Kautex Melt Flow Sensor

PURDUE UNIVERSITY | The Data Mine

KAUTEX A Textron Company

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BACKGROUND

The **Melt Flow Index (MFI)** is a measure of the rate that a known mass of a polymer flows as it melts. Kautex uses a **blow mold machine (BMM)** (Fig. 1) for their processing, so continuously monitoring MFI values is extremely important to ensure consistency in extrusion and final products. Currently, MFI values fluctuate in Kautex's production line. Thus, a more consistent MFI value will lead to more efficient processing, and better control over quality and performance of the final products.

Goal: Create a machine learning model to **predict MFI values in real time**, which will help increase efficiency of production, reduce plastic waste, and improve quality control at Kautex.

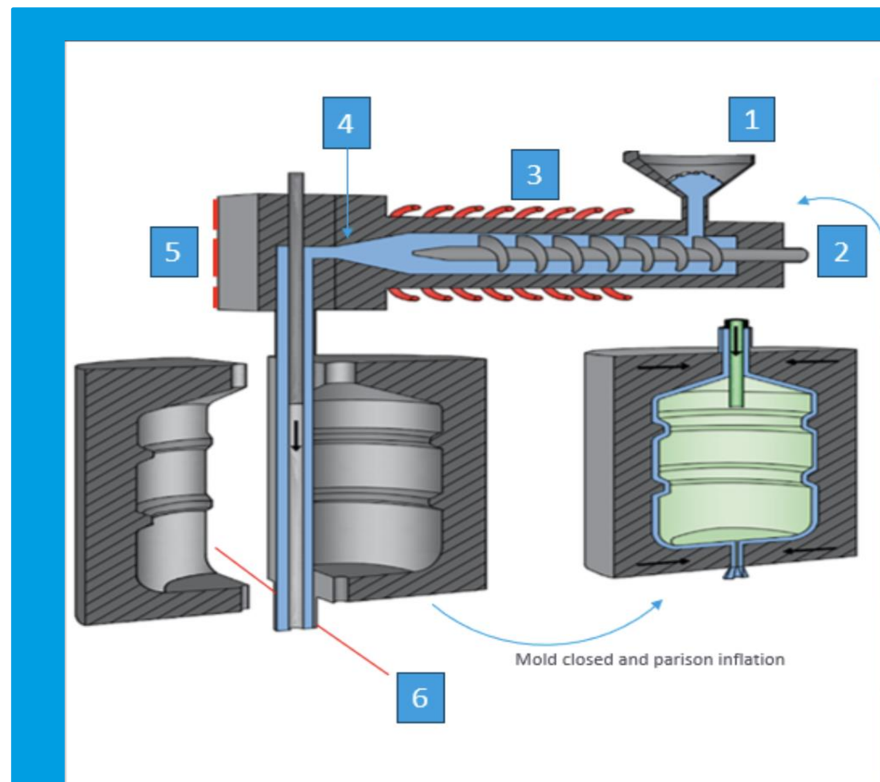


Fig. 1: Blow mold machine process from hopper (1) to extruder tip (4).

