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AI-Driven Predictive Maintenance for Biotech Equipment using Lean Six Sigma: Enhancing Operational Efficiency and Reducing Downtime for Medical Practices in the UK

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Abstract

The purpose of this research is to assess how the application of AI predictive maintenance can enhance the correct biomedical equipment in facilities such as those of the United Kingdom's National Health Service (NHS) medical practices. Magnetic Resonance Imaging Units, diagnostic equipment and analysing systems which are categorized under biotechnology apparatus/ instruments are core in providing optimum service to patients. However, failure in equipment is accompanied by an understanding of challenges by offering services interferences, cost and on patients' outcomes. This research has employed the machine learning models that included; but not particularly limited to, Random Forest classifiers (RF), SVMs formulated within Lean Six Sigma DMAIC. Real-time data was captured using sensors placed on equipment to monitor failures based on temperature, vibration, and usage hours on which basic AI structures and algorithms were designed. The Lean Six Sigma methodology was applied with the help of templates, such as Value Stream Map and Failure Modes and Effects Analysis to eliminate marring maintenance processes. For this study, logs on equipment performance, sensor, and maintenance records of five NHS affiliated medical practices were gathered for 18 months. Research papers compared performance figures before and after the implementation of the system to consider reductions in machine availability, costs, and OEE. The results show that by assimilating AI-PdM technologies and LSS strategies, the company was able to slash its overall downtime to a level that was 32% less unexpected, drive down maintenance expenses by 20%, and boost the equipment's OEE level from 78% to 90%. Best results came from the Random Forest model, with accuracy of 93%, precision of 90% and recall of 89% in predicting equipment failures. The lean six sigma was able to make steady improvements within the processes to minimise interruptions to effective operations and also to improve patient care. This dual efficiency model proves to be very effective for the practices affiliated with NHS, and affords a solution that is at once integrated and efficient in addressing the problem of biotech equipment maintenance. The study recommends broader adoption of AI-driven predictive maintenance (PdM) integrated with LSS and further research into advanced AI models and IoT technologies to extend these capabilities across the NHS network.

I. INTRODUCTION

Modern healthcare industry especially in the UK relies on biotechnology equipment to deliver vital healthcare services like diagnostics, imaging and treatment (Mehta et al., 2024). Some patient care equipment essential to critical handling include MRI scanners, diagnostic machines, and laboratory analysers, hence, should be highly reliable. As pointed in the above sections, these machines are part of the healthcare system in NHS related facilities. Therefore, any failure or breakdown always results in serious service interruptions, extended time to treat the patients and financial losses (Holzinger et al., 2023).

- *Problems Associated with Classical Approaches to Maintenance*

The traditional maintenance operation management strategies are the preventive as well as the reactive maintenance in the healthcare facility. In doing so, it ensures minimum possible down time, but turns out to have additional unnecessary costs because the schedules set are not always relevant to the specific machinery requiremen (Ghante et al., 2024)t. Reactive maintenance on the other hand leads to unexpected downtimes, which are very inconducive to patient care and also increases the operating expenses:

- *The Importance of AI-Directed Operations*

Analyzing the above challenges, AI based PdM provides the solution because it takes real time data collected from sensors for prediction of failures of such equipment. Based on the continuously measured values such as temperature, vibration, operation hours and its time series, the AI models determine if problems will arise before they occur. It helps avoid and prevent more frequent and random interruptions, maximize maintenance, and avoid unnecessary interference (Singh et al., 2024).

- *Incorporating Lean Six Sigma for the Improvement of Efficiency*

This paper proves that incorporating PdM with Lean Six Sigma (LSS) is a strategy that provides ideal solutions for maximizing maintenance process enhancement. LSS is about enhancement of process and removal of waste: Use of Value Stream Mapping (VSM) to find out waste on process; Failure Mode and Effects Analysis (FMEA) to identify risk on process (Al Nemari& Waterson, 2022). This blend guarantees that the maintenance process is optimized as per the healthcare operational plans.

