PREDICTIVE MACHINE LEARNING FRAMEWORK FOR POTENTIAL DELAY

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Abstract

Delays relating to order deliveries in elastic manufacturing can significantly disrupt production timelines, affect supply chain efficiency, and diminish customer satisfaction. This research presents a machine learning-based framework to address these challenges by predicting manufacturing delays, explaining their underlying causes, and estimating delay durations to improve operational reliability. The study employs a three-layer architecture: a binary classification layer to predict whether an order delivery delay will occur, an explainability layer using Local Interpretable Model-Agnostic Explanations (LIME) to provide insights into each prediction, and a regression layer to estimate the duration of the delay and the expected delayed delivery date. The dataset, spanning more than three years (from 2021-01-08 to 2024-06-24), includes 37,411 order records and 75,723 delivery records, reflecting the complexities of elastic manufacturing order fulfillment. Extensive data preparation was conducted to standardize formats, handle missing values, and normalize features.Classification models such as Logistic Regression, XGBoost, and Neural Networks were utilized for classification tasks, while Linear Regression and XGBRegressor were employed for regression tasks.The inclusion of explainability techniques ensures transparency in decision-making, making the model robust and interpretable. This framework provides actionable insights for proactive delay management, helping elastic manufacturing firms enhance delivery performance and customer satisfaction.

Keywords: Elastic Manufacturing, Order Delivery Delays, Machine Learning, Predictive Modeling, Explainable AI

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Introduction

Machine learning (ML) has become a cornerstone in advancing manufacturing processes within the Industry 4.0 paradigm. By integrating smart sensors and connected devices, ML enables real-time data collection, analysis, and actionable intelligence that can revolutionize traditional manufacturing approaches. Applications such as predictive maintenance, quality improvement, process optimization, and supply chain management have gained significant traction, fostering innovation and efficiency in production environments (Peres et al., 2020).

In the context of predictive maintenance, ML techniques have proven invaluable in identifying early signs of equipment failure, thereby reducing unplanned downtimes and operational costs. For instance, predictive models leveraging supervised learning algorithms like Random Forests and Neural Networks effectively classify and predict machine faults by analyzing historical and real-time sensor data. These approaches enhance machine utilization rates and extend component lifespans (Çınar et al., 2020).

Another critical area where ML excels is process optimization. ML-driven analytics streamline operations by identifying inefficiencies and suggesting optimal parameter settings. This capability supports real-time decision-making, enabling manufacturers to meet dynamic demands with minimal waste and improved productivity (Rai et al., 2021). Furthermore, anomaly detection using unsupervised learning methods has enhanced fault detection and operational reliability across various industrial applications (Abualsauod, 2023).

The elastic manufacturing industry is characterized by its intricate processes and high susceptibility to delays, which significantly impact operational efficiency, cost management, and customer satisfaction. Delays in this industry are not only a challenge to meeting production schedules but also have cascading effects on costs, productivity, and the reputation of manufacturers. These issues are especially critical in the production of materials like polyester/spandex blends, which require precise handling and adjustments in real time to maintain quality standards. The factors contributing to these delays are multifaceted and include material variability, machine breakdowns, workforce inefficiencies, supply chain disruptions, and environmental conditions.

Material variability, particularly in elastic materials like spandex and polyester, is one of the major contributors to production delays. These materials often exhibit inconsistencies in properties such as tensile strength and elasticity, necessitating frequent adjustments during production, which increases processing times (Abir, 2020). Furthermore, the supply chain's inability to deliver high-quality materials promptly exacerbates production inefficiencies, as seen in industries heavily reliant on imported components (Kulasekara, Harshini, & Illankoon, 2023). Additionally, machine breakdowns in elastic manufacturing are often caused by the unique wear patterns of machinery used for processing these materials. The lack of real-time monitoring and predictive maintenance systems frequently leads to prolonged downtimes, further delaying production timelines (Arachchige et al., 2019).

The workforce's skill level is another significant factor influencing delays. Inadequately trained operators handling specialized materials often introduce errors that necessitate rework, adding to production time and costs (Katiraee et al., 2021). These issues are magnified in complex processes like dyeing and heatsetting, where temperature variations and improper chemical handling can lead to defects and material wastage. Studies have shown that dyeing processes are particularly prone to delays, as they require stringent control of environmental factors such as water quality and temperature to maintain consistency in elastic materials (Bulathsinghala, n.d.).