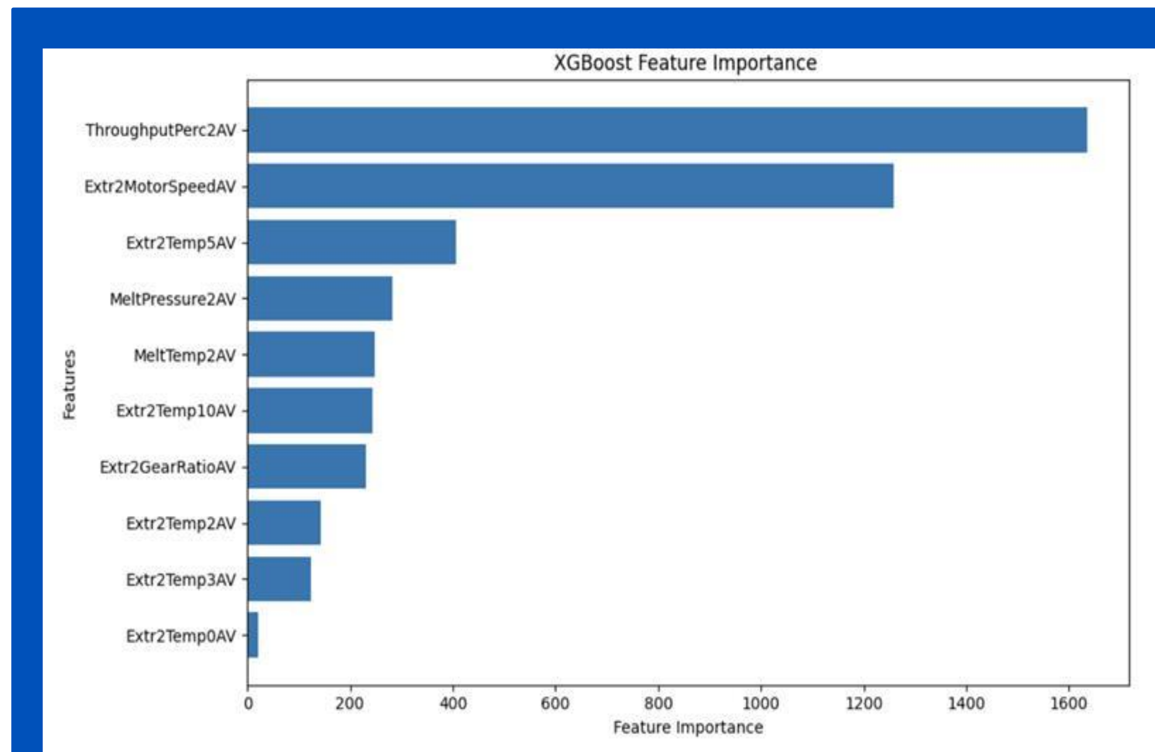


Fig. 4: Chart of Feature Importance. Features are organized based on how often they were used to split data across trees.

RESULTS

Theoretical MFI Value Correlation

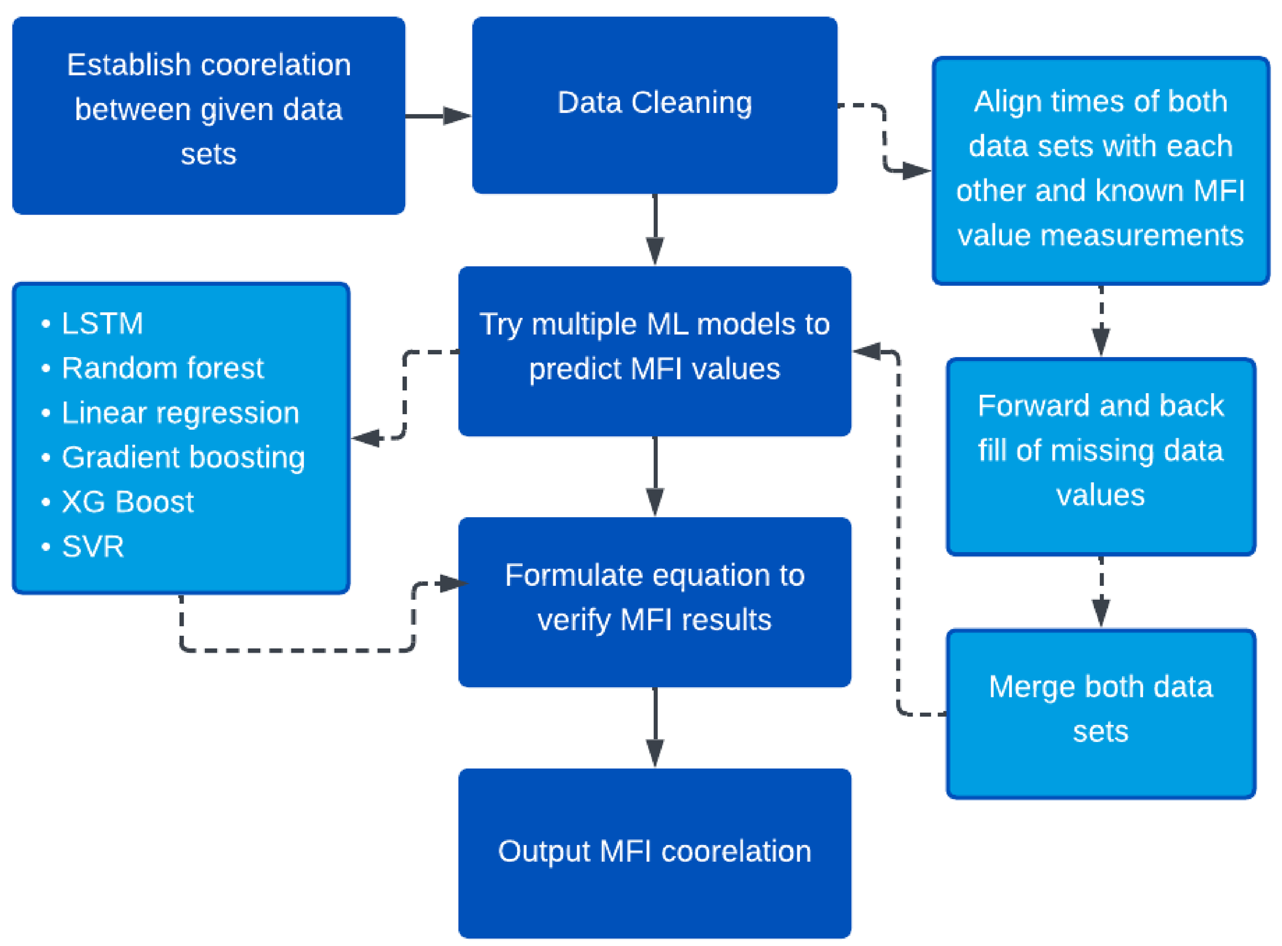
$$MFI = Consistency\ index * \frac{Temperature}{Pressure^{\frac{3}{2}}}$$

