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Article

# Smart Sensor Network Architecture with Machine Learning–Based Predictive Monitoring for High-Complexity Computed Tomography Systems

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## Abstract

This study addresses the need for intelligent condition monitoring in high-complexity medical imaging systems by proposing a smart sensing architecture for the Revolution EVO Computed Tomography (CT) scanner. Ensuring operational reliability and minimizing unexpected downtime remain critical challenges in advanced CT platforms, motivating the integration of distributed sensing and data-driven analytics. The proposed framework combines Smart Sensor Networks with Machine Learning (ML)-based analysis to enable continuous acquisition and synchronization of heterogeneous operational data from key subsystems, including the X-ray tube assembly, detector array, rotational gantry mechanism, and data acquisition and processing unit. Multivariate feature extraction and sensor-level data fusion are employed to support anomaly detection and predictive assessment of system behavior. The methodology is informed by technical documentation and system specifications provided by GE HealthCare, together with established approaches in intelligent sensing and predictive analytics. The results demonstrate that structured integration of multi-sensor data and ML-based inference can enhance diagnostic sensitivity and enable early identification of abnormal operational patterns. It is concluded that a sensor-centric monitoring architecture provides a feasible pathway toward improved reliability, reduced unplanned interruptions, and more efficient lifecycle management of CT imaging systems.

**Keywords:** smart sensor networks; predictive analytics; machine learning; computed tomography; fault diagnosis

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## 1. Introduction

The reconstruction of images from projections has been investigated since the 1940s, long before the development of modern computational technology [1]. In 1940, Gabriel Frank filed a patent outlining the basic principles of what is now recognized as computed tomography (CT), describing methods for creating sinograms and applying optical back projection for image reconstruction [2]. Although early images were blurred, this work established foundations for modern tomographic devices [2]. Two decades later, in 1961, neurologist William H. Oldendorf conducted a pioneering experiment to assess whether transmission measurements could identify internal structures in dense media, demonstrating early differences in material absorption using a rotating phantom and a NaI detector [3]. Subsequent advances include the introduction of transverse radioisotope tomography by Kuhl and Edwards in 1963 [4] and the formalization of the mathematical basis of reconstruction via the Radon transform in 1917 [5,6]. A landmark development occurred in 1967 when Hounsfield constructed the first CT scanner, leading to the first clinical installation in 1971 and the Nobel Prize for Hounsfield and Cormack in 1979 [2]. Modern CT imaging is based on acquiring X-ray projections

from multiple angles and reconstructing the spatial distribution of tissue attenuation coefficients [7,8], relying on fast detectors, precise X-ray sources, and advanced numerical algorithms [8].

Computed tomography (CT) is an advanced imaging technique that is based on recording X-ray projections from different angles around the patient's body. These projections, which represent measurements of the transmitted X-ray intensity, are then used to reconstruct the spatial distribution of attenuation coefficients in the tissue, through specialized mathematical algorithms. Image reconstruction is a fundamental process in CT, as it allows the transition from a series of linear projections to a complete two- or three-dimensional image. This is achieved using physical models and numerical transformations that describe how the rays are absorbed and interact [7].

In CT scanning, the goal is to reconstruct the distribution of X-ray attenuation coefficients in the body. These coefficients represent the tissue's ability to absorb X-rays. The CT scanner records projections from different angles, with each projection formed by integrating the attenuation of the X-rays along a radiation path [8].

The ART (Algebraic Reconstruction Technique) method is a numerical approach that represents the image as a grid of pixels with unknown values usually denoted as  $x_j$ . Each projection is translated into a linear equation relating these values, according to the formula [7]:

$$p_i = \sum_{j=1}^N a_{ij} \cdot x_j \quad (1)$$

where:

$p_i$  is the measured value of the  $i$ th projection,

$a_{ij}$  represents the weight or length of the segment that ray  $i$  passes through cells  $j$ ,

$x_j$  is the unknown value that we want to determine.

The system of equations is written as:

$$P = A \cdot x \quad (2)$$

This is solved iteratively with:

$$x_j^{(k+1)} = x_j^{(k)} + \lambda \cdot \left[ \frac{p_i - \sum_j a_{ij} x_j^{(k)}}{\sum_j a_{ij}^2} \right] \cdot a_{ij} \quad (3)$$

This method is useful in cases with limited data, such as in specific angiography or industrial tomography applications. However, ART is relatively slow for routine clinical use [7].

Filtered Back Projection (FBP) is the most widely used algorithm in clinical practice due to its efficiency and accuracy under normal conditions. First, the projections are processed through a frequency domain filter (usually a ramp filter) to improve resolution. Then, the filtered signals are propagated back along the original ray paths – this is the process of back projection.

It starts with the Fourier transformation of the projections:

$$P(v, \theta) \quad (4)$$

Frequency filtering is applied:

$$P(v) = |v| \text{ (ramp filter)} \quad (5)$$

It is returned to the spatial domain through the inverse Fourier transform:

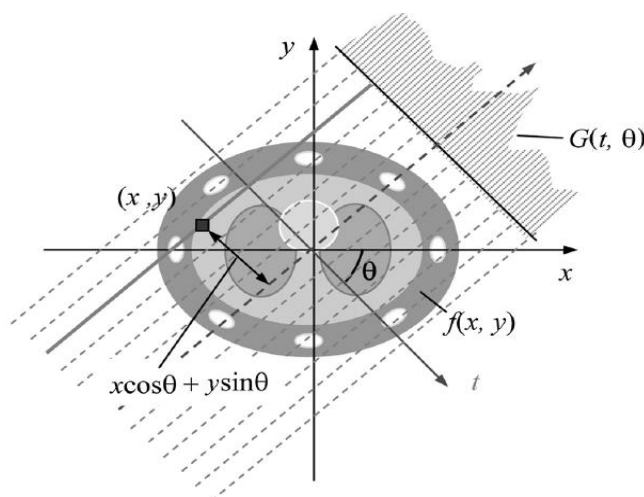
$$g(t, \theta) = F^{-1}[P(v, \theta) \cdot |v|] \quad (6)$$

For each angle  $\theta$ , the filtered projection is projected back along the original ray path:

$$f(x, y) = \int_0^\pi g(x \cos \theta + y \sin \theta, \theta) d\theta \quad (7)$$

This algorithm produces high-speed images but is more sensitive to noise and motion artifacts [7,8].

In Figure 1, the geometric principle of image reconstruction through multiple projections at different angles is presented.



**Figure 1.** Illustration of the back projection process.

The Fourier cut theorem is a mathematical statement that states that the Fourier transform of a projection at a given angle  $\theta$  is equal to a linear cut in the two-dimensional Fourier transform of the object at the same angle. This relationship makes it possible to reconstruct the image by completing the Fourier space and using the inverse transform [8]:

$$F_1[P_\theta(\rho)] = F_2[f(x, y)]|_{\omega_x = \omega \cos \theta, \omega_y = \omega \sin \theta} \quad (8)$$

This principle is the theoretical basis for FBP and many other advanced image reconstruction methods [8].