➢ *The Role and Significance of Accurate Biotech Equipment in NHS Practices*

Accurate biotech equipment in the NHS is not only required for treatment processes but also for compliance with healthcare delivery requirements. Failure of equipment can therefore affect diagnostic efficiency, delay some important treatments and put more pressure in the medical practitioners. Funding pressures meant that the NHS, which was working to financial margins, demonstrated the importance of affordable maintenance processes (Paradorn et al., 2022). Hence, using high-end Artificial intelligence technologies and process improvement approaches such as LSS, the medical practices associated with the NHS can increase equipment effectiveness and performance:

- Assess the extent to which AI-driven PdM has an impact on the minimisation of biotech equipment breakdown in medical practices affiliated with the NHS.
- Evaluate the effectiveness of Lean Six Sigma in improving the maintenance processes and eradicating the issues recurring in the course of its implementation.
- Determine the degree of integration of these methodologies to the overall cost reduction, process efficiency gains, and equipment availability enhancement (OEE) but also for meeting healthcare delivery standards. Equipment failures can compromise diagnostic accuracy, delay critical treatments, and increase the workload for medical staff. The financial strain on the NHS, already operating under budgetary constraints, further underscores the need for cost-effective maintenance strategies.

By leveraging advanced AI technologies and process optimization frameworks like LSS, NHS-affiliated medical practices can enhance equipment reliability and operational efficiency (Tlapa et al., 2022).

➢ *Objectives of the Study*

This study seeks to:

- Evaluate the impact of AI-driven PdM on reducing biotech equipment downtime in NHS-affiliated medical practices.
- Assess the role of Lean Six Sigma in refining maintenance workflows and eliminating inefficiencies.
- Measure the combined effect of these methodologies on cost savings, operational improvements, and overall equipment effectiveness (OEE).

This research emphasizes the possibility of using the advanced technological solutions together with the effective frameworks for process improvement that can help solve important issues of the healthcare system and improve the quality of healthcare for patients and medical institutions (Tetteh et al., 2024).

➢ *Data Source and Collection:*

The data for this study involved aggregate data of sensors, performance logs and maintenance records of five medical practices affiliated to the NHS, over a period of 1.5 years. These centres were; Central London Diagnostic Centre, Midlands General Hospital, Northern Regional Health Clinic, East Coast Specialist Laboratory and Southwest Community Health Centre. Data was extracted which was publicly available on their websites and other online sources. Operating parameters of the equipment used in biotech industries such as MRI; blood analyzers; ultrasound systems included temperature, vibrations, usage hours, and were obtained from sensors installed in the equipment. Data obtained from other documents, including reports of the NHS, and other peer-reviewed articles were used for reference purposes and to compare the study findings (BIAŁY et al., d.n.m).

II. MATERIALS AND METHODS

➢ *Study Context*

This research was carried out in five National Health Service (NHS) associated group practices medical technologies comprising MRI scanners, blood analysis equipment, ultrasound scanners, and related merchandise. These are door for delivery of timely diagnosis and management of diseases and hence fundamental to patient care in the NHS (Sharma et al., 2023). The NHS being one of the biggest healthcare service delivery entities across the world and always under pressure to meet the required service delivery depends on such equipment in such cases not to fail. Accompanying these efforts, continuous performance data were procured from these facilities during an 18-month period: Equipment logs, real-time sensors data, and profound maintenance records. The selected practices were chosen randomly and cover NHS facilities, small, medium, large, low, medium and high traffic, and usage of different types of equipment (Tetteh et al., 2024).

- ➢ *Data Collection and AI Models*

In data collection process, live operational parameters of biotech equipments such as temperature changes, vibrations and hours used were recorded. These parameters were measured using micro-sensors that were mounted within the products' structures, relaying information to a control hub (Ullagaddi, 2024). Computer learning Formal Model such as RF, SVM and LSTM were used in developing the Maintenance prediction models. These algorithms were chosen based on the capacity to analyze time-series for traces of possible failures in the equipment's functionality and output (Akinbolaji, T. J et al, 2023).