To predict MFI values, the trial consisted of using five various machine learning models: LSTM, Random Forest, Linear Regression, Gradient Boosting, XG Boost, and SVR. Out of these models, XG Boost had the best prediction results. Thus, XG Boost is the primary model being used, which was hyper parameterized to get best results.

MFI Value Correlation Results

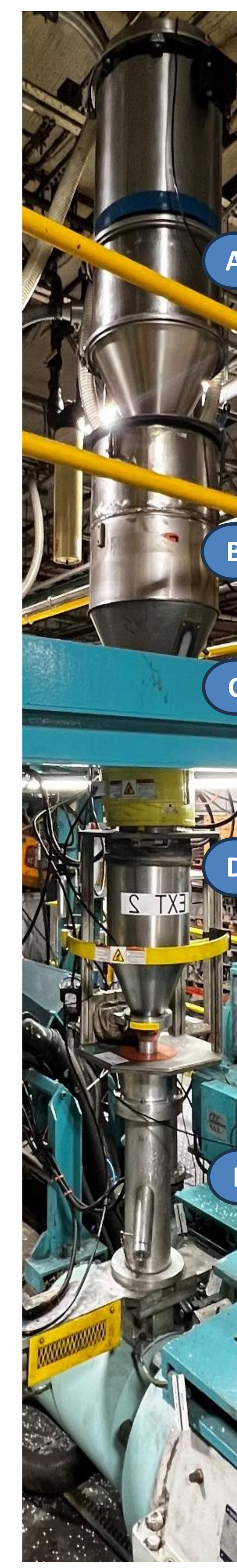
- Mean Squared Error: 0.00004825
- R^2 value: 0.9788

PROJECT WORKFLOW



MACHINE LEARNING MODELNG PROCESS

An **XG Boost machine learning algorithm** was used to build a regression model to predict MFI values from historical data and various data parameter inputs. Python libraries were imported to support data manipulation, model building, feature scaling, model evaluation, and data visualization. The dataset was split into **training and testing sets using an 80/20 ratio**. Inputs were scaled using Standard Scaler to normalize the training and testing data to a range of 0 to 1. The XGB Regressor was initialized with the mean squared error (MSE) loss function, and **hyperparameters were tuned using Grid Search** based on negative MSE value. After training the model with these optimized parameters, its **performance was evaluated using MSE and R^2 values**. Visualizing feature importance from the XG Boost model based on weight (Fig. 4), is helpful to understand the results and which features had the greatest impact on the predictions.



CONCLUSIONS

- The XG Boost model was the most successful in trials, with a very strong predictive accuracy.
- Based on Fig. 4, the most important features are Throughput Percentage and Motor Speed.
- Temperature and Pressure values are secondary contributors to the model.

FUTURE GOALS

- Integrate XG Boost model into real-time data pipeline on production lines.
- Enable seamless communication via API for live MFI predictions.
- Develop scalable deployment strategy for international plants
- Customize system and provide training for successful global rollout.
- To design an experimental framework to validate MFI relationship with pressure and temperature

THEORETICAL MANUAL CALCULATIONS

Utilized a combination of Buckingham Pi Theorem and Control Volume Analysis for Non-Newtonian Fluids to theoretically model relationship between input and output parameters to compare it with machine learning algorithm.

