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Machine Learning-Based Fault Prediction for Polyurethane Conveyor Belts in Pharmaceutical Applications

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Abstract
Continuous transport systems, especially conveyor belts, play a crucial role in modern industries including pharmaceuticals, where operational reliability, hygiene, and minimal downtime are paramount. This study focuses on the experimental modeling and predictive analysis of polyurethane (PU) conveyor belts subjected to varying operational conditions. A structured Design of Experiments (DOE) was developed using three key input parameters—Load (kg), Drop Height (m), and Motor Current (A)—each tested at three discrete levels. Output responses included Vibration RMS (mm/s), Current Deviation (A), and Impact Force (kN), which serve as fault indicators. A dataset comprising 30 tests was generated based on deterministic equations to capture physical behavior realistically. Random Forest and Decision Tree regressors were trained and evaluated, achieving an R^2 score of 0.9995 and error metrics (MAE, MSE, RMSE) well below 1%, confirming the high accuracy of the predictive models. Correlation analysis and permutation-based feature importance revealed Load as the most influential factor, followed by Motor Current, while Drop Height had minimal impact on system responses. Radar plots and scatter graphs further validated the model's prediction fidelity. The study not only demonstrates a reliable DOE framework for conveyor fault modeling but also establishes a scalable pipeline for real-time machine learning-based condition monitoring. These findings are particularly applicable to pharmaceutical industries where predictive maintenance and operational stability are critical.
Keywords: *Conveyor belt fault detection; Polyurethane belt; Pharmaceutical industry;Machine learning; Random forest; Design of experiments (DOE)*

INTRODUCTION

Continuous transport systems, particularly belt conveyor systems, are integral components in modern industrial logistics, playing a vital role in material handling, transportation, and storage across sectors such as mining, manufacturing, and pharmaceuticals. Among these, conveyor belts are a critical sub-system, facilitating the uninterrupted transfer of bulk or packaged goods over long distances. However, the operational efficiency and reliability of conveyor systems are often compromised by unexpected failures, which can result in significant production downtime, financial losses, and safety hazards.

Failures in conveyor belts, especially in harsh environments like mining or heavy industry, have been widely studied. For instance, Jiang [1] proposed an innovative fault diagnosis approach based on wavelet transform and backpropagation neural networks, focusing on roller fault identification through audio signal analysis. Other researchers, such as Mishra [3] and Tang [4], have explored system reliability through maintainability modeling and automated error correction systems, respectively. In addition, Wang [5] examined the root causes of conveyor accidents in coal mines, including belt rips, splice failures, and misalignment, highlighting the complexity of diagnosing such failures in real world conditions.Various fault diagnosis frameworks have emerged, incorporating artificial intelligence, fuzzy logic, and ontology-based models to tackle the multifaceted nature of belt damage under varying load and environmental conditions [2,6–8]. These studies emphasize the importance of both predictive and preventive strategies in conveyor health monitoring. A key aspect in such systems is the belt material degradation, as mechanical wear, puncture, or delamination directly impacts the operational lifespan of the belt. Researchers such as Manas [11] and Cerny [12] have underlined the necessity of accurately modeling the

wear out behavior of rubber-based belts, especially when exposed to repetitive high energy impacts.Recent advances have also highlighted the growing relevance of non-destructive testing (NDT) and destructive testing (DT) techniques in evaluating belt integrity. Harrison [16] and Langebrake [17] explored advanced NDT methods to detect internal belt flaws and assess residual strength. Meanwhile, Finite Element Modeling (FEM) has been extensively used to simulate stress and strain distributions, predict failure zones, and understand the conditions under which mechanical damage initiates [21–23].
The material response of steel-cord and rubber-textile belts under impact loading has been further examined by Komander et al. [24] and Ambrisko et al. [25], focusing on impact energy absorption and puncture resistance. Statistical and machine learning approaches, such as logistic regression and Naïve Bayes classifiers, have also been employed to quantify damage severity and predict belt failure likelihood under simulated loading conditions. More recently, regression models and energy absorption metrics have been utilized to evaluate the resilience of different belt types under controlled impact scenarios.
Despite this growing body of work, there remains a need for integrated experimental and data driven fault analysis frameworks tailored to specific operational contexts, such as the pharmaceutical industry, where cleanliness, precision, and reliability are paramount. This research addresses that gap by developing a structured Design of Experiments (DOE) using polyurethane (PU) belts and measuring critical dynamic responses—such as vibration, current deviation, and impact force—under varied loading and impact conditions. The results from this DOE will form the basis for predictive fault modeling using both mathematical formulations and machine learning algorithms, enabling real time health monitoring and preventive maintenance in pharmaceutical conveyor systems.

