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RESEARCH ARTICLE

Real-Time Decision Support System for Dynamic Optimization in Multi-Product Process Manufacturing

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ABSTRACT The implementation of adaptive optimization in multi-product process manufacturing is a crucial strategy for the reduction of unplanned downtime and the enhancement of overall productivity. Nevertheless, the availability of real-time decision support tools for dynamic adjustments in large-scale industries is currently limited. In response to this challenge, we propose a novel model that processes data collected from extensive manufacturing operations. By leveraging Explainable Artificial Intelligence, we developed a real-time decision support system designed to dynamically adjust process parameters following varying input variables. The proposed model achieved a capture rate of 62% of the minority of products that cause micro-stoppages due to non-compliance with specifications. This approach provides a robust framework for adaptive optimization in complex and large-scale manufacturing environments, enhancing productivity and resilience against unplanned disruptions.

INDEX TERMS Manufacturing, downtime, machine availability, explainable artificial intelligence, decision support system, industry 4.0, machine learning.

I. INTRODUCTION

The manufacturing sector faces challenges due to inefficiencies in production, with micro-downtime being a key factor in operational delays. Micro-downtime, termed "Micro failures" refers to short interruptions in production that do not require maintenance intervention [1]. Although fleeting, accumulating these interruptions can result in significant production losses [2]. A substantial portion of micro-downtime is linked to adjusting process parameters and product corrections to maintain strict tolerances [27]. Upholding these tolerances is essential for operational efficiency and maintaining competitiveness in a demanding market.

The compliance of a product with technical specifications depends on selecting the appropriate process parameters [3]. Nevertheless, the relationship between these parameters and product quality remains unclear [3]. This ambiguity frequently results in a lack of clarity regarding the underlying causes of non-conformities, leading to unplanned shutdowns of the industrial process for corrections. Such unplanned shutdowns may be attributed to either equipment degradation or inadequate process parameters adjustment [4].

In various industries, operators adjust process parameters due to their expertise. This is often done manually through a trial-and-error method [3]. This intricate and lengthy process involves multiple adjustments until product quality standards are achieved [3]. However, this approach can lead to incorrect settings and quality inconsistencies. Additionally, contextual production variables, such as material properties, can influence the quality of produced components [5].

Advanced data analysis solutions provides several benefits for improving manufacturing capacity, quality, and productivity while minimizing defect-related costs. These costs include

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TABLE 1. List of acronyms.

Acronym	Meaning
AI	Artificial Intelligence
PCA	Principal Component Analysis
LIME	Local Interpretable Model-agnostic Explanations
XAI	Explainable Artificial Intelligence
ML	Machine Learning
BIC	Bayesian Information Criterion
LGBM	Light Gradient Boosting Machine
LSTM	Long Short-Term Memory
XGBoost	Extreme Gradient Boosting
CatBoost	Categorical Boosting
GMM	Gaussian Mixture Model

direct material losses and unplanned downtimes, negatively affecting cycle times and machine availability. Managing these processes can be complex, especially in monitoring and handling non-compliant or defective products.

Integrating Artificial Intelligence (AI) and industrial data can enhance industry competitiveness and efficiency [6]. Data is a valuable asset for innovative businesses.

Machine Learning (ML), a branch of AI that employs data-driven algorithms, offers great opportunities for modernizing manufacturing operations in the era of Industry 4.0 [26]. Its application allows real-time analysis of large data sets, revealing trends that operators might miss. This capability enables proactive optimization and early anomaly detection in manufacturing processes, thereby enhancing management and performance.

Despite its advantages, adopting ML faces challenges, including a lack of understanding of its potential and concerns about job displacement due to automation. This underscores the importance of informed decision-making in implementing machine learning in industrial settings.

The objective of this contribution is to develop a decision support tool to **predict product conformity during the early stages of manufacturing assembly**, based on process parameters, material characteristics, and operational environmental conditions. From the constructed model, it would then be possible to gain insights into the impact of input variables and their influence on the assembly process.

The remainder of the paper is organized as follows. Section II discusses related work in the field of dynamic optimization of manufacturing process parameters. Section III introduces the proposed model within this context. Section IV is dedicated to applying this model in the tire manufacturing industry. Finally, we conclude our study and suggest future research directions in Section V.

II. RELATED WORK

In recent years, research on the dynamic adjustment of manufacturing process parameters has emerged as a critical area of focus [28]. Numerous studies have applied AI techniques across various industries, including plastics [3], [7], [8], metallurgy [5], [9], [10], [11], [12], [13], [14], [15], [16], automotive [17], and semiconductors [18], [19], among others. This growing interest can be attributed to the abundance of data collected in industrial environments, coupled with advancements in automation and semi-automation technologies. These studies attempt to explain the relationship between independent process variables and the dependent variable, sometimes aiming to determine the importance of each independent variable and its contribution to the predicted value. The dependent variable can represent product compliance forecasts, quality, or, in some cases, the yield of an industrial process.

Most studies on real-time process parameter adjustment rely on experimental or simulated data. Among those using data collected from a real-world environment, three articles by Jiang et al. [18], [19], and Chen et al. [17] address a large-scale manufacturing process. Additionally, the data types adopted in these studies include images, numerical data, or signals. It is also important to note that a wide variety of product types is encountered in the manufacturing industry, a characteristic that is not considered in the identified research, which generally focuses on a limited number of products or even a single one.

In the specific context of our study, we face three major challenges: managing high-dimensional data, accounting for heterogeneous data, and dealing with the complexity inherent in complex production processes.

Regarding the first challenge, five articles address problems related to high-dimensional data. In these cases, the authors tackle the complexity of high dimensionality by using feature selection techniques. Chen et al. [8] evaluate the effect of parameters influencing quality attributes through a statistical analysis of variance and then verify the optimal combination of independent variables via regression feature selection analysis. The elimination of irrelevant features allows the construction of a model with improved performance and reduced computational cost. However, this approach can not be directly applied to a production process, as even though some variables may be statistically redundant, it is crucial to understand the subtleties between them and select those relevant to the production context. The articles by Chen et al. [17] and Jiang et al. [18] address the issue of high-dimensional data using Pearson correlation to discard redundant attributes manually. Jiang et al. [18] go further by applying feature selection methods, such as Mutual Information and Recursive Feature Elimination, to enhance prediction performance and, more critically, to identify the key process parameters. Furthermore, Straßer et al. [11] calculate Variance Inflation Factors to assess the degree of multicollinearity in the data, thus ensuring model stability. To further simplify data representation, Chen et al. [17] introduce the Principal Component Analysis (PCA) algorithm, eliminating redundant inter-influencing factors among variables and retaining only those that contain most of the correlation. However, using techniques like PCA is generally not recommended for industrial data. This method replaces the original variables with principal components that capture most data variance. However, interpreting results from principal components can be complex and sometimes unintuitive, thus limiting the model's ability to provide actionable insights. In a production context, this approach faces the same limitations as eliminating highly correlated features.

With regard to the second challenge, Strasser et al. [11] are the only researchers to incorporate a single categorical input. The authors apply Dummy Coding, an approach that transforms a variable with m categories into $m - 1$ binary attributes with 0 and 1 as potential values, to include this attribute in a linear regression model. However, due to complexity, this technique becomes less practical when dealing with attributes with many categories. A large number of binary attributes makes the model harder to train and even interpret.