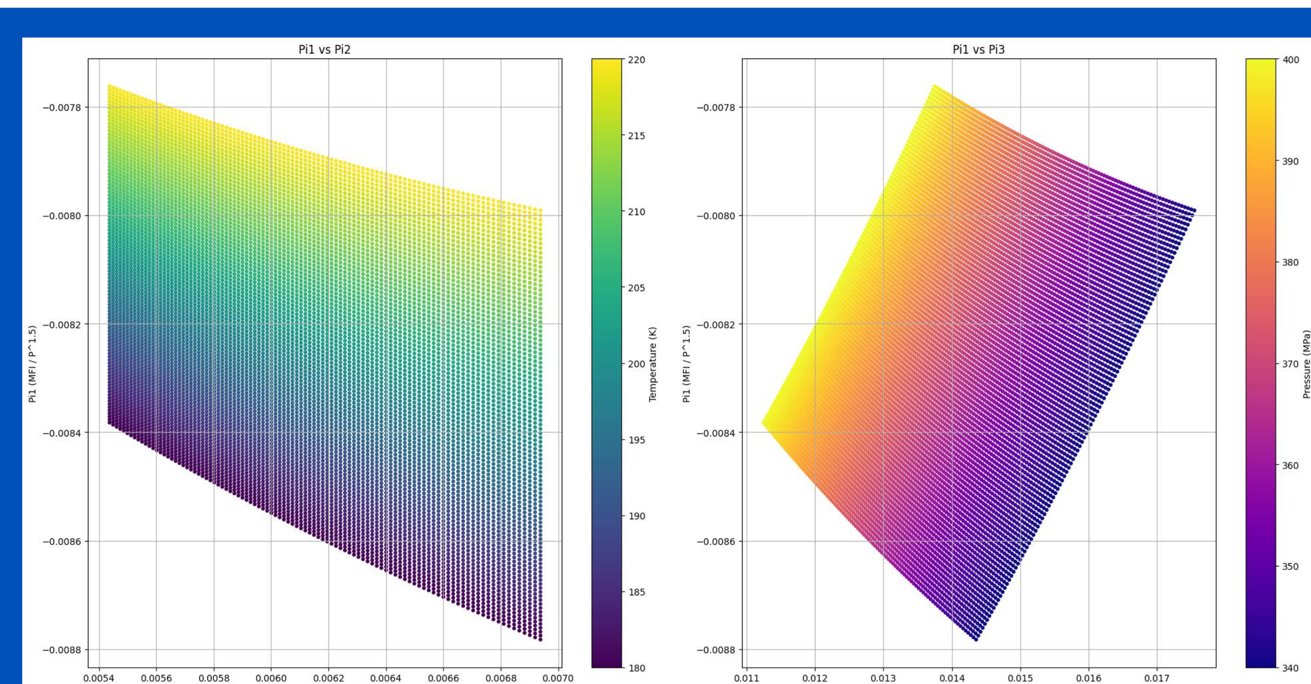


Fig. 2: Theoretical correlation between Pi groups showing correlation between extruder temperature and pressure as it relates to MFI.

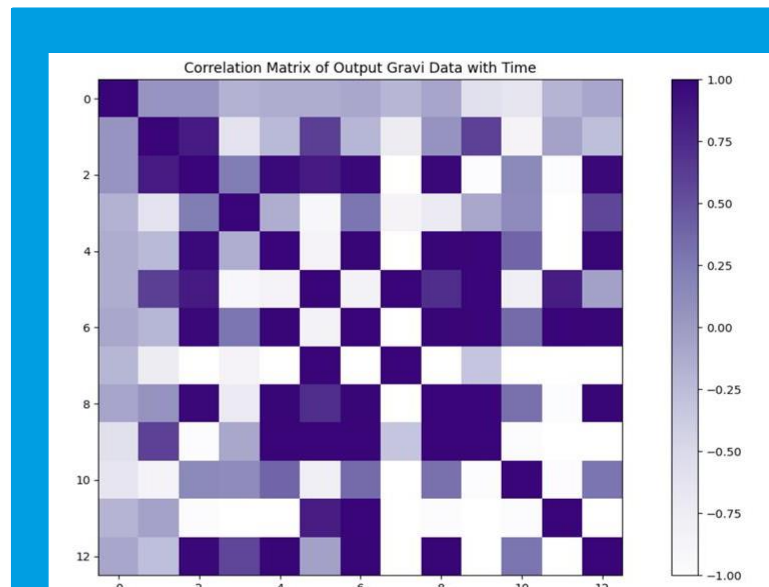


Fig. 3: Confusion Matrix showing correlation between data parameters and time.

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