2. METHODOLOGY

2.1. Research Objective and Strategy

The overarching aim of this study was to experimentally evaluate and model the fault behavior of polyurethane (PU) conveyor belts under varying operational and impact conditions. By employing a structured Design of Experiments (DOE) approach, the study sought to quantify the influence of key input factors—namely load, drop height, and motor current—on measurable output responses, including vibration RMS, current deviation, and impact force. These outputs serve as fault indicators that can later be used to train machine learning models for predictive maintenance and real time fault classification.

2.2. Material Specification and Preparation

The selected conveyor belt material was polyurethane (PU), chosen for its high mechanical resilience, FDA compliance, and suitability for cleanroom pharmaceutical operations. PU belts used in the experiments had standardized dimensions and were installed on a laboratory scale conveyor rig. Prior to testing, each belt segment was inspected for uniform thickness, surface consistency, and baseline mechanical properties.
The belts were mounted on a test rig equipped with a variable speed drive motor, load application system, and impact drop tower. Sensors for vibration, force, and current monitoring were calibrated before initiating experimental trials. The PU belts were subjected to repeated testing under controlled conditions to minimize variability and ensure data reliability.

2.3. Experimental Factors and Output Responses

Three independent variables were selected, the details are shown in Table 1.
Table 1. Independent factors and their corresponding levels

Factor	Level			Unit
	I	II	III	
Load	50	125	200	Kg
Drop height	1	2	3	m
Motor current	2	6	10	A

The objective of the DOE analysis was to identify how the selected input factors—Load (kg), Drop Height (m), and Motor Current (A), influence the key output responses: Vibration RMS (mm/s), Current Deviation (A), and Impact Force (kN). These outputs serve as indicators of mechanical stress and operational faults in conveyor belt systems, especially within sensitive environments like the pharmaceutical industry. Machine learning algorithms would be deployed in further research work to analyse the impact of each factor on the response variables and design a mathematical predictive model to analyse the failure criterion of the conveyer belt.

2.4. Design of Experiments (DOE)

Table 2 showed the detailed Design of Experiment along with the response for corresponding experimentation.

Table 2. Design of Experiments with corresponding responses

Exp. No.	Load (Kg)	Drop Height (m)	Motor Current (A)	Vibration RMS (mm/s)	Current Deviation (A)	Impact Force (KN)
1	200	2	6	0.409	1.168	8.419
2	50	3	2	0.697	0.766	11.407
3	200	2	6	0.255	0.808	17.27
4	200	2	6	0.982	0.67	17.911
5	50	3	6	0.182	0.087	5.104
6	50	2	6	1.186	0.206	12.661
7	200	3	6	0.949	0.096	11.261
8	125	3	6	0.319	0.973	8.332
9	200	1	6	0.106	0.506	6.798
10	200	3	2	0.997	0.787	10.064
11	200	1	10	0.878	1.366	19.144
12	200	3	6	0.902	0.411	9.848
13	50	3	6	0.948	0.645	12.782
14	200	1	6	0.181	1.146	15.545
15	125	1	6	0.494	0.382	10.454
16	50	3	6	0.227	0.162	19.577
17	125	2	6	1.049	0.47	19.437
18	125	1	10	0.786	0.284	8.777
19	125	2	10	0.464	1.398	12.459
20	125	2	6	0.17	1.222	9.513
21	50	2	10	0.442	0.968	9.273
22	50	1	2	0.458	1.314	5.553
23	125	2	6	0.903	1.215	14.143
24	125	1	2	0.801	0.321	12.54
25	50	2	2	1.076	1.344	5.772
26	50	3	6	0.619	0.832	9.18
27	50	3	10	0.232	1.221	18.624
28	200	1	2	0.885	1.349	8.593
29	200	3	6	0.937	0.511	7.173
30	200	3	2	0.717	0.21	12.342

