Predictive Maintenance For Healthcare Equipment Using Machine Learning

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***Abstract*—MRI machine, ventilators, defibrillator, infusion pumps, aspirators and patient monitoring apparatus are critical in hospitals in which the inability to work without any warning can result in devastating effects such as high risks, inability to continue treatment and increased operational costs. Old fashioned maintenance systems such as reactive and time-based preventive maintenance are not very efficient as they fail to identify failures before time. This paper describes a predictive maintenance backend solution to medical critical equipment based on Machine Learning (ML) and IoT data which aims at predicting failures in advance and minimizing the downtime. The suggested system obtains sensor based operation data like temperature, vibration, voltage, air flow, and pressure, maintenance history and fault history. Preprocessing of the collected data is done by cleaning, normalization, and extraction of the statistical features to enhance the performance of the model. Random Forest, XGBoost, and LightGBM are used as ML models that are trained to both classify the health state of equipment and predict the risk of failure.The results of maintenance history and prediction are kept in a SQLite database, with a Flask server serving as a backup. Experimental results indicate that team-based models are useful to classify equipment health, whereas risk-scoring enhances useful decision support to biomedical engineers in intelligent healthcare facilities.**

***Index Terms*—Predictive maintenance, medical equipment, machine learning, IoT, anomaly detection, failure prediction, smart hospitals.**

I. INTRODUCTION

Medical equipment is also a very important aspect in the contemporary healthcare systems since it is used in aiding in diagnosis, monitoring as well as life saving treatment procedures. The MRI scanners, ventilators, defibrillators, infusion pumps, aspirators, and physiological monitoring systems are some of the key equipment in hospitals and emergency care organizations that are in constant use [3], [4], [8]. Any unforeseen malfunction of such devices may have severe outcomes such as the delay of treatment, wrong diagnosis, higher price of operation, and worst, patient safety may be at risk of being endangered in the worst cases possible [14], [15].

Conventionally, hospitals have maintained their approach to maintenance based on reactive maintenance and preventive maintenance where devices are serviced or repaired upon failing and upon a medical timetable respectively. Whereas preventive maintenance will minimize the risk of unforeseen failure in contrast to reactive approaches, preventive maintenance usually leads to unnecessary servicing, increased maintenance expenses, not to mention the fact that the approach is not a guarantee of avoiding unexpected breakdowns between scheduled servicing times [1], [2]. Besides that, flaws are so numerous that they accumulate over time under the influence of wear and strain of the operations, and can not be properly detected even by using time-based schedules only, see [11].

It is now a possibility of getting real time operational information of the medical equipment including the temperature, vibration, voltage, air flow, pressure, power consumption, and the usage cycles of the equipment used in the medical service delivery and research institutions with the emergence of the Internet of Things (IoT) and biomedical sensors and intelligent healthcare infrastructure [5], [6]. This has provided impetus to Predictive Maintenance (PdM) approach that is a factual model of failure prognostication of devices by approximating the utilization of ML to prognosticate prematurely about failure occurrence before it strikes [3], [14]. PdM helps hospitals to plan maintenance, minimize unplanned downtimes, organize their spares in a more effective way and extend the life of equipment in general, as well as this technology helps to increase the life of equipment in general and in particular PdM helps to organize the spares of medical equipment in a more efficient way, as well as the equipment life in general may be increased by the help of PdM, as well as its resources help to extend the life of medical equipment in general and the spares of equipment in particular PdM [10].

Nevertheless, the challenge of developing a predictive maintenance of the medical equipment is not as simple as it is the case with the industrial machinery. The medical equipment falls within the category of safety-critical conditions and it must be highly accurate and reliable. The fact that most predictive models only generalise to devices working under different conditions, non-standardised data and also due to lack of failure records necessary to generallyise predictive models, can undermine the generalization ability of predictive models in general [14]. Furthermore, hospitals are supposed to be equipped with scalable, cost-effective and real time monitoring maintenance systems which are not supposed to interfere with the clinical work processes in any manner [7], [8].