To address the third challenge, Jiang et al. [18] proposed a segmentation approach based on a Gaussian Mixture Model (GMM) to predict the final test yield in the semiconductor industry at an early stage, aiming to reduce noise caused by process variations. The GMM models industrial data distributions as a combination of multiple Gaussian distributions, effectively capturing variability and underlying patterns. Since machine learning models perform best when data are independently and identically distributed, this segmentation improves reliability, generalization, and overall model performance. By minimizing variation within each group, the approach enhances prediction accuracy and enables better identification of process dynamics. This method will be tested as part of this study.

In the existing literature, models are applied independently to each product or a limited set of products [3], [5], [18], [19], which does not accurately reflect the realities of multi-product manufacturing industries and limits their practical applicability. Several studies rely on deep learning models [3], [5], [7], [10], [13], which effectively capture complex and nonlinear relationships in data but require extensive datasets and computational resources, making them less feasible for real-time industrial applications. Additionally, a scarcity of interpretability in predictive models hinders their transition to actionable recommendations for process adjustments [3], [5], [7], [8], [10], [16]. In contrast, our approach integrates predictive modeling with the provision of explanations for recommendations that are actionable. Furthermore, it incorporates future adaptive real-time optimization, thereby addressing the key limitations of conventional methodologies in this field.

To our knowledge, no study addresses the problem of forecasting product compliance in a multi-product assembly process using heterogeneous data, comprising both numerical and categorical data, from a real industrial environment.

III. PROPOSED MODEL

After an initial task involving the **understanding of the business** context, with a particular focus on the identified critical process, the overall process for the proposed model comprises five main phases: (A) Data Understanding, (B) Data Preprocessing, (C) Modeling, (D) Evaluation, (E) Explainability. The different stages of this approach are depicted in Figure 1. The figure consists of two panels. The left panel presents the model proposed by Jiang et al. [18]. The right panel illustrates our proposed model for addressing the challenges of large-scale manufacturing, highlighting the aspects that characterize our model in orange.

A. DATA UNDERSTANDING

This step involves understanding the available data for exploration. Wang [20] proposes a classification of manufacturing variables to consider when leveraging data: **product variables, machine variables, manufacturing process variables, raw material variables, environmental variables, operator variables, production line variables, planning variables, quality control variables, service variables, supply chain variables, and target variables**.

Data visualization is a widely used for improving data comprehension, facilitating comparison, trend analysis, and outlier detection. It provides a powerful means to gain insights into the dataset and assess data quality by identifying errors and their potential causes.

B. DATA PREPROCESSING

As emphasized by the Cross Industry Standard Process for Data Mining (CRISP-DM) methodology, several tasks are typically required for handling industrial data.

Outliers and missing values, whether from errors or natural variability, are critical to address during data pre-processing in industrial analytics. These steps ensure data reliability and robustness for subsequent modeling.

Feature engineering, particularly with industry-specific approaches, integrates domain expertise to enhance model learning and align outputs with real-world constraints. This fosters actionable insights and supports seamless practical implementations in operational settings. A crucial aspect that is not addressed in the article by Jiang et al. [18], where feature selection was carried out without consideration of the importance of each feature.

Leveraging **diverse data types**, including numerical and categorical, requires standardization and appropriate encoding. Unlike Jiang et al. [18], who focused solely on numerical data, a comprehensive approach maximizes the use of all available information for improved outcomes.

C. MODELING

The goal is to design a solution for multi-product manufacturing processes by using domain expertise to effectively **regroup data**. This approach balances generalization with product- or machine-specific nuances, uncovering patterns such as machine stoppages or maintenance clusters that enhance model accuracy.

Data splitting is critical for evaluating machine learning models but can introduce bias if not done carefully. Combining it with **cross-validation** mitigates overfitting and ensures robust model generalization, especially for small or imbalanced datasets.

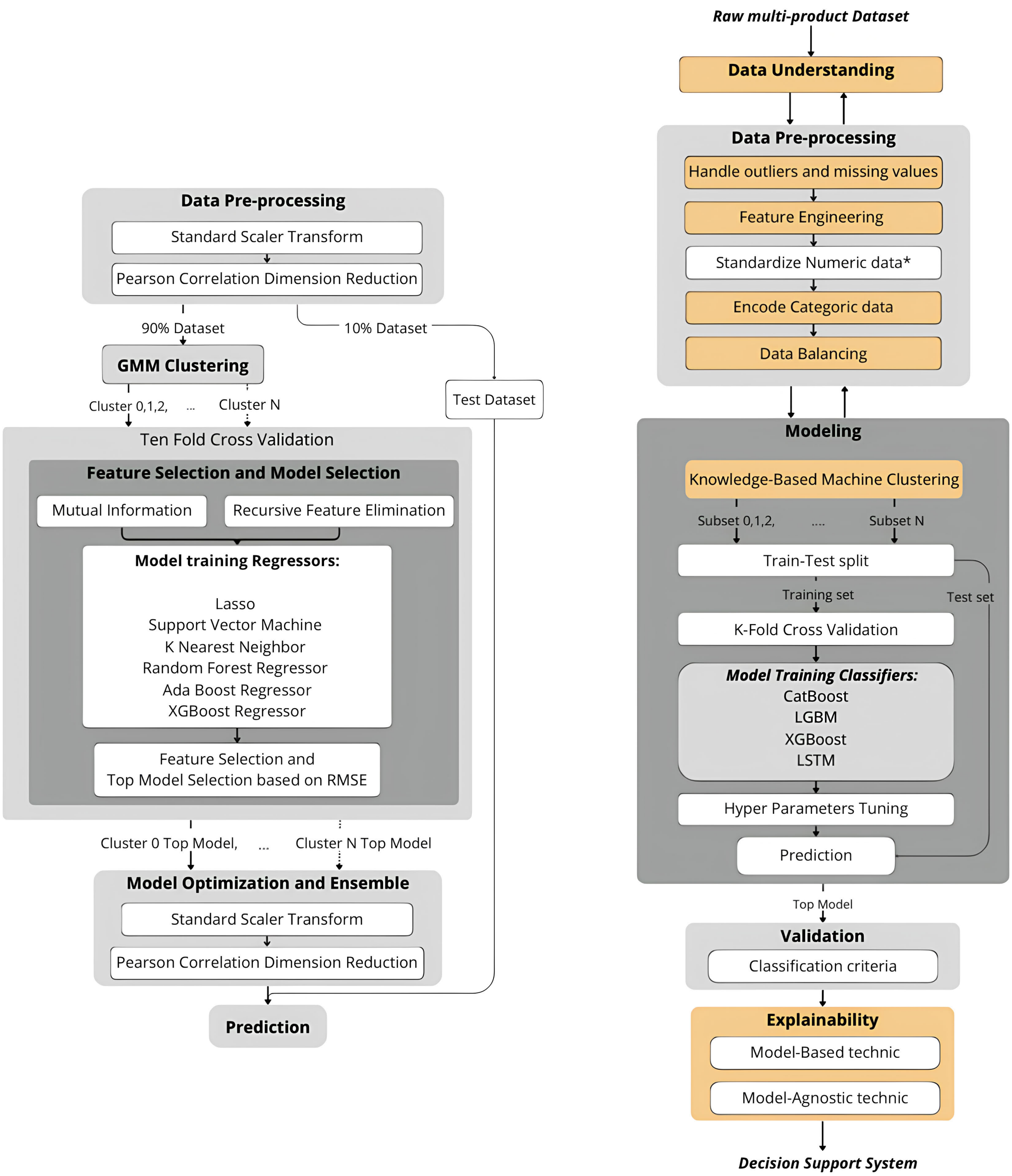

FIGURE 1. Model proposed by JIANG et al. (Left) and our proposed model for multi-product processes (Right).