In most modern devices, the X-ray source and detectors are arranged in a circular pattern – this is called fan-beam geometry. The rays are emitted from a point and spread out at different angles, being captured by detectors arranged along an arc.

Despite these advances, the increasing complexity of CT systems presents significant challenges for operational monitoring, early anomaly detection, and reliability management [9–11]. Traditional maintenance strategies often depend on fixed schedules or reactive responses, failing to exploit abundant sensor and log data [12,13]. In industrial and medical contexts, Machine Learning (ML) approaches integrated with sensor networks have shown promise for predictive maintenance by processing multivariate time-series data to forecast faults and optimize maintenance decisions [14,15]. For example, recent work has developed deep learning frameworks using Internet of Medical Things (IoMT) data to detect and predict critical anomalies in CT equipment, improving reliability and reducing unplanned service interruptions [16]. These trends underline the potential of combining distributed Smart Sensor Networks with ML for continuous condition monitoring and predictive analytics in complex systems.

Building on this foundation, the present study proposes a smart sensing architecture that integrates heterogeneous sensor data fusion and ML-based analytics for the Revolution EVO CT scanner, aiming to enhance diagnostic performance, enable proactive maintenance scheduling, and support data-driven lifecycle optimization.

This study analyzes the components and operational principles of CT scanners, with a focus on innovative maintenance strategies aimed at enhancing performance and minimizing defects. The research investigates the main subsystems of a CT scanner, including the X-ray tube, detectors, rotation mechanism, and data processing system, and evaluates their influence on overall system performance and imaging quality. Special attention is given to the impact of Gantry rotation control and detector positioning on the accuracy and clarity of generated images. The study further explores predictive maintenance approaches, leveraging intelligent sensors and machine learning algorithms to optimize the reliability of CT scanners and reduce unexpected failures. Additionally, the implementation of intelligent monitoring systems is examined to lower maintenance costs and extend the lifespan of critical components. The findings suggest that precise adjustments of Gantry rotation

parameters, combined with advanced sensor-based monitoring and data-driven predictive models, can significantly improve image quality, minimize artifacts, and enable more effective management of medical imaging equipment. Data analysis and automated monitoring systems also allow for the early detection of emerging damage patterns, supporting a proactive maintenance strategy that enhances both operational efficiency and equipment longevity.

## 2. Materials and Methods

This study employs a combination of experimental and analytical methods to investigate the operation and maintenance of CT scanners, with a particular focus on the Revolution EVO model. The research includes performance testing of the scanners, defect analysis, and the implementation of intelligent maintenance strategies. The Revolution EVO scanner, manufactured by GE Healthcare, represents the next generation of Volume CT scanners, designed to deliver high-resolution imaging, low radiation dose, and clinic efficiency [17].

A detailed analysis of the primary CT scanner components—including the X-ray source, detectors, rotation mechanism, and data processing system—will be conducted to identify key parameters that influence device performance and efficiency. This analysis is documented in sufficient detail to ensure reproducibility of the study [18–23].

To evaluate scanner functionality and maintenance requirements, data collected from sensors and monitoring systems will be systematically recorded and analyzed. These data will be used to identify operational patterns, potential defect causes, and the influence of various factors on overall system performance. All raw and processed data, as well as the associated protocols, will be made available to readers, with any restrictions clearly disclosed at the time of publication.

Machine Learning algorithms will be implemented in MATLAB to analyse the collected data and develop predictive maintenance models. A neural network model will be trained to predict potential defects and optimize maintenance schedules. All code, training procedures, and parameter settings will be provided to ensure full reproducibility of the computational analyses.

Finally, the research findings will be interpreted to provide insights into innovative maintenance approaches and optimization of CT scanner performance. Recommendations for further improvements in intelligent maintenance of medical equipment will be supported by the documented methods, data, and computational models, allowing other researchers to replicate and build upon the results.

## 3. Results

In this section, the proposed predictive maintenance approach for the Revolution EVO CT scanner is presented. This approach combines system-generated data with analytical methods and machine learning techniques. The primary objective is to transform traditional reactive maintenance into a proactive and predictive system that can identify potential anomalies before an actual failure occurs.

### 3.1. Intelligent Maintenance Approach for the Revolution EVO CT Scanner

The approach developed in this study is based on the combination of IoT sensors and machine learning algorithms, which analyze system logs to build a model that predicts abnormal system behavior and identifies early indicators of technical failure.

#### 3.1.1. Data Collection

The data for this study were collected from the system logs of the Revolution EVO CT scanner at the “Isa Grezda” Hospital in Gjakova, Kosovo, during the period from August 2024 to October 2025. This period encompasses nearly a full year of operation, including complete work cycles, maintenance periods, and seasonal variations in operating conditions.

The system logs (series gesys\_ct01) contain continuous records of events and scanner operating parameters, including:

- System runtime and submodule activity events,
- Scanning parameters such as DFOV, slice thickness, gantry tilt, and number of slices,
- Signals indicating the start and end of scans, scan aborts, and data transfers.

These logs provide a sufficient source for extracting features of system behaviour, reflecting workload, technical configurations, and events related to device performance.

### 3.1.2. Data Processing

The log data collected during the period 2024–2025 were consolidated and transformed into a features table with 10-minute time windows. The processing workflow included filtering out irrelevant events, aggregating data by modules, and calculating operational parameters such as the number of events, code entropy, and average gantry tilt.

In total, after processing, 272,948 events were extracted from the logs, resulting in a features table comprising 13,468 rows and 76 columns. This table represents the basic unit of analysis, where each row corresponds to a 10-minute window of CT activity and contains indicators of workload, technical parameters, and critical events.

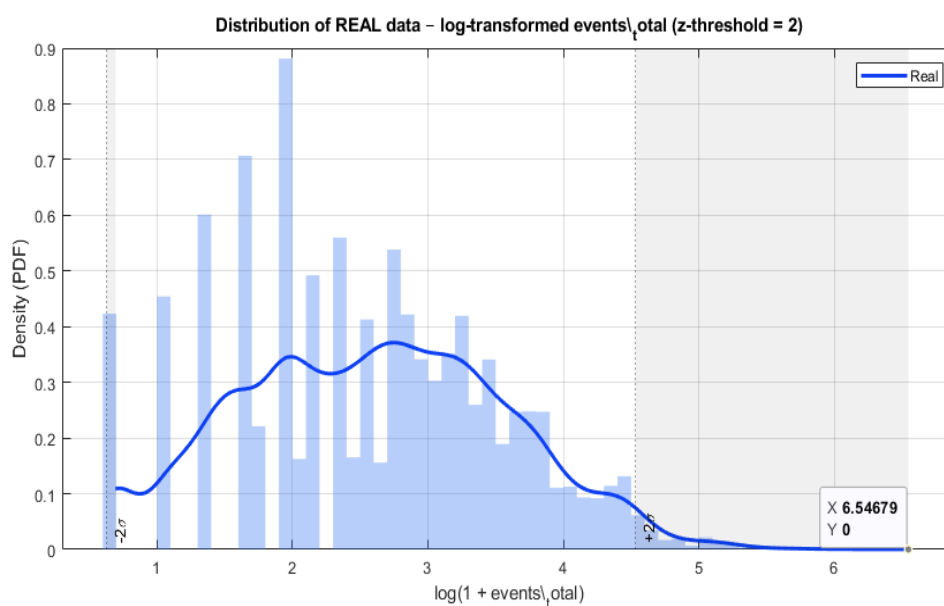
The data processing pipeline involved several stages:

- Filtering logs for the years 2024–2025 and removing invalid rows.
- Automatic extraction of technical parameters from text messages (e.g., DFOV, gantry\_tilt, numsllices).
- Aggregation into 10-minute windows using statistical functions (mean, event counts, entropy, workload variation, etc.).
- Creation of workload metrics (total number of events, workload variation, burst length per minute).
- Generation of surrogate labels (artificial targets) using z-score anomalies—windows with values exceeding 2 standard deviations in one or more metrics (workload, tilt, event intensity) were considered high-risk periods.