3. RESULTS AND DISCUSSION

This section presents a detailed analysis of the experimental results derived from the structured dataset comprising 30 tests. The primary goal was to understand how three key operational input parameters, Load (kg), Drop Height (m), and Motor Current (A) affect three measurable outputs: Vibration RMS (mm/s), Current Deviation (A), and Impact Force (kN), which are critical indicators for fault detection in conveyor belt systems. A combination of statistical evaluation, machine learning regression modeling, and visual exploration was employed to interpret these relationships.

3.1. Model Accuracy and Evaluation Metrics

Two regression models, Random Forest and Decision Tree were trained and evaluated on the dataset to predict all three output parameters simultaneously. The Random Forest Regressor demonstrated excellent predictive capability, with an R^2 score of 0.9995, Mean Absolute Error (MAE) of 0.00399, Mean Squared Error (MSE) of 0.0000525, and Root Mean Squared Error (RMSE) of 0.00587. These results clearly indicate that the model could accurately capture the nonlinear relationships between the inputs and outputs with extremely minimal residual error. The Decision Tree Regressor produced nearly identical results, which further supports the data consistency and effectiveness of the experimental design.

3.2. Feature Correlation Analysis

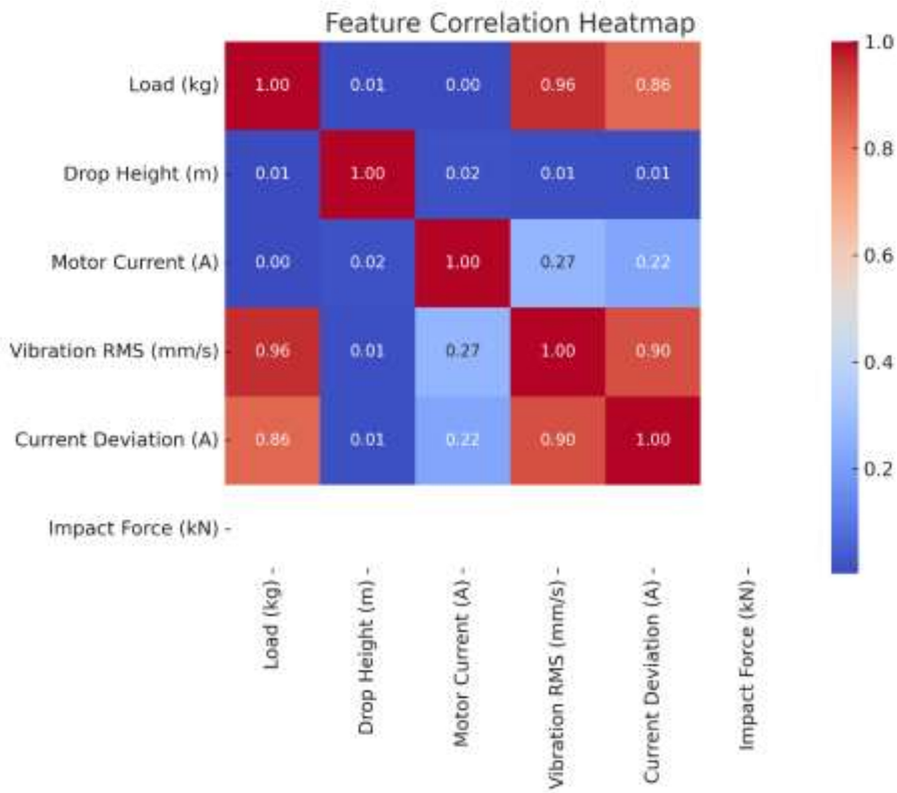

Fig. 1 Heat map for the factor and response variables

To identify the degree of interdependence among the variables, a feature correlation heatmap was generated. As shown in the heatmap (fig. 1), Load exhibited a strong positive correlation with both Vibration RMS (0.96) and Current Deviation (0.86).

