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Stratification of Medical Equipment Using Clustering Algorithm and Optimized Maintenance Scheduling

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ABSTRACT

Medical equipment maintenance in healthcare facilities requires strategic prioritization to optimize resource allocation and ensure patient safety. This study presents a novel approach for stratifying medical equipment using K-means clustering algorithm combined with optimized maintenance scheduling. A comprehensive dataset of 1,973 medical equipment from X Hospital, Chennai, was analyzed using features including purchase cost, downtime, usage patterns, and preventive maintenance costs. The clustering algorithm successfully stratified equipment into three priority categories: High Priority (658 equipment, 33.4%), Medium Priority (657 equipment, 33.3%), and Low Priority (658 equipment, 33.4%). The silhouette score of 0.154 indicates reasonable clustering validity. Optimized maintenance scheduling based on priority stratification resulted in estimated annual cost savings of Rs. 1,580,337 (4.26% reduction) and downtime reduction of 20,207 days (17.1% improvement). High-priority equipment received monthly preventive maintenance intervals (30 days), medium-priority equipment received bi-monthly intervals (60 days), and low-priority equipment received quarterly intervals (90 days). The implementation requires 14,470 annual PM activities, 59,194 inspections, and 4,604 calibrations, totaling 79,584 maintenance hours annually. The study demonstrates that data-driven equipment stratification can significantly improve maintenance efficiency and reduce operational costs in healthcare settings.

Keywords: Medical equipment, clustering algorithm, maintenance scheduling, healthcare management, predictive maintenance

INTRODUCTION

Medical equipment forms the backbone of modern healthcare delivery, encompassing thousands of devices ranging from simple diagnostic tools to sophisticated life-support systems. Healthcare facilities typically manage diverse equipment portfolios with varying operational requirements, maintenance needs, and patient safety implications. Traditional maintenance strategies have historically relied on manufacturer-recommended schedules or reactive repairs following equipment failures, failing to account for varying criticality levels, usage patterns, and impact on patient care.

When diverse equipment types are managed uniformly, the result is often suboptimal resource allocation, increased operational costs, and potential safety risks. A ventilator used in an intensive care unit requires fundamentally different maintenance attention compared to a wheelchair or routine blood pressure monitor, yet many healthcare facilities apply similar maintenance protocols across all equipment categories.

The stratification of medical equipment and optimization of maintenance scheduling is increasingly recognized as a crucial strategy for enhancing reliability and operational efficiency within healthcare settings. Recent studies have underscored the importance of data-driven approaches and machine learning models in enabling effective maintenance management.

This research addresses the critical need for intelligent equipment grouping based on usage patterns and importance, enabling more focused and timely maintenance through clustering algorithms and optimized scheduling strategies.

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LITERATURE REVIEW

The application of clustering algorithms in healthcare equipment management has gained significant attention in recent years. Boppana (2023) emphasized the role of data analytics in predictive maintenance for healthcare equipment, highlighting how real-time data and advanced algorithms facilitate early fault detection and maximize equipment uptime [4].

Roy Chowdhuri et al. (2023) developed structured prioritization techniques aimed at preventing unexpected device failures, thereby supporting patient safety and continuity of care [5]. Similarly, Akpan and Anyi-Akparanta (2024) introduced hospital-based reliability models employing statistical approaches to forecast equipment failure probabilities, which guide maintenance scheduling and resource allocation more effectively [6].

Zamzam et al. (2021) showcased the application of unsupervised machine learning algorithms—particularly K-means clustering—to stratify medical equipment according to preventive, corrective, or replacement maintenance priorities. Such data-driven stratification aids clinical engineers by making workload prioritization more objective and efficient [7] .

The World Health Organization (2025) advocates for integrated inventory and maintenance management systems that enable accurate device stratification and scheduling, ensuring the safety and availability of medical devices in healthcare facilities [8].

Alahmadi et al. (2025) advanced the development of predictive maintenance models integrating machine learning and optimization algorithms, marking a transition from reactive to reliability-centered, data-informed maintenance strategies [9] . Ma et al. (2023) applied artificial intelligence to predict the remaining useful life and potential failure of medical equipment, thereby supporting proactively planned maintenance interventions [10].