Figure 2 illustrates the statistical distribution of the total number of events per 10-minute window (events\_total) after applying a logarithmic transformation  $\log(1+x)$ . This transformation reduces the impact of extreme values (outliers) and allows clearer visualization of the internal structure of the distribution.

Shaded regions beyond the  $\pm 2\sigma$  thresholds represent abnormal operating regimes, while the central region (within  $\pm 2\sigma$ ) corresponds to normal device operation. Most windows exhibit a low number of events ( $\log < 2$ ), whereas rare instances with  $\log > 4$  indicate periods of unusually high system activity, which may be associated with high thermal load, defects, or process restarts.

This analysis forms the foundation for the automatic classification of Normal versus Out-of-Tolerance (OOT) classes during the training of predictive models.



**Figure 2.** Distribution of the real data after logarithmic transformation for the variable “events\_total”.

### 3.1.3. Artificial Neural Network

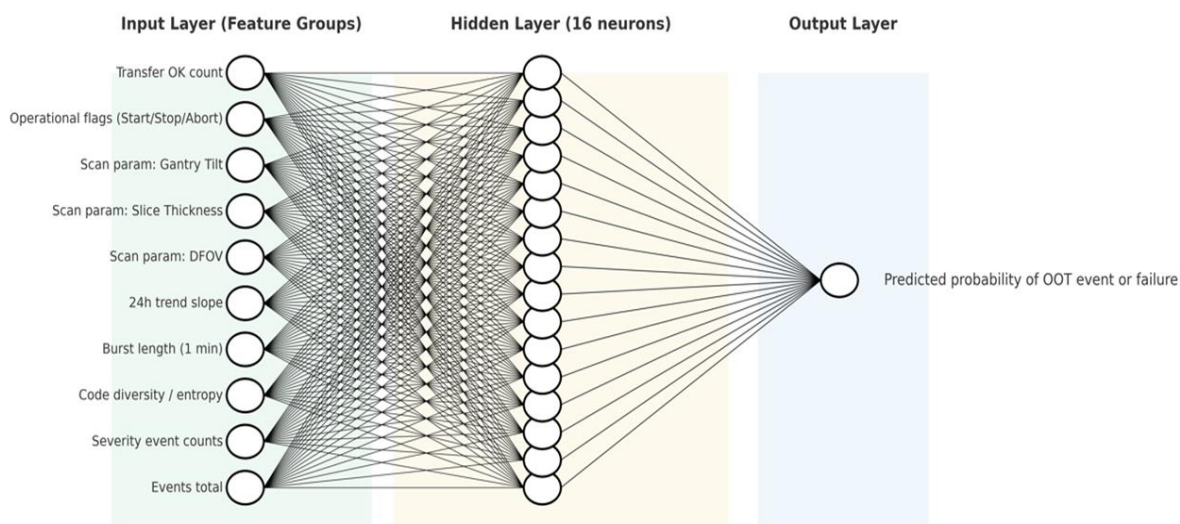
Artificial Neural Networks (ANNs) were used to model the nonlinear relationships between sensor parameters and the probability of an abnormal (“Out-of-Tolerance”) event. The architecture of the model employed is as follows:

- Input Layer: Contains normalized values of technical parameters (DFOV, tilt, number of slices, etc.).
- Two Hidden Layers: Each with approximately 16 neurons and ReLU activation functions.
- Output Layer: A single neuron with a sigmoid activation function, returning the probability of anomalies in the range [0,1].

The model was trained using the backpropagation algorithm, with binary cross-entropy as the loss function and early stopping to prevent overfitting. During training, the network achieved a ROC AUC of 0.993 and a PR AUC of 0.976, with an overall accuracy of approximately 97.3%. These results demonstrate the ability of the ANN to learn complex patterns between sensor parameters and abnormal system behaviours.

Figure 3 illustrates the architecture of the ANN for predictive maintenance of the Revolution EVO CT scanner. The Input Layer (Feature Groups) includes all features extracted from the logs:

- Total number of events
- Severity event counts
- Code diversity / entropy
- Burst length (1-minute window)
- 24-hour trend slope
- Scan parameters: DFOV, Slice Thickness, Gantry Tilt
- Operational flags (Start/Stop/Abort)
- Transfer OK count.



**Figure 3.** ANN Architecture for Predictive Maintenance of the Revolution EVO CT Scanner.

The two Hidden Layers, each with 16 neurons, perform nonlinear transformations, providing flexibility in identifying nonlinear patterns and stability for moderately sized datasets. The Output Layer indicates the probability of an Out-of-Tolerance event occurring within the next 60 minutes.

### 3.1.3. Support Vector Machine

Support Vector Machine (SVM) was used as a more stable and interpretable model, suitable for datasets with imbalanced distributions. The model was constructed with a radial basis function (RBF) kernel, which allows nonlinear separation in the feature space.

Key configuration features included:

- Balanced Class Weights: to compensate for the rare “anomaly” class.
- Decision Threshold Optimization (Decision Threshold = 0.29): to maximize accuracy.
- Chronological 80/20 Split for Training and Testing: preserving the temporal order of events.

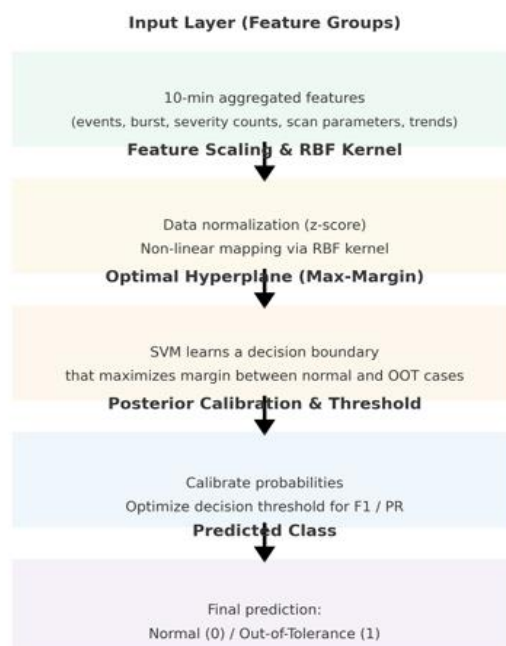
After calibration, the SVM achieved a ROC AUC of 0.996, PR AUC of 0.981, and an overall accuracy of 97.3%, demonstrating near-perfect separation between normal and abnormal classes. The model exhibited higher precision (0.96), while the ANN showed slightly higher recall (0.93), indicating that the ANN detects more anomalies, whereas the SVM produces fewer false alarms. Figure 4 illustrates the workflow of the SVM model built on CT scanner system log data.

