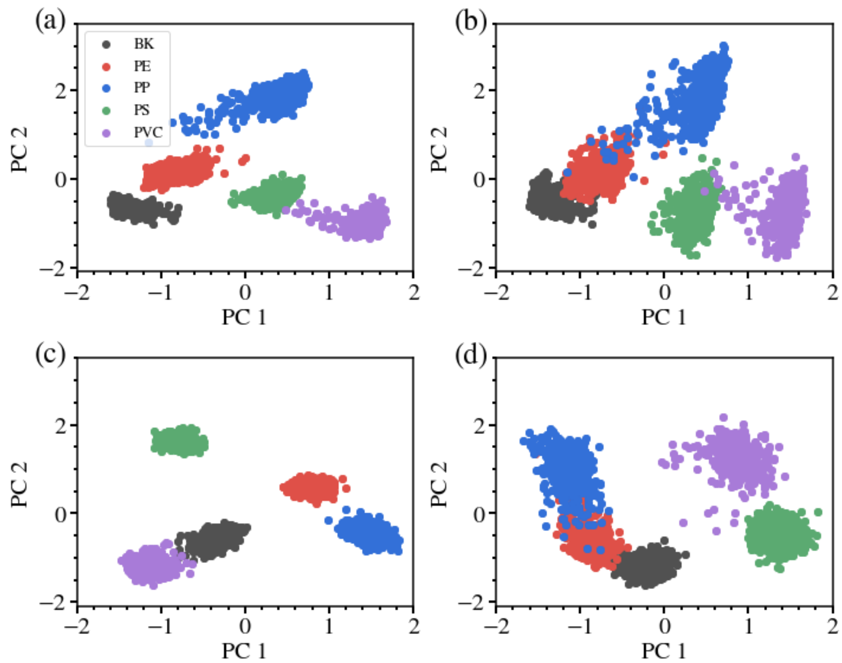

Figure 6. Scatter plots of the first and second principal components of (a) raw IR spectra, spectra (b) after smooth preprocessing, (c) after detrend preprocessing, and (d) after both smooth and detrend preprocessing. The distinct clusters of the various plastic types facilitate classification.

3.2 Binary Mixed Plastic Prediction

We used the best of five-fold cross-validation models of various preprocessing methods to predict the composition of the binary/quaternary mixed plastics. Among all the models, the one with both smooth and detrend obtained the best results as shown in **Figure 7**. The prediction results of the models trained with other preprocessing methods (shown in **Figure S5-7**) were not accurate enough, indicating the smooth and detrend preprocessing was beneficial for ML feature extraction.

For the binary mixed samples BK/PS, BK/PVC, PE/PVC and PS/PP, our model predicted approximately 50% of each component. The results were consistent with our experimental design, in which the two halves of the moving platform were covered by two different plastic sheets respectively. The percentages were not exactly 50% because during the spectra measurements, it was difficult to cover the platform surface perfectly 50%.

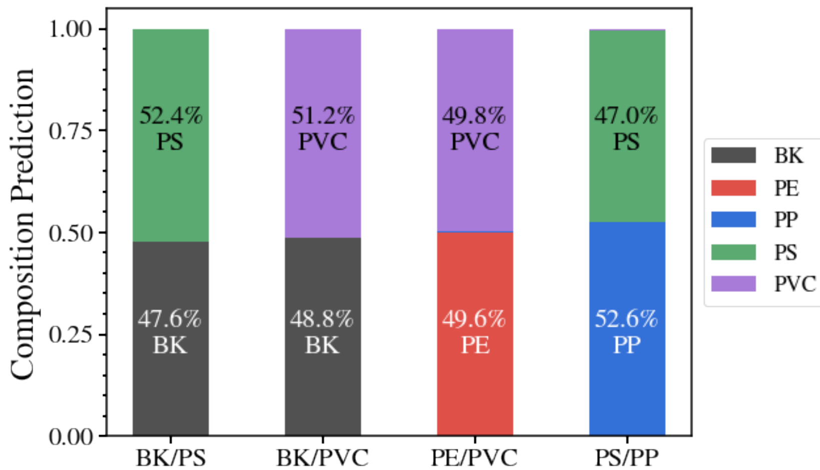

Figure 7. Composition prediction of (a) the binary and (b) quaternary mixed plastic samples with the data using both smooth and detrend preprocessing.

In addition to the correctly predicted components, we also observed prediction errors in the binary mixes, for example, 0.6% in PE/PVC and 0.4% in PS/PP. The errors were mainly from the spectra that were scanned across the boundaries of the binary mixes. In our experiments, the moving platform angular velocity was 2.5 rad/s. At 100 Hz spectra collection rate, there were 251 spectra collected per revolution, in which 2 spectra were collected across the boundaries, corresponding to 0.8% boundary spectra in each binary dataset. The boundary spectra were distorted because it contained the information from both components, and depending on the level of the distortion, the ML model may make incorrect predictions. Therefore, the maximum possible error due to the boundaries should be 0.8%, and all the errors from the binary mixes were less, indicating our ML model can make correct prediction even with some of the distorted boundary spectra. Based on the results of the binary mixes, we were confident that our PlasticNet can predict mixed plastic samples on a moving platform with high accuracy.

Finally, we challenged our PlasticNet with the quaternary mix, which mimicked PVC, PP and PS flakes moving on a Urethane (BK) conveyor belt. 3 plastic flakes were placed on the moving platform, each flake was approximately 20×20 mm^2 to 25×25 mm^2. The results are shown in **Figure 8**. The predictions were consistent with the sizes of the flakes, more importantly, there were only 0.2% of the spectra that were incorrectly classified, showing that our ML model can make accurate predictions on MPW on a moving platform.

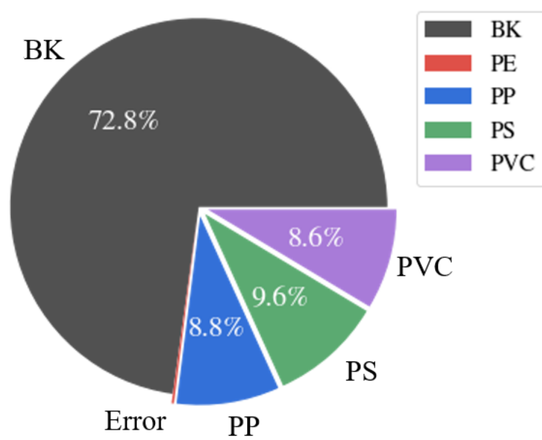

Figure 8. Composition prediction of quaternary mixed plastic samples. The prediction error is only 0.2%.

4. Conclusions

We developed a convolutional neural network (CNN) framework to classify the MIR spectrum of MPW on a moving platform. The experimental setup mimicked MPW on a conveyor belt. The results showed that our ML model can predict the MPW components with overall accuracy close to 100%, providing a promising solution towards the real-time online characterization of MPW for industrial applications where high throughput and accuracy are required.

5. Acknowledgements

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