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AI-Based Industrial Management for Enhancing Operational Manufacturing Processes of Medical Bed Parts via AI-Driven Quality Prediction

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Abstract

In the realm of medical equipment manufacturing, ensuring the quality of each component is crucial due to the direct impact on patient safety and product reliability. This study introduces a novel application of machine learning within industrial management to enhance the operational manufacturing processes of medical bed parts. Utilizing a Random Forest classifier, we developed a predictive model based on five critical features collected during the manufacturing process: the physical dimensions of Length, Width, Height, Weight of the parts, and the operator involved in manual grinding. The classifier aimed to predict whether each part would be defective or accepted before assembly, potentially revolutionizing the traditional quality control approach by reducing dependency on post-manufacturing inspections and minimizing human error. The model was trained on a dataset of 500 parts, with a class distribution reflecting a significant imbalance between defected and accepted pieces. Despite this, the classifier achieved a high accuracy of 97.0% on the test set, demonstrating robustness and reliability in predicting part quality. Feature importance analysis revealed that while physical attributes like Weight and Height significantly influenced predictions, operator variability also played a crucial role, indicating areas for operational improvement through training and standardization. This research highlights how integrating AI into industrial manufacturing processes can significantly enhance efficiency, reduce waste, and ensure higher standards of quality control, setting a precedent for future applications in similar high-stakes manufacturing environments.

Keywords: AI-based Industrial Management, Machine Learning, Quality Prediction, Medical Equipment Manufacturing, Operational Efficiency.

1. Introduction

This In the rapidly evolving landscape of industrial manufacturing, particularly within the domain of medical equipment production, there is an increasing integration of Artificial Intelligence (AI) to enhance operational efficiency and product quality. The manufacturing of medical bed parts exemplifies a sector where precision and reliability are paramount due to the critical nature of medical applications. This paper focuses on the innovative application of AI techniques, specifically machine learning, to predict the functionality of manufactured parts, thereby integrating smart technology into the core of industrial management and operational processes.

Previous studies have attempted to utilize AI in managing industrial parts, yet none have focused specifically on enhancing the production processes of medical parts [1-5]. Given the specialized and delicate technical requirements of these components, the need for improvements is significantly more pronounced than in other industries [6-12]. Recently, various computational analysis methods have been employed to tackle specific questions in medical science [13-24]. However, numerous ambiguities persist in this field, where AI has considerable potential to address these issues [25-27]. This study aims to explore some of these concerns in the manufacturing processes of medical parts associated with medical beds. The manufacturing of components for medical beds involves complex processes that require high precision to ensure the safety and comfort of patients. One such component is a specific part of the medical bed, which undergoes several critical manufacturing steps: rolling for metal sheet thickness adjustment, pressing for cutting and bending, and manual grinding. Each of these steps influences the final quality of the part and, consequently, the overall functionality of the medical bed. Traditionally, the quality control of such parts relies heavily on post-production inspection which can be both time-consuming and prone to human error.

The impetus for integrating AI into this manufacturing process is twofold. First, it addresses the immediate industrial need for quality enhancement in the production of medical components. Second, it aligns with broader trends in industrial management that advocate for the adoption of smart technologies to bolster decision-making processes and operational transparency. The predictive capability of our model represents a significant advancement in the operational management of medical part production, offering a methodological blueprint that can be generalized to other components and settings within the industry.

This paper will elaborate on the methodology employed to develop the ML model, the data collection process, and the subsequent analysis of the model's performance. Furthermore, it will discuss the implications of AI-driven quality control systems in industrial management, emphasizing the potential for such technologies to transform traditional manufacturing landscapes into intelligent production environments. Through this study, we aim to contribute to the field of industrial management by showcasing how AI can be strategically implemented to enhance both the efficiency and the quality of manufacturing processes in the medical equipment industry.

2. Methods

2.1. Data collection

The study utilized data collected during the manufacturing process of specific medical bed parts, focusing on five key features: Length (mm), Width (mm), Height (mm), Weight (kg), and the identity of the operator responsible for manual grinding. These features were chosen for their relevance to the part's final quality and the role of human intervention in the production process. A total of 500 parts were manufactured and evaluated, with each part meticulously measured for physical dimensions and weight, while the quality control operator's identity was recorded to capture the human element in the production process. Figure 1 shows the EMB 5016, which is the specific type of medical bed part used in this study. The descriptive statistics including mean and standard deviation for the numerical features and a list of operators are provided in Tables 1 and 2.