Hyperparameter tuning, through methods like Grid Search, Random Search, or Bayesian Optimization, optimizes model performance by efficiently exploring the hyperparameter space.

D. VALIDATION
Validation should align with the study's objectives, especially when dealing with imbalanced datasets. Metrics like Precision, Recall, and F1-score are more suitable than Accuracy alone for evaluating the model's ability to identify rare but critical classes.

E. EXPLAINABILITY
Explainable Artificial Intelligence (XAI) ensures predictions align with operational knowledge, fostering trust and confidence in AI-driven solutions. Explainability can be achieved using Model-Specific or Model-Agnostic techniques, enhancing the understanding of model behavior in industrial applications.

IV. EXPERIMENTATION
Our approach was tested using a real-world case study centered on the analysis of data from tire manufacturing

processes, which involve multiple complex steps. The industrial objective is to enhance the plant's daily productivity. The production of a tire begins with the selection of raw materials, including rubber, additives, carbon black, and silica, which play a critical role in determining the final product's quality. These materials are combined in industrial mixers, forming a homogeneous mixture that is later heated and extruded into bands of varying thicknesses and profiles. In the next stage, metal and textile reinforcement cords are integrated to give the tire the strength to withstand heavy loads. This occurs during the calendering process, where rubber layers are precisely pressed onto the reinforcement cords. Following calendering, the assembly phase combines all components, such as the belt plies and tread, into a unified structure. The tires are then cured in specialized ovens, a crucial step that hardens and shapes the rubber, ensuring the final product's durability and performance. After curing, each tire undergoes a thorough inspection and a series of performance tests to verify that it meets stringent safety and quality standards before reaching the market.

This section details the methodology employed in this industrial context to identify and mitigate the key process factors contributing to these inefficiencies.

A. DATA UNDERSTANDING

The present study investigates the assembly process in automated tire manufacturing, with a particular focus on productivity analysis, which is impacted by frequent short-duration stoppages. Given the influence of seasonal demand fluctuations on production volumes, machine workloads, and key process parameters, a full-year dataset (from January to December 2023) covering all automated machines was utilized. This comprehensive dataset encompasses product variations, operating conditions, long-term trends, and fluctuations in minor corrective stoppages, thereby ensuring a comprehensive understanding of production dynamics. Moreover, the possession of a sufficiently large dataset is imperative to ensure reliable modeling and robust training of machine grouping models, particularly when the dataset is segmented according to machine clusters.

The dataset is collected from machine logs and integrated sensors. Accuracy is insured through regular maintenance that minimizes drift or measurement errors. These monitoring systems have been operational for years, with a dedicated team managing the data quality. Furthermore, machines undergo systematic calibration with each product type change to maintain process stability and product quality despite variations in materials and assembly parameters. This ensures that the collected data accurately reflects operational conditions, strengthening the reliability of the analysis.

To prepare the data, we applied pivot transformations to the product and calibration parameter tables, restructuring parameters as attributes. Each observation corresponds to a unique tire identifier, enabling nuanced analysis and streamlined table joins. The final dataset integrates tables from the industrial partner, encompassing approximately 3.5 million observations across 500 product types with distinct specifications.

The data understanding and collection phase involves documenting and analyzing the assembly process to identify relevant variables. Scheduling, service, and supply chain parameters are excluded, leaving only variables directly related to the process. We therefore consider the following data:

1) **Product Variables**: Include the specific dimensional characteristics of each manufactured tire, such as width, height, diameter, etc.
2) **Calibration Variables**: This category encompasses all calibration procedures applied to the produced tires, including applied pressures, length adjustments, and tolerances concerning the length of joints, which must be strictly adhered to.
3) **Production Variables**: Each observation in this category provides detailed information about each tire, including the name of the recipe used, the family of green tires to which this recipe belongs, the manufacturing machine, and the final measurements of each dimension after the assembly process.
4) **Production Line Variables**: Include temporal data related to the production cycle of the tires, as well as individual delays experienced by each tire, such as the delay code and the start and end times of the delays concerning the assembly of the three carcass plies, which are the focus of this study.
5) **Semi-Finished Product Variables**: Comprise information about the rolls used in the assembly, including the unique identifier of the roll, the time required for its production, and its generation and consumption time.
6) **Environmental Variables**: These data include temperature and humidity collected by a sensor located in the assembly area, with measurements taken every minute.
7) **Target Variables**: A binary variable representing the conformity of assembled green tires, ensuring that the measured joint lengths after assembly fall within the specified tolerances.

We differentiate between two categories of variables: **adjustable and non-adjustable**. The former includes parameters such as calibration settings, while the latter encompasses product characteristics, contextual data (e.g., temperature and humidity), and other variables that can not be modified.

Preliminary exploration of the data reveals that the primary cause of unplanned stoppages is non-compliance with the specifications of the tires being assembled. Currently, operators manually adjust parameters or make corrections to the product assembly, resulting in decreased productivity and reduced machine availability. This situation presents an opportunity to leverage the available data for significant benefits.

We begin by visualizing important measurements from this process, specifically the lengths of the joints, which serve as the basis for defining compliance. Compliance can be defined in various ways. We define a compliance index based on