While traditional delay mitigation strategies such as Lean Manufacturing and Just-in-Time (JIT) principles have demonstrated some success, they are often insufficient in addressing the increasing complexity and variability of modern elastic manufacturing processes. Lean Manufacturing focuses on reducing waste and improving process flows, whereas JIT emphasizes inventory minimization and timely material usage. However, both approaches lack the predictive power needed to proactively address delays before they occur (Gomero-Campos et al., 2020). For example, queuing theory has been employed to optimize resource allocation and process efficiency, but its utility is limited in environments where real-time data integration is critical (Saini, Singh, & Sharma, 2024).

The advent of machine learning and predictive analytics has opened new avenues for addressing these challenges. Machine learning models analyze historical and real-time data to identify patterns and predict potential delays, allowing for preemptive actions that minimize downtime and enhance productivity. These techniques have been successfully applied in industries such as quarry production (Kannan et al., 2022), train operations (Cao et al., 2020), and aviation (Khan et al., 2021), where they have improved decisionmaking, optimized scheduling, and reduced operational inefficiencies. However, the application of machine learning in elastic manufacturing remains limited, despite its significant potential to address the unique challenges posed by material variability, process complexity, and environmental factors.

This research aims to integrate machine learning with traditional delay mitigation frameworks to develop a robust predictive model tailored to elastic manufacturing. By leveraging historical production data, real-time analytics, and advanced algorithms, this study seeks to enhance operational efficiency, reduce costs, and improve on-time delivery rates in elastic manufacturing. The proposed approach not only addresses the limitations of existing methods but also provides a scalable and adaptable solution for the dynamic and evolving manufacturing landscape.

Related Works

Delay prediction and mitigation are critical challenges across multiple industries, including manufacturing, transportation, and construction. The adoption of machine learning (ML) and artificial intelligence (AI) methodologies has significantly contributed to addressing these challenges. While research on elastic manufacturing is limited, valuable insights can be derived from studies in related domains.

In manufacturing, predictive models have been effectively utilized to address delays caused by machine breakdowns, scheduling inefficiencies, and supply chain disruptions. Kannan et al. (2022) explored the application of ML techniques such as Multilayer Perceptron (MLP) neural networks and Logistic Regression to predict production delays in a quarry company. The study achieved an F-measure of 0.973, highlighting the models' capability to handle production variability and improve decision-making. The research also demonstrated the potential of ensemble methods like Random Forests in capturing complex interactions between delay factors, further validating their utility in production delay prediction (Kannan et al., 2022).

The construction sector, characterized by dynamic and multifaceted processes, often faces significant project delays. Yaseen et al. (2020) proposed a hybrid Random Forest-Genetic Algorithm (RF-GA) model to predict construction delays based on historical data and delay risk factors. The hybrid model achieved 91.67% accuracy, significantly outperforming classical Random Forest models. This study emphasized the importance of integrating optimization algorithms with ML models to improve prediction accuracy and support proactive risk management strategies (19).

In transportation, reinforcement learning (RL) has emerged as a promising technique for mitigating delays under uncertain conditions. Cao et al. (2020) applied Q-learning to optimize route selection and minimize the probability of delay occurrence in stochastic transportation systems. Their approach dynamically adapted to real-time traffic conditions and achieved superior computational efficiency and accuracy in simulations conducted on real-world traffic networks in cities like Singapore and Munich. This study highlighted RL's potential in developing scalable and adaptive solutions for transportation delay problems.

The aviation industry has extensively explored ML techniques to address flight delay propagation challenges. Alfarhood et al. (2024) demonstrated the effectiveness of CatBoost, achieving 76% accuracy in predicting flight delays using a large dataset incorporating weather data and flight details. Similarly, Khan et al. (2021) developed a hierarchical integrated machine learning model that predicted delay statuses and durations with improved precision. By leveraging advanced sampling techniques and neural networks, their model provided robust decision-making support in handling highdimensional and unbalanced data.

Time-series analysis has also been employed to address delay-related problems. Wang et al. (2021) combined Autoregressive Integrated Moving Average (ARIMA) models with Long Short-Term Memory (LSTM) networks to forecast short-term order demand in manufacturing. Their study demonstrated that LSTM outperformed traditional ARIMA in scenarios with irregular demand patterns, highlighting its suitability for capturing nonlinear and temporal dependencies. The application reduced forecasting errors, showcasing its utility in scenarios requiring precise delay mitigation strategies.