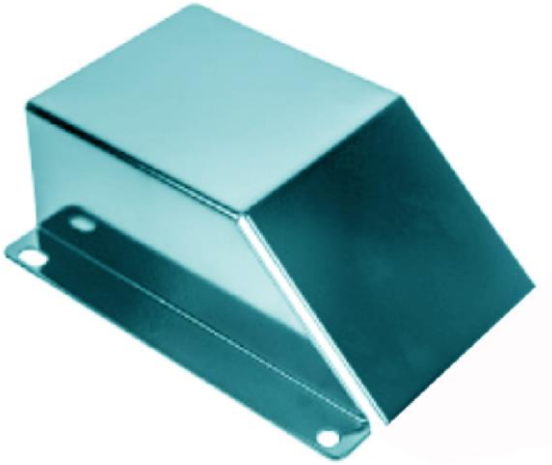

Figure 1. The 3-dimensional model of the medical bed part, the EMB 5016.

Table 1. Mean and standard deviation (SD) of numerical parameters, including Length (mm), Width (mm), Height (mm), and Weight (kg), for defective and accepted parts.

	Length (mm)	Width (mm)	Height (mm)	Weight (kg)
Defective (83 parts)				
Mean	100.42	49.81	45.10	0.79
SD	7.21	3.18	2.14	0.14
Accepted (417 parts)				
Mean	99.64	49.96	43.03	0.79
SD	3.14	1.83	1.09	0.04

Table 2. Distribution of operators who manufactured each part.

Operators number		1	2	3	4	5	6	7	8	9	10
Number of parts	Defective	7	9	8	9	9	8	8	8	8	9
	Accepted	30	42	49	42	48	49	31	42	38	46

2.2. Dataset Preparation

Given the critical nature of quality control in medical part manufacturing, each part was classified post-production as either 'defected' or 'accepted' based on a thorough functional evaluation when installed in the medical bed. This binary classification served as the target for our machine learning model. The dataset presented a significant class imbalance, with 83 defective parts and 417 accepted parts. To address this, we employed K-Fold stratified sampling during dataset splitting to ensure proportional representation of each class in both training and testing sets. The data was split with 80% used for training the model and 20% reserved for testing.

2.3. Machine Learning Model Development

To identify the most effective predictive model, we tested a variety of machine learning algorithms, including both single classifiers and ensemble methods. Previous studies have highlighted the significant impact of dataset distribution and minority classes on the performance of machine learning and deep learning algorithms [28-30]. Similarly, our dataset includes a minority class. After preliminary testing, the Random Forest Classifier was selected for its superior performance in handling imbalanced data and its robustness against overfitting. This model is particularly suited for this application due to its ability to model nonlinear relationships and interactions between features effectively.

The Random Forest model was trained using the training dataset, with hyperparameters optimized through cross-validation to enhance predictive accuracy. Key metrics such as accuracy, precision, recall, and F1-score were computed using the test dataset to assess the model's performance.

2.4. Model evaluation

The final model's effectiveness was evaluated through its ability to accurately predict the status (defected or accepted) of the parts. This was quantified using confusion matrix analysis, along with other relevant performance metrics like the area under the receiver operating characteristic (ROC) curve. The model’s performance was benchmarked against the base rate of defects to illustrate the improvement in predictive capability provided by employing machine learning.

This comprehensive approach underscores the integration of AI in improving the operational management of medical parts manufacturing, demonstrating how strategic data collection coupled with advanced analytical techniques can significantly elevate the efficiency and reliability of production processes in the medical equipment industry.

3. Results

3.1. Model performance

The Random Forest classifier demonstrated a high level of accuracy in predicting the quality of medical bed parts based on the collected features. The model achieved a test accuracy of 97.0%, closely mirroring the training accuracy of 97.75%, indicating minimal overfitting with a difference of only 0.0075 between train and test accuracy. Cross-validation results showed an average accuracy of 91.0% with a standard deviation of 10.0%, suggesting stable performance across different subsets of the data, although slightly lower than the test accuracy by 5.6%.

