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Leveraging Machine Learning for Real-Time Performance Prediction of Near Infrared Separators in Waste Sorting Plant

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ABSTRACT

Many small and medium enterprises (SME) often fail to fully utilize the data they collect due to a lack of technical expertise. The ecoKI platform, a low-code solution that simplifies machine learning application for SMEs, showed a promising answer to the challenge. This study explores the application of ecoKI platform to design process monitoring tools for waste sorting plants. NIR separator data were processed through ecoKI's building blocks to train two neural network architectures—MLP and LSTM—for predicting NIR separation efficiency. The results showed that the models accurately predicted NIR output and effectively identified regions where NIR separation performance declined, demonstrating the potential of data-driven approaches for real-time performance monitoring. This work highlights how SMEs can leverage existing data for operational efficiency and decision-making, offering an accessible solution for industries with limited machine learning expertise. The approach is adaptable to various industrial contexts, paving the way for future advancements in automated, data-driven optimization of equipment performance.

Keywords: Machine Learning in Waste Management, Waste Sorting Automation, Performance Monitoring

INTRODUCTION

Data utilization in SMEs, including waste sorting facilities, is often not maximized, preventing them from fully capitalizing on the data they collect. This underutilization stems from several key challenges. First, SMEs typically have limited technical resources and expertise in data analytics and machine learning, which hinders their ability to process and analyze the vast amounts of data generated by their operations [1]. Second, the integration of advanced data-driven technologies requires significant investment in both time and training, which many SMEs find difficult to accommodate within their existing operational structures [2]. As a result, valuable insights that could drive efficiency improvements, cost savings, and enhanced decision-making remain untapped.

Wang et al. demonstrated that the ecoKI platform is a viable solution for those challenges, as it is a low-code platform, requires no prior machine learning knowledge and is simple to use [3]. EcoKI simplifies the transformation of raw measurement data into actionable insights by providing pre-built building blocks and intuitive interfaces, allowing users to implement advanced machine learning solutions without any programming expertise. This feature makes ecoKI particularly well-suited for SMEs, as it lowers the technical barrier, enabling them to harness their data effectively and implement data-driven solutions with ease.

As part of the EnSort project [4], which aims to enhance automation and energy efficiency in waste sorting plants, this study explores the application of the ecoKI platform to process measurement data into actionable insights. Transforming raw data into real-time performance monitoring tools enables operators to track system efficiency more effectively and detects anomalies. Additionally, these performance measurements can be integrated with advanced automation systems, facilitating operations optimization to achieve energy savings and improved overall performance.

NEAR-INFRARED SEPARATORS

Near-infrared (NIR) spectroscopy can distinguish non-carbon-black plastic with a very high accuracy, as demonstrated in various studies [5-10]. In a waste sorting plant, the final stage of the sorting section typically comprises NIR separators [11, 12, 13]. These separators are arranged in pairs, consisting of a primary separator and a cleaner separator, as illustrated in Figure 1. Kroell et al. showed that this arrangement generates product with higher purity compared to parallel arrangement [14].

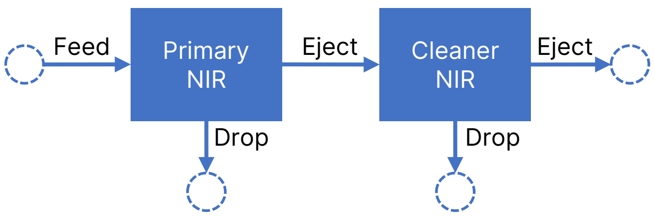


Figure 1: NIR Arrangement in Waste Sorting Plant.

The primary NIR separator is designed to maximize the recovery of targeted materials from the waste stream. The cleaner NIR separator, in turn, enhances the purity of the recovered materials by removing unwanted contaminants. Additionally, NIR separators serve a dual function by acting as flow measurement devices, enabling the measurement of the surface flow rate of the material stream.

Multiple datasets (NIR Dataset 1 and 2) were collected from primary-cleaner NIR separator pair in a waste sorting plant located in Northern Europe. The sampling interval of the measurements is 1 minute. Due to the inherent noise in the system, a moving average over the last 5 minutes is applied to smooth the data and improve its reliability.