METHODOLOGY

Data Collection and Dataset

The study utilized a comprehensive dataset of 1,973 medical equipment records from Kilpauk Hospital, Chennai. The dataset included equipment spanning multiple categories (A, B1, B2, C) with varying criticality levels and maintenance requirements.

Feature Selection

Four primary features were selected for clustering analysis:

- Purchase Cost (Rs.): Equipment acquisition value
- Downtime per Year (Days): Annual equipment unavailability
- Usage per Week (Hours): Weekly operational hours
- Preventive Maintenance Cost per Year (Rs.): Annual maintenance expenses

Data Preprocessing

Data preprocessing involved standardization using StandardScaler to ensure comparable feature scales across all variables. Missing values were minimal (less than 2%) and were handled through appropriate imputation techniques.

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Clustering Algorithm Implementation

K-means Algorithm: The study implemented K-means clustering with the following parameters:

- Number of clusters: 3 (determined through silhouette analysis)
- Random state: 42 for reproducibility
- Maximum iterations: 300 Initialization method: k-means++

Criticality Score Calculation: A composite maintenance criticality score was calculated using weighted features:

$$Criticality\ Score = 0.4 \times \frac{Downtime}{Max(Downtime)} + 0.3 \times \frac{PM\ Cost}{Max(PM\ Cost)} + 0.3 \times \frac{Usage}{Max(Usage)}$$

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Optimization Framework

Priority-based maintenance intervals were established:

- **High Priority**: 30-day PM intervals, 7-day inspections, 90-day calibrations
- **Medium Priority**: 60-day PM intervals, 14-day inspections, 180-day calibrations
- **Low Priority**: 90-day PM intervals, 30-day inspections, 365-day calibrations

RESULTS AND DISCUSSION

Clustering Results

The K-means algorithm successfully stratified the 1,973 medical equipment into three distinct priority categories with nearly equal distribution, as shown in Figure 1.

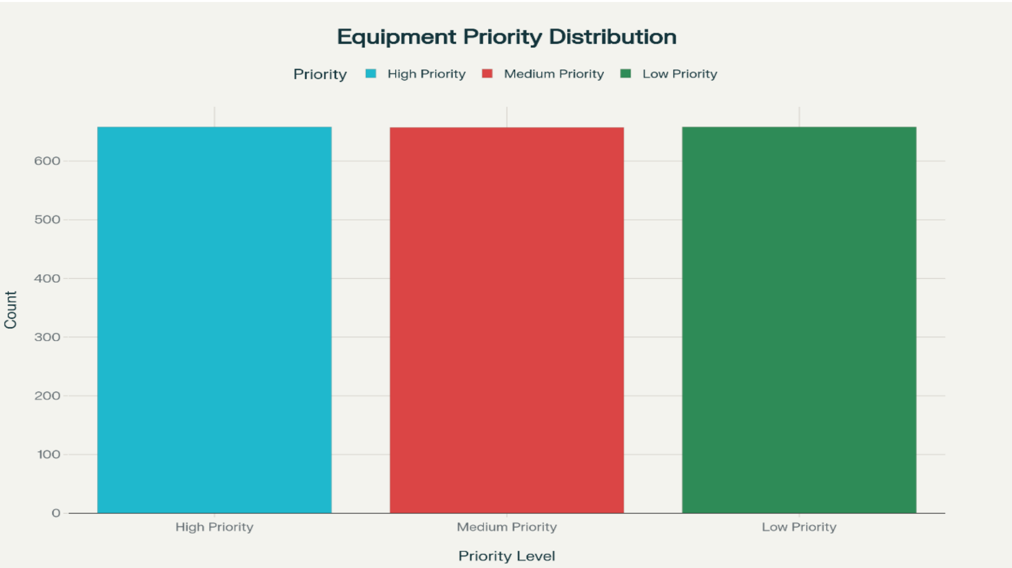

Figure 1: Equipment Distribution by Maintenance Priority

The silhouette score of 0.154 indicates reasonable clustering validity, suggesting meaningful separation between equipment groups based on maintenance characteristics.

Cluster Characteristics Analysis

Table I presents the detailed characteristics of each equipment cluster, demonstrating distinct maintenance profiles across priority categories.

