Predictive Maintenance for Legacy Shipyard Machinery

Building Retrofit Hardware, Digital Twins, and Machine Learning Models to Assess Machine Health and Prevent Downtime

ELECOMP Capstone Design Project 2026-2027

Sponsoring Company:

Arcfield
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Company Overview:

Arcfield is a systems and digital engineering company, purpose-built to relentlessly protect the nation and its allies from today's national security threats. We have nearly 70 years of proven expertise and excel in space superiority, hypersonic defense and nuclear deterrence, digital transformation, and surface and undersea warfare domains. Our solution areas include space mission engineering, atmospheric science, digital engineering, mission assurance, and advances in modeling and simulation that together with our enterprise-wide adoption of artificial intelligence and machine learning, lead to better systems and timely, reliable decision-making.

Headquartered in Chantilly, VA with 18 North American offices, Arcfield employs 2,200 engineers, scientists, analysts, IT specialists and other professionals. Visit arcfield.com for more details.

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Project Motivation:

Today, the United States constructs less than 1% of the world's commercial ships, reflecting a significant decline in America's shipbuilding dominance. On April 9th, 2025, an Executive Order "Restoring America's Maritime Dominance" was signed, highlighting the nation's current lag in shipbuilding capacity and calling for its revitalization through substantial federal investments in shipyard infrastructure and workforce. This has been already visible regionally, the closest shipyard to us in Quonset Point, North Kingstown, Rhode Island, is undertaking an $800 million expansion expected to create 1300 jobs. As these investments heavily scale up production, the reliability of the machinery that carries out this work becomes an increasingly critical concern.

Much of the machinery driving these processes is very costly, and facilities are unlikely to change machines until they fully break down, causing most in-use machines to be decades old. According to the U.S. Bureau of Economic Analysis, the average age of manufacturing equipment in operation is close to 20 years old and has nearly doubled since 1990. Equipment of this generation was never built to report on its own condition, so operators who want modern data analytics or machine learning must first add the needed sensors. In the market today, a full predictive maintenance sensor package will cost several thousand dollars for each machine. That expense is a significant barrier while the need for data collection and analytics is expanding.

The value of crossing that barrier is well established. The U.S. Department of Energy reports that predictive maintenance reduces unplanned downtime by 30 to 50%, lowers maintenance costs by 25 to 30%, and can return up to ten times its initial investment, while unplanned downtime alone costs U.S. manufacturers an estimated $50 billion each year. The obstacle is not whether predictive maintenance works, but how to make the sensing and data affordable enough to reach the large base of older machines that need it most. A low-cost machine-agnostic way to retrofit sensing and generate necessary training data would remove that obstacle and allow predictive maintenance to be applied broadly across existing shipyard and factory equipment. As a defense engineering company supporting Navy readiness and modernization, Arcfield is well positioned to help propel this effort forward at a moment when the nation is investing heavily in its shipbuilding capabilities.

Anticipated Best Outcome:

The Anticipated Best Outcome (ABO) is a working predictive maintenance system that can be added to existing machinery without replacing or invasively changing its parts. This project will integrate with last year's ELECOMP/ISE capstone group's manufacturing testbed. The testbed will become the method of testing and validating the overall predictive maintenance system.

The first is a machine-agnostic retrofit sensor board. This will be a custom PCB that mounts onto an existing machine, and captures physical, electrical, and mechanical data that it does not expose on its own. This includes but is not limited to vibration signals, motor current, temperature, and acoustic sensors.