The system under consideration focuses to separate polypropylene, polyethylene, and their variants, such as polypropylene foil, high-density polyethylene, and polyethylene film. To simplify the analysis and evaluation, the total flow of all targeted materials was calculated from the dataset.

METHODOLOGY

Machine learning-driven data utilization for performance monitoring has been widely adopted across various fields for maintenance and planning purposes. For instance, Hundi and Shahsavari employed Neural Networks, Random Forests, and Support Vector Machines to estimate power plant performance and identify early-stage equipment malfunctions [15]. In road construction, Cano-Ortiz et al. applied machine learning techniques to assess pavement performance and guide road rehabilitation efforts [16]. Similarly, Gupta et al. used machine learning models to predict the hydrodynamic performance of ships, enabling better estimations of power demand and fuel consumption for planned voyages [17].

The next section will explain how ecoKI platform can be used to develop machine learning models for separation performance prediction.

Output Prediction

The performance of a primary NIR separator is evaluated based on the amount of targeted material it directs to the cleaner. To predict the outflow, two machine learning model was trained in ecoKI platform and the optimal model was selected based on a balance between complexity and accuracy.

The ecoKI platform offers multiple ready-to-use pipeline templates tailored for different use cases. Each pipeline consists of modular building blocks that represent key steps in the machine learning development process. These blocks provide adjustable options for users with advanced knowledge while also offering default settings for those with limited experience.

In this work, the machine learning models were developed with the Artificial Neural Network (ANN) pipeline. The illustration of the ANN pipeline and its building blocks are presented in Figure 2. The settings for each building blocks are listed in Table 1. The followings sections give a brief explanation on the respective building blocks and their settings.

Data Reader first reads the raw dataset. After the user selects the input features and target variable for the machine learning model, the relevant data is extracted from the dataset. Currently, the dataset used for training is the NIR Dataset 1 and the total targeted material flow in the feed stream and eject stream are the input and target variable, respectively.

Data Sequence Generator generates input-target sequences based on a defined sequence length to

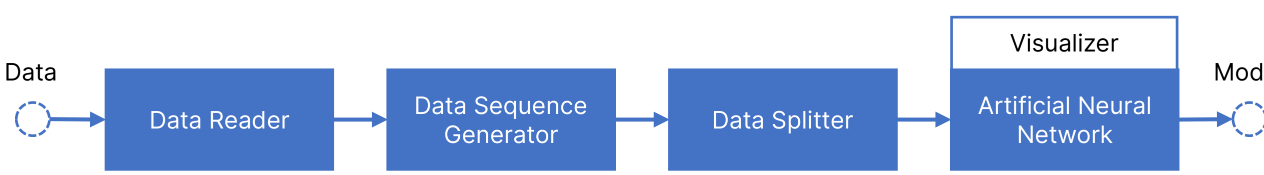


Figure 2: Artificial Neural Network Pipeline.

prepare the data for model training. The default value for input step setting is 5 and output step setting is 1, which means the block will pair sequence of five past input data with a one step ahead output.

Data Splitter splits the sequence into a training and a test dataset based on the specified fraction. The default setting is 10% of the data is reserved for testing, and the remaining 90% is used for training.

Artificial Neural Network block trains an Artificial Neural Network model using the training and test dataset. As of the time of writing, this block supports two ANN models: the Multi-Layer Perceptron (MLP) model and the Long Short-Term Memory (LSTM) model. The neural network structure is fixed with two hidden layers (Layer 1 and 2) positioned between the input and output layers. However, the number of neurons in each hidden layer is adjustable. By default, both hidden layers are set to have two neurons. In this study, both models were used with the default neuron configuration, except for the LSTM model, where Layer 1 was set to four neurons instead of two.

Visualizer is connected to the Artificial Neural Network block. It provides graphical representation of the training results, facilitating model evaluation.

Table 1: ecoKI Building Blocks Settings.

Building Block	Setting	Value
Data Reader	Inputs columns	Target inflow
	Feature column	Target outflow
Data Sequence Generator	Input steps	5
	Output steps	1
Data Splitter	Test fraction	0.1
Artificial Neural Network	Model	MLP (LSTM)
	Layer 1 nodes	2 (4)
	Layer 2 nodes	2

Disturbance Detection

To detect disturbances or deterioration in NIR performance, the predicted material flow is compared with the actual flow. Since the predictor was developed using disturbance-free data and solely depend on the input stream, any significant discrepancy between the predicted and actual values indicates potential system disturbances.