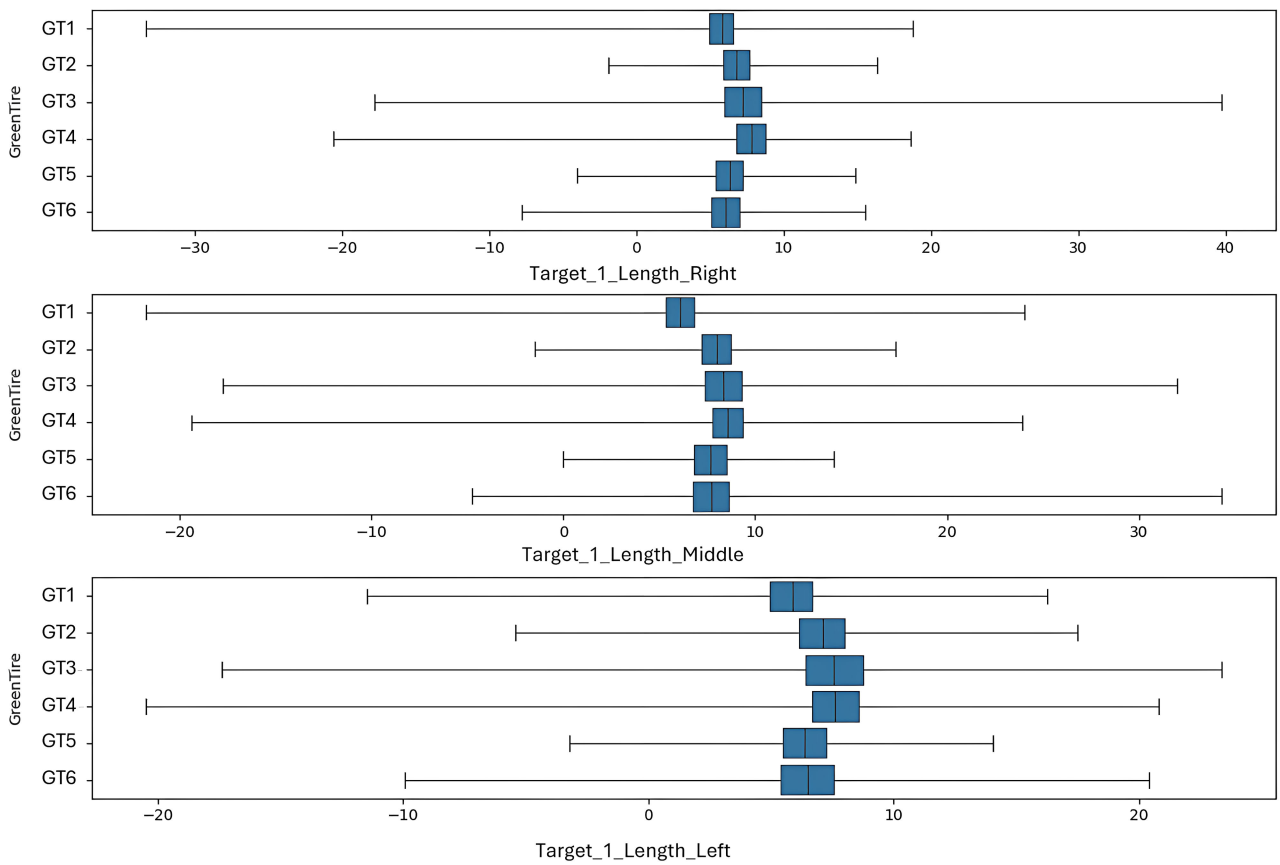

FIGURE 2. Lengths of joints for each type of tire.

adherence to specifications regarding the three layers of a tire. In other words, the lengths of the joints of each layer must fall within specified ranges for each product. A value of "1" is assigned if all specifications are met, while a value of "0" is assigned if at least one specification is not met. Figure 2 presents a box plot showing the distribution of joint lengths, highlighting a minority of extreme values resulting from erroneous machine readings. These anomalies, which do not accurately represent the minority class of product nonconformity under study, introduce bias into the developed models. To address this, we established a threshold based on domain expertise, allowing us to cap values within the range of −5 mm to 15 mm while ensuring that meaningful non-compliant data was preserved.

Next, we analyze the compliance rate during the assembly process and visualize the quality rate after the inspection phase. As shown in Figure 3, no major quality issues are observed, as operators address non-conformities during the process or after inspection. However, the primary challenge lies in the time spent addressing non-conformities. The assembly process exhibits a 22% non-compliance rate with specifications, contributing to frequent unplanned stoppages and reduced machine availability.

Figure 4 shows the tire count for each delay code, revealing that many tires experienced Micro-Failures during assembly

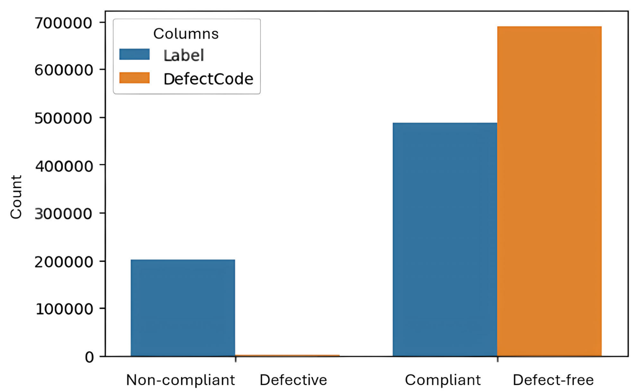

FIGURE 3. Proportion of quality and compliance data.

due to component tolerance non-compliance. Figure 4 illustrates the cumulative downtime for each delay code, highlighting substantial production time losses. These times were calculated after removing outliers, as depicted in Figure 6.

A binary attribute indicating belt layer changes during the assembly process was created to assess their impact on compliance. Visualization of the first 10 cases in Figure 7 shows that for 6 layers (Serial=1, 3, 4, 12, 13, 22), the

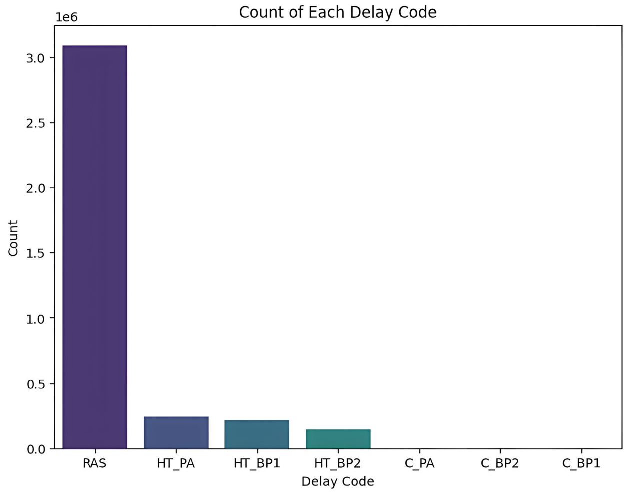

FIGURE 4. Tire count of each delay code.

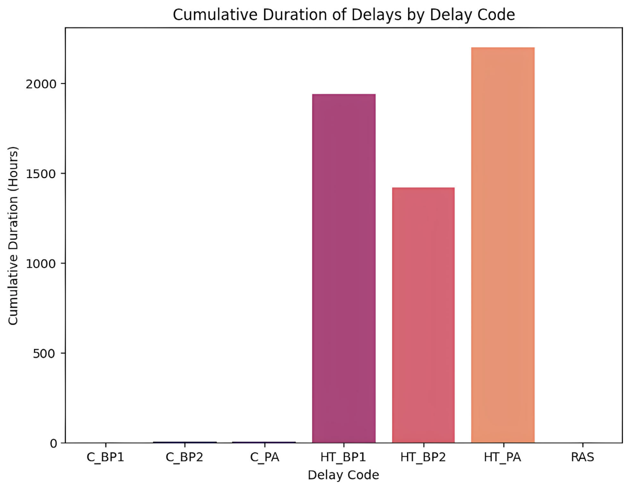

FIGURE 5. Cumulative duration of delays by delay code.

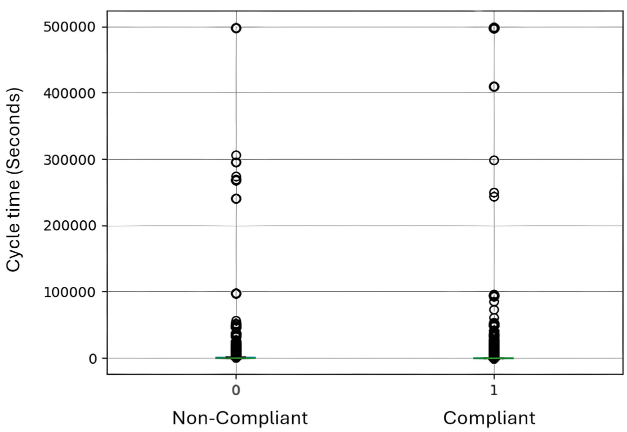

FIGURE 6. Box plot of production cycle durations.

non-compliance rate is 50% or higher, with one layer (Serial=3) reaching a 100% non-compliance rate.