These studies underscore the transformative role of ML and AI in delay prediction and mitigation across industries. By adapting these approaches to the unique challenges of elastic manufacturing, the current research aims to develop predictive frameworks that enhance operational efficiency and minimize production delays.

Research Methodology

This study follows the CRISP-DM (Cross Industry Standard Process for Data Mining) methodology, which organizes data analysis and model development into six phases: Business Understanding, Data Understanding, Data Preparation, Modeling, Evaluation, and Deployment. Each phase is customized to address the unique requirements of predicting production delays in an elastic manufacturing context (Schröer, Kruse, & Gómez, 2021).

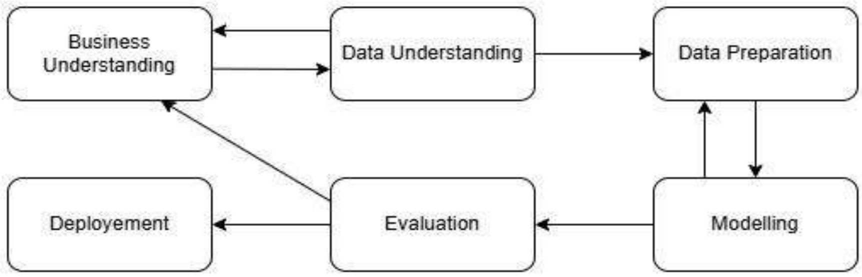

Figure 01: Research Methodology

Business Understanding

This research focuses on addressing order delivery delays experienced by an elastic manufacturing firm in Sri Lanka, which have hindered timely order delivery, reduced customer satisfaction, and impacted organizational performance. The study aims to analyze the elastic manufacturing process, identify inefficiencies, and develop predictive solutions to improve production flow and delivery timeliness.

The elastic manufacturing process consists of four critical stages:

- *White Elastic Manufacturing*: Involves the production of raw elastic materials.
- *Dyeing Process*: Coloring elastic materials based on specific requirements.
- *Packaging*: Preparing elastic materials for delivery.
- *Dispatching*: Transporting finished goods to customers.

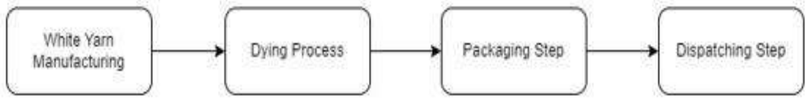

Figure 02: Elastic Manufacturing Stages

The research objectives are:

- To identify the key factors contributing to order delivery delays by analyzing the manufacturing process.
- To develop a predictive model using machine learning techniques to forecast potential disruptions.
- To validate and refine the predictive model to ensure its accuracy and reliability.
- To implement explainability techniques, allowing stakeholders to understand predictions and take corrective actions.

By addressing these delays, the study aims to enhance organizational efficiency, improve customer reliability, and maintain the firm's competitiveness in the market.

Data understanding

This study utilizes data collected between January 8, 2021, and June 24, 2024, encompassing critical aspects of elastic manufacturing orders and deliveries. The data is structured into two datasets: the orders dataset, comprising 37,411 records representing unique elastic production orders, and the deliveries dataset, with 75,723 records detailing the fulfillment of these orders. A single order may involve one or multiple deliveries, reflecting the complexity of the process. Key variables in the datasets include order-specific details such as order dates, planned and actual delivery dates, product group categorizations, and delivery metrics, including quantities and timestamps. These datasets collectively provide a comprehensive view of the order lifecycle, enabling a detailed analysis of patterns, trends, and delays in the manufacturing and delivery processes. This understanding forms the foundation for identifying inefficiencies and building predictive models to improve order delivery performance. (*The proprietary dataset used in this study, obtained from an industry partner, is not shared with this paper due to non-disclosure agreement (NDA)-related constraints.*)

Data preparation

This study utilizes data collected between January 8, 2021, and June 24, 2024, encompassing critical aspects of elastic manufacturing orders and deliveries. The data is structured into two datasets: the orders dataset, comprising 37,411 records representing unique elastic production orders, and the deliveries dataset, with 75,723 records detailing the fulfillment of these orders. A single order may involve one or multiple deliveries, reflecting the complexity of the process. Key variables in the datasets include order-specific details such as order dates, planned and actual delivery dates, product group categorizations, and delivery metrics, including quantities and timestamps. These datasets collectively provide a comprehensive view of the order lifecycle, enabling a detailed analysis of patterns, trends, and delays in the manufacturing and delivery processes. This understanding forms the foundation for identifying inefficiencies and building predictive models to improve order delivery performance.