To evaluate the effectiveness of this tool, a part of NIR Dataset 2 was artificially modified to simulate reduced NIR performance. The alteration was done by changing the actual outflow value with 50% of the inflow. The targeted material outflow in normal and disturbed conditions is shown in Figure 3. Both flow profiles appear similar, despite modifications applied between 21:00 and 22:00 on September 3. This highlights that relying solely on the flow profile is insufficient for anomaly detection, as the changes would likely go unnoticed by operators under normal monitoring conditions. By overlaying the disturbed outflow profile with the predicted normal outflow profile, the operator will be able to clearly observe the range in which the disturbance occurs, as the two lines will not overlap during the disturbance period.

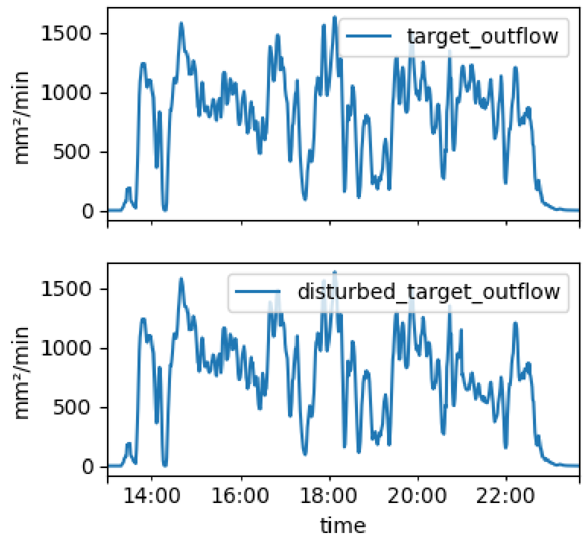


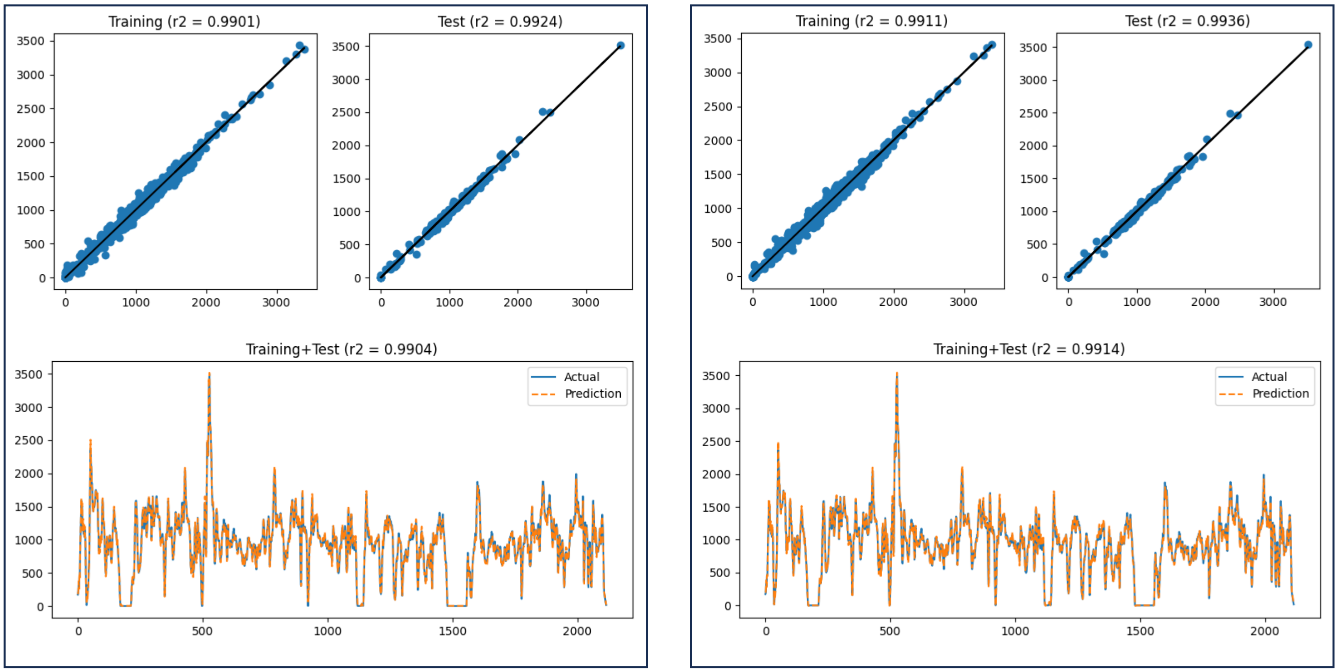
Figure 3: Material Outflow Profile on Disturbance Detection (NIR Dataset 2).