B. DATA PREPROCESSING

This project, funded by a Canadian governmental grant, follows stringent protocols for handling sensitive data. To ensure confidentiality, anonymization and encoding were used to replace machine names, product identifiers, and production parameters with generic labels. The key steps in data preprocessing included:

1) **Handling outliers and missing values**: Visualization techniques such as box plots, violin plots, and histograms were employed to identify these outliers, with the first two methods proving particularly effective for detecting anomalies across multiple groups. Missing values have been removed.
2) **Feature Engineering**: This phase involves selecting, transforming, and creating relevant input variables from raw data. Initially, domain expertise reduced the variables to around one hundred, further refined through correlation analysis to eliminate redundant parameters while considering their roles in the production process. Techniques like PCA, which replace original variables with principal components, are discouraged for industrial data due to their complexity and lack of interpretability [21]. Instead, feature selection methods that preserve the original variables' significance are preferred. Additionally, creating variables to facilitate hypothesis testing can enhance the learning process.We evaluate the following hypotheses: (A) *Hypothesis on the Influence of Product States at Observations $n-3$, $n-2$, and $n-1$ on the Product at Time n*: To this end, a dedicated table was established to record the cycle times of tires and the delays observed, featuring an attribute for stop codes when interruptions occur in the assembly of the three carcass plies. In the absence of a stop code, a value of *NaN* is assigned. If a code is present, additional columns specify the start and end times of the interruption, allowing for the calculation of its duration. Specifically, six supplementary columns are introduced. Three categorical columns retain the delay codes for the tires preceding the current tire at observations $n-1$, $n-2$, and $n-3$, alongside three numerical columns that specify the delay duration for the tires at observations $n-1$, $n-2$, and $n-3$, including the tire at time n. (B) *Hypothesis on the Impact of Temperature on the Assembly Process*: Literature concerning polymer materials, including rubber, presents physical models correlating temperature and humidity to elasticity. Consequently, we integrated environmental variables associated with the production or storage conditions of the tire. For each tire, the average, maximum, and minimum temperature and humidity of the production day are calculated. The storage duration of materials utilized in the tire's composition before consumption is also computed and incorporated into the dataset. (C) *Hypothesis on*

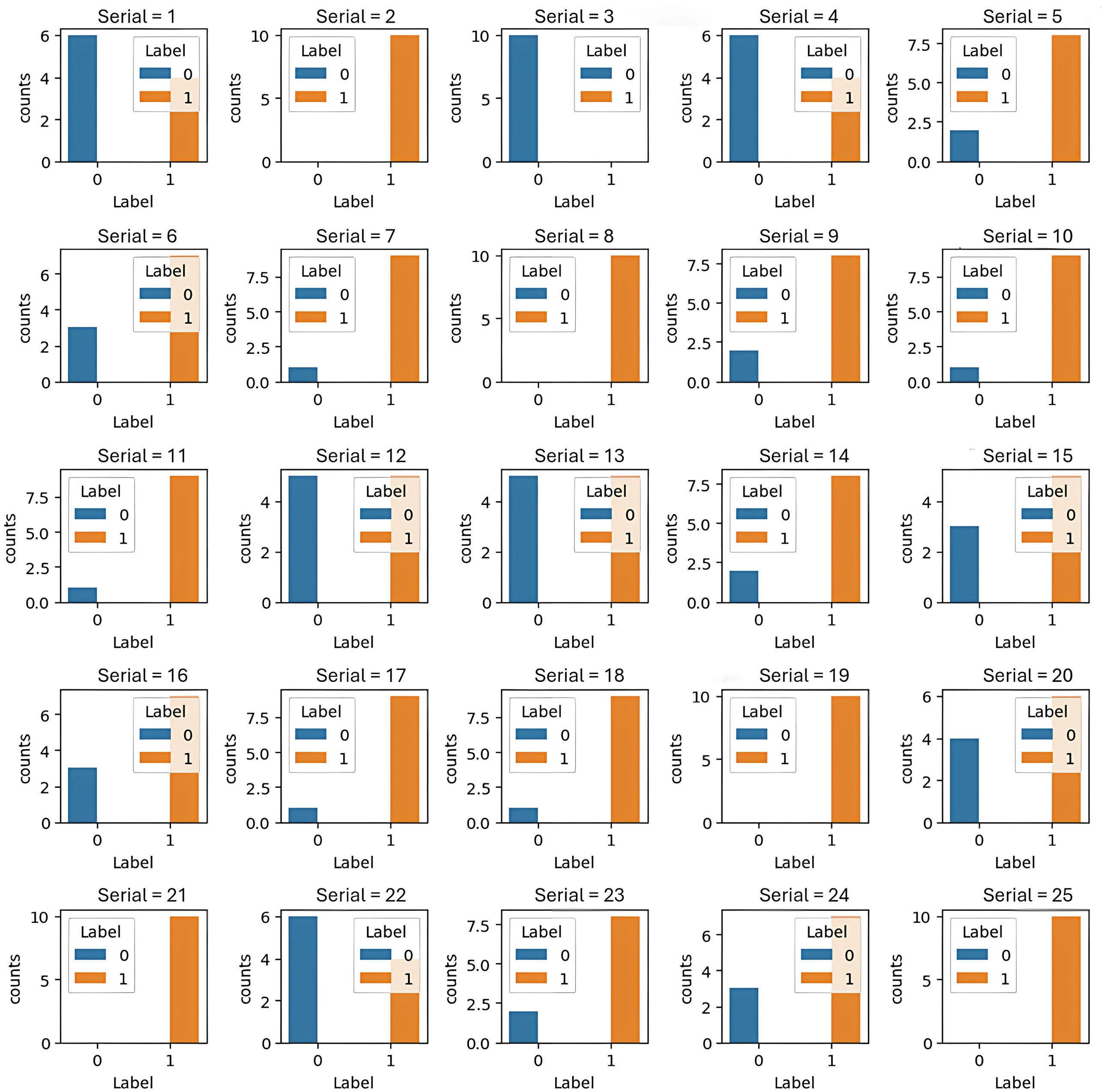

FIGURE 7. **Compliance of the first 10 tires from each belt layer.**

the Succession of Non-Conformities: This hypothesis examines the possibility that conformity is linked to sequences of defective tires. We integrated a variable designed to count successive defective tires, allowing for identifying tires that follow two consecutive non-conforming units. (D) Our observations also revealed issues related to *the variation between the length of the ply entered by the operator and the length measured after cutting*. An attribute documenting the variation between these two values was added to the data. (E) Additionally, we noted that during assembly, the occurrence of successive non-conformities may be associated with the physical changes materials undergo as a roll of material nears depletion. This insight led us to add an attribute indicating how many *tires remain to be produced with the material currently in use*.