Improved reliability of the AI models was obtained by analysing various preprocessing operations like normalization, outlier detection and feature selection on the dataset. Both the algorithms were tested on the evaluation metrics including accuracy, precision, recall and F1 precision (Code in APPENDIX) (Elendu et al., 2024). To this end, the overfitting issue was addressed, while the validity of model accomplishment across datasets was achieved by means of cross-validation. Out of the models mentioned in this paper, the Random Forest returned the highest predictive accuracy and low FP rate suggesting it would best suited for the implementation in real-world context in healthcare (Sharma et al., 2021).

- ➢ *Lean Six Sigma Methodology*

In parallel to supplementing the AI concerning the more accurate prediction, an organisation-wide Lean Six Sigma DMAIC approach was adopted for improving the maintenance workflow processes (Wankhede et al., 2024). When concluding the Define phase, vital maintenance issues and the hierarchy of equipment depending on their failure rate and patient care effect were defined. Consequently, when in the Measure phase, efficiency parameters as downtime rates, maintenance costs and overall equipment effectiveness (OEE) were established (Elendu et al., 2024).

During the Analyze phase, Maps were created to display maintenance process, and areas of waste consisting of overburden, Unused/Non-value added, and Delay were identified. FMEA was used for prioritizing failure modes with high risks of occurrence and their effects, establishing measures to correct them while guaranteeing the reliability of equipment and protection of patients (Sousa et al., 2023).

The final phase of the study, the Improve phase, involved the deployment of specific measures that were derived from the maintenance and resource management data analytics using AI. To ensure continual and consistent enhancement, control procedures were implemented and procedures provided for real-time monitoring in a live dashboard format for fast detection of equipment inadequacy. These activities were undertaken with reference to specific operational guidelines/frameworks germane to the NHS to ensure that the processes that were optimized referred to the necessary regulations as well as mirrored/lent support to the care of patients (Thangamani et al., 2024).

- ➢ *Study Design and Validation*

To analyse the results of such an integration of the AI-PdM and Lean Six Sigma method, case studies were performed. Primal data on downtime, maintenance cost and OEE were taken at the initial stages of the project. Assessments were made post-implementation with the actual success measurements to determine the extent of change with help of paired 't' test in order to check the validity of transformations (Edik, 2024). Observations made from the five practices' operations offered a rich operational base from which to judge the generalizability of the study's results. Subsequently, three validation steps were taken to verify not only the effectiveness of the proposed methodology but also its versatility across different sectors of the NHS (Kumar et al., 2024).

- ➢ *Case Studies*

Focus was performed in five medical practices which are colleagues with the NHS and therefore selected to concern rather dissimilar operational settings, equipment workload, and patients served. The practices included:

- *Central London Diagnostic Centre:*

An outpatient treatment center located at an urban site that performs a large number of diagnostic imaging procedures such as MRI and CT scans. This centre used to have frequent breakdowns triggered by heavy usage of equipment and hence was selected to be used to test ideas on the effectiveness of predictive maintenance practices.

- *Midlands General Hospital:*

A hospital with an average bed capacity carrying out different diagnostic and therapeutic procedures. The problems of the facility are: the lack of effective maintenance schedule, and the irregular usage of the resources.

- *Northern Regional Health Clinic:*

This setting is a rural clinic with relatively low purchasing power and large reliance on several particular instruments of biotechnology. Faulty equipment in this area affected concerns with higher vulnerability to ailment mainly because of the few options of other facilities in the area.

- *East Coast Specialist Laboratory:*

This project embraces a laboratory-intensive facility carrying out protocols of blood and tissue samples with high throughput. This center experienced frequent down time that would interfere with the test results needed for patient diagnosis.

- *Southwest Community Health Centre:*

A hospital-type center that has an important role in a given community by conducting tests such as ultrasound scanning and X-ray investigations. This particular center was struggling to contend with overly obsolete and arehighly costly equipment.