RESULTS AND DISCUSSION

Output Prediction

The training and testing performance of the MLP and LSTM model are evaluated from ecoKI Visualizer output presented in the left part and right part of Figure 4, respectively. The scatter plot of the training data and the prediction is shown on the top-left and the scatter plot of the test data and the prediction is shown on the top-right. The majority of the data in the training set falls below 2500 mm²/min, while most of the test set data lies below 2000 mm²/min. Despite using the default setting, the generated models demonstrates excellent accuracy as shown by the coefficient of determination. These results imply that ecoKI's automated pipeline effectively optimizes key aspects of model development, enabling users to achieve high-performance predictions without manual fine-tuning. This suggests that even users with minimal expertise in machine learning can leverage ecoKI to develop reliable models, making advanced AI technology more accessible to SMEs. Furthermore, the high accuracy achieved with default settings indicates that ecoKI's pre-configured parameters are well-calibrated for general use cases, reducing the need for extensive trial and error.

The MLP model was ultimately selected as the predictor due to its simplicity, which is evident from the



MLP LSTM

Figure 4: LSTM and MLP ecoKI Visualizer. In each model, Top-Right: Training result, Top-Left: Test result, Bottom: Combined result. x and y axis in top plots and y axis in bottom plot are flow in mm^2/min, while x axis in bottom plot are the index of the data.

significantly lower number of estimated parameters compared to the LSTM model, as detailed in Table 2. The MLP model, with just 21 parameters, is less complex than the LSTM model, which has 109 parameters. This simplicity not only made the model easier to train but also enhanced its generalization capability. With fewer parameters to optimize, the MLP model was less prone to overfitting, allowing it to generalize more effectively to new, unseen data. This combination of simplicity and robust generalization made the MLP model the preferred choice for the task.

Table 2: Machine Learning Model Summary.

Model	Structure	Trainable Params
MLP	Dense(2), Dense(2)	21
LSTM	LSTM(4), Dense(2)	109

Disturbance Detection

When the actual flow profile is overlaid with the predicted flow profile, as shown in Figure 5 (top), any deterioration in NIR performance becomes immediately apparent. During periods of normal operation, the trained model accurately predicts the outgoing material flow, even when tested on a separate dataset, demonstrating strong generalization capabilities.

The recovery profile, displayed in Figure 5 (bottom), reveals fluctuations, including drops and peaks, corresponding to moments when the machine experienced brief stoppages. These fluctuations are likely due to the cleaner NIR stopping and restarting slightly earlier than the primary NIR. The flat 50% recovery rate near the end of the profile indicates a region where the data has been modified. Approximately 30 minutes before the end, the recovery rate began to decline. However, the flow profile indicates that this behavior is expected as the actual flow match with the predicted flow.

The ability to detect disturbances by comparing actual and predicted flow profiles underscores the practical value of this tool in monitoring and maintaining system performance. By providing real-time insights into deviations from expected behavior, the tool enables early identification of potential issues, allowing operators to take corrective actions before significant disruptions occur. This proactive approach not only enhances process stability but also improves overall efficiency by minimizing unplanned downtime. Furthermore, the tool's strong generalization capability ensures reliable predictions across different datasets, making it a valuable asset for industries seeking to optimize operations with minimal manual intervention.