To enhance the predictive power of the models, comprehensive feature engineering was applied to these datasets. Categorical features such as 'Product Group', 'End Use Code', and 'Customer Code' were encoded using one-hot encoding to ensure compatibility with machine learning models. Temporal features were derived from date fields, such as 'Days to Action' (difference between order date and planned delivery date), to capture seasonality and operational lead times. Continuous variables such as 'Order Quantity' and 'Delivery Duration' were scaled using Min-Max normalization to ensure consistent model performance. Additionally, missing values were excluded from the analysis. (Missing values were very minimum in the dataset due to data stored via computerized system, as a result missing values were removed) These engineered features significantly improved the model's ability to detect patterns and generate accurate predictive insights from the complex manufacturing and delivery data.

Modeling

The modeling phase of this research consists of a threelayer machine learning architecture designed to predict and explain delays in elastic manufacturing and estimate delay durations. The first layer is a binary classification model that predicts whether a delay is likely to occur or not. Various models were employed for this classification task, including Logistic Regression, ensemble methods like XGBoost, and Neural Networks, to ensure robust and accurate predictions.

For every classification prediction, the second layer introduces an explainability mechanism using Explainable Artificial Intelligence (XAI) techniques. The Local Interpretable ModelAgnostic Explanations (LIME) method was implemented to provide detailed explanations for each prediction, ensuring transparency and helping stakeholders understand the factors influencing the model’s decisions (Salih et al., 2024).

The third layer is a regression layer, activated only if a delay is predicted. This layer estimates the delay duration and calculates the expected delayed delivery date. Models like Linear Regression and XGBRegressor were used for this purpose, leveraging the delay-related features to provide precise predictions.

This three-layer architecture integrates predictive accuracy, explainability, and actionable insights, making it a comprehensive solution for identifying and managing delays in elastic manufacturing processes(see Figure 3).

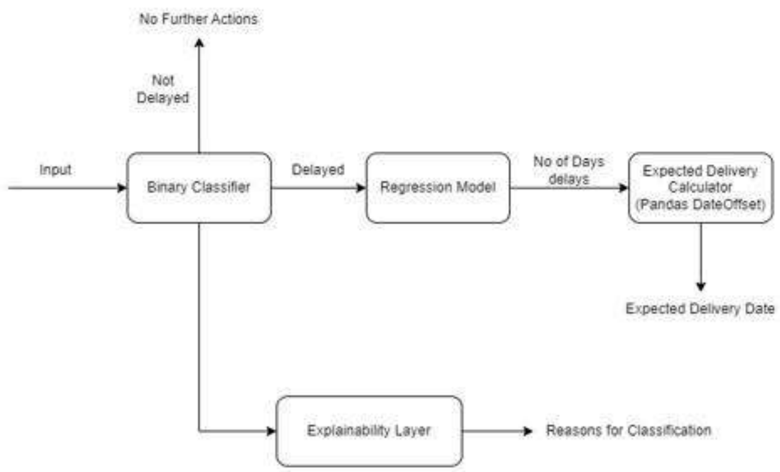

Figure 03: Three Layers Model Architecture

All experiments were conducted on Google Colab using a Python 3 Google Compute Engine backend with the following hardware configuration:

- System RAM: 12.7 GB
- GPU RAM: 15.0 GB (NVIDIA Tesla T4)
- Disk: 112.6 GB available storage

Evaluation

The effectiveness of the machine learning models in predicting delays will be assessed using a variety of standard evaluation metrics. Two types of models will be evaluated: classification models, which predict whether a delay will occur, and regression models, which estimate the duration of a delay. The evaluation will focus on assessing the performance of these models to ensure their robustness and reliability in predicting delays and estimating their durations in the elastic manufacturing process.

For classification models, the following metrics will be used: accuracy, precision, recall, F1-score, and ROC-AUC (Receiver Operating Characteristic - Area Under the Curve). Additionally, a confusion matrix will be presented to provide a comprehensive visualization of the model's performance across different classes (e.g., delayed vs. non-delayed operations). The confusion matrix details true positives (TP), true negatives (TN), false positives (FP), and false negatives (FN), offering insights into where the model may struggle, such as over- or under-predicting delays.