The current paper will suggest the solution to these issues as a Machine learning predictive maintenance backend of critical medical equipment. The system dwells on the main categories of equipment that constitute MRI scanners, ventilators, defibrillators, aspirators, infusion pumps and physiologic monitoring systems. A Flask API is a platform that utilizes multi-source dataset to infer the statistical features, to make machine learning models (Random Forest, XGBoost and LightGBM) and risk classification and recommendation as the backend uses the Flask API to classify risks and make recommendations [12], [13].

A. Key Contributions

The main contributions of this work are:

- A unified predictive maintenance framework for multiple heterogeneous healthcare devices, unlike existing works focusing on single-device systems.
- A hybrid prediction mechanism combining machine learning models with fallback risk scoring to ensure continuous system operation.
- Integration of multi-source datasets with statistical feature engineering for improved prediction robustness.
- A real-time deployable backend system using Flask and SQLite for decision support and maintenance planning.

II. RELATED WORK

Due to the increased need to minimize maintenance costs, equipment downtime, and enhance operational reliability, predictive maintenance (PdM) has proven to be a significant field of research. The implementation of PdM is especially essential in healthcare settings since any medical equipment malfunction directly impacts the patient safety, the quality of the diagnosis, and emergency management. Previously used maintenance systems were largely based on reactive maintenance (mend and fix) and preventive maintenance (service at a pre-determined time). Even though the preventive methods will minimize unforeseen failures, they tend to bring additional undue replacements of parts, and they do not necessarily ensure that failures can be averted between maintenance periods.

A number of papers have investigated machine learning methods to predict equipment failure using sensor data. Conventional ML systems, including Support Vector Machines (SVM), K-Nearest Neighbors (KNN), Decision Trees, and Logistic Regression, had been used to classify faults within industrial machines and they showed a reasonable level of accuracy with structured data but lower accuracy with noisy and complex real world data.

Ensuring that these limitations are overcome, random forest and gradient boosting like XGBoost have been embraced because they have good generalization power. XGBoost is an efficient and scalable structured predictive modelling training. LightGBM also boasts of quick training and high performance on large structured data.

The DNNs in the form of CNN and LSTM are capable of learning temporal degradation trends, especially when used in vibration detection, though they demand large annotated datasets and more processing power. Thus, lightweight ML models are still more feasible when it comes to a real-time implementation on the hospital environment.

Public benchmark datasets (AI4I 2020) are some of the popular data sets used to evaluate PdM algorithms, such as hydraulic condition monitoring datasets and IMS bearing datasets. These datasets can be used to test ensemble and gradient boosting models to various operational conditions.

III. Research Gap

Based on the analysis of the current literature, one can observe that there has been an impressive advancement in the respect of the implementation of machine learning and IoT technologies in predictive maintenance in the industrial and healthcare sectors. A number of the studies have shown that predictive maintenance can be very effective to minimize downtime and enhance equipment reliability through sensor data and past maintenance records [2], [4], [7]. Nonetheless despite these accomplishments there are still gaps in research that are yet to be addressed particularly in critical medical equipment.

To start with, the existing body of predictive maintenance research is founded on the industrial equipment or certain types of equipment, such as yarn machines, CT scanners, and MRI machines and, thus, cannot be applied to the heterogeneous hospital environment where various medical devices are present simultaneously and in different conditions [1], [5], [9]. It is a scalability and real world implementation limitation in a healthcare setting because it lacks a multi-device predictive maintenance architecture.

Secondly, several works heavily rely on deep learning and multimodal between-and-within-architects, which require large labeled datasets and massive computeability expenses to deliver the output of the described architectures at the question [3], [15]. Even though these techniques can be very precise, they pose a challenge to hospitals in the form of low data, high cost of a system and inability to apply it in real time. The resource-constrained healthcare settings that can be subjected to the lightweight and interpretable models have not been investigated.

The other gap that is highly evident is the lack of management of data imbalance and frequent failure. Medical equipment failure is extremely rare compared to the normal operation conditions, hence the datasets are highly unbalanced. The majority of studies do not even address this issue or study models based on controlled datasets that are not realistic simulations of hospital real-life situations, instead, they use them [4], [7]. This renders predictive models unreliable as used in real life healthcare applications.