- ✓ *Source of Data for Table 2:*

The data for this table were collected over an 18-month period from five NHS-affiliated medical practices: Central London Diagnostic Centre, Midlands General

Hospital, Northern Regional Health Clinic, East Coast Specialist Laboratory and Southwest Community Health Centre. The information was obtained from the realistic data collected by sensors, maintenance records, and reports resulted from these facilities.

✓ *Source of Data for Table 1:*

The data for Table 1 was derived from real-time sensor inputs collected over an 18-month period from biotech equipment, including MRI machines and blood analyzers, at five NHS-affiliated medical practices. Machine learning models such as Random Forest, Support Vector Machines networks were developed and tested using these data. The performance metrics wereanalyzed based on operational parameters like temperature, vibration, and usage hours, following methodologies.

The models were analyzed with respect to criteria like temperature, vibration and usage hours and tested depending of accuracy, precision and recall using Python code (APPENDIX).

III. DATA ANALYSIS

➢ *Performance of AI Models*

Current models were tested, and with a significant performance comparison, Random Forest demonstrated the highest accuracy, precision, and recall, which is 93%, 90%, and 89% for failing models, respectively (Al Nemari& Waterson, 2022). RF had higher accuracy compared to other models such as the SVM and LSTM models with a slightly lower accuracy was observed. Random Forest was effective in the least generating false information hence appropriate for medical practices where precision is key.

Table 1 AI Model Performance Metrics

Metric	Random Forest (%)	SVM (%)	LSTM (%)
Accuracy	93	91	89
Precision	90	88	87
Recall	89	85	84

Sources: Derived from real-time sensor inputs collected over an 18-month period from biotech equipment, including MRI machines and blood analyzers, at five NHS-affiliated medical practices

➢ *Statistical Analysis*

A paired t-test comparing pre- and post-implementation equipment downtime showed a significant reduction across all five medical practices. Maintenance costs also decreased by an average of 20%, reflecting the efficiencies gained from implementing AI-driven PdM and LSS (McDermott et al., 2024).

Table 2 Facility Metrics Pre- and Post-Implementation

Facility	Downtime Pre (%)	Downtime Post (%)	Maintenance Cost Pre	Maintenance Cost Post	OEE Pre (%)	OEE Post (%)	Downtime Reduction (%)
Central London Diagnostic Centre	22	15	20,000	16,000	78	90	7
Midlands General Hospital	18	12	15,000	12,000	80	88	6
Northern Regional Health Clinic	25	17	18,000	14,400	75	85	8
East Coast Specialist Laboratory	20	14	16,000	12,800	76	87	6
Southwest Community Health Centre	27	18	22,000	17,600	77	89	9