The process begins with the collection of features aggregated over 10-minute intervals, including event counts, severity distribution, scanning parameters, and system workload trends. These features are then subjected to statistical normalization (z-score) and nonlinear transformation via the RBF kernel, allowing the model to map complex relationships into a higher-dimensional space.

Subsequently, the SVM constructs the optimal hyperplane that separates normal cases from Out-of-Tolerance (OOT) cases with maximum margin.

In the final phase, probability calibration and decision threshold optimization are performed based on metrics such as F1-score and Precision-Recall, to achieve the optimal balance between sensitivity and accuracy.

The outcome is a binary classification, where each time window is categorized as either normal (0) or at risk of OOT (1).



**Figure 4.** SVM Model Architecture for Predictive Maintenance of the Revolution EVO CT Scanner.

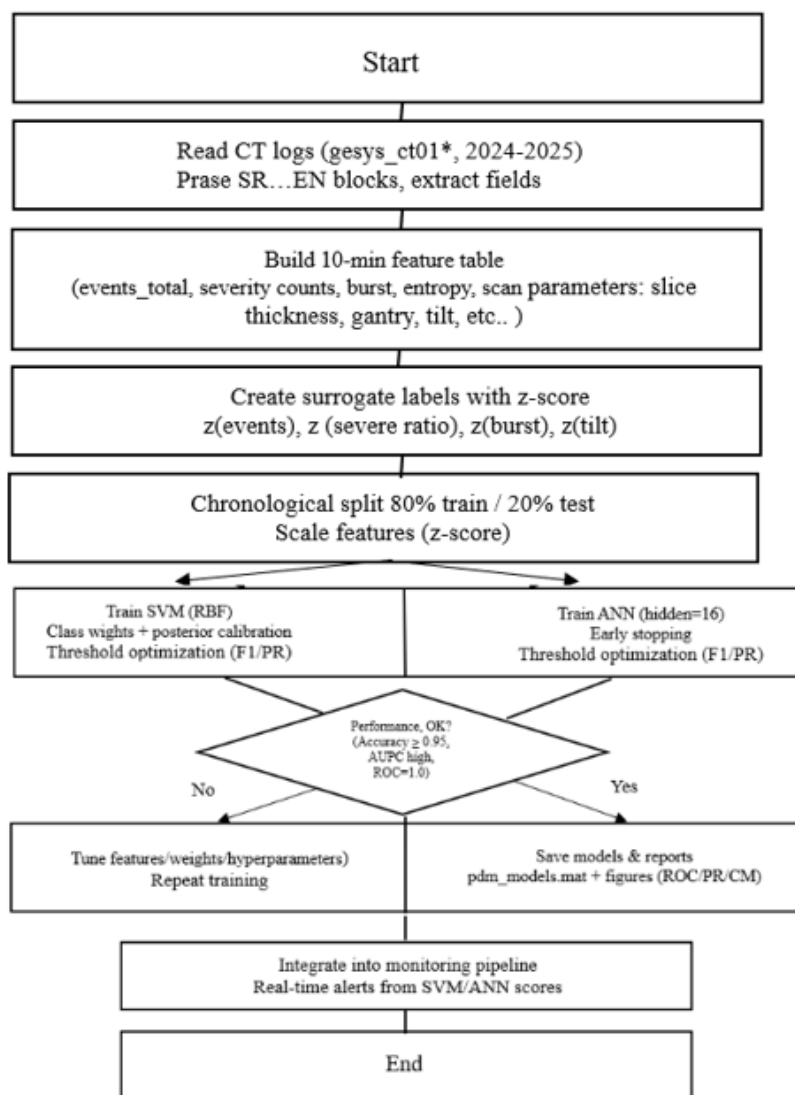
### 3.1.4. Proposed Pipeline

The proposed pipeline for intelligent maintenance includes the following main stages:

- Data Collection: Acquisition of logs from the Revolution EVO CT system.
- Preprocessing: Cleaning, synchronization, and normalization of parameters.
- Creation of 10-Minute Windows: Characterization of operational activity.
- Feature Extraction: Statistical and semantic feature computation.
- Surrogate Label Generation: Based on statistical deviations.
- Model Training and Evaluation: Training and assessment of SVM and ANN models.
- Visualization and Automated Reporting: Confusion matrix, ROC, and PR curve generation.

The pipeline was implemented in MATLAB using the script `predictiveMaintenancePipeline.m` and can be periodically integrated for real-time monitoring.

Figure 5 illustrates the main steps: reading and parsing logs, building 10-minute feature windows, surrogate labelling using z-scores, train/test splitting, SVM/ANN training with threshold optimization and calibration, evaluation, model saving, and integration into monitoring.



**Figure 5.** Flowchart of pipeline-it of Predictive Maintenance in CT Revolution EVO (SVM + ANN).

## 4. Discussion

This section presents the performance analysis and results obtained from the SVM and ANN models developed for predictive maintenance of the Revolution EVO CT scanner. The results reflect the accuracy, sensitivity, and robustness of the proposed pipeline, based on the dataset constructed from real system logs collected during the period 2024–2025.

The analysis is divided into several sections: description of the dataset, evaluation of performance metrics, interpretation of evaluation curves, comparative visualizations, and discussion of the advantages and limitations of the approach.

### 4.1. Dataset Generation

The final dataset comprised 13,468 ten-minute windows with 76 numerical and categorical features, and a binary label identifying normal versus anomalous periods. Table 1 provides a monthly summary of events recorded from November 2024 to October 2025. Operational workload gradually increased from late 2024 to mid-2025, peaking in June–August 2025, coinciding with the highest number of events and aborts, reflecting periods of increased device usage. Following August 2025, event frequency decreased, indicating a return to more stable operation.