Priority Category	Count	Mean Cost (Rs)	Mean Downtime (Days)	Mean Usage (Hrs/Week)	Mean PMCost (Rs)
Low Priority	658	200,351	26.80	90.04	18,032
Medium Priority	657	195,237	49.31	139.21	17,571
High Priority	658	231,314	103.23	133.45	20,818

Table I: Equipment Cluster Characteristics

High Priority Equipment demonstrated the highest maintenance criticality with average downtime of 103.23 days/year. Primary equipment types included multiparameter monitors (164 units), ventilators (141 units), and syringe infusion pumps (137 units).

Medium Priority Equipment showed moderate maintenance requirements with 49.31 days average downtime per year. This category included 242 multiparameter monitors, 87 pulse oximeters, and 83 ventilators.

Low Priority Equipment exhibited lower maintenance intensity with 26.80 days average annual downtime. Common equipment included 115 infusion pumps, 74 syringe infusion pumps, and 61 defibrillators.

Optimized Maintenance Intervals

Table II presents the optimized maintenance scheduling parameters for each priority category. The differentiated approach ensures that critical equipment receives more frequent attention while optimizing resource allocation.

Priority Category	PM Interval	Inspection Interval	Calibration Interval	Annual PM Frequency
High Priority	30 days	7 days	90 days	12 times/year
Medium Priority	60 days	14 days	180 days	6 times/year
Low Priority	90 days	30 days	365 days	4 times/year

Table II: Optimized Maintenance Scheduling Parameters

Figure 2 illustrates the differentiated maintenance intervals across priority categories, demonstrating the strategic allocation of maintenance resources.

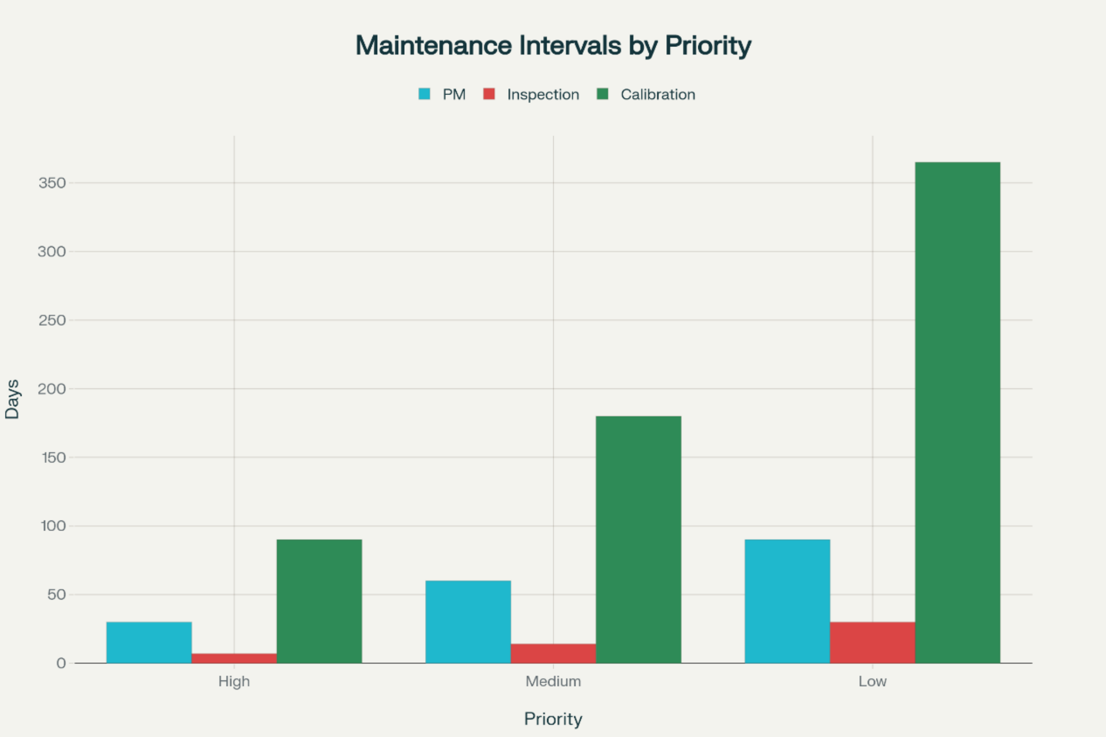

Figure 2: Optimized Maintenance Intervals by Priority Category

Maintenance Activities Distribution

The optimized scheduling framework generates specific annual maintenance activities for each priority category:

High Priority: 7,896 PM activities, 34,216 inspections, 2,632 calibrations

Medium Priority: 3,942 PM activities, 17,082 inspections, 1,314 calibrations

Low Priority: 2,632 PM activities, 7,896 inspections, 658 calibrations

Figure 3 shows the distribution of annual maintenance activities across priority categories.