3) **Data Formatting**: Significant discrepancies in numerical variable values were addressed using *Min-Max Standardization* to ensure compatibility with scale-sensitive models. For categorical variables, *Cat-Boost encoding* was employed to minimize risks of information loss, data leakage, or overfitting, particularly for attributes with many categories. Additionally, pressure variables were discretized into categories with

TABLE 2. Performance comparison of models.

Models	Optuna	Weight sampling	Accuracy	Recall		Precision		F1-score	
				Conf.	N.Conf.	Conf.	N.Conf.	Conf.	N.Conf.
Catboost			80	97	17	81	61	88	29
	x		70	71	65	88	38	79	48
		x	80	97	20	82	63	88	31
	x	x	70	72	65	88	39	79	48
LGBM			80	97	15	81	61	88	24
	x		69	70	64	88	37	78	47
		x	80	97	17	81	62	88	27
	x	x	69	71	65	88	38	78	48
XGBoost			80	97	17	81	63	88	27
	x		69	71	64	88	38	78	47
		x	80	96	22	82	60	88	32
	x	x	71	73	63	88	39	80	48

TABLE 3. LGBM results on machine segments.

Blocs	Accuracy	Recall		F1-score		Precision		Iteration	Learning rate	Depth	Leaves
		Conf.	N.Conf.	Conf.	N.Conf.	Conf.	N.Conf.				
C	70	72	66	79	47	89	37	566	0.066	6	133
G	70	71	66	79	50	88	40	793	0.044	10	113
J	70	73	58	80	39	90	29	923	0.016	12	135
H	70	72	62	77	54	83	48	780	0.087	12	78
D	70	72	62	80	42	90	32	832	0.039	15	45
F	72	73	63	81	41	92	30	967	0.015	5	81

TABLE 4. CatBoost results on machine segments.

Blocs	Accuracy	Recall		F1-score		Precision		Iteration	Learning rate	Depth	Leaves
		Conf.	N.Conf.	Conf.	N.Conf.	Conf.	N.Conf.				
C	69	70	66	78	49	88	39	781	0.027	9	512
G	70	71	66	79	50	88	41	550	0.099	9	512
J	70	71	63	80	39	92	28	508	0.068	6	64
H	70	72	64	77	55	83	48	588	0.021	10	1024
D	72	74	62	81	43	90	32	644	0.087	8	256
F	72	74	64	82	43	91	32	661	0.031	7	128

TABLE 5. XGBoost results on machine segments.

Blocs	Accuracy	Recall		F1-score		Precision		Iteration	Learning rate	Depth	Leaves
		Conf.	N.Conf.	Conf.	N.Conf.	Conf.	N.Conf.				
C	69	70	65	78	46	88	36	705	0.016	7	74
G	69	70	68	78	49	88	39	703	0.048	9	31
J	70	73	57	81	38	90	29	729	0.035	5	171
H	70	74	61	78	54	82	48	746	0.022	14	87
D	73	77	56	83	42	89	34	972	0.025	12	48
F	71	73	62	81	40	91	29	845	0.006	5	44

0.05 bar increments, reflecting operator adjustment practices.

4) **Data Balancing**: A dataset is considered imbalanced if the minority class constitutes less than 35% of the data [22]. In this project, the minority class represents 22%. To address this, observation weighting was employed. This approach ensures better representation of minority classes without altering the data structure, unlike oversampling, which can introduce duplicates or synthetic samples, risking overfitting [23]. Moreover, weighting is computationally efficient as it maintains the dataset's size. We used the *compute_sample_weight* function from Python's *sklearn.utils* library to calculate weights.

TABLE 6. LSTM results on machine segments.

Blocs	Accuracy	Recall		F1-score		Precision	
		Conf.	N.Conf.	Conf.	N.Conf.	Conf.	N.Conf.
C	68	74	45	79	37	84	31
G	64	67	52	74	39	83	31
J	67	71	47	78	31	87	23
H	64	72	45	74	42	77	39
D	70	76	41	80	32	86	26
F	72	78	39	83	30	88	25

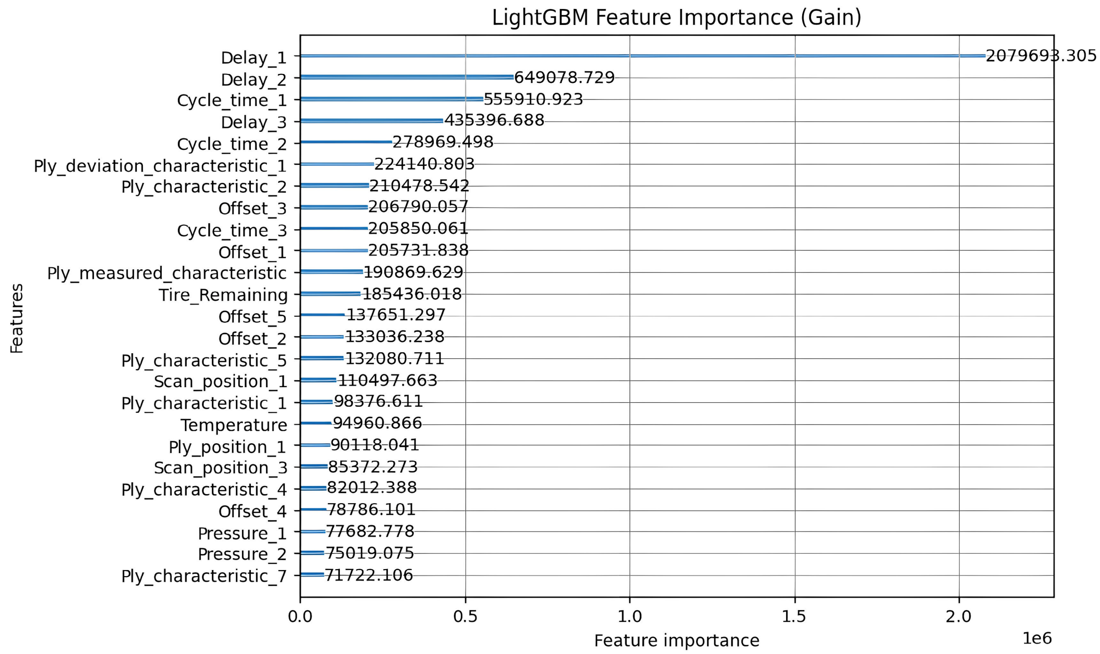

FIGURE 8. Attribute importance based on gain criterion.