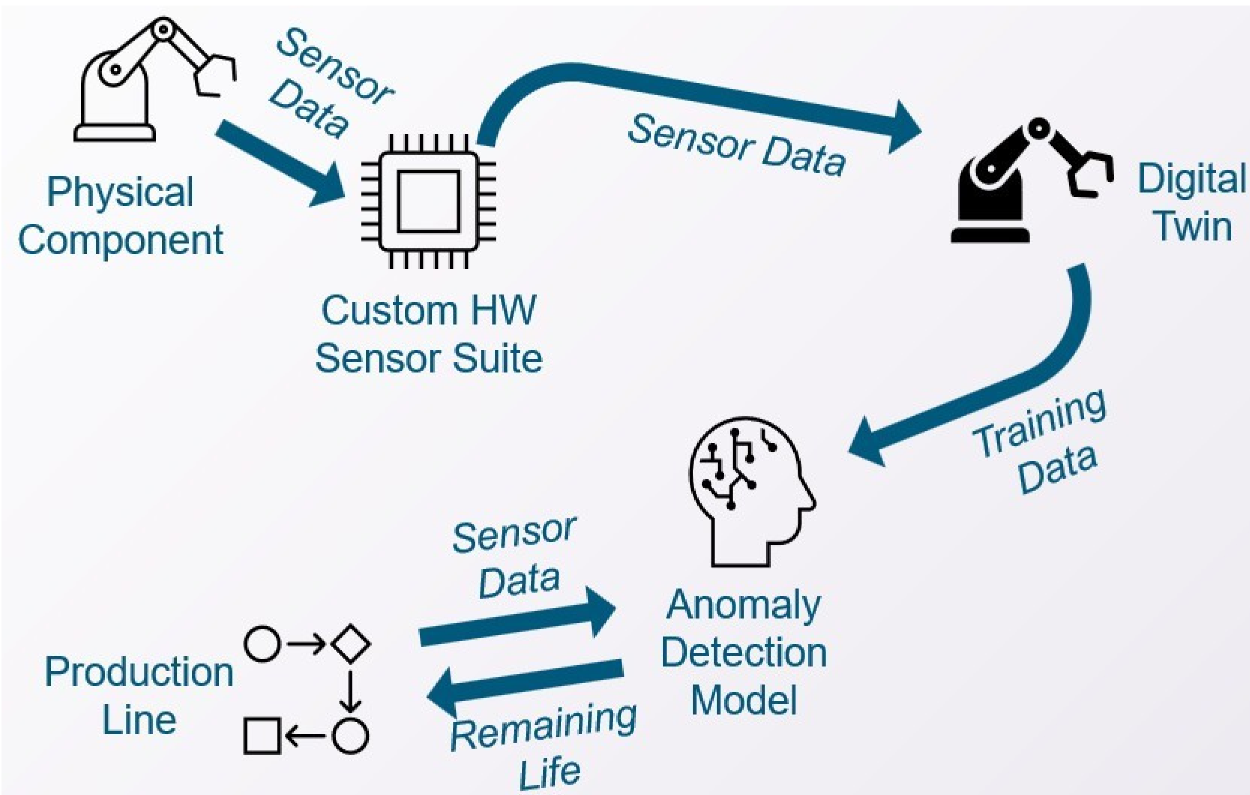
The second is an expanded version of an existing digital twin. Last year's project produced a MuJoCo digital twin of the physical manufacturing line testbed. This year the team will extend it to sweep its physics parameters by generating multiple physics-based scenarios to create labeled examples of the testbed's normal state, as well as the wear and degradation for each machine. This creates a training dataset before any machine actually wears out, while also supplying the kinematics data needed for part three.

The third is an ensemble of three (or more if the team sees fit) anomaly detection machine learning models that work together to judge machine health. The first model trains on the kinematics data from the digital twin, the second on real ROS2 network data from the real testbed, and the third is trained on real data from the functioning testbed.

In the ABO, the board is validated across one or more machines to prove the design is machine-agnostic, and the finished system is tested against both induced wear and simulated attacks to show it can distinguish between the two.

Project Details:

The overall system consists of four connected parts, shown in Figure 1: the production line (a physical testbed ready for use), the retrofit sensor PCB, the digital twin, and the ensemble anomaly detection machine learning models that produce a predictive maintenance pipeline that is repeatable between machines.



Phase 1: Research and Requirements

In this initial phase, the designers build a shared understanding of the project and its foundational topics, including predictive maintenance, retrofit sensing, digital twins, ROS2, data analysis, and machine learning techniques. Designers are expected to research existing approaches to each and define requirements the system must meet.

In the second part of this phase, designers work with the technical directors to select the sensors, components, and tools the project will use. Evaluation methods such as Pugh matrices will be used to justify selections before moving into the design phase.