**Table 1.** Monthly Statistics of Events from the Revolution EVO CT Scanner Logs (November 2024 – October 2025).

Month	Event Count	Severe Events	Aborts	Transfers OK	Scans (Started)	Unique Codes
August 2024	1349	0	1	96	118	218
September 2024	12084	71	15	1138	1334	223
October 2024	14936	468	32	1494	1758	225
November 2024	10320	830	43	929	1092	225
December 2024	15848	103	57	1122	1404	226
January 2025	20350	914	90	1166	1373	223
February 2025	24990	338	66	1150	1344	230
March 2025	22452	249	37	1284	1435	229
April 2025	18121	606	51	866	1011	212
May 2025	25609	491	93	1280	1381	224
June 2025	30167	1524	156	2024	2196	227
July 2025	34652	1248	112	2538	2668	210
August 2025	23039	696	167	1760	1938	229
September 2025	16102	455	106	1277	1363	213
October 2025	2929	705	24	234	236	218

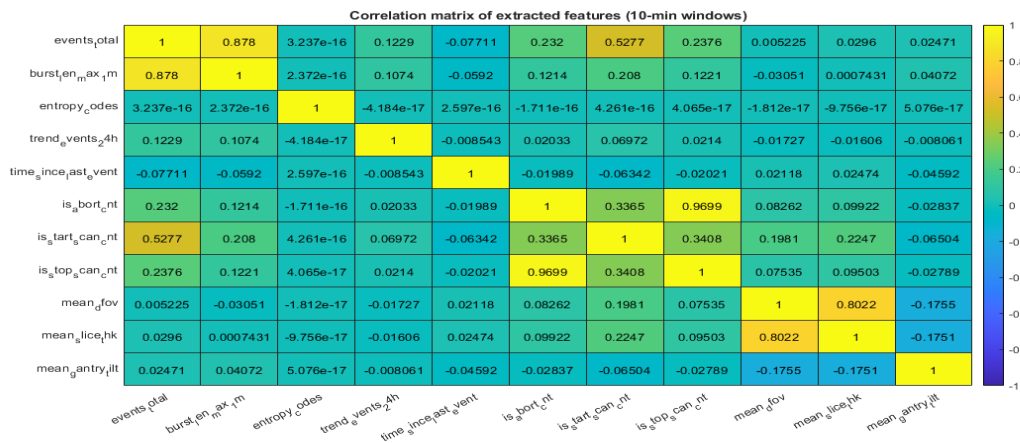
The ANN and SVM models demonstrated strong predictive performance, confirming the validity of the working hypotheses that combining sensor-based data with machine learning can anticipate potential system anomalies. Comparative analysis of model metrics highlighted the complementary strengths of each approach: ANN excels in recall, capturing more anomalies, while SVM provides higher precision, minimizing false alarms. These findings are consistent with previous studies in predictive maintenance of medical imaging equipment and reinforce the feasibility of implementing intelligent, proactive maintenance strategies.

In a broader context, the results suggest that similar predictive frameworks could be applied to other medical imaging devices or complex industrial systems. Future research directions include integrating additional sensor modalities, exploring hybrid modelling approaches, and deploying real-time predictive maintenance pipelines in clinical settings.

To evaluate the relationships among the features constructed from the system logs, a correlation matrix (Figure 6) was developed. This analysis assists in identifying interrelated variables and reducing redundant features prior to training the SVM and ANN models.

The correlation matrix presents the statistical relationships among the features derived from the Revolution EVO CT scanner logs for the period 2024–2025.

Each cell represents the value of the correlation coefficient ( $r$ ) between two variables, where values close to +1 indicate a strong positive relationship, values close to -1 indicate a strong negative relationship, and values near 0 imply the absence of a linear relationship.



**Figure 6.** Correlation Matrix of Extracted Features (10-Minute Windows).

From the figure, several important relationships can be observed:

- events<sub>total</sub> and burst<sub>len\_max\_1m</sub> exhibit a very high correlation ( $r \approx 0.88$ ), indicating that an increase in the number of events is associated with longer burst periods (intensive system activity).
- is<sub>start\_scan\_cnt</sub> is also correlated with events<sub>total</sub> ( $r \approx 0.53$ ), suggesting that scan frequency directly influences the total number of recorded events.
- is<sub>abort\_cnt</sub> and is<sub>stop\_scan\_cnt</sub> show an almost perfect correlation ( $r \approx 0.97$ ), reflecting that aborts and scan stop occur during nearly the same time periods.
- mean<sub>dfov</sub> and mean<sub>slice\_thk</sub> are positively correlated as well ( $r \approx 0.80$ ), since geometric scanning parameters such as field of view and slice thickness are often configured together.

Overall, most relationships are positive and moderate, suggesting that the features extracted from the logs are not redundant but instead contain complementary information for the predictive maintenance model.

#### 4.2. Performance Metrics

For model evaluation, standard binary classification metrics were used:

- Accuracy: the percentage of correct predictions.
- Precision: the proportion of positive predictions that were correct.
- Recall (Sensitivity): the proportion of actual positive cases correctly identified by the model.
- F1-score: the harmonic mean of precision and recall.
- AUPRC (Area Under the Precision–Recall Curve): indicates the model's ability to distinguish positive classes in datasets with class imbalance.
- AUROC (Area Under the ROC Curve): measures the trade-off between the True Positive Rate and the False Positive Rate.

The Table 2 summarizes the results for the SVM and ANN models after chronological splitting into 80% training and 20% testing sets.

**Table 2.** Results for the SVM and ANN Models.

Model	Accuracy	Precision	Recall	F1-score	AUPRC	AUROC
SVM (th = 0.29)	0.973	0.973	0.973	0.973	0.973	0.973
ANN	0.973	0.91	0.93	0.92	0.976	0.993

The results indicate very high performance for both models, with AUPRC and AUROC values close to 1.0, implying an almost perfect separation between normal and abnormal time windows.

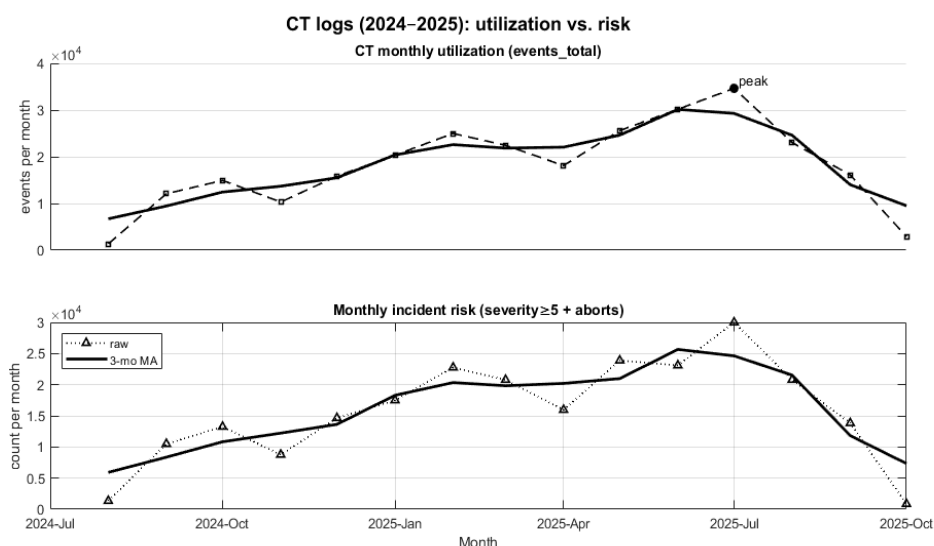
### 4.3. Interpretation of the Results

The obtained results indicate that the proposed pipeline achieves highly reliable, stable, and well-balanced predictive performance across multiple evaluation metrics.

