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# Leveraging AI and Machine Learning to Maximize Machine Uptime & Utilization

ebook for Healthcare Industry


# Contents



*"The number of signals coming from connected machines in the IoT market have surpassed the ability for humans to keep track of them years ago. I am excited to see Glassbeam taking a leadership role in leveraging artificial intelligence to change the rules of the game for the healthcare market.*

**Lise Getoor**

Professor of Computer Science and
Associate Dean of Research
UCSC's Baskin School of Engineering

# Introduction

The pressures facing healthcare delivery organizations are well documented: increased regulatory oversight, financial challenges, heightened competition, a shrinking talent pool, and many more.

Also well-known is the army of consultants, systems integrators and technology companies promising that their solutions will address one or more of these market trends. All too often, implementation fails to deliver the promised results, leaving the healthcare organization with a big bill and little to show for it.

What if there were new solutions, built on the powerful capabilities of artificial intelligence (AI) and machine learning (ML) that provided proven, quantifiable cost savings of 30% or more, and consistent improvements in uptime for some of the most expensive equipment healthcare facilities operate?

Harbor Research, a leading strategy, and technology research firm, notes utilizing AI/ML to leverage complex machine data from healthcare imaging equipment alone will provide $11.1 billion in revenue value (decreased costs/increased revenue generation) by 2022.

AI/ML has the potential to positively disrupt how healthcare organizations use machine data. Effectively leveraging this class of unstructured data and combining that with other data sources such as DICOM, HL7, CMMS, and RIS systems can enable healthcare delivery organizations to:

- Maximize machine uptime; reduce costs and optimize revenue.
- Meet more stringent standards for medical equipment maintenance.
- More rapidly train technical staff and monitor staff performance.
- Track equipment utilization rates.
- Determine capital purchase needs.

# What Challenges Do AI and ML Solve for Connected Medical Equipment?

Medical devices such as Computed Tomography (CT), Ultrasound, X-ray, Positron Emission Tomography (PET), and Magnetic Resonance Imaging (MRI) machines have not only high upfront acquisition cost, but also high maintenance cost. For instance, their parts breakdown for various reasons such as normal wear and tear, incorrect usage or improper maintenance, consequently disrupting patient care and loss of revenues.

For example, one of the critical components in a CT scanner is an X-Ray tube, which generally needs to be replaced within 2-3 years depending on usage; however, many times tubes fail prematurely due to lack of proactive analysis on its error conditions, leading to several days of downtime at a facility.

Most clinical engineering departments follow one of the two popular approaches for handling part failure or breakdown. They replace parts either reactively or on a time-based schedule. In the former case, a part is replaced when it malfunctions or stops working. In the latter case, a part is replaced on a predetermined maintenance schedule irrespective of whether it is giving any problem.

The traditional approaches for handling part breakdowns described above are inefficient. In the reactive approach (replace on failure), a part can fail at an unexpected time and cause extended machine downtime due to the time required to locate, order and receive a replacement part and schedule a technician to do the replacement. It may take 1-3 days for a replacement part to arrive. During this time a device cannot be used and thus an expensive asset sits idle.

On the other hand, if a part is replaced on a predetermined schedule, it may get replaced prematurely. A part may have material service life remaining at the time it is replaced. Thus, this approach causes wastage.

## Specific examples of challenges facing Clinical Engineering Departments today

- Predicting CT Scanner parts that can fail well in advance, so that unplanned downtimes can be avoided – X-ray tubes, Collimators, Digital Acquisition Systems
- Predicting MRI part failures so that unplanned downtimes can be avoided – Coldheads, Gradient Amplifiers, Coil malfunctioning
- Identifying problems in the environmental data that if not fixed early can cause MRI quenches and critical parts to fail – Compressors, Chillers, Room humidity, Water temperature
- Looking for anomalies on hundreds of parameters within the specific component, across connected components or outside the system as an early indicator to a possible failure
- Tracking and forecasting capacity utilization by each facility and machine to optimize utilization

# What Does an AI and ML Solution Look Like?

There are two broad ways to use AI and ML technology with connected medical equipment fleet: 1. Predictive maintenance by deploying Part Failure (PF) models and 2. Proactive maintenance using Anomaly Detection (AD) models.

Predictive maintenance can predict the failure of a part a few days before it happens. Therefore, a replacement can be ordered a few days before it is needed. This approach minimizes the unplanned device downtime when a part fails. At the same time, it eliminates the need to prematurely replace an expensive part.