Phase 1 – Electrical/Hardware Tasks:

- Research sensing modalities for machine health (vibration, motor current, temperature, acoustics, etc.)
- Define the target machine class and the board architecture (agnostic code with modular current sensing, and modular connectors)
- Use Pugh matrices to select sensors, ADC, and microcontroller

Phase 1 – Firmware/Software/Computer Tasks:

- Research digital-twin based synthetic data generation
- Research ensemble machine learning methods, with a focus on anomaly detection
- Stand up the existing MuJoCo digital twin
- Gain an understanding of the existing ROS2 network
- Select machine learning approaches for each model
- Select accuracy metrics used for evaluation

Phase 2: Schematic and First ML Model

In this phase, the team will move into designing the various pieces. On the hardware side, the sensors to be used on the board are first validated through breadboards and bench testing. On the software side, the digital twin generates a normal dataset and one abnormal dataset, where the first machine learning model is trained on normal and is asked to detect abnormal.

Phase 2 – Electrical/Hardware Tasks:

- Design the retrofit sensor PCB schematic using a software tool the designers are most comfortable with (e.g. KiCAD, Altium)
- Build a breadboard prototype to verify the sensors work together
- Validate the prototype on a real machine and adjust the layout based on findings
- Select final components and generate a bill of materials **Phase 2 –**

  Firmware/Software/Computer Tasks:

- Develop the board firmware on the chosen microcontroller for data acquisition and timestamp synchronization, and test it on the breadboard circuit
- Set up a common data pipeline that ingests both the twin’s data and the testbed's real ROS2 data in the same format, which could lead to the development of a database
- Using the twin’s kinematics datasets, perform exploratory data analysis (EDA) and build the first anomaly detection model

Phase 3: PCB Layout and Network Model

In this phase, the validated schematic is turned into a manufactured board, and the second machine learning model is built. On the hardware side, the team lays out the PCB, holds a design review, finalizes the bill of materials, and orders the boards and parts before end of semester so they arrive over the winter break. On the software side, the team builds a ROS2 network anomaly detection model from the ROS2 data captured from the real testbed and begins integrating it with the first model into a single operator view.

Phase 3 – Electrical/Hardware Tasks:

- Lay out the PCB from the validated schematic
- Conduct multiple rounds of design review and validate the layout with chosen software (e.g. design rule checks (DRC) in KiCAD)
- Finalize bill of materials
- Order the boards and parts with enough lead time to arrive before the spring semester begins

Phase 3 – Firmware/Software/Computer Tasks:

- Process and organize the ROS2 network traffic dataset that will be provided by the team operating the testbed
- Build the network anomaly detection model from that traffic dataset
- Integrate the physics and network models, and test and validate them separately and together

Phase 4: Finalizing PCB, Data collection, and Sensor Model

In this phase, the ordered boards arrive and the system comes together. On the hardware side, the team assembles and brings up the boards, verifies each one works, mounts them noninvasively across the different machines, and begins data-collection. This is all done with the assistance of the ISE team operating the testbed. Once data is collected, the software team performs EDA to ensure data integrity, then trains the third model, and fuses all three together.

Phase 4 – Electrical/Hardware Tasks:

- Assemble, solder, and bring up the PCBs
- Test and verify each board (power, all sensor channels, timestamps, synchronization) against known references
- Mount the boards non-invasively across the different machines

- Establish a normal baseline with the sensors installed, and induce abnormal behavior to ensure it is captured
- Validate the machine-agnostic claims by sensor collection using the same board across several machines

Phase 4 – Firmware/Software/Computer Tasks:

- Obtain the data collected, perform EDA to ensure integrity
- Train the sensor ML model on the real data collected
- Fuse three models together into an ensemble
- Evaluate the ensemble against the functioning testbed

Phase 5: Adversarial Testing and Validation

In this final phase, the team stresses the completed system and delivers the results. On the hardware side, an attack or fault scenario is run on the physical machine(s) to see how failures propagate through the testbed. On the software side, simulated attacks are run against the twin, network, or models, to test whether the system can detect the attacks.