Moreover, most of the existing systems are limited to the fault detection or classification and do not transform predictions into practical maintenance data, such as risk scoring, maintenance priorities, cost estimates, and further organization of the service schedule plans into services [8], [11]. Biomedical engineers and hospital administrators find these systems to be rather ineffective because they do not have decision-support mechanisms.

More, predictive models cannot be simply extrapolated outside of the hospitals and device manufactures in which the simulated or industrial benchmark datasets are run due to the inaccessibility of standard datasets of medical equipment and extrapolation of research across different hospitals and equipment manufactures of different firms [4], [12]. Large scale deployment is also complicated by the problem of privacy, the heterogeneity of data and inconsistencies in their logging.

Lastly, most of the publications on IoT-based monitoring have ended up collecting sensor data or using a threshold to generate an alert but omitting an end-to-end implementation of the entire system, which involves data preprocessing, model training, real-time prediction, visualization, and management of historical records, among others, as required [10], [14].

IV. PROPOSED METHODOLOGY

The suggested predictive maintenance backend is developed as a pipeline which should have a modular structure which would allow both offline training and online inferences. The system is loosely coupled following a layered architecture in which data ingestion, preprocessing, model inference and persistence can be upgraded in isolation. This provides better maintainability, and allows scalability in a multi-device hospital environment and allows to add additional sensor streams without necessarily re-architecturing the whole system.

In real-world hospital maintenance processes, various departments could be using equipment with varying duty cycles and environmental parameters (e.g. ICU ventilators and diagnostic imaging systems). Thus, the suggested backend is concerned with the generation of interpretable results like risk score, risk category, health percentage, and recommended maintenance window, which may be utilized directly by biomedical engineers and maintenance supervisors directly.

A. System Workflow

The overall backend operation is geared at the conversion of raw operation measurements into predictive maintenance actionable decision. It may be run in two modes:

- **Offline Mode:** Training and testing of model with reference to past data.
- **Online Mode:** API service Inference and real-time record storage.

The overall backend flow is:

1) Collect sensor/ operational information and history.
2) Preprocess and clean data through scaling, encoding and cleaning.
3) estimate statistical characteristics of raw sensor time-series.
4) Compare and contrast ML models and benchmark and custom datasets.
5) ML model inferring or default risk scored fall back.
6) SQLite Forecasts and maintains records.
7) Receive deliverables through REST APIs and receive reports back.

In addition, the backend stores the same feature vector in training and deployment to avoid the mismatch issue (feature drift due to the disappearance/appearance of fields).

B. Datasets and Partitioning

The training pipeline is designed using multiple datasets to ensure robustness and generalization across different operational conditions:

- AI4I 2020 Predictive Maintenance Dataset
- Hydraulic System Condition Monitoring Dataset
- IMS Bearing Dataset
- Final structured healthcare dataset (formatted dataset)

These datasets include sensor parameters such as temperature, vibration, pressure, airflow, voltage, and maintenance history.

The dataset is divided into training and testing sets using an 80:20 stratified split to preserve class distribution.

In cases of class imbalance, Synthetic Minority Oversampling Technique (SMOTE) is applied to balance fault and non-fault classes.

C. Preprocessing Pipeline

Preprocessing activities will involve:

- Enterprises: Numeric feature selection and cleaning.
- Treatment of missing values on the basis of imputation.
- Label encoding / one-hot encoding Categorical encoding.
- StandardScaler scaling.
- Name of features to make features consistent in training and deployment.

D. Statistical Feature Engineering

In case of time-series sensor data, a statistical feature extraction is used to transform raw signals into structured vectors. Extracted features include:

- Mean

- Standard deviation
- RMS
- Minimum and maximum
- Skewness
- Kurtosis

Hydraulic dataset: divided into cycles of 60 samples and annotated with percentile based logic of anomaly.

IMS Bearings: The data is file-based, which includes vibration segments in a form of features and labeled using RMS thresholds.

E. ML Model Training

The system trains and compares three trained classifiers that are appropriate on structured datasets of maintenance:

- Random Forest Classifier (200 estimators).
- XGBoost Classifier (Number of estimators=300, learning rate=0.05)
- LightGBM Classifier (300 estimators, and learning rate = 0.05).