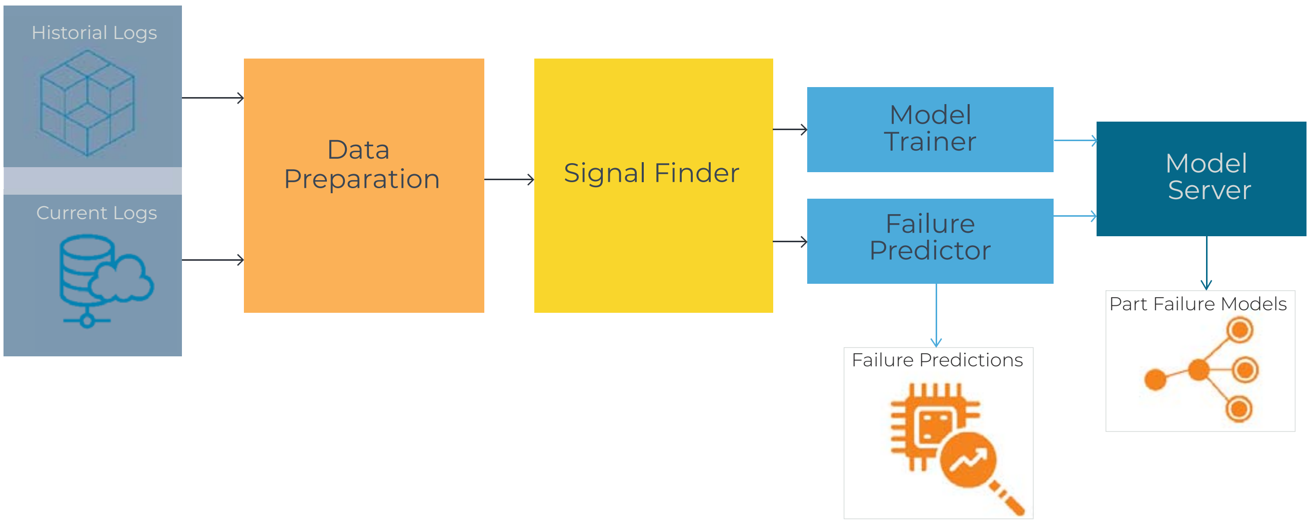
Proactive maintenance is founded on the principles of analyzing how certain attributes, individually or as a correlated group, behave within set thresholds, flagged either by supervised or unsupervised machine learning techniques. Such ML models offer a far better approach than rule-of-thumb for identifying abnormal or extreme sensor values. Instead of using heuristics or relying on domain expertise, ML-based anomaly detection techniques use historical data to infer the boundaries for the normal range of values for a sensor.

Glassbeam is a pioneer in spearheading advanced solutions for the healthcare industry based on these AI/ML techniques. We have created the patent-pending machine learning technology to predict part failures in medical devices such as X-ray tube failures in CT Scanners. These are the essential components of our artificial intelligence technology stack used in predictive maintenance programs used by leading healthcare providers and offered as value added services among our partners.

> *"Glassbeam's cloud-based solution gives our service engineers real-time dashboards, alerts, and alarms on the health of the equipment they support. We are excited to be partnering with Glassbeam on this journey and expanding our solution coverage to include other imaging modalities.*

**Corey Holtman**

Co-Founder & CFO
Gateway Diagnostic Imaging, Texas



# Stages of Designing AI and ML Solutions

Methodologies for building predictive and proactive maintenance solutions differ as they deal with different kinds of data attributes and ML algorithms.

As an example, for detecting anomalies in sensors values or readings consist of two key steps. First, a model has to be trained with historical values recorded by a sensor. Second, the current value of that sensor is provided as an input to the trained model, which returns a decision indicating whether that value is normal or anomalous.

Step one is referred to as the model training and step two is referred to as scoring or inference. Note that the historical sensor values are not labeled as anomalous or normal. Therefore, this is as an unsupervised machine learning problem. Glassbeam extracts sensor values for both model training and inference from the event logs generated by a medical device. However, event log data in its natural form is not directly usable for anomaly detection (AD).

The primary purpose of event logs is troubleshooting, so it captures information in a human-readable format. Moreover, event logs are stored in semi-structured or multi-structured formats. A few data preparation steps are needed to transform event log files to a structured dataset that can be used for AD.