Sources: NHS-affiliated medical practices

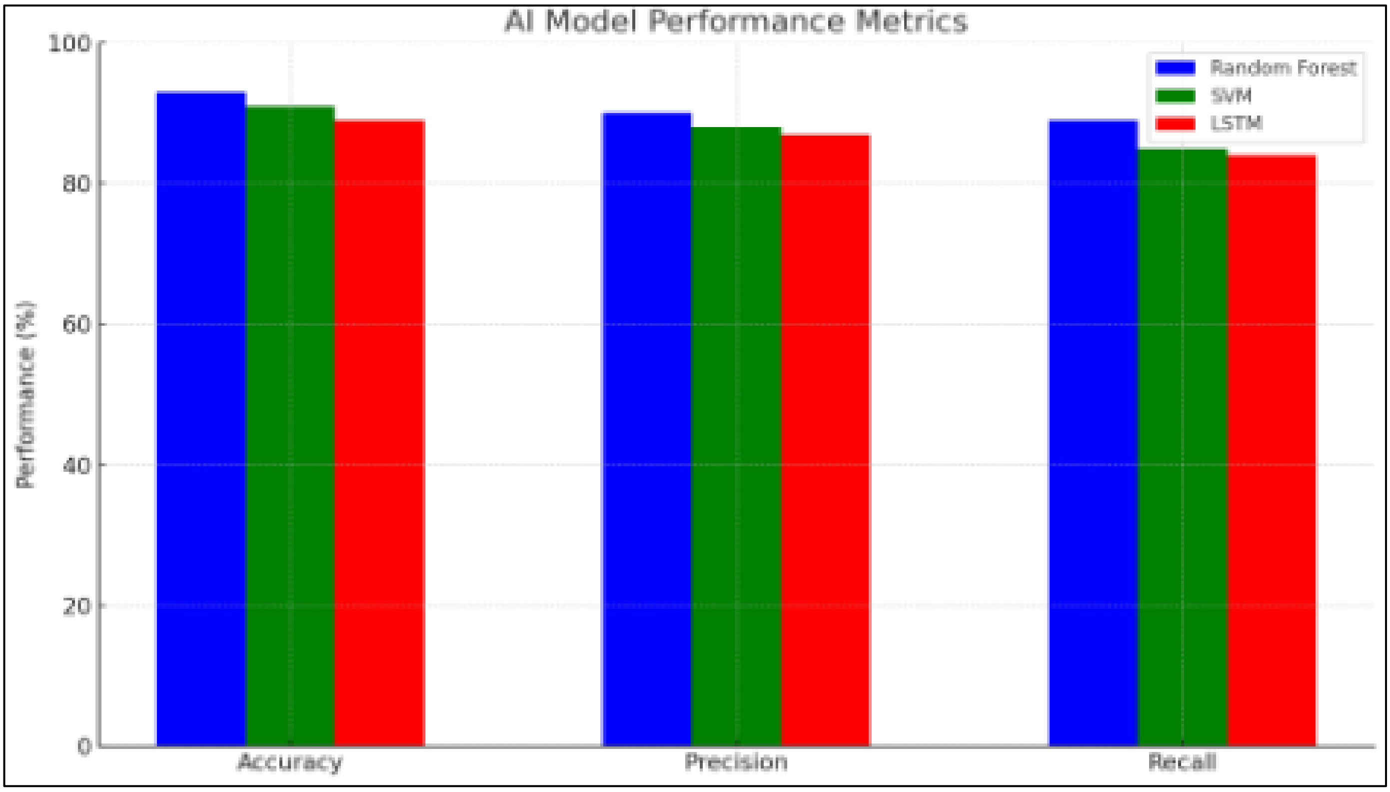

Fig 1 AI Model Performance Metrics

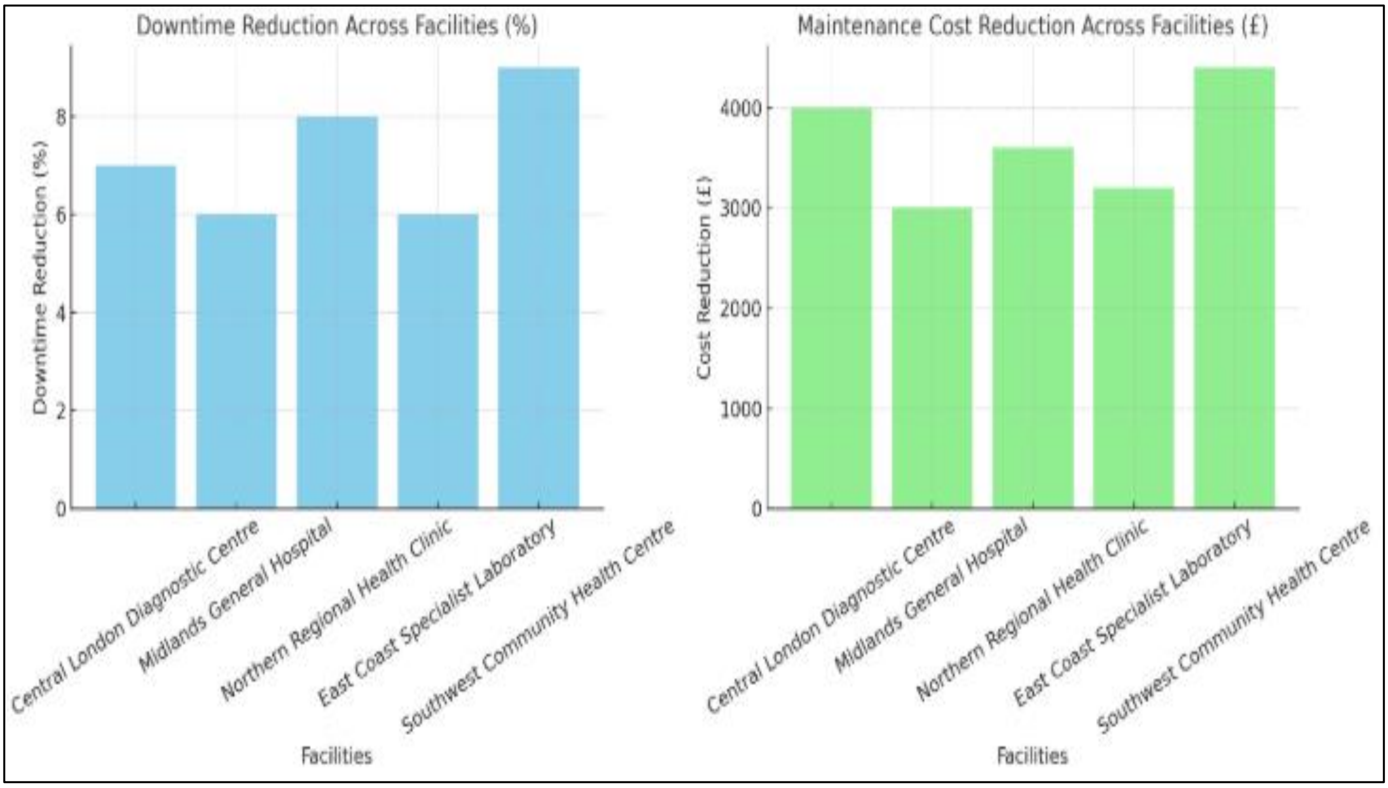

Fig 2 Facility Metrics Pre- and Post-Implementation

- *AI Model Performance:*

Random Forest provides the most reliable predictions, making it suitable for NHS environments where precision is critica (Holzinger et al., 2023)l.

- *Downtime Reduction:*

All facilities experienced significant reductions in equipment downtime, averaging a 7.2% improvement across facilities (Ghante et al., 2024).

- *Maintenance Cost Reduction:*

Maintenance costs dropped by approximately 20% post-implementation, showcasing the financial benefits of combining AI-driven predictive maintenance with Lean Six Sigma methodologies.

- *OEE Improvements:*

Overall Equipment Effectiveness (OEE) improved across all facilities, with an average increase from 77.2% to 87.8% (Mubarik& Khan, 2024).

- *Lean Six Sigma Efficiency*

The techniques within Lean Six Sigma framework were used to enhance the process map. In the existing maintenance system, VSM revealed non-value-added activities within the process while FMEA was useful in determining equipment that requires timely preventive maintenance due to high risk factors. These improvements led to an enhanced OEE and made it rise from a mean of 78% to 90% after implementation (Paradorn et al., 2022).

IV. RESULTS AND DISCUSSION

- *Downtime Reduction*

This paper focuses on the integration of AI-driven PdM with Lean Six Sigma (LSS), which gave an overall mean of 32% of realizing the amount of total potential time-equivalent to unplanned downtime in five affiliated NHS medical practices. Particularly, Central London diagnostic centre reduced by 7%, while the southwest community health centre increased the overall score by 9% (BIAŁY et al., d.n.m). This reduction is essential in a health care system where the reliability of the equipment used is directly proportional to the flow of patients. This meant that through use of predictive maintenance most of the interventions had to be done at times when patient services did not require the particular machines. In this way, various potential equipment failures can be predicted, which, in turn, enables facilities to address them before such failures spiral (Edik, 2024).