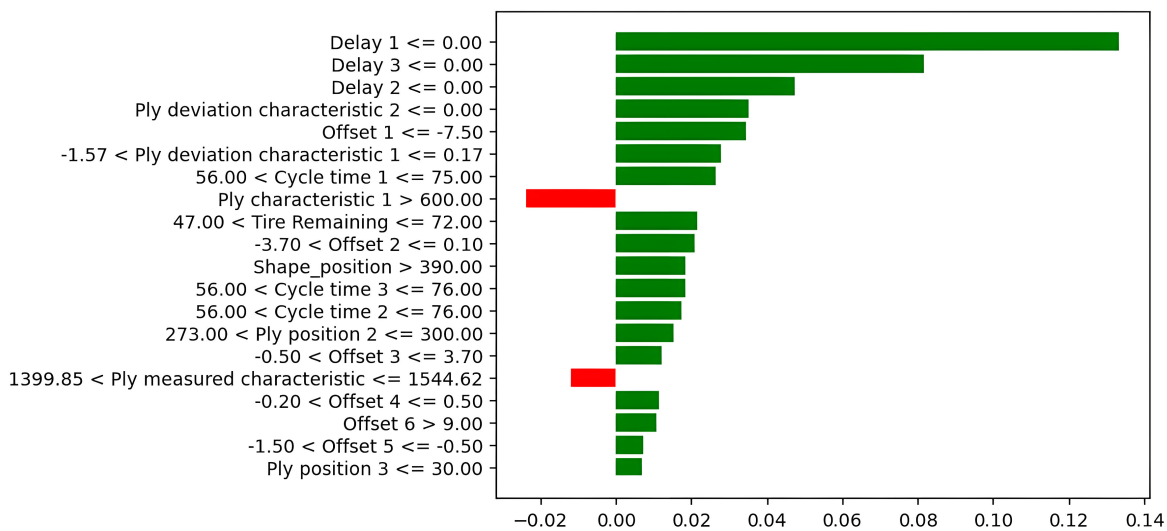

FIGURE 9. LIME for a predicted observation conforming to specifications.

C. MODELING

To ensure the reliability and generalizability of this study, several measures were taken to minimize confounding factors. First, we focused on automatic tire assembly machines of the same generation to ensure performance comparability. Contextual data, including factory temperature, humidity,

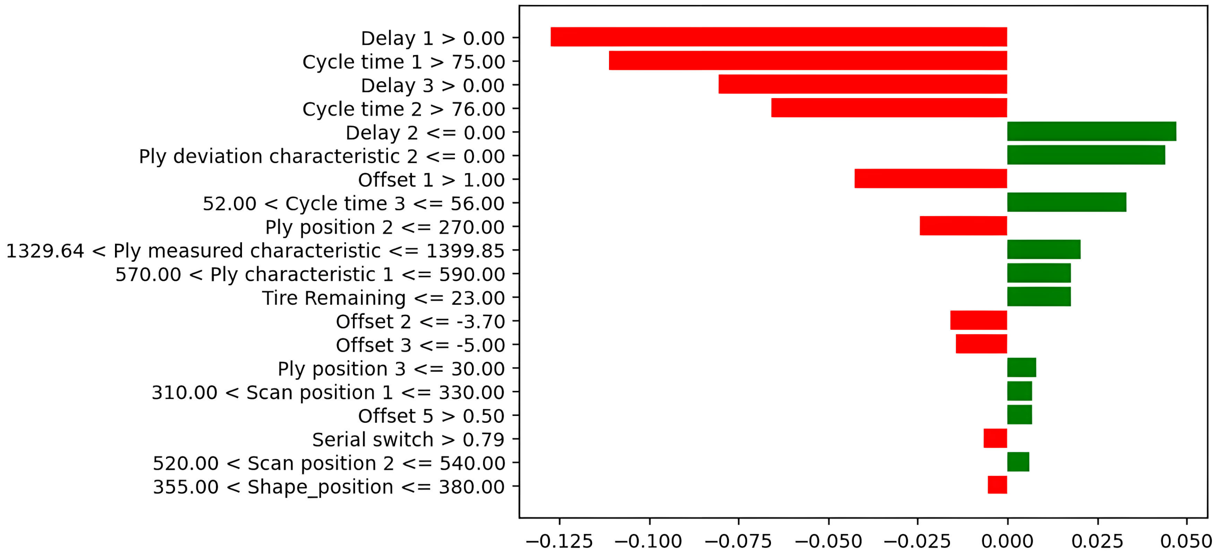

FIGURE 10. LIME for a predicted observation non-conforming to specifications.

TABLE 7. Results from the GMM approach.

Attribute	MAE(%)	RMSE(%)
Target_1_Length_Right	32.88	42.73
Target_1_Length_Middle	**13.41**	**17.43**
Target_1_Length_left	31.95	41.53
Target_2_Length_Right	19.66	25.92
Target_2_Length_Middle	17.20	22.35
Target_2_Length_left	19.94	25.92
Target_3_Length_Right	19.65	25.54
Target_3_Length_Middle	19.27	25.04
Target_3_Length_left	19.13	24.87

and the storage duration of semi-finished materials, were incorporated to account for their impact on production, particularly on the quality of rubber. The subsequent step involved the segmentation of the machines according to shared operational conditions. These conditions included maintenance schedules, calibration protocols, and usage patterns. This approach establishes more homogeneous groups allowing models to capture machine-specific behaviors while maintaining generalizability.

Each cluster is treated independently and undergoes 5-fold cross-validation to ensure an optimized train-test split and mitigate overfitting. This technique systematically tests models on multiple data subsets, providing a robust and unbiased performance evaluation across all selected models. The models include Categorical Boosting (CatBoost), Light Gradient Boosting Machine (LGBM), Extreme Gradient Boosting (XGBoost), and Long Short-Term Memory (LSTM). For LSTM, which captures sequential dependencies in manufacturing data, 5-fold cross-validation is particularly important as it helps prevent overfitting to time-dependent patterns, which is crucial in industrial processes where seasonal fluctuations and recurring trends can influence model performance. To further improve model accuracy, hyperparameters are fine-tuned using Optuna [25]. This optimization framework efficiently explores the hyperparameter space, enhancing the performance of the models by identifying the most effective parameter settings.

Two alternative approaches are tested. The first eliminates clustering, training a single model on the entire dataset. The second, inspired by [18], employs a multiple regression model predicting the lengths of nine dependent tire joint variables. Optimal segmentation is determined using the Bayesian Information Criterion (BIC), with the Elbow Method suggesting 14 of 15 segments yield the lowest BIC. However, seven segments are used, as the marginal gain beyond this is negligible.

D. VALIDATION

Table 2 presents the classification results using the models *CatBoost*, *LGBM*, *XGBoost*, and *LSTM* supplemented by optimization options provided by Optuna [25] and weight sampling. The models demonstrate similar performance levels. The results obtained by combining parameter optimization and weight sampling help balance the performance between the minority and majority classes.

In real-time industrial applications, the acceptable number of iterations and learning rate largely depend on the size of the data. For our study, 500 to 1000 iterations are considered acceptable to mitigate the risk of overfitting, while learning rates between 0.01 and 0.1 are commonly used. These parameters are determined based on experience, balancing model precision with computational cost. The results, though comparable, vary based on model parameters. The *CatBoost* model achieves optimal performance after 490 iterations, with a learning rate of 0.02 and a depth of 12 levels. The *LGBM* model reaches its best performance after 790 iterations, with a learning rate of 0.046, a depth

TABLE 8. Performance metrics of attributes for Segments A and B.