The formulas for these classification metrics are as follows:

- Accuracy:

$$= \frac{TP + TN}{TP + TN + FP + FN}$$

- Precision

$$= \frac{TP}{TP + FP}$$

- Recall (Sensitivity):

$$= \frac{TP}{TP + FN}$$

- F1-Score:
  2 * Precision*Recall/(Precision + Recall)
- ROC-AUC: The ROC-AUC evaluates the area under the Receiver Operating Characteristic curve, which plots the true positive rate against the false positive rate at various thresholds. While this metric does not have a formula in this context, it is computed as part of model evaluation using standard libraries.

For regression models, which aim to estimate the time of a delay, the following metrics will be employed:

- Mean Absolute Error (MAE):

$$\text{MAE} = \frac{1}{n}\sum_{i=1}^{n} |y_i - \hat{y}_i|$$

- Root Mean Squared Error (RMSE):

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n} (y_i - \hat{y}_i)^2}$$

- R-Squared (R^2):

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2}$$

where $\bar{y}$ is the mean of the actual values.

By employing these metrics, the performance of the classification and regression models will be thoroughly assessed. The confusion matrix will highlight specific areas where the classification model may misclassify delays, while metrics such as accuracy, precision, recall, and F1-score will quantify the overall classification performance. For the regression model, metrics such as MAE, RMSE, and R-squared will measure how accurately the model estimates delay durations, providing insights into the predictive accuracy and reliability (Esaki, 2021; Vujovic, 2021). Together, these evaluation methods ensure a robust and detailed assessment of the machine learning models applied to delay prediction and estimation in the elastic manufacturing process.

Deployment

The proposed predictive framework was deployed using a modular client-server architecture to support real-time interaction and scalability. The server-side component was developed using Flask, which serves the trained machine learning models through RESTful API endpoints. These APIs handle incoming data, perform model inference, and return classification or regression outputs in response to user or system queries.

The client-side interface was built using React, enabling interactive input submission and visualization of prediction results and feature attributions (e.g., via SHAP). The frontend communicates with the Flask backend asynchronously, ensuring low-latency interactions and a smooth user experience for manufacturing operators and planners.

On average, classification predictions and regression predictions were generated within 1 to 3 seconds, while the explainability component using LIME took approximately 4 to 6 seconds per prediction

Results And Discussion

Classification Layer

For the classification task, multiple machine learning models were evaluated to predict manufacturing delays, with their performance metrics presented in the table. Among these, the CatBoost Classifier achieved the highest overall performance, with an accuracy of 72.5% and balanced metrics across precision, recall, and F1-scores for both delayed (Class 1) and on-time delivered (Class 0) instances. The XGBoost Classifier also demonstrated competitive performance, with an accuracy of 71.8%, and provided strong balance across all performance metrics.

The MLP Classifier and DNN Model exhibited moderate overall performance with accuracies of 66.9% and 65%, respectively. However, these models were notably effective in predicting delayed instances (Class 1) due to their high recall scores (85% and 84%, respectively), indicating strong sensitivity in identifying delays. Despite this, the MLP and DNN struggled with the prediction of on-time deliveries (Class 0), as indicated by their lower recall scores for this class.

On the other hand, Logistic Regression was the lowest performing model, with an accuracy of 65.3% and comparatively weaker precision, recall, and F1-scores across both classes. This highlights its limitations in handling the complexity and variability of the dataset.

Overall, the CatBoost Classifier and XGBoost Classifier are identified as the most effective models for this task, combining strong overall performance with balanced predictive capabilities. While the MLP and DNN models offer moderate performance, their high recall for delayed instances makes them valuable for use cases prioritizing sensitivity to delays. In contrast, Logistic Regression demonstrates limited applicability in this context.

Metric	XGBoost	Logit	CatBoost	MLP	DNN
Accuracy	0.718	0.653	0.725	0.669	0.65
Precision (On Time)	0.73	0.64	0.73	0.75	0.73
Precision (Delayed)	0.71	0.67	0.72	0.63	0.61
Recall (On Time)	0.68	0.67	0.69	0.48	0.45
Recall (Delayed)	0.76	0.64	0.76	0.85	0.84
F1-Score (On Time)	0.7	0.65	0.71	0.59	0.56
F1-Score (Delayed)	0.73	0.65	0.74	0.72	0.71

Figure 04: Classification models performance comparison

Regression Layer

The regression models evaluated showed varying performance, with Random Forest achieving the lowest MSE (53.61) and XGBoost performing competitively (MSE: 56.87). Linear models such as Ridge and Lasso Regression had higher MSE values (68.80 and 72.83), while SVR exhibited the highest MSE (75.71). The moderate R^2 scores across all models suggest a reasonable ability to explain the variance in the delay duration factor, indicating that while performance can be improved, the current models provide a baseline for further refinement through advanced feature engineering and modeling techniques.