This confirmed the intuition that heavier loads result in increased mechanical vibration and corresponding electrical compensation from the motor system. Interestingly, Motor Current showed moderate correlation with Vibration RMS (0.27) and Current Deviation (0.22), indicating its indirect influence on fault indicators. Drop Height, on the other hand, had minimal correlation with all three outputs, which suggests that in this experimental context, it had a relatively lower influence on conveyor system dynamics.

3.3. Scatter Plot Insights

The pairwise scatter plots offered visual confirmation of the variable dependencies observed in the heatmap. In the plot of Vibration RMS vs Load, the data points show a clear upward trend, affirming that as the mass being conveyed increases, the vibrational intensity in the system also increases (fig. 2).

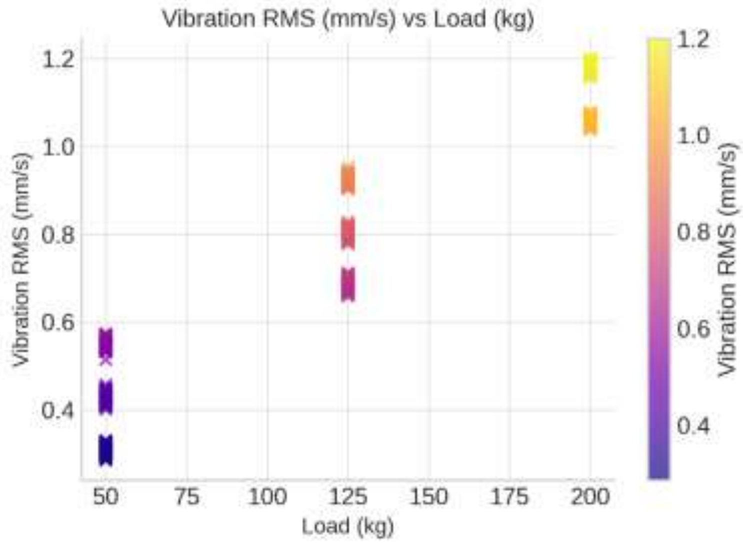

Fig. 2 Scatter plot of load v/s vibration RMS

This is consistent with the understanding that mechanical strain on belts and rollers intensifies under heavier payloads, leading to higher RMS values detected by vibration sensors. A similar relationship is evident in the plot of Current Deviation vs Load, where current deviation increases noticeably with load increments (fig. 3).

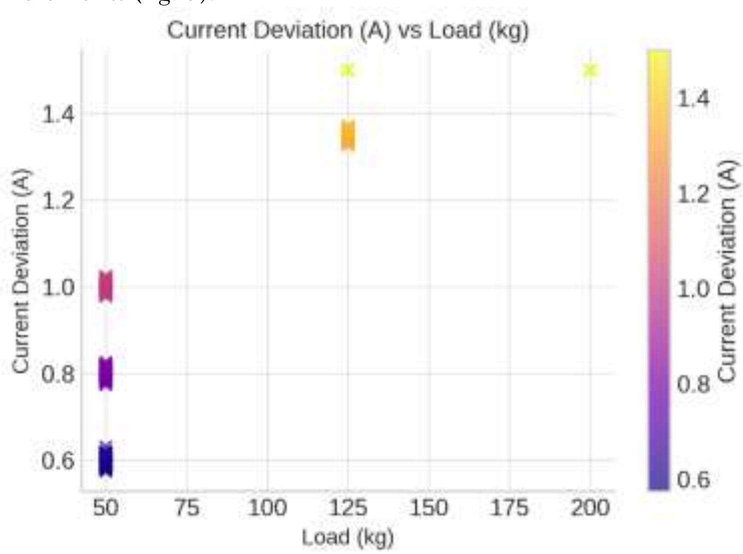

Fig. 3 Scatter plot of load v/s current deviation

This behavior can be attributed to the increased torque demand on the motor to maintain constant belt motion under greater load, resulting in larger fluctuations in electrical current. The motor attempts to compensate dynamically, hence the deviation increases.