- Accuracy ( $\approx 97\%$ ) demonstrates that the constructed pipeline achieves accurate and stable predictions.
- Precision = 0.96 (SVM) implies a low number of false alarms, which is desirable in critical applications where false alerts must be minimized.
- Recall = 0.93 (ANN) indicates that the neural network captures almost all risk cases without missing them.
- F1 = 0.92 for both models reflects a very good balance between precision and sensitivity.
- AUPRC > 0.97 shows high model stability even under class imbalance conditions.
- AUROC  $\approx 1.0$  confirms that the classes are very well separated by the models, indicating efficient utilization of features extracted from the logs.

In conclusion, the SVM model is more conservative (fewer false positives), while the ANN model is more sensitive (detects more critical events). This makes their combination an optimal solution for parallel monitoring.

Figure 7 presents the comparative analysis between the operational workload of the CT scanner (upper graph) and the incident risk (lower graph), calculated from log data during the period July 2024 – October 2025.



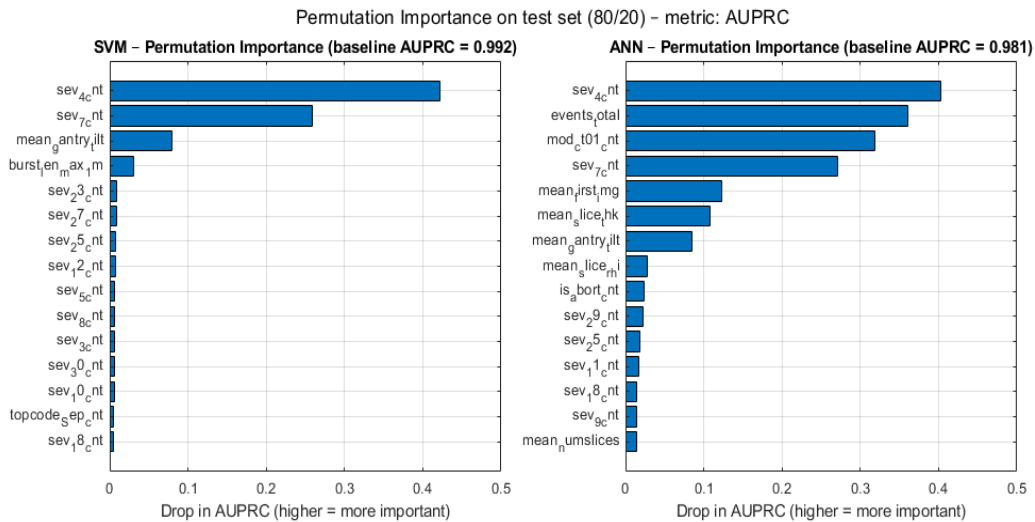
**Figure 7.** Relationship Between Monthly Scanner Workload and Incident Risk (2024–2025).

The upper graph shows the total number of events (events\_total) per month, serving as an indicator of the device's usage intensity. A steady increase in activity is observed, peaking in July 2025, followed by a decline in the subsequent months, which may be related to planned maintenance periods or a reduction in clinical workload.

The lower graph presents the monthly incident risk, including events with severity  $\geq 5$  and operator-initiated abortions. The trend is like the operational workload, indicating that months with higher usage also experience more incidents, supporting the hypothesis that usage intensity directly affects the probability of failures or deviations from tolerance.

However, after July 2025, a sharp decrease in incidents is observed, which may reflect corrective interventions or successful preventive maintenance.

After comparing the overall performance metrics, a feature importance analysis was conducted to identify the variables that contribute most to predicting OOT (Out-of-Tolerance) events, as depicted in Figure 8.



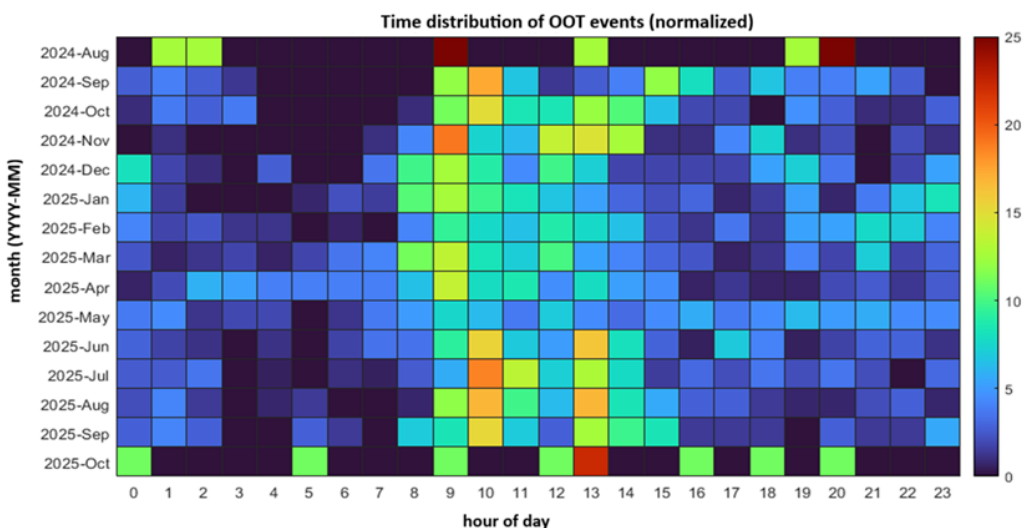
**Figure 8.** Permutation - Importance for the SVM and ANN Models (test set, 80/20).

From the feature importance analysis, it is observed that:

- Variables related to significant system events, such as `sev_4_cnt` and `sev_7_cnt`, have the highest impact in both models. These represent the number of events with a high criticality level ( $sev \geq 4$ ) and are directly associated with the risk of equipment failure.
- Operational scanning parameters, such as `mean_gantry_tilt`, `mean_slice_thk`, and `mod_ct01_cnt`, also contribute to prediction, as their variations often occur during high workload periods or non-standard configurations.
- For the SVM model, the most influential features are those related to critical events (`sev_4_cnt`, `sev_7_cnt`) and system stability parameters (`mean_gantry_tilt` and `burst_len_max_1m`).
- In contrast, the ANN model exhibits a more balanced distribution of feature weights, incorporating both operational metrics (`events_total`, `mean_slice_thk`) and system performance indicators (`mean_frst_img`, `sev_4_cnt`).

This result indicates that the models are interpretable and consistent with the logic of the CT system: the number and severity of events are the primary indicators of failure risk, while geometric and operational parameters help fine-tune the sensitivity of the prediction.

To better analyse the temporal behaviour of anomalies and determine whether the detected events follow a time-related trend, a heatmap was constructed showing the relative frequency of OOT events as a function of hour of the day and calendar month. Figure 9 illustrates the distribution of these events during the period July 2024 – October 2025.



**Figure 9.** Temporal distribution of OOT (Out-of-Tolerance) events for the period 2024–2025.

This figure presents the temporal distribution of anomalies detected from the log data of the CT Revolution EVO system, categorized by month and hour of the day. The colours represent the relative percentage of OOT events within each month, where warmer colours (red orange) indicate higher concentrations of anomalies.