The following practices are incorporated in order to enhance reliability during training:

- Stratified randomization in order to maintain fault/non-fault ratio.
- Balancing of classes with SMOTE only in need.
- metric evaluation Accuracy, Precision, Recall, and F1-score.

Along with these measures, the confusion matrix analysis is employed during the experimentation in order to confirm whether the model is biased on the majority (normal) class. This is significant in hospital settings since a missed fault prediction (false negative) is usually more significant than a false alarm.

F. Mathematical Formulation

The mathematical formulation of the predictive models is described as follows.

Random Forest: Random Forest is an ensemble learning method that combines multiple decision trees. The prediction is obtained by averaging outputs from all trees:

$$y = \frac{1}{N}\sum_{i=1}^{N} T_i(x)$$

where: - N is the number of decision trees, - $T_i(x)$ is the prediction of the i^{th} decision tree, - x is the input feature vector.

XGBoost: XGBoost minimizes a regularized objective function:

$$L = \sum_{i=1}^{n} l(y_i, \hat{y}_i) + \sum_{k=1}^{K} \Omega(f_k)$$

where: - $l(y_i, \hat{y}_i)$ is the loss function (e.g., logistic loss), - $\Omega(f_k)$ is the regularization term controlling model complexity, - f_k represents individual decision trees.

This formulation helps reduce overfitting while improving prediction accuracy.

G. Experimental Setup

The machine learning models are configured as follows:

- Random Forest: 200 estimators
- XGBoost: 300 estimators with learning rate 0.05
- LightGBM: 300 estimators with learning rate 0.05

H. Hybrid Prediction Engine

At deployment, a runtime prediction engine is deployed. The predictor supports:

- ML-based prediction with the access to the trained models.
- Fallback risk scoring in the absence of models or poor quality of input.

Such hybrid solution is more robust in a system as a hospital monitoring backend should be able to remain operational even without a model file, or corrupted, or even when the device can only get biased sensor data.

Fallback risk rating takes into account:

- Preventive or corrective or emergency maintenance.
- Priorities (low/medium/high).
- Equipment (working, degraded, warning).
- Random variation of uncertainty (to model actual uncertainty).

Risk thresholds:

- Risk at least 0.7 critically.
- $0.5 \leq$ Risk $< 0.7 \rightarrow$ WARNING
- $0.3 \leq$ Risk $< 0.5 \rightarrow$ NORMAL
- Risk $< 0.3 \rightarrow$ HEALTHY

The hybrid architecture has the benefit of providing constant service availability, and ensuring that the backend will never fail silently and provide a meaningful response.

I. Output and Decision Support

The backend generates:

- Risk score (0–1)
- Health category (Healthy/Normal/Warning/Critical)
- Equipment Health % = (1 $-$ risk) $\times$ 100
- Levels of probability of failure (Low/Medium/High/Very High)
- Following maintenance estimation (1–90 days)
- Trend estimation (stable/ gradually degrading/rapidly degrading).
- Scheduling of recommendations depending on the type of device and maintenance.

J. DB (Flask and SQLite) Deployment

The predictive intelligence can be incorporated in the maintenance operations of the hospital through the deployment layer which is the backend. It offers a lightweight REST based inference and record keeping service.

The backend uses:

- REST API server used to route requests and predict them.
- Storing the equipment records, prediction logs, and maintenance history in SQLite database.

- MaintenanceDB wrapper to encapsulate SQL operations to make the application logic clean.

Core endpoints:

- POST /api/predict-maintenance (maintenance core prediction endpoint)
- POST /api/insert-maintenance-record (with the saving of records manually)
- POST /api/auto-save-prediction (store prediction automatically)
- GET/api/get-maintenance-records (research all records).
- POST/api/discover-record-status/id(change the status).
- DELETE/api/ delete-record /id (delete a record)
- GET/api/export-records (download/ export history).

Regarding the security in the backend, simple validation is done to verify that before processing, the required fields are provided. Additional chans can be made to role-authenticate the engineers and administrators and limit the input rate to prevent accidents.