Attribute	Segment A		Segment B	
	MAE (%)	RMSE (%)	MAE (%)	RMSE (%)
Target_1_Length_Right	0.6817 (33.32%)	0.8532 (41.71%)	0.6551 (13.08%)	0.8389 (16.75%)
Target_1_Length_Middle	**0.6030 (7.30%)**	**0.7975 (9.65%)**	**0.5283 (5.80%)**	**0.6655 (7.31%)**
Target_1_Length_left	0.6437 (30.31%)	0.8049 (37.91%)	0.5727 (11.27%)	0.7316 (14.40%)
Target_2_Length_Right	0.8797 (14.35%)	1.1014 (17.96%)	0.6969 (10.93%)	0.8713 (13.66%)
Target_2_Length_Middle	0.7173 (10.20%)	0.9149 (13.00%)	0.6046 (8.02%)	0.7629 (10.12%)
Target_2_Length_left	0.8853 (14.32%)	1.1137 (18.01%)	0.6976 (10.88%)	0.8703 (13.58%)
Target_3_Length_Right	0.8745 (14.24%)	1.0948 (17.83%)	0.9175 (14.24%)	1.1530 (17.89%)
Target_3_Length_Middle	0.7533 (11.56%)	0.9561 (14.68%)	0.7128 (10.56%)	0.8939 (13.24%)
Target_3_Length_left	0.8919 (13.66%)	1.1165 (17.09%)	0.9745 (14.02%)	1.2235 (17.60%)

of 9 levels, and 90 leaves. In contrast, *XGBoost* performs best with 995 iterations, a learning rate of 0.039, a depth of 9 levels, and 188 leaves. Given these results, *LGBM* may be the most suitable for visualizing and interpreting trees, as it is faster than both *XGBoost* and *LSTM*, and slightly quicker than *CatBoost*.

By designing multiple models by segmenting the entire dataset into sub-datasets based on industrial expertise and applying sample weighting and Bayesian search for hyper-parameters, same as the first. The results, presented in Tables 3, 4, 5, and 6 show similar performance across segments in terms of recall for both classes. However, *segment G and H* stand out with higher *Precision* and *F1-scores*, likely due to the ratio between the conforming and non-conforming tire classes. The disparity observed in the precision values of the different models can be attributed to the percentage of the minority class within the dataset. The proportions of the minority class for *segment H, G, C, D, J, and F* are 28%, 22%, 21%, 17%, 16%, and 15%, respectively. These observations are consistent across the various tested models, with one notable exception: the *LGBM* model consistently delivers the best results.

In the final strategy, the individual performances vary from one segment to another. This leads to reduced overall performance due to the poor results from specific segments, as illustrated in Table 7. Table 8 presents the performance metrics of two segments among the seven, highlighting the variability that impacts the overall model performance.

E. EXPLAINABILITY

Figure 8 illustrates the importance of the features by measuring the reduction in the loss criterion when a feature is used for a split within a decision tree. The figure confirms the hypothesis that the characteristics of previous tires are significant in predicting the conformity of the tire currently being assembled. Furthermore, it validates our assumption that the adjustment of the lengths of the carcass layers or the impermeable layer plays a crucial role in this prediction. Weather factors and the duration of storage of the layers within the factory are positioned in the last third of the list in this graph.

While figure 8 highlights the relative importance of each variable in the prediction process, it does not reveal the direction in which adjustments should be made. Our goal is to provide operators with a tool that, for each new tire in the assembly phase, not only identifies relevant attributes but also clarifies how these attributes influence the specifications. This would allow for determining the direction of necessary adjustments for modifiable parameters. This requirement led us to adopt Local Interpretable Model-agnostic Explanations (LIME) [24] to clarify these aspects.

The graphs shown in Figures 9 and 10, based on LIME, provide a tool for determining the importance of each attribute in the predicted value, indicated by the height of the bars, as well as the direction of their influence on this value.

In Figure 10, which illustrates a predicted observation classified as non-conforming, it is observed that the non-adjustable parameters, including Cycle time 1 exceeding 75 seconds, Cycle time 2 exceeding 76 seconds, and Ply position 2 being below 270 mm, are associated with an increased likelihood of producing a non-conforming tire as well as the occurrence of a serial switch. Regarding the adjustable parameters, the analysis reveals that deviations in Offset 1, Offset 2, and Offset 3 beyond 1 mm, while remaining below 3.7 mm and 5 mm, respectively, significantly elevate the risk of a tire being classified as non-conforming.

These two techniques would enable the design of an interface that could be provided to operators based on the model, as shown in Table 9.

The table presents an active tire that is potentially non-conforming and suggests an increase in pressure while recommending no adjustment for the length of the plies. It also provides forecasts for the following three tires and suggestions for adjusting the parameters for upcoming production. The interface enables the operator to increase or decrease pressure and length, confirm the adjustments, acknowledge the alert without action, or skip the adjustment.

TABLE 9. Decision support system interface.

Decision Support System Interface			
Status: [Likely Non-conforming]			
Pressure: 0.05 bar **Humidity:** 21% **Material #:** 12345			**Length:** 1200 mm **Temperature:** 24°C **Length Remaining:** 50 m
The upcoming tire is likely non-conforming. Please adjust settings for the next tire:			
Pressure: INCREASE (±0.05 bar)			
	[-]	0.5 bar	[+]
Length: No adjustment needed (±1 mm)			
	[-]	1200 mm	[+]
Previous Tires:			
Tire #104: No adjustment needed Tire #103: Increase Pressure Tire #102: Decrease Material Length			
	[Confirm Adjustment]	[Acknowledge Alert]	[Skip Adjustment]

V. CONCLUSION

In this paper, we proposed an innovative approach for predicting the output of an assembly process based on input variables, including process parameters, material characteristics, and operational environmental conditions. This approach allows us to explore the large-scale and digitized manufacturing industry by exploiting industrial data. Specifically, we leverage heterogeneous data (both categorical and numerical) or apply domain-specific feature engineering techniques to translate domain knowledge into data. In the modeling section, we designed a solution for multi-product processes, striking a balance between a general and specific solution. We grouped based on product- or machine-specific nuances, drawing upon historical production records.

This research could lead to the development of a decision support tool based on data collected throughout the tire assembly process. While it is not feasible at this stage to recommend specific parameter values, the tool can help users identify in advance whether a tire is likely to be defective and provide guidance on whether to increase or decrease an adjustable parameter, such as pressure or length. However, this solution remains only partially actionable, as it does not offer precise adjustment values. This limitation highlights the need for research such as the use of a complementary optimization model.

The objective was to provide a better understanding of the relationship between process parameters and the conformity of assembled tires, thereby offering additional insights to help adjust parameters for tires expected to be non-conforming. Appropriate process adjustments lead to specifications adherence, eliminating unplanned downtime due to corrections during assembly. This solution enhances machine availability and improves productivity.

Three gradient boosting models were developed and compared to determine the conformity index at the end of the assembly process. Three different modeling approaches were tested: models were trained on the entire dataset, then on subsets concerning each segment, and finally based on segments identified by GMM. The performances of the various models were relatively similar. The choice was made to use LGBM due to its transparency, which facilitates adoption and speed compared to the other two gradient-boosting models. Explainability techniques were incorporated into this model, first allowing the identification of the relative importance of attributes and then visualizing the direction of impact of each attribute for each observation to be predicted.

Although the LGBM model successfully identifies a significant number of non-conformities, achieving a recall rate of 66% for the non-conforming class, further research is necessary to improve the model's reliability, focusing on increasing the accuracy of predictions. Furthermore, it is insufficient for the tool to merely identify the most influential process parameters and suggest the direction of adjustments; it must also recommend a combination or range to achieve the desired specifications. Our future work will include reinforcement learning and metaheuristics to estimate appropriate adjustments for adjustable parameters.

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