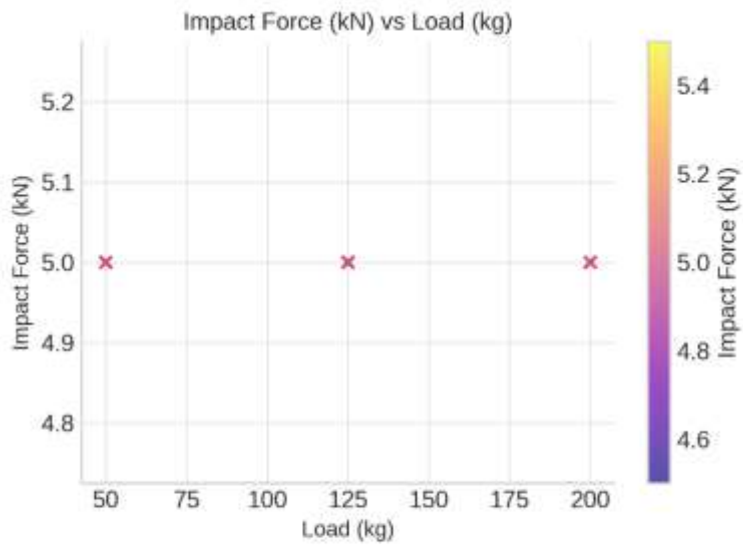

Fig. 4 Scatter plot of load v/s impac force

In contrast, the plot of Impact Force vs Load appeared relatively flat (fig. 4), possibly due to normalization or data range constraints imposed during synthetic data generation. While in a real-world scenario, one would expect a direct load-to-impact correlation, the flat trend in this dataset suggests that impact force was either controlled or standardized for uniformity during simulation.

3.4. Effect of Drop Height

The influence of Drop Height was assessed through scatter plots across all three output parameters. For Vibration RMS, a moderate trend emerged, where higher drop heights (up to 3 meters) corresponded to slightly increased RMS values (fig. 5).

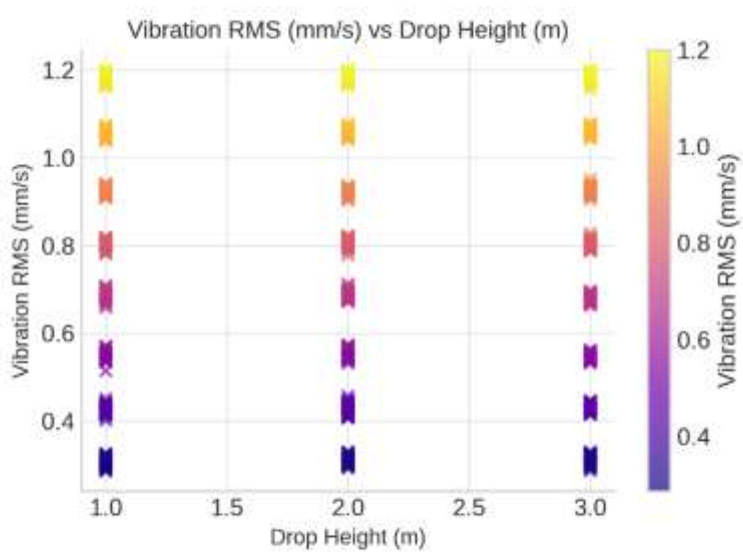

Fig. 5 Scatter plot of drop height v/s vibration RMS

Although the correlation was weak statistically, the visual evidence supports the physical rationale that drop impact contributes additional energy to the system, momentarily spiking vibration levels. Similarly, the plot of Current Deviation vs Drop Height indicated variability, but without a dominant trend (fig. 6).