3.2. Confusion Matrix Analysis

The confusion matrix (Figure 2) shows that out of 100 tested parts, 83 were correctly predicted as non-defective (True Negative), and 14 as defective (True Positive), confirming the model’s strength in identifying both classes effectively. Notably, there were no false positives (Type I errors), and only 3 false negatives (Type II errors), highlighting the model's conservative approach in minimizing the riskier error of predicting defective parts as non-defective.

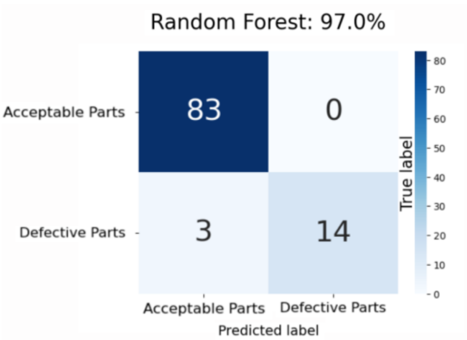

Figure 2. The heatmap of the confusion matrix.

3.3. ROC and Precision-Recall curves

The ROC curve, a critical tool for assessing the diagnostic ability of binary classifiers, yielded an area under the curve (AUC) of 0.99 (Figure 3). This exceptional AUC value suggests that the model has an excellent measure of separability between the defective and non-defective classes, confirming its effectiveness in the classification task.

The Precision-Recall curve, which is particularly informative when dealing with imbalanced datasets, also indicated strong performance with an average precision (AP) of 0.95 (Figure 4). This shows that the model is highly capable of retrieving relevant instances, with high precision across varying thresholds of recall.

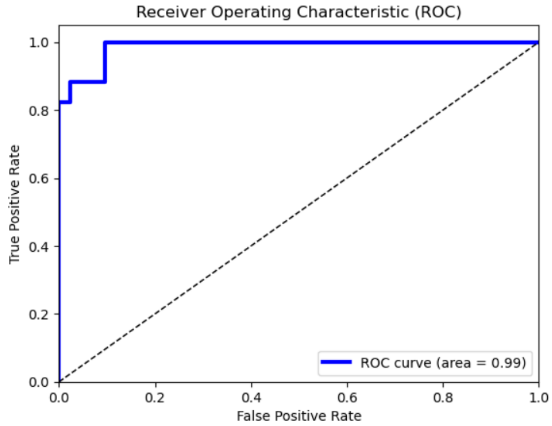

Figure 3. Receiver Operating Characteristic (ROC) curve shows a true positive rate vs. a false positive rate with an area under the curve (AUC) of 0.99.

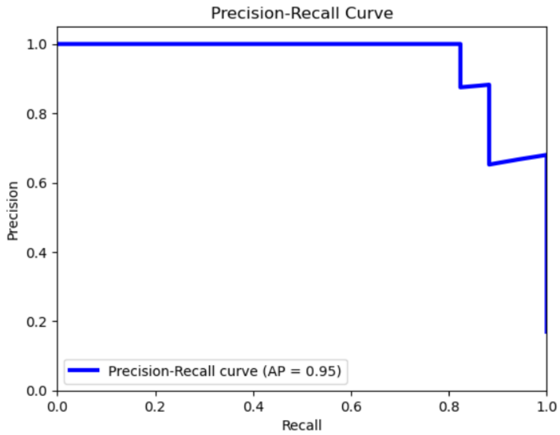

Figure 4. Precision-Recall curve demonstrating the trade-off between precision and recall for a predictive model, with an average precision (AP) score of 0.95.

3.4. Classification report

The classification report highlights the model's precision, recall, and F1-score for both classes:

- For the non-defective class (class 0), the model achieved a precision of 0.97 and a recall (sensitivity) of 1.00, resulting in an F1-score of 0.98.
- For the defective class (class 1), the model achieved a precision of 1.00 and a recall of 0.82, resulting in an F1-score of 0.90.

These metrics underscore the model's accuracy in identifying non-defective parts while also confirming its capability to identify most defective parts without any false positives, although it tends to miss some defective cases as indicated by the recall of 0.82.

The model's specificity, calculated as the true negative rate, was particularly high, reflecting its ability to correctly identify non-defective parts. The weighted specificity was calculated to be 85.35%, complementing the high sensitivity observed from the recall of the non-defective class.