V. Proposed System Architecture

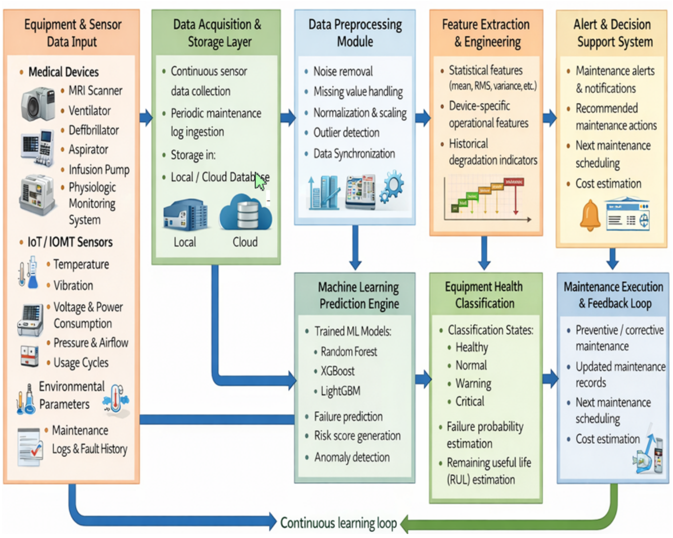


Fig. 1. Architecture of the Proposed Predictive Maintenance System

The suggested architecture is a Predictive Maintenance System of Healthcare Equipment based on Machine Learning at both ends. The system constantly monitors the medical devices, analyzes the way they operate, predicts the possibility of failure, and maintains maintenance decision making in a closed feedback loop. This system is explained in fullworking as per the logical flow as presented in the architecture.

1) Equipment and Sensor Data Input Layer: The first stage of the system includes significant medical equipment, which is located in a hospital environment, including MRI scanners, ventilators, defibrillators, aspirators, infusion pumps, and physiologic monitoring systems. These are devices that are connected to IoT/IOMT sensors that continuously monitor real-time working parameters.

The collected data includes:

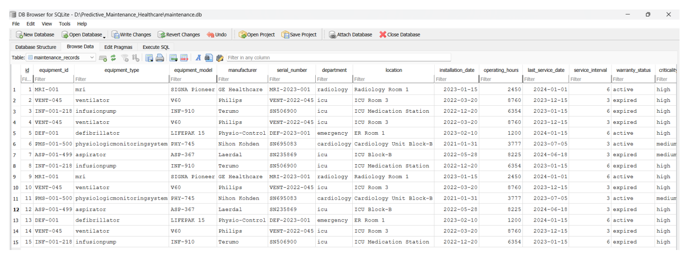
- Temperature changes and thermal changes.
- Online indication of mechanical wear.
- Patterns of voltage and power consumption.
- Airflow measurements and pressure measurements.
- Utilization cycles and working hours.
- Environmental conditions
- Maintenance records and the records of historical faults.

It is a layer that constitutes the basis of the predictive maintenance pipeline as it offers raw condition-monitoring data that captures the actual state of the functioning of each device.

2) Data Acquisition and Storage Layer: Medical equipment reads the data which is transmitted to the Data Acquisition and Storage Layer. The responsibilities of this layer are:

- Constant consumption of real time sensor streams.
- Regular consumption of records and fault history of maintenance.
- Co-ordination of diverse data.

Depending on the deployment requirements, data obtained will be stored in a local database (on-premise hospital servers) or in cloud database. Such scalable storage policy enables scalability and reliability besides safe access to further processing.