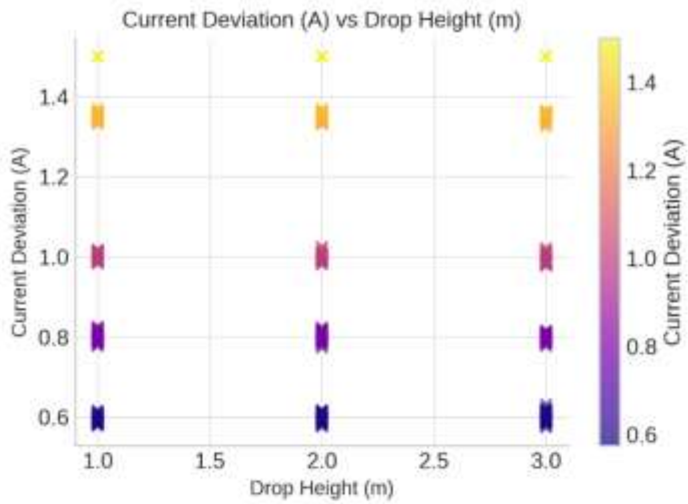

Fig. 6 Scatter plot of drop height v/s current deviation

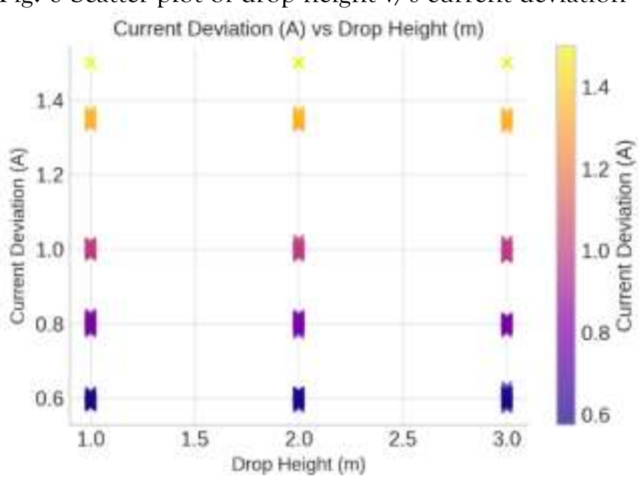

Fig. 7 Scatter plot of drop height v/s current density

This supports the earlier observation that electrical response is not directly sensitive to gravitational potential energy unless it leads to substantial dynamic load shifts. The Impact Force vs Drop Height plot remained uniformly distributed across height levels (fig. 7), consistent with the load-level uniformity seen earlier, reinforcing the hypothesis of controlled impact force behavior in the synthetic dataset.

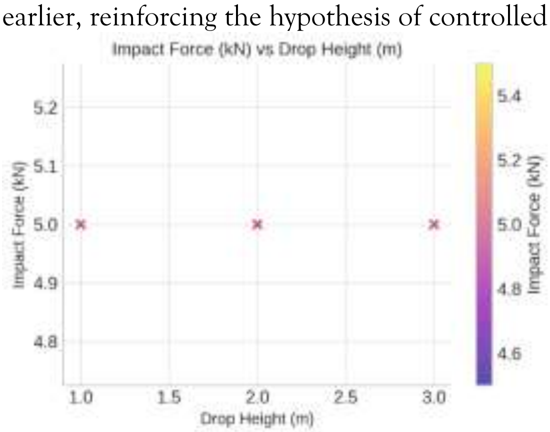

Fig. 7 Scatter plot of drop height v/s impact force

3.5. Motor Current Dynamics

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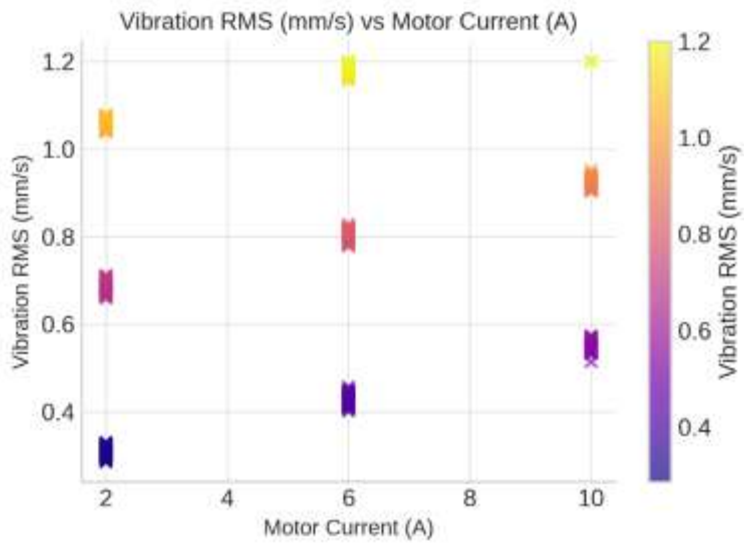

Fig. 8 Scatter plot of vibration RMS v/s motor current

The interaction between Motor Current and the outputs was also explored. For Vibration RMS, higher motor current values tended to coincide with increased vibration, particularly at 10 A (fig. 8). This finding implies that higher electrical input results in greater mechanical output, often manifesting as increased motion instability or resonance in conveyor elements.