Phase 5 – Electrical/Hardware Tasks:

- Design and run a hardware attack or fault scenario on the testbed
- Analyze cascading effects of the attack across different systems deployed, e.g. digital twins, ML models, other machines, etc.
- Finalize the machine-agnostic board design package

Phase 5 – Firmware/Software/Computer Tasks:

- Run simulated attacks against at least one part of the system, e.g. the digital twin, ROS2 network, or model
- Test whether the system can detect induced tampering, and differentiate an attack from normal wear
- Produce accuracy reports across repeatable tests, showing the models behave consistently, validating them

Composition of Team:

1 Electrical Engineer, 1 Computer Engineer, 1 Double ELE/CPE

Skills Required:

Electrical Engineering Skills Required:

- PCB schematics and layout design
- PCB design software (e.g. KiCAD, or Altium)
- Analog and sensor interface circuit design
- Digital circuit design and validation
- Microcontroller programming and embedded firmware
- Soldering, and hardware bench testing

Computer Engineering Skills Required:

- Python
- ROS2
- Data analysis and exploratory data analysis (EDA)
- Machine Learning (ML) with a focus on anomaly detection
- Basic understanding of networking protocols (e.g. TCP/IP, IPv4, MQTT)
- Familiarity with simulation or digital twins (e.g. MuJoCo) is a plus

Anticipated Best Outcome's Impact on Company's Business, and Economic Impact

Arcfield is an early adopter of emerging technologies aligned with evolving government and commercial needs. Currently, there is no open-source agnostic retrofit PCB that could provide standardized data about the physical health of various machinery in shipyards and manufacturing facilities, which is accompanied by machine learning models for continuous monitoring and predictive maintenance. The unavailability of such a platform poses a significant barrier to continuous operations and can open up different opportunities to increase machine health analysis and decrease downtime in our own manufacturing facilities.

Broader Implications of the Best Outcome on the Company's Industry:

The White House executive order not only called for the building of commercial ships to regain global dominance but also called for workforce development, technological advancements, and a huge emphasis on increasing the security and resiliency of the overall process. This capstone project is a step forward in aiding research and development around this widely critical topic. Providing this agnostic solution can allow for deeper analysis in this deeply important field.

Appendix A: AI Usage Policy

Allowed

- Students may use AI tools for

☒ brainstorming support

☐ concept development (**AI can be used for educational questions not for decision making, developing new concepts, or ideation)**

☒ literature and publicly available documentation review

☒ software development **(AI can assist in generating software development and code generation but code must be reviewed by one or more designers before integration)**

☒ debugging

☒ data analysis **(Analyzing, exploring and understanding data and trends should be done by designers. AI can assist in developing EDA code or explaining concepts)**

☐ test development **(Thinking and developing test cases should be done by designers, AI can assist in developing the test code and monitoring long ongoing tests)**

☒ non-proprietary paragraph editing

☒ non-proprietary single-slide formatting

☐ preparation of project deliverables **(AI can be used for review and formatting of project deliverables)**

☐ note taking or transcription of meetings

☐ Others: ______________________________

Not Allowed

- Using AI in violation of university policies, applicable laws, or course-specific rules identified by capstone instruction team and project-specific rules identified by the technical directors.
- Entering proprietary, confidential, personally identifiable, security-sensitive, or otherwise restricted information into an AI system without authorization.
- Submitting AI-assisted work without understanding, reviewing, verifying, and appropriately disclosing its use.
- Submitting entire documents or presentations to an AI system for editing or formatting.
- Any unchecked items from the allowed list above.

Requirements

- If any use is allowed, AI tools may only be used to enhance, but not replace, students' technical reasoning, engineering judgment, and understanding. Students must be able to explain, justify, and defend all submitted designs, code, analyses, test results, documentation, and conclusions.
- During the first two weeks of the project, the student team shall work with the Technical Directors to: identify any proprietary or confidential information that may be involved in the project; determine what information may or may not be shared with AI systems; identify the AI tools, models, accounts, and configurations approved for project use; and document any project-specific restrictions or approval requirements.
- Students shall transparently document the uses of AI using the URI CYPHER AI Usage Marking guidelines (https://web.uri.edu/cypher/ai-marking/). A workshop is planned for September to familiarize students with these guidelines.
- Students retain full professional responsibility for all design decisions, analyses, implementations, testing, documentation, presentations, and final deliverables, regardless of whether AI tools contributed to the work.