	id	equipment_id	equipment_type	equipment_model	manufacturer	serial_number	department	location	installation_date	operating_hours	last_service_date	service_interval	warranty_status	criticality
1	1	MRI-001	mri	SIGNA Pioneer	GE Healthcare	MRI-2023-001	radiology	Radiology Room 1	2023-01-15	2450	2024-01-01	6	active	high
2	2	VENT-045	ventilator	V60	Philips	VENT-2022-045	icu	ICU Room 3	2022-03-20	8760	2023-12-15	3	expired	high
3	3	INF-001-218	infusionpump	INF-910	Terumo	SN506900	icu	ICU Medication Station	2022-12-20	6354	2023-01-15	6	expired	high
4	4	VENT-045	ventilator	V60	Philips	VENT-2022-045	icu	ICU Room 3	2022-03-20	8760	2023-12-15	3	expired	high
5	5	DEF-001	defibrillator	LIFEPAK 15	Physio-Control	DEF-2023-001	emergency	ER Room 1	2023-02-10	1200	2024-01-15	6	active	high
6	6	PMS-001-500	physiologicmonitoringsystem	PHY-745	Nihon Kohden	SN695083	cardiology	Cardiology Unit Block-B	2021-01-31	3777	2023-07-05	3	active	medium
7	7	ASP-001-499	aspirator	ASP-367	Laerdal	SN235869	icu	ICU Block-B	2022-05-28	8225	2024-06-18	3	expired	medium
8	8	INF-001-218	infusionpump	INF-910	Terumo	SN506900	icu	ICU Medication Station	2022-12-20	6354	2023-01-15	6	expired	high
9	9	MRI-001	mri	SIGNA Pioneer	GE Healthcare	MRI-2023-001	radiology	Radiology Room 1	2023-01-15	2450	2024-01-01	6	active	high
10	10	VENT-045	ventilator	V60	Philips	VENT-2022-045	icu	ICU Room 3	2022-03-20	8760	2023-12-15	3	expired	high
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15	15	INF-001-218	infusionpump	INF-910	Terumo	SN506900	icu	ICU Medication Station	2022-12-20	6354	2023-01-15	6	expired	high

Fig. 2. SQLite database storing equipment and maintenance data.

3) Data Preprocessing Module: Raw sensor data is usually full of noise and gaps in data and inconsistencies. Therefore, Data Preprocessing Module is a module that carries out cleaning and preparation tasks that are necessary before the machine learning using the data.

The pre-processing steps include:

- Filtering of noise to get rid of sensor disturbances.
- Imputation methods of dealing with missing values.
- Standardization of the ranges of features by normalization and scaling.
- To detect the abnormal spikes outlier.
- Information synchronization between sensors and time points.

This step is used to make sure that the input data is clean and consistent, and that it is appropriate to extract the features and train the model accurately.

4) Feature Extraction and Engineering: The system then obtains meaningful features upon preprocessing that are employed to represent the degradation and health trends of equipment. This module converts raw signals of the sensors into features to be used with machine-learning, such as:

- Mean, RMS, variance, minimum and maximum, which are statistical characteristics.
- Operational indicators of the device (e.g., an airflow stability of ventilators, thermal drift of MRI systems, etc.).
- Trends of degradation learned in the past using sensors.

The feature engineering improves the predictive power of the models by emphasizing the patterns that are strongly related to the failure of equipment and a decline in its performance.

5) Machine Learning Prediction Engine: The processed features are fed into the Machine Learning Prediction Engine which is at the heart of the intelligence in the system. The engine will include trained machine learning models including:

- Random Forest
- XGBoost
- LightGBM

These models work on the feature vectors to perform:

- Failure prediction
- Risk score generation
- Anomaly detection

The engine is able to determine complex relationships between sensor behavior and failure events, and therefore identifies early abnormal operating conditions.

6) Equipment Health Classification Module: Depending on the results of the prediction engine, the system presents four interpretable equipment health states:

- Healthy
- Normal
- Warning
- Critical

Besides classification, the module aims at estimating:

- Failure probability
- Useful Life of the equipment (RUL)

The results of this kind of information would give maintenance teams a clear and actionable insight into the equipment condition.

7) Alert and Decision Support System: The Alert and Decision Support System is activated when the estimated risk goes beyond prescribed limits. This module:

- Produces maintenance notifications and warnings.
- Proposes proper maintenance measures.
- Recommends the best subsequent maintenance plans.
- Estimates maintenance cost

The products can help biomedical engineers and hospital administrators make a wise and proactive decision about maintenance instead of responding to unforeseen failures.

8) Maintenance Execution and Feedback Loop: The final one is the implementation of maintenance whereby preventive or corrective measures will be adopted as per the suggestions of the system. After maintenance:

- In the database, maintenance records are updated.
- Equipment status is revised
- Post-maintenance is data of new sensor.