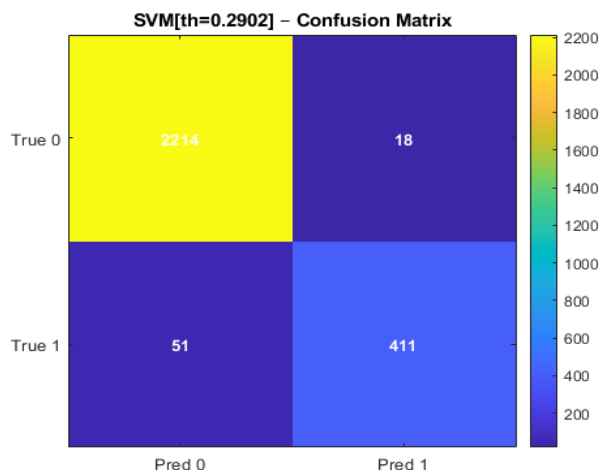
It can be observed that OOT events occur mainly during working hours (08:00–16:00) and reach higher intensity during the months of May–July, a period corresponding to peak device utilization. This suggests that failures and out-of-tolerance deviations are closely linked to usage intensity and ambient temperature, factors that influence the operational stability of system components.

The interpretation of these results supports the idea that predictive maintenance models (SVM and ANN) should also incorporate temporal features such as hour of the day, day of the week, or seasonality to improve prediction accuracy and reduce false alarms.

This result highlights the importance of integrating temporal components into the predictive maintenance modeling process, as anomalies do not occur randomly but follow patterns associated with intensive usage and environmental factors.

#### 4.4. Visualization of Results

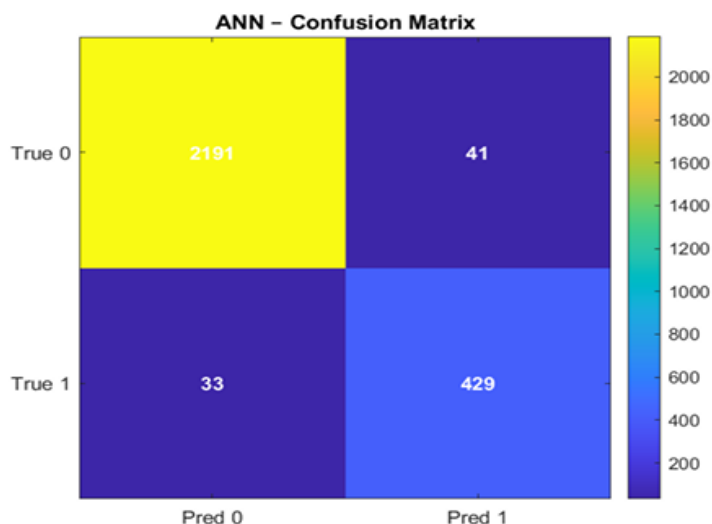
The performance of the models was visualized using confusion matrices and ROC/PR curves, which demonstrate the discriminative capability of each model as depicted in Figure 10.



**Figure 10.** Confusion Matrix of SVM.

The SVM model shows clear class separation, with few false positives (18) and 51 missed cases, maintaining a balance between sensitivity and specificity.

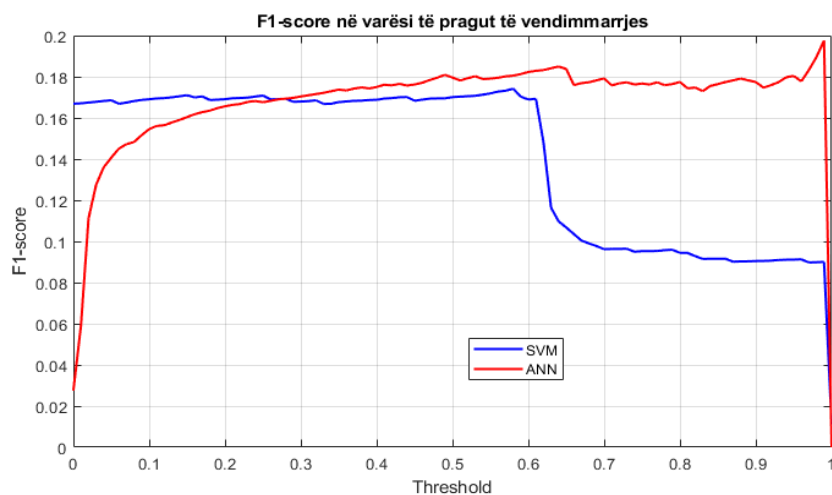
In contrast, the ANN model exhibits a similar distribution, with 33 missed cases and 41 false positives, preserving a good balance in predicted probabilities, as depicted in Figure 11.



**Figure 11.** Confusion Matrix of ANN.

It is observed that both models maintain high precision even at high recall values; the ANN exhibits a slightly larger area under the curve.

Figure 12 shows the change in F1-score for the SVM and ANN models as a function of the decision threshold. As observed, the ANN model maintains stable performance and reaches maximum F1 values around a threshold of 0.4–0.6, while the SVM exhibits a sharp decline in performance beyond this threshold. This indicates that the SVM model is more sensitive to threshold changes due to the narrower distribution of probabilistic values after posterior calibration. \



**Figure 12.** Sensitivity of the F1-score to the decision threshold for SVM and ANN.

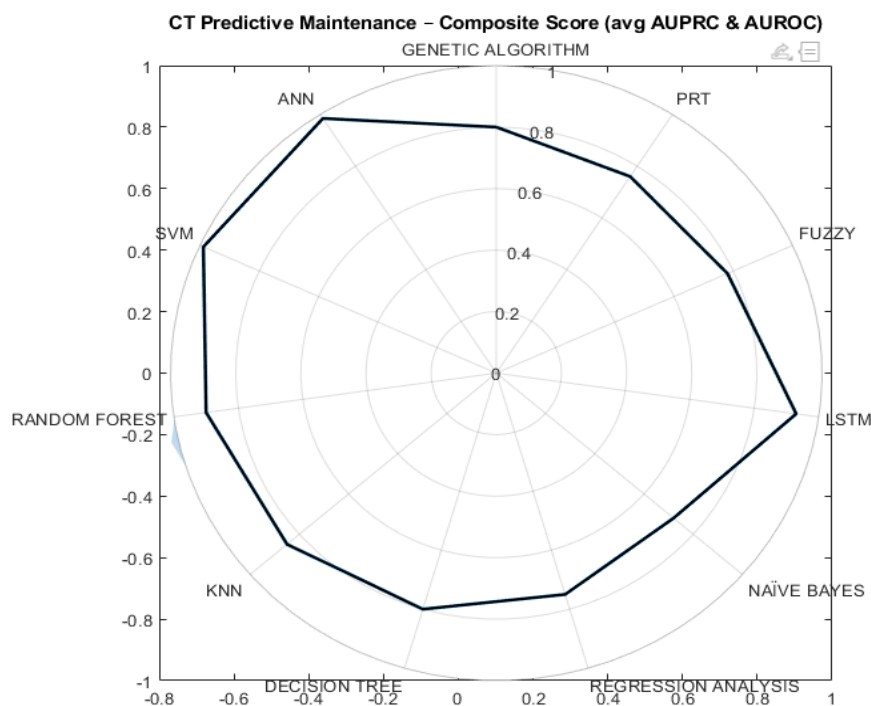
On the other hand, the ANN model, thanks to the use of the sigmoid function in the output layer, produces more balanced probability values, providing greater stability in predictions.