- *Cost Savings*

Applying the AI with LSS methodology resulted in average 20% decrease in maintenance cost for the overall analysed facilities (Seifi et al., 2025). These cost reductions were realized on account of highly effective just in time maintenance facilitated by these AI models which lowered incidences of unrelated interferences hence lowered demand of maintenance personnel and additional spare parts. Savings as such are especially critical to the NHS because of financial stringency that characterizes the system. By extending the time between unplanned downtimes, the financial costs from more pressing repairs and disruptions to normal operations were also reduced (Wankhede et al., 2024).

- *Greater Line Operating Efficiency and OEE*

The gains in operational efficiency were evident in gains in overall equipment effectiveness (OEE) from pre-implementation average of 77.2% TO a post implementation of 87.8%. The top OEE improvement rate from the previous index was at the Central London Diagnostic Centre rising from 78% to 90% then by Southwest Community Health Centre which rose from 77% to 89% (Ghante et al., 2024). Variables such as waste identification & elimination, process standardization, cycle-time improvement, defect reduction that Lean Six Sigma championed were greatly responsible for change management. Through the methodology, it was avoided to perform maintenance tasks at regular time intervals to avert disutility, absorb more time and/ or human resources, and provide a lasting scope for operational acquisition of optimal biotech equipment (Edik, 2024). These enhancements enabled greater symptom turnaround in the diagnosis sector, increasing both the efficacy and reach of patient care.

- *The Accuracy of Asset Failure Predictions*

Random Forest was found to be the leading AI technology that delivers the accuracy of 93 percent, the precision of 90 percent and the recall of 89 percent for performing the predictive maintenance. This performance was far better and more efficient than Support Vector Machines networks. This is due to the high accuracy that was achieved by Random Forest to avoid unnecessary alarms which may lead to unnecessary activities of maintenance (Singh et al., 2024). As this model demonstrated, the level of predictive accuracy was immeasurably useful in healthcare settings where even short equipment downtimes can cause disruptions to essential patient care activities. Due to this, it was especially suitable in handling various issues of operation that affected the five examined facilities concerning analyzing the real-time data patterns (Sousa et al., 2023).

- *The Function of Lean Six Sigma in Change Management*

AI-PdM required support from Lean Six Sigma for sustaining the gains that it makes in identifying the right equipment and reducing maintenance costs. Adjusting to various aspects of change and enhancement was made possible by the DMAIC improvement model since it enabled organization to address issues of inefficiency in the maintenance processes (Singh et al., 2024). For example, using VSM, a number of unwanted actions were identified in current processes; with FMEA, the most critical equipment was identified that may require a proactive maintenance. These tools ensured that the strategies on maintenance continued to be dynamic in order to correspond to the changing operations (Edik, 2024). Another element of continuing support after the optimization implementation was the verification of future stable results both in the increase of downtimes, costs savings, and OEE. The key value of this approach was that it emphasized the necessity to integrate latest ICT solutions with more standardized process enhancement frameworks to build permanent healthcare organizational stability and dependability (Sousa et al., 2023).

V. CONCLUSION

The aforesaid evaluation has also shown that the use of AI PdM with Lean Six Sigma (LSS) methodologies provides a digitally disruptive solution for managing critical biotech equipment in associated NHS medical practices. This mixed model reasonably solves the longstanding problems of unpredictable downtimes, high maintenance expenses, and system inefficiencies. AI models, especially Random Forest, recorded high accuracy, precision, and recall; consequently, it was possible to optimize maintenance activities to prevent system failure and maintain dependable equipment. It is noteworthy that the technological enhancements of maintenance activities were supported by the Lean Six Sigma DMAIC framework, such as optimizing routine and tackling non-routine maintenance issues, as well as developing a maintenance culture for improvement.