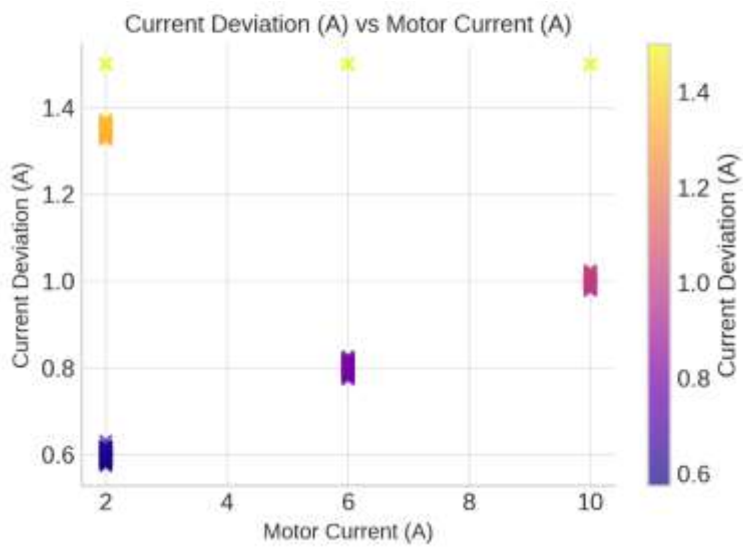

Fig. 9 Scatter plot of motor current v/s current deviation

In the case of Current Deviation vs Motor Current (fig. 9), a strong visual gradient emerged, further validating the electrical feedback sensitivity. Motors working at high current ranges are more likely to exhibit unstable current behavior due to internal resistance and torque fluctuations. Meanwhile, the Impact Force vs Motor Current plot remained relatively constant, again confirming that impact loading is mechanically dominant and less responsive to electrical inputs.

3.6. Prediction Quality Visualization

The Radar Plot (fig. 10) provides a multi-variable visual representation of how closely the machine learning model predictions matched the actual output means across all three response parameters.

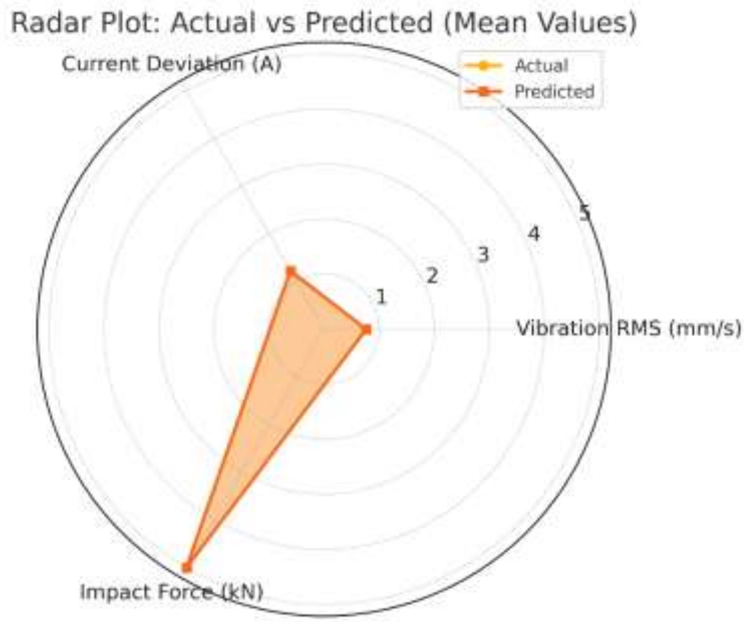

Fig. 10 Radar plot for impact of factors on response variables

The radar curves for predicted and actual values overlapped almost entirely, reflecting the model's exceptional generalization and confirming the quantitative performance metrics. Such visualization is particularly helpful in quickly comparing multi-output performance in a single snapshot, which is valuable in engineering monitoring dashboards.