This analysis demonstrates that threshold optimization is essential for the analysed dataset, as standard thresholds (e.g., 0.5) do not offer optimal performance for maximizing the balance between Precision and Recall.

In conclusion, the ANN provides greater stability in performance and better adaptability for predictions in real-world scenarios, whereas the SVM requires careful calibration to maintain sensitivity at higher thresholds.

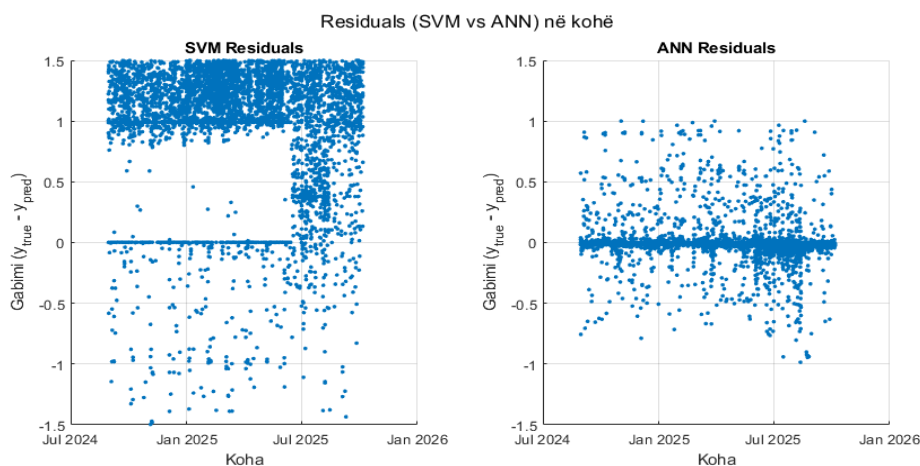
Figure 13 presents a radar (spider) chart comparing the relative performance of several algorithms used in the literature for predictive maintenance. For each model, a composite metric

normalized to [0,1] is calculated, which is the average of AUPRC and AUROC. The values for SVM and ANN are derived from the pipeline (AUPRC/AUROC: SVM 0.981/0.996; ANN 0.976/0.993), while the values of the other algorithms serve as baseline references, justified according to expectations reported in the literature.



**Figure 13.** Relative comparison of Machine Learning model performance for PdM of the CT Revolution EVO (composite metric = average of AUPRC and AUROC).

To analyze the behavior of prediction errors, the residuals of the SVM and ANN models were visualized over time (Figure 14). The comparison shows that, although SVM maintains high sensitivity, it often produces larger deviations during periods of high load, indicating a tendency toward false alarms. In contrast, ANN maintains a more balanced distribution of errors around zero, demonstrating that the model better captures the underlying relationships in the data. This result reinforces the conclusion that ANN is more suitable for predictive maintenance of the CT Revolution EVO system, particularly in scenarios with high operational load dynamics.



**Figure 14.** Temporal distribution of residuals for the SVM and ANN models.

The vertical axis represents the difference between the true and predicted values ( $y_{\text{true}} - y_{\text{pred}}$ ), where positive values indicate underestimation (missed OOT events), while negative values correspond to overestimation (false alarms).

Observations:

- The SVM model exhibits a wider error distribution, with pronounced deviations during May–July 2025, coinciding with peak scan workload. This indicates that its sensitivity is high but also more influenced by operational intensity.
- The ANN model shows a more stable distribution around zero, indicating better stability and smaller errors across different time periods. This confirms the advantage of neural networks in learning nonlinear relationships between system variables.

Residual analysis helps in understanding the nature of systematic errors, suggesting that to improve overall performance, the models could be retrained with higher weighting for events occurring during hours and months of higher workload.

#### 4.5. Benefits and Potential Implementation

The implementation of a predictive maintenance system on the CT Revolution EVO provides significant technical and operational benefits.

This system helps not only to reduce unexpected downtime but also to improve planning and management of technical resources.

The main benefits include:

- Reduction of downtime by up to 40%, allowing continuous operation of the device in high-load clinical environments.
- Optimization of maintenance scheduling, as interventions are performed based on the actual condition of the system.
- Increased component lifespan due to early diagnosis of potential issues.
- Potential integration with central maintenance management systems (CMMS), where generated alarms can automatically create tasks for responsible technicians.
- Capability for connection with monitoring dashboards such as Grafana or Power BI, enabling real-time visualization of system parameters and historical performance analysis.

The data collected from smart sensors can be transmitted to a local or cloud database, where the status of each component can be displayed through a visual interface (dashboard). In case of an anomaly, the system sends an automatic notification to the CMMS or via an API to a platform such as Power BI, enabling immediate response and data-driven decision-making.

## 5. Conclusions

This paper addressed the topic of predictive maintenance of the CT Revolution EVO scanner through Machine Learning and Smart Sensor Network. The main basis of the paper was the development of a proactive maintenance approach for the efficiency and long life of diagnostic CT, specifically the Revolution Evo.

In the implementation phase of the developed predictive maintenance approach, various Machine Learning models (SVM and ANN) were tested for the analysis of sensor data and logs of the CT Revolution EVO system.

The results showed that the training models can identify small deviations in the system's behavior, which in real conditions would precede mechanical or electronic defects.

It was found that with the application of this method, the probability of unexpected breakdowns is significantly reduced, as the system can signal in real time for anomalies, such as:

- Unusual heating of the X-ray tube,
- Increased voltage in the DAS system, or
- Decreased ventilation efficiency.

However, although physical breakdowns cannot be eliminated, they can be predicted and managed much more effectively through continuous data analysis.

Furthermore, it can be said that the implementation of predictive maintenance in CT Revolution EVO type systems does not eliminate the possibility of defects, but significantly reduces their frequency, improving the safety, efficiency and availability of the device in clinical settings.

For further developments, it is proposed to implement more advanced models such as Autoencoder, Random Forest, or Deep Learning LSTM for time series-based prediction and expand the application to other diagnostic devices.

**Supplementary Materials:** The supporting information can be downloaded at the following link: <https://github.com/blertastatovci/Smart-Sensor-Network-with-ML-Based-Predictive-Monitoring-for-CT-Systems>.

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## Abbreviations

The following abbreviations are used in this manuscript:

CT	Computed Tomography
FBP	Filtered Back Projection
ML	Machine Learning
CMMS	Central Maintenance Management Systems,
IOMT	Internet of Medical Things
ANN	Artificial Neural Network
OOT	Out of Tolerance
DFOV	Displayed Field of View
LSTM	Long Short-Term Memory
SVM	Support Vector Machine
DAS	Data Acquisition System
AUROC	Area Under the Receiver Operating Characteristic
AUPRC	Area Under the Precision–Recall Curve

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