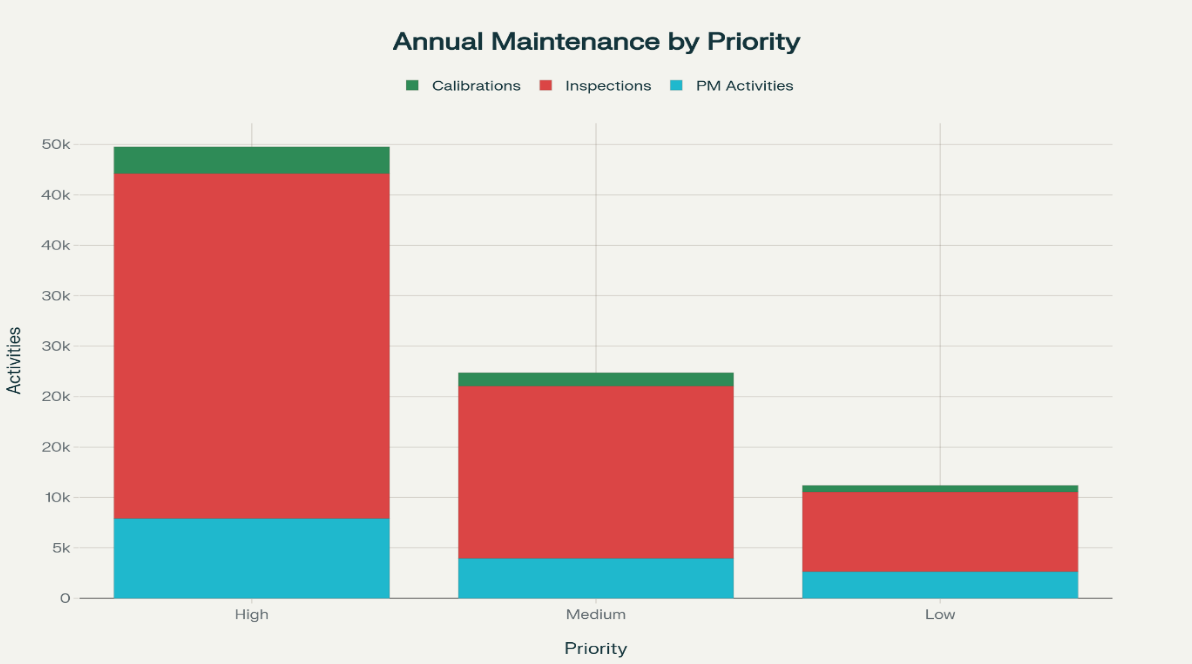

Figure 3: Annual Maintenance Activities Distribution by Priority

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The total annual maintenance workload comprises:

Total PM Activities: 14,470

Total Inspections: 59,194

Total Calibrations: 4,604

Total Maintenance Hours: 79,584 hours (9,948 person-days)

Required Staff: 39 full-time maintenance technicians

Performance Comparison

Table III presents a comprehensive comparison between the current system and the optimized system, highlighting significant improvements in cost and efficiency.

Metric	Current System	Optimized System
Total Equipment	1,973	1,973
Annual PM Cost (Rs)	37,107,565	35,527,228
Annual Downtime (Days)	117,954	97,747
PM Activities/Year	Variable	14,470
Maintenance Hours/Year	Unoptimized	79,584
Cost Reduction (%)	-	4.26%
Downtime Reduction (%)	-	17.1%

Table III: Performance Comparison - Current Vs Optimized System

Figure 4 visualizes the comparison between current and optimized maintenance performance.