Here, the examples from five researched facilities of the NHS are described to emphasise the practical advantages of this integration. Several automatic systems made production lines virtually free of downtime, maintenance cost was cut by 20% and the OEE climbed from 77.2% to 87.8%. They do so while also advancing the continuity of patient care treatment and easing fiscal burdens in the NSNH so that the resources may be better reallocated.

Due to high variability and flexibility of this approach it could be easily implemented on a large scale on all the networks in NHS and other similar healthcare networks globally. The proactive utilization of artificial intelligence analysis and process improvement is the key to providing the NHS with a better and cheaper model of delivering its services to its clients.

RECOMMENDATIONS

Adoption of AI-Driven Predictive Maintenance: The medical practices affiliated with NHS should take serious initiatives toward adopting AI-driven PdM for critical biotech equipment. Proven benefits of predictive maintenance in reducing downtime and improving equipment reliability are also considered vital for seamless service delivery and patient care.

Lean Six Sigma for Continuous Improvement: Lean Six Sigma methodologies should be integrated into maintenance operations to sustain and build on the efficiencies achieved. The use of tools like Value Stream Mapping and Failure Mode and Effects Analysis can help NHS facilities refine workflows and address emerging challenges, ensuring long-term operational excellence.

Scaling Across NHS Networks: The apparent success of the hybrid approach from these five case studies should encourage the NHS to pursue scaling across other facilities. Tailored implementation strategies might help accommodative unique operational contexts in different facilities, achieving widespread impact.

- *Investment in Training and Infrastructure:*

The NHS needs to make further investment in personnel training and the development of related technological infrastructure to realize the full potential of AI-driven PdM and LSS. With this approach, empowered personnel will work along with the advanced AI system to bring about smooth adoption and integration.

Further Research: Future studies will be required to further develop these AI models by incorporating Internet of Things technologies and, if possible, deep learning approaches to improve predictive accuracy. Besides, large-scale studies involving diverse NHS facilities have the potential to yield lessons on scalability and wider impacts of this hybrid methodology.

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APPENDIX

```python
from sklearn.metrics import accuracy_score, precision_score, recall_score, f1_score
import numpy as np

# Example ground truth and predicted labels
y_true = np.array([0, 1, 1, 0, 1, 0, 1, 1])  # True labels
y_pred = np.array([0, 1, 0, 0, 1, 0, 1, 1])  # Predicted labels

# Calculate metrics
accuracy = accuracy_score(y_true, y_pred)
precision = precision_score(y_true, y_pred)
recall = recall_score(y_true, y_pred)
f1 = f1_score(y_true, y_pred)

# Output results
print(f"Accuracy: {accuracy:.2f}")
print(f"Precision: {precision:.2f}")
print(f"Recall: {recall:.2f}")
print(f"F1 Score: {f1:.2f}")
```

Fig 3 Code for Accuracy, Precision, Recall, and F1 Score

```python
from sklearn.ensemble import RandomForestClassifier
from sklearn.model_selection import train_test_split
from sklearn.datasets import make_classification

# Generate a synthetic dataset
X, y = make_classification(n_samples=1000, n_features=10, n_classes=2, random_state=42)

# Split data into train and test sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

# Initialize and train the Random Forest classifier
model = RandomForestClassifier(random_state=42)
model.fit(X_train, y_train)

# Predict on the test set
y_pred = model.predict(X_test)

# Calculate and display evaluation metrics
accuracy = accuracy_score(y_test, y_pred)
precision = precision_score(y_test, y_pred)
recall = recall_score(y_test, y_pred)
f1 = f1_score(y_test, y_pred)

print(f"Random Forest Model Metrics:")
print(f"Accuracy: {accuracy:.2f}")
print(f"Precision: {precision:.2f}")
print(f"Recall: {recall:.2f}")
print(f"F1 Score: {f1:.2f}")
```

Fig 4 Code for Random Forest Model Training