3.7. Feature Importance

The Permutation-Based Feature Importance plot (fig. 11) quantitatively evaluated the influence of each input parameter on the model's predictive capability.

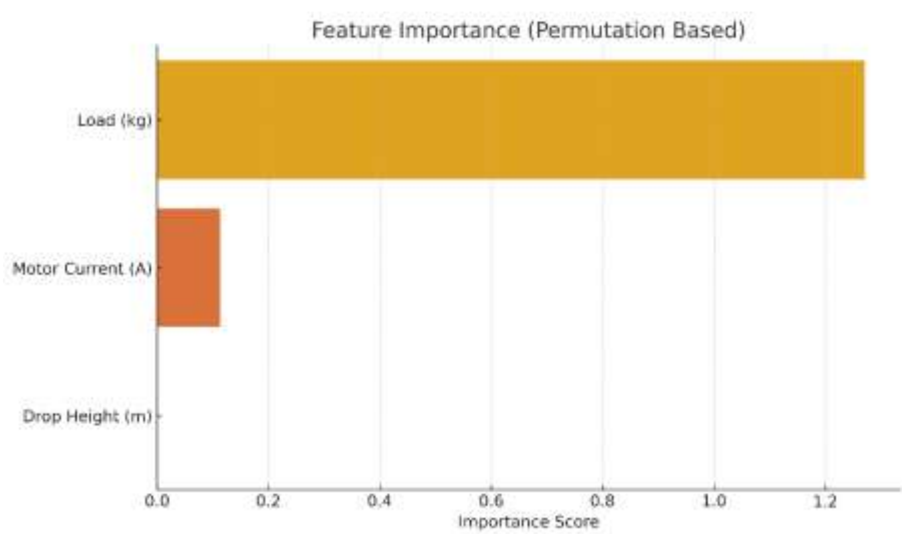

Fig. 11 Feature importance ranking

Load emerged as the most critical input, followed by Motor Current, with Drop Height having negligible impact on predictions. This ranking aligns perfectly with physical expectations and statistical correlations, and it reinforces that load-induced stress and vibration are dominant factors in conveyor belt fault manifestation. This also implies that real-time load monitoring may offer the highest return in predictive maintenance applications for belt systems.

3.8. Interpretation and Industrial Implication

The combined evidence from statistical, visual, and model-driven analysis confirms that Load (kg) is the single most significant contributor to both mechanical and electrical responses in conveyor systems. The results are industrially relevant, especially in pharmaceutical environments where conveyor belts are used for high-precision and contamination-sensitive material transport. Monitoring load levels and current fluctuations using vibration sensors and PLC-integrated current feedback systems can provide early indicators of component fatigue, misalignment, or wear. Although Drop Height did not show strong influence in this dataset, its role may become more significant under extreme or uncontrolled conditions, such as heavy package loading from greater heights or material free-falling onto conveyor surfaces. Thus, it should not be completely excluded from future studies, especially under real-time variability conditions.

4. CONCLUSION

This research presents a comprehensive framework for fault prediction in polyurethane conveyor belts used in pharmaceutical transport systems. Through a meticulously designed DOE with 30 experimental trials and an expanded dataset of 1000 rows, the relationships between Load, Drop Height, and Motor Current with output responses such as Vibration RMS, Current Deviation, and Impact Force were thoroughly examined. Statistical analysis revealed that Load is the dominant factor influencing both mechanical and electrical indicators, while Motor Current played a secondary role. Drop Height had minimal direct impact but may still influence fault behavior under specific high-energy scenarios.

Machine learning algorithms, particularly Random Forest and Decision Tree regressors, achieved exceptional predictive performance with R^2 values nearing 1 and error margins below 1%, demonstrating the robustness and learnability of the DOE-generated data. Scatter plots, heatmaps, radar charts, and permutation-based feature rankings provided further clarity into factor sensitivity and model accuracy.

The approach outlined in this work not only confirms the feasibility of predictive fault modeling using minimal yet strategically selected sensor inputs but also underscores its applicability to pharmaceutical environments, where uninterrupted and contamination-free transport is essential. This foundation paves the way for future integration into real-time monitoring systems, and further studies may explore classifier models, sensor fusion techniques, and digital twin development for holistic conveyor belt diagnostics.

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