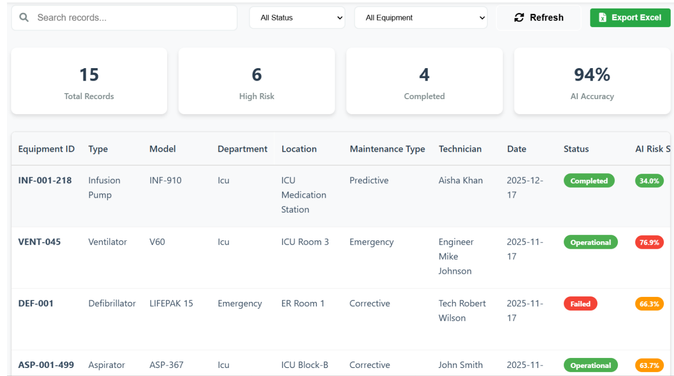

Fig. 3. Alert and decision support dashboard with AI risk and maintenance status.

This new information gets fed-back to the system and this creates an ever-learning process. The machine learning models may be retrained regularly with new data available periodically which will enable the system to evolve with the changing behavior of the equipment and increase the accuracy of the prediction over time.

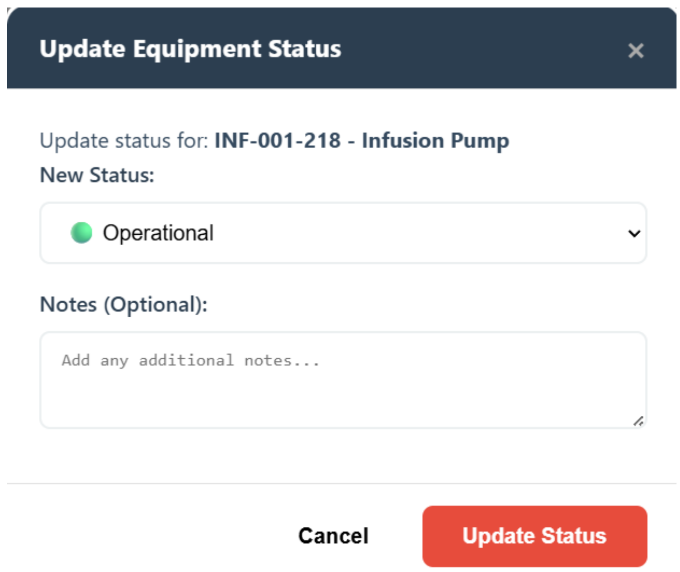

Fig. 4. Equipment status update interface in the feedback loop.

9) Continuous Learning and System Improvement: The closed-loop architecture will guarantee continuous improvement by:

- Getting successful experience in new failure patterns.
- Getting used to aging and usage of devices.
- Improving long term prediction.

This renders the suggested system to be scalable, adaptive, and capable of deployment in a smart healthcare setting over the long term.

VI. Results and Analysis

The predictive maintenance model was tested on predictive maintenance benchmark datasets and a systematized final dataset of predictive maintenance. The experiments support the hypothesis that ensemble-based ML models have high predictive power and dynamic stability.

A. Model Behavior

- Gradient boosting models (LightGBM ,XGBoost) is effective at learning complicated nonlinear patterns of failure on structured sensor data.
- Random Forest is more stable in its performance and offers a better interpretation with feature importance.

B. Interpretability of Risk Score.

An important advantage of the backend is the conversion of predictions to a continuous risk score and not binary classification. The risk groups assist in making a speedy decision to the biomedical engineers and the hospital engineering departments.

C. Record Storing and Auditing

Persistence in SQLite supports:

- Tracking of maintenance history.
- Repeated warning notification.
- Reports that can be exported to be reviewed by the administration.

D. Practical Insights

- Risk-based scheduling assists in preventive maintenance and reduces downtimes.
- Statistical feature engineering can also be used to perform failure learning in situations with limited explicit labels.

E. Model Performance Evaluation

TABLE I
MODEL PERFORMANCE COMPARISON

Model	Accuracy	Precision	Recall	F1-score
Random Forest	98.5%	98%	97%	97.5%
XGBoost	99.2%	99%	98%	98.5%
LightGBM	99.5%	99.3%	99%	99.1%

The results demonstrate that ensemble models outperform traditional approaches. LightGBM achieved the highest performance among all models.