Explainability Layer

Figure 5: Explainability of the Classification

To enhance the interpretability of the machine learning model's predictions, the Local Interpretable Model-agnostic Explanations (LIME) framework was employed. For each classification, LIME generates a visual representation that identifies the most influential features contributing to the prediction. This explainable layer provides insights into the factors driving the model's decisions, offering transparency and facilitating trust in its outputs

D. Most important factors contribute to Delays

The analysis of feature importance for delay prediction revealed that Days to Action, Product Group, End Use Code, and Customer Code, Order Quantity are the most important key factors influencing delays in the manufacturing process. These features collectively contribute to the accuracy of delay predictions, highlighting the multifaceted nature of the manufacturing environment.

Each of these features provides critical insights into potential delay drivers. Order Quantity reflects considerations related to production volume, which can impact capacity planning and resource allocation. Days to Action corresponds to lead time and scheduling efficiency, highlighting how promptly production or delivery processes are initiated. Categorical features such as Product Group Codes (e.g., SJ and SW), End Use Codes (e.g., BIN and BRST), and Customer Codes (e.g., P00210T) offer contextual information about product types and customer-specific requirements. For instance, the Customer Code "P00210T" uniquely identifies a specific customer, allowing for analysis of customer-related patterns or constraints. Together, these variables support a comprehensive understanding of the factors that contribute to delays.

Conclusion

In conclusion, this study presents a comprehensive predictive machine learning framework to support proactive delay management in elastic manufacturing. The framework integrates a three-layer architecture consisting of a binary classification model to detect potential delays, an explainability layer using LIME to interpret the predictions, and a regression layer to estimate the delay duration. This design not only improves predictive accuracy but also fosters transparency and trust among manufacturing stakeholders. The results demonstrate that machine learning techniques such as CatBoost and XGBoost outperform basic heuristics in predictive accuracy and adaptability to complex manufacturing conditions. Although the study did not perform a full empirical evaluation against traditional rule-based systems, it is evident that ML models offer superior flexibility, scalability, and generalization. Unlike rule-based methods that rely on static thresholds and simplistic assumptions, ML approaches capture non-linear patterns and interactions across diverse production variables, enabling more nuanced and dynamic decision-making

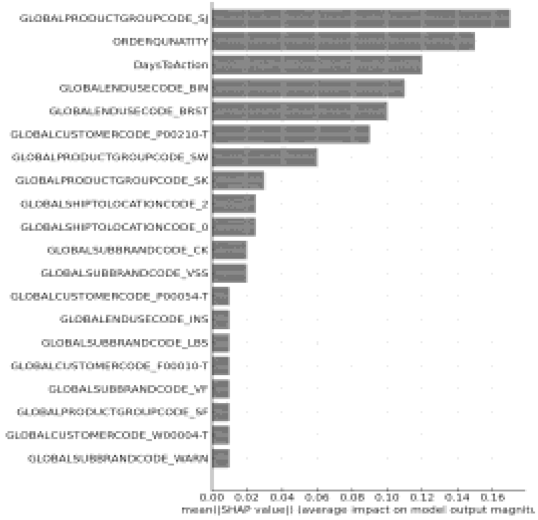

Figure 06: Most important factors contributing to Delays - Using Shapley Additive exPlanations

The current implementation is limited to batch-mode predictions using historical data and does not support live data streaming or real-time responsiveness. In fast-paced manufacturing environments, this could restrict the system's applicability for immediate intervention. Future research should focus on integrating real-time data ingestion via streaming platforms like Apache Kafka or MQTT, enabling predictions to be generated continuously and incorporated into live scheduling systems. Moreover, the introduction of online or incremental learning algorithms would allow the model to adapt dynamically as new production data becomes available. Deployment on cloud or edge-based infrastructure could also enhance scalability and latency performance. In addition, enhancing the explainability layer by incorporating more advanced and computationally efficient methods would make the model insights even more accessible to operations managers. Testing the framework across multiple manufacturing facilities with different operational setups would also be valuable for improving generalizability. Altogether, the proposed framework contributes significantly to intelligent manufacturing and opens avenues for future advancements in delay prediction and real-time decision support.

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