How ecoKI Lowers the Barrier for SMEs

As demonstrated in the previous section, ecoKI's default settings achieved a high prediction accuracy, highlighting its ability to generate robust models with minimal input. This is particularly beneficial for SMEs, as ecoKI directly addresses the barriers to adopting machine learning:

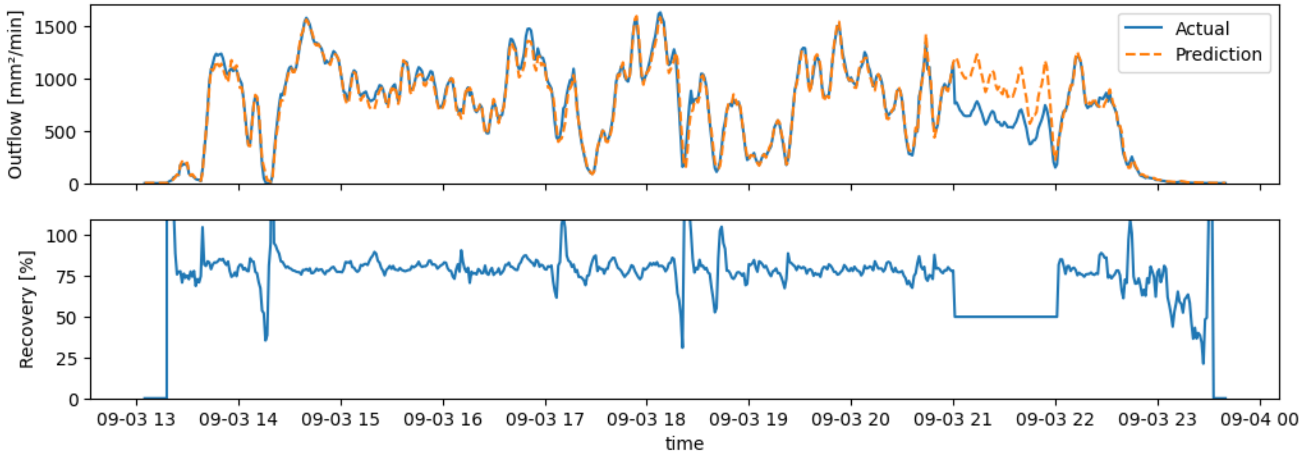


Figure 5: Material Outflow Profile on Disturbed System with Prediction Overlay (Top) and Percent Recovery of Targeted Material (Bottom).

- **No-code, automated platform**: Build and deploy accurate models with just a few clicks, as shown by the 99% accuracy.
- **Pre-configured settings**: Default parameters allow users with limited experience to achieve reliable results.
- **Flexibility for advanced users**: Offers customization for experienced users while remaining user-friendly for beginners.
- **Cost-effective, cloud-based solution**: Eliminates the need for expensive infrastructure, making AI accessible to SMEs.
- **Seamless integration**: Easily integrates with existing systems, enabling SMEs to apply AI without disrupting workflows.

By lowering the technical and financial barriers, ecoKI empowers SMEs to utilize their data to develop machine learning models that enhance operational efficiency, reduce downtime, and improve decision-making.

CONCLUSION

This study successfully demonstrated the application of basic MLP and LSTM models to predict NIR separator output, achieving over 99% accuracy on the training data. The MLP model exhibited strong generalization by accurately predicting outcomes on a separate test dataset. The model's reliance solely on the targeted material feed flow made it effective in detecting instances of performance deterioration in the NIR separator.

The machine learning models were developed using ecoKI's built-in pipeline, building blocks, and default settings for most of the blocks, showcasing the platform's ability to transform raw measurement data into actionable insights without requiring programming expertise. This feature makes ecoKI an ideal solution for small and medium-sized enterprises (SMEs), as it removes the technical barriers to AI adoption and enables businesses to leverage machine learning for operational improvements. The no-code, automated approach, along with pre-configured settings, ensures that even users with limited machine learning experience can develop high-quality models.

While ecoKI proves highly effective for waste sorting applications, it is worth noting its limitations. The platform's model structure offers limited adjustability, which may restrict its use for significantly more complex or customized modeling needs. Nevertheless, ecoKI's approach has significant potential for expansion across various industrial contexts, positioning it as a valuable tool for SMEs seeking to harness machine learning for real-time performance prediction and process optimization.

In conclusion, ecoKI offers a powerful, user-friendly solution for leveraging machine learning to predict the performance of NIR separators in waste sorting plants. By enabling SMEs to tap into AI-driven insights without extensive technical expertise or costly infrastructure, ecoKI paves the way for smarter, more efficient decision-making and process improvement. Future work could explore its scalability and adaptability in diverse industrial settings, cementing ecoKI as a game-changer in the use of machine learning for operational performance prediction.

DATA AVAILABILITY

The data that has been used is confidential.

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