The task of analyzing event logs from a medical device to determine whether a sensor value is anomalous can be divided into the 5 subtasks:

# Benefits of AI and ML Solutions

## Extend the life of expensive parts

- When a part is malfunctioning and failure is predicted, preventive maintenance (PM) can be scheduled to correct the issue without replacing the part. For example:
  - Seal leaks in the line
  - Refill oil/dielectric fluid etc.
  - Cleaning filters
  - Replacing smaller components, such as fans, detector modules, etc.
  - Reconnecting loose cables
  - Drying, degasification, dehydration, and filtration of high vacuum tubes

## Avoid total system failure

- When environmental metrics are not monitored, there is a chance that the system may eventually prevent scanning. For example:
  - Magnet quench
  - Water level too low in the cooling system
  - Compressor down
  - Gantry too hot
  - Tube failing to reach requisite temperature
  - Patient table positioning errors
- Many of these ‘hard down’ issues can be eliminated with predictive maintenance that can be done without incurring any downtime (planned or unplanned).

## Automate service calls

- When a predictive maintenance solution is in place, a manual service call can be eliminated as the system would notify the field service engineer before an end user calls the service center.
- This eliminates the inherent delays in human intervention and relay of critical information.

## Eliminate unnecessary truck rolls

- Field service engineers are typically on-the-move and almost always never at the facility when they receive a service call. They usually need to rush on site to determine the root cause of the problem, identify remedial measures and then return on site a second time to resolve the issue.
- A predictive monitoring solution would give them the info they need to determine these remedial measures even before they go onsite the first time, thereby eliminating the second truck roll.

## Reduce redundant preventative maintenance through predictive monitoring

- Typically, machines are maintained blindly on a schedule (monthly or quarterly), regardless of machine performance.
- With a predictive maintenance solution, there is advance notice when an issue is likely to occur, so PM can be scheduled around that instead of being time-bound. So if the machine is running well, monthly PM can become quarterly. Or Quarterly PMs can reduce to 3 or 2 PMs a year.

## Eliminate unplanned downtime

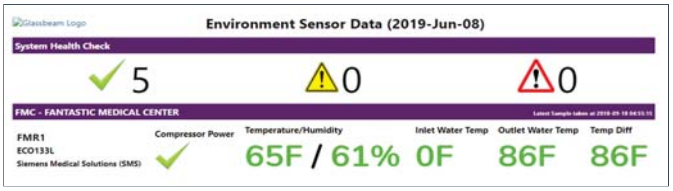
- When one can schedule preventive maintenance instead of reacting to an emergency system down, one moves the maintenance period from operating hour to lean or off hours. This dramatically improves system availability during operating hours, thereby increasing system utilization and uptime.
- As a byproduct, this improves the patient experience as the last thing any patient wants is a system failure during a scan, being moved to another room or getting stuck in a queue due to last-minute rescheduling.

# Specific Use Cases

## Forecast Cooling Issues

How to implement the program:

- Track and forecast environmental parameters
  - * Room temperature and humidity
  - * Cabinet Temperature and humidity
- Track and forecast on external cooling parameters
  - * Magnet pressure
  - * Helium level
  - * Cold head temperature & duty cycle
  - * Water flow and temperature
  - * Compressor power
- Track and forecast on internal system parameters
  - * Gantry temperature
  - * Exam room temperature
  - * Heater outlet temperature
  - * Plenum and rail temperature
  - * Gantry fan speed
  - * Component voltages
  - * Detector module temperatures
  - * CPU and board temperatures




## Predict Tube Failures

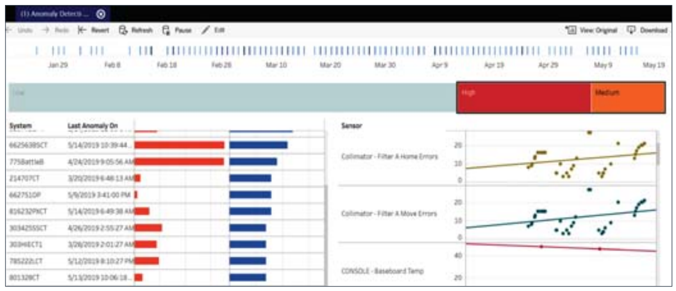
How to implement the program:

- Track tube lifetime
  - * Tubes are usually expected to reach the end of life after 700K scan seconds or 70 to 150M millamp seconds (mAs)
- Track tube arcs
  - * Every tube arc results in a minor reduction in the life of a tube. Arcs are expected to happen every now and then, but how often is it happening? This directly relates to the life of the tube.
- Track error codes
  - * Tube issues can manifest in the form of various error codes, such as overheating, image artifacts, scanning errors out of tolerance, mA out of range, hardware warning, etc.
  - * A predictive model on this combination of errors can result in effective tube failure prediction

## Anomaly Detection on System Parameters

How to implement the program:

- Track all system metrics and build statistical anomaly detection on
  - * Tube arcs/spits
  - * Filter move errors
  - * Gantry, rail, plenum temperatures
  - * Fan speed
  - * Network send/received errors and retries
  - * Packets drops
  - * Collimator errors
- Track number of anomalies and rates of increase in anomalies
  - * Usually these anomalies are pre-indicators to component failures,
  - * So alerts based on these would result in many system problems being resolved ahead of time




*“Data transformation is the unspoken bridge between connectivity and analytics. As connected machines become more pervasive and intelligent, there is a huge untapped market opportunity for data management, transformation, and eventually analytics with machine learning for multi-structured log data. Glassbeam is purpose-built to address these challenges, allowing end-users to realize new levels of value from data, while also achieving significant predictive cost and time savings.*

**Glen Allmendinger**

Founder and President
Harbor Research

# Assessing Business Impact of AI and ML Driven Maintenance Programs

Healthcare delivery organizations must be intently focused on maximizing the uptime of their machines to earn maximum revenue and provide optimal patient care. Downtime for expensive equipment is a revenue death spiral for healthcare organizations.

Here's an example of how much those costs can total: an MRI machine can provide on average of $2,500 in revenue per hour of service. If a machine goes down for 24-48 hours, the revenue loss to the hospital ranges from $60,000 to $120,000. Assuming the system goes down five or six times per year, the annual downtime can result in loss of revenues between $300,000 to $720,000. If the healthcare delivery organization has 10 MRI machines, the total annual revenue loss can be $3M to $7.2M! If the facility can reduce repair time to four to six hours and each machine only goes down two or three times per year, the annual revenue loss drops dramatically by over 50%.

Another revenue drain is policies regarding the frequency of parts replacement. OEMs may state certain critical parts in their MRI and CT scanners should be checked and replaced every few months as part of a preventive maintenance (PM) schedule. However, these parts can malfunction at any point in time, depending upon hundreds of operational machine data parameters inside these machines. A good example is an x-ray tube in a CT scanner.

Many times provider organizations procure x-ray tubes three months in advance as part of their budgetary cycle without any data-driven inputs on a machine's actual health. They end up replacing tubes when actually the fault lies in some other mechanical part of the system. Optimal replacement times for parts should instead be reliant on several data inputs based on the age of the machine, a number of scans performed, image quality rendered and other machine data signals. Without proper diagnostics, many healthcare organizations incur extra costs from either excessive downtime or needless replacement of expensive parts.

Increased regulation can also hinder revenue optimization. In 2013, the Centers for Medicare and Medicaid Services (CMMS) and other accreditation agencies, revised their equipment maintenance standards. They now require that hospitals must strictly follow all OEM maintenance recommendations on all equipment.

OEMs tend to be conservative in their maintenance recommendations to avoid legal liability. This strains a facility's budget in two ways: First, increased maintenance negatively impacts the hospital's budget by requiring machines be taken offline more frequently, and, as noted above, replacing parts on a time basis versus a needs basis can end up costing the hospital more.

A third benefit of deploying AI/ML to leverage machine log data involves personnel. Many experienced clinical engineers are retiring or otherwise leaving healthcare delivery organizations. With the unemployment rate at an 18-year low of 3.9%, it can be difficult to find qualified replacements. Predictive and prescriptive analytics generated by AI/ML solutions can provide both insights into machine performance, as well as direct more junior clinical engineers what activity is required to ensure maximum uptime.

In addition, AI/ML solutions monitor the performance of equipment while clinical engineers are performing scans and other services, and can offer insights into how the engineers can improve their efficiency.

> "*We have recently adopted what we consider a game-changing AI/ML solution to help us facilitate service management, asset utilization and performance improvement, all as part of the UCSF Health's 2020 strategic goals. Reducing or eliminating costs of service level agreements for parts, software and service, based on service intelligence derived from AI/ML provide cumulative metrics for each imaging system.*

Ramana Sastry

Director of Clinical Engineering
UCSF Medical Center

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## About Glassbeam

Glassbeam is disrupting the status-quo as a comprehensive fleet-wide analytics solution for analyzing machine uptime and utilization data in a single pane of glass. We are the premier machine data analytics company bringing structure and meaning to complex data generated from any connected machine in the Industrial IoT industry. Our next- generation cloud-based platform is designed to transform, analyze, and build Artificial Intelligence applications from multi-structured logs, for proactive/predictive maintenance. We proudly partner with Smart hospitals to provide a true competitive advantage in the delivery of care.

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