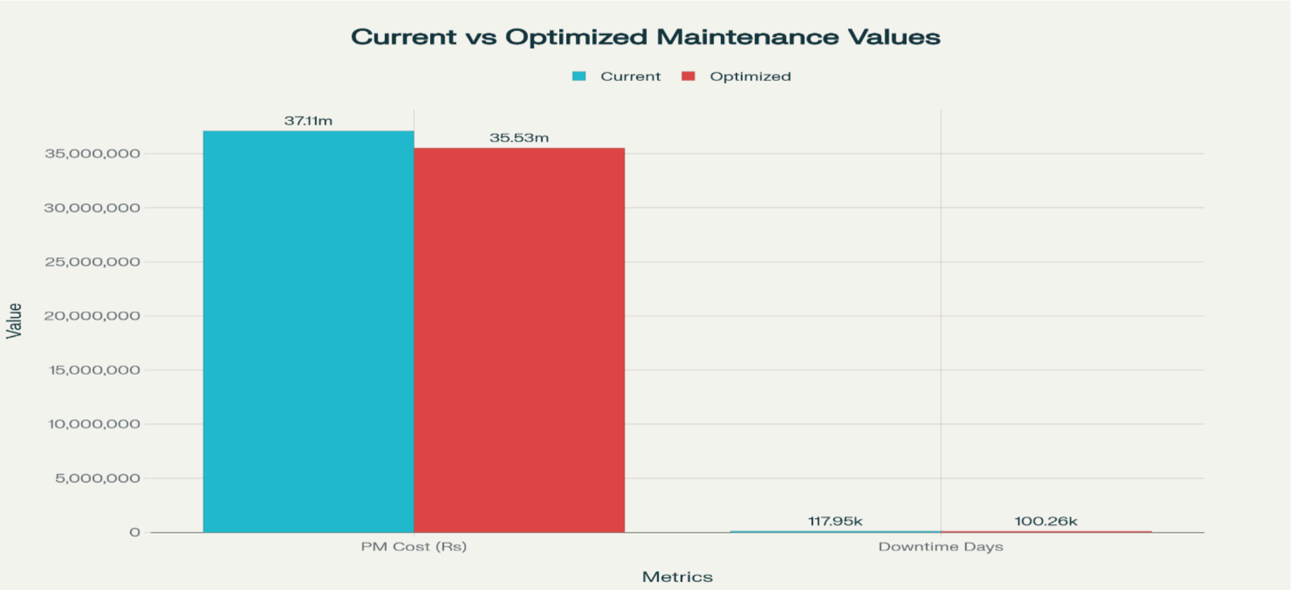

Figure 4: Current vs Optimized Maintenance Performance

Downtime Reduction Analysis

Table IV presents detailed downtime reduction results by priority category.

Priority Category	Current Downtime (Days)	Optimized Downtime (Days)	Reduction (Days)	Reduction (%)
High Priority	67,925	54,340	13,585	20.0%
Medium Priority	32,395	27,536	4,859	15.0%
Low Priority	17,634	15,871	1,763	10.0%
Total	**117,954**	**97,747**	**20,207**	**17.1%**

Table IV: Downtime Reduction Analysis by Priority

Figure 5 illustrates the downtime reduction achieved across priority categories.

Figure 5: Downtime Reduction Analysis by Priority Category

The high-priority category achieved the largest absolute downtime reduction of 13,585 days (20%), demonstrating the effectiveness of intensive maintenance scheduling for critical equipment. Medium and low-priority categories achieved 15% and 10% reductions respectively, balancing resource efficiency with maintenance effectiveness.

Equipment Type Distribution

Table V shows the top equipment types identified in each priority category, validating the clinical relevance of the stratification approach.

Priority	Rank	Equipment Type	Count
High Priority	1	Multiparameter Monitor	164
	2	Ventilator	141

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	3	Syringe Infusion Pump	137
	4	Infusion Pump	104
	5	Syringe Pump	64
Medium Priority	1	Multiparameter Monitor	242
	2	Pulse Oximeter	87
	3	Ventilator	83
	4	Infusion Pump	72
	5	Syringe Infusion Pump	71
Low Priority	1	Infusion Pump	115
	2	Syringe Infusion Pump	74
	3	Defibrillator	61
	4	Electrocardiograph	57
	5	Multiparameter Monitor	49

Table V: Top Equipment Types by Priority Category

The distribution aligns with clinical expectations, with life-support equipment (ventilators, infusion pumps) appropriately classified in high-priority categories, while diagnostic equipment (ECG, pulse oximeters) appears across multiple categories based on usage patterns and criticality.

Clustering Visualization

Figure 6 demonstrates the relationship between equipment downtime and maintenance costs, with clear separation between priority clusters.