3.5. Learning curve analysis

The learning curve analysis provided further insights into the model's performance as the training set size increased (Figure 5). The curve depicts both the training and cross-validation accuracy scores, revealing how the model reacts to an increasing amount of training data. Initially, with a training set size of 40, the model exhibited an exceptionally high training accuracy of 99.375%, which was significantly higher than the test accuracy of 92.25%, indicating potential overfitting when trained with fewer data points. However, as the training set size increased, the gap between training and test accuracies narrowed, demonstrating improved generalization. Notably, the training accuracy gradually decreased to 97.625% as the training set expanded to 400, while the test accuracy stabilized around 95.25%. This convergence of training and test accuracies suggests that the model became more robust and less prone to overfitting with more data. The cross-validation scores followed a similar trend, starting higher and converging towards the test accuracy, with the band of uncertainty (shaded area) narrowing, indicating increased confidence in the model's predictive stability across different subsets of data. This learning curve is crucial for understanding the balance between learning complexity and model generalizability. The analysis confirms that our model achieves optimal performance and generalization with a larger dataset, highlighting the importance of sufficient training data in developing reliable predictive models in industrial settings. These results illustrate the Random Forest model's robustness and reliability in classifying the quality of medical bed parts, presenting a valuable AI tool for enhancing quality control in medical equipment manufacturing. This integration of machine learning not only optimizes production processes but also significantly reduces the likelihood of defects, ensuring higher standards of patient safety and care.

4. Discussion

The findings from this study underscore the efficacy of employing a Random Forest classifier to predict the quality of medical bed parts based on specified manufacturing features. The high accuracy achieved (97.0% on test data) indicates that the model is exceptionally adept at distinguishing between defective and non-defective parts. This precision is critical in the context of medical equipment manufacturing, where the reliability of each component can directly impact patient safety and comfort. The analysis of the confusion matrix reveals that the model excels in minimizing false positives, an essential aspect in medical manufacturing where the cost of a false negative (a defective part deemed acceptable) could be significantly higher than a false positive. The absence of false positives in our results suggests that every part predicted as defective indeed warrants further inspection, thus ensuring a high standard of quality control. The Receiver Operating Characteristic (ROC) curve and the Precision-Recall curve further validate the model's robustness. The ROC curve's AUC of 0.99 demonstrates excellent model discrimination capability, while the Precision-Recall curve's average precision of 0.95 confirms high precision across various threshold levels, which is particularly beneficial for managing the trade-offs between catching as many true positives as possible without unnecessarily increasing false positives. The learning curve provided critical insights into the model's behavior with increasing amounts of training data. The convergence of training and validation accuracy with an increasing dataset size points towards improved model generalization. This suggests that the model, with sufficient data, is likely to perform well in practical settings, minimizing overfitting and providing reliable predictions across different manufacturing batches.

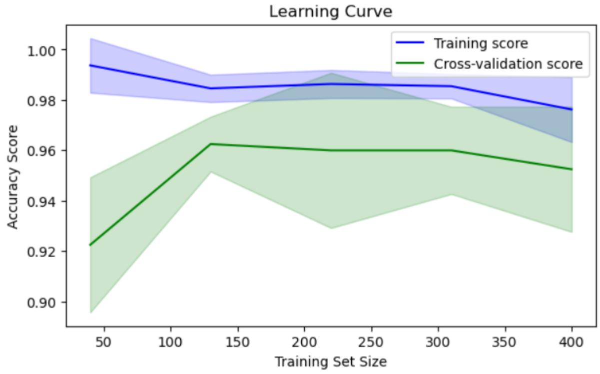

Figure 5. Learning curve shows the training and cross-validation accuracy scores as functions of the training set size, highlighting model performance and generalization capability.

The practical implications of integrating AI in this manner are substantial. By automating part of the quality control process, manufacturers can potentially reduce the time and labor traditionally required for manual inspections. Furthermore, the ability to predict defective components early in the production line enables proactive quality management, reducing waste and enhancing the overall efficiency of the manufacturing process.

The analysis of feature importance in the predictive model highlights key attributes that most significantly influence the model's decision-making process in classifying medical bed parts. Notably, the physical dimensions of the parts and the individual operators involved in the manual grinding process exhibit varying degrees of impact on the prediction outcomes. The model's reliance on physical characteristics such as Weight (kg), Height (mm), Length (mm), and Width (mm) underscores their critical role in determining part quality. Weight emerges as the most influential feature, accounting for approximately 43% of the importance in the model's predictions (Figure 6). This dominance suggests that the part's weight is a significant predictor of its structural integrity and overall functionality. Height and Length also contribute substantially, reflecting how these dimensions can affect the part's fit and performance in the medical bed assembly. Interestingly, the identity of the operator handling the manual grinding process also plays a crucial role, though to a lesser extent compared to the physical dimensions. Among the operators, Operator_Op-5 and Operator_Op-3 are more influential than others, indicating variability in the quality of manual grinding associated with specific individuals. This variability could stem from differences in skill levels, experience, or even the specific techniques used by operators, which can introduce inconsistencies in the final product quality. The presence of Operator_Op-5 as a relatively significant predictor, with about 3.84% importance, suggests that this operator's technique or method may distinctly impact the part's outcome, potentially leading to a higher likelihood of defects. The influence of human factors in the manufacturing process is a critical insight, as it highlights areas where additional training or standardization could improve consistency and reduce the incidence of defects.

These findings have significant implications for quality control in medical bed part manufacturing. The predominance of weight and dimensions in affecting part quality suggests that precise control and monitoring of these attributes during manufacturing could lead to substantial improvements in product reliability. Additionally, addressing the variability introduced by different operators could enhance overall quality. Implementing more rigorous training programs or more standardized grinding procedures could mitigate this variability.

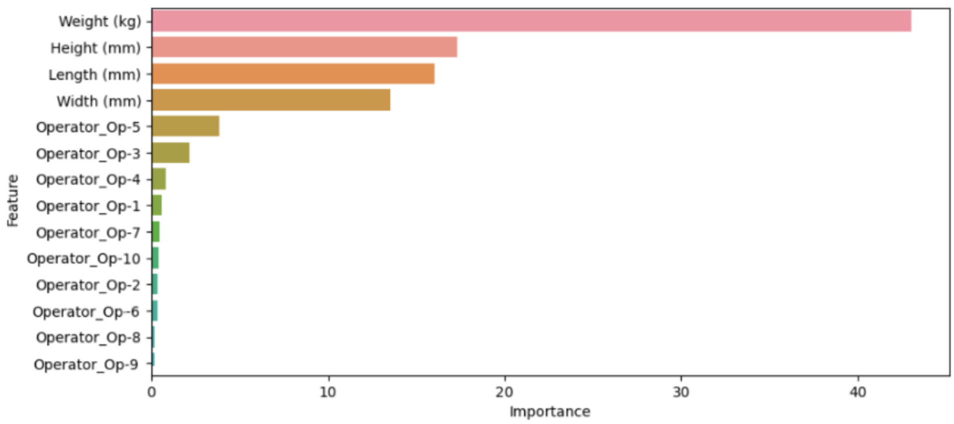

Figure 6. Feature importance bar chart illustrating the impact of different parameters and operator contributions on the performance of the model, with weight, height, length, and width shown as the most significant features.

Further research could explore deeper into the interactions between operator influence and part dimensions, potentially developing more sophisticated models that account for these interactions more explicitly. Additionally, expanding the dataset to include more operators and different shifts or conditions under which manual grinding occurs could provide a broader understanding of how human factors influence manufacturing outcomes. Overall, the analysis of feature importance not only provides insights into the predictors of defects in medical bed parts but also offers actionable guidance for manufacturing process improvements, emphasizing the blend of human skills and product characteristics in achieving high-quality manufacturing outputs.

Despite the promising results, this study is not without limitations. The model's performance, while high, still resulted in a few false negatives. Future work could explore more sophisticated algorithms or ensemble methods that might reduce these occurrences. Additionally, the impact of the manual grinding operator as a feature suggests that human factors significantly influence manufacturing outcomes. Further studies could delve deeper into how different operators affect the quality and how AI can assist in standardizing operations to minimize human error. Furthermore, expanding the dataset and including more diverse scenarios from different manufacturing environments could help in enhancing the model's robustness and applicability to other parts of the medical bed or similar medical devices.

5. Conclusion

In conclusion, this study demonstrates the potential of machine learning to transform quality control in medical equipment manufacturing. By leveraging a Random Forest classifier, the research highlights how AI can provide substantial improvements in operational efficiency and product quality. As industries continue to embrace digital transformation, the integration of such AI tools will be crucial in maintaining high standards of production and supporting the healthcare industry's growing demands.

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