F. Model Comparison Discussion

Among the evaluated models, LightGBM achieved the highest accuracy due to its efficient gradient-based leaf-wise growth, which allows better handling of complex nonlinear relationships in structured data.

XGBoost also performed competitively but required higher computational cost. Random Forest provided stable and interpretable results but showed slightly lower accuracy compared to boosting methods.

Additionally, the use of SMOTE contributed to improved recall for failure classes by addressing class imbalance. Without SMOTE, the models showed a bias toward the majority (normal) class, resulting in higher false negatives.

G. Experimental Validation

The models were evaluated on combined datasets consisting of approximately 13,538 samples aggregated from multiple sources. The data was divided using an 80:20 stratified train-test split to preserve class distribution.

To ensure robustness and generalization capability, 5-fold cross-validation was performed. The performance metrics reported in Table I represent the average results obtained across all folds.

The high accuracy achieved by LightGBM is attributed to its efficient gradient-based leaf-wise growth strategy, which enables better handling of complex nonlinear relationships in structured sensor data.

Although high accuracy values are observed, the results are influenced by controlled benchmark datasets. In real-world deployment, performance may vary due to noise, missing data, and device-specific variations. These factors may introduce uncertainty and affect prediction reliability in practical healthcare environments.

H. Dataset Characteristics

The combined dataset consists of approximately 13,538 samples collected from multiple sources. The class distribution based on the predictive dataset is as follows:

- Failure class: 52.37%
- Normal class: 47.63%

The dataset is relatively balanced, reducing bias toward a dominant class and improving model reliability.

I. Evaluation Metrics

Evaluation was performed using Accuracy, Precision, Recall, and F1-score. Additionally, confusion matrix analysis was conducted to assess classification performance. The results indicate that the proposed models effectively minimize false negatives, which is critical in healthcare applications where missed failure predictions can have serious consequences.

J. Comparison with Existing Work

Compared to existing predictive maintenance systems, the proposed system demonstrates significant improvements. Most existing works focus on single-device prediction or industrial equipment, whereas the proposed system supports multiple heterogeneous medical devices within a unified framework.

Additionally, traditional approaches lack decision-support capabilities, while this system integrates risk scoring, health classification, and maintenance recommendations. The hybrid prediction mechanism further enhances system reliability by ensuring continuous operation even in the absence of trained models.

VII. CONCLUSION

The paper developed a predictive maintenance backend system based on Machine Learning and IoT platform to predict the failure of critical medical devices including MRI

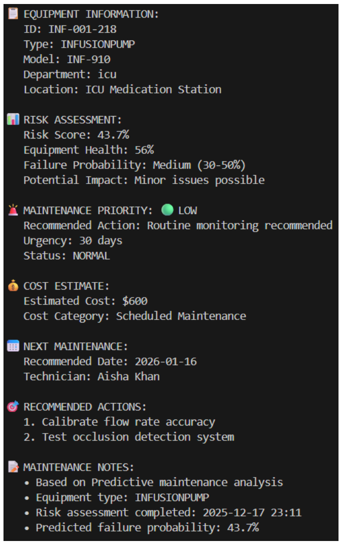

Fig. 5. Predictive maintenance risk and recommendation output.

scanners, ventilators, defibrillators, aspirators, infusion pumps and physiologic monitoring systems. The proposed system addresses the reactive and preventive schedule limitation by allowing the prediction of failures early, classify risks and performing proactive maintenance schedule.

The framework includes the preprocessing, statistical feature extraction, and the training of a model with the help of Random Forest, XGBoost, and LightGBM. Flask and SQLite are used to perform deployment to facilitate record tracking, auditing and decision support outputs. The results reveal that the ensemble models are effective in faults classification and the risk scoring can improve the interpretation to maintenance teams.

Future directions will include the incorporation of real IoT hardware streams, the integration of time-series deep learning models in cases where large labeled data is received, and deploying to edge/cloud to constantly monitor various departments and hospitals.

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