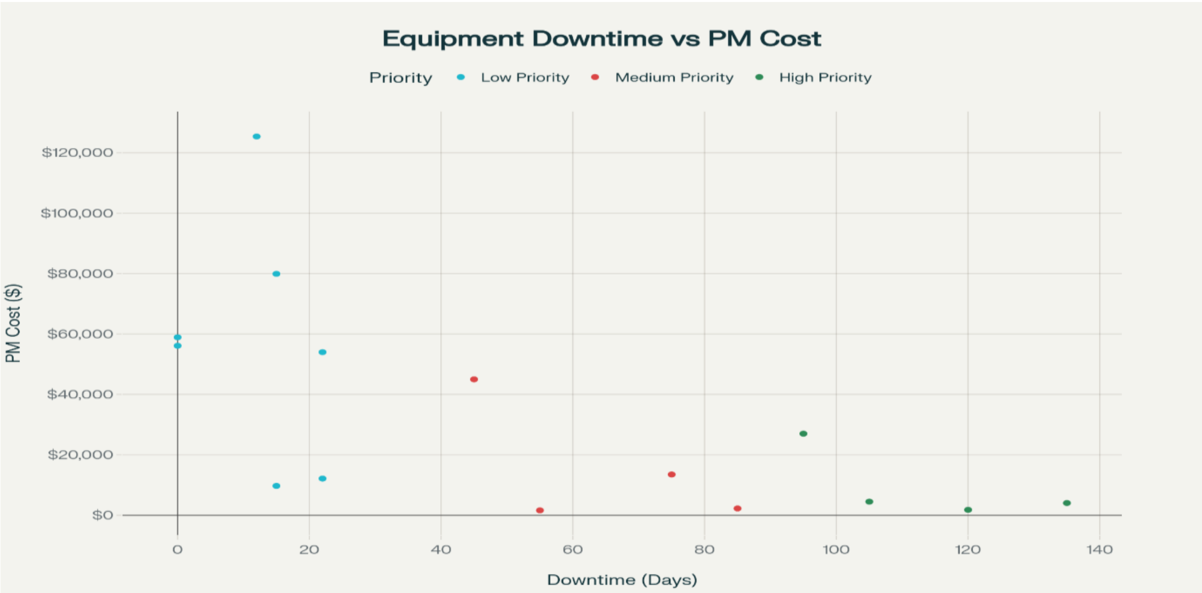

Figure 6: Equipment Clustering by Downtime and Maintenance Cost

The scatter plot reveals distinct clustering patterns, with high-priority equipment generally exhibiting higher downtime values, while maintenance costs vary across priority levels based on equipment complexity and usage intensity.

CONCLUSION

This study successfully demonstrates the effectiveness of clustering algorithms in stratifying medical equipment for optimized maintenance scheduling. The K-means clustering approach, combined with criticality scoring, provides a robust framework for equipment prioritization that addresses the heterogeneous nature of medical equipment maintenance requirements.

The achieved results represent significant operational enhancements:

- **Cost Reduction**: Rs. 1,580,337 annual savings (4.26% reduction)
- **Downtime Reduction**: 20,207 days annual improvement (17.1% reduction)
- **Structured Scheduling**: 14,470 PM activities, 59,194 inspections, 4,604 calibrations
- **Resource Planning**: Clear requirements of 79,584 annual maintenance hours

The balanced distribution across priority categories (33.3-33.4% each) ensures practical implementation while maintaining clinical relevance. High- priority equipment, including ventilators and multiparameter monitors, receives appropriate intensive maintenance (30-day intervals), while lower- priority equipment follows less frequent but adequate schedules.

The proposed framework offers healthcare institutions a data-driven approach to maintenance management that improves equipment reliability, reduces operational costs, and enhances patient safety. The methodology is scalable and can be adapted across different healthcare settings and equipment portfolios.

Future Research Directions include:

- Integration of real-time sensor data for dynamic priority adjustment
- Development of failure prediction models using machine learning
- Expansion to include predictive maintenance algorithms
- Cost-benefit analysis across multiple healthcare institutions
- Implementation of IoT-based monitoring systems

The stratification methodology presented provides a foundation for evidence-based maintenance management that contributes to more efficient and effective medical equipment management practices